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Household Finance and Wealth Management:
The Influence of Income and Human Capital on Portfolio Strategies

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Summary

INTRODUCTION

Context and Motivation of the Study

The term "economics" comes from the Ancient Greek οἶ'κονομία —the combination of οἶκος ("house") and νόμοος ("custom" or "law")—regarding household management. In the classical economic theory, Aristotle and Xenophon described oikonomia as the art of managing family resources to ensure well-being; however, as political economy evolved, the concept expanded to include the functioning of national and global markets, leaving the realm of families behind.

Today the term encompasses a broader field of studies of which, only recently, "Household Finance" emerged as an autonomous branch and earned his own identity. In 2006 John Campbell coined its name and highlighted the need to study families not only as consumers, but as complex financial actors. This development marks a return to the roots of economics, recognizing the importance of household financial decisions in the modern context.

Traditionally financial economics was divided into asset pricing and corporate finance studies, taking in consideration household finance only in the field of asset pricing. During the years the importance of the financial services and instruments used by households has been highlighted: Peter Tufano in his study "The size of the industry" (2011) points out how the total value of US assets held by households in 2010, according to the FED, was $72 trillion, of which $48 trillion were financial assets, while the rest tangible assets (real estate for the most part), while liabilities hover around $14 trillion in debt (mostly mortgages).

As a benchmark: corporations have $28 and 13$ trillion in assets and liabilities; so families hold twice as much assets and as much debt as corporations, hence traditional financial theories have largely marginalized household behavior in favor of corporate and institutional agents.

Recent updates indicate that household assets have grown further, driven by rising real estate prices and the expansion of financial markets, but also accompanied by growing inequalities in the distribution of wealth. These disparities require a more in-depth analysis of household financial behavior to develop fairer economic policies.

Households face and manage many difficulties:

- **Propriety and Health**.
- Paying for **goods and services** through checks, savings and credit cards.
- They invest in **durable goods** like vehicles and residence houses.
- They invest in **human capital** through their children's education.

Which generate financial risks such as:

- **Debt**: Many families are heavily dependent on mortgages and consumer loans, with high exposure to interest rates.
- **Asset risk**: Fluctuations in real estate and financial markets can erode the value of family assets.
- **Income volatility**: Linked to unemployment, changes in labor markets and economic instability.

Non-financial risks include unexpected health expenses, elder or childcare needs, and educational costs. These risks are intertwined with financial choices, influencing families' ability to save and invest, so they take decisions by personally gathering information about financial instruments and markets or they can rely on third-party advisors. During the years many normative models have been proposed and used as benchmark for a well financial behavior, but many biases act when agents face the task of managing their household's finances:

- **Loss aversion:** Individuals give more importance to on losses than gains of equal value, leading to under participation in stock markets.
- **Overconfidence:** excessive confidence in one's abilities can lead to suboptimal decisions, such as undiversified or risk-clustered investments.
- **Temporal bias:** the present tends to be overestimated compared to the future (present bias), leading to underestimation of retirement savings.
- **Endowment effect:** individuals attribute greater value to the assets they already own, hindering diversification.

In recent decades household financial behavior has been influenced by factors such as income inequality, credit rationing and changes in housing markets, moreover the rise of fintech are revolutionizing the way families manage finances. Platforms such as robo-advisors, financial management apps and peer-to-peer lending tools offer new investment and savings opportunities, often accessible even to individuals with limited skills; that, coupled with external shocks like the global crisis of 2008 and the COVID-19 Pandemic, shows the vulnerabilities of families. During these crises, many families have experienced reduced income, increased debt, and difficulty coping with sudden expenses. At the same time, the pandemic has accelerated the adoption of digital technologies, pushing families to integrate fintech tools into their daily financial decisions.

This field also examines the influence of institutional environments, limited and uneven financial sophistication, and the need for specific regulations to protect households. Unlike corporate finance or asset pricing, it focuses on the financial decisions of the average household rather than wealthy, financially sophisticated individuals. Moreover, households have characteristics that distinguish them from other economic agents, including the opportunity to leverage a source of income throughout the life cycle, namely Human Capital: an intangible and non-transferable asset that carries idiosyncratic risk, cannot be insured against, is difficult to predict, and accumulates slowly over the course of an individual's life.

SECTION 1 - LITERATURE

Within this field, the relationship between household characteristics (e.g., human capital, age, gender, education, and regional differences) and portfolio composition has been widely explored. However, key gaps remain in understanding how these variables interact over time and how they influence long-term financial outcomes. For instance, while previous studies have examined the impact of education on investment in risky assets, less attention has been paid to the interplay between regional economic conditions and household decisions.

In Campbell's study "Household finance" (2006), published in The Journal of Finance, he makes a distinction between *positive household finance*, represented by what households actually do and *normative household finance*, represented by the body of knowledge about what households should do. For many households the discrepancies between observed and ideal behavior are rationalized by small frictions ignored by standard theory and have minor consequences, but for the minority composed by poorer and less educated ones, there are larger discrepancies and more serious consequences, called *investment mistakes*, central to the field of HF.

Positive hf asks how households actually invest, but the answer is challenging since they tend to guard their financial privacy jealously. That's why most of the choices about their portfolio is studied through surveys. At the time the most complete dataset on financial wealth was thought to be the Survey of Consumer Finances (SCF), conducted in U.S., which had a good coverage on all aspects of wealth (liquid and illiquid assets) and sampled the wealthy, thus disproportioning the influence on asset demand. The issue was that it could shed light on diversification because it was not disaggregated enough. Other surveys had similar problems: the Panel Study of Income Dynamics (PSID) asked questions on wealth every 5 years, but financial assets were divided into only three broad categories that correspond roughly to cash, bonds, and stocks. In the present study we will use modern datasets mostly regarding Eurozone and Italy:

- **SHIW**: Survey on Household Income and Wealth
- **HFCS**: Household Finance and Consumption Survey

Normative household finance asks how households should invest and standard textbooks have tried to answer this challenging question trying but they used to neglect the many implications

In the past ten years several contributions have re-examined the life-cycle behavior of investor portfolios. Inspired by empirical findings from novel microeconomic data on household finances, several papers have provided new models of optimal portfolio rebalancing over the life cycle that go beyond the seminal dynamic framework of Merton (1969, 1971), Mossin (1968) and Samuelson (1969). The Merton-MossinSamuelson (MMS) models generate two sharp predictions. First, individuals should participate in risky asset markets at all ages—a proposition that extends to a dynamic context the participation principle . Second, the share invested in risky assets should not vary over the life-cycle. The implications of the MMS model are in contrast both with the limited participation that we observe in the data at all ages and with the widespread advice of the financial industry to invest substantially in stocks when young and reduce the exposure to the stock market when older—an advice that translates into the popular rule of thumb of investing a share of financial wealth in stocks equal to 100 minus the investor's age (e.g. 75% in stocks when 25 years old and 25% when 75). We are then naturally faced with two questions. First, is it possible to reconcile the recommendations of professional financial planners with the normative predictions of dynamic portfolio choice by relaxing the restrictive assumptions of the early models? Second, how do investors actually choose their risk exposure over their lifetime?

SECTION 2 – Data

To analyze the national context and carry out the research, a database based on the Survey on Household Income and Wealth (SHIW), launched in the 1960s to collect data on the income and savings of Italian families, was used. Over the years, the survey has expanded its scope, now also including information on wealth and other aspects of the economic and financial behavior of families, such as payment methods used.

The sample used in the most recent surveys includes about 7,000 families (16,000 individuals), distributed across about 300 Italian municipalities in the 2020 wave.

The results of the survey are published regularly in the statistical series of the Bank of Italy. The data on families are freely available, in anonymous form.

A description of the Historical Archives and the variables they contain is included, as well as information on the panel component of the sample and the questionnaires used in each edition of the survey. An Excel file with the historical series of a large set of economic indicators is available in the section dedicated to the survey results. Data on the main economic indicators are also available in the Statistical Database (BDS).

To analyze Italian condition in the Euro-System landscape, we will instead use the Household Finance and Consumption Survey (HFCS).

2.1 SHIW

Figure 1, Banca D'Italia – Logo

Information about the survey:

- Survey period: every 2 years (biennial), starting from 1965.
- Latest available waves: until 2020 (data published in 2022).
- Sample: approximately 7,000 families, equivalent to approximately 16,000 individuals, distributed across approximately 300 Italian municipalities.

- Collection method: direct interviews (CAPI – Computer-Assisted Personal Interviewing).
- Representativeness: representative sample of the population resident in Italy, stratified by geographical area and demographic size of the municipality.
- Panel: includes a panel component (families interviewed in multiple waves) useful for longitudinal analyses.

Main information contents:

- Family and individual income
- Work and employment conditions
- Financial assets and liabilities
- Real estate wealth
- Expenditure and consumption
- Debts and mortgages
- Saving habits
- Use of financial instruments
- Education and demography

Accessibility and use:

The anonymous microdata are freely available for study and research purposes through the Bank of Italy website.

Summary of Content:

Information are broken down according to the main characteristics of the head of household. The data are collected biennially from 1977 to 2020, on a national sample basis, and refer to collected answers, ex post through direct interviews.

The categories of the head of households in most of the tables considered are:

1. Gender of the head of household

- Male
- Female

2. Age of the head of household

- 30 years and under
- 31–40 years

- 41–50 years
- 51–65 years
- Over 65

3. Educational qualification

- Up to primary school diploma
- Lower secondary school diploma
- High school diploma
- University Degree

4. Employment status

Employees, further divided into:

- Workers
- Employees
- Officials
- Managers
- Self-employed, further divided into:
- Freelance professionals
- Entrepreneurs or generic self-employed workers
- Not employed

NB: some sub-categories are not available in the first years of the survey (indicated as "not collected" or with dots ".").

5. Country of origin

- Italy
- Other (foreigners or immigrants)

6. Geographical area of residence

- North
- Centre
- South and Islands

7. Total

Overall average for all families.

Example, Historical Table S12 – SHIW :

Characteristics		Survey year 1977	1978	1979	…
Gender					
male		3457	4282	5067	…
female		2420	2958	3427	…
Age					
30 and under		3616	4577	5155	…
31-40		3565	4253	5271	…
41-50		3704	4629	5685	…
51-65		3673	4346	5027	…
over 65		1823	2407	2655	…
Educational qualification					
up to primary school certificate		2708	3132	3640	…
lower secondary school certificate		3431	4409	4908	…
uppery secondary school diploma		4641	5341	6709	…
university degree		6094	7982	9029	…
Work status					
Employee	*not collected*	3594	4402	5161	…
	blue-collar worker	.	.	.	.
	office worker	.	.	.	.
	officer	.	.	.	.
	manager, executive	.	.	.	.
	all	3594	4402	5161	…
Self-employed	*not collected*	4365	5219	6504	…
	member of a profession	.	.	.	.
	business owner, other self-employed	.	.	.	.
	all	4365	5219	6504	..,
Not employed	*not collected*	1759	2207	2501	…
	not employed	.	.	.	.
	all	1759	2207	2501	…
Country of origin					
not collected		3304	4061	4782	…
Italy		.	.	.	.
Other		.	.	.	.
Geographical area					
North		3675	4450	4959	…
Centre		3455	4549	6231	…
South and Islands		2684	3228	3755	…
All		**3304**	**4061**	**4782**	**…**

2.2 HFCS

Figure 2, European Central Bank and HFCS – Logo

Data from the HFCS are also distributed as part of harmonized international datasets. Since 2010, the survey has provided data for Italy for the Eurosystem Household Finance and Consumption Survey, coordinated by the European Central Bank. Here the household reference person is chosen according to the international standards of the so-called Canberra Group (UNECE 2011), which uses the following sequential steps to determine a unique reference person in the household:

- household type [determined by one of the partners in

  a) registered or de facto marriage, with dependent children,

  b) one of the partners in a registered or de facto marriage, without dependent children, and

  c) a lone parent with dependent children]

- the person with the highest income
- the eldest person

Net wealth is defined as the difference between total (gross) assets and total liabilities.

Total assets consist of real assets and financial assets.

Real assets include:

- value of the household main residence (for owners)
- value of other real estate property
- value of vehicles (cars and other vehicles, such as boats, planes or motorbikes)

• value of valuables

• value of self-employment businesses of household members.

Financial assets consist of:

• deposits (sight accounts, saving accounts)

• investments in mutual funds

• bonds

• investments held in non-self-employment private businesses

• publicly traded shares

• managed investment accounts

• money owed to households as private loans

• other financial assets: options, futures, index certificates, precious metals, oil and gas leases, future proceeds from a lawsuit or estate that is being settled, royalties or any other.

• private pension plans and whole life insurance policies.

Current value of public and occupational pension plans is not included.

Total liabilities (debt) consist of:

• outstanding amount of household main residence mortgages and other real estate property mortgages

• outstanding amount of debt on credit cards and credit lines/bank overdrafts

• outstanding amounts of other, non-collateralized, loans (including loans from commercial providers and private loans).

Example, Historical Table S12 – SHIW :

Example, Statistical Table A4 Net wealth, means - breakdowns:

(EUR Thousands)

		euro area	BE	CZ	IT	EE	…
Total population	ALL	292,1	408,0	138,9	350,0	157,7	…
		(4.3)	(18.0)	(4.4)	(11.9)	(17.7)	…
Income	Bottom 20%	95,2	173,0	76,0	99,0	60,6	…
		(3.6)	(15.8)	(4.6)	(8.0)	(10.7)	…
	20-40%	143,0	262,9	103,2	146,0	86,9	…
		(6.0)	(23.9)	(5.1)	(9.2)	(7.4)	…
	40-60%	192,0	391,1	122,2	218,8	108,5	…
		(5.8)	(61.0)	(10.9)	(18.2)	(35.3)	…
	60-80%	301,0	470,0	144,7	287,0	170,2	…
		(7.9)	(65.1)	(7.7)	(17.1)	(36.6)	…
	80-90%	456,1	590,4	193,5	486,0	167,9	…
		(19.1)	(72.9)	(15.8)	(47.7)	(16.2)	…
	90-100%	1002,8	899,3	303,9	1513,5	558,3	…
		(32.6)	(66.1)	(27.4)	(94.8)	(150.1)	…
Net wealth	Bottom 20%	-0,9	4,9	-1,1	7,9	3,3	…
		(0.4)	(1.4)	(2.7)	(1.7)	(0.8)	…
	20-40%	38,0	98,4	47,1	80,8	27,8	…
		…	…	…	…	…	…

SECTION 3. Components of lifetime wealth

This section seeks to answer key questions about the distribution of household wealth, the asset classes in which they invest, the composition of financial portfolios, the percentage of indebted households, and the most common types of liabilities and tries to explain how it evolved in the years.

The analysis is based on data from the SHIW and provides an introduction to the topics covered in the rest of the chapter. The section is organized as follows:

- **Assets**: Household balance sheets are analyzed starting with human capital, then moving on to tangible wealth, divided into various categories of real and financial assets.
- **Liabilities**: The distribution of liabilities across household wealth brackets is studied.

3.1 Tangible Assets

There are two main categories of tangible assets in which people can invest their savings: real assets and financial assets. Real assets include real estate whether residential or commercial, durable goods (e.g. cars and vehicles), valuables (art, gold, jewelry and so on) and wealth from private activities of entrepreneurship (assets involved in owned businesses). Financial assets range from simple instruments such as cash and checking accounts to sophisticated instruments such as derivatives.

Differences between real and financial assets - Liquidity

Real assets are characterized by low liquidity. Real estate and Display a marked level of specificity and only a small fraction of their total stock is available for sale (Piazzesi and Schneider, 2009). This was particularly evident during the 2008 financial crisis; the real estate market experienced a dramatic decline in liquidity. Homes and commercial properties took months, if not years, to sell, often at significantly reduced prices. In contrast, stock markets maintained a high level of liquidity while experiencing significant volatility and decline in value. Investors could sell stocks almost immediately, although at lower prices, due to the organized and regulated structure of financial markets. This contrast highlights how the illiquid nature of real estate can amplify financial distress during times of crisis.

Durable goods suffer from significant information asymmetries and are subject to the classic "lemons" problem described by Akerlof (1970). These assets entail high transaction and legal costs and are frequently taxed highly in many countries.

Return

Real assets offer partially non-monetary returns. For example, residential real estate and durable goods provide additional consumer services beyond their resale value: a home, in addition to being a financial investment, offers a sense of security and stability for the family or the emotional value of having a personal place to personalize. Similarly, durable goods such as cars or appliances, while subject to depreciation, provide direct utility in daily use, improving the quality of life and reducing dependence on external services. These non-financial aspects help explain why many families choose to invest in real assets despite their illiquidity and associated costs (Piazzesi, Schneider, and Tuzel, 2007).

Furthermore, entrepreneurial wealth entails significant private benefits that are often difficult to quantify (Hamilton, 2000; Moskowitz and Vissing-Jorgensen, 2002). This characteristic complicates the estimation of the expected return and risk associated with real assets.

Control

Real assets are directly controlled by their owners and do not imply any promises or claims by third parties.

In contrast, financial assets represent claims on the income generated by real assets owned or managed by others. This requires monitoring mechanisms and incentive contracts to ensure the delegation of control.

Markets and access to information

Financial assets are generally traded in more developed and liquid markets than real assets. The variety of financial instruments is very large and continues to grow thanks to financial innovation.

Because many financial assets are traded in organized markets, information about their past performance is public and relatively easy to access.

However, financial instruments vary greatly in complexity. Some of them have payment structures and features that are difficult for many households to understand, making it difficult to interpret the available information.

Who Owns Tangible Wealth?

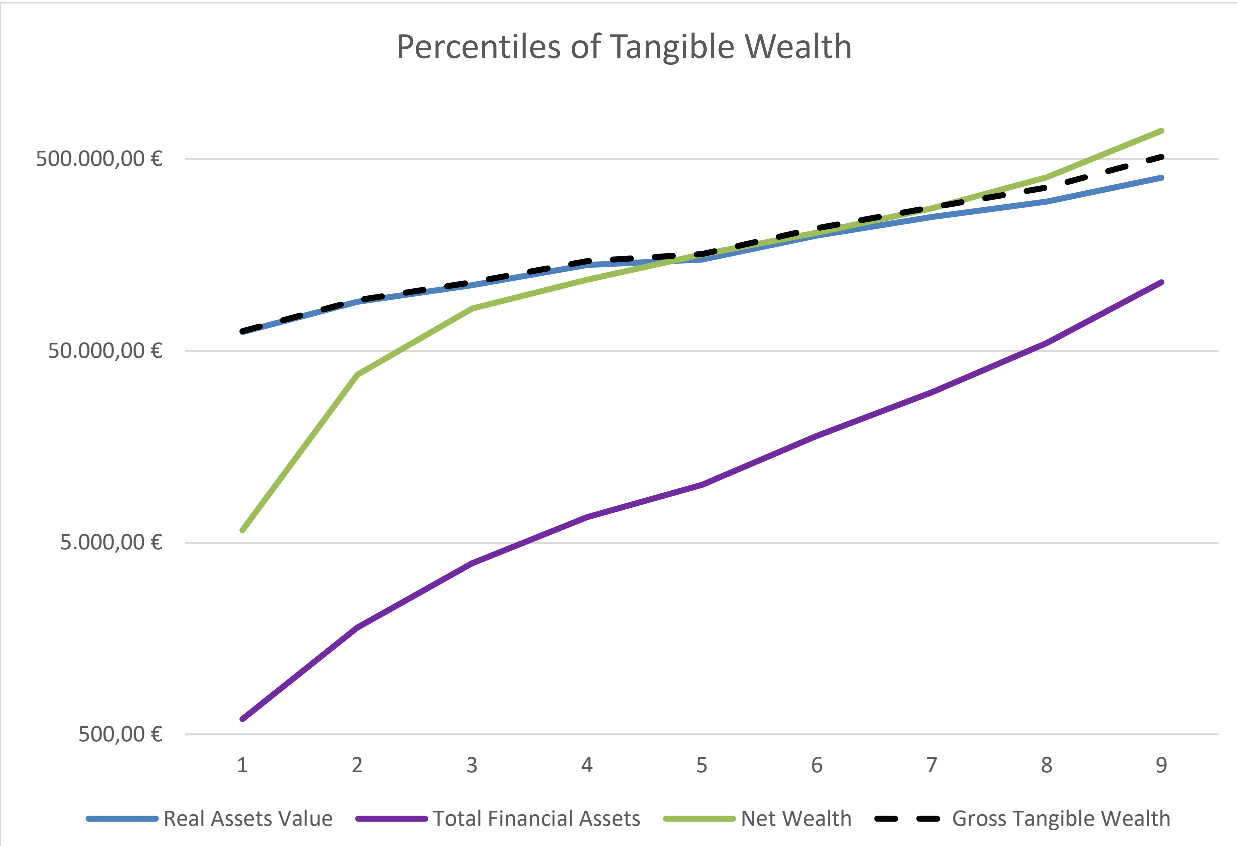


Figure 3, Wealth distribution. *Average holdings of tangible wealth (gross and net), real wealth and financial wealth in dollars by deciles of gross tangible wealth. Sample of Italian households in the 2021 wave of the HFCS;*

The graph shows the distribution of tangible wealth across household percentiles. It distinguishes between Real Assets Value, Total Financial Assets, Net Wealth and Gross Tangible Wealth, highlighting the main components of household wealth. We observe that the distribution of wealth is highly skewed, with significant increases in all variables towards the highest percentiles.

- **Real Assets Value** (blue line) indicates a more gradual growth, reflecting the more homogeneous distribution of real asset ownership in the population, although it is more concentrated in the richest groups.

- **Total Financial Assets** (purple line) are relatively lower in most percentiles, but grow dramatically in the highest deciles, further contributing to the wealth gap.
- **Net Wealth** (grey line), representing a concentration of wealth among the richest households, increases significantly in the upper percentiles.
- **Gross Tangible Wealth** (black dotted line), follows the same trend, showing growth in the highest deciles.

The data expresses how the richest households hold a concentrated percentage of tangible wealth, owning significantly more assets than the lowest percentiles, the real wealth of the 9th percentile is 8 times larger than the average in the bottom one. This concentration may cause imbalanced effects on asset pricing and other economic dynamics because they depend heavily on minor shifts in the asset composition of a small group of privileged and high-net-worthy investors.

In the following chapters, this relationship will be explored in more detail, analyzing how portfolio composition aligns with different levels of tangible wealth and how wealth concentration influences financial behavior and risk-taking by households.

The Wealth Allocation in Real Assets

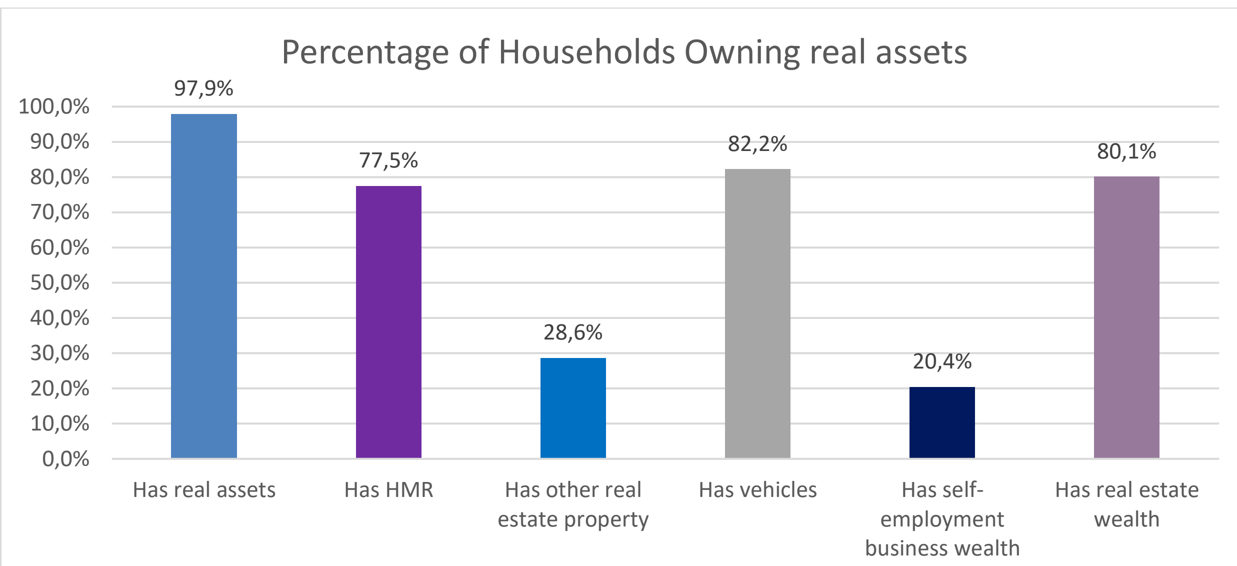


Figure 4, Wealth participation. *Fraction of households with positive asset holdings of vehicles, real estate, private business. Sample of Italian households in the 2021 wave of the HFCS.*

The graph shows the percentage of households owning different types of real assets. The most striking aspect is that a vast majority of households (97.9%) own at least one real asset. The largest component of this category is the primary residence (HMR), owned by

77.5% of households, followed by vehicle ownership (82.2%) and total real estate wealth (80.1%). However, ownership of other real estate (28.6%) and business (20.4%) shows a much lower participation.

This variation in participation may reflect differences in the costs of access to these categories of assets. While assets such as vehicles are more accessible and commonly owned even by households with modest levels of wealth, participation in markets such as second homes or business is more limited, requiring greater financial resources or specific skills. Ownership of real estate other than the primary residence appears significant only for a minority, suggesting that households focus primarily on purchasing their primary home.

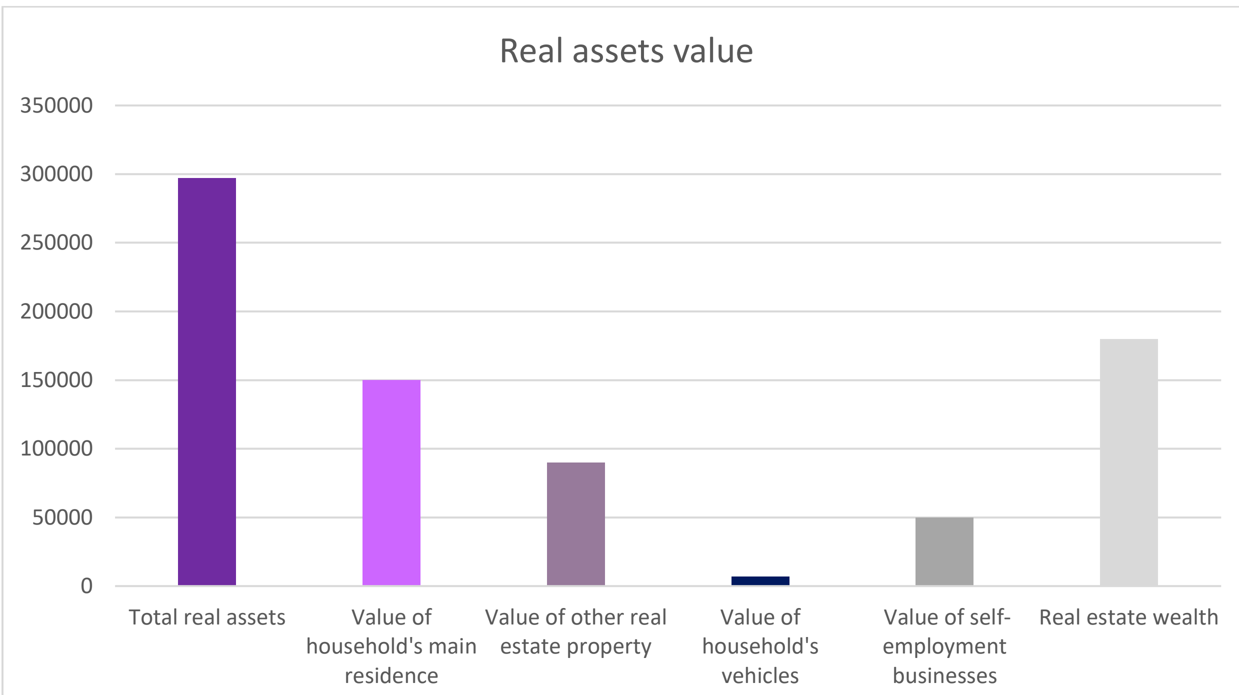


Figure 5, Real Assets distribution. *Average holdings of real wealth value in Euros divided into categories. Sample of Italian households in the 2021 wave of the HFCS;*

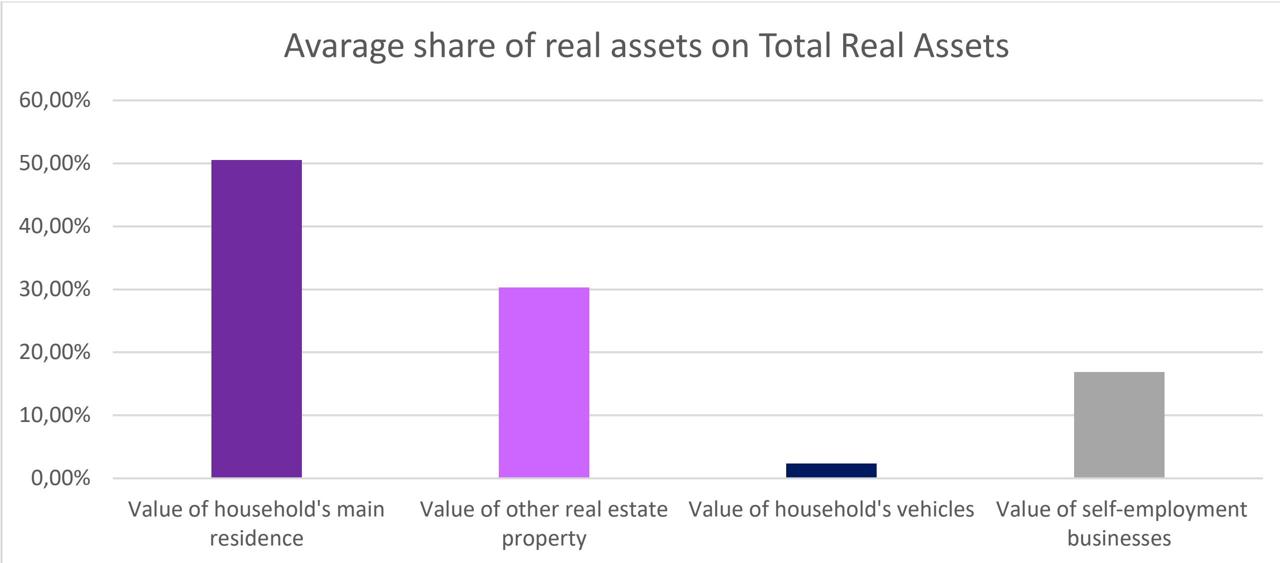


Figure 6, Real Assets distribution. *Average share of each real assets category on total real assets. Sample of Italian households in the 2021 wave of the HFCS;*

Figure 5 illustrates the total value of households' real assets, broken down into four main categories: primary residence, other real estate, vehicles, and independent entrepreneurial activities. the primary residence appears to be being the most significant component. This explains its weight in household wealth accumulation. Moreover, other real estate assets have considerable share, of course lower, addressing the importance of property ownership. In contrast, vehicles, despite being widely owned, account for only a small fraction of total real assets. Another important contribute is explained by the Independent entrepreneurial activities, slightly larger than vehicles but still a small portion compared to real estate.

Figure 6 represents the average percentage share of each category in total real assets. The primary residence remains the predominant component, approximately 50% of households' real wealth. Other real estate constitutes a remarkable portion, while private business activities and vehicles, contribute a marginal amount. This connection between absolute value and percentage share shows how real wealth is strongly concentrated in real estate, with a smaller role played by other categories of real assets.

The correlation between the two graphs underlines the outstanding importance of real estate in household wealth, in absolute and relative terms. The distribution perfectly represents the typical pattern of wealth accumulation, particularly in Italy, where real estate, especially main residence, is the highest composition of wealth. The substantial share of other real estate suggests that some households leverage additional properties for diversification or income generation purposes, potentially using them as a strategy to balance their portfolios.

