Abstract

This paper seeks to estimate the age-wage profiles and depreciation rates of human capital for different levels of education in Italy, which are crucial variables that impact overall economic growth and development. To achieve this goal, we use a dynamic panel dataset provided by the Banks of Italy, covering the period from 1980 to 2019. Our analysis aims to estimate the depreciation rates for primary, secondary, and tertiary education levels separately. By doing so, we provide a comprehensive understanding of the differences in human capital depreciation across various education levels.

Furthermore, we also investigate gender differences in human capital depreciation rates. We estimate the depreciation rates separately for men and women to determine whether there are any differences in the depreciation rates between genders. This analysis is critical to understanding gender disparities in the labor market, which can have long-term implications for economic growth and development.

Overall, our study contributes to the literature on human capital and economic growth by providing insights into the dynamics of human capital depreciation in Italy. Our findings will be valuable to policymakers and researchers in designing effective policies to promote economic growth and development in Italy. Additionally, the gender-specific analysis of human capital depreciation rates will inform policy interventions aimed at promoting gender equality in the labor market.
(Finding)

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 Ben-Porath model to analyze cross-regional differences in wage profiles and the evolution of wage inequality. 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 a population with higher depreciation rates and poor human capital can limit potential growth.

This paper aims to estimate the age-wage profiles and depreciation rates for different education levels while minimizing assumptions, following Hendriks' methodology. 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 depriciation rate of human capital for different levels of education?

2. Is there a difference in the depriciation rate 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 specialized skills and knowledge, which can lead to higher wages and greater career opportunities.

2.2 Specification

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

- $log(wage)_{i,y}$
- $log(hours)_{i,y}$

(and where i is the individual i of the year y) 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
- $sex = 0, 1$ Sex $(= 1iffemale)$

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

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. Finally, the method relies on cross-sectional data, which limits the ability to make causal inferences about the effects of education on wages over time.

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.The reasoning behind these assumptions is that in panel data, we cannot follow the same individual over time due to a lack of a unique identifier. As a result, we cannot identify individual effects, and we need to impose these restrictions

to obtain consistent estimates.
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 dynamic panel data approach. 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 methodology 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 dynamic 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 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 table 4 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. To calculate $\log(wagei, t)$, 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 $\log(wage_{i,t})$ 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 $\log(wage_{i,t})$:

1. Sum monetary and non monetary components
2. Deflating for CPI
3. dividing for the mountly hours and multiply for 13 month
4. take logs
5. merging with other dataset with individual data

3.2 Descriptive statistics

The tables presented in this paper (see Tables1 and2) display the mean, standard error, and t-test for difference in mean for log(wage) and annual working hours for four different groups based on education level and gender: those 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 suggest that individuals with a secondary school education level tend to earn higher wages than those with a lower level of education. However, 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. 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 analysing data at the aggregate level.
The table4 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

This section presents our findings on the difference in the human capital evolution for different education and gender characteristics. First, we examine whether attain secondary education level change the wage age profile. Furthermore if there exists some gender differences in the wage age profile for the same level of education. Second, we focus in estimating the hours-age profile for the same subgroups.

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 Table 5. 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 education**??**, the results indicate that an increase of one year in age leads to an increase of approximately 10.3% in wages. On the other hand, for individuals with higher education **??**, an increase of one year in age leads to an increase of approximately 12.2% 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. The low value of $\bar{R}^2$ suggests that the regression has 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.

The graph1 provides a visual representation of the relationship between education levels and wages across different age cohorts. The findings support the theory that higher levels of human capital lead to higher wages. Specifically, the graph shows that individuals with higher education levels consistently earn higher wages compared to those with lower education levels across all age cohorts.

Furthermore, the graph 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 table 6 shows clear evidence of a lower return on education for females, with $\beta_{2,female}$ being less than $\beta_{2,male}$. This gap is even wider for individuals with higher levels of education, as $\Delta_{secondary}$ is less than $\Delta_{lower\ secondary}$. The gender gap in wages can be decomposed into two factors that widen it over time: firstly, the increase in wages as a result of acquiring working experience represented by β_{Age}, and secondly, the decrease in wages represented by β_{Age^2}.

