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Returns to education and the Italian case: what role for macro-regional differences?

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Simone

Abstract

The purpose of this thesis is to provide an empirical analysis concerning private returns to education in Italy and to evaluate how macro-regional differences affect individuals' earnings dynamics. We developed our analysis following the Human Capital Theory and adopting new measures of cognitive and non-cognitive abilities from the PIAAC Survey of Adult Skills (2012). We adopted two different techniques: ordinary least squares (OLS) and instrumental variable estimation (IV). In line with the previous literature, we realized that OLS final estimates were biased due to the endogeneity of the educational term, so we decided to tackle the issue using instrumental variables. We estimated an average return to education of 7.1% at a nationwide level and we found evidence of non-homogeneous returns among macro-regions; in particular, we observed higher returns in Southern (8.9%) and Central Italy (8.7%) compared to the North (5.8%). Moreover, we found evidence of a gender pay gap both at nationwide and macro-regional level. We then look at differences between interesting subgroups with these results: we did not find evidence that support the Signalling Theory; we observed higher returns for females in the North, but the situation is reversed in Central and South Italy; returns to schooling may vary according to the schooling level and, in particular, we found evidence of higher returns in higher levels of schooling education; finally, when the type of contract is taken into consideration, results indicate lower returns for part-time workers.

Preface

You may wonder what led two students of management engineering to focus on such a peculiar topic. The answer is simple: in the recent years, Italy has gone through an unstable and at times worsening political and economic situation, which has affected many areas among which education; we believe that a clear picture of the status quo is necessary for policy-makers to intervene, so we hope to provide it regarding returns to education.

Focusing on this topic, the overview is especially dire; the "*Education and training sector monitoring report 2018 Italy"* by the European Commission shows that Italy spends in educational attainment less than other EU countries and achieves worse results, with ample regional disparities. The government expenditure in education was 3.9% of GDP in 2016, one of the lowest in Europe (the average is 4.7%), and the situation is worse if we look at tertiary education. In this field the government expenditure was just 0.3% of GDP, the second lowest in Europe after only UK, where private investment are simply incomparable.

The issue has relevant social ramification, since a certain degree of education is necessary to perform many daily-life activities, such as reading the instruction of a new product or enrolling your child at school. This consideration led to the concept of functional illiteracy, defined by the OECD as follows:

> "*a person is functionally illiterate who cannot engage in all those activities in which literacy is required for effective functioning of his group and community and also for enabling him to continue to use reading, writing and calculation for his own and the community's development*".

In Italy, the ratio of individuals who are defined as functionally illiterate is 47%, meaning that almost one out of two people has difficulties in reading and understanding beyond a basic level (for reference, the number is 21.8% in UK, 14.4%

in Germany and 7.5% in Sweden)[1]. This negative trend for Italy is particularly dangerous because of the central role that education has not only in the development of the individual, but also on the economic development and growth of a country as whole[2].

In our thesis we, however, do not focus on the relationship between education and economic growth, but on the impact of education on private earnings, which can be seen as a microeconomic parallel of the aforementioned macroeconomic variable. This distinction carries on in the definition of “private” and “social” returns to education, with the former that looks at the individual and the latter at society in general. It is important to underline that private returns to education critically underestimate the full returns to society, because they only look at the benefits to the individual without considering their *spill-over* to other people in the same firm, industry, city, region or economy.

Our final aim is to provide policy-makers with a state-of-the-art review of private returns to education and updated estimates on Italy, with subdivision by macro-regions. We believe these to be the first and necessary elements to formulate appropriate policies, address some of these issues of and try to “make things better”.

[1] Data taken from the 2009 Human Development Report, published for the United Nations Development Programme (UNDP).

[2] See (OECD, 1998).

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Chapter 1

Introduction

Education has been universally recognized by the academic scene to be a key determinant in individuals' development. Not only it promotes inclusion and social mobility, but it also plays a central role in predicting individuals' success in the labour market. The educational level is, in fact, one of the major contributors of human capital development, or, in other words, the enhancement of all those competencies, knowledges, experiences and personal attributes that make a worker more productive at performing labour tasks.

For these reasons, the empirical evaluation of returns to education has been a central topic for many economists operating in the labour economic field, but, unfortunately, providing reliable estimates is not a trivial matter. Despite hundreds of researches has confirmed the existence of a high and relevant correlation between educational attainment and earnings, in fact, there is not yet convincing evidence that estimated returns can be causally interpreted. The issues are mainly caused by the endogeneity of the educational variable: the absorption of knowledge is not randomly assigned across the population, it is instead a function of many determinants (e.g. personal characteristics, schooling path, school quality, country of study) which must necessarily be included in the analysis, even if some of them cannot be easily measured. Over the years, different techniques and methodologies have been applied to the topic. In the first part of this thesis we will provide a state-of-the-art review of the most important and widely-known approaches, while in the second part we will develop a model and apply it to the Italian subset of PIAAC[3] data, with focus on differences at macro-regional level (North, Center and South).

Chapter 2 details the Human Capital Theory (HTC). We will first provide an overview regarding the initial conceptualization of the topic, starting from its inception and going through the theoretical and empirical analyses by (Becker, Gary, 1964), (Schultz,

[3] Programme for the International Assessment of Adult Competencies.

Theodore) and (Mincer, 1958). We will than go through the main critiques raised against the so called “Mincerian model” and the strategies that were proposed to overcome them.

Chapter 3 contains the core part of our thesis and it is focuses on an empirical analysis of the Italian case. Following the path we delineated in Chapter 2, we develop a model and provide reliable estimates of returns to educations in Italian macro-regions. In the final part of this chapter, we will delve deeper and apply the model again to specific subgroups, in order to find additional insights.

Chapter 4 consists of a summary of the main findings of our empirical analysis, as well as a description of main limitations and potential pitfalls concerning both the models and the data sample adopted. Finally, we will provide some proposals for future research.

Chapter 2

The Human Capital Theory

The Human Capital Theory (HCT) is the foremost approach that has been successfully used in the academic literature to evaluate the importance of education and other social factors in promoting economic development. The fundamental idea upon which the theory lays on is that the collection of competences, knowledge and personal characteristics of a person (which takes the name of Human Capital) is used to perform labour and create value. So, since education is one of the prime ways to increase Human Capital, it is possible to estimate its effect on society by exploiting this relationship, with the final objective of maximising the creation of value.

