The depreciation of human capital evidence from Italy

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Abstract

This study aims to estimate age-wage profiles and human capital depreciation rates for different education levels in Italy, using a dynamic panel dataset covering the period from 1980 to 2019. Specifically, we estimate depreciation rates for primary, secondary, and tertiary education levels, providing a comprehensive understanding of differences in human capital depreciation. We also investigate gender differences in depreciation rates, which can have implications for long-term economic growth and development. Our findings indicate that achieving a secondary education level compared to lower secondary leads to a 1% increase in the return of human capital and a 0.5% decrease in time spent working. Additionally, the study suggests that the gender gap in wage-age and hours-age profiles is wider for higher-educated women, with a return on human capital of 2.2% per year lower compared to men.

1 Introduction

The Ben-Porath model has been widely used in economic research to explain differences in wage-age profiles resulting from variations in human capital. Human capital encompasses the knowledge, skills, and abilities individuals gain through education and training, enabling them to participate in the labor market and contribute to the economy. While human capital is subject to depreciation over time, individuals can invest in their human capital to improve it. The difference equation that describes human capital includes a depreciation rate, a cohort-specific productivity parameter, a curvature parameter, and age t.

Numerous studies have employed the modelBen-Porath (1967) to analyze cross-regional differences in wage profiles Baker and Holsinger (1997) and the evolution of wage inequality as in Joshi et al. (2021) and inErosa et al. (2012). However, there is still a need to explore how human capital evolves over time for individuals with different levels of schooling, with a focus on potential differences in the wage profiles of women. Understanding the evolution of human capital is crucial to identifying potential constraints to long-term economic growth as shown in Mincer (1981), as a population with higher depreciation rates and poor human capital can limit potential growth. Moreover, identified different returns on human capital, allows to better understand the incentive to invest in education.

This paper aims to estimate the age-wage profiles and depreciation rates for different education levels while minimizing assumptions, following HendriksHendricks (2013)' method $\log y$. Additionally, we will examine the impact of gender discrimination on the long-term human capital of women, which can generate different returns to education. The findings of this study will provide valuable insights into the dynamics of human capital accumulation and depreciation in Italy. This research also informs policy interventions aimed at promoting economic growth and development by highlighting potential constraints to long-term growth and the importance of reducing discrimination in the labor market.

Ultimately, this research contributes to the broader literature on the role of education and human capital in economic growth and development, as well as the importance of promoting gender equality in the labor market.

2 Empirical part

The empirical questions that we are going to answer are the followings:

1. What is the return in remuneration of human capital for different levels of education?
2. Is there a difference in the remuneration of human capital between male and female?

2.1 The model predictions

The Ben-Porath model suggests that the depreciation rate of human capital is a linear function of time and depends on the level of human capital. This is because individuals with higher human capital face a higher depreciation rate, similar to the relationship between capital and growth in the growth theory. As such, we can expect that individuals with lower education levels, and therefore lower levels of human capital, will experience a lower depreciation rate compared to those with higher levels of education.
In terms of the wage-age profile, individuals with lower education levels will typically invest less in human capital and reach their maximum wage sooner and at a lower level compared to those with higher education levels. This is due to the fact that individuals with higher levels of education are more likely to have skills and knowledge, which can lead to higher wages and greater career opportunities later in the careers.

2.2 Specification

We use regression on the Conditional Expectation Function (CEF) as a method to estimate the relationship between the dependent variable:

- $\log wage_{i,t}$
- $\log hours_{i,t}$

(and where i is the individual i at the age t) and independent variables:

- age, age^2: the age and the age squared of the individual i of the year y
- *i.cohort* is the list of dummies of the cohorts

- $i.years$ is the list of dummies for the years class (class size = 5).

while controlling for:

- $educ = 3, 5$ Educational level: 3 : middle school, 5 : High school level
- $female = 0, 1$ Sex ($= 1 iff female$)

There are four specification that we are going to use

1. $\log wage_{i,y} = \beta_1 age_i + \beta_2 age_i^2 + i.cohort + i.years | educ = 3, 5$
2. $\log wage_{i,y} = \beta_1 age_i + \beta_2 age_i^2 + i.cohort + i.years | educ = 3, 5, sex = 0(male), 1(female)$
3. $\log hours_{i,y} = \beta_1 age_i + \beta_2 age_i^2 + i.cohort + i.years | educ = 3, 5$
4. $\log hours_{i,y} = \beta_1 age_i + \beta_2 age_i^2 + i.cohort + i.years | educ = 3, 5, sex = 0(male), 1(female)$

We adopt the specifications given by Hendricks (2013) denoted as 1 and 2. However, we do not include a gender fixed effect in the regression analysis, as we aim to allow gender to affect the estimates of η and η^2 in a time-varying manner. This approach is similar to that proposed by Joshi et al. (2021). We also refrain from using the month of job as a proxy for experience, as it may result in collinearity issues. Moreover, since the dataset excludes periods of unemployment, we can assume that $exp + edu \approx \eta$. The CEF method has several limitations. First, it assumes that the age and education variables capture all the relevant dimensions of human capital, which may not be the case. Other important factors, such as experience or on-the-job training, are not explicitly considered in the model. Second, the method may suffer from omitted variable bias if there are unobserved characteristics that affect both wages and education levels. Third, the CEF method assumes that the relationship between age, education, and wages is linear, which may not hold in reality.