Further analysis reveals that women have lower remuneration for human capital, as seen in the results in columns (3) and (4) of table 6. For the same level of education, the remuneration increases slightly over the years, but by approximately 3% less for women compared to men. This finding justifies the wide difference in wages shown in table1. The regression results in columns (1)**??**, (2)**??**, and (3)**??** indicate that there is no significant difference in the depreciation rate between genders. However, in column (4)**??**, a lower depreciation rate is observed for females with higher levels of education, suggesting that the negative difference in depreciation rates is wider for females with higher education compared to males.
The results highlight 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. 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 gender.
The chart2 illustrates that male wage-age profiles do not differ widely than women across all cohorts. Now we take a look at the same results for secondary school.
The chart in Figure**??** illustrates a lower gender gap in wage-age profiles compared to the previous chart2.
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.

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 difference in the hours- age profiles for individual with different levels of education. Second we will look at difference in the hours-age profile as before but conditioning on gender. In the following table7, we estimate with OLS the second specification2 for lower secondary and secondary education level.

In Table7, our analysis shows that individuals with lower levels of education tend to start working earlier in life, compared to those with higher education. This is reflected in the negative coefficients of the Age variable in column (2), indicating that annual working hours tend to decrease over time for this group.

On the other hand, for those who spend more time in school, the slope of the hours-age relationship is positive, which is consistent with the idea that higher-educated individuals tend to increase the number of hours worked over time, as they continue to invest in their human capital early in their careers, and gradually reduce their working hours as they gain experience. Indeed,The Human capital model predicts that individuals with lower education levels 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.3). 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 level. Notwithstanding, for women the slope are flatter across all level of education, meaning that women increases more mildly the time spent working. Moreover, female with low education has a steeper negative hours-age profiles, signaling that low educated women tends to decrease at faster rate the participation in the labour market in the intensive margin.
To visually compare the predicted working hours by cohort for males (in red) and females (in blue) at different levels of education, we plotted the results in Figure4 and Figure**??**. 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 Figure **??**).
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.

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

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

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

	no edu	primary	lower secondary	secondary 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)
Sex (female==1)	0.00	0.26	0.40	0.55	0.66
	(.)	(0.45)	(0.49)	(0.50)	(0.48)

7 Figures

Table 4: Density of class 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		

Table 5: Regression table

	(1)	(2)
Age	0.126***	0.109***
	(0.018)	(0.006)
age2	-0.001***	-0.001***
	(0.000)	(0.000)
Cohort=1	0.000	0.000
	(.)	(.)
Cohort=2	0.193	-0.068
	(0.571)	(0.425)
Cohort=3	0.211	0.065
	(0.552)	(0.417)
Cohort=4	0.292	0.213
	(0.553)	(0.416)
Cohort=5	0.593	0.349
	(0.559)	(0.418)
Cohort=6	0.671	0.489
	(0.571)	(0.421)
Cohort=7	0.773	0.644
	(0.585)	(0.425)
Cohort=8	0.809	0.787*
	(0.602)	(0.430)
Cohort=9	1.011	0.907**
	(0.621)	(0.435)
Cohort=10	1.114*	1.083**
	(0.642)	(0.441)
Cohort=11	1.202*	1.233***
	(0.664)	(0.448)
Cohort=12	1.412**	1.442***
	(0.688)	(0.456)
Cohort=13	1.555**	1.606***
	(0.716)	(0.465)

Table 6: Regression table

	(1)	(2)	(3)	(4)
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=1	0.00000	0.00000	0.00000	0.00000
	(.)	(.)	(.)	(.)
Cohort=2	0.29058	-0.02480	0.01113	-0.64192
	(0.77224)	(0.95719)	(0.46547)	(1.15478)
Cohort=3	0.37242	-0.09774	0.14511	-0.51986
	(0.74712)	(0.92618)	(0.45777)	(1.11582)
Cohort=4	0.39230	0.13843	0.34038	-0.50753
	(0.75424)	(0.92177)	(0.45778)	(1.11414)
Cohort=5	0.75616	0.31993	0.46877	-0.31268
	(0.76920)	(0.92526)	(0.46020)	(1.11516)
Cohort=6	0.89543	0.35865	0.61190	-0.15061
	(0.79335)	(0.93384)	(0.46457)	(1.11796)
Cohort=7	1.06565	0.41208	0.77574*	0.00401
	(0.82147)	(0.94565)	(0.47030)	(1.12183)
Cohort=8	1.09779	0.43642	0.89099*	0.21241
	(0.85504)	(0.96054)	(0.47710)	(1.12647)
Cohort=9	1.31981	0.63473	1.01152**	0.33683
	(0.89309)	(0.97701)	(0.48483)	(1.13188)
Cohort=10	1.41338	0.72764	1.16132**	0.56822
	(0.93484)	(0.99488)	(0.49366)	(1.13799)
Cohort=11	1.56401	0.74957	1.34798***	0.64533
	(0.97660)	(1.01428)	(0.50325)	(1.14505)
Cohort=12	1.79007*	0.96137	1.55260***	0.86499
	(1.02299)	(1.03578)	(0.51423)	(1.15331)
Cohort=13	2.09027*	0.97505	1.73053***	0.99635
	(1.07755)	(1.06028)	(0.52656)	(1.16336)