Obviously, many factors go into the computation of what actually is the "economic value of a human being", and in order to account for them the models that have been developed over the years has become progressively more and more complex. We'll run through the history of the Human Capital Theory from its initial conceptualization up to the recent years.

2.1 Inception and first contributors

The concept of Human Capital can be traced back to the 18th century to the Scottish economist and philosopher Adam Smith (1994), also known as the *father of modern economy*. In his book "*An Inquiry into the Nature and Causes of the Wealth of Nations*", he makes the case that increasing the human capital of an enterprise (through coaching and education), is beneficial for the business, and ultimately for the country and its population as a whole. As you can see, Adam Smith's interest in this book is not the individual, but the progress of a nation, but the fundamentals of the Human Capital are already present in his work.

The theme was brought back to the academic attention with the flowering of the branch of economics called "development economics" in the first half of the 20th century, centred on the use of economics to improve the well-being of people and foster economic growth. Among the many scholars who covered the subject in this stage, we want to mention the American economist (Schultz, Theodore, 1961)(Schultz, 1961), who, in his paper "*Investment in Human Capital*", rallied for the importance of the Human Capital and scolded the academic public for shying away from the subject. He argued, with engaging emphasis, that the growth rates of national outputs had been significantly larger compared to the increase of land, man-hour and other physical capital (the traditional driving forces of economy), and attributed the difference mostly to the underlying growth of knowledge and skills. It is important to say that he recognized that most economists had stressed the relevance of the Human Capital at one point or another in their work, however, only sporadically it had been truthly incorporated in it.

This was also due to the fact that the Human Capital Theory was initially characterized by a negative connotation, since, in computing the economic value of education, men were looked at only as tools. However, Schultz openly opposed the conception that talking about investing in human being somehow diminished their value by reducing them to mere material components; he claimed that: "*by investing in themselves, people can enlarge the range of choice available to them; it is one way free man can enhance their welfare*". Moreover, he argued that the failure to treat human resources as a proper form of capital actually fed into the traditional notion of labour as the capability to perform manual work with little usage of skills; meaning that all labourers were viewed as equally capable, not unlike an assortment composed by the same tools. The acknowledgment that skills have a real economic value frees workers from this grave and profound misconception.

The Human Capital Theory was then officially formalized by the American economist (Becker, Gary, 1964) with the publication "*Human Capital*". The book eventually became a milestone of the field and was looked up as standard reference for more than a decade; Becker also went on to win a Nobel Prize in Economics in 1992 for his contributions to the topic. It's interesting to say, however, that the initial objective of his work was quite different. He actually wanted to evaluate the money rate of return to college and high school education in the United States, but he then realized that the theory wasn't quite there yet; despite the presence of some important pioneering work, the general framework was still fragmented. For this reason, Becker began to formulate a general analysis of investments in human capital, but he soon realized that he was doing much more than filling a formal gap; his work provided a unified explanation to a wide array of empirical phenomena, whose interpretation had either eluded researchers or had made necessary some ad-hoc solutions[4]. In the "Human Capital" Becker addresses these and other issues, as well as the effects of various forms of human capital investments on earnings (education and on-the-job training in particular), motivated by a desire to improve workforce quality the productivity of the entire country.

He also studied the relationship between enterprise and worker in the case of industry-specific skills and showed how the firm should both bear the costs and get the benefits of the training. He showed that education should be preferred at the beginning of the working life rather than afterwards, because the benefits are earned for a longer time and at a lower cost (both in time and resources). Following the same reasoning, more capable workers should study more, too, since they can reach higher levels of earnings.

In this thesis we will not go more in depth about Becker's work and especially about the models he used, since these arguments will all be revisited and further explored by the authors who came after him. However, it is interesting to delve on his thoughts about the possible future developments of the Human Capital model, that he mentions in the last part of his book. A first possibility he talks about is the inclusion of various kinds of ability in the model (e.g. IQ, CogAT[5]), that he himself thought to be very important but was not able to address it since *economists have been surprisingly ignorant of the quantitative effects of different kinds of ability on earnings and productivity* [cit.]. A second development is related to the so-called "social gains" of education, namely the impact on society as a network, not just the individual. A third one is a more complete and in-depth analysis on the different kind of schools and their different contribution to human capital (and earnings). This breakdown should include different professions (e.g. lawyer, engineer), types of major (e.g. arts, economics) and degree (bachelor, master, PhD), but also should not disregard academies and more niche scholastic programs. Becker also spent some words on possible applications of

[4] Some examples of these phenomena were the positive skewedness of the earnings distribution or the fact that earnings increase with age at a decreasing rate, in a more pronounced manner the higher the level of skill required.

[5] A test of cognitive abilities for young people mainly used in American schools.

his work and the HCT in general, (that rapidly multiplied in the academic scene after the publication of his book) and in his opinion the most important one was to differences in incomes between regions and countries, either over-time or cross-sectionally at a single moment in time.

Commenting these last few paragraphs, we can say that Becker's predictions were correct and all the routes he delineated were pursued, some with more success than others. Also, we can be glad: our work in this thesis is perfectly in line with Becker's thoughts, since the final object is to use a model which includes cognitive and non-cognitive abilities to evaluate territorial differences among Italian macro-regions.

2.2 Mincer and the Mincerian model

Theodore Schultz and Gary S. Becker's studies on the Human Capital Theory were later embedded in the work of the Polish economist Jacob Mincer, who is considered one of the major contributors to the field of labour economics and definitely one of the most renowned economists of the time. His pioneering research completely revolutionized the field and laid the foundation for all future studies in the area, so much that still today the so-called "Mincerian model" is the starting point of many papers and articles (including this thesis). It is also interesting to say that the first occurrence of the term "Human Capital" in modern economics is also attributable to (Mincer, 1958). For all the reasons listed above Jacob Mincer is also known as the *father of the modern labour economics*, and he is regarded as one of the most influential economists of the 20^{th} century (although he was never awarded the Nobel Prize in Economics despite the numerous nominations).

In the following sections we will provide a comprehensive description of Mincer's schooling model, which was firstly introduced in his article of 1958 and then completed and revised in (Mincer, 1974). We will roughly follow the path undertook in his masterpiece, starting from a simple formulation and then adding more and more elements.