2.3 Identification strategy

To estimate the depreciation rate of human capital for different levels of education, we need to implement an identification strategy that allows us to separate the effects of age, education, cohort and year on wage profiles. In

this section, we describe the identification strategy we use in our study.
To begin with, we assume that the cohort effects are the same for all agents in the same 5-year cohort. This assumption is motivated by the fact that individuals who are born in the same 5-year period tend to share similar social, economic, and political experiences during their formative years. For example, individuals who were born during a period of economic growth may have had more educational opportunities compared to those who were born during a period of economic recession. By assuming that cohort effects are constant across individuals in the same 5-year cohort, we can control for unobserved heterogeneity that is specific to a particular cohort.In order to ensure consistent estimates, it is necessary to impose these restrictions. Without them, there would be a problem of collinearity.
Secondly, we assume that the initial human endowment is the same within the same cohort. This assumption implies that individuals who are born in the same 5-year cohort have similar levels of human capital at the beginning of their careers, before they have invested in additional education or training. By assuming that the initial human endowment is constant within the same cohort, we can control for unobserved heterogeneity that is specific to a particular birth cohort.
The same assumption applies to year effects, meaning that individuals within the same cohort experience the same effects on wages over a period of 5 years. The restrictions imposed on the model are based on some naive assumptions about the behavior of individuals with respect to their education and human capital. For instance, it is reasonable to assume that individuals who are born in the same 5-year cohort would have similar opportunities for education and training. Similarly, individuals who start with the same initial human capital endowment within the same cohort are likely to face similar labor market opportunities over time.
While these assumptions may not hold perfectly in reality, they provide a useful framework for identifying the key factors that drive the age-wage profile and depreciation rates of human capital for different levels of education in Italy. By controlling for cohort and year effects in our analysis, we can isolate the effect of age and education on wages and estimate the rate of human capital depreciation for different groups of individuals.
To estimate the depreciation rate of human capital for different levels of education, we use a longitudinal panel data. Specifically, to estimate the age-wage profiles and the depreciation rates of human capital for different levels of education in Italy, we employ an OLS approach. We run two separate

OLS regressions for individuals with a lower-secondary education and those with a high school level education, respectively. The dependent variable is the natural logarithm of the wage, and the key independent variables are age and age squared. We control for cohort effects and year effects by including birth year dummies and calendar year dummies, respectively. Additionally, the wage variable is corrected for inflation using the consumer price index.
Moreover, to examine gender differences in the evolution of human capital, we perform four separate regressions conditioned on gender and two levels of education, as specified in2. To capture the potential variation in gender effects over time, we employ the regression on the conditional expectation function. Additionally, we use the same method $\log y$ to estimate the gender gap in the hours-age profile.
Applied Overall, our identification strategy allows us to separate the effects of age, education, and cohort on wage profiles and estimate the depreciation rate of human capital for different levels of education. By using a longitudinal panel data approach and controlling for individual-specific unobserved heterogeneity and time-varying factors, we can obtain more accurate estimates of the depreciation rate of human capital, which is a crucial variable that affects overall economic growth and development.

3 Data and descriptive statistics

3.1 Data

The data used in this study are obtained from the Family Income Survey of the Bank of Italy, which spans a period from 1980 to 2020 with $\sim 100.000 obs$. The sample comprises employees[1] both men and women born between 1940 and 2020. To expand our sample size, we have divided the population into 56 birth cohorts, where each cohort covers five consecutive birth years. We have also applied the same division for years, where each group includes five years. The following table4 tabulate the distribution on observations for cohort. The cohort with the highest density of observations is cohort 10, whereas the younger and older cohorts have relatively few observations. The objective of the study is to estimate wage-age profiles, which required the use of employee income reports merged with family and individual statistics.

[1]We drop the observation for self-employed since including would rise an issue of undereporting

To calculate
$logwage_{i,t}$, we employed a series of transformations. Firstly, we summed the monetary and non-monetary components of income. Secondly, we deflated the income figures using the Consumer Price Index (CPI). Thirdly, we divided the income figures by the monthly hours worked and multiplied by 13 months to obtain the annual income. Fourthly, we took the logarithm of the annual income figure. Finally, we merged the resulting dataset with individual-level data.
The process of computing
$logwage_{i,t}$ was essential for the analysis, as it allowed us to measure the variation in wages over time, which is critical for estimating wage-age profiles. By merging different datasets, we were able to obtain a more comprehensive picture of the factors influencing wage dynamics in Italy. We follow these steps to get
$logwage_{i,t}$:

1. Sum monetary and non monetary components
2. Deflating for CPI
3. dividing for the monthly hours and multiply for 13 month
4. take $\log s$
5. merging with other dataset with individual data

3.2 Descriptive statistics

The tables presented in this paper (see Tables1 and2) provide a detailed overview of the descriptive statistics for two key variables: the logarithm of wages and annual working hours. The tables show the mean, standard error, and t-test for the difference in mean for each variable across four different groups based on education level and gender. Specifically, the groups are defined by individuals with a low level of secondary school education, those with a secondary school education level, and these subgroups further differentiated by sex.
The statistical results from the tables indicate that individuals with a secondary school education level tend to earn higher wages than those with a lower level of education. Moreover, the wage gap between genders is more

pronounced among those with a secondary school education level. In other words, women tend to earn less than men across all education levels, and the difference is wider for those with a higher level of education.
In terms of annual working hours, the statistics indicate that individuals with a lower level of education tend to work more hours than those with a higher level of education. However, this trend is reversed when looking at gender differences. Women tend to work fewer hours compared to men across all education levels as show in Goldin and Polachek (1987). Interestingly, this gender gap in working hours narrows as the level of education increases. It is important to note that the data used in the analysis covers a period from 1980 to 2020, during which the participation of women in the labor market has increased significantly. Thus, the true difference in working hours between genders may be even greater for individuals with the same characteristics.
In order to better understand the relationship between education level and economic outcomes, it is often useful to examine a specific cohort in a given year. This approach is particularly relevant when working with panel data, as it allows for a more detailed analysis of trends and patterns over time. By focusing on a single cohort, we can examine the distribution of key economic variables such as wage, income, and annual hours worked, conditional on different levels of education. This type of analysis can reveal important insights into the labour market for specific subgroups, and help to identify disparities and trends that may not be apparent when analyzing data at the aggregate level.
The table3 presented in this study reports on the wage and working hours of a specific cohort in the year 2008. The descriptive statistics show that wages are positively correlated with education level, which is consistent with the trend observed in the previous tables12. Additionally, the statistics reveal a decreasing trend in working hours as the level of education increases. This finding suggests that individuals with higher levels of education are able to earn higher wages while working fewer hours, potentially due to their possession of skills or abilities that increase their productivity as according to the human capital model. It is important to note that this specific cohort has a mean age of 50, which is a significant age for the human capital model. This is because at this age, individuals have typically spent their time endowments in work without investing in human capital. Therefore, these summary statistics must be interpreted in light of the fact that this cohort represents middle-aged workers who have already invested significant time and resources into their careers.