In subsequent papers, it could be interesting to analyze how this composition of wealth varies according to the levels of income or total wealth, to identify any differences between less wealthy and richer families, but available data are not enough to proceed in this work. Furthermore, the impact of entrepreneurial activities in diversifying the wealth portfolio could be further explored to understand the role of human capital and entrepreneurial initiative in value creation.

3.2 Intangible Assets

Intangible assets are non-physical resources that individuals and households possess. They can strongly influence the economic well-being and financial decision-making. These assets encompass financial instruments (bonds, stocks, government securities, savings), education, professional skills, intellectual property, social networks, reputation, and human capital itself. These elements provide to a household the ability to generate income, access credit, and respond to economic fluctuations.

Liquidity and Transferability

Intangible assets generally have very low liquidity and can't be transferred directly. Unlike financial assets, personal resources such as skills, knowledge, and social networks cannot be directly traded or easily monetized. They can hardly be evaluated and typically their value is based on personal characteristics, context, and market demand, making them impossible to be used collateral. However, certain intangible assets, such as educational qualifications and professional certifications, can indirectly increase access to credit markets by signaling reliability and future income stability.

Among financial intangible assets, bonds, stocks, and government securities have higher liquidity compared to education or human capital. Today almost every financial instrument can be sold in specific markets or be used as collateral through the process of collateralization, while intellectual capital requires development and adaptation to maintain importance.

Return and Depreciation

Intangible assets yield returns indirectly: through increased earning potential, incremented employability, and career progression. For example, education, professional training, and certifications raise lifetime income expectations and improve career opportunities. However, they still can appreciate or depreciate based on external economic conditions.

Human Capital and Labor Market Returns

- **Appreciation** occurs by continuously investing in education, training, and skill growth, this improves job stability and future earnings.
- **Depreciation** arises because of technological obsolescence, industry shifts, or declining labor market demand, this can reduce the value of individual's human capital.

The returns on human capital are not linear and are hard to predict. Investments on education in the earliest phases of life ensure higher lifetime earnings, while not focusing on personal skills can lead to depreciation in the long term.

Financial Intangible Assets and Market Behavior

Intangible financial assets, such as stocks, bonds, government securities, and investment funds, behave differently from human capital and social capital because they are market-tradable and subject to financial cycles.

Stocks and Equities - Higher volatility, higher potential growth

- Equities appreciate when company profits rise and the economy grows.
- Stocks depreciate following market downturns, inflation, or business failures, but the equity risk premium compensates for the higher risk taken by investors, making them a long-term tool to build more wealth over time.

Government Bonds and Fixed-Income Securities - Lower Risk, Lower Return

- Bonds offer stable but way lower returns; they have interest payments and face-value repayment once they reach maturity.
- Government bonds, such as BOT (Buoni Ordinari del Tesoro) or BTP (Buoni del Tesoro Poliennali), appreciate when interest rates fall but lose value when interest rates rise.
- In economic downturns, investors shift toward safe assets like government bonds, increasing demand and prices.

Savings and Deposits – Stable (no risk), Minimal Return

- Savings accounts and deposits do not fluctuate in value like equities but have low returns.
- Inflation can erode purchasing power over time, effectively depreciating savings if interest rates are too low, usually they don't completely cover inflation effect.

Mutual Funds and ETFs - Diversified Return and Risk Exposure

- Mutual funds aggregate multiple asset classes, balancing growth potential and risk through diversification.
- Depreciation risk depends on market exposure, funds heavily invested in declining sectors will lose value. Investors have near to zero control over these assets but they usually trust the funds' management strategies.

Measurement and Estimation

The valuation of intangible assets is complex due to their **non-physical nature and dependence on future expectations**.

Common methods include:

- **Human Capital Valuation** – Estimates lifetime earnings potential using discounted cash flow models.
- **Financial Asset Valuation** – Prices stocks, bonds, and savings using market-based metrics.
- **Survey-Based Approaches** – Household wealth studies like SHIW (Survey on Household Income and Wealth) and HFCS (Household Finance and Consumption Survey) capture data on education, skills, and expected future income.

Since intangible assets involve uncertainty, valuation models must adjust for risk, discounting future income streams to reflect economic and labor market fluctuations.

Distribution of Intangible Assets

The distribution of intangible assets is highly based on education level, geographic location, age, and professional experiences. Education is the key factor at determining access to high-income career paths and adaptability to economic change.

- Highly educated households commonly accumulate greater intangible wealth, benefiting from higher job mobility, financial stability, and more investment opportunities.
- Lower-educated households have limited access to professional progression, reducing their ability to accumulate financial and human capital over time, often excluding them from the financial market.

In fact, financial intangible assets also follow wealth inequality patterns: higher-income families hold a larger share of equities and investment portfolios, while lower-income households rely more on government securities and savings accounts.

Conclusion

Intangible assets represent a fundamental pillar of household wealth, shaping economic stability, long-term financial behavior, and career prospects. While they lack direct liquidity and transferability, their impact on earning potential and investment capacity is substantial.

Understanding the nature, risks, and distribution of intangible assets is crucial for policy-making and financial advisory strategies aimed at promoting inclusive economic growth and addressing wealth inequality.

3.2.1 Human Capital

Human capital consists of personal attributes, such as skills, personality, education and health, that determine the ability to generate income from work. It can be defined as the discounted present value of the income streams that a person expects to earn over the remaining lifetime. It accumulates gradually through formal education and work experience, building the foundation for future earnings, and reaches its maximum value in the early years of working life and progressively declines as the number of remaining productive years and expected income streams decline.

Estimating the value of human capital is complex, as it requires forecasting future income and taking into account uncertainties related to career, health, individual productivity and general economic conditions.

Human capital is not transferable or easily liquidated. This nature makes it unsuitable as collateral for obtaining credit, limiting access to financial markets for families without other forms of wealth.

Being subject to inherent risks, such as job loss or reduction in income, human capital represents a basic source of risk, which cannot be eliminated or insured outside of public income support systems, such as unemployment insurance. Despite concerns that the return on human capital may be correlated with stock markets, evidence shows that such correlation is weak or non-existent. Therefore, from a portfolio allocation perspective, human capital cannot be assimilated to a 'risk-free bond', as it represents a risky asset. However, the risk that characterizes human capital is of a different nature than the systemic risk of financial markets. Although there is a degree of uncertainty related to individual, sectoral and macroeconomic factors, the correlation between the risk affecting human capital and the systemic risk of the financial market is generally low. Consequently, human capital can be considered an asset that embodies a non-diversifiable risk, but that does not necessarily move in sync with the fluctuations of financial markets.

Education level also plays a significant role in determining the value of human capital and its behavior over the life cycle: young people with a high level of education (e.g. a bachelor's degree) possess significantly higher human capital than those with lower levels of education.

Education not only affects the level of human capital, but also changes its profile: for individuals with low qualifications, human capital tends to decline linearly, while for those with advanced education, it can grow rapidly in the early stages of their careers before declining.

In the early years of working life, human capital represents the predominant component of total wealth, since savings and tangible assets are still limited. As families age, they start to accumulate tangible wealth, while human capital declines. However, the pace of this change varies according to the level of education: families with low education see a slower decline in human capital and a lower accumulation of tangible wealth. In contrast, families with a higher level of education accumulate wealth more rapidly and experience a more marked decline in human capital.

In conclusion, human capital is a crucial resource for households, especially in the early stages of working life, when it represents the majority of an individual total wealth. However, its non-transferable nature and the inherent risk it entails highlight the importance of accumulating tangible wealth over time, to reduce vulnerability to income shocks and ensure greater economic stability.

3.2.2 Financial Portfolio

The financial portfolio represents the set of liquid assets and investment instruments held by households. Its composition provides important information on savings habits, attitudes towards risk and short and long-term economic planning choices.

From current accounts to mutual funds, from government bonds to life insurance, each component of the portfolio reflects a different balance between liquidity, security and expected return. Analyzing how these assets are distributed among individuals of different ages and genders helps to better understand not only the economic, but also cultural, informational and behavioral differences that influence the relationship of households with savings and investment.

This chapter looks at the average composition of the portfolio, the spread of the various financial instruments and the main differences between men and women, between young and old. The goal is to provide a clear picture of the financial choices of Italian families, highlighting trends, preferences and possible critical issues.

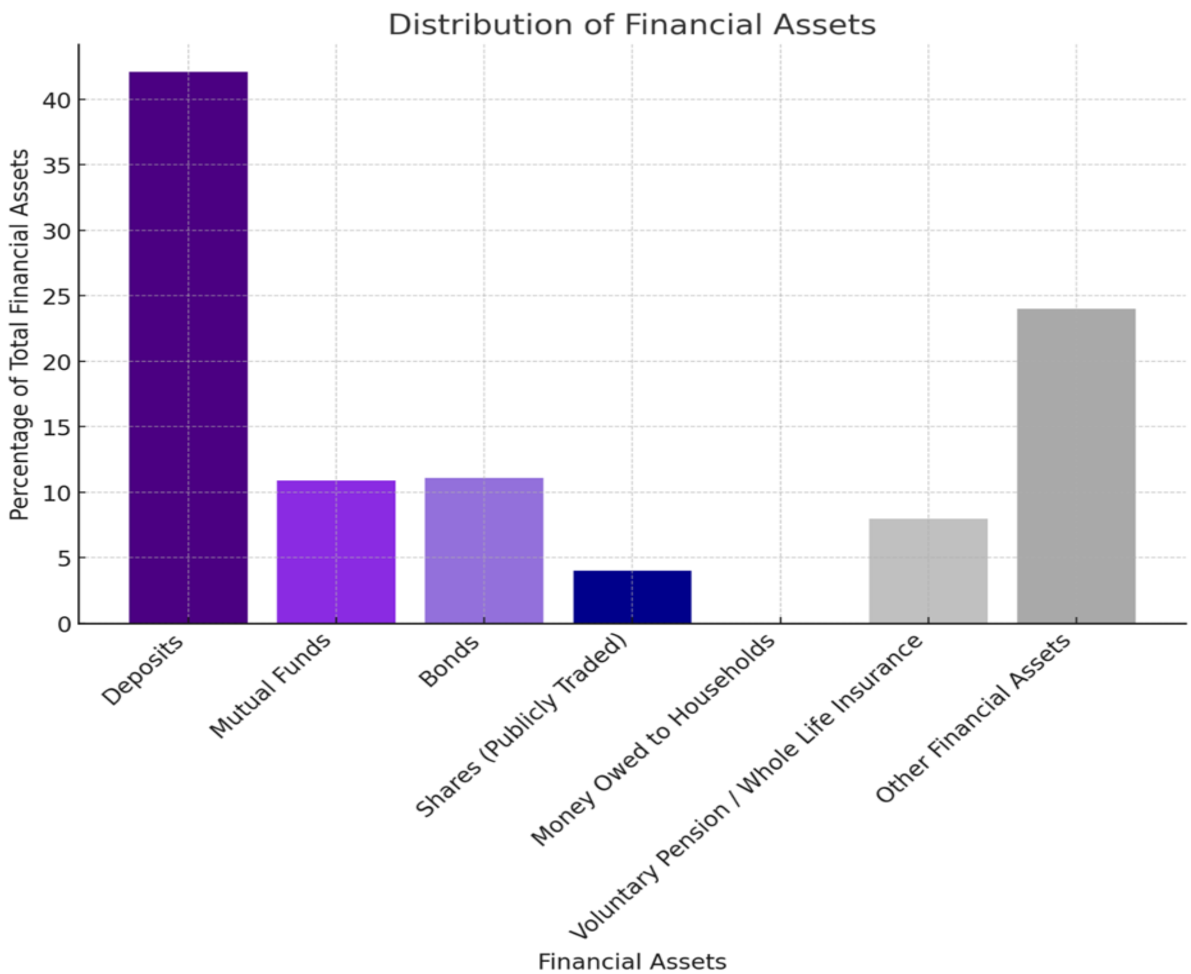


Figure 7, Total debt by Age Group. *Sample of Italian households in the 2021 wave of the HFCS;*

The bar chart illustrates the composition of household financial assets, highlighting the distribution among different investment categories.

Deposits (42.1%): The most significant component, indicating a preference for liquidity and low-risk savings. This suggests a conservative investment behavior, with households prioritizing security over potential returns.

Other Financial Assets (24%): This broad category includes various investment instruments, reflecting diversified holdings that are not specifically categorized.

Bonds (11.1%) & Mutual Funds (10.9%): Represent a notable portion of assets, signaling an interest in fixed-income securities and managed investment strategies, likely for stability and long-term growth.

Voluntary Pension/Whole Life Insurance (8%): Indicates a portion of financial planning dedicated to retirement security and long-term wealth accumulation.

Publicly Traded Shares (4.0%): A relatively small percentage, suggesting that direct equity market participation is limited among households, potentially due to risk aversion or lack of financial literacy.

Money Owed to Households (0%): This absence suggests that intra-household lending is either minimal or not accounted for in this dataset.

The data reflects a risk-averse investment behavior, with a strong inclination toward safer assets such as deposits, bonds, and managed funds, rather than direct market exposure. This conservative allocation may have implications for long-term wealth growth and financial resilience.

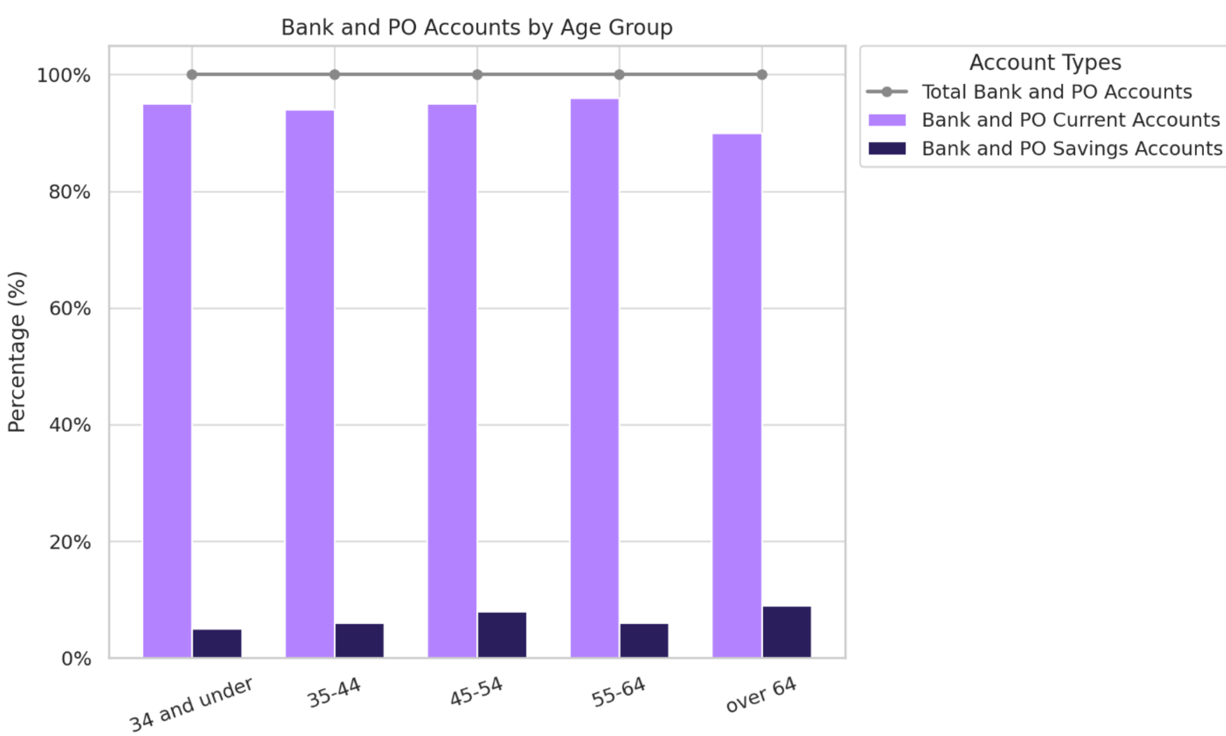


Figure 8, Bank and Post Office accounts ownership percentage by Age Groups. *Average share of households owning accounts by age groups. Sample of Italian households in the 2020 wave of the SHIW;*

The graph shows the distribution of bank and postal accounts among different age groups. Three main elements stand out:

- **High prevalence of current accounts:** In all age groups, almost all individuals have a current account (Bank Current Accounts and PO), with percentages ranging between 90% and 96%. In the daily management of personal finances these tools seem to hold a central role.
- **Savings accounts:** Savings accounts are less widespread and have less incidence, with a percentage ranging between 5% and 9%. This suggests that, despite many people having access to bank accounts, only a small portion uses different savings tools.
- **Account ownership is stable:** The sum of current and savings accounts is constant at 100% in all age groups, indicating that almost all individuals, regardless of age, have at least one bank or postal account.

Alternative investment instruments like dedicated accounts appear to be decorative compared to the propension to save on common bank accounts, probably due to deep link to financial behavioral aspects.

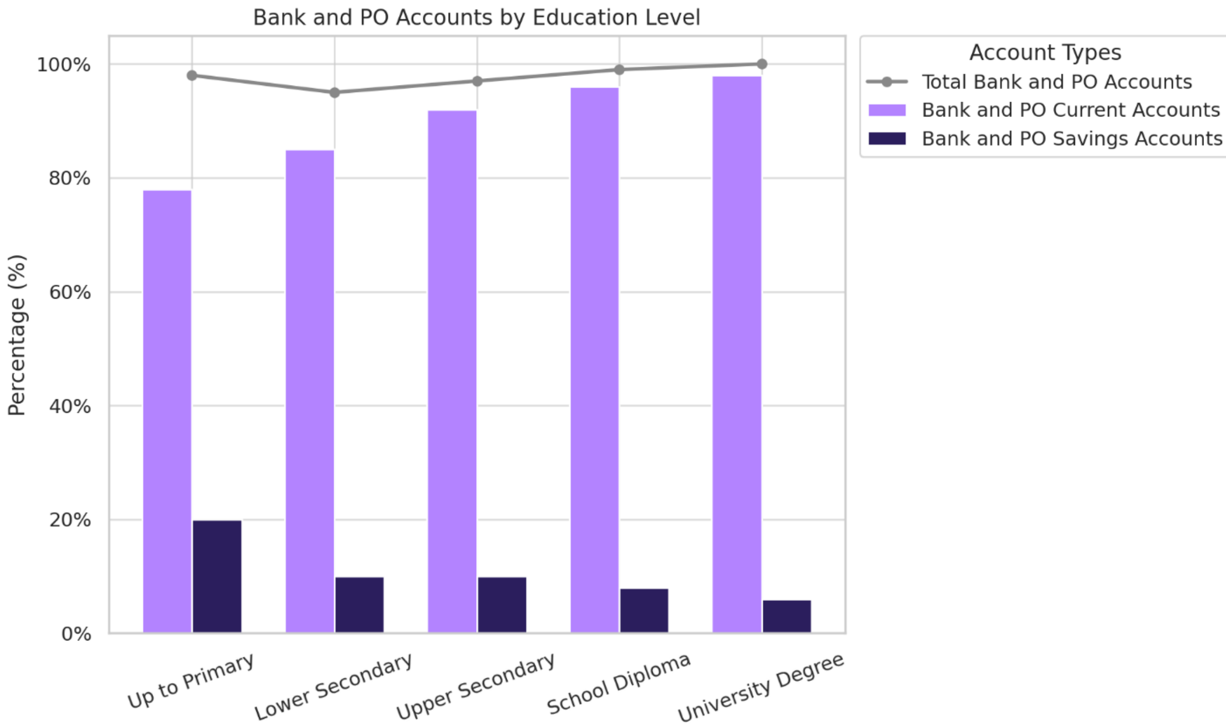


Figure 9, Bank and Post Office accounts ownership percentage by Education Level. *Average share of households owning accounts by education level. Sample of Italian households in the 2020 wave of the SHIW;*

The graph shows the distribution of bank and postal accounts among individuals with different levels of education.

- **Increasing access to current accounts with the level of education**: There is a clear upgoing trend of in the percentage of individuals with current accounts as the level of education increases. While approximately 78% of individuals with primary education have a current account, this percentage increases to 98% among those with a university degree.
- **Decreasing use of savings accounts**: Contrary to current accounts, savings accounts show a decreasing trend with education. The percentage of individuals with savings accounts is higher among those with a lower level of education (~20% for primary school) and decreases for higher levels of education (~6% for graduates). This could highlight that individuals with more education prefer alternative investment instruments to traditional savings accounts.

- **Almost complete coverage of both accounts:** The gray line remains constant at around 100% for all levels of education, explaining the complete access to financial services, regardless of the level of education.

There is a correlation between education and financial behavior: those with a higher education are more likely to have a current account, but less likely to use standard savings accounts, probably in favor of more advanced investment strategies.

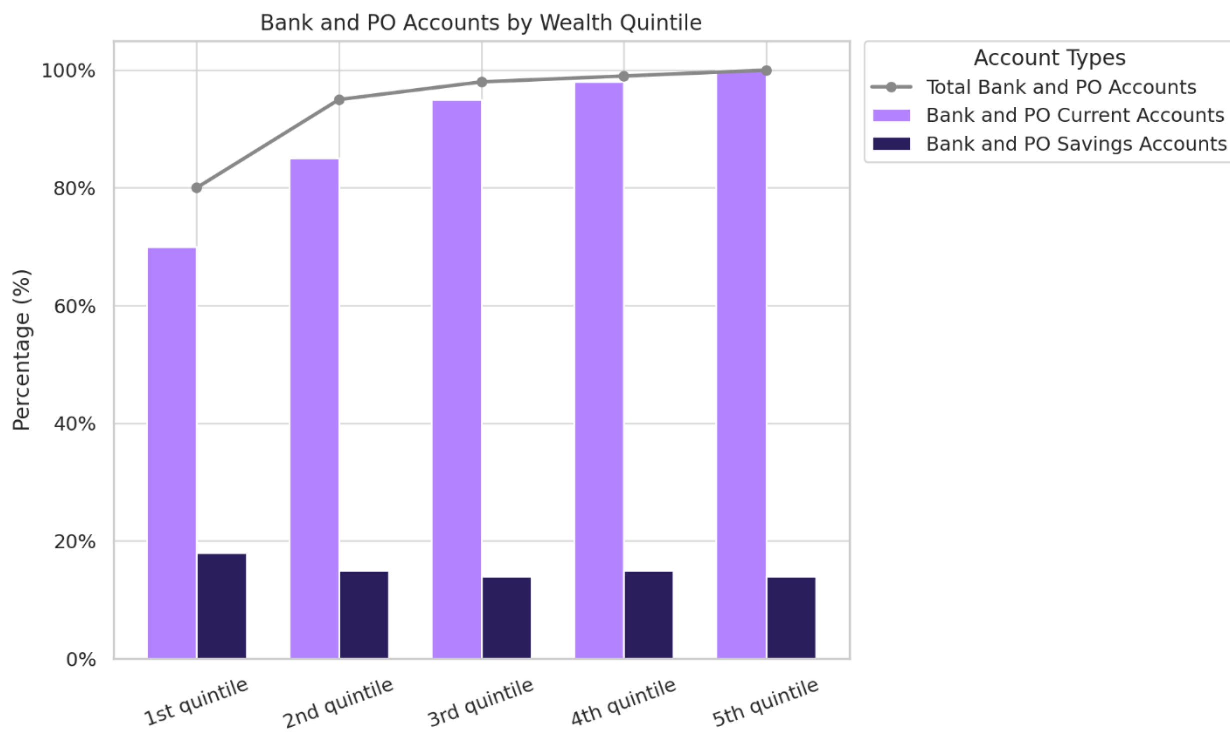


***Figure 10, Bank and Post Office accounts ownership percentage by Wealth Quantiles**. Average share of households owning accounts by wealth quantiles. Sample of Italian households in the 2020 wave of the SHIW;*

The graph shows the distribution of bank and postal accounts in relation to wealth quintiles. The following aspects are highlighted:

- **Increasing access to current accounts with wealth**: The percentage of individuals with a current account (Bank and PO Current Accounts) progressively increases from 70% in the first quintile (the least wealthy) to 100% in the fifth quintile (the wealthiest). People with greater wealth are more likely to have bank accounts.

- **Savings accounts remain constant:** The percentage of individuals with savings accounts (Bank and PO Savings Accounts) remains relatively stable between 14% and 18% in all quintiles. This suggests that the propensity to have a savings account does not vary dramatically as a function of wealth.
- **Near-universal access to banking services in the upper quintiles**: The gray line represents the total percentage of individuals who have at least one bank or postal account (Bank and PO Accounts). It is noted that in the highest quintiles, almost 100% of people have at least one bank account, while in the lower quintiles the percentage is slightly lower.

Figure 10 confirms that access to basic banking services is strongly correlated with wealth, with a greater prevalence of current accounts in the wealthiest groups. However, the use of savings accounts shows a slightly descending trend, suggesting that savings strategies may be influenced by factors other than wealth.

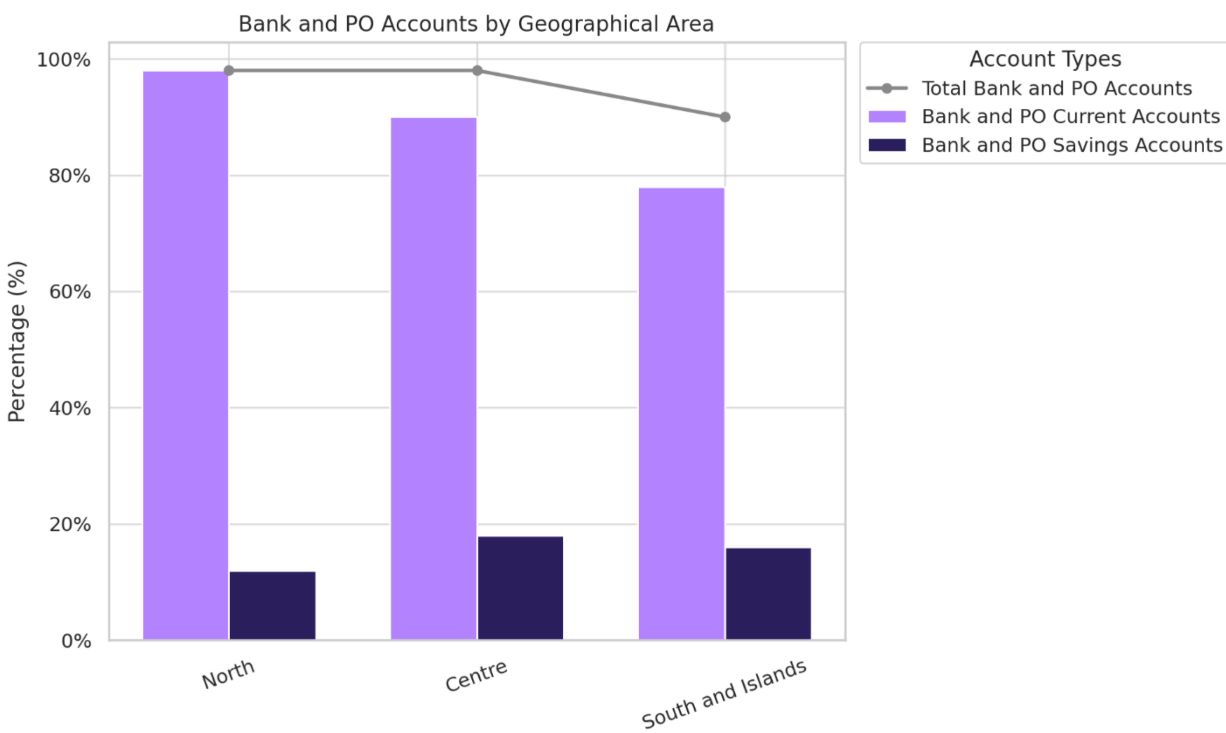


Figure 11, Bank and Post Office accounts ownership percentage by Geographical Area*.* *Average share of households owning accounts by geographical area. Sample of Italian households in the 2020 wave of the SHIW.*

Figure 11 shows the distribution of bank and postal accounts in three macro-geographical areas. The following points are highlighted:

- **Higher diffusion of current accounts in the North:** 98% of individuals in the North have a current account (Bank and PO Current Accounts), compared to 90% in the Centre and 78% in the South and the Islands. This probably reflects greater accessibility to financial services and a different level of banking between the geographical areas.
- **Higher use of savings accounts in the Centre**: The share of individuals with savings accounts (Bank and PO Savings Accounts) is higher in the Centre (18%) than in the North (12%) and the South (15%). This could indicate a different propensity to save or a greater offer of bank savings products in this area.
- **Lower bank coverage in the South and the Islands:** While in the North and the Centre almost 100% of individuals have at least one bank or postal account, in the South and the Islands the percentage drops to 90%. This suggests lower financial inclusion in these regions, which could be linked to socio-economic and infrastructural factors.

This graph confirms that regional differences in access to banking services may exist, with the North showing the highest levels of banking and the South presenting a significant gap.

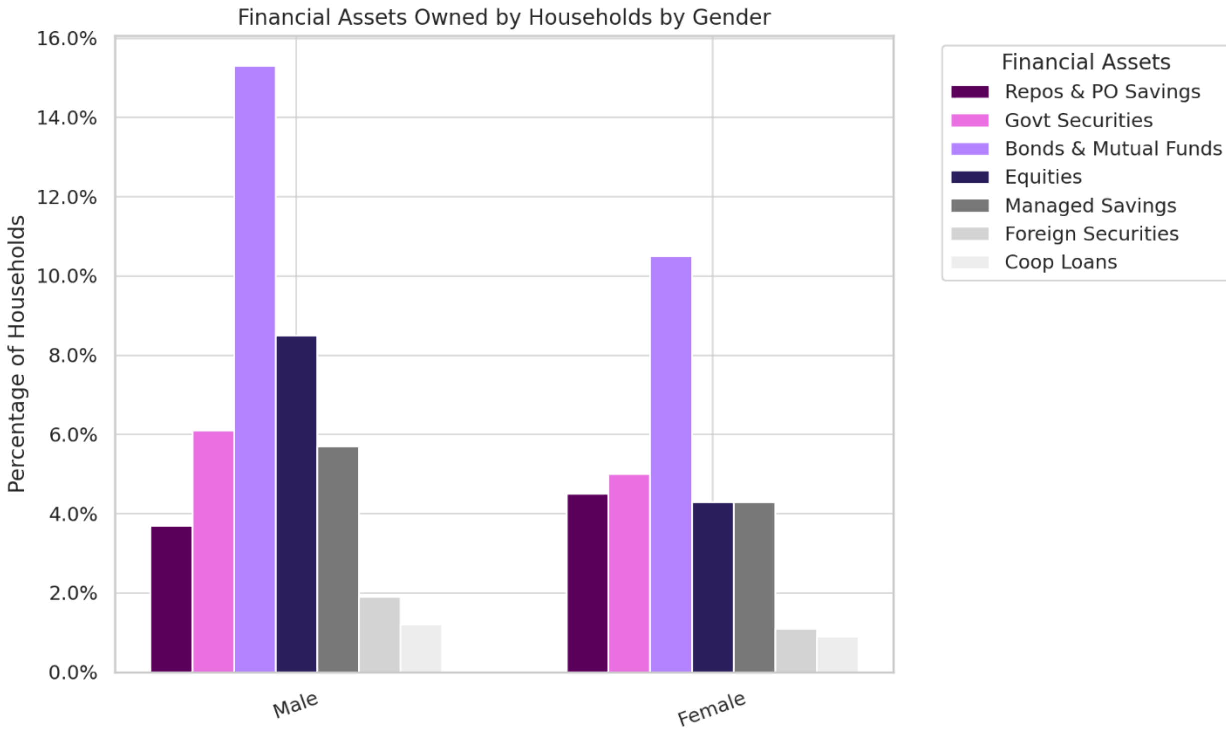


Figure 12 Financial Assets Owned by Households by Gender. *Average share of financial assets divided into categories and by gender. Sample of Italian households in the 2021 wave of the HFCS;*

Figure 12 shows the distribution of financial assets between men and women. Almost all households, regardless of gender, have at least one bank or postal account, with very high percentages for both groups (~96%). However, differences emerge in investment preferences. **Men tend to hold a higher share of riskier financial assets**, such as bonds, shares and managed investment instruments (e.g. mutual funds), while women have slightly lower shares in these categories. This discrepancy could be attributed to differences in financial literacy levels, risk appetite and income differences between genders, factors that influence the ability and willingness to invest in variable return instruments.