2.2.1 Theoretical analysis and the base of the Mincerian equation

As outlined in the Human Capital Theory, human capital investments are directly linked to individual economic outcomes. In order to find the optimal level of human capital investments for an individual, first of all it is necessary to classify the different kinds of investments and analyse the associated benefits and costs of each of them. Fortunately, there are only two main categories: schooling and on-the-job training; it is possible to further subclassify them in different ways (e.g. considering the different levels of schooling), but for now we'll keep it simple.

Both of these types of investments bring about an increase in individual earnings, but they also entail direct and indirect costs. Schooling fees, book purchase, transport and living costs are examples of direct costs, but it is also necessary to consider the time expense that goes into the investment, since each period time spent in school or in job training generates an opportunity cost due to the lost revenue. This is especially true for schooling rather than on-the-job training, since an additional schooling year postpones the entrance in the labour market by the same amount, thus decreasing the present value of future earnings. So, due to the hefty time investment necessary, the choice taken is usually to invest in education during the early stages of life, when the opportunity costs are lower.

Another element that should be considered in this process is how much the investment are going to be rewarded in the future labour market, which also introduces a forecasting issue. In fact, since the schooling process takes many years and the labour market changes quickly in the modern economy, when the individual will effectively be available to work the situation will probably be significantly different from expectations.

Reliable estimations on the aspects discussed above (and more) are required to compute the internal rate of return (IRR) of investments in human capital, and therefore to calculate the optimal level that maximise net earnings for the individual.

Now, for sake of simplicity, suppose that individuals just live two time periods, youth and adulthood, and the only way to improve human capital is by investing in education (in this first part we will not consider post-schooling investments). An individual has two choices[6]:

1. He could decide to work in both periods, receiving a wage Y_1 as unskilled worker; or
2. He could decide to attend school in the first period by paying both a direct cost γ (schooling fee) and an indirect cost Y_1 (due to the opportunity cost of not working), and then work in the second period receiving a wage Y_2 (with $Y_2 > Y_1$).

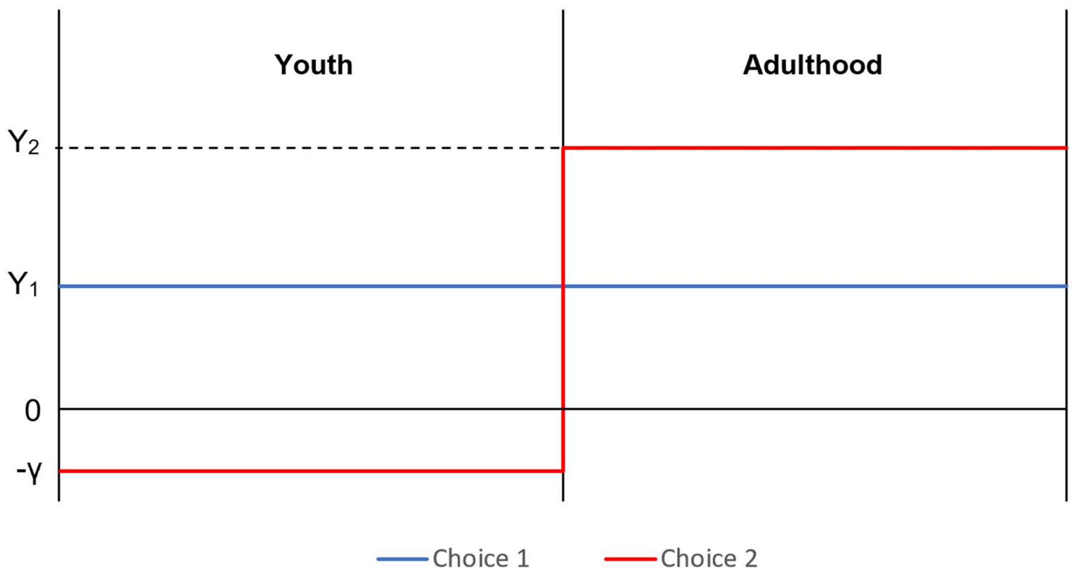


Figure 1 - Comparison between working and going to school, elaboration by (Checchi, 2006)

Under these conditions, it is possible to compute the IRR associated with the choice of attending school by equalising costs and benefits as follows:

$$\gamma + Y_1 = \frac{Y_2 - Y_1}{1 + IRR} \tag{1}$$

$$\mathrm{IRR} = \frac{Y_2 - Y_1}{\gamma + Y_1} - 1 \tag{2}$$

You can notice how the IRR increases when the earning differential grows and decrease when the total costs go up, which is quite reasonable.

[6] We present the model illustrated by (Checchi, 2006) based on (Mincer, 1974).

This computation can be extended with ease to the case of a multiperiod scenario with variable wages (Y_t), direct cost of schooling (γ_t) and a lifecycle up to retirement of *m* years. The extended model can be written as:

$$\sum_{t=1}^{s}\left[\frac{\gamma_t + Y_t}{(1+IRR)^{t-1}}\right] = \sum_{t=s+1}^{m}\left[\frac{Y_{s,t} - Y_t}{(1+IRR)^{t-1}}\right] \tag{3}$$

Note that in this formulation we are considering only costs and benefits related to the individual, not the impact on society as a whole (the so-called “social externalities”), so the IRR shown here represents the private rate of return to investments in schooling. It is actually possible to include social externalities in this model and we will report the socially augmented formula below, however we do so only for sake of completeness, since our focus is private return to education. The formulation includes a public budget for school attendance (P_t) and an aggregate measure of all social benefits (*externality*):

$$\sum_{t=1}^{s}\left[\frac{\gamma_t + Y_t + P_t}{(1+IRR_{soc})^{t-1}}\right] = \sum_{t=s+1}^{n}\left[\frac{Y_{s,t} - Y_t}{(1+IRR_{soc})^{t-1}}\right] + externality \tag{4}$$

Going on, unfortunately equation (3) as it shown was far too demanding to be used by Mincer in the empirical analysis, since it requires information all over the life cycle of the individual. However, it can be rewritten to unveil the original Mincerian model under certain assumptions:

1. Direct costs of education are offset by part-time labour incomes (or, alternatively, they are negligible compared to opportunity costs)

$$\gamma_t = 0 \text{ for t} \in [1; s] \tag{5}$$

2. The length of the working life (*n*) is identical for everybody regardless of the number of schooling years, meaning that a person who studies more will retire at an older age (this assumption seems to be coherent with empirical data, and even more so when compared to the alternative assumption that people retire at the same age);

3. Wages are constant along the lifecycle:

$$Y_{\mathrm{t}} = Y \quad \text{and} \quad Y_{s,t} = Y_s \;\; \forall t \tag{6}$$

Under these conditions, the formulation of the model simplifies greatly:

$$Y = \frac{Y_s}{(1 + IRR)^s} \tag{7}$$

If we take the logarithm of both sides and call *IRR* as r_s (return of an additional year of education), we finally reach what is known in the literature as the base of the Mincerian equation:

$$\ln Y_s = \ln Y_0 + r_s s \tag{8}$$

Where Y_0 is the present value of net earnings without schooling. This final (for now) formulation shows that, under specific assumptions, the logarithm of earnings is a strict linear function of time spent at school.