In conclusion, the descriptive statistics presented in this paper provide valuable insights into the labor market outcomes of individuals with different levels of education. Our analysis revealed that, on average, individuals with higher levels of education tend to earn higher wages and work fewer hours than those with lower levels of education. We also found that there are significant gender disparities in labor market outcomes, with women generally earning less and working fewer hours than men.

4 Empirical results

The empirical results section of this paper is dedicated to presenting our comprehensive analysis of the relationship between human capital evolution and education and gender characteristics. In this section, we aim to shed light on several key questions that are relevant to understanding the dynamics of the labor market. Specifically, we explore the impact of attaining a secondary education level on the wage age profile, and whether gender differences exist in the wage age profile for individuals with the same level of education. Additionally, we investigate the hours-age profiles for individuals with lower levels of education and those with higher levels, assessing how investing in human capital affects the hour-age profile. Lastly, we examine the gender gap in these profiles to identify potential disparities and trends that may exist. Through this analysis, we hope to provide valuable insights into the labor market for specific subgroups and contribute to the broader understanding of human capital evolution.

4.1 The estimation of wage age profile

According to the human capital theory, the wage-age profile reflects the relationship between an individual's age and their wages, which is influenced by their investment in human capital over time. To explore this relationship, we use regression analysis with specification1 and present the results in Table5. The key parameters include β_{age2}, which indicates the decline in wages over time and reflects depreciation, and β_{age}, which represents the return on investment in human capital over time. All the coefficients are statistically significant, providing valuable insights into the dynamics of the labor market and the role of human capital investments in shaping the wage-age profile.
If we focus on individuals with lower education5, the results indicate that

an increase of one year in age leads to an increase of $\approx 11\%$ in wages. On the other hand, for individuals with higher education 5, an increase of one year in age leads to an increase of approximately $\approx 12.6\%$ in wages. These findings are consistent with the human capital theory, which suggests that having a secondary level education instead of a lower secondary education leads to higher returns, while the depreciation rate remains the same for both groups. However, the low value of $R^2_{overall} \approx 11\%$ suggests that the regression has very limited predictive power, possibly due to the restrictions imposed to isolate the cohort and year fixed effects.
To visually inspects the results we show the predicted wages by cohorts.
In this section, we present a graph (see Figure1) that visually depicts the relationship between education levels and wages across different age cohorts. The results are intriguing, as they suggest that there is a notable difference in the wage gap between older and younger cohorts. The graph shows that the wage gap is larger for the older cohort, while the younger cohorts have a narrower difference. This finding is consistent with the notion that higher educated individuals tend to spend part of their time endowment continuing to invest in their human capital during the early stages of their careers, while the lower educated tend to have more experience as they started working early, thus accumulating specialized skills. It is worth noting that this observation may indicate that specialized skills have a higher depreciation rate and a lower return on the long term. It would be interesting to extend the model to include two types of human capital assets: one with a higher short-term return and higher depreciation, and another that is more costly but has lower depreciation, and then let the agent choose the optimal level of the two assets following the idea of Krueger and Kumar (2004).
The findings of our study support the theory that higher levels of human capital lead to higher wages. Specifically, the graph1 demonstrates that individuals with higher levels of education consistently earn higher wages compared to those with lower education levels across all age cohorts. This observation highlights the importance of investing in human capital, particularly at the early stages of one's career, to enhance earning potential in the long term.
Furthermore, the graph1 also shows that the wage gap between education levels widens over time. This suggests that younger cohorts have a smaller wage gap because the lower-educated individuals are more experienced in the labor market, while the higher-educated individuals are just starting out. However, as time goes by, the market starts to remunerate better those

individuals who have invested in higher human capital.
Building upon these findings, we extend our analysis to include the effects of gender on wages by conducting a regression analysis similar to the one before but with gender as a conditioning variable. This will allow us to examine the gender wage gap across different education levels and age cohorts, providing important insights into the dynamics of the labor market and the role of gender in wage determination.

The results presented in Table6 indicate that there is clear evidence of a lower return on education for females, with $\beta_{age,female}$ (as shown in columns66) being lower than $\beta_{age,male}$ (shown in columns66). This effect is more pronounced for individuals with higher levels of education, as the marginal gap with respect to age is wider, with $\Delta_{secondary} \approx 2.2\%$ per year for those with secondary education, and $\Delta_{lower\ secondary} \approx 1.4\%$ per year for those with lower secondary education. This result is consistent with previous research Erosa et al. (2012) and implies a lower return on investment in human capital for females. Interestingly, there is no statistically significant difference in the depreciation of capital over time between males and females, as $\beta_{eta^2}|female, sex = \beta_{eta^2,female}|female, sex$ and is approximately 0.83%.

The gender wage gap can be decomposed into two factors that widen it over time: the increase in wages as a result of acquiring working experience, represented by β_{Age}, and the decrease in wages, represented by β_{Age^2}.

These findings emphasize the importance of considering gender as a conditioning variable in wage regression analysis, as it provides valuable insights into the dynamics of the labor market and the role of human capital investments in shaping the wage-age profile. Moreover, the results suggest that women have lower remuneration for their human capital, which partially explains the wide difference in wages shown in Table1. To better understand the difference in the evolution of wage-age profiles for women and men, we plot a chart of the predicted $\log(wage)$ comparing individuals with the same level of education but with different genders.

The chart2 illustrates that male wage-age profiles conditional on different level of education across all cohorts, while the chart3 only for cohort 6. Now we take a look at the same results for secondary school and lower secondary. The chart3 show an higher gender gap for low educated that does not fade out as the time passes. It is important to remember that the prediction on wage is base only on th observables, thus women that drop out the job and stay home are not take into account, thus the gap that we observe is only for the women that stays in the market. Moreover the wage gap is less accentuated for women with higher education, but this can be justified by the fact that female that choose to remain in the market are the ones without childbearing obligations or the ones that are paid more.[2] Futhermore, the mean age in cohort 6 is 48, thus the graph3 approximates the gender gaps only in the neighborhood of this age. Regardless the strong bias due to endogeneity about the extensive margin decision, the wage age profiles for females remains lower than man, meaning female has a lower return on year of education compare to man.