Another interesting aspect is the share of **government bonds and bond funds**, which is higher among men than among women, suggesting that **men may be more inclined to invest in fixed income instruments**. On the other hand, **women hold a slightly higher share of postal savings and guaranteed savings instruments**, which indicates a preference for **less risky and more liquid** investments.

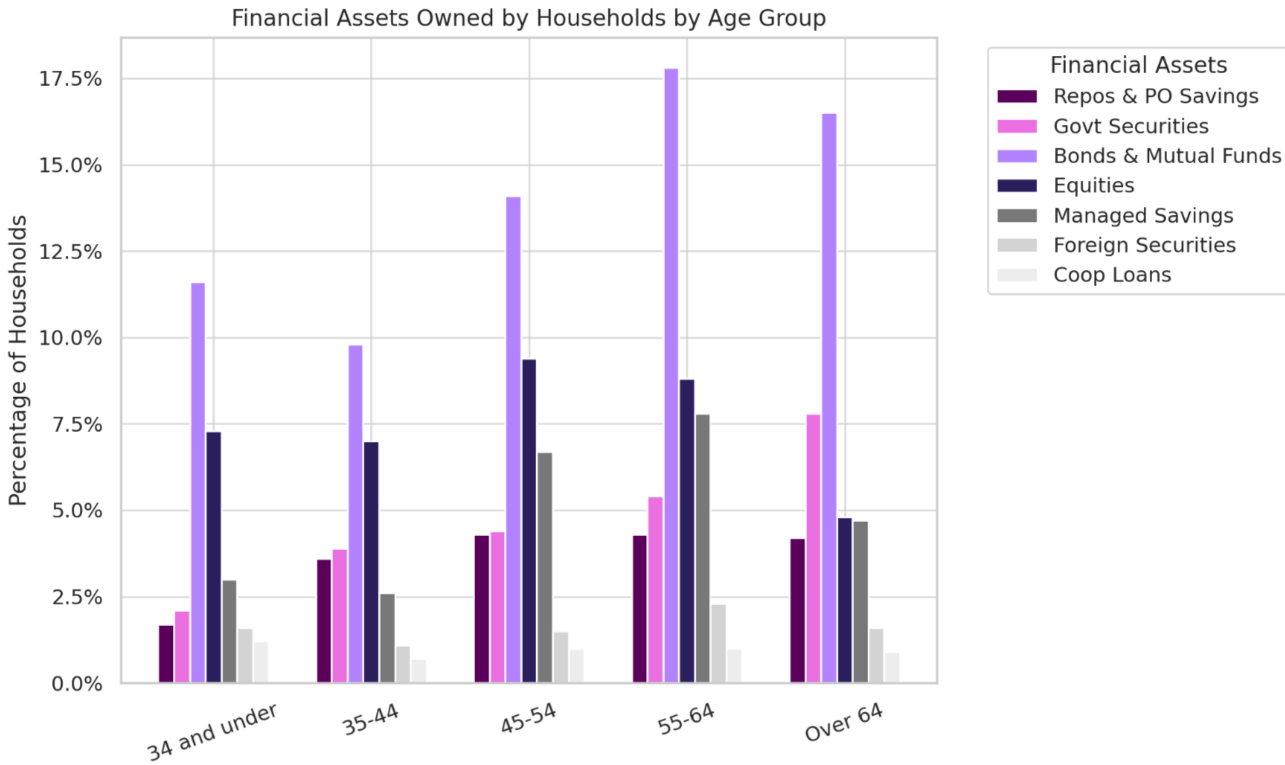


Figure 13, Financial Assets Owned by Households by Age groups. *Average share of financial assets divided into categories and by age groups. Sample of Italian households in the 2021 wave of the HFCS.*

Figure 13 highlights two main trends. On the one hand, there is a **propensity to save and invest increases with age**: while the younger groups (34 years and under) mainly own bank accounts and postal deposits, the older age groups hold a greater share of diversified financial instruments.

An interesting aspect is the increase in the holding of **bonds and mutual funds among the older age groups.** For example, the **55-64** and **over 64** age groups record the highest percentage of investments in bonds and government bonds. This is coherent with a more conservative approach to wealth management, typical of older people or close to retirement or already retired, who prefer less volatile instruments and with more predictable returns.

In contrast, **young people under 35 have a lower portfolio diversification** and invest less in medium-long term instruments, probably due to a lower saving capacity, lower financial literacy and a higher propensity to liquidity to face unexpected expenses or future investments (for example, buying a house). Furthermore, the share of investments in shares and other equity instruments is limited, suggesting that young people may be less inclined to take significant financial risks.

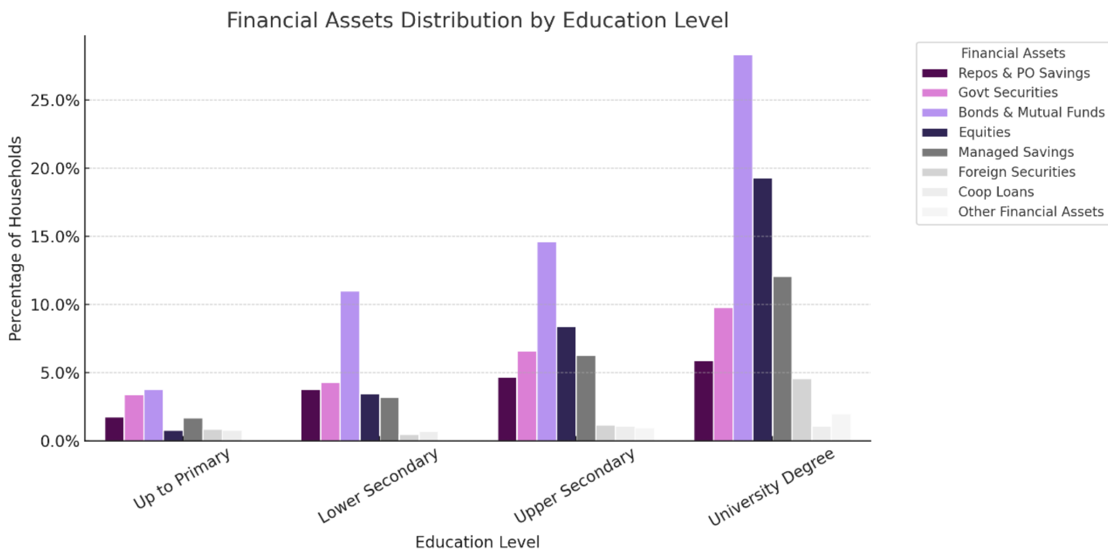


Figure 14, Financial Assets Owned by Households by Education Level*. Average share of financial assets divided into categories and by education level. Sample of Italian households in the 2021 wave of the HFCS.*

Education plays a key role in households' propensity to invest in complex financial instruments. The graph clearly shows that households with a **higher level of education** (Upper Secondary) **tend to own a higher share of diversified financial instruments** than those with lower levels of education.

In households with a **primary school education,** the percentage of bonds, stocks and managed investments owners, is noticeably lower than better educated groups. Ascribable to not only lower disposable income, but also **lower financial literacy**, which may limit knowledge and access to advanced investment tools. In contrast, households with a **high school diploma** show a **propensity to invest in stocks and mutual funds**, with a higher share of government bonds and managed savings instruments. This suggests that higher education could promote a better understanding of investment opportunities, thus increasing the ability to diversify the financial portfolio.

Is interesting to note that, even among the most educated, the percentage of **participation in the stock market remains relatively low**, a sign that Italian families tend to favor safer instruments over riskier investments.

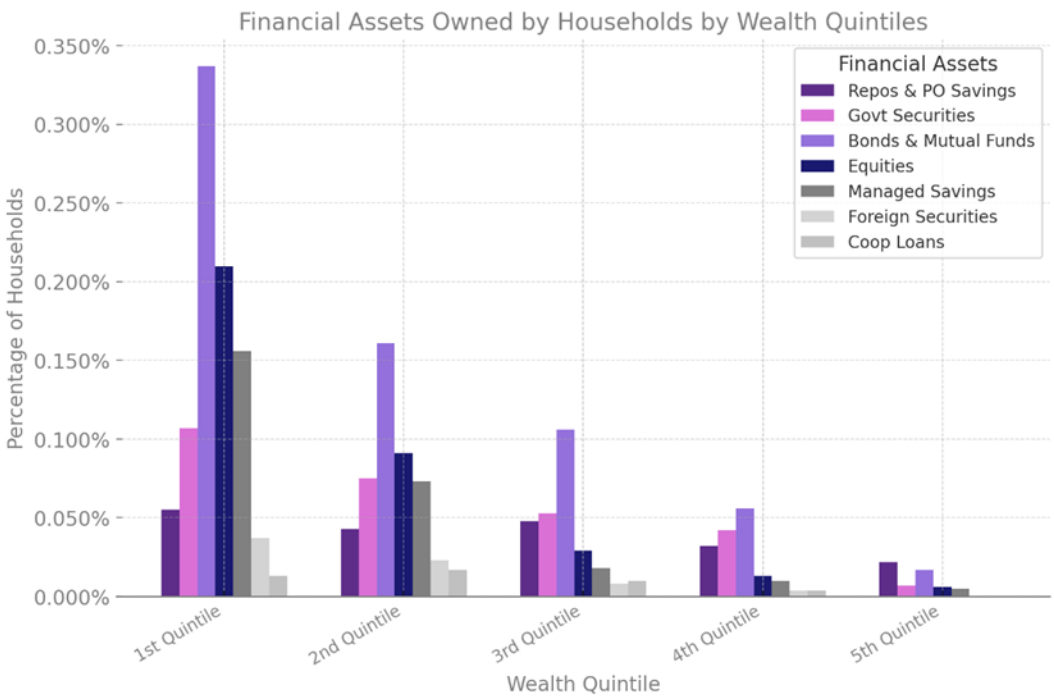


Figure 15, Financial Assets Owned by Households by Wealth Quantiles*. Average share of financial assets divided into categories and by wealth quantiles. Sample of Italian households in the 2021 wave of the HFCS;*

Figure 15 highlights a correlation between the level of wealth of households and the composition of their financial portfolio. Households belonging to the **lower wealth quintiles** (1st and 2nd quintile) own **almost exclusively bank accounts and postal deposits**, while those belonging to the **upper quintiles** (4th and 5th quintile) **have easier access to diversified financial instruments.**

Households in the **5th quintile hold** a significant share of bonds, stocks and mutual funds, this is a consequence of a greater investment capacity and a propensity to diversify portfolios. Moreover, these households have higher participation in **government bonds and managed savings instruments,** reflecting availability of more capital to allocate to medium-long term investments.

While households belonging to the **1st quintile** seems to focus on **low-risk and highly** liquid financial instruments (current accounts and savings book). Their investments in stocks or funds is almost zero, suggesting that the access to more complex investment instruments could be limited by economic and cultural factors, such as a lower availability of financial resources and a lower propensity for risk. Overall, this graph confirms that **wealth strongly influences household investment decisions.** We can see that richer households can afford to allocate a greater portion of their assets in more sophisticated and risky financial instruments, while those with fewer resources focus on safer and more immediately accessible assets.

3.2.3 Liabilities

A set of obligations held towards third parties is referred to as liability. These include different types of debt and represent a key component of the household budget, impacting the ability to spend, save and the investment portfolio. Liabilities can be assumed for various motivations: to purchase a home, cover expenses, finance education or unexpected needs. The main forms of debt are: mortgages, credit card debt, consumer debt and personal or education loans.

Mortgages are the most important ones in terms of duration and amount. These loans are granted to purchase a real estate asset, secured by the property itself. Mortgages can present a fixed or variable rate, impacting financial stability of households in the long term.
Credit card debt is a form of short-term liability that allows consumers to make immediate purchases by postponing payments. However, credit cards have very high interest rates, making this type of debt particularly costly if not repaid in short term. Consumer debt includes loans to purchase durable goods, such as vehicles or to support common expenses.

These loans can be secured or unsecured through an asset, in the first case creditors can pretend lower interest rates. But even if they allow families to maintain their standard of living, they can become problematic if they accumulate too much.

Finally, personal and education loans are a category of debt that is used to cover educational expenses or general financial needs.

The analysis of liabilities and their implications for the economic well-being of families is crucial to understanding the dynamics of debt and its consequences for financial stability in the long term.

Liabilities Distribution

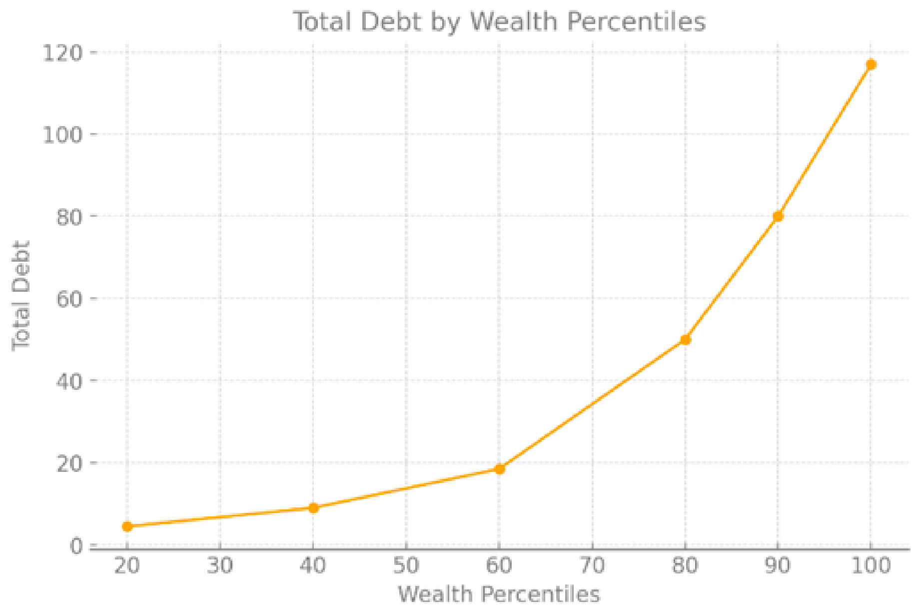


Figure 16, Total debt by wealth percentiles. *Sample of Italian households in the 2021 wave of the HFCS;*

Figure 16 shows a strong relationship between the level of wealth and the amount of total debt. Households in the lowest percentiles of the wealth distribution present a relatively low level of debt, while debt increases for the highest percentiles. This trend is consistent with what was discussed previously: richer households have a greater propensity to take out mortgages, which represent the most relevant form of debt in absolute terms. Furthermore, the increase in debt in the highest percentiles suggests that these households have greater access to credit and are more likely to use it for long-term investments.

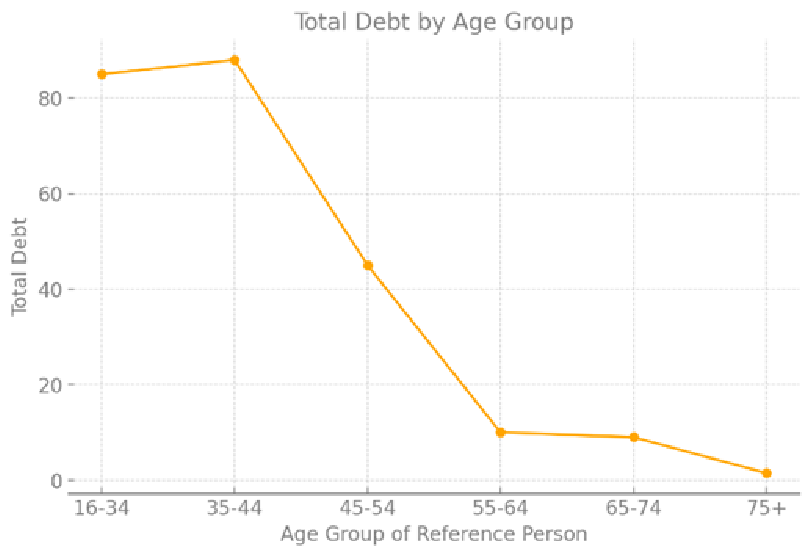


Figure 17 Total debt by Age Group. *Sample of Italian households in the 2021 wave of the HFCS;*

Figure 17 shows the trend of total debt by age group of the main household member. It is observed that debt is highest in the 35-44 and 45-54 age groups and then decreases dramatically in the subsequent age groups. This trend is consistent with the financial life cycle of families: indebtedness tends to be maximum in the phase in which a mortgage is taken out to purchase a first home or to finance expenses related to family and education. As age advances, debt progressively decreases, reflecting the process of repaying loans and a reduced need for indebtedness in the older age groups of the population.

SECTION 4 - Research

The analysis began by collecting and structuring historical and projected salary data for each combination of gender, age group, region and education level. The initial database contained the nominal values of wages observed up to a given year, which were subsequently interpolated to obtain an estimate of the missing years and projected up to 2035 through a regression model.

We needed to interpolate and forecast future salaries, so we applied a linear regression based on the real historical data. This choice allowed to obtain a more accurate estimation of wage growth, depicting the effects of linear trends and possible variations in the labor market. The model was calibrated using available data, and inflation was considered year by year to obtain values in real terms, avoiding distortions due to nominal wage growth. After having constructed the salary series for each combination of categories up to 2035,

it was necessary to calculate the human capital for each individual, understood as the present value of future income from work. Human capital was calculated by applying a real discount rate, since salaries had already been adjusted for inflation. The calculation was carried out by adding the discounted salaries of each individual up to the year of retirement, taking into account work progression (i.e. the transition from one age group to another and the associated salary increase).
Subsequently, the financial wealth accumulated over time was estimated, starting from a hypothetical initial condition based on age. The model used an estimated savings rate (1 - propensity to consume) and an average return on investments to accumulate financial wealth year after year. This was a very useful step to integrate human capital with financial wealth and understand how these two components interact to each other in order to understand the composition of total assets.
Finally, basing the computation on the correlation between labor income and financial markets, we applied the optimal stock investment allocation model using Munk's methodology. The equity allocation was calculated accounting the relationship between human capital and financial wealth. This has made possible to obtain a dynamic investment strategy, in which the share of shares varies over time depending on the individual's stage of life and their exposure to work risk.
The analysis produced a final dataset containing, for each individual, information relating to interpolated salaries, actualized human capital, accumulated financial wealth and the optimal share of investments in shares. All these elements allow us to have a complete vision of the process of wealth accumulation over time and of the optimal portfolio decisions for each category of individuals.

4.1 Initial problems in data management.

The analysis of the data provided by the Survey on Household Income and Wealth (SHIW) highlighted some initial critical issues. The data were divided into macro-categories and covered a time interval from 1977 to 2022. However, the categories were not structured in a form immediately usable for a regression model. In particular, the information on the average salary was disaggregated into the following categories:

- **Gender**: Male, Female
- **Age**: Under 30, 31-40, 41-50, 51-65, Over 65
- **Level of education**: Primary school, Lower secondary school, Upper secondary school, Degree
- **Work sector**: Agriculture, Industry, Public Administration, Public services, other sectors

- **Professional status**: Employee, Self-employed, Retired, Unemployed non-retired
- **Number of members of the household**: 1-5
- **Geographical area:** North, Center, South and Islands
- **Country of origin**: Italy, Abroad

For the regression, **only a few independent variables** of interest **were selected**: **Gender, Age** (excluding over 65s since human capital was calculated only on the basis of income from work, assuming 65 years as the retirement age), **Level of education and Geographical area.**

4.1.2. Choice of Equivalent Income for Analysis

For the research a specific type of income had to be selected, in order to more accurately measure the effect of human capital on investment choices. The average Equivalent Income (excluding financial capital) with the modified OECD scale was chosen. Other options were: the version with the square root scale and wages calculated on financial capital.
This choice was motivated by the following factors:

- **Exclusion of financial capital**: It allowed to isolate the income derived exclusively from human capital (wages, salaries, self-employment income), avoiding distortions related to accumulated financial wealth.
- **Comparison with economic literature**: The modified OECD scale is widely used in economic studies, facilitating comparisons with other researches.
- **Differences with the square root scale**: The square root scale assigns a lower weight to additional members of the household, useful if one wants to minimize the impact of family size on income distribution.

4.1.3. Generation of Individual Observations

A significant obstacle in the analysis was the lack of complete individual observations with all the selected variables. To overcome this limitation, a method based on the overall mean of annual salaries and the percentage variation of the individual categories with respect to the mean was implemented.

For example, from Table S15 of the SHIW Appendix for the year 1977:

- Average total income: 1620

- Males: 1650 (+1.85% compared to the mean)
- Females: 1592 (-1.7% compared to the mean)

Applying this method, the individual income for each year was calculated as:

$$Income = Average\_Income \times (1+gender\_difference) \times (1+age\_difference) \times (1+education\_difference) \times (1+region\_difference)$$

It can be useful to review the differences between the categories because they can briefly explain what we expect to see at the end of the analysis.

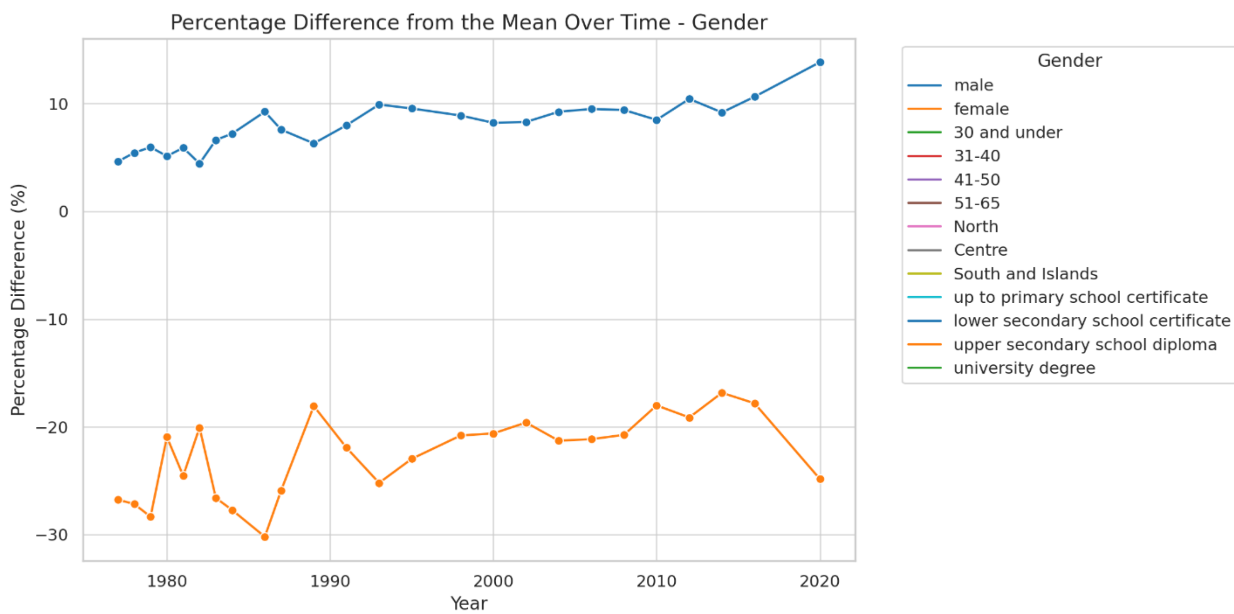


Figure 18, Percentage Difference from the Mean over Time by Gender. *Average fluctuations of salaries divided into categories. Sample of Italian households in the 2020 wave of the SHIW;*

Figure 18 illustrates the gender gap in earnings. Males consistently remain above the mean, while females remain below it, reinforcing the existence of a persistent gender wage gap. While there is some fluctuation over time, the gap has shown limited convergence, indicating structural barriers affecting female earnings potential.

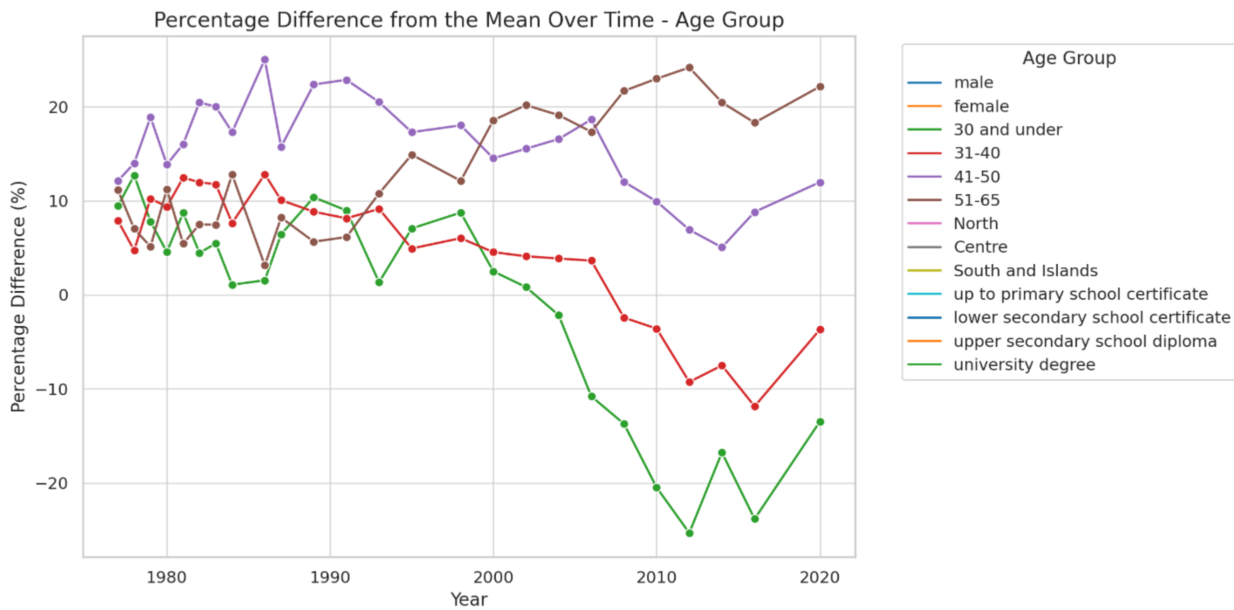


Figure 19, Percentage Difference from the Mean over Time by Age Group. *Average fluctuations of salaries divided into categories. Sample of Italian households in the 2020 wave of the SHIW;*

Figure 19 displays the percentage difference from the mean over time for different age groups. Notably, the "51-65" age group consistently remains above the mean, indicating higher relative earnings, possibly due to greater work experience and seniority. The "30 and under" and "31-40" groups show a declining trend, particularly after 2000, suggesting that younger workers have faced increasing financial challenges over time.

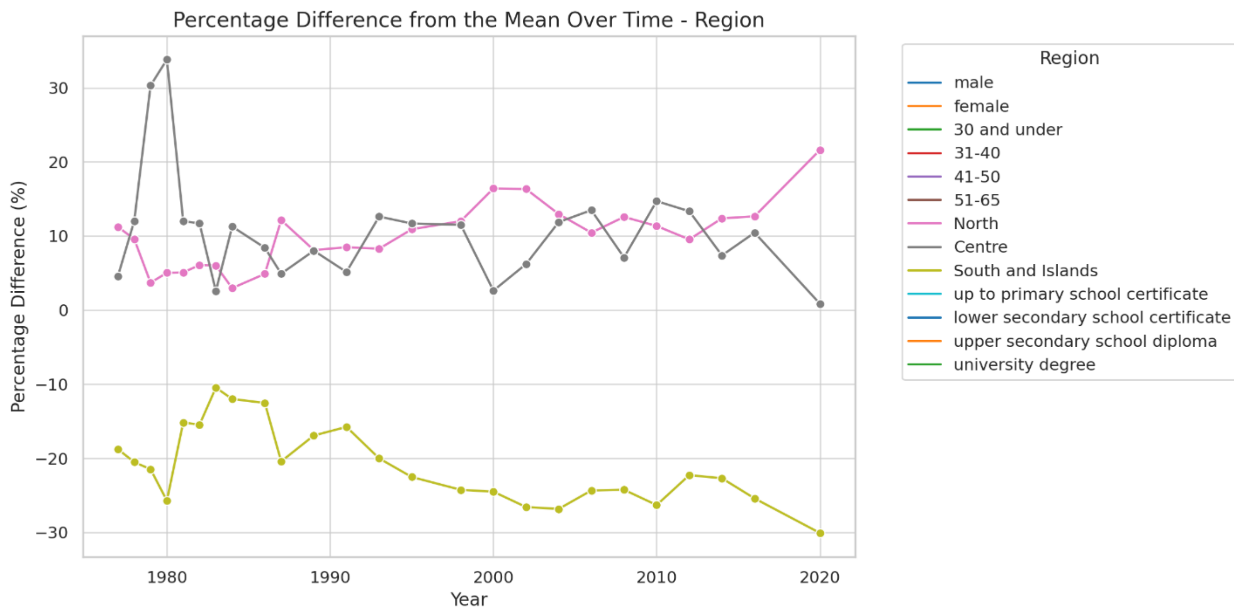


Figure 20, Percentage Difference from the Mean over Time by Region. *Average fluctuations of salaries divided into categories. Sample of Italian households in the 2020 wave of the SHIW;*

Figure 20 examines geographical disparities in earnings. The "North" and "Centre" regions consistently stay above the mean, reflecting stronger economic conditions and labor market opportunities in these areas. In contrast, the "South and Islands" region exhibits negative deviations, signifying ongoing economic disadvantages and lower earning potential in southern regions.

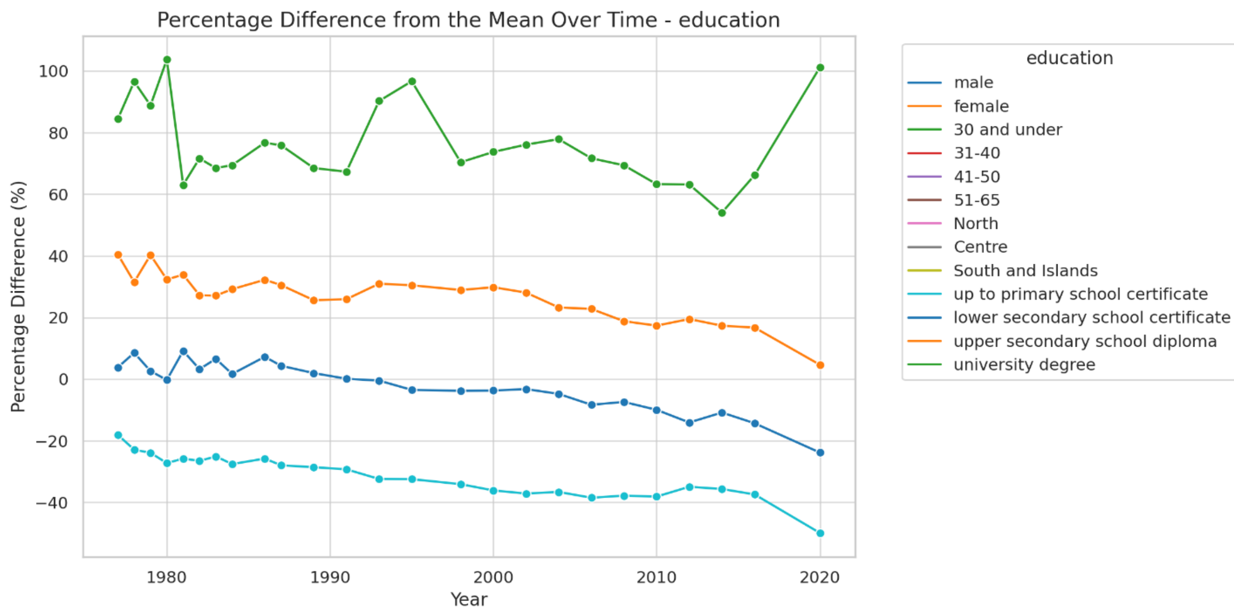


Figure 21, Percentage Difference from the Mean over Time by Education. *Average fluctuations of salaries divided into categories. Sample of Italian households in the 2020 wave of the SHIW;*

Figure 21 highlights the impact of education on earnings differences. University degree holders consistently outperform other educational categories, with a significant positive deviation from the mean. Conversely, individuals with lower secondary and primary education remain below the mean, highlighting the persistent income disparity based on educational attainment. The declining trend for secondary school diploma holders in recent years suggests a potential devaluation of mid-level education credentials in the job market.