2.2.2 Post-school investments

The first draft of the Mincerian model is by far the most famous empirical approximation of the individual earning function, however, it is only half of the complete formula. Indeed, it doesn't take into account post-schooling investments, despite the fact that most individuals keep investing in themselves and developing their skills much after the completion of schooling. So, the next step is to understand how the individual earning function changes over the working life.

Assuming that an individual starts working right after the completion of schooling, we denominate C_0 the amount of resources that he will invest in fostering his job skills and acquiring job-related information (including both direct and opportunity costs) in the first year of work experience (year 0). His net earnings in that year (Y_0) are equal to the difference between gross earnings[7] (E_0) and the investments in human capital (C_0). Note that from an empirical point of view it is actually better to consider net earnings, since gross earnings are not directly observable (this is not to say that net earnings are exactly equal to observed earnings, but certainly it's a far better approximation that the gross ones).

[7] Also known in the literature as "initial earning capacity after s years of schooling" (E_s or Y_s).

So, net earnings at year 0 can be written as:

$$\mathrm{Y}_0 = \mathrm{E}_0 - C_0 = E_s - C_0 = Y_s - C_0 \tag{9}$$

In his second year of work experience (year 1), the individual will invest an amount C_1 to increase his human capital, but this time he will earn more due to the return (r) of the investments made the year before:

$$\mathrm{Y}_1 = \mathrm{Y}_s + \mathrm{rC}_0 - \mathrm{C}_1 \tag{10}$$

Generally, gross earnings (E_j) and net earnings (Y_j) at year j are given by:

$$E_j = E_s + \sum_{t=0}^{j-1} r_t C_t \tag{11}$$

$$\mathrm{Y}_j = \mathrm{E_j} - \mathrm{C_j} = \mathrm{Y_s} + \sum_{t=0}^{j-1} r_t C_t - \mathrm{C}_j \tag{12}$$

You can notice how the base of the Mincerian equation (8) can be seen as a special case of the equation above when schooling is the only kind of investment in human capital. It is also interesting to notice how net earnings keep increasing with experience as long as investments C_j are either decreasing or increasing at a lower rate than the rate of return. This behaviour can be easily demonstrated by looking at the following inequality:

$$\Delta Y_j = Y_{j+1} - \mathrm{Y_j} = \mathrm{r_j C_j} - \left(\mathrm{C_{j+1}} - \mathrm{C_j}\right) > 0 \tag{13}$$

However, even if net earnings might decrease due to fluctuating investments, gross earnings (E_j) will always keep increasing:

$$\Delta E_j = r_j C_j \tag{14}$$

The growth will be linear if both r_j and C_j remain constant, however this solution is not recommended and leads to sub-optimal results. In fact, according to the theory of optimal allocation of human capital investments along the life cycle, firstly outlined by (Becker, 1965) and successively improved by (Ben-Porath, 1967), post-schooling investments should be undertaken early in life, slowly decline over the working life and finally stop years before retirement. There are three main reasons behind this:

1. Considering finite lifetimes, late investments produce returns over a shorter period of time, so the total benefits are smaller compared to the same investment done at a younger age;
2. Given that investments in human capital are profitable, a postponement only reduces the present value of net gains;
3. Since the earnings of an individual increase over time, investments in later periods generate a higher opportunity cost.

Considering the model expressed in equation (12), and keeping in mind the consideration made afterwards, it is finally possible to draw the earning profile of an individual over his working life:

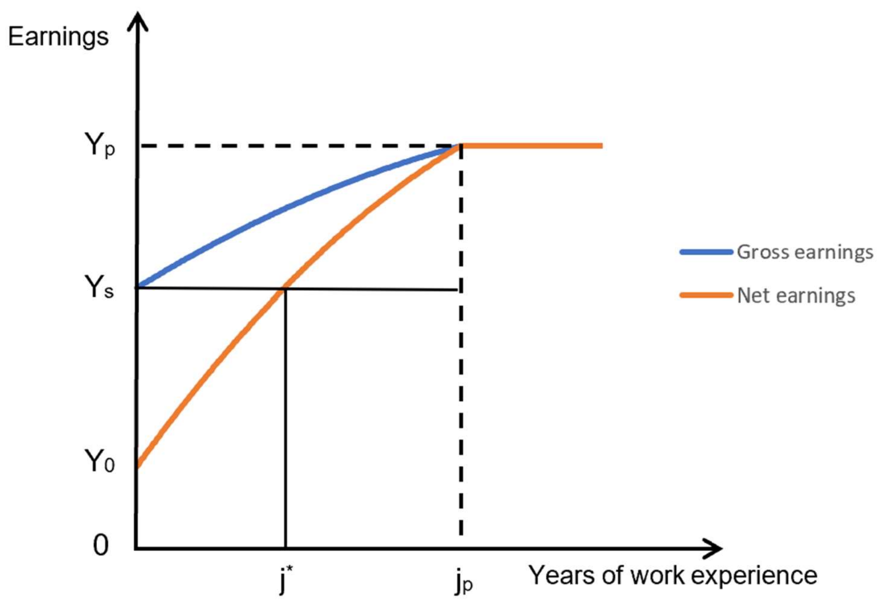


Figure 2 - Individual earning profile with post-school investments

In the graph we show both gross earnings E_j (blue) and net earnings Y_j (orange), with the first ones being always equal or higher than the second ones (the difference is the amount of post-school investments C_j). Y_p is the peak level of earnings reached at year j_p, when no more investments in human capital are undertaken.