Overall the estimate return in education are consistent with the human capital theory even here the comparison was by individual with lower secondary and secondary education level, it would had been better the comparison with individuals with a bachelor. However it is not possible since the are only few observations ≈ 600 to get significant estimate of the key dependent variables. Regarding the gender differences it is clear that there is a lower return on human capital for female compare to man, notwithstanding this gap is strongly underestimated for the motivations written above.

4.2 The estimation of hour age profile

Working hours is a fundamental variable in the human capital model, as it is the outcome of an optimization process whereby individuals choose how much of their time endowment to allocate towards increasing their human capital, and how much to devote to working. In this sense, working hours can be seen as a proxy for investment in human capital, as individuals who invest more time in developing their skills and knowledge may have fewer hours available for paid work.

First, we will look at the difference in the hours-age profiles for individuals with different levels of education. Second, we will look at the difference in the hours-age profile as before but conditioning on gender. In the following Table 7, we estimate with OLS the second specification 2 for lower secondary and secondary education level. In column (1) 7, the results of the regression for the group that has achieved a secondary school education level are reported, while in column (2) 7, the results of the regression on the individuals

[2] Studying the decision of drop out of women can be useful to understand the reservation wage and thus to instrument the observability of wage; moreover the drop rates is so high that estimating the effect of having child for female increases the wage by 8% this is clearly due to the fact the the participation rates after first child shrink dramatically leaving only female with higher wages and the once without child

that achieved only lower secondary school are reported.
Our analysis shows that individuals with lower levels of education tend to start working earlier in life compared to those with higher education. Indeed, the β_{age} is positive for those who spend more time in school, while negative[3], meaning that for the higher educated, the time endowment spent in working is increasing over time with a rate of 0.7% per year. The observation that the time spent working decreases over time with a rate of -0.5% per year for lower-educated individuals is in line with the idea that higher-educated individuals tend to increase their working hours over time as they invest in their human capital early in their careers, and gradually reduce their working hours as they gain experience. This pattern is consistent with the human capital model, which predicts that individuals with lower levels of education tend to start working earlier in life to maximize their immediate earnings, while those with higher education may delay their entry into the labor market as they invest in their human capital.
To visually inspect these results, we plot the predicted values for working hours by education level, separating each cohort (figure.4). This allows us to see the trends in working hours across different levels of education for each cohort, providing further insight into the relationship between human capital and working hours
In the presented graph, the red line represents the hours-age profiles for individuals with lower secondary school education. These individuals tend to start spending their time endowment working earlier compared to those with secondary education. Additionally, individuals with lower education have a higher hours-age profile, which decreases over time. The peak of the red group's hours-age profile is reached in the early years of their working career, and then the curve slightly decreases over time. In contrast, for those with higher education, the peak is reached between 40 and 50 years old, and then starts to decrease. It is important to emphasize that individuals with higher education spend less time working for all years, and this trend is observed in all cohorts.
To look a gender differences in the hours-age profile we run the same regression specification as above4, but conditioning on gender. The results are showed in the table8. As in the results without conditioning on gender, the slope of the hours-age profile is negative for individual with higher education

[3]both statistically significant, even if for the higher educated only at 10%, while for the low educated at 1%

level. Notwithstanding, for women the slope are flatter across all level of education, indeed $\Delta_{female-male}\beta_{age} \approx 0.1\%$ per year, meaning that women increases more mildly the time spent working[4]. Moreover, female with low education has a steeper negative hours-age profiles $\beta_{eta}|female \approx -1.7\%$ per year and $\Delta_{female-male}\beta_{age} \approx 1.2\%$ per year, signaling that low educated women tends to decrease at faster rate the participation in the labour market in the intensive margin compare to the higher ones, moreover the gender gap is wider compare to the more educated.

To visually compare the predicted working hours by cohort for males (higher educate in orange, lower educated in red) and females (lower educated in blue and higher educated in green) at different levels of education, we plotted the the predicted values of the regression of8in Figure5, while in the Figure6 we plot the predicted value for the middle-age cohort 7.

The figure5 illustrates that, across all cohorts, men have higher hours-age profiles than women, indicating that women have lower participation in the intensive margin compared to men, regardless of educational attainment. Additionally, for women with lower education, the hours-age profile declines rapidly in the initial stages of their working lives, particularly between ages 20 and 30. Consequently, the gap between low-educated females and males widens considerably during this period, reaching its peak at around ages 40. Conversely, for women who stay in school longer, there is an increase in participation (intensive margin) during the early stages of their careers, between ages 20 and 30, when the hours-age profile reaches its maximum. Subsequently, the participation rate either declines or remains stable. However, it is worth noting that the decrease in hourly worked for women is significantly underestimated since the probability of dropping out of the labor force after having the first child is around 30% for individuals with lower and secondary school education, as demonstrated by Bratti et al. (2005), which implies that a large proportion of female labor force participation is unobservable.

Additionally, the gender gap in the hourly-age profile reaches its peak at around age 50 for those with higher education, which is in line with the idea that women who stay in school longer tend to have their first child later, thereby delaying their childbearing years to later stages of their working lives. Subsequently, after age 50, the gap begins to decrease slightly but

[4]considering that women that drops the job after having children are unobservable, this gap can be even higher

remains significant until the end of their working careers. Interestingly, the gender gap in the hourly-age profile is wider for those who spent more time in schooling, as observed in the younger cohort. One possible explanation can be that Women who pursue higher levels of education may face additional pressure to conform to traditional gender roles, such as being a caregiver for children and elderly family members, which can lead to a reduction in their labor force participation or hours worked. This can be particularly true during the early stages of their careers when they are starting families or establishing themselves in their chosen fields. On the other hand, men who pursue higher education may face fewer societal expectations to prioritize caregiving responsibilities over their careers. Thus, they may be able to invest more time and effort into their careers, leading to higher hours worked and a wider gender gap in the hourly-age profile.

The hours-age profiles for lower educated women were consistently lower than for men across all cohorts, indicating that this gender gap persists over time. However, for higher educated individuals, the gender differences were not apparent (as shown in Figure5).