Key Observations:

- **Education remains the strongest predictor of income differences**, with higher education yielding significant financial benefits.
- **Age plays a crucial role**, as older workers tend to earn more than younger workers, likely due to accumulated experience.
- **Gender disparities persist**, with males systematically earning more than females.
- **Regional inequalities are evident**, with the South staying behind the North and Centre.

These findings reinforce the importance of education, experience, and location in shaping income disparities and long-term financial stability.

Subsequently, using a Python program, synthetic observations were generated by adding a random variation factor, extracted from a normal distribution with mean 1 and standard deviation 0.2. This introduced a level of "statistical noise" to ensure greater variability in the simulated data.

Finally, a number of 500 observations was set for each year, in line with the number of families interviewed annually in the Bank of Italy survey.

4.1.4. Interpolation of Missing Data and Salary Forecasting

Another issue encountered was the lack of salary data for some specific years, including: 1985, 1988, 1990, 1992, 1994, 1996, 1997, 1999, 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, 2017, 2018, 2019.

To address this gap, a regression interpolation was applied. For each missing year, a single observation was generated for each unique combination of categories, which was then integrated into the overall regression to obtain a salary forecast up to 2035.

4.1.5. Limitations of the Salary Forecast

The decision to extend the forecast only up to 2035 stems from the fact that predicting salaries beyond a 10-year time horizon becomes statistically unreliable. Salary dynamics can be influenced by unpredictable factors, such as economic crises, regulatory changes and technological revolutions, making long-term estimates less reliable.

4.1.6. Results

Year	Gender	Age Group	Region	Education	Salary
1977	female	30 and under	centre	lower secondary school certificate	3051,230
1977	female	30 and under	centre	lower secondary school certificate	3101,550
2006	female	30 and under	north	upper secondary school diploma	160352,535
2018	male	31-40	South and islands	lower secondary school certificate	168153,866
2035	male	51-65	centre	upper secondary school diploma	480842,645

Table 1, Example of Results of Observation generated for Salary estimation and projection.

4.1.7. Conclusion

The adopted approach has allowed to transform the aggregate data into coherent individual observations, suitable for a regression analysis. The use of equivalent income without financial capital has allowed to focus on the impact of human capital on the investment choices of families, while the interpolation of the data has guaranteed a homogeneous temporal basis on which to build future projections.

In the next chapters, this data structure will be used to examine the relationship between labor income, wealth accumulation and propensity to financial investments.

4.2 Projection of Observations and Salary Forecast

4.2.1 Objective of the Projection

The objective of the projection is to obtain an estimate of future incomes to analyze the evolution of human capital and its impact on investment strategies. The forecast was carried out until 2035, considering that forecasts beyond this time horizon become less reliable due to macroeconomic uncertainty and structural changes in the labor market.

4.2.2 Database and Initial Regression

The following were used to perform the forecast:

- Observations generated with Python based on salary averages and percentage changes by category.
- Interpolated data for missing years (1985, 1988, 1990, etc.), obtained through regression.

Categorical variables (gender, age, region, and education) were encoded into numbers using Stata's encode command, so they could be used in the regression model. The data were then sorted by category and year to ensure consistency in the regression.

4.2.3 Inflation Correction

Since historical wages were expressed in nominal values, it was necessary to revalue them to the purchasing power of 1977 to ensure temporal comparability. This was done using a revaluation factor calculated on the basis of historical inflation.

Cumulative Factor: Brings each year back to the 1977 reference value and allows past wages to be adjusted to the base year 1977, correcting them for the erosion of purchasing power.

For each year t, the wage was updated with the formula:

$$W_{1977}=W_t/\mathit{Cumulative\ Factor}(t)$$

Where the Revaluation Factor varies according to the inflation observed in each year. For example:

A 2022 wage was divided by 0,189562, therefore increased by 427,3% about 5 times more than the nominal value.

A salary from 2010 was revalued with a different factor, based on its historical inflation.

All values of the Cumulative Factor can be found in the Appendix: 1.INFLATION.

After this correction, the updated data was used for the salary forecast.

4.2.4 Linear Regression Model

The linear regression was performed with the following model:

$$\mathit{Real\ Salary}=\beta 0+\beta 1\cdot \mathit{Year}+\beta 2\cdot \mathit{Gender}+\beta 3\cdot \mathit{Age\ Group}+\beta 4\cdot \mathit{Region}+\beta 5\cdot \mathit{Education}+\varepsilon$$

Implemented in Stata with the command:

regress real_salary year i.gender_num i.age_group_num i.region_num i.education_num

The resulting regression coefficients were then exported and used in Excel to estimate future wages.

The Stata results can be found in the Appendix: 2.STATA.

Regression Coefficients:

Coefficient	Value
Intercept	-14800000
Year	7.466
Female	0,0000
Male	42526,33
30 and under	0,0000
31-40	10174,16
41-50	28367,85
51-65	33634,37
Centre	0,0000
North	4.144
South and Islands	-44027,48
Lower Secondary School	0
University Degree	103.181
Up to Primary School	-33.669
Upper Secondary School	11.809

Table 2, Regression coefficients after interpolation for future salaries projection.

4.2.5 Projection Formula in Excel

Using the coefficients obtained from the regression, the forecast formula for the salary was applied in an excel file. Since the initial data were already expressed in real terms (purchasing power 1977), no further correction for inflation was necessary in the forecasts.

Final Results Example:

Year	Gender	Age Group	Region	Education	Salary
1977	female	30 and under	centre	lower secondary school certificate	3051,230
1982	female	31-40	centre	university degree	32918,303

1992	male	30 and under	north	upper secondary school diploma	102965,132
1999	male	51-65	South and islands	upper secondary school diploma	136563,284
2004	female	41-50	South and islands	up to primary school certificate	73258,478
2020	male	51-65	north	upper secondary school diploma	587488,191
…	…	…	…	…	…

Table 3, Example of Results of future salary Projection for missing and future years.

4.3 Calculation of Human Capital

Definition of Human Capital

Human capital represents the present value of future earnings discounted for risk and time preference.

We follow the Guiso-Sodini model, incorporating labor income volatility and market risks.

The fundamental equation is:

$$HC_a = \sum_{\tau=a}^{T} \beta^{\tau-a} y_\tau$$

where:

The Discount Factor $\boldsymbol{\beta} = \frac{1}{1+r_m}$

Education	Discount Rate
Up to primary school certificate	0,955473238
Lower secondary school certificate	0,95561213
Upper secondary school diploma	0,955444618
University degree	0,955556976

Table 4, Discount rates.

y_τ = expected labor income at age τ ,

r_m = risk-adjusted discount rate (accounts for income volatility and stock correlation).

T= retirement age (65 years).

4.3.1 Estimating Labor Income

Where does income data come from?

- We use a **salary dataset** containing historical and projected earnings for different groups:
  - **Gender**
  - **Age group**
  - **Region**
  - **Education level**
- Income is already **inflation-adjusted**, so we only need to account for **income risk**.
- For each combination of category, we have a different salary for each year:

Example:

Year	Gender	Age Group	Region	Education	Salary
1977	female	30 and under	centre	lower secondary school certificate	3051,230
1982	female	31-40	centre	university degree	32918,303
1992	male	30 and under	north	upper secondary school diploma	102965,132
...	...	...	...	...	...

Table 5, Example of final observation for Human capital calculation.

How do we handle career start and retirement?

- Work start age is standardized at 26, because before 26 years old is rare that individuals would own a house.

- **Annual earnings** from the career start **until retirement** (assumed at **65 years old**) are tracked and the program updates yearly the transition from an Age Group to another to update:
  - Salary
  - Saving rate

  While discount rates and income volatility only depend on Education Level.

4.3.3: Estimating Financial Wealth

From SHIW we can extract the Financial Wealth value of 2020 households divided into categories.

Characteristics	Financial assets
male	11000
female	5440
34 and under	5000
35-44	8000
45-54	10000
55-64	10000
up to primary school certificate	4000
lower secondary school certificate	6807
uppery secondary school diploma	10300
university degree	33896
North	16953
Centre	11500
South and Islands	3500
All	**9500**

Table 6, Mean Financial Assets records divided into categories from SHIW.

To estimate the value of the combinations the same approach as Chapter 4.1.3. has been taken, and the values have been adjusted according to the inflation factor, for each starting year (1977, 1980, 1990).

Gender	Age Group	Region	Education	Estimated Ft	Adjusted Ft
Male	Up to 34 years	North	Up to Primary School	1957,701648	16228,30562

Male	Up to 34 years	North	Lower Secondary School	2201,772629	18251,52426
Female	Up to 34 years	South and Islands	University Degree	2683,277927	22242,94713
Female	35-44 years	North	Up to Primary School	2885,469959	23919,01156
Female	55-64 years	South and Islands	Upper Secondary School	8160,701441	67647,87533
…	…	…	…	…	…

Table 7, Individual Head of Household characteristics with Financial wealth, adjusted for inflation.

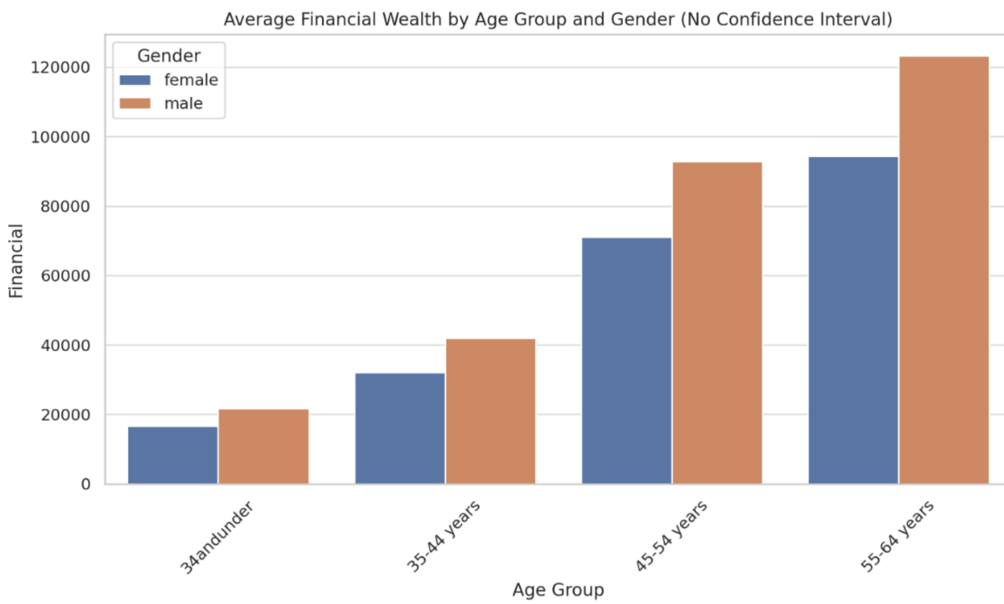


Figure 22. Average Financial Wealth by Age Group and Gender. *Average financial wealth across different age groups, disaggregated by gender. Data refer to observations generated on a sample of Italian households from the 2020 wave of the SHIW;*

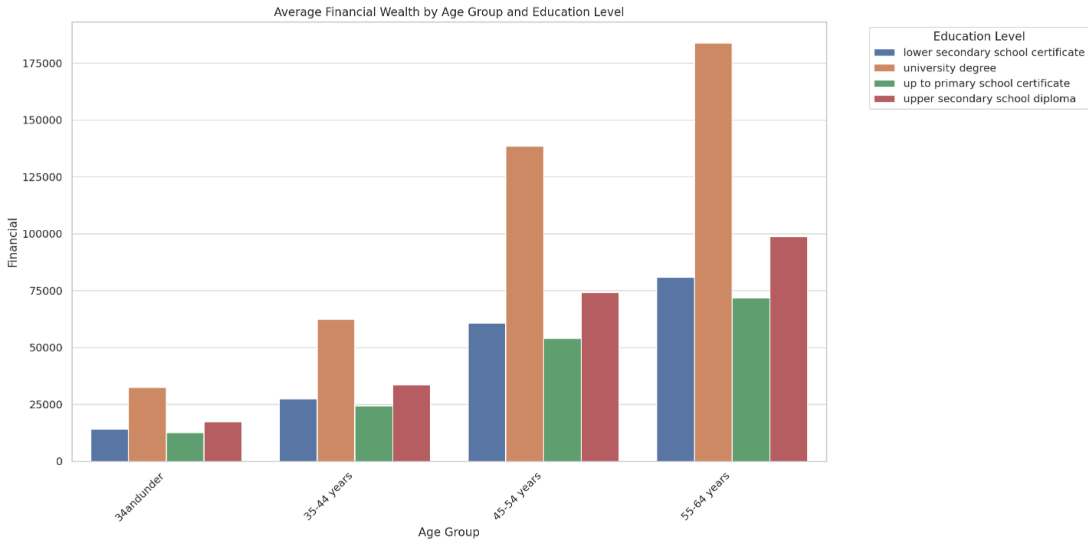


Figure 23. Average Financial Wealth by Age Group and Education Level*. Average financial wealth across different age groups, disaggregated by level of education. Data refer to observations generated on a sample of Italian households from the 2020 wave of the SHIW.*

4.3.4 Computing Human Capital Step-by-Step

For each individual in the dataset the computation follows these steps:

1. **Extract their salary trajectory** (historical & projected earnings).
2. **Apply the risk-adjusted discount rate** (β).
3. **Sum all discounted future earnings**.

Later to apply it to Munk's formula for Optimal Allocation:

4. **Combine it with starting financial wealth.**
5. **Compute optimal portfolio allocation** using Munk's formula.

The Python Program can be found in the Appendix: 4.CODE Compute_human_capital.

The output of the program compute Human Capital by incrementing the age and upgrading the salary of the unique ID household's head, for each "current year" and the results are like the following table:

ID	Gender	Region	Education	Starting Year	Starting Age	Current Year	Current Age	Years Calculated	Human Capital (€)
3415	male	north	university degree	1977	50	1977	50	0	7203,94
3415	male	north	university degree	1977	50	1978	51	1	16190,97
3415	male	north	university degree	1977	50	1979	52	2	28595,29
3415	male	north	university degree	1977	50	1980	53	3	48027,31
3415	male	north	university degree	1977	50	1981	54	4	67585,36
3415	male	north	university degree	1977	50	1982	55	5	91235,57
3415	male	north	university degree	1977	50	1983	56	6	124033,8
3415	male	north	university degree	1977	50	1984	57	7	172112,1
3415	male	north	university degree	1977	50	1985	58	8	230490,3
3415	male	north	university degree	1977	50	1986	59	9	288207
3415	male	north	university degree	1977	50	1987	60	10	358628,5
3415	male	north	university degree	1977	50	1988	61	11	433135,4
3415	male	north	university degree	1977	50	1989	62	12	520656,2
3415	male	north	university degree	1977	50	1990	63	13	602572,4
3415	male	north	university degree	1977	50	1991	64	14	697535,9

Table 8, Evolution of professional life expectations represented by Human Capital. *From starting age to retirement, Human Capital is calculated from Salaries information year by year.*

4.3.5 Visualizing Results

To **analyze and interpret** human capital:

- **Generate graphs** showing Salary evolution
- **Track HC evolution over a lifetime** (career start to retirement).

- **Compare groups** (education, region, gender).

Salaries are calculated on base year 1977, the first given year in the Database. First we have to check salary evolution to know what to expect from the model.

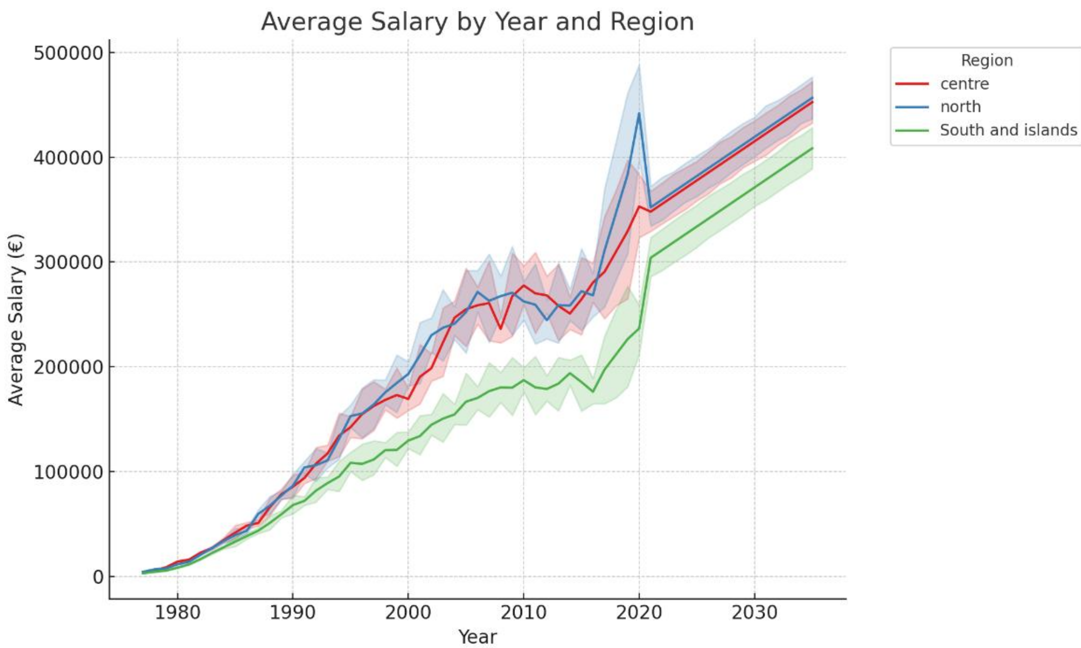


Figure 23, Average Salary by Year and Region. *Average salary trends over time across Italian macro-regions. Data refer to generated observation on Italian households sample of SHIW over the period 1975–2035.*

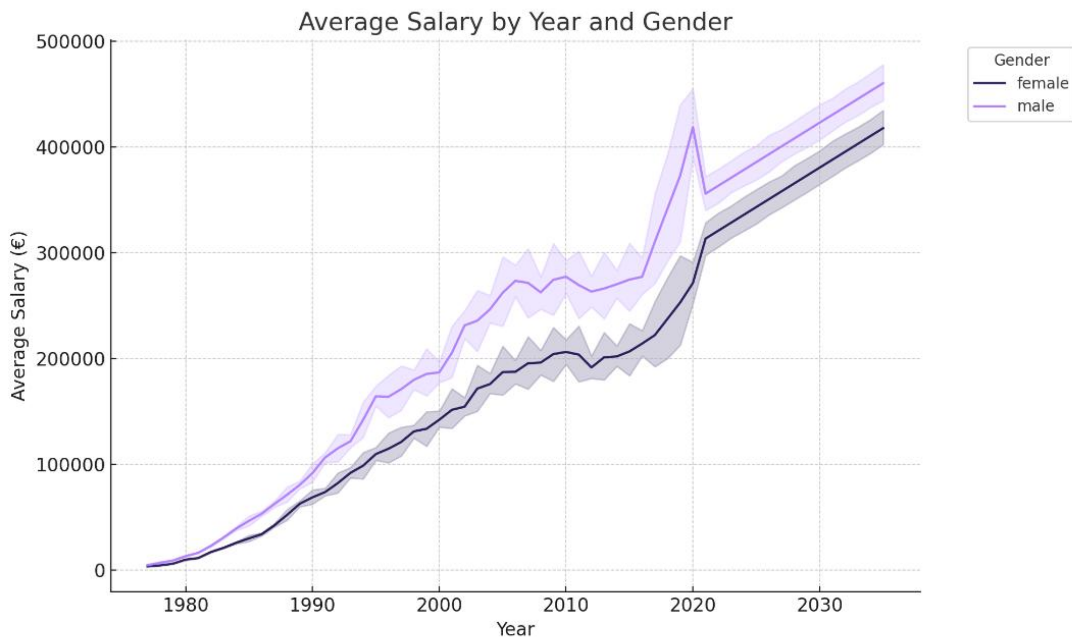


Figure 24. Average Salary by Year and Gender*. Average salary trends over time divided by genders. Data refer to generated observation on Italian households sample of SHIW over the period 1975–2035.*

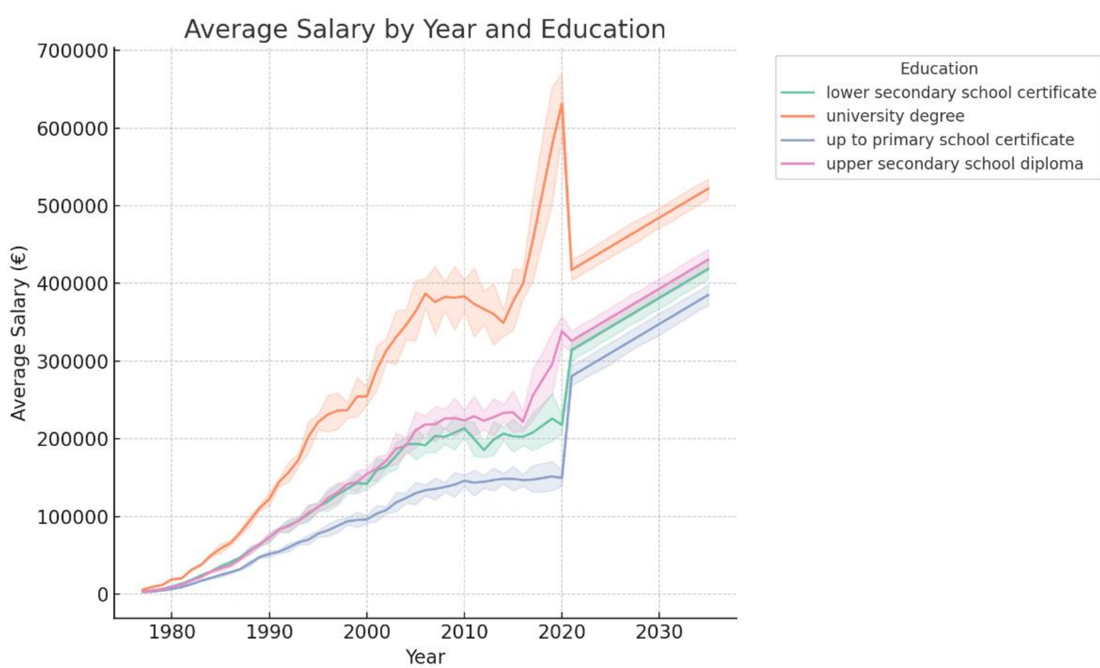


Figure 25, Average Salary by Year and Education Level*. Average salary trends over time divided by education level. Data refer to generated observation on Italian households sample of SHIW over the period 1975–2035.*

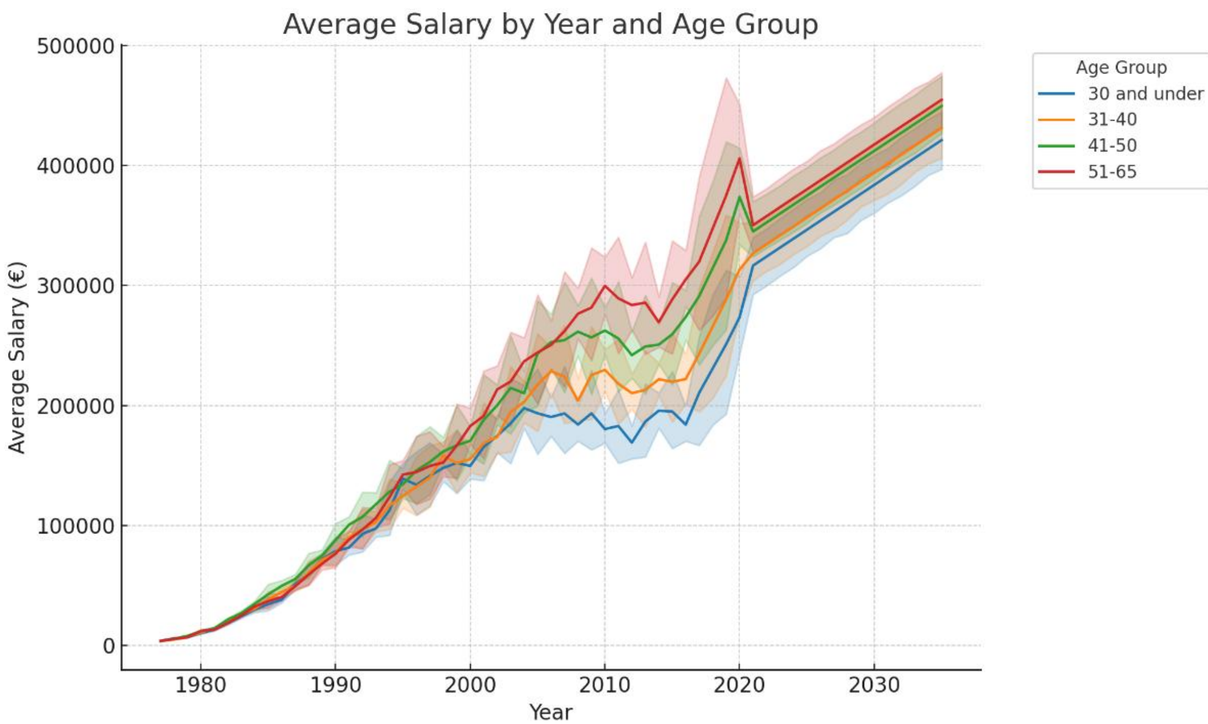


Figure 26, Average Salary by Year and Age Group*. Average salary trends over time divided by age groups. Data refer to generated observation on Italian households sample of SHIW over the period 1975–2035.*

Average Salary Trend by Region (Figure 23): the graph shows that the North has consistently recorded higher average salaries than the Center and the South and Islands, with a difference that has been maintained over time. However, all regions show an increasing trend, with a more marked acceleration after 2020. The South and Islands maintains the lowest average salary level for the entire period, highlighting a persistent structural gap.

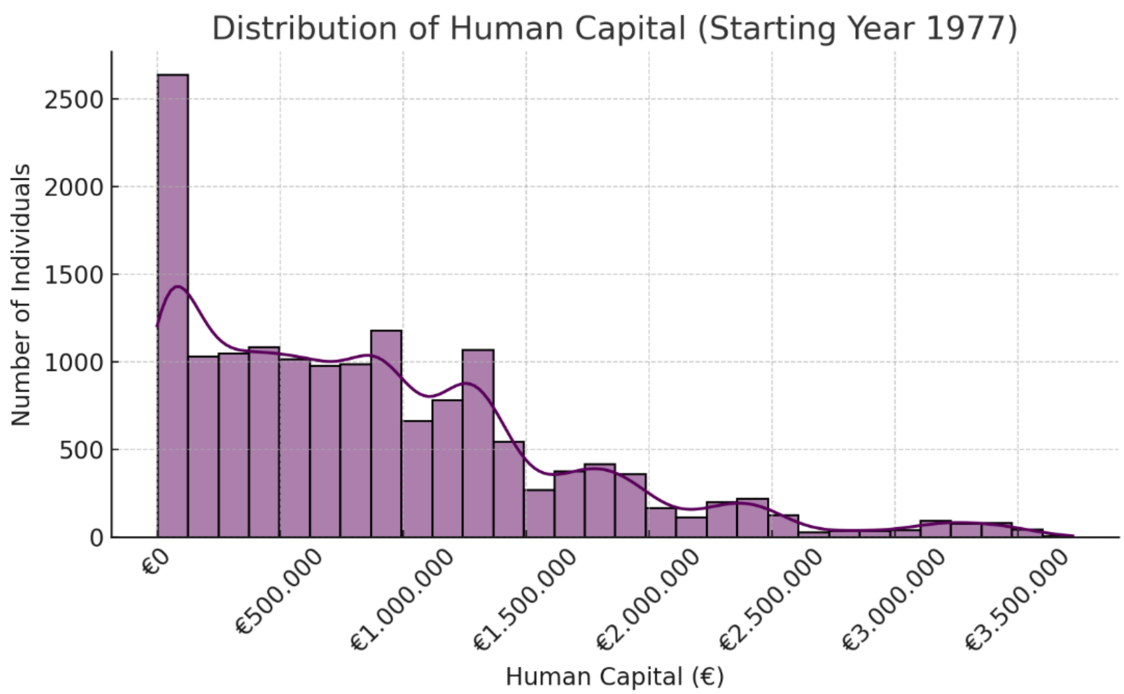
Average Salary Trend by Gender (Figure 24): even though both genders have seen constant salary growth over time, the graph highlights persistent salary inequality: men earn more than women on average. The gap has slightly narrowed in recent years, but is still significant.

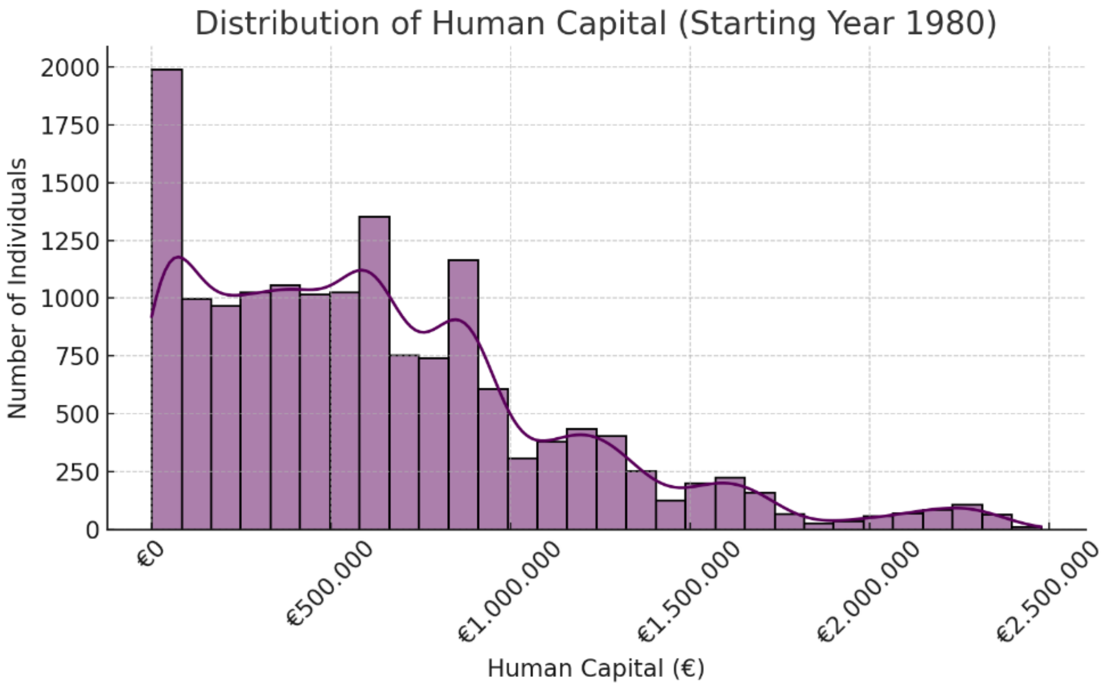
Average Salary Trend by Level of Education (Figure 25): the level of education has a very significant impact on average salary. Graduates (university degree) have the highest salaries overall, with a significant peak after 2020. They are followed by high school graduates and those with a lower secondary school diploma. People with only primary school have the lowest salaries, and the gap with graduates is very wide and growing over time.

Average Salary Trend by Age Group (Figure 26): the 51-65 age group has the highest average salaries, followed by the 41-50 and 31-40 groups. The youngest (30 and under) have the lowest salaries, but with a more dynamic growth over time. This trend reflects the typical salary progression of the working career and the accumulation of experience.