You can notice how the individual earning profile is a concave function, since marginal benefits from investments decline over time while marginal costs increase, as it was shown before. Finally, you can also see the "overtaking year of experience" (j^*), which is the amount of time it takes for net earnings to exceed the value of gross earnings at year zero ($E_0 = Y_s$). It might seem a trivial concept, but it holds high value for practical purposes, since if you know j^* you can use it to estimate net earnings Y_s, which are not directly observable. Considering equation (12), constant returns (r) and not increasing investments in post-schooling education, it is also possible to find an upper value for it:

$$j^* \leq \frac{1}{r} \tag{15}$$

2.2.3 Empirical analysis and the human capital earning function

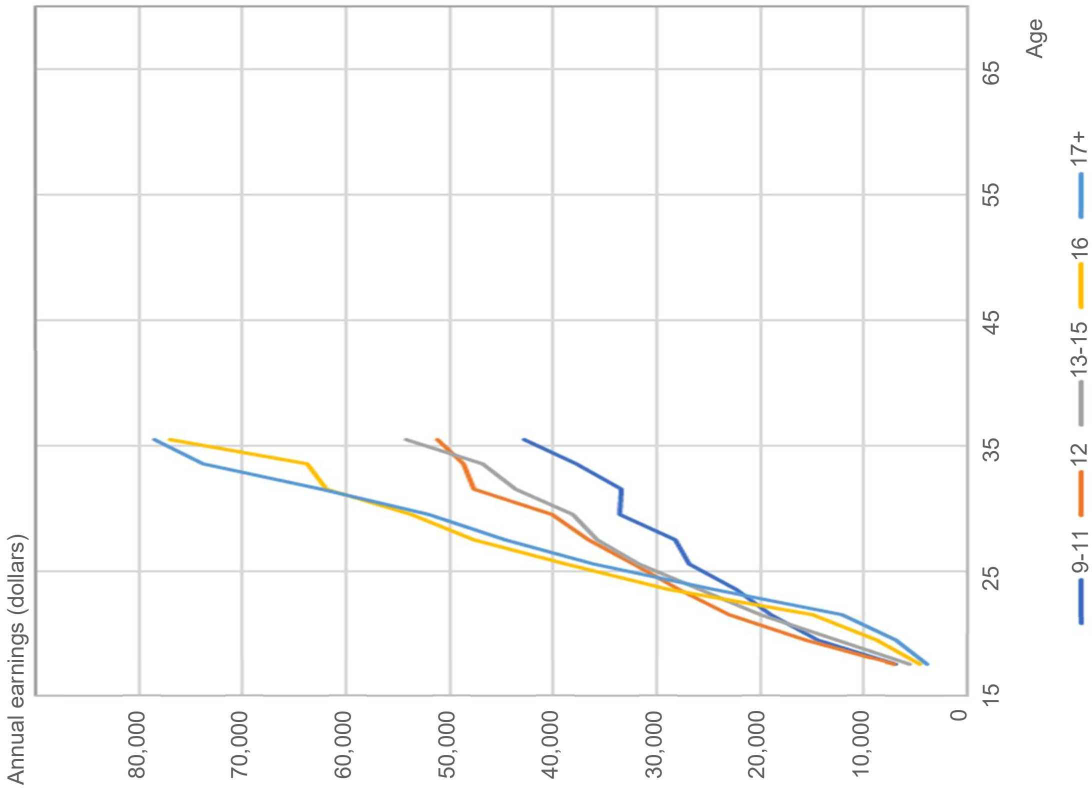
Mincer conducted his analysis on two samples. The first one is a cross-sectional dataset from the 1960 US population Census, containing 31,093 observations coming from white, non-farm, non-student men up to age 65. The second one, instead, is longitudinal dataset containing 28,678 observations on earnings collected yearly for 40 years after completion of schooling. In the latter case, the oldest age observed ranges from 55, for men with 8 years of schooling, and 64, for those with 16 years of schooling.

The graphs depicted in Figure 3 show the mean earnings by years of age in the first sample used by Mincer (*bottom*) and in a more recent sample coming from the NLSY97[8] *(top).*

Looking at the graphs, it is possible to make some considerations:

- Earnings do not grow continuously through the working life, instead they seem to grow at a high rate in the early stages, then they reach a plateau which last longer at lower years of schooling, and finally they decay in a pattern that seems to show convergence among the different schooling years;

[8] A sample of 8,984 young men and women born between 1980 and 1984 and living in the United States. In of the last available round of 2016, the age of the respondents ranged between 31 and 36 years old.



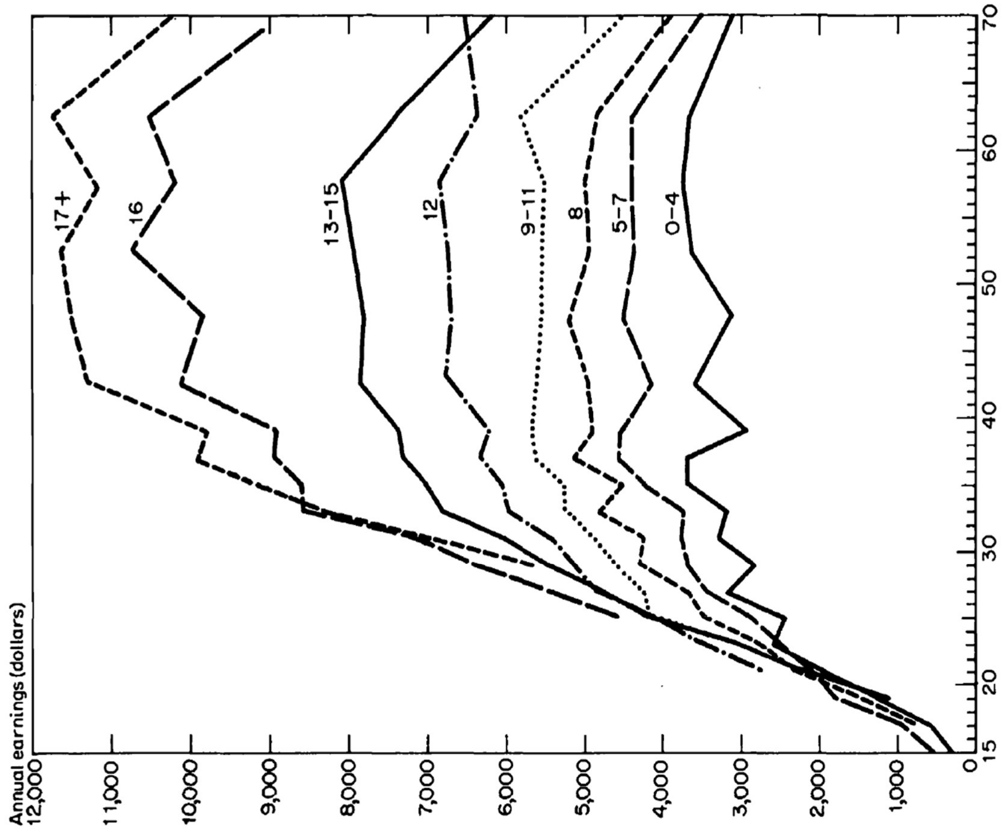


Figure 3 - Average annual earnings by Age grouped by schooling years. The graph at the bottom is an elaboration by (Mincer, 1958)while the one at the top is an original elaboration of ours using data from the NLSY97.