Table 7: Regression table

	(1)	(2)
Age	0.007*	-0.005***
	(0.004)	(0.002)
age2	-0.000*	0.000
	(0.000)	(0.000)
Cohort=1	0.000	0.000
	(.)	(.)
Cohort=2	-0.113	0.037
	(0.145)	(0.116)
Cohort=3	-0.039	-0.004
	(0.138)	(0.114)
Cohort=4	-0.159	-0.033
	(0.138)	(0.114)
Cohort=5	-0.160	-0.057
	(0.139)	(0.114)
Cohort=6	-0.127	-0.090
	(0.142)	(0.115)
Cohort=7	-0.117	-0.097
	(0.145)	(0.116)
Cohort=8	-0.124	-0.123
	(0.148)	(0.117)
Cohort=9	-0.087	-0.146
	(0.152)	(0.118)
Cohort=10	-0.070	-0.162
	(0.157)	(0.120)
Cohort=11	-0.091	-0.178
	(0.162)	(0.121)
Cohort=12	-0.080	-0.218*
	(0.167)	(0.123)
Cohort=13	-0.122	-0.241*
	(0.174)	(0.126)

Table 8: Regression table

	(1)	(2)	(3)	(4)
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=1	0.00000	0.00000	0.00000	0.00000
	(.)	(.)	(.)	(.)
Cohort=2	-0.13760	0.07929	-0.03013	0.46014
	(0.14760)	(0.29400)	(0.09635)	(0.41163)
Cohort=3	-0.10543	0.23539	-0.06168	0.48116
	(0.14087)	(0.28318)	(0.09468)	(0.39732)
Cohort=4	-0.20832	0.13923	-0.08701	0.45683
	(0.14170)	(0.28144)	(0.09463)	(0.39654)
Cohort=5	-0.18678	0.18071	-0.09606	0.42358
	(0.14387)	(0.28197)	(0.09506)	(0.39671)
Cohort=6	-0.16999	0.26024	-0.10718	0.37671
	(0.14797)	(0.28412)	(0.09592)	(0.39757)
Cohort=7	-0.15366	0.26256	-0.11159	0.37367
	(0.15262)	(0.28723)	(0.09704)	(0.39881)
Cohort=8	-0.16466	0.26819	-0.11397	0.32613
	(0.15837)	(0.29116)	(0.09839)	(0.40032)
Cohort=9	-0.10940	0.28913	-0.13872	0.29984
	(0.16486)	(0.29555)	(0.09991)	(0.40206)
Cohort=10	-0.11109	0.33528	-0.15067	0.28485
	(0.17208)	(0.30035)	(0.10166)	(0.40403)
Cohort=11	-0.14873	0.33111	-0.17438*	0.27265
	(0.17967)	(0.30559)	(0.10356)	(0.40635)
Cohort=12	-0.11318	0.31906	-0.20267*	0.20888
	(0.18759)	(0.31141)	(0.10576)	(0.40910)
Cohort=13	-0.22320	0.32614	-0.20836*	0.15475
	(0.19735)	(0.31824)	(0.10827)	(0.41240)