4.3.6. Human Capital Results

These graphs are not individual-level estimates but aggregated subgroup averages. Consequently, maximum values may appear lower than expected due to averaging across populations with varied income and career profiles.





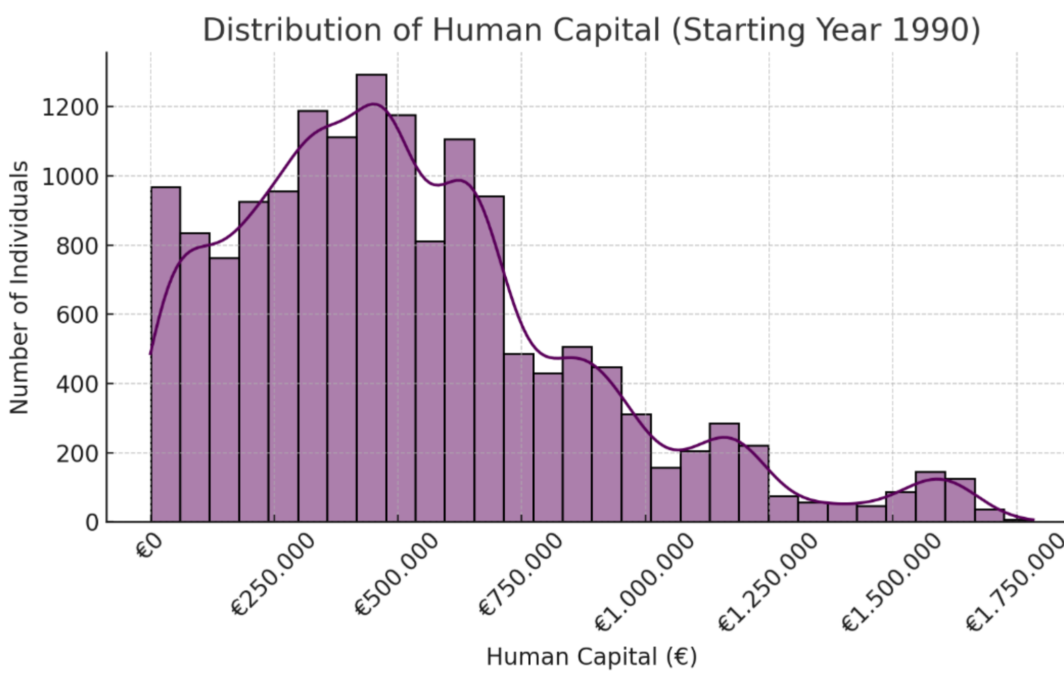


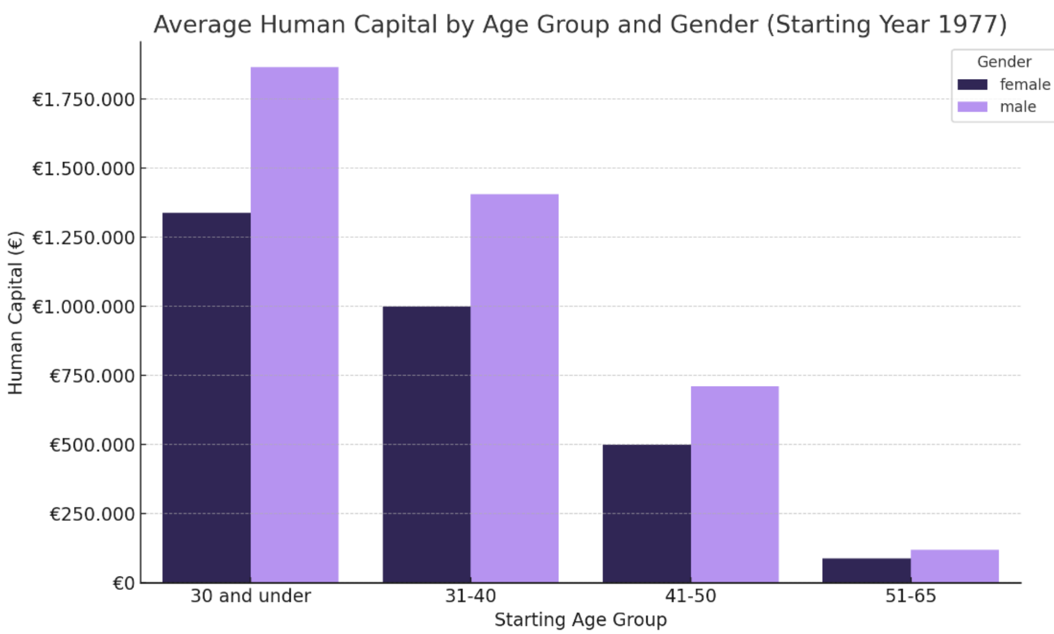
Figure 27/28/29. Distribution of Human Capital (Starting Year: 1977/1980/1990). *Simulated individual-level data based on the 2020 wave of the SHIW, adjusted to respective base year.*

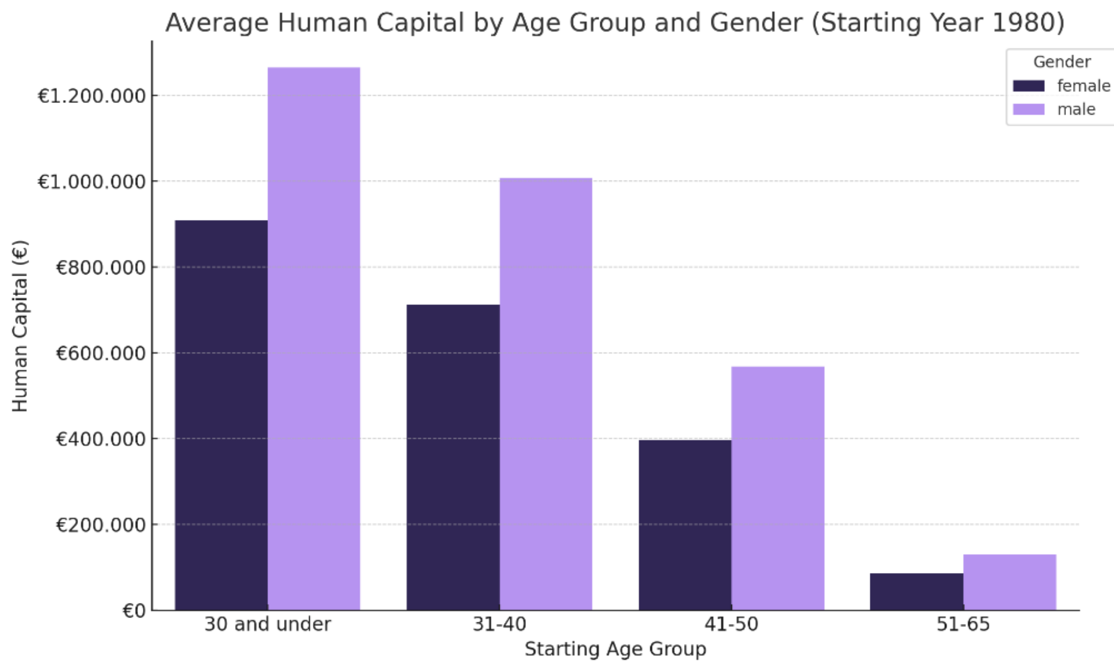
In all cases, the distribution is skewed to the right, with a strong concentration of individuals with little or no human capital and a tail that extends towards higher values. However, some significant evolutions can be noted between the three scenarios:

In 1977 and 1980, the distributions present multiple peaks and a greater dispersion, with human capitals that even exceed 2.5 million euros.

In 1990, the distribution appears more compact and symmetric, with most individuals concentrated in a range between €250.000 and €750.000, and with fewer outliers at the extreme values.

This evolution reflects the effect of the starting year on the remaining length of the working career: the later the starting year, the lower the average of the calculated human capital, since there are fewer years of income from work to accumulate or because, by starting in 1990, during the simulation more and more simulated salaries are used, even predicted ones, that are not totally reliable from a statistic point of view. Of course this analysis can be improved in further studies.





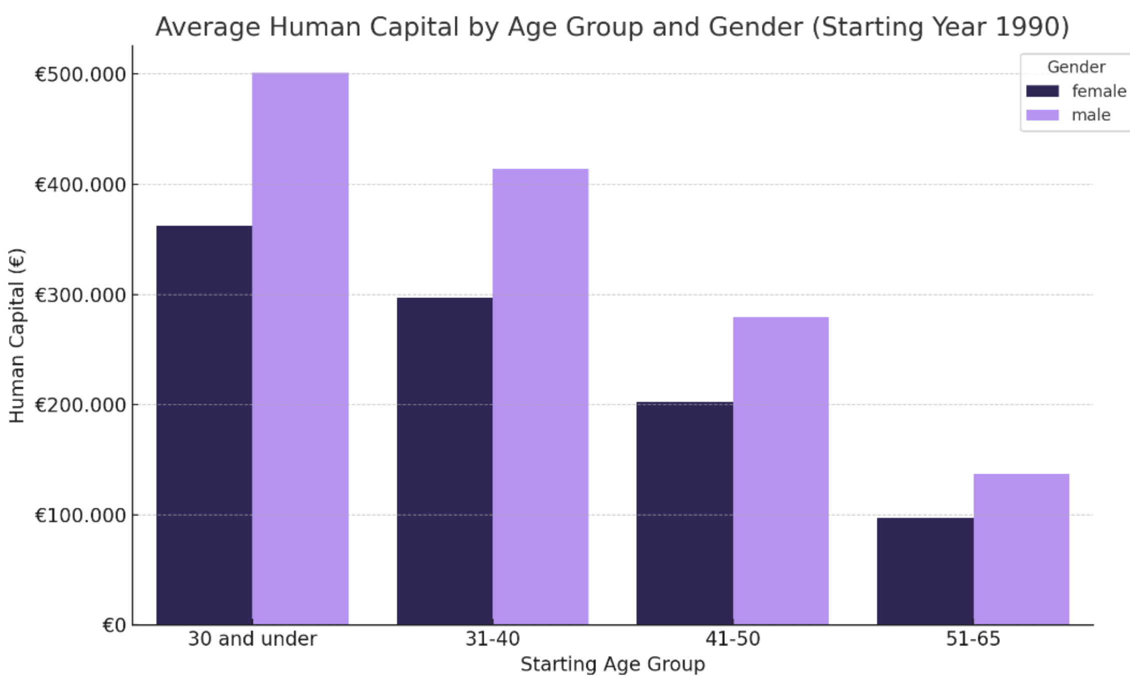
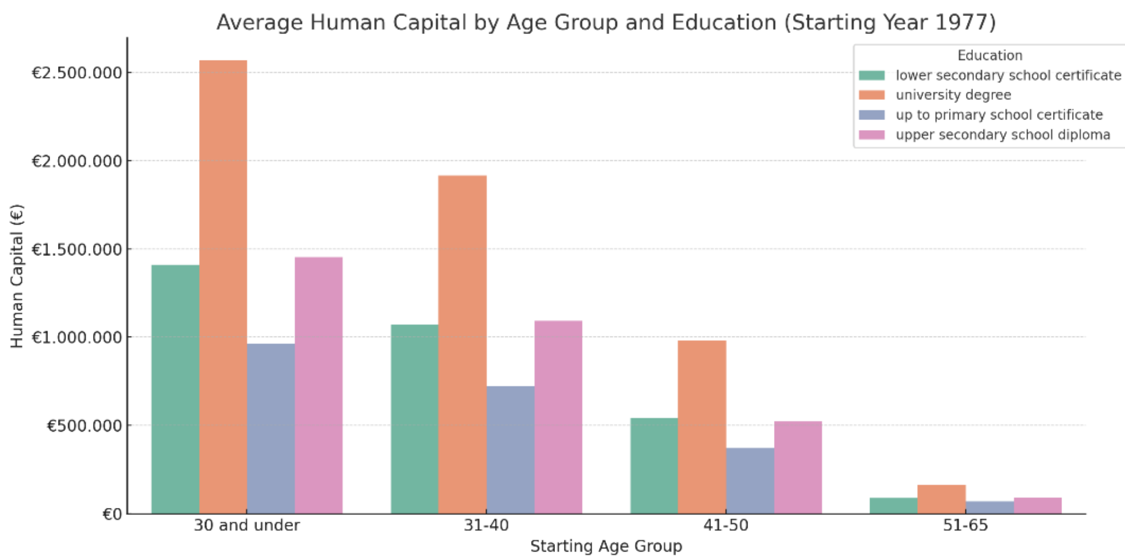


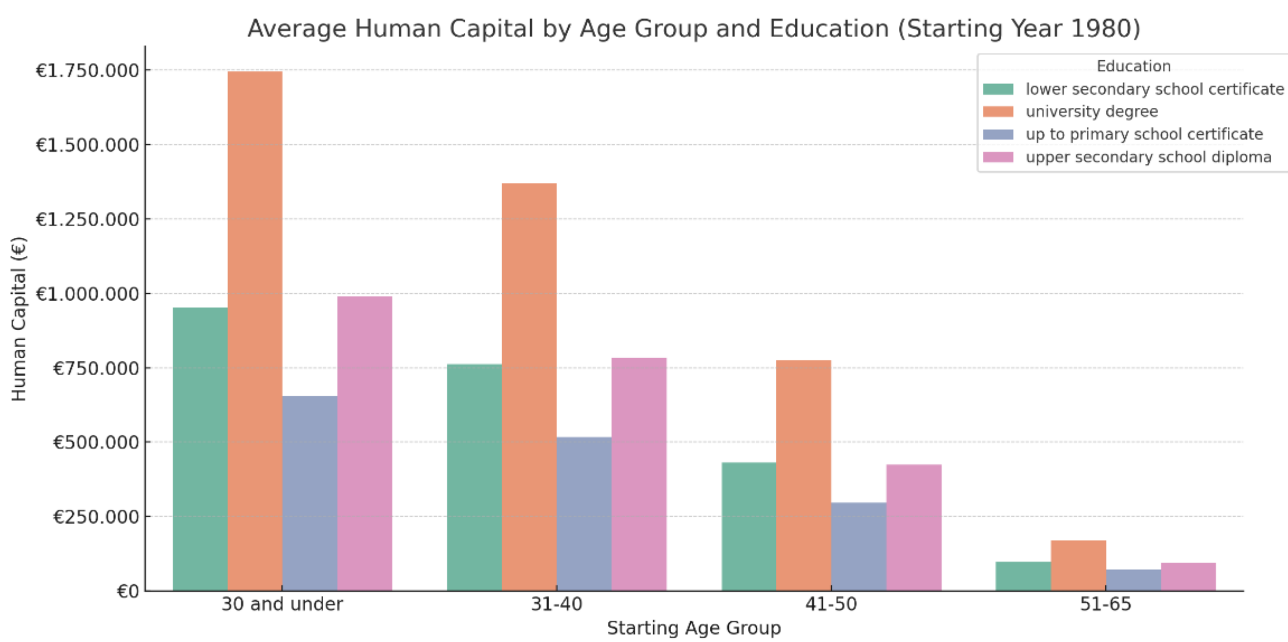
Figure 30/31/32. Average Human Capital by Age Group and Gender (Starting Year: 1977/19801990). *The values displayed represent the average human capital computed at the intersection of gender and starting age group. Simulated individual-level data based on the 2020 wave of the SHIW, adjusted to respective base year.*

In all three time frames, a clear decline in human capital is observed as the starting age increases, consistent with the shorter remaining duration of working life.

Furthermore, the overall values decrease as the starting year advances (from 1977 to 1990), due to the different wage structure and the methodology of discounting human capital over time.

By checking genders, males systematically present a higher average human capital than women, reflecting both wage inequalities and different career expectations. This gap is particularly marked in the youngest age groups, where human capital reaches its highest levels.





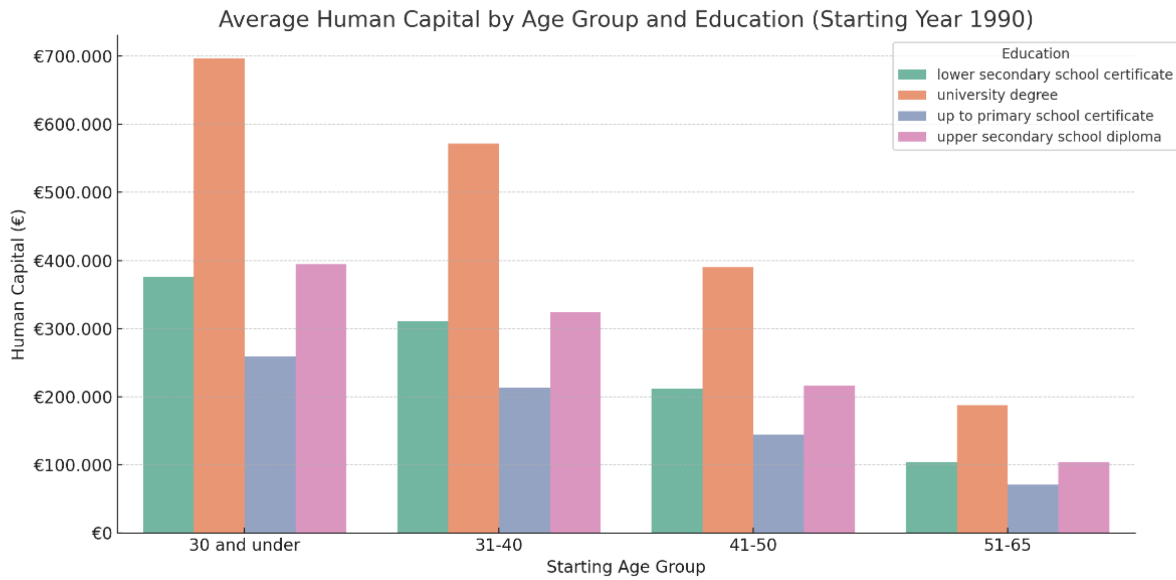
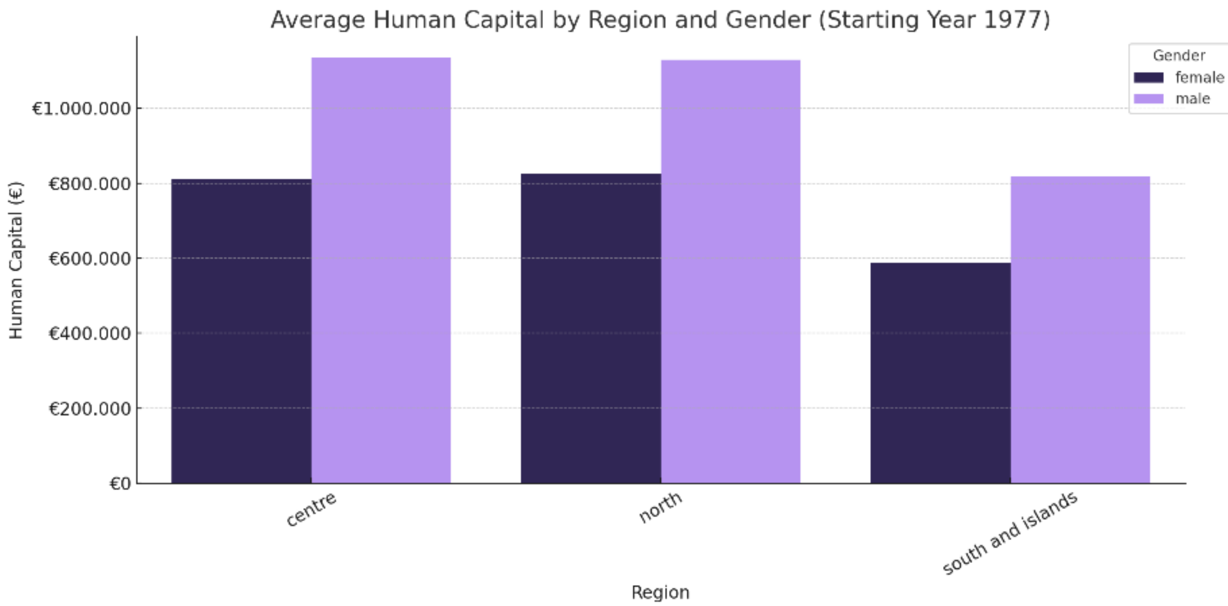


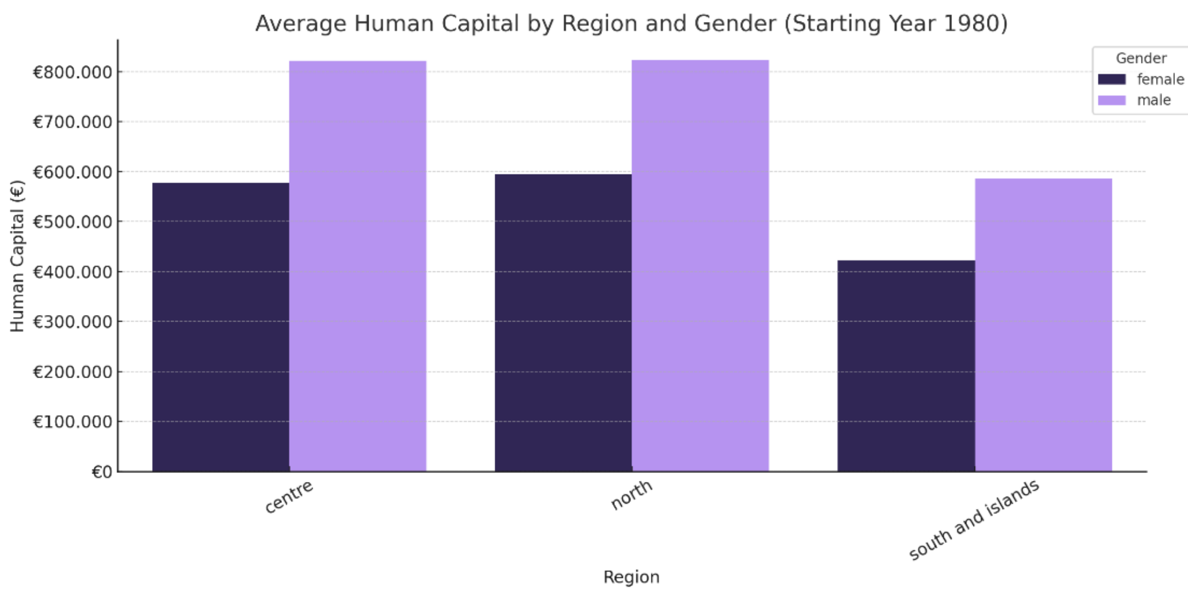
Figure 33/34/35. Average Human Capital by Age Group and Education (Starting Year: 1977/1980/1990). *The values displayed represent the average human capital computed at the intersection of education level and starting age group. Simulated individual-level data based on the 2020 wave of the SHIW, adjusted to respective base year.*

In all three cases, we observe that:

- Human capital decreases with age, consistently with the reduction of residual working life.
- Individuals with a university degree systematically possess a higher average human capital than other educational categories, especially in the younger age groups.
- Subjects with lower educational qualifications show lower average values, confirming the strong link between educational level and future income potential.
- The differences between educational levels attenuate with increasing age, as careers become shorter and human capital flattens out between groups.

The comparison between the three years shows an overall reduction in average human capital over time, in line with the hypothesis of a later starting point in the life cycle, which implies fewer working years and therefore less future income to discount or because, by starting in 1990, during the simulation more and more simulated salaries are used, even predicted ones, that are not totally reliable from a statistic point of view. This analysis can be improved in further studies.


Average Human Capital by Region and Gender (Starting Year 1977)
Gender
female
male
Human Capital (€)
€0
€200.000
€400.000
€600.000
€800.000
€1.000.000
centre
north
south and islands
Region


Average Human Capital by Region and Gender (Starting Year 1980)
Gender
female
male
Human Capital (€)
€0
€100.000
€200.000
€300.000
€400.000
€500.000
€600.000
€700.000
€800.000
centre
north
south and islands
Region

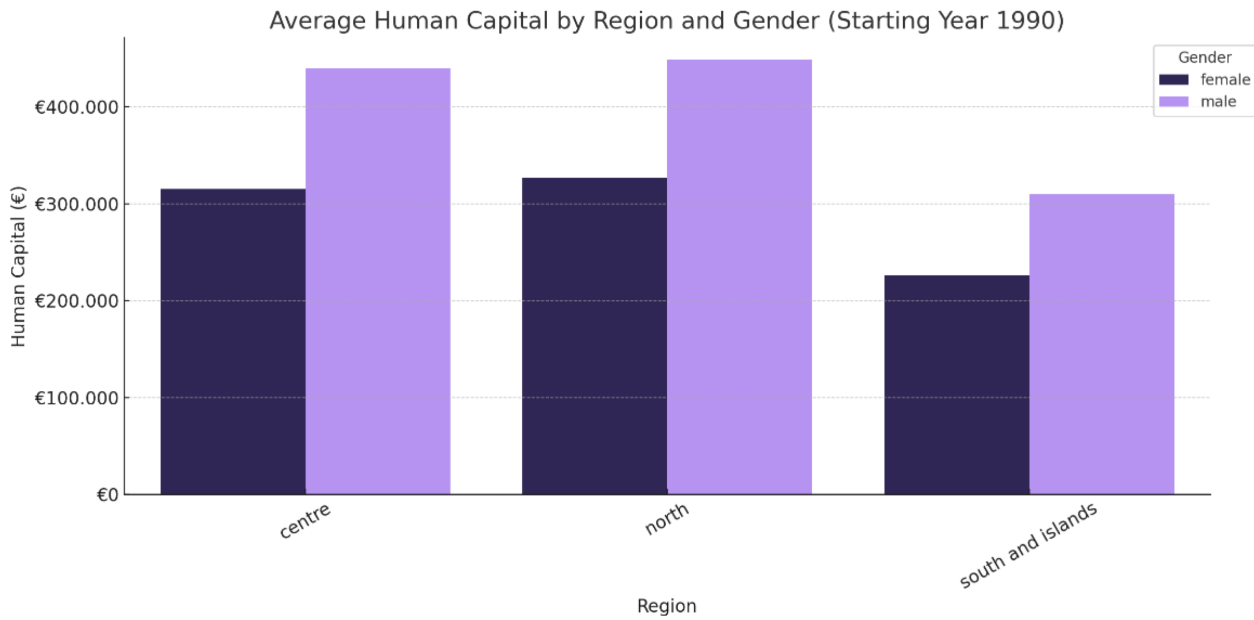
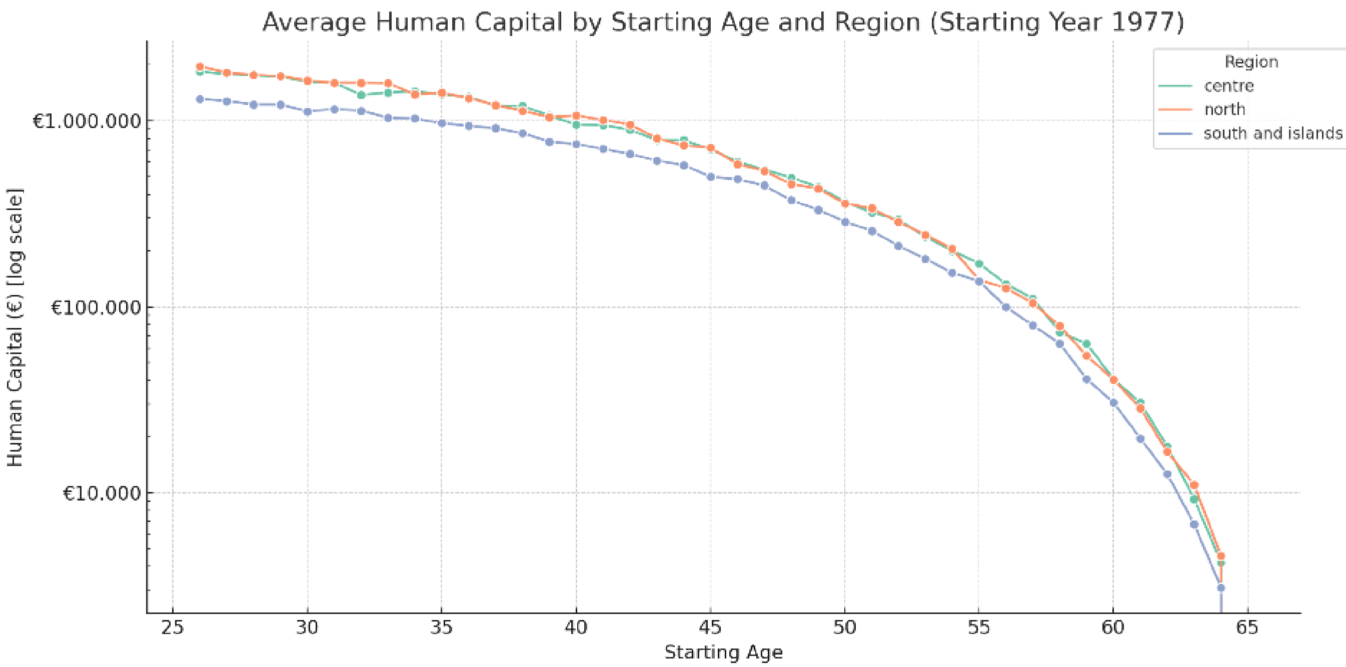


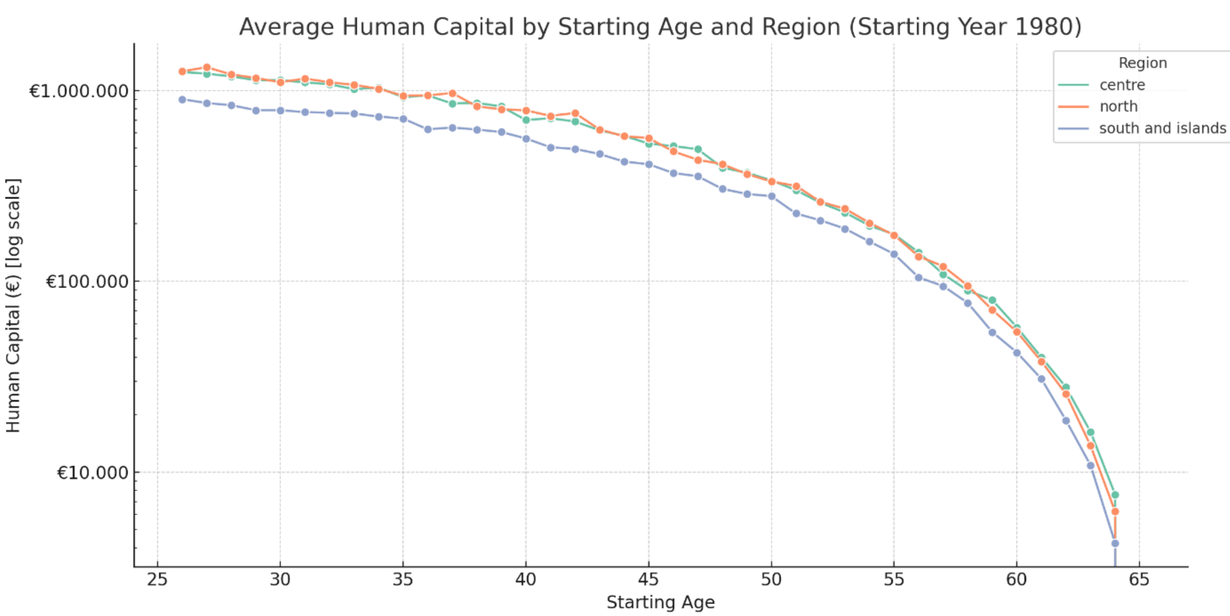
Figure 36/37/38. Average Human Capital by Region and Gender (Starting Year: 1977/1980/1990). *The values displayed represent the average human capital computed at the intersection of region and gender. Simulated individual-level data based on the 2020 wave of the SHIW, adjusted to respective base year.*

Gender differences: in all regions and for each year considered, the average human capital of men is systematically higher than that of women, highlighting the persistence of the gender gap in terms of work and wages.