Overall, our empirical findings are in line with the human capital theory, as we found a positive and statistically significant effect of education on human capital remuneration, and a concave wage-age profile as predicted by the model with depreciation $\Delta > 0$. Additionally, the hours-age profile supports the human capital model's predictions, with higher educated individuals having an increasing hours-age profile, and lower educated individuals having a decreasing one. Furthermore, our analysis of the gender gap in the hours-age profile shows that women tend to have a lower participation in the intensive margin compared to men, regardless of their level of educational attainment. The gap is wider for lower educated women, and it decreases slightly for higher educated women after the age of 50, which is consistent with the fact that they tend to have their first child later and shift childbearing years later in their working life. It is also interesting to note that the gender gap in the hourly-age profile at the beginning of the career is wider for those who spent more time in schooling, as seen in the younger cohort. These findings provide insights into the complex interplay between education, gender, and labor market outcomes.

5 Conclusions

In conclusion, this paper has provided an analysis of the gender wage gap in a European country, focusing on the role of education and human capital. The empirical findings are consistent with the human capital theory, as we observe a positive statistically significant effect of education on the remuneration of human capital and a concave shape of the wage-age profile, in line with the model with $\Delta > 0$.

Furthermore, the analysis shows that the gender wage gap widens over time, mainly due to differences in the remuneration of human capital between men and women. Women have a lower remuneration of human capital, even for the same level of education, which can be partly explained by differences in working hours, as women tend to invest less time in developing their skills and knowledge.

The results also indicate that individuals with lower levels of education start working earlier, with the aim of maximizing their immediate earnings, while those with higher levels of education may take longer to start working as they invest in their human capital. This is reflected in the hours-age profile, which decreases over time for those with lower education, while it increases for those with higher education.

However, it is important to note that the analysis has certain limitations. Firstly, the restriction imposed on cohort fixed effects and years fixed effects, which may not capture all the heterogeneity in the data. Secondly, the analysis only focuses on a single country, and the results may not be generalizable to other contexts. Finally, the study does not account for the potential impact of discrimination and other factors that may contribute to the gender wage gap.

Overall, this study provides insights into the factors that contribute to the gender wage gap and highlights the importance of education and human capital in determining individuals' earnings. Further research is needed to explore the role of other factors, such as discrimination and family responsibilities, and to investigate the effectiveness of policies aimed at reducing the gender wage gap.

6 Tables

Table 1: Descriptive statistics wages

Education level	Male	Female	Diff.
Lower Secondary	51.71	48.06	3.642061***
	(33.06)	(40.60)	(.9713213)
Secondary	124.03	113.09	5.360341***
	(91.37)	(73.14)	(.5809988)
Diff.	-18.47816***	-16.75988***	
	(.7922257)	(1.07596)	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Descriptive statistics annual working hours

Education level	Male	Female	Diff
Lower Secondary	1,952.12	1,642.11	310.0051***
	(393.85)	(537.70)	(12.13044)
Secondary	1,811.48	1,507.51	253.783***
	(484.11)	(491.03)	(4.887414)
Diff.	27.01869 ***	-29.20347***	
	(6.180364)	(11.81991)	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Figures

Table 3: Descriptive statistics of cohort=10 and year=2008

	no edu.	primary	lower second.	second. 3y	second.
Mean of log (wage)	3.61	3.63	3.67	3.69	3.75
	(.)	(0.06)	(0.03)	(0.02)	(0.02)
Mean of work hour	1,920.00	1,886.70	1,811.86	1,780.06	1,678.31
	(.)	(116.59)	(50.03)	(31.46)	(38.77)
mean_y	71261.03	71261.03	71261.03	71261.03	71261.03
	(.)	(0.00)	(0.00)	(0.00)	(0.00)
Female	0.00	0.26	0.40	0.55	0.66
	(.)	(0.45)	(0.49)	(0.50)	(0.48)

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Table 4: Freq. density of cohorts

Cohort	N.obs	Freq.Perc.	Cum.
1	42	0.04	0.04
2	619	0.59	0.63
3	1816	1.74	2.37
4	3333	3.20	5.57
5	6869	6.58	12.15
6	9495	9.10	21.26
7	11401	10.93	32.19
8	11971	11.48	43.66
9	13347	12.79	56.46
10	14240	13.65	70.11
11	10862	10.41	80.52
12	8222	7.88	88.40
13	6291	6.03	94.43
14	4291	4.11	98.55
15	1517	1.45	100.00
Total	104316	100	

Table 5: Regression on $log(wage)$

	(1)Sec.	(2)Lower sec.
Age	0.126***	0.109***
	(7.07)	(17.45)
age2	-0.000871***	-0.000832***
	(-4.70)	(-12.96)
Constant	-0.199	0.0380
	(-0.25)	(0.08)
Year fixed effect	Yes	Yes
Cohort fixed effect	Yes	Yes
Observations	10088	28968

t statistics in parentheses

Regression on $log(wage)$ for lower secondary group (1) and for secondary school (2)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Table 6: Regression on $E[log(wage)|female, educ]$

	(1)M., H. educ.	(2)F. H. educ.	(3)M., L. educ.	(4)F., L. educ.
Age	0.13710***	0.11522***	0.11396***	0.10093***
	(0.03092)	(0.02028)	(0.00794)	(0.01015)
age2	-0.00090***	-0.00083***	-0.00089***	-0.00070***
	(0.00032)	(0.00021)	(0.00008)	(0.00010)
Cohort f.e	Yes	Yes	Yes	Yes
years f.e.	Yes	Yes	Yes	Yes
Constant	-0.83300	0.44851	-0.12925	0.69487
	(1.22242)	(1.11800)	(0.54144)	(1.17340)
Observations	4593	5495	19045	9923

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Regression $E[log(Hours)|educ]$

	(1)$educ = 1$	$educ = 0$
Age	0.007*	-0.005***
	(0.004)	(0.002)
age2	-0.000*	0.000
	(0.000)	(0.000)
Cohort f.e	Yes	Yes
years f.e.	Yes	Yes
Constant	7.280***	7.789***
	(0.190)	(0.128)
Observations	10088	28968