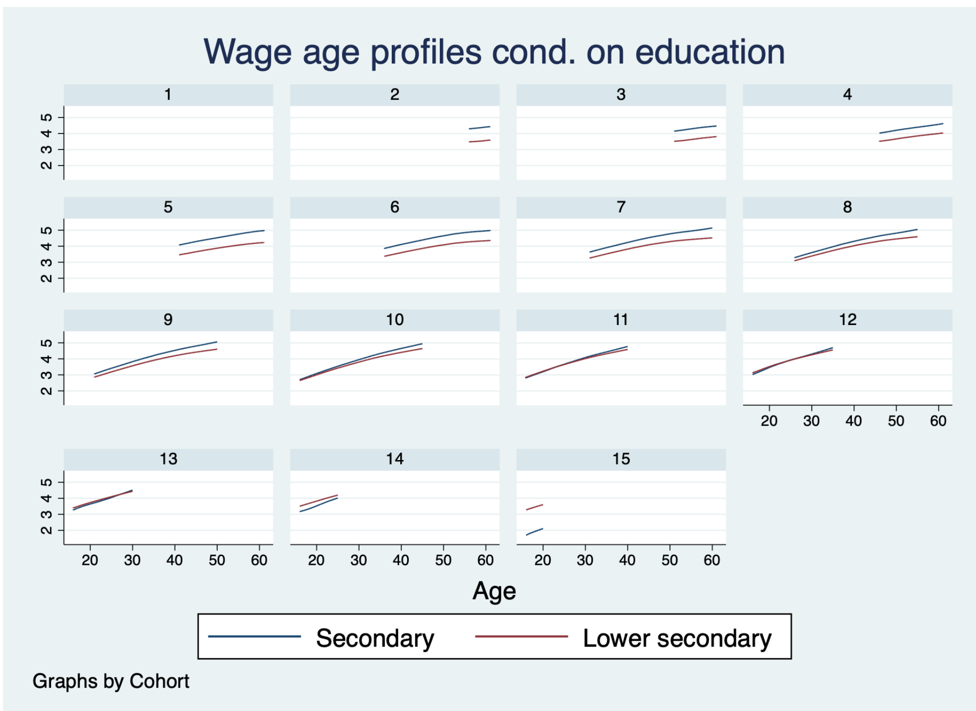

Figure 1: Predicted wage-age profiles by cohort

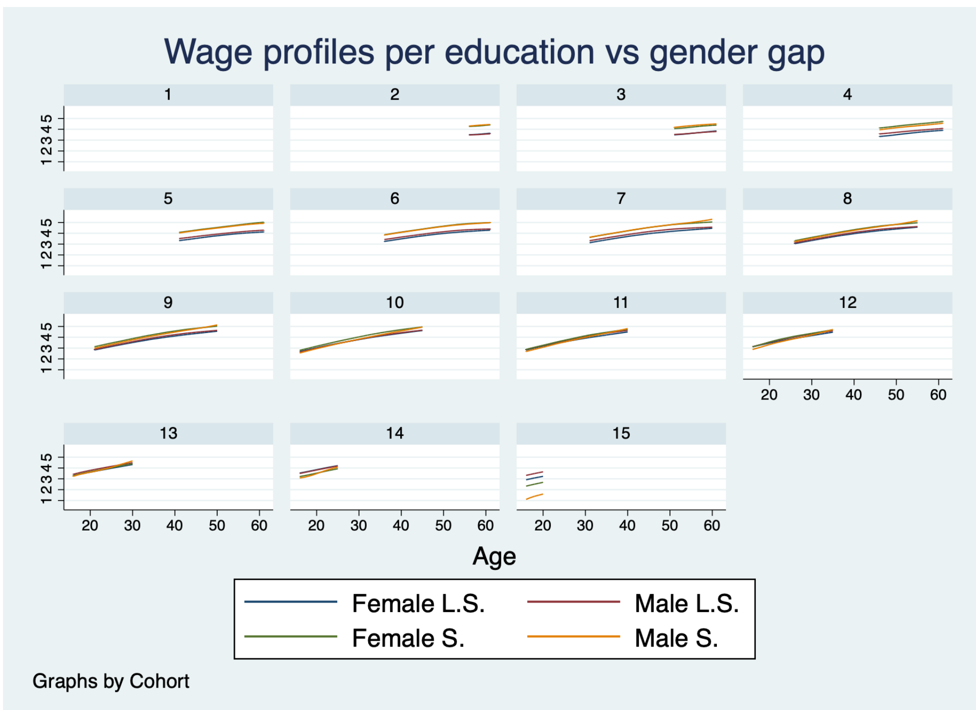

Figure 2: Gender gap in the wage age profiles for