Territorial gaps: the North has the highest values of average human capital, followed by the Center, while the South and the Islands show lower levels. This distribution reflects the traditional Italian territorial disparities in terms of job opportunities and income.

Decreasing trend over time: comparing the three starting years (1977 → 1980 → 1990), we note an overall decrease in average human capital, consistent with the fact that, at the same age, an individual simulated in 1977 has more future working years than one simulated in 1990 and the less reliability of the model due to the salaries predictions.


Average Human Capital by Starting Age and Region (Starting Year 1977)
Region
centre
north
south and islands
€1.000.000
€100.000
€10.000
Human Capital (€) [log scale]
25
30
35
40
45
50
55
60
65
Starting Age


Average Human Capital by Starting Age and Region (Starting Year 1980)
Region
centre
north
south and islands
€1.000.000
€100.000
€10.000
Human Capital (€) [log scale]
25
30
35
40
45
50
55
60
65
Starting Age

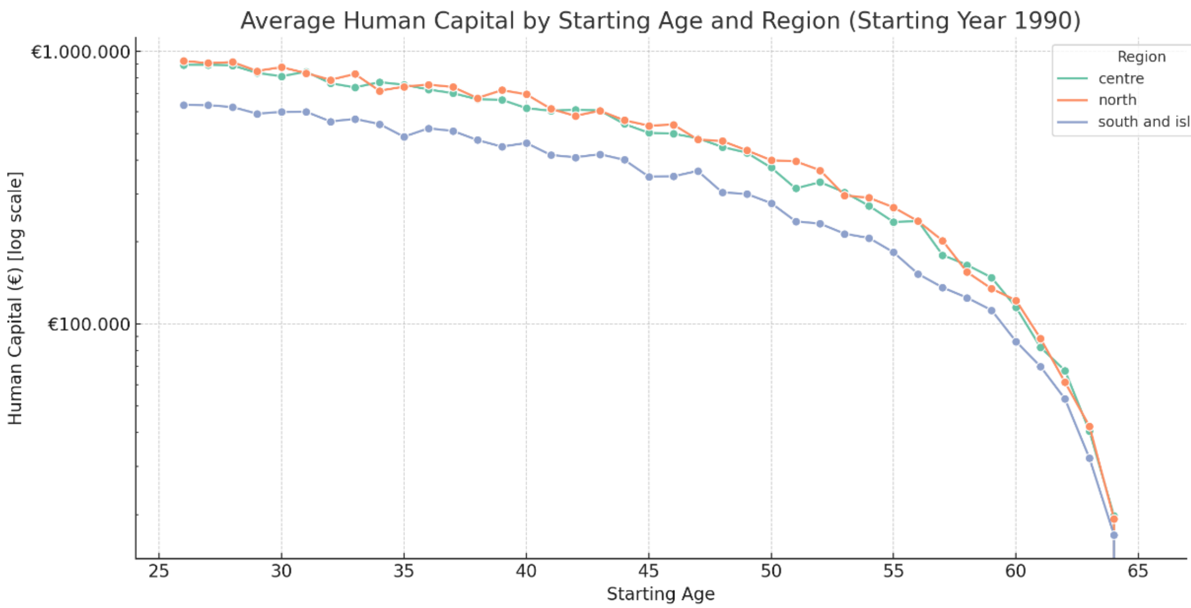


Figure 39/40/41. Average Human Capital by Starting Age and Region (Starting Year: 1977/1980/1990)*. The values displayed represent the average human capital computed at the intersection of starting age and region. Simulated individual-level data based on the 2020 wave of the SHIW, adjusted to respective base year.*

In all scenarios, a clear geographic hierarchy is observed: the North systematically presents higher levels of human capital, followed by the Center and, finally, the South and Islands, which records the lowest values. This gap is particularly marked at younger ages (25–40 years), where the differences can even exceed €200.000.

Human capital decreases with increasing starting age, reflecting the lower amount of remaining working years. However, the speed of decrease differs between regions: in the South, the decline is faster and the levels already start from lower values.

The trend is consistent in all starting years, but again, a general reduction in absolute levels of human capital can be noted from 1977 to 1990
In summary, these graphs highlight:

- A strong territorial heterogeneity in human capital, already present at a young age.
- A negative impact of age on the amount of human capital, more visible in the South.
- A downward trend of human capital in the most recent cohorts, potentially linked to less favorable economic conditions.

4.4 Munk's Theory

Munk's theorem provides a strategy for optimal portfolio allocation, combining both financial wealth and human capital. Unlike traditional models that only focus on financial investments, Munk's framework recognizes that human capital itself is an asset and affects investment decisions. It **incorporates human capital** into the traditional mean-variance framework of Markowitz, providing a more realistic approach to household financial decisions over the life cycle.

Munk's model is built upon two key components:

1. **Human capital (L_t)**: An illiquid and non-diversifiable resource representing the present value of future labor earnings.
2. **Financial wealth (F_t)**: The liquid and investable portion of total wealth.

The main idea is that **young individuals possess a large amount of human capital but little financial wealth**, whereas over time, human capital is gradually converted into investable savings.

At its core, the theorem tells us:

- **How much of your wealth should be invested in risky assets (**in this study, the assets are simplified into one single asset represented by the FTSE MIB INDEX: Financial Times Stock Exchange, Milano Indice di Borsa)
- **How human capital influences this investment decision**
- **How risk aversion changes the optimal allocation**

Munk's Formula:

$$\pi_t^* = \frac{1}{\gamma}(1+\lambda_t)\Sigma^{-1}(\mu - rf) - \lambda_t \Sigma^{-1} Cov(r, rL)$$

Where:

- $\pi*$ = **Optimal risky asset allocation**
- γ = **Risk aversion coefficient**

- Σ= **Variance-covariance matrix of risky asset returns** (will be **simplified since we use one risky asset**)
- μ = **Expected return of the risky asset**
- rf= **Risk-free rate**
- $\mu - rf$ **= Risk market premium**
- λ_t = **Lamda,** Lt/Ft **ratio**
- Lt = **Human capital (present value of future labor income)**
- Ft = **Financial wealth**
- Cov(r, r_L) = **Covariance between labor risky asset returns and income returns**

Since we are using only one risky asset, this simplifies further to:

$$\pi_t^* = \frac{(1+\lambda_t)(\mu - r_f)}{\gamma\sigma^2} - \frac{\lambda_t \cdot \mathrm{Cov}(r, r_L)}{\sigma^2}$$

This means:

- The portfolio allocation is a combination of a **speculative component** (first term) and an **income-hedging** component (second term).
- The speculative component scales with the **human capital-to-wealth ratio.**
- If labor income is **highly correlated with the risky asset, the second term reduces exposure to that asset.**

Economic Interpretation

The First Term:

$$\frac{(1+\lambda_t)(\mu - r_f)}{\gamma\sigma^2}$$

- This term suggests that **the higher the proportion** of human capital relative to financial wealth, **the greater the individual's ability to invest** in risky assets.
- **Young individuals,** who have a high λ_t, **should allocate more to equities** compared to older individuals.

The Second Term:

$$-\lambda_t \frac{Cov(r, r_L)}{\sigma^2}$$

- Introduces a **hedging effect**: if **human capital is highly correlated** with the stock market, t**he individual should invest less** in risky assets to reduce overall risk.
- **If the correlation is low or negative**, human capital can **act as a "bond,"** allowing for **higher financial risk-taking.**

Implications Over the Life Cycle

- **Young workers**: They have **high human capital** ($L_t \gg F_t$), so they can **afford a more aggressive portfolio** (higher πt^*).
- **Mid-career individuals**: Over time, human capital decreases while financial wealth increases, leading to **a gradual reduction in risky asset allocation**.
- **Older individuals** and retirees: They have low human capital, so they tend to maintain a more **conservative portfolio** with less exposure to risky assets.

Munk's model provides an intuitive explanation of investment choices over the life cycle, addressing some limitations of traditional Markowitz theory, which did not account for human capital as a component of total wealth.

Intuitively, **human capital behaves more like a risk-free asset than like a risky one** (e.g., stocks). To maintain the optimal overall risk exposure, **young individuals**—who typically have a high ratio of human capital to financial wealth—**end up shorting the risk-free asset and heavily investing in stocks.**

When borrowing constraints are in place (such that $\pi^* \leq 1$), the optimal solution becomes an **entirely stock-based portfolio** for all sufficiently risk-tolerant investors, and even for many risk-averse ones, provided their human capital is large relative to their financial assets.

Summary of the component of the entire process

Component Computed	Methodology Used	Value
L_t - Human Capital	Discounted future wages	-
F_{t0} - Financial Wealth	From historical database (HSIW)	-
$\lambda_t = L_t / F_{t0}$	-	-
μ - Stock Market Returns	Historical FTSE MIB data	0.0507
r_f – Risk Free Returns	BOT, standardized	0.03
***Cov(rL,r)* - Covariance**	NumPy covariance function	0.005
Σ / σ - Variance	Variance from historical FTSE MIB data	0.207

Table 9, Summary of Components of Munk's Theorem.

Additional information about each term can be found in the Appendix: 3.Analyzing the Process.

Moreover, the allocation to stocks decreases as risk aversion increases. So we used 3 different set of Risk Aversion parameter:

Risk Aversion Coefficient (γ) by Age Group

Assigning different γ values based on demographic categories as a prudent approach, because risk tolerance often varies among different groups.

Following, the framework:

Case 1 – Standard Risk Aversion:

Age Group	Risk Aversion γ
30 and under	3.8
31-40	4
41-45	4
46-50	4.5

51-55	5
56-60	5.5
61-65	6

Table 10, Base Risk Aversion.

Case 2 – More conservative individuals:

Age Group	Risk Aversion γ
30 and under	4.3
31-40	4.5
41-45	4.5
46-50	5
51-55	5.5
56-60	6
61-65	6.5

Table 11, More Conservative Risk Aversion.

Case 3 – Less conservative individuals:

Age Group	Risk Aversion γ
30 and under	3
31-40	3.5
41-45	3.5
46-50	4
51-55	4.5
56-60	5
61-65	5.5

Table 12, Less Conservative Risk Aversion.

4.5 Results

The Results were gathered in 3 different simulations, each one depicts the choices the household individual should have made in a determined starting year (1977, 1980 and 1990) when deciding to invest in the risky asset.

π_t^* values have been limited:

- Percentage Values < 0 will be set at 0
- Percentage Values > 100 will be set at 1

Summary – Base Risk Aversion

Starting Year	Average (%)	Min λ_t (%)	Max λ_t (%)	Average π_t^* (%)
1977	37.22492	0.02458	112.2862	39.07141
1980	47.19311	0.058477	138.3161	40.34039
1990	86.38573	0.58265	231.8377	46.08211

Table 13, Summary of Human Capital/Financial Wealth Ratio (λ_t) and Average Optimal Risky Asset Allocation (π_t^*). *Base Risk Aversion*

Less Conservative 1980:

Starting Year	Average (%)	Min λ_t (%)	Max λ_t (%)	Average π_t^* (%)
1980	47.19311	0.05848	138.31609	63.84552

Table 14, Summary of Human Capital/Financial Wealth Ratio (λ_t) and Average Optimal Risky Asset Allocation (π_t^*). *Less Risk Aversion*

More Conservative 1980:

Starting Year	Average (%)	Min λ_t (%)	Max λ_t (%)	Average π_t^* (%)
1980	47.19311	0.05848	138.31609	0.70943

Table 15, Summary of Human Capital/Financial Wealth Ratio (λ_t) and Average Optimal Risky Asset Allocation (π_t^*). *More Risk Aversion*

The drastic reduction in the optimal risky asset allocation (π_t*) observed in the more risk-averse simulation, from 63.85% in the less conservative version to 0.71% in the more conservative one, is a result consistent with the sensitivity of the Munk formula to the relative risk aversion coefficient (γ).

Although the increase in the aversion parameter was only 0.5 points (e.g. from $\gamma = 3$ to $\gamma = 3.5$), the effect on the optimal allocation is nonlinear. This is because the model combines multiple factors, including:

- **High λ ratio (human capital/financial wealth):** in 1980, the average λ is 47.19, indicating that human capital is much more relevant than financial wealth. This amplifies the effect of perceived risk on the entire portfolio, making the investor extremely sensitive to changes in γ**.**
- **High Implicit Leverage from Human Capital:** in the model, human capital acts as a risk-free or nearly risk-free asset, so a young individual with a lot of human capital already implicitly "leverage" his or her portfolio. If risk aversion increases, even slightly, the model responds by cutting exposure to risky assets almost entirely, because it considers the exposure already too aggressive compared to the new risk tolerance.
- **Composite effect of γ and λ:** the optimal allocation term in Munk includes the ratio of risk premium to variance multiplied by $(1 / \gamma) \times (1 + \lambda)$. Even small changes in γ, when combined with high values of λ, lead to large changes in πt^*.

This has a multiplicative effect that leads to a near-zeroing of the equity allocation.

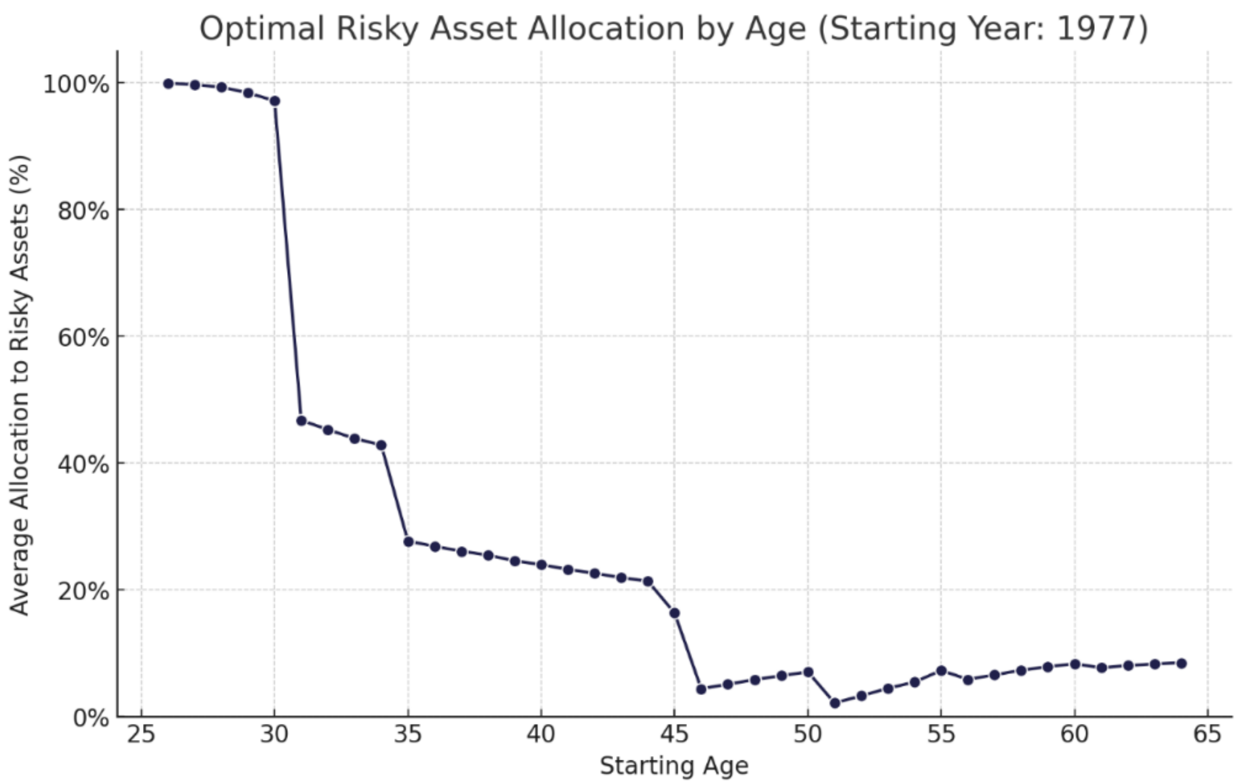
Conclusion

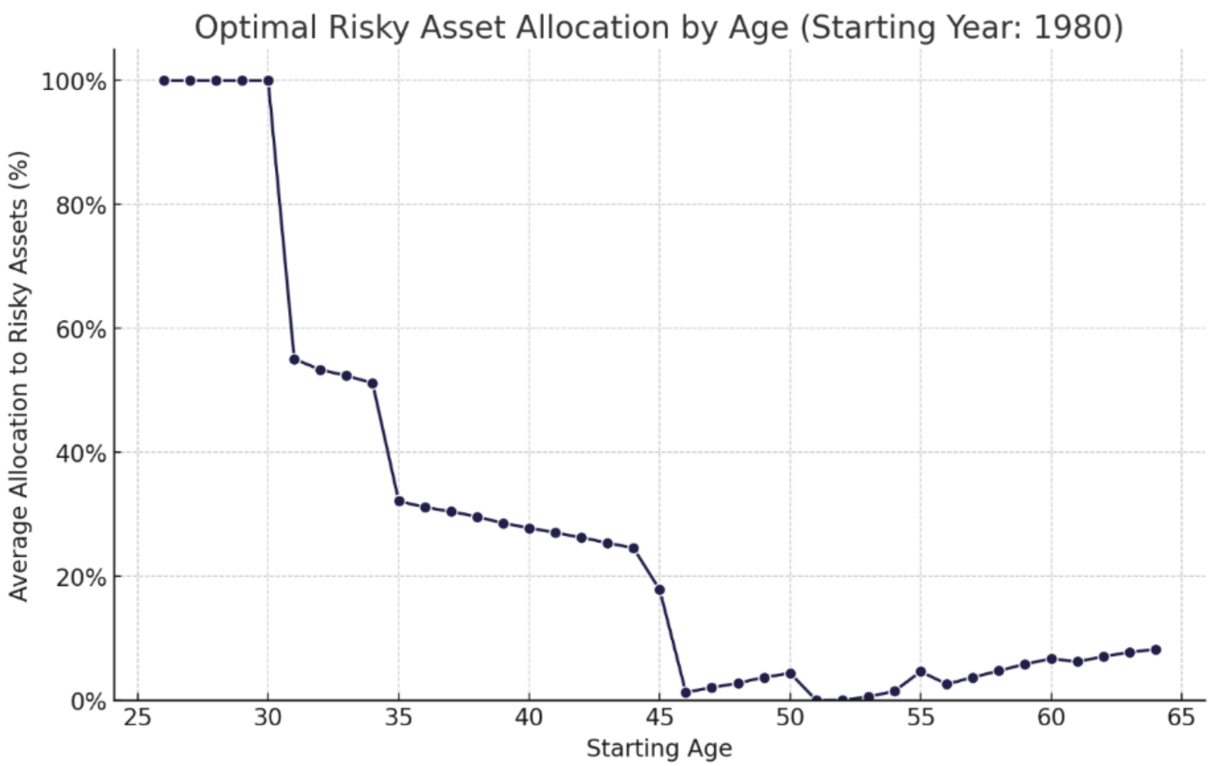
The model highlights how even small variations in psychological parameters (γ) can have enormous impacts, especially in the presence of high values of human capital. This suggests the importance of accurately estimating the degree of risk aversion and of cautiously interpreting asset allocation policies for young or high-human-capital individuals.

Risky Asset Allocation Base Risk Aversion – Graphical Analysis

The figures illustrate group-level average allocations to risky assets across age cohorts. It does not reflect individual portfolio trajectories but rather smoothed trends resulting from heterogeneous labor income paths and financial positions within each age group.

By Age:





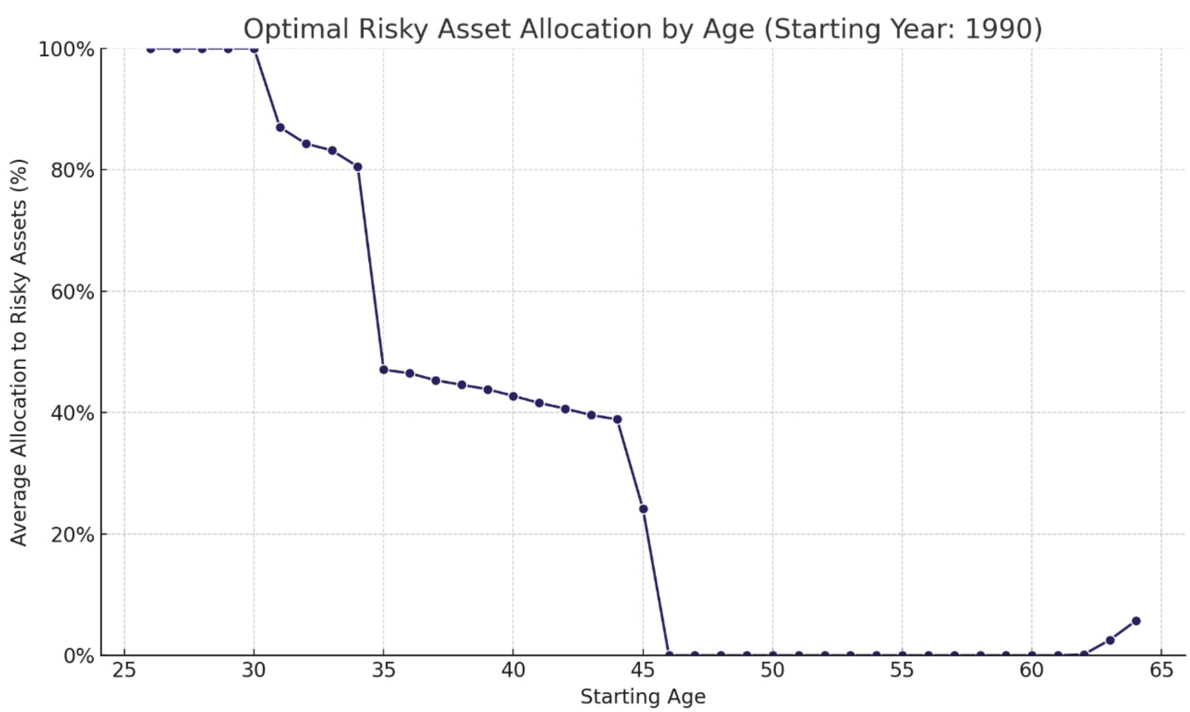
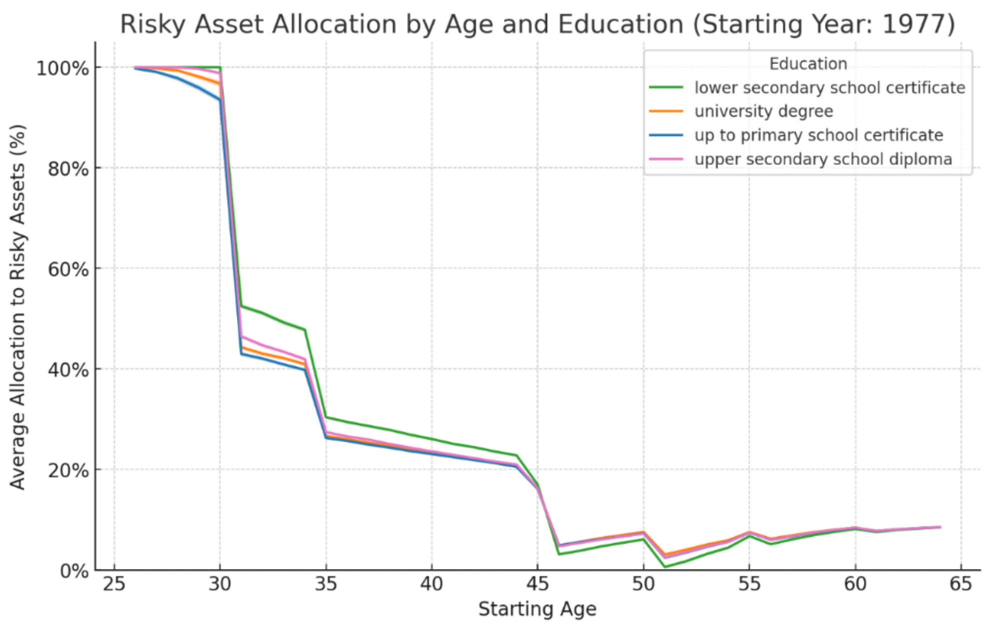
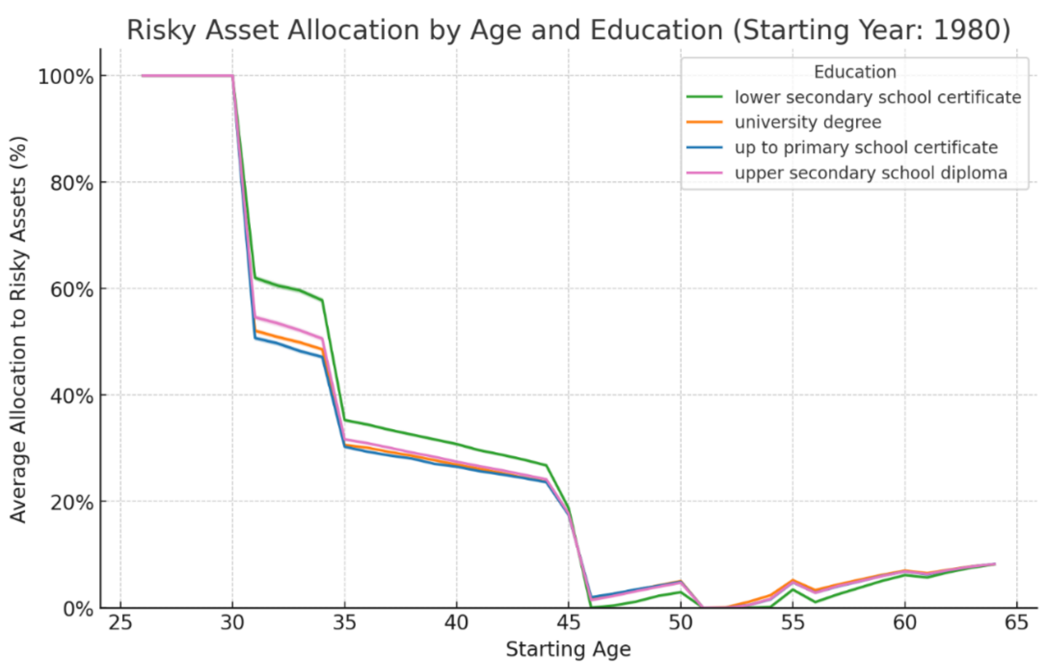


Figure 42/43/44, Average Risky Asset Allocation by Starting Age (Starting Year: 1977/1980/1990). *Data are computed from a simulated sample calibrated on Italian households from the 2020 wave of the SHIW, adjusted to respective base year.*

Clear downward trend in risk appetite with increasing age, according to the theoretical assumptions and predictions. Age gap 45-55 shows a repetitive trend that may be explained by the database structure of financial wealth, divided into categories wide categories that can't incorporate all the differences in the range. Allocation drops near zero approaching retirement as we expect from the model.

By Education:





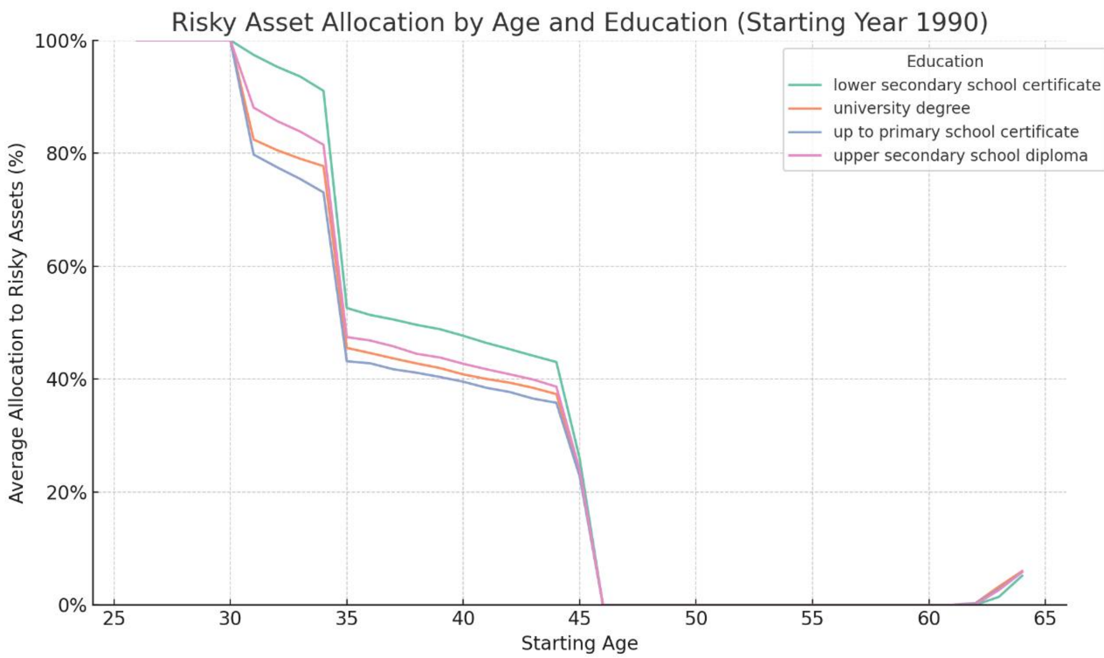


Figure 45/46/47, Average Risky Asset Allocation by Starting Age and Education Level (Starting Year: 1990). *Data are computed from a simulated sample calibrated on Italian households from the 2020 wave of the SHIW, adjusted to base year 1990.*

The graphs show the optimal allocation to risky assets on age and education level, for three different waves with starting years of 1977, 1980 and 1990. Slight variation in early life behavior among education groups. Risk preference seems to converge past age 40.