- Earnings are definitely higher for higher levels of schooling, with the exception of the early years when workers with low levels of schooling have an edge on their counterparts (who are still at school);
- The two graphs seem to show the same pattern in the initial stages despite the more than 40 years elapsed between them, with only two minor differences: the overall increase of annual earnings in absolute value (due to macroeconomics trends) and the absence of the lower-education brackets in the more recent sample (due to compulsory education).

You can see how empirical data seem to be coherent with the model and the scenario explained in the theoretical analysis, however the decay in earnings at the end of the working life was not predicted. One could expect that it may be due to the depreciation of knowledge over the years or to some kind of loss of ability linked to age, but it does not seem to be the case. In fact, if we consider not yearly average annual earnings but weekly earnings instead, the decline disappears completely, as you can see in Figure 4.

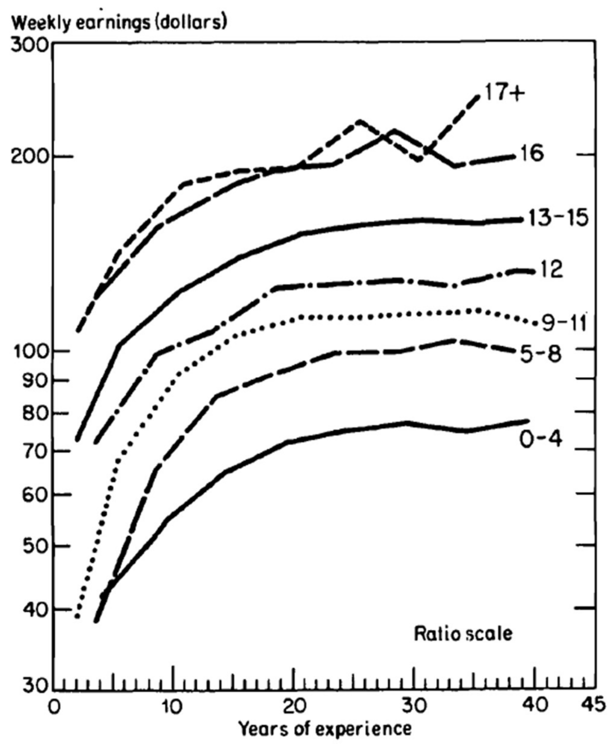


Figure 4 - Average weekly earnings by experience, grouped by schooling years. Elaboration by (Mincer, 1958)

This behaviour suggests that the decline is simply due to a decrease in the number of weeks worked per year, rather than a reduction of salary.

At this point it we can enrich the base of the Mincerian equation (8) including post-school investments; however, since we have no direct measure, Mincer uses experience (*t*), computed as the difference between age and years of schooling and the pre-schooling period (6 years)as proxy of said investments. Note that the experience term should not be linear but concave, to account for the reduction in (annual) earnings at the end of the working life. So, the formulation of the model becomes:

$$\ln E_t = \ln E_s + \beta_1 t - \beta_2 t^2 \tag{16}$$

Where E_t is gross earnings after *t* years and E_s is gross earnings after *s* years of schooling, which can be further broken down to show the Initial Earning Capacity E_0 (gross earnings without either schooling nor work experience):

$$\ln E_t = \ln E_0 + r_s s + \beta_1 t - \beta_2 t^2 \tag{17}$$

Where r_s are is the return to education while at school. Unfortunately, the proper form of the experience function depends on the individual's post-school investments function, but there is no indication towards a specific form. Mincer outlined four possible functions, which are based on four similar hypotheses on post-school investments.

Let k_j be the investment ratio at year *j*, with:

$$E_j = k_j C_j \tag{18}$$

The options are the four possible combinations that you end up with if you consider investments/investment ratio and linear/exponential decay.

1. Investments decline linearly:

$$C_t = C_0 - \frac{C_0}{T}\mathrm{t} \tag{19}$$

2. The investment ratio declines linearly:

$$k_t = k_0 - \frac{k_0}{T} t \tag{20}$$

3. Investments decline exponentially:

$$C_t = C_0 e^{-\beta t} \tag{21}$$

4. The investment ratio declines exponentially:

$$k_t = k_0 e^{-\beta t} \tag{22}$$

For sake of simplicity, at this point it is more convenient for computation to consider investments and earnings functions as continuous functions of time. The following functions were developed starting from (11) and shifting from a discrete to a continuous domain (absolute and logarithmic forms):

$$E_t = E_s + r_t \int_{j=0}^{t} C_j dj \tag{23}$$

$$\ln E_t = \ln E_s + r_t \int_{j=0}^{t} k_j dj \tag{24}$$

The next step is to insert the four possible post-school investment functions into the proper formulation of the model. At this point, from an empirical point of view is more convenient to have net earnings instead of the gross ones, since, as previously said, gross earnings are not directly observable.

So, four formulations of the model are obtained:

1. $$Y_t = (E_s - C_0) + C_0\left(r + \frac{1}{T}\right)t - \frac{rC_0}{2T}t^2 \tag{25}$$

2. $$\ln Y_t = \ln E_s + rk_0 t - \frac{rk_0}{2T}t^2 + \ln(1 - k_t) \tag{26}$$

3. $$Y_t = E_s + \frac{rC_0}{\beta} - \frac{(r+\beta)C_0}{\beta}e^{-\beta t} \tag{27}$$

4. $$\ln Y_t = \ln E_s + \frac{rk_0}{\beta} - \frac{rk_0}{\beta}e^{-\beta t} + \ln(1 - k_0 e^{-\beta t}) \tag{28}$$

As outlined by Mincer, the logarithmic forms 2 and 4 are preferred for the empirical analysis for two reasons:

- Schooling data used are in years, so it is easier to insert them in the model through Mincer basis equation (8);
- The logarithmic form reduces the need for interaction terms, permitting an application of the same estimation equation to the whole cross section.