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Regression table $E[log(hours)|female, educ]$

	(1)[1, 0]	(2)[1, 1]	(3)[0, 0]	(4)[1, 1]
Age	0.00788	0.00706	0.00202	-0.01676***
	(0.00567)	(0.00597)	(0.00163)	(0.00357)
age2	-0.00009	-0.00008	-0.00006***	0.00014***
	(0.00006)	(0.00006)	(0.00002)	(0.00004)
Cohort f.e	Yes	Yes	Yes	Yes
years f.e.	Yes	Yes	Yes	Yes
Constant	7.43107***	6.78971***	7.69220***	7.47544***
	(0.22349)	(0.33563)	(0.11123)	(0.41583)
Observations	4593	5495	19045	9923

The regressions are conditinal on education and female,
indeed the column has as [index] [educ,female] if educ==1 the group
has a secondary school education level, otherwise it has a lower secondary one.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)
	l_hours	l_wage
overall		
group_1	7.542***	3.971***
	(4319.00)	(437.48)
group_2	7.366***	3.896***
	(1872.07)	(328.45)
difference	0.176***	0.0742***
	(40.79)	(4.97)
explained	-0.000203	-0.0184***
	(-0.94)	(-5.52)
unexplained	0.176***	0.0926***
	(40.79)	(6.35)
explained		
age	-0.00489***	-0.0519***
	(-3.92)	(-4.50)
age2	0.00469***	0.0336***
	(3.66)	(3.90)
unexplained		
age	0.717***	0.370
	(6.53)	(1.00)
age2	-0.372***	-0.224
	(-6.20)	(-1.11)
_cons	-0.169***	-0.0535
	(-3.29)	(-0.31)
N	28968	28968

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)	(2)	(3)
	l_hours	l_wage	l_wage
overall			
group_1	7.542***	3.971***	4.363***
	(4319.00)	(437.48)	(163.35)
group_2	7.366***	3.896***	4.434***
	(1872.07)	(328.45)	(249.40)
difference	0.176***	0.0742***	-0.0707*
	(40.79)	(4.97)	(-2.20)
explained	-0.000203	-0.0184***	0.0436***
	(-0.94)	(-5.52)	(5.83)
unexplained	0.176***	0.0926***	-0.114***
	(40.79)	(6.35)	(-3.60)
explained			
age	-0.00489***	-0.0519***	0.122**
	(-3.92)	(-4.50)	(3.16)
age2	0.00469***	0.0336***	-0.0788*
	(3.66)	(3.90)	(-2.11)
unexplained			
age	0.717***	0.370	0.830
	(6.53)	(1.00)	(0.70)
age2	-0.372***	-0.224	-0.391
	(-6.20)	(-1.11)	(-0.65)
_cons	-0.169***	-0.0535	-0.553
	(-3.29)	(-0.31)	(-0.94)
N	28968	28968	10088

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)
	l_hours
overall	
group_1	7.542***
	(4319.00)
group_2	7.366***
	(1872.07)
difference	0.176***
	(40.79)
explained	-0.000203
	(-0.94)
unexplained	0.176***
	(40.79)
explained	
age	-0.00489***
	(-3.92)
age2	0.00469***
	(3.66)
unexplained	
age	0.717***
	(6.53)
age2	-0.372***
	(-6.20)
_cons	-0.169***
	(-3.29)
N	28968

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)
	l_hours
overall	
group_1	7.458***
	(1531.09)
group_2	7.258***
	(1389.15)
difference	0.200***
	(28.04)
explained	-0.00188*
	(-2.40)
unexplained	0.202***
	(28.18)
explained	
age	0.00555
	(0.85)
age2	-0.00743
	(-1.11)
unexplained	
age	0.571*
	(2.13)
age2	-0.259
	(-1.88)
_cons	-0.110
	(-0.83)
N	10088