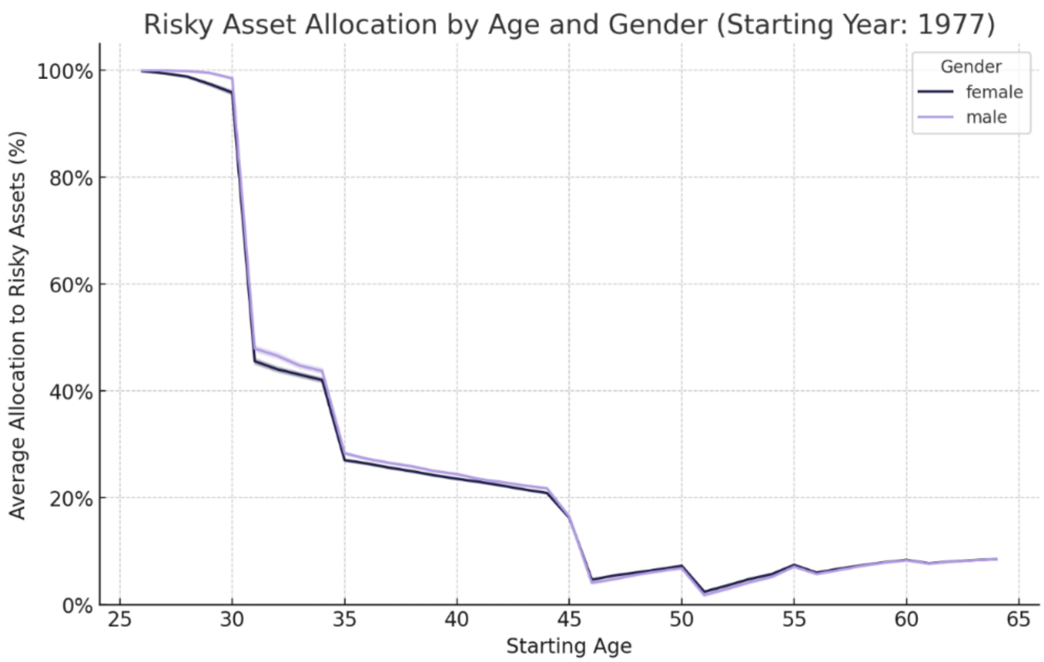
The allocation behavior follows a consistent trend:

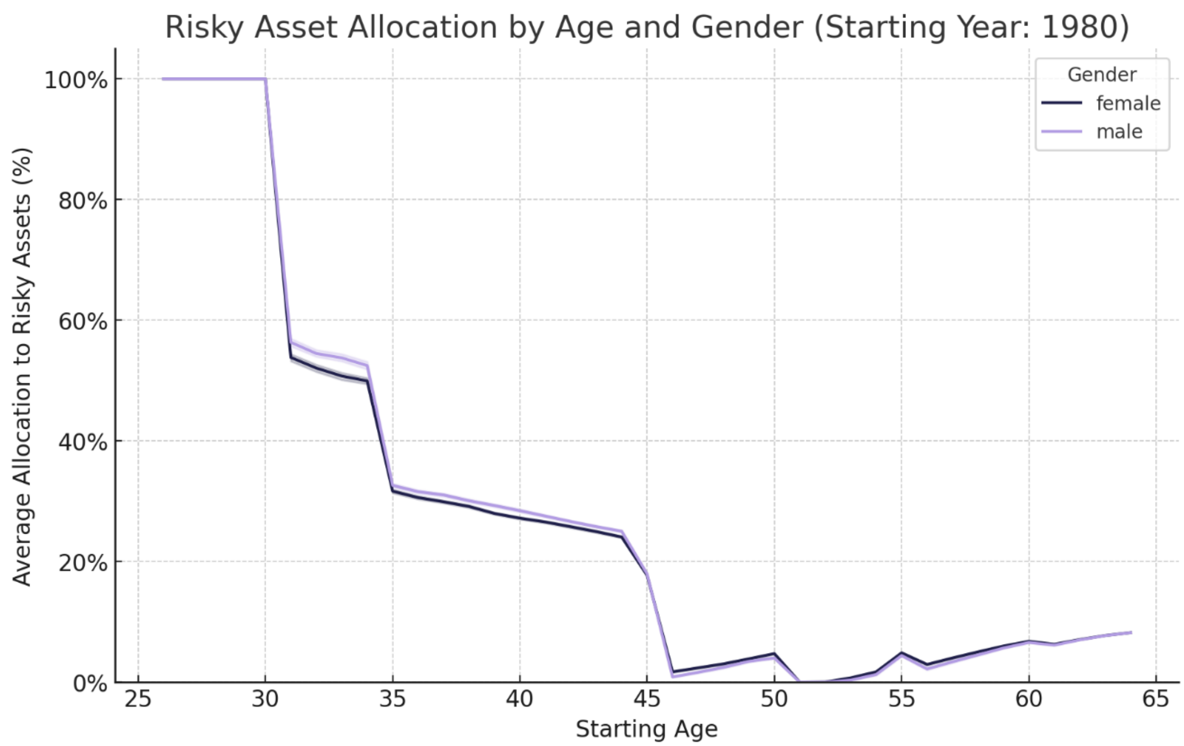
- Decreasing allocation with age: Regardless of the level of education, the percentage allocation to risky investments is very high (up to 100%) in the early years of working life, and then decreases with increasing age, to values close to zero around the age of 45-50.
- Convergence between levels of education: The differences between the lines corresponding to the various levels of education are small. However, those with a lower secondary school certificate tend to allocate slightly more capital to risky assets than the other groups.
- University level and prudence: Surprisingly, individuals with a university degree tend to have a slightly lower share of risky allocation, especially in the middle ages. This could reflect greater caution due to higher human capital and higher financial wealth, flattening the results.

- Differences between startin years: the 1990 cohort shows a sharper reduction in the risk share already at age 45, suggesting a more prudent profile or a different human capital/financial wealth ratio compared to previous cohorts.

In summary, education marginally influences the optimal risk allocation, but age remains the main determinant in the investment strategy according to the model analyzed.

By Gender:





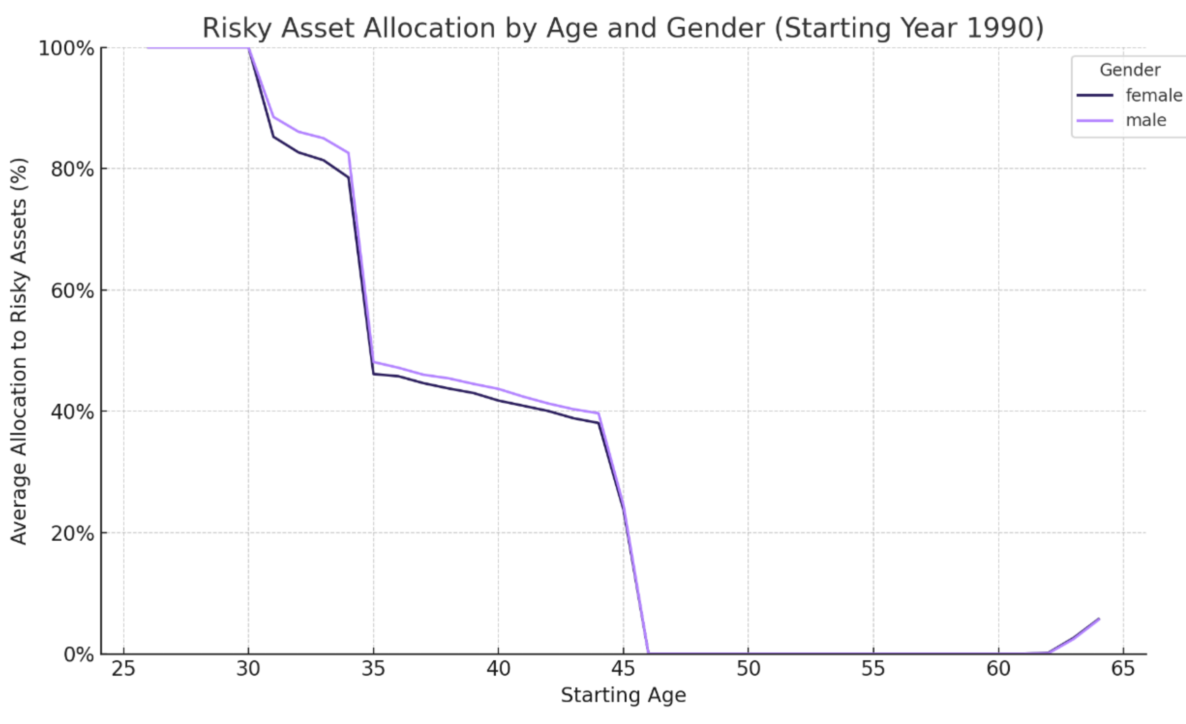
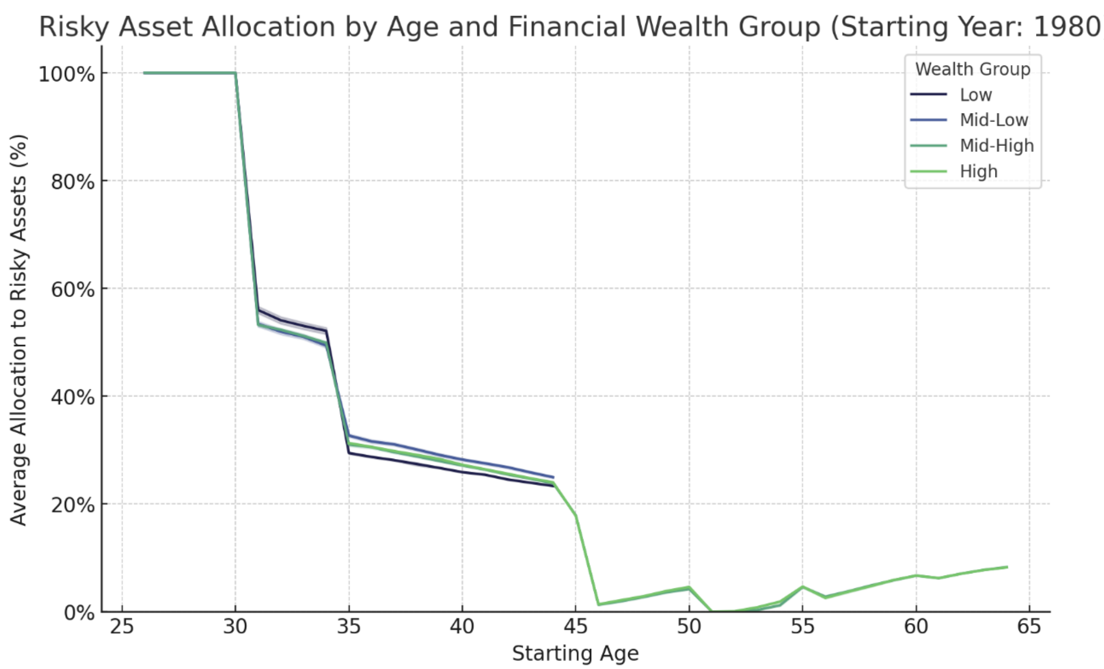


Figure 48/49/50, Average Risky Asset Allocation by Starting Age and Gender (Starting Year: 1977/1980/1990). *Data are computed from a simulated sample calibrated on Italian households from the 2020 wave of the SHIW, adjusted to base year 1990.*

Gender differences are minimal, but according to the model, males should display slightly higher risk exposure at younger ages compared to females.

Younger individuals show higher average allocation to risky assets. The trend declines sharply beyond age 35, nearing zero as retirement approaches. The allocation then decreases with increasing age, to values close to zero especially when we analyze the range around the age of 45-50.

By Financial Wealth Group – 1980 and 1990



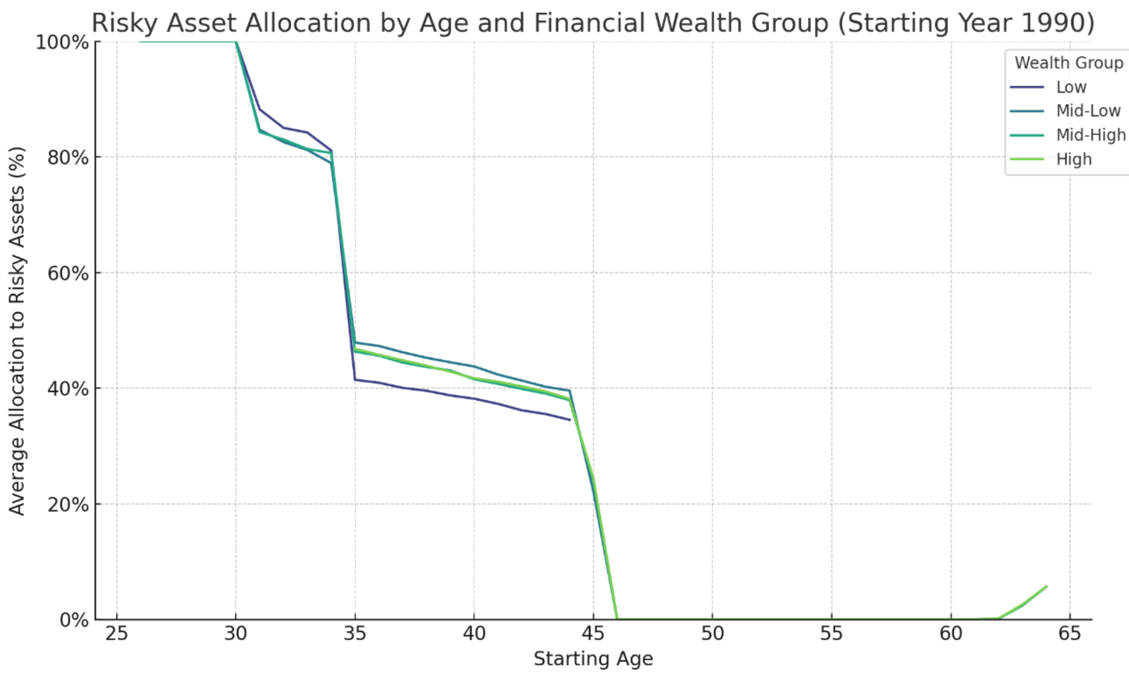
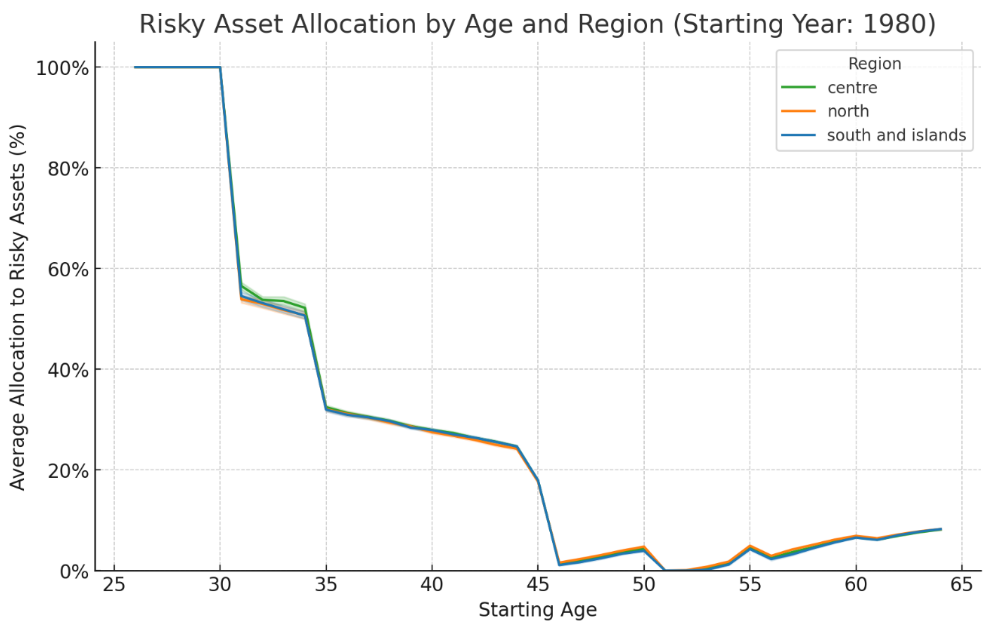


Figure 51/52. Average Risky Asset Allocation by Starting Age and Financial Wealth (Starting Year: 1980/1990). *Data are computed from a simulated sample calibrated on Italian households from the 2020 wave of the SHIW, adjusted to respective base year.*

The analysis confirms that age is the main driver of risk allocation, but also highlights a slight tendency for groups with greater financial wealth to adopt more conservative strategies in the second part of the life cycle.

By Region – 1980 and 1990



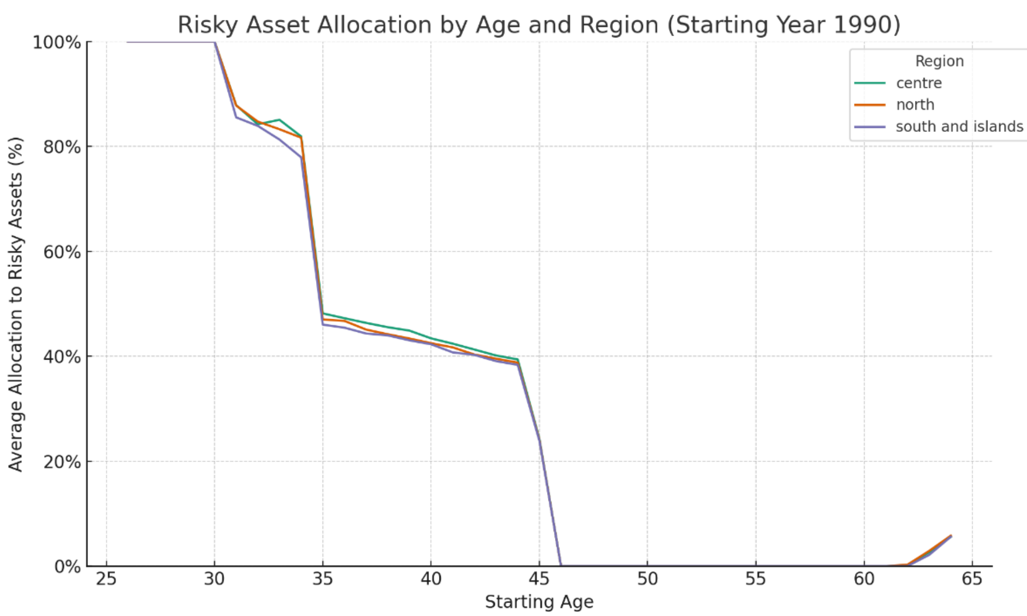
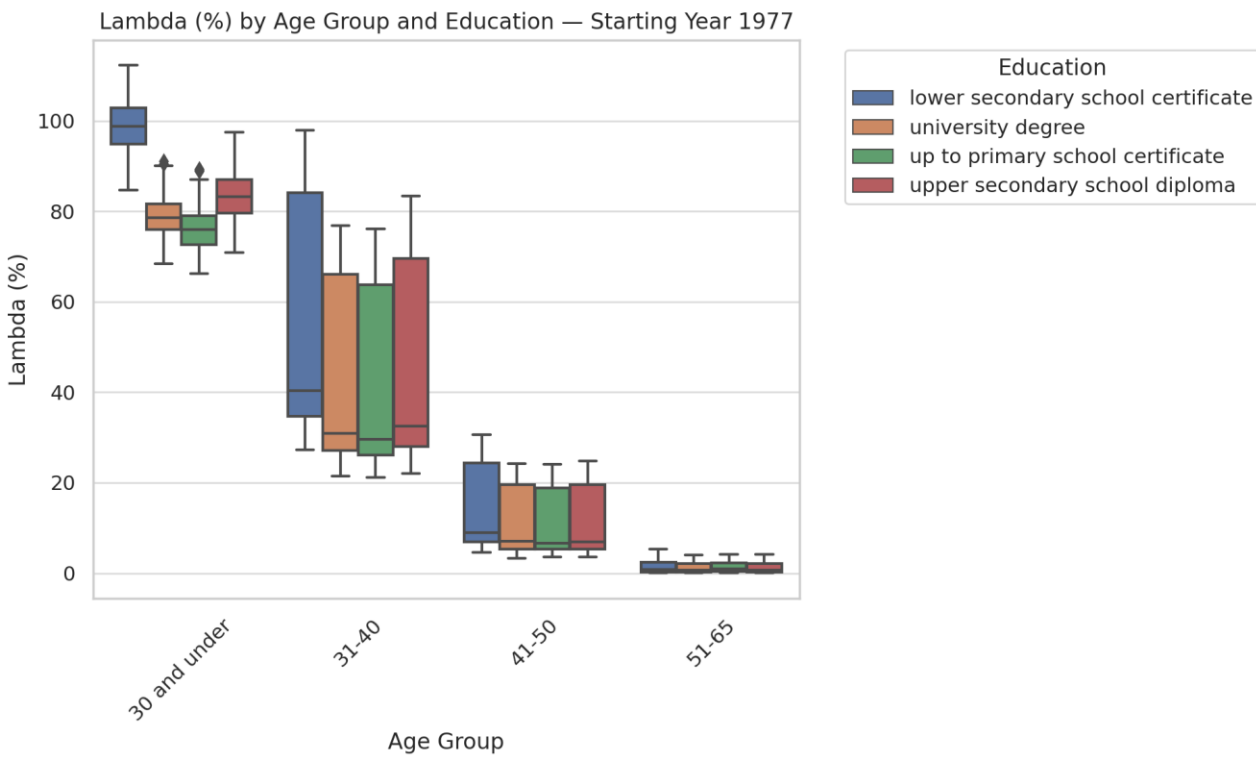
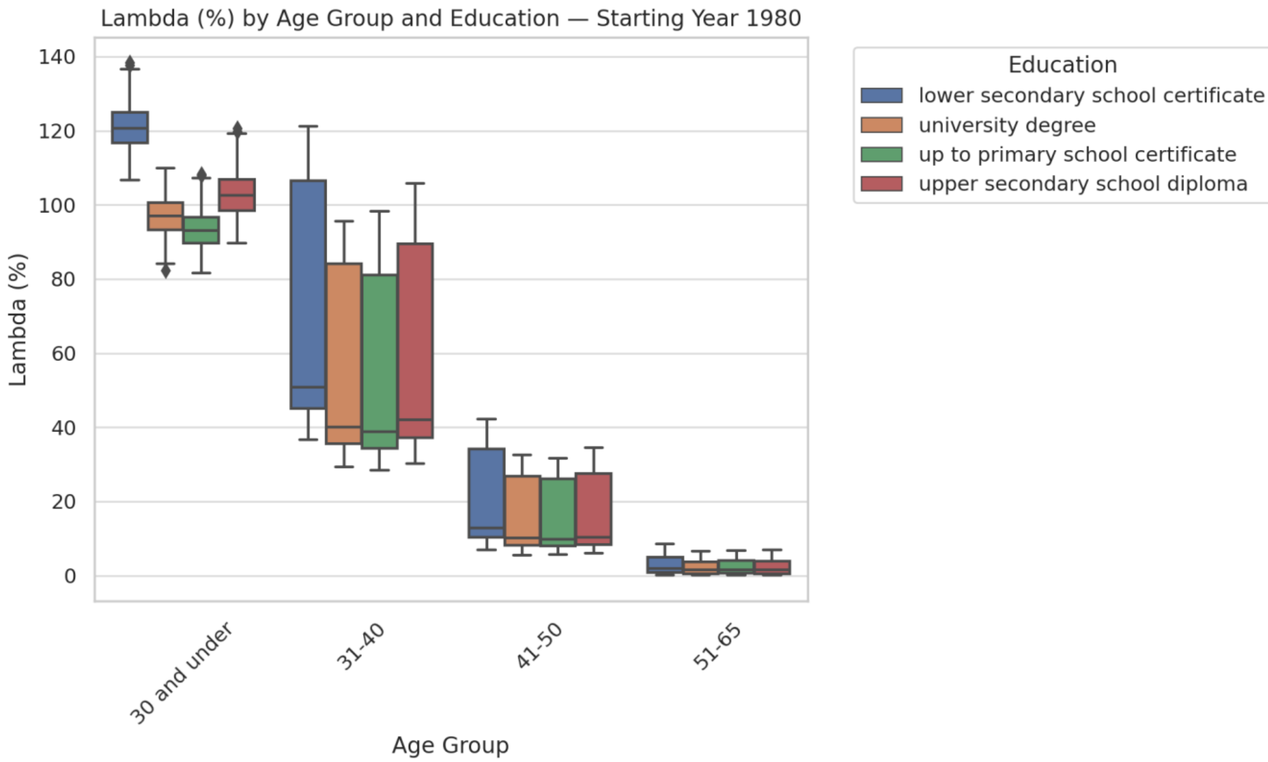


Figure 53/54. Average Risky Asset Allocation by Starting Age and Region (Starting Year: 1980/1990). *Data are computed from a simulated sample calibrated on Italian households from the 2020 wave of the SHIW, adjusted to respective base year.*

Regional differences in risky asset allocation are subtle, with the North showing slightly higher risk appetite around age 30–35. Overall patterns remain consistent across all regions, with evident differences in the 45-55 range between the two starting years. The reasons could be the same we analyzed in the previous chapter.

Lamda Analysis:





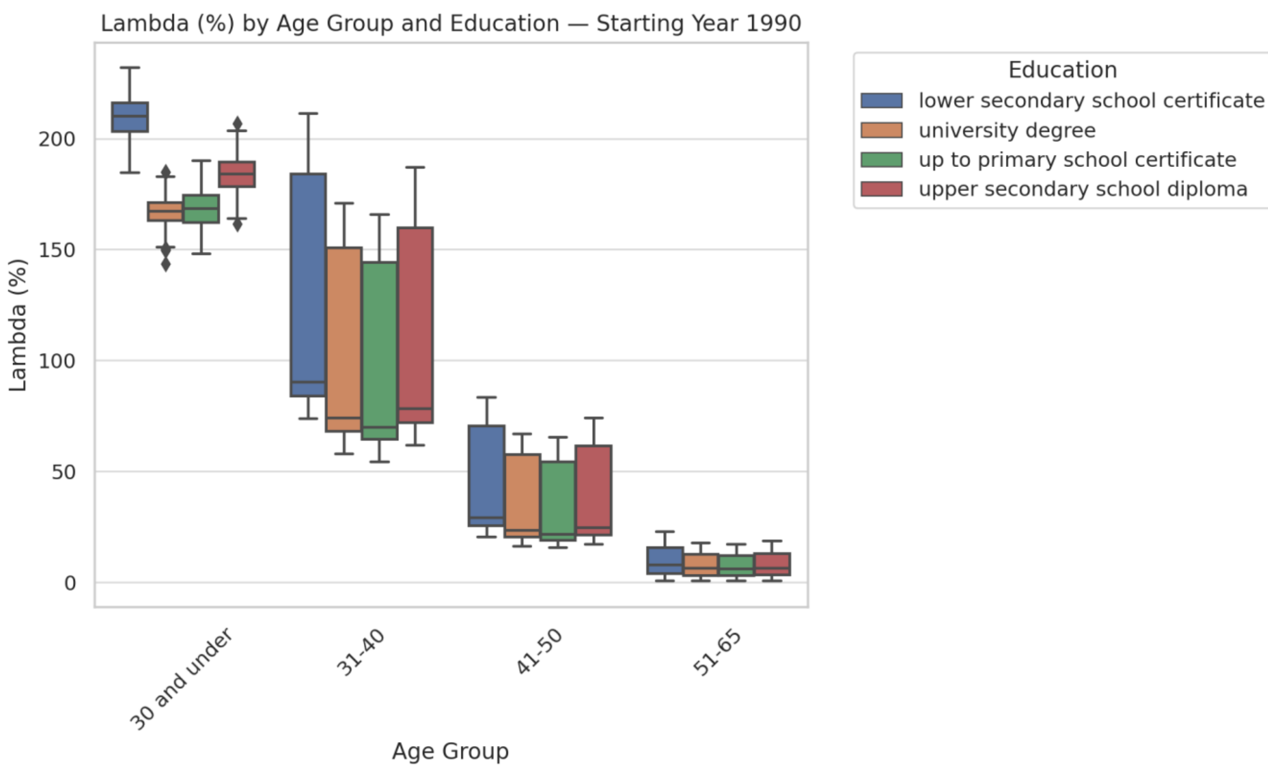


Figure 55/56/57. Lambda (%) by Age Group and Education (Starting Year: 1977/1980/1990)*.*
The values displayed represent the distribution of the human-to-financial wealth ratio (λ) across

education levels and age groups. Simulated individual-level data based on the 2020 wave of the SHIW, adjusted to respective base year.

In general, it is observed that:

- The value of λ decreases with age in all scenarios: the youngest have a relatively higher human capital compared to financial wealth.
- As the years go by (from 1977 to 1990), λ tends to increase for all age groups and levels of education, probably reflecting an increased importance of human capital compared to financial wealth.
- The differences between levels of education are less marked within each age group, but there is a tendency for lower levels of education to show higher average values of λ in the youngest age groups.

In summary, the data show marked age-related heterogeneity of λ, with an overall increase over time, and only weak differences across educational levels.

SECTION 5 - CONCLUSIONS

Summary of Findings

This study aim was to analyze optimal asset allocation by incorporating human capital into the portfolio decision framework. Using the Munk model, we computed optimal risky asset allocation (π_t*) for individuals based on their age, education level, gender, and financial wealth. The analysis demonstrated that:

- **Human capital significantly impacts** investment choices, with higher human capital leading to greater allocation to risky assets.
- **Risk aversion is also a key element in the framework**, increasing with age, leading to a decrease in the percentage allocated to risky assets over time.
- **The lambda ratio (λ = L/F) plays a fundamental role** in determining risk-taking behavior.
- **Education and gender influence investment** decisions, but not always in expected ways.

Key Observations from the Data

The results reveal distinct patterns. Notably:

Individuals aged 30 and under should invest the total amount of their wealth in risky assets, while those in the **45-60 age group should allocate almost no wealth on risky**

assets. Only later in life, when Human Capital tends to zero, they should invest on stocks to maintain an optimal allocation and reduce their exposure to the risk of loss of value due to inflation.
This trend confirms the predictions of the life cycle theory, according to **which the capacity to "absorb" financial risk is maximum in the early years and decreases as retirement approaches.**

The lambda ratio exhibits a decreasing trend with age, from an average of ~130 at younger ages to ~20 or lower for older individuals, explaining the relative importance of human to financial capital. In the 45-60 years range the accumulated financial wealth is relatively high but the human capital is decreasing. Probably the combination of these values of λ and the risk aversion factor generates.

Gender differences show that **males should invest more on average while females**, confirming statistical significance, **should invest slightly less** because their income will be lower. This statistically significant difference unfortunately still **reflects gender inequalities in the labor market**, with long-term effects on financial planning.

The impact of education follows an unexpected pattern, with university graduates investing less than individuals with secondary school certificates, while individuals with only primary education should allocate less than other categories. This counterintuitive result may be explained by the fact that university graduates generally possess higher human capital but also higher starting financial wealth, which reduces the need for financial risk-taking, as their income acts as a stable asset and their lamda ratio could be lower compared to the lower levels of education. These factors, combined with model dynamics, where a **high human-to-financial wealth ratio (λ) can reduce the optimal allocation to risky assets,** help explain why more educated individuals may invest less aggressively than expected.

Comparison of the model with the Italian, European and US Investment Landscape

To validate our findings, we compare the model's predictions with real-world investment behaviors in Italy:

In Italy, ~29% of households invest in risky assets, whereas our model predicts an allocation of 100% for each individual being under 30 in every category and almost everyone before retirement (even later) should invest a percentage in equities.

From HFCS tables, the distribution of wealth among Italian households is 18,7% in financial assets (of which only 4% in equities, 11% in bonds, 11% in Mutual Funds, 43% in deposits) and 81,7% in real estate, diverging from our simulated results: individuals below 45 should invest at least ~20% of their financial wealth on stocks.

This discrepancy between theory and empirical behavior suggests that **cultural preferences, lack of trust in financial markets, and limited financial literacy significantly shape investment decisions in Italy.**

Europe Comparison

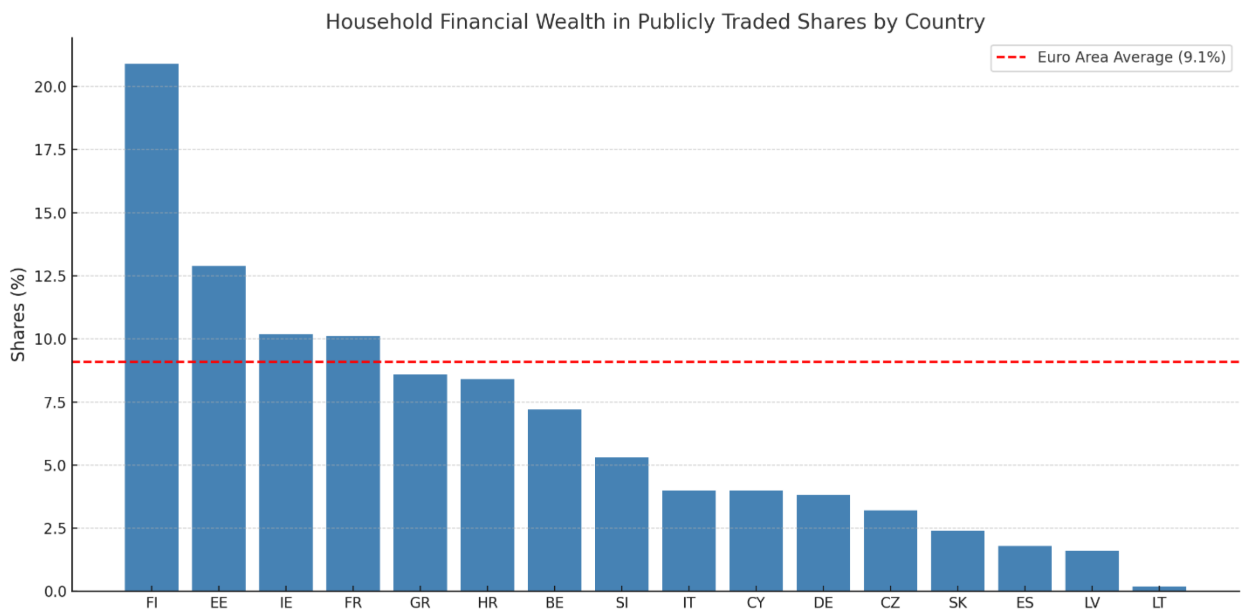


Figure 58, Publicly Traded Shares on Total Financial Assets of the Main European Countries compared to the Euro Area Avarage (red line).