Nonetheless, equation form 4 leads to a so-called Gompertzian function, which is a kind of function that is characterized by a slow growth rate at the beginning and at the end of a time window and a fast growth rate in between. Since the formula has not been much used after Mincer, we have decided not to include it, however it is available in chapter 5 of Mincer's book.

We shall focus on option 2, which is characterized by a parabolic form. By making some minor adjustments, it is possible to write the formula in this way:

$$\ln Y_t = \ln E_0 + r_s s_i + r_t k_0 t - \frac{r_t k_0}{2T} t^2 + \ln\left(1 - k_0 + \frac{k_0}{T} t\right) \tag{29}$$

Estimated empirically by:

$$\ln Y_t = a + b_1 s + b_2 t + b_3 t^2 + v \tag{30}$$

Mincer estimated the model applying ordinary least squares (OLS) to the longitudinal sample with 28,678 observation collected over 40 years. In the following lines we will display the results:

Table 1 - Regressions of individual earnings on schooling and experience as computed in (Mincer, 1958)

	Equation form	**R^2**
S(1)	$\ln Y = 7.58 + 0.070s$ (43.8)	6.7%
P(1)	$\ln Y = 6.20 + 0.107s + 0.081t - 0.0012t^2$ (72.3) (75.5) (-55.8)	28.5%
P(2)	$\ln Y = 4.87 + 0.255s - 0.0029s^2 - 0.0043st + 0.148t - 0.0018t^2$ (23.4) (-7.1) (-31.8) (63.7) (-66.2)	30.9%
P(3)	$\ln Y = f(D_s) + 0.068t - 0.0009t^2 + 1.207 \ln W$ (13.1) (10.5) (119.7)	52.5%

The numbers in brackets represent the test statistic (t-ratio), and as you can see they are strongly significant in all cases.

Equation S(1) is the "reduced" Human Capital form, which considers only schooling, and, as you can see, it is only able to explain a small fraction of the variability of the data.

Equation P(1) is the parabolic formulation of the model as described above, and despite its limitations (same earnings functions for individuals belonging to the same schooling group and same returns to schooling for everybody), the inclusion of experience term was able to increase the explanatory power of the model up to almost one third of the total variability.

Equation P(2) is an upgraded version of the parabolic formulation shown used above which includes a quadratic term for schooling and an interaction term. In particular, the addition of the quadratic term allows systematically different rates of return among individuals with different levels of schooling, and the negative coefficient of the s^2 term tells us that returns are structurally lower at higher levels of schooling. These changes increase the explanatory power of the model ever so slightly.

Equation P(3) further pushes the parabolic formulation including variation in weeks worked (*ln W*) and dummy variables for each level of schooling (akin to the schooling term in P(2)'s formulation). Note that the resulting coefficient of ln*W* is higher than 1 in modulus, hinting at an existing correlation between weeks worked and earnings, and furthermore the addition of said term in the formulation makes the interaction term *st* insignificant. In any case, after these additions, the explanatory power of the model increases greatly and R^2 reaches 52.5%.

These were the final results that Mincer was able to reach in his work, but he thought that the power of the Human Capital analysis on earnings shown by him was greatly undermined by the availability of data at the time. In particular, the same post-school investments were taken for people belonging to the same level of schooling, and he estimated the within-group variability to be about one third of total variability. The remainder contains the effects of quality of schooling, unemployment, individual returns rate and other factors.

Overall, variation of weeks worked in the year, schooling and post-school investments accounted for 2/3 of the total inequality of earnings of adult, white, urban men in the USA in 1959.

2.3 The pitfalls of the Mincerian model

As we have seen, Mincer's specification is an empirical approximation of the Human Capital Theory, and it was used successfully to estimate individual returns to education. However, despite the evidence coming from the Mincerian estimation, most economists followed the pioneering papery by (Griliches, 1977) and hesitated in interpreting the earnings gap between more and less educated workers as a reliable proof of the causal effect of education, asserting that Mincerian returns to education could be biased and inconsistent due to problems of endogeneity. In particular, there were at least three sources of bias:

- Omitted variables;
- Measurement errors;
- Heterogeneity of returns to education among the population.

As specified by Mincer himself in the final parts of his work, omitted variables issues arise because there are other determinants of individual income distribution. The process of investment in human capital cannot be restricted just to schooling and on job training investments, other variables must be considered into the human capital model, such as individual level of ability, family background, gender and ethnicity. For example, individuals with higher ability are expected to be more productive and, as a consequence, more remunerated in the labour market. Moreover, human capital begins to be shaped at the very early stages during an individual life cycle, and much of this process is carried out “at home”: parents can influence their children’s human capital building “directly” by investing into their early education (e.g. high-quality school programs) and “indirectly” by transmitting interests and/or motivation. Finally, it is also worth to consider if any discrimination effect is in place and obstruct skilled individuals from obtain better paid jobs.

A second source of bias is related to measurement error, which arises whenever a variable of interest is measured with an additive error component. For example, suppose we want to estimate the following simplified relationship where *ln Earnings* is the logarithm of hourly wage and *Years of schooling* is a measure of education:

$$\ln Earnings = \beta \cdot Years\ of\ schooling + \varepsilon \tag{31}$$

Suppose that we do not have information on the true value of *Years of schooling*, as it is measured with an additive error (in survey data this issue is mainly be caused by the respondents themselves who provide untrue answers either intentionally or accidentally):

$$Years\ of\ schooling^{*} = Years\ of\ schooling + u \tag{32}$$

For the sake of simplicity, consider the following hypotheses:

- the error term in the independent variable has a zero mean

$$E(u) = 0 \tag{33}$$

- and it is uncorrelated with *In Earnings* and *Years of schooling*.

If we substitute (32) into (31), the measurement error in *Years of schooling* becomes part of the error term in the regression equation, but since *Years of schooling** and the error term of (32) are positively correlated, OLS final estimates will be biased.

$$\ln Earnings = \beta \cdot Years\ of\ schooling^{*} + (\varepsilon - \beta u) \tag{34}$$

That is a clear example of classical error measurement, but things become more and more complex whenever more variables are added to the model (i.e. multivariate regressions) and in case hypothesis 4 does not hold (i.e. non-classical measurement error).