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

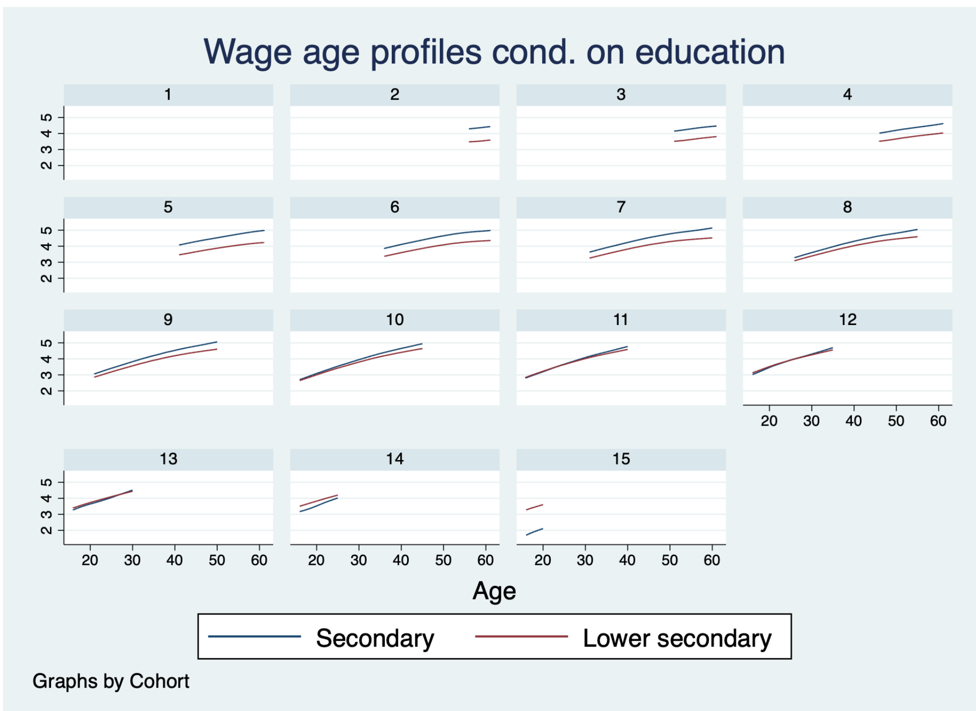

Figure 1: Predicted wage-age profiles by cohort

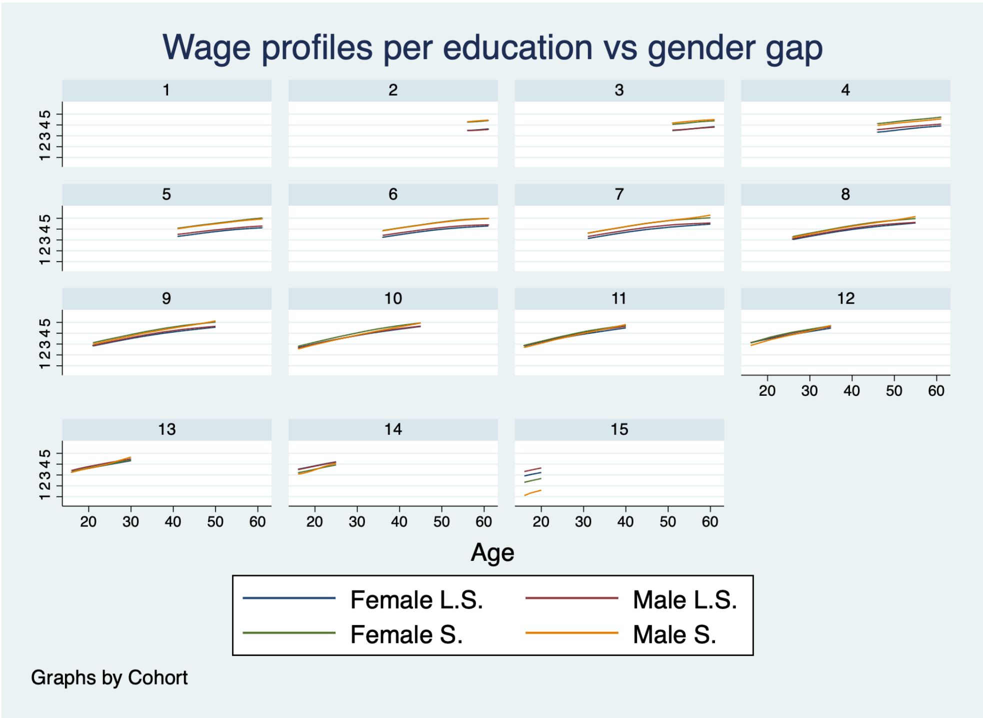

Figure 2: Gender gap in the wage age profiles for different education level

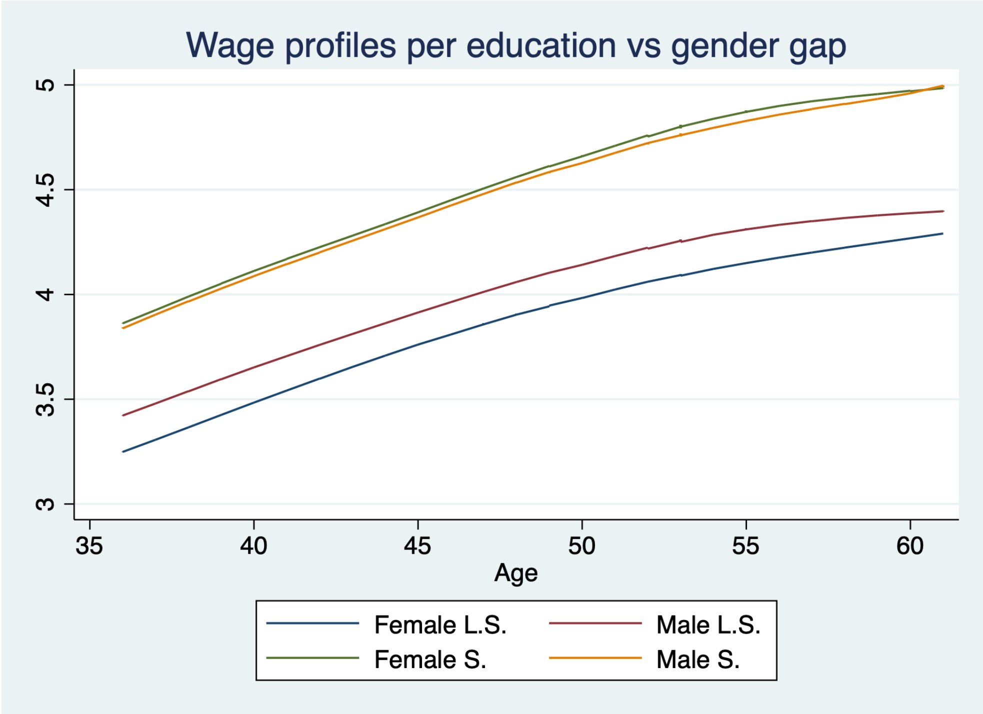

Figure 3: Gender gap in the wage age profiles for different education level in the cohort 8