Italy appears to be low in the rankings with only 4% of financial wealth invested in stocks, **strongly below the Eurozone average**.

In contrast, Finland is the leader with over 20%, followed by Estonia (12.9%) and Ireland (10.2%), demonstrating a greater propensity for equity investment.

Countries like France, Greece and Croatia also outperform Italy, showing a lower risk aversion or perhaps greater financial literacy.

Among the countries that invest less in stocks Spain (1.8%), Latvia (1.6%) and Lithuania (0.2%), behave similar to Italy.

Even in **mutual funds, Italy does not lead** the way, with a share of 10.9%, just below the European average of 11.7%.

Countries such as Belgium (29.7%) and Luxembourg (29.9%) instead show a strong preference for this instrument, probably thanks to a more efficient distribution network and a more developed financial culture.

This comparison highlights how I**taly confirms itself as a more conservative** country in financial choices, **preferring liquidity and deposits** rather than investments in higher-yield but riskier.

Overall Italian behavior shows a very limited propensity towards investments in stocks, unlike many European partners. This trend can compromise the long-term return potential of family portfolios, especially in a context of low rates and rising inflation. Encouraging financial literacy and awareness of the benefits of diversification could reduce the gap with other EU countries.

US Comparison

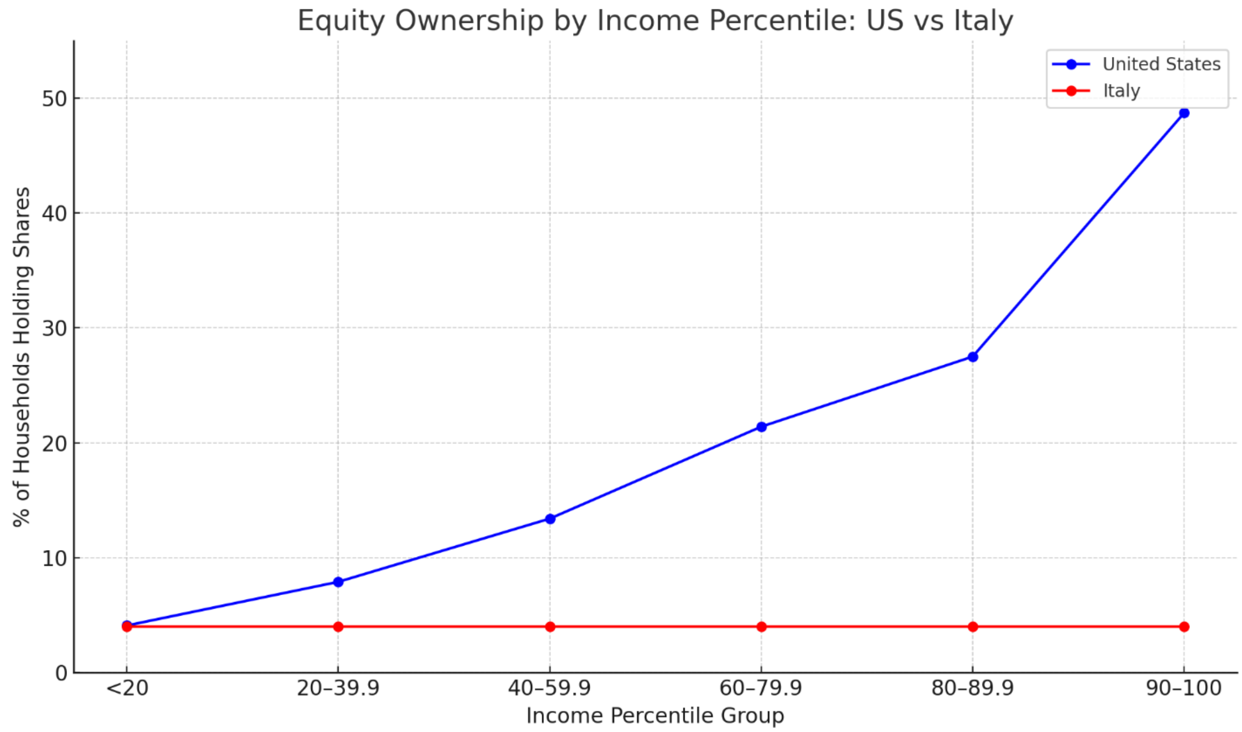


Figure 59, Equity Ownership on Total Financial Assets, *Comparison with US.*

- In the United States: the percentage of households investing in stocks increases sharply with increasing income, from 4% for the poorest (top 20%) to nearly 49% for the richest decile. This indicates a strong correlation between wealth and stock ownership.
- In Italy: in contrast, the average percentage of Italian households owning stocks remains constant at around 4% according to ECB HFCS data.

Moreover in the United States nearly half of households in the top 10% own stocks.

This contrast highlights profound differences in financial culture and investment behavior:

- In the US, equity investment is considered an integral part of financial planning, even among middle-class families. Access to private pension funds, greater financial literacy, and trust in markets contribute to the spread of equity ownership.
- In Italy, on the contrary, the preference for liquidity (42% deposits) and real estate (over 80% of wealth) slows down equity investment. Italian families are

extremely cautious, sometimes due to a lack of trust in the markets, but often also due to poor financial literacy.

The theoretical model adopted in our study suggests that especially young people with high human capital (and therefore low financial capital) should invest almost entirely in risky assets. However, the **Italian reality is very far from this prediction**.

The comparison between the United States and Italy highlights a systemic divergence:

- In Italy, little investment is made in risky financial instruments.
- In the USA, the portfolio diversifies with the increase in income, including stocks, funds and insurance instruments.

This reinforces the importance of financial education policies and the need to integrate the concept of human capital in investment planning. In a context where public welfare is under pressure, not investing is the greatest risk.

Implications for Financial Planning

These findings have important implications for investors and policymakers:

- Young investors should recognize the role of human capital in portfolio decisions and should be encouraged to take on more risk early in life. They should be aware of the possibility to consider their labor income as a valid leveraging option, similar to a bond-like security.
- Financial advisors can use these insights to provide personalized asset allocation strategies based on human capital and risk aversion levels.
- Public policy can encourage financial literacy programs, ensuring that individuals understand the impact of human capital on investment choices.

Limitations and Future Research

While this study provides valuable insights, several limitations exist:

- Parameters and models were simplified to address the lack of data and the limitations of the analysis that could be performed.
- The assumption of constant risk aversion within each age group may not fully capture real-world behavior. Moreover, in Table 14, by slightly changing the risk aversion parameter (±0.5 points) drastically changes the results of the simulations. Risk aversion is probably the most important

factor in the research, so it must be calculated precisely and not to be approximated.

- Market conditions and economic shocks are not explicitly modeled and they may influence allocation decisions. These simulations are weak and probably not close to be able to consider these changes.
- The prediction of future salaries has been executed with a simple linear regression, further studies could propose different and more valid approach.
- Future research could refine the model by incorporating dynamic labor income risk and different macroeconomic scenarios, but also studying more deeply factors like risk aversion, correlation between labor return and market rates of return, perhaps by obtaining access to a greater number of empirical data, proposing anonymous surveys to a larger segment of the population and recording the data more frequently and, of course, by integrating a vector of different risky assets.

Conclusion

This study has demonstrated that incorporating human capital into asset allocation leads to more realistic and ideally more remunerative investment strategies.

Overall, the results of our research align with lifecycle theory and provide a qualitative framework for optimizing portfolio choices. By further refining these models, we can strengthen financial decision-making for families, but also policymakers. Today financial markets grow more and more complex and so does individuals' interest for retirement planning. In such scenario integrating human capital into financial advice is no longer merely a refinement, but should become a priority.

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APPENDIX

1.INFLATION

Base Year 1977:

Year	Annual Inflation (%)	Cumulative Factor
1977	13,5	1
1978	12,6	0,881057
1979	20,6	0,782466
1980	18	0,648811
1981	17,6	0,54984
1982	16,2	0,467551
1983	12,3	0,402368
1984	9,3	0,358297
1985	8,2	0,327811
1986	4,2	0,302967
1987	5,2	0,290756
1988	5,5	0,276384
1989	6,6	0,261975
1990	6,3	0,245755
1991	5,9	0,23119
1992	4,7	0,21831

1993	4,4	0,20851
1994	3,9	0,199722
1995	5,6	0,192225
1996	2,7	0,182032
1997	1,9	0,177246
1998	1,5	0,173941
1999	2,2	0,171371
2000	3	0,167682
2001	2,4	0,162798
2002	2,8	0,158982
2003	2,2	0,154652
2004	1,9	0,151323
2005	2,2	0,148501
2006	1,7	0,145304
2007	3	0,142876
2008	1,6	0,138714
2009	1,3	0,13653
2010	2,1	0,134778
2011	3,2	0,132005
2012	2,2	0,127912
2013	0,7	0,125159
2014	-0,6	0,124289
2015	0,3	0,125039
2016	1	0,124665
2017	0,9	0,123431
2018	0,9	0,12233
2019	0,5	0,121239
2020	0,4	0,120635
2021	4,8	0,120155

2022	10	0,114652
2023	0,8	0,104229
2024		0,103401

Base Year 1980:

Year	Annual Inflation (%)	Cumulative Factor
1980	18	1
1981	17,6	0,85034
1982	16,2	0,73179
1983	12,3	0,651639
1984	9,3	0,596193
1985	8,2	0,55101
1986	4,2	0,5288
1987	5,2	0,502662
1988	5,5	0,476457
1989	6,6	0,446958
1990	6,3	0,420468
1991	5,9	0,397043
1992	4,7	0,379219
1993	4,4	0,363237
1994	3,9	0,349602
1995	5,6	0,331063
1996	2,7	0,322359
1997	1,9	0,316348
1998	1,5	0,311673
1999	2,2	0,304964
2000	3	0,296082
2001	2,4	0,289142

2002	2,8	0,281267
2003	2,2	0,275212
2004	1,9	0,270081
2005	2,2	0,264267
2006	1,7	0,259849
2007	3	0,252281
2008	1,6	0,248308
2009	1,3	0,245121
2010	2,1	0,24008
2011	3,2	0,232635
2012	2,2	0,227628
2013	0,7	0,226045
2014	-0,6	0,22741
2015	0,3	0,22673
2016	1	0,224485
2017	0,9	0,222482
2018	0,9	0,220498
2019	0,5	0,219401
2020	0,4	0,218527
2021	4,8	0,208518
2022	10	0,189562
2023	0,8	0,188057
2024		0,188057

Base Year 1990:

Year	Annual Inflation (%)	Cumulative Factor
1990	6,3	1

1991	5,9	0,944287
1992	4,7	0,901898
1993	4,4	0,863887
1994	3,9	0,83146
1995	5,6	0,787367
1996	2,7	0,766667
1997	1,9	0,752372
1998	1,5	0,741253
1999	2,2	0,725297
2000	3	0,704172
2001	2,4	0,687668
2002	2,8	0,668937
2003	2,2	0,654538
2004	1,9	0,642333
2005	2,2	0,628506
2006	1,7	0,618
2007	3	0,6
2008	1,6	0,590551
2009	1,3	0,582973
2010	2,1	0,570982
2011	3,2	0,553277
2012	2,2	0,541367
2013	0,7	0,537604
2014	-0,6	0,540849
2015	0,3	0,539231
2016	1	0,533892
2017	0,9	0,52913
2018	0,9	0,524411
2019	0,5	0,521802

2020	0,4	0,519723
2021	4,8	0,495919
2022	10	0,450835
2023	0,8	0,447257
2024		0,447257

Table 16,17,18, Annual Inflation and Cumulative Factor by Base Year

2.STATA

```
. regress simulated_salary year i.gender_num i.age_group_num i.region_num i.education_num

      Source |       SS           df       MS      Number of obs   =    12,500
-------------+----------------------------------   F(10, 12489)    =   3168.51
       Model |  4.1775e+11        10  4.1775e+10   Prob > F        =    0.0000
    Residual |  1.6466e+11    12,489  13184493.4   R-squared       =    0.7173
-------------+----------------------------------   Adj R-squared   =    0.7171
       Total |  5.8241e+11    12,499    46596800   Root MSE        =      3631

------------------------------------------------------------------------------------------------
                 simulated_salary | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
----------------------------------+-------------------------------------------------------------
                             year |   398.1704   2.471097   161.13   0.000     393.3267    403.0141
                                  |
                       gender_num |
                            male  |   63.30574   64.97086     0.97   0.330    -64.04715    190.6586
                                  |
                    age_group_num |
                           31-40  |   2079.383   91.88249    22.63   0.000     1899.279    2259.487
                           41-50  |   3272.446   92.15799    35.51   0.000     3091.802     3453.09
                           51-65  |   3738.962   91.63962    40.80   0.000     3559.335     3918.59
                                  |
                       region_num |
                           North  |   217.2436   79.62935     2.73   0.006     61.15781    373.3294
               South and Islands  |  -984.9727   79.56832   -12.38   0.000    -1140.939   -829.0065
                                  |
                    education_num |
               university degree  |   4218.952    92.4686    45.63   0.000     4037.699    4400.205
up to primary school certificate  |  -1041.145   92.43813   -11.26   0.000    -1222.338   -859.9522
  upper secondary school diploma  |   1191.054   91.03709    13.08   0.000     1012.607    1369.501
                                  |
                            _cons |  -786530.1   4931.436  -159.49   0.000    -796196.5   -776863.7
------------------------------------------------------------------------------------------------
```

Figure 60, Regression modeled by Stata for Future Salaries

3.ANALYZING THE PROCESS: Finding the Components of Munk's Formula

The journey to determine all components of Munk's portfolio allocation model has involved multiple steps of data processing, computation, and validation. Below, we will summarize how we systematically found each variable needed for Theorem 1 in Munk's model.

Step 1: Understanding Munk's Formula

Munk's model provides an **optimal portfolio allocation strategy** incorporating both **financial wealth and human capital**. The **key formula** (from Theorem 1) states:

$$\pi_t^* = \frac{1}{\gamma}(1 + \lambda_t)\Sigma^{-1}(\mu - rf) - \lambda_t\Sigma^{-1}Cov(r, rL)$$

Where:

- $\pi*$ = **Optimal risky asset allocation**
- γ = **Risk aversion coefficient**
- Σ = **Variance-covariance matrix of risky asset returns** (will be **simplified since we use one risky asset**)
- μ = **Expected return of the risky asset**
- rf = **Risk-free rate**
- $\mu - rf$ = **Risk market premium**
- λ_t = **Lamda, Lt/Ft ratio**
- Lt = **Human capital (present value of future labor income)**
- Ft = **Financial wealth**
- Cov(r, r_L) = **Covariance between labor risky asset returns and income returns**

Simplified as :

$$\pi_t^* = \frac{(1 + \lambda_t)(\mu - r_f)}{\gamma\sigma^2} - \frac{\lambda_t \cdot \mathrm{Cov}(r, r_L)}{\sigma^2}$$

Step 2: Determining Each Component

Each term in the equation required **data extraction, transformation, and validation**. Below is the step-by-step breakdown.

Equity Return μ and Standard Variation *σ*

- **FTSE MIB Compound Annual Growth Rate (CAGR)**: 5.07% over the last 27 years.
- **FTSE MIB Standard Variation**: 20.7%, standardized to 20%.
  Source: FTSE MIB records.

Risk-Free Rate (r_f)

- **Italian 10-Year Government Bond Yield (BTP)**:
  As of March 14, 2025: 3.94%, standardized to 3%.
  Source: Trading Economics - For historical yields, the Italian Ministry of Economy and Finance provides data.

Key Observations

- **Lt decreases over time** as fewer years of income remain before retirement.
- **If r_m is high, future salaries are discounted more**, reducing L_t.
- **If income growth is high**, **L_t can remain significant** even later in life.

How It Affects λt =L_t/F_t

- When young → $L_t \gg F_t$ → λ_t is high → More investment in risky assets.
- When old → L_t decreases → λ_t is low → Portfolio shifts toward safer assets.
- At the beginning of a career → λ_t is large (even more than 100) since most wealth is in future wages.
- As financial wealth grows with savings and investments → λ_t declines over time.
- Approaching retirement → λ_t drops below 1 as human capital vanishes.

Covariance between labor income and the risky asset

To calculate the **covariance between labor income and the risky asset (equity return)**, we need:

Labor Income Data

- Annual salary data for different years.
- Salary data have been adjusted for inflation to ensure comparability.
- These are available for multiple years (e.g., 1977-2035) for statistical accuracy.

Risky Asset Returns (FTSE MIB)

- Historical yearly returns for the FTSE MIB index.
- These should be in the same time frame as the salary data.
- They are unavailable for the full period, we will work with the common period available: 1997-2024.

Matching Salaries & Returns by Year

- We need corresponding salary and FTSE MIB return values for each year.
- Both should be in percentage change format (e.g., salary growth rate, stock return).

Computing Covariance

- Convert salary data and FTSE returns into percentage changes.
- Align them by year.
- Compute the covariance between labor income growth and FTSE returns.

What we need

1. Salaries (previously calculated through generated observation with income prediction and adjusted to base year 1977)
2. FTSE MIB yearly returns (only from 1997 to 2024)

Since we have FTSE MIB data only from 1997 to 2024, we will compute the covariance between labor income growth and FTSE MIB returns using the available period.

Date	Index value	TR Value	Index code
31/12/1997	24.401,54	24.401,54	FTSEMIB
02/01/1998	24.913,97	24.913,97	FTSEMIB
05/01/1998	25.733,86	25.733,86	FTSEMIB

07/01/1998	25.960,80	25.960,80	FTSEMIB
…	…	…	…

Table 19, FTSE MIB Index values over time.

Steps to Compute Covariance

1. **Extract Labor Income Growth Rates** (from your salary data) and **Returns**.
   a. Compute the **year-over-year percentage change** in salaries.
   b. Example: $growth\ rate = \frac{salarary_t - salary_{t-1}}{salary_{t-1}}$
   c. We will do this for each available year from **1997 to 2024**.
   d. Compute Labor Income Return (explained below)
2. **Extract FTSE MIB Returns** (historical stock market returns).
   a. We need **yearly percentage returns** from **1997 to 2024 (from *Table 19*)**.
3. **Align Labor Income return & FTSE MIB Returns by Year** .
   a. Both time series should have the **same years**.
   b. If some years are missing, we will interpolate or drop them.
4. **Compute Covariance**
   a. Using the standard formula: $\frac{1}{N}\sum_{i=1}^{N}(S_i - \bar{S})(R_i - \bar{R})$
   b. Where:
      i. S_i = Salary growth in year i
      ii. R_i = FTSE return in year i
      iii. $\bar{S}$,$\bar{R}$= Mean of salary growth and FTSE return

How to Compute Labor Income Return Correctly for Covariance

Instead of simply calculating salary growth rates, we should compute the return on human capital, which includes both:

1. Labor income growth (how much wages increase).
2. The effect of discounting future earnings (since income is expected over multiple years).

Labor income return should reflect the **change in human capital** L_t, which is:

$$R_t = \frac{L_t - L_{t-1} + y_t}{L_{t-1}}$$

Where:

- L_t = Human Capital at year t (**discounted sum of future wages**).
- L_{t-1}= Human Capital at year t−1t-1t−1.
- y_t = Current labor income (wages earned in year t).

This formula **captures both**:

- Wage growth **(how salaries change)**.
- The **change in discounted future earnings**.

- $L_t - L_{t-1}$ is negative → Because fewer years of salary remain.
- Adding y_t (current labor income) → Offsets part of the loss.
- Dividing by L_{t-1} → Normalizes the change into a return rate.

Although the empirical estimate of the covariance between labor income returns and the risky asset was approximately 0.0169, a lower value of 0.005 was used in the simulations to ensure model robustness and prevent excessive sensitivity. This choice reflects a conservative stance aligned with existing literature and long-run economic reasoning, while also avoiding unrealistically low allocations to risky assets in early life stages, as it happened in the model, since there were too many negative results.

Final Results & Model Validation

After computing all components, we:

- **Validated labor income trends** using wage growth data.
- **Compared labor-income covariance with literature benchmarks**.
- **Ensured human capital followed expected depreciation patterns**.

4.CODES

Each code is to be considered modified for the respective starting year/risk aversion factors/inflaction factors.

Generate_random_observation

```
import pandas as pd
import numpy as np

def generate_random_observations(file_path, diff_file_path, output_path, variation_mean=1,
variation_std=0.1):
    """
    Generate random observations based on category data, mean values, and category differences,
including education levels.

    Parameters:
        file_path (str): Path to the input Excel file containing salary data.
        diff_file_path (str): Path to the Excel file containing percentage differences for
categories.
        output_path (str): Path to save the output Excel file with random observations.
        variation_mean (float): Mean of the normal distribution for salary variation.
        variation_std (float): Standard deviation of the normal distribution for salary
variation.

    Returns:
        None: Saves the generated observations to the specified output path.
    """
    # load the salaries
    data = pd.ExcelFile(file_path)
    df = data.parse(data.sheet_names[0])

    # Extract mean salaries for each year from the "All" category
    mean_salaries = df[df["Categorie"] == "All"].set_index("Anno")["Stipendio_medio"].to_dict()

    # Load the category difference percentages
    df_differences = pd.read_excel(diff_file_path)
    df_differences = df_differences[df_differences["Categoria"] != "All"]  # Remove 'All' row

    # Define categories
    genders = ["male", "female"]
    age_groups = ["30 and under", "31-40", "41-50", "51-65"]
    regions = ["North", "Centre", "South and Islands"]
    education_levels = ["up to primary school certificate", "lower secondary school certificate",
"upper secondary school diploma", "university degree"]

     # missing years to generate additional observations
    missing_years = [1985, 1988, 1990, 1992, 1994, 1996, 1997, 1999, 2001, 2003, 2005, 2007,
2009, 2011, 2013, 2015, 2017, 2019, 2018]
    valid_years = [year for year in mean_salaries.keys() if year not in missing_years]

   observations = []

    for year in valid_years:
        # 500 obs per year
        for _ in range(500):
            gender = np.random.choice(genders)
            age_group = np.random.choice(age_groups)
            region = np.random.choice(regions)
            education = np.random.choice(education_levels)

            mean_salary = mean_salaries.get(year, 0)

            diff_gender = df_differences.loc[(df_differences["Anno"] == year) &
(df_differences["Categoria"] == "Sesso") &
                                             (df_differences["Valore"] == gender),
"Differenza_percentuale"].mean()
```

```
            diff_age = df_differences.loc[(df_differences["Anno"] == year) &
(df_differences["Categoria"] == "Età") &
                                          (df_differences["Valore"] == age_group),
"Differenza_percentuale"].mean()
            diff_region = df_differences.loc[(df_differences["Anno"] == year) &
(df_differences["Categoria"] == "Regione") &
                                             (df_differences["Valore"] == region),
"Differenza_percentuale"].mean()
            diff_education = df_differences.loc[(df_differences["Anno"] == year) &
(df_differences["Categoria"] == "educazione") &
                                                (df_differences["Valore"] == education),
"Differenza_percentuale"].mean()
            print(df_differences[df_differences["Categoria"] == "educazione"])


            # calculate individual salary applying percentage differences
            individual_salary = mean_salary * (1 + diff_gender) * (1 + diff_age) * (1 +
diff_region) * (1 + diff_education)
            variation_factor = np.random.normal(loc=variation_mean, scale=variation_std)
            individual_salary *= variation_factor

            observation = {
                "year": year,
                "gender": gender,
                "age_group": age_group,
                "region": region,
                "education": education,
                "simulated_salary": round(individual_salary, 2),
            }
            observations.append(observation)

    # generate additional observations for missing years
    for year in missing_years:
        for gender in genders:
            for age_group in age_groups:
                for region in regions:
                    for education in education_levels:
                        observation = {
                            "year": year,
                            "gender": gender,
                            "age_group": age_group,
                            "region": region,
                            "education": education,
                            "simulated_salary": None,
                        }
                        observations.append(observation)

    # convert to excel
    observations_df = pd.DataFrame(observations)
    observations_df.to_excel(output_path, index=False)
```

Compute_human_capital

```
import pandas as pd
import numpy as np
import random
import time
from itertools import product

def compute_human_capital(merged_file, discount_rate_file, output_file, hc_summary_file,
investment_return=0.03, final_year=2035, start_year=1990):
    start_time = time.time()

    # Load merged dataset
    df = pd.read_excel(merged_file)
    discount_rates = pd.read_excel(discount_rate_file)
```

```
    required_columns = ["year", "gender", "age_group", "region", "education", "salary", "savings 
rate"]
    for col in required_columns:
        if col not in df.columns:
            raise ValueError(f"Missing column in dataset: {col}")

    # Define valid age ranges per group
    age_group_ranges = {
        "30 and under": (26, 30),
        "31-40": (31, 40),
        "41-50": (41, 50),
        "51-65": (51, 65)
    }

    def get_age_group(age):
        for group, (min_age, max_age) in age_group_ranges.items():
            if min_age <= age <= max_age:
                return group
        return None

   # Define conversion factor from base 1977 to 1990
    conversion_factor = 0.120635 / 0.519722622991384

    processed_observations = set()

    genders = df["gender"].unique()
    age_groups = df["age_group"].unique()
    regions = df["region"].unique()
    education_levels = df["education"].unique()
    category_combinations = list(product(genders, age_groups, regions, education_levels))
    total_combinations = len(category_combinations)


    with pd.ExcelWriter(output_file, engine='xlsxwriter') as writer:
        human_capital_summary = []
        results = []

        for i, (gender, initial_age_group, region, education) in enumerate(category_combinations, 
1):
           if initial_age_group not in age_group_ranges:
                continue

            df_filtered = df[(df["gender"] == gender) &
                             (df["age_group"] == initial_age_group) &
                             (df["region"] == region) &
                             (df["education"] == education)].copy()

            if df_filtered.empty:
               continue

            # Get the corresponding discount rate for the education level
            education_discount_rate = discount_rates.loc[
                discount_rates["Education"] == education, "discount rate"
            ].values[0]

            for idx, row in df_filtered.iterrows():
                identifier = (idx, row["gender"], row["age_group"], row["region"], 
row["education"], row["salary"], row["savings rate"], row["year"])
                if identifier in processed_observations:
                    continue  # Skip if this observation was already processed
                processed_observations.add(identifier)


                # Compute human capital only
                current_year = start_year
                start_age = random.randint(*age_group_ranges[initial_age_group])
                current_age = start_age
                years_calculated = 0
                human_capital = 0
                last_known_salary = None
```

```
                while current_year <= final_year and current_age < 65:
                    salary_row = df[(df["year"] == current_year) &
                                    (df["gender"] == gender) &
                                    (df["region"] == region) &
                                    (df["education"] == education)]

                    if salary_row.empty:
                        if last_known_salary is None:
                            current_year += 1
                            current_age += 1
                            years_calculated += 1
                            continue
                        salary = last_known_salary
                    else:
                        sampled_row = salary_row.sample(n=1, random_state=random.randint(1,
10000))
                        salary = sampled_row["salary"].values[0]
                        last_known_salary = salary

                    # Adjust salary from base 1977 to base 1980 using conversion factor
                    adjusted_salary = salary * conversion_factor

                    human_capital += adjusted_salary * (education_discount_rate **
years_calculated)

                    results.append([idx, gender, region, education, start_year, start_age,
current_year, current_age, years_calculated, human_capital, education_discount_rate,
initial_age_group])

                    current_age += 1
                    current_year += 1
                    years_calculated += 1

                human_capital_summary.append([
                    idx, gender, region, education, start_year, start_age, years_calculated,
                    human_capital, initial_age_group
                ])

        df_human_capital = pd.DataFrame(results, columns=[
            "ID", "Gender", "Region", "Education", "Starting Year", "Starting Age",
            "Current Year", "Current Age", "Years Calculated", "Human Capital (€)", "Discount
Rate", "Starting Age Group"
        ])

        df_human_capital.to_excel(writer, sheet_name="Human_Capital_Results", index=False)

    hc_summary_df = pd.DataFrame(human_capital_summary, columns=[
        "ID", "Gender", "Region", "Education",
        "Starting Year", "Starting Age", "Years Calculated",
        "Human Capital (€)", "Starting Age Group"
    ])
    hc_summary_df.to_excel(hc_summary_file, index=False)
```

Calculate_optimal_allocation

```
import pandas as pd
import numpy as np

def calculate_optimal_allocation(input_file, net_wealth_file, output_file, mu, rf, sigma,
cov_r_rl, net_wealth_factor=(0.120635 / 0.218527)):
    # Caricare i dati
    df = pd.read_excel(input_file)
    df_net = pd.read_excel(net_wealth_file)


    # Verifica colonne richieste
    required_columns = ["Human Capital (€)", "Gender", "Starting Age Group", "Education",
"Starting Year", "Starting Age", "Years Calculated"]
```

```
    for col in required_columns:
        if col not in df.columns:
            raise ValueError(f"Missing column in dataset: {col}")

    if not all(col in df_net.columns for col in ["Gender", "Age Group", "Education", "Region",
"Adjusted Financial Wealth"]):
        raise ValueError("Missing required columns in net wealth file")

    # Pulizia Age Group
    df_net["Age Group"] = df_net["Age Group"].astype(str).str.strip().str.replace(" ",
"").str.lower()

    def map_starting_age_to_wealth_group(age):
        if age < 35:
            return "34andunder"
        elif 35 <= age <= 44:
            return "35-44years"
        elif 45 <= age <= 54:
            return "45-54years"
        elif 55 <= age <= 64:
            return "55-64years"
        elif age >= 65:
            return "65yearsandover"
        else:
            return None

    df["Mapped Age Group"] = df["Starting Age"].apply(map_starting_age_to_wealth_group)
    df["Mapped Age Group"] = df["Mapped Age Group"].astype(str).str.strip().str.replace(" ",
"").str.lower()

    # Merge
    df_merged = pd.merge(
        df,
        df_net,
        left_on=["Gender", "Education", "Region", "Mapped Age Group"],
        right_on=["Gender", "Education", "Region", "Age Group"],
        how="left"
    )

   # Applica il fattore alla net wealth
    df_merged["Adjusted Financial Wealth"] = df_merged["Adjusted Financial Wealth"] *
net_wealth_factor

    # Calcolo lambda
    df_merged["Lambda (L/F)"] = df_merged["Human Capital (€)"] / df_merged["Adjusted Financial
Wealth"]

    # Risk aversion dinamica
    def risk_aversion_by_age(age):
        if age <= 30:
            return 3.8
        elif 31 <= age <= 40:
            return 4
        elif 41 <= age <= 45:
            return 4
        elif 46 <= age <= 50:
            return 4.5
        elif 51 <= age <= 55:
            return 5
        elif 56 <= age <= 60:
            return 5.5
        elif 61 <= age <= 65:
            return 6
        else:
            return 6.5

    df_merged["Risk Aversion (γ)"] = df_merged["Starting Age"].apply(risk_aversion_by_age)

    # Calcolo dell'allocazione ottimale
    sigma2 = sigma ** 2
    df_merged["Optimal Risky Asset Allocation (π_t*)"] = (
```

```
        ((1 + df_merged["Lambda (L/F)"]) * (mu - rf)) / (df_merged["Risk Aversion (γ)"] * sigma2)
-
        (df_merged["Lambda (L/F)"] * cov_r_rl) / sigma2
    )
    df_merged["Optimal Risky Asset Allocation (π_t*)"] = df_merged["Optimal Risky Asset
Allocation (π_t*)"].clip(lower=0, upper=1)

    # Colonne finali
    output_columns = [
        "Gender", "Starting Age Group", "Education","Region", "Starting Year", "Starting Age",
"Years Calculated",
        "Human Capital (€)", "Adjusted Financial Wealth",
        "Risk Aversion (γ)", "Lambda (L/F)", "Optimal Risky Asset Allocation (π_t*)"
    ]

    df_final = df_merged[output_columns].copy()
    df_final.to_excel(output_file, index=False)

# Parameters
mu = 0.0507
rf = 0.03
sigma = 0.2
cov_r_rl = 0.005
net_wealth_factor = (0.120635 / 0.218527)
```