different education level

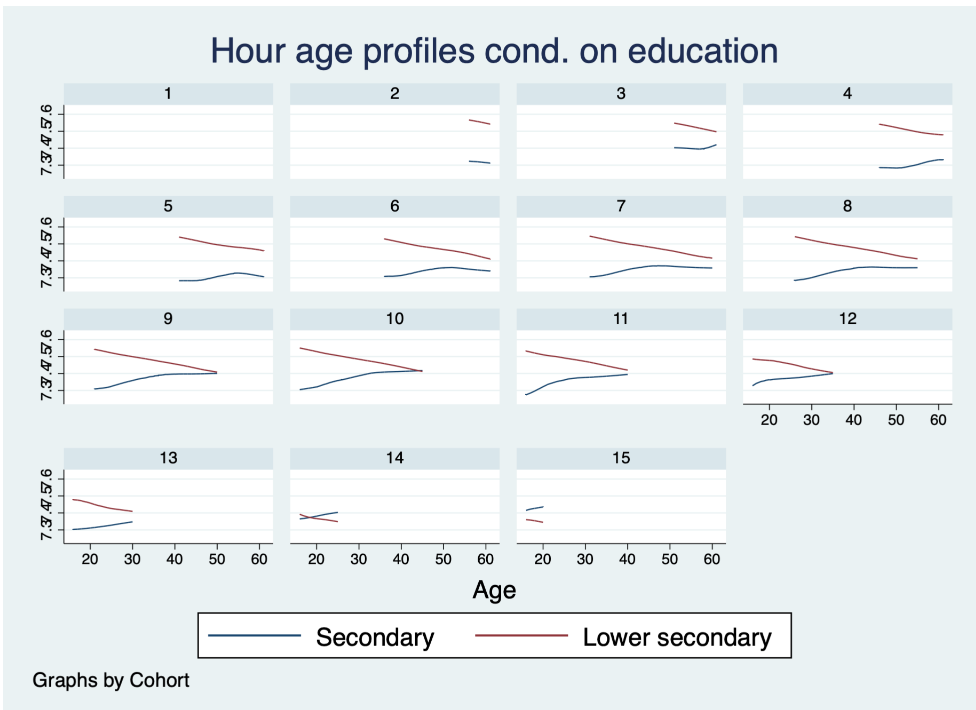

Figure 3: Hours-age profile

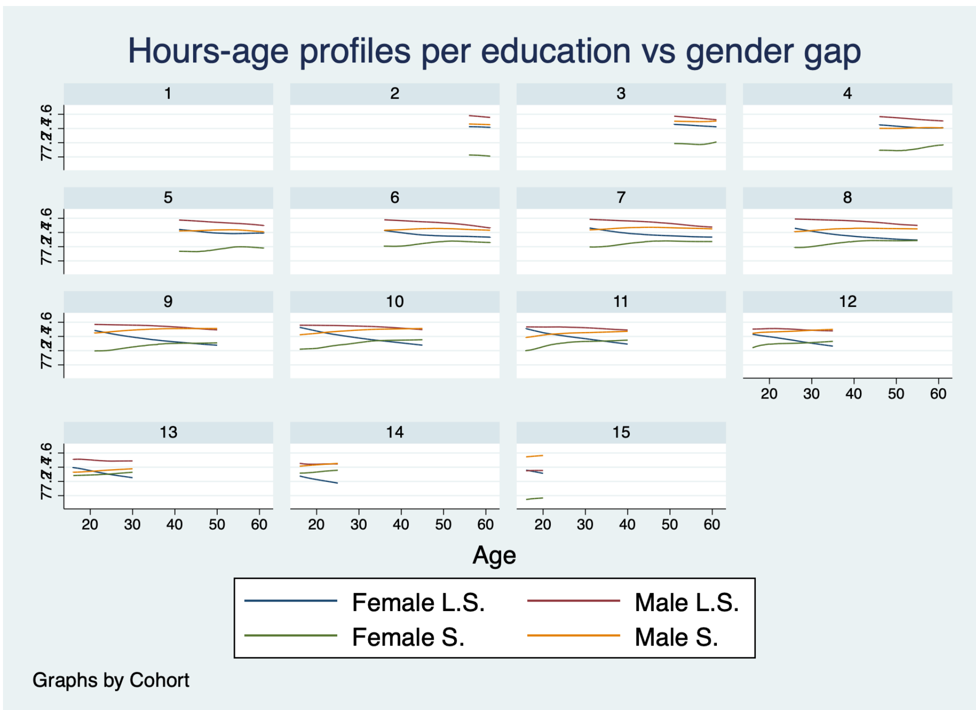

Figure 4: Hours-age profile and gender gap