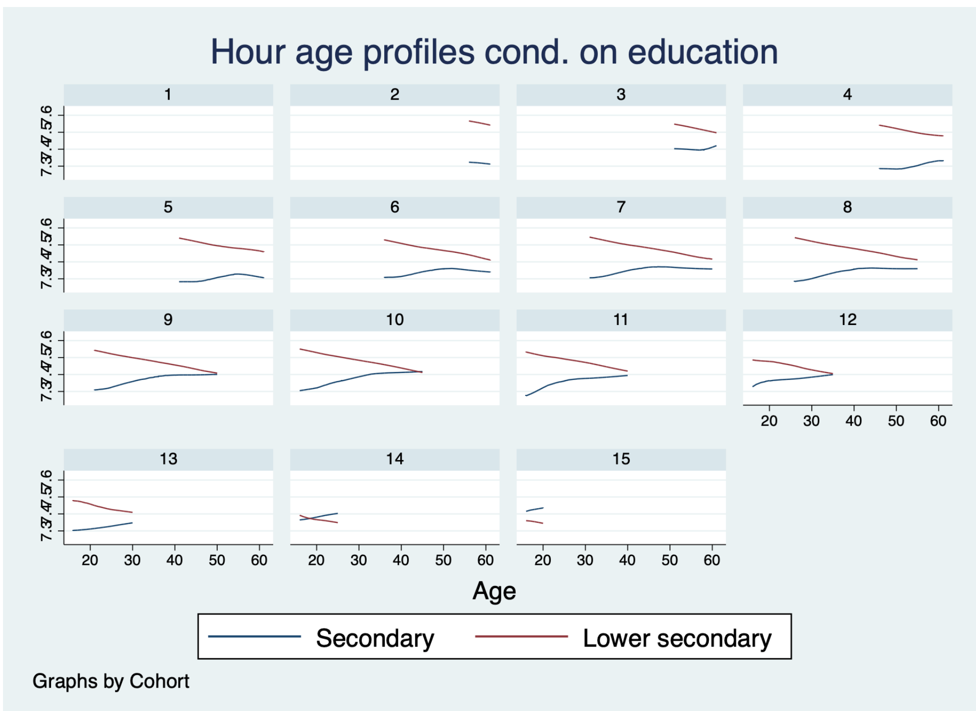

Figure 4: Hours-age profile

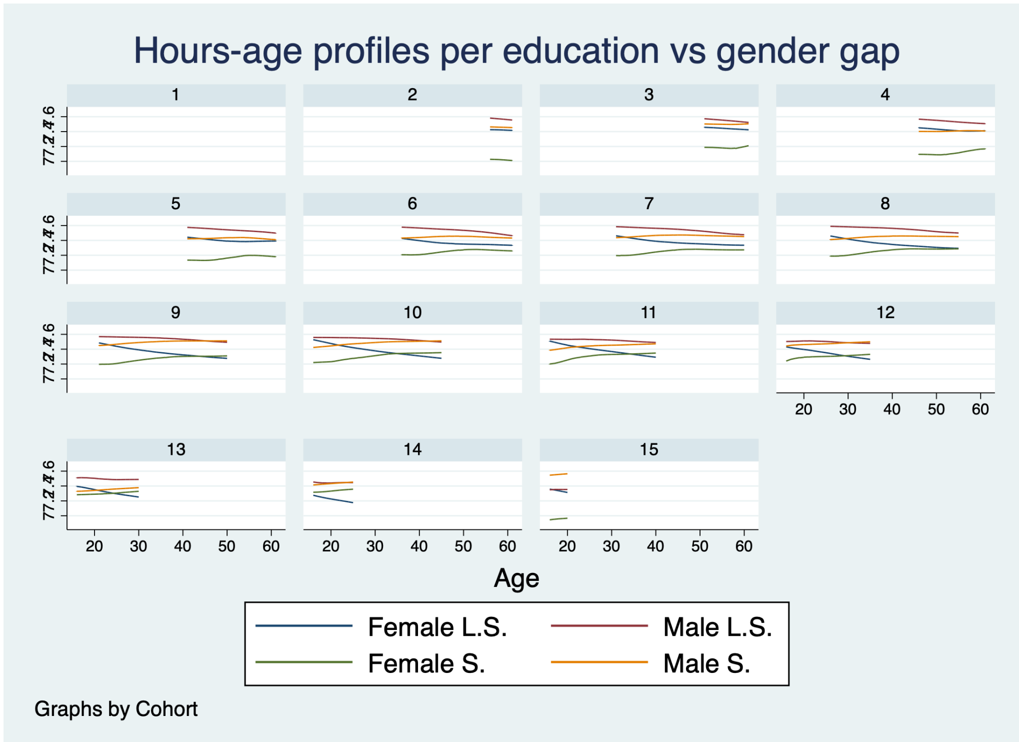

Figure 5: Hours-age profile and gender gap

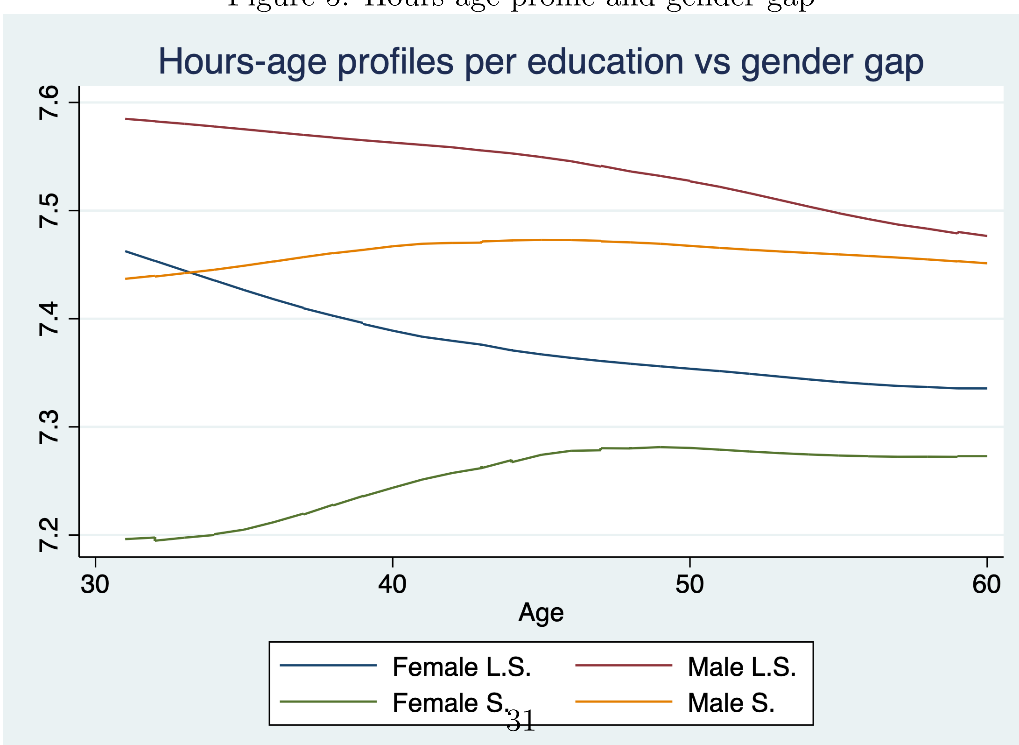

Figure 6: Hours-age profile and gender gap in the cohort 8