A final source of bias derives from heterogeneity of returns to education. Within Mincer specification, schooling could be seen as an investment decision which depends on the comparison between the discounted value of future earnings and the total costs coming from attending school. Unfortunately, however, individuals have different decision processes concerning the choice between attending school and finding a job. This induce differences in the optimization process and, as a consequence, differences in the final IRR, which cannot be equal for the whole population.

Differences in individuals' decision processes are mainly due to two reasons:

- Differences in discount rates across individuals, which could be the result of differences in the family's wealth considering a context with financial market imperfections (the higher the wealth, the lower the discount rates); and
- Differences in the individual level of ability, since the more talented individuals can convert schooling into human capital more efficiently, exploiting higher returns for a fixed amount of education compared to lower talented individuals.

In consideration of what said above, education cannot be simply treated as an exogenous variable which is randomly assigned across population and returns to education cannot be homogeneous for the whole population; they do depend on specific individual characteristics. A conceptual framework which considers the implications of these extensions have been extensively described in (Card, David, 1999).

In recent years, considerable effort has been made in order to cope with these issues, aiming at providing reliable estimates of the return to education. Three main routes have been taken:

1. Ability;
2. Instrumental variables; and
3. Twins analysis.

These three different strategies will be properly described in the next sections.

2.4 Ability

The idea that the level of ability of an individual impacts earnings is not novel nor unconventional, however its addition in the Mincerian model is not immediate.

Now, before addressing any kind of study or paper, it is necessary to address a more fundamental question: "what is ability"? In the framework of estimating returns to schooling, when researches talked about "ability" they typically referred to "cognitive abilities" and those intellectual characteristics that make an individual to be denoted as "intelligent". Now you could say that this definition is very limiting, and in fact recent trends seem to be going precisely in this direction, with researches trying to incorporate also non-cognitive abilities and other "kinds" of intelligence (e.g. emotional intelligence), obtaining very important results.

A second fundamental question we need to answer before going on is how to actually measure ability, but care that we don't want to get bogged down in questioning which specific test is better (not yet, at least); here we just want to introduce an important distinction between tests of potential and tests of achievement:

- Tests of potential want to measure the inherent ability of an individual (typically a child); results depend mostly on genetics and hereditary traits, but also environmental factors in the early stages of life have a (limited) impact; the output tends to be stable over time, with only little fluctuation.

- Tests of achievement want to measure the current level of development of an ability, usually at the end of an educational experience or path; results depend not only on genetics and hereditary traits, but also heavily on schooling inputs, non-cognitive abilities and environmental factors; the output can be very malleable over a very broad range of age[9].

The problem with this distinction is that in many cases it has simply been overlooked by researches, with measures of achievement tests being used as proxy of cognitive abilities and completely ignoring the effect of non-cognitive abilities, other environmental factors and the fact that different tests may target different facets of cognitive ability[10]. Obviously, doing so leads to incorrect conclusions and it should be avoided. The consequent question now is which kind of test should be preferred for research purposes, but actually, as it is posed, it is way too optimistic; in most cases the choice is simply limited to the availability of data, and achievement tests tend to be the more prevailing ones in data samples. If it were possible to choose, having a potential and "purer" measure of cognitive ability would be preferable to obtain unbiased results, but you work with what you have. Regarding non-cognitive abilities, instead, talking about a "purer" measure is simply nonsensical, since whatever the model or the measurement system you choose, results are highly affected by environmental factors and are malleable until a much later age compared to "pure" cognitive abilities (characteristic which also suggest that a longitudinal study would be the appropriate way to assess their impact).

A third and final question, that need to be at least mentioned before going ahead, is: "How do skills and education interact among each other?". In the recent literature it has been proven that cognitive and non-cognitive skills impact earnings directly through their own contribution and indirectly through the contribution of education[11]. Unfortunately, it's not simple to measure it, complex models and specific datasets are

[9] (Cunha et al. 2005).
[10] (Tim Kaultz, James J. Heckman, Ron Diris, Bas ter Weel, & Lex Borghans, 2014.
[11] (Urzua, Heckman, & Stixrud, 2006).

required (a longitudinal study would be the appropriate way to analyse the relationship between these variables).

2.4.1 Cognitive ability

After this (long) premise, we are finally able to dig in how ability was included in the Mincerian model. In doing so, we have decided to follow a chronological path, thus first considering cognitive abilities, and only after introducing non-cognitive ones. Among the authors who first used measures of ability in this context we have decided to present the work of (Griliches, 1977), whose pioneering studies led all successive research in the field. In the paper *"Estimating the returns to schooling: some economic problems"*, in fact, he obtained some important results by evaluating the impact of cognitive abilities on the NLS Young Men data sample, considering schooling both as exogenous and endogenous.

He used two measures of ability available in the survey, KWW[12] and IQ (Intelligent Quotient), obtaining overall better results with the latter. We would like now to spend a few words on IQ, since it is definitely the most widely known measure of cognitive ability. IQ is good proxy for multiple reasons, first of which is that it was specifically designed to capture the level of cognitive ability of an individual, and not his level of preparation in any topic; secondly, it is one of the best predictors of success in life that psychologists were able to find[13]. However, this is not to say that IQ corresponds exactly to "innate cognitive abilities"; actually, it has been proven to be correlated to early environmental factors, too, and still today there is an open debate among psychologists regarding what exactly it measures. It seems also to be related to the capability of learning new skills more quickly[14], characteristic that may be particularly interesting in this context.

In any case, going on with Griliches's results, both measures of ability were shown to be small but significant either in the exogenous and the endogenous schooling case, however, while in the first instance the returns to schooling were lower compared to the original OLS, in the second they were actually higher, at the price of a lower

[12] Knowledge of the World of Work, a late achievement measure of cognitive ability which doesn't merit much attention.
[13] (Sternberg, Grigorenko, Bundy, & Merrill-Palmer, 2001).
[14] (Schmidt & Hunter, 2004).

coefficient for ability. This outcome means that not only OLS estimations of return to schooling provides under-estimated values, but also that cognitive abilities affect earnings mostly through schooling.

2.4.2 The Bell Curve

A second collection of works that we want to present consists of the controversial *"The Bell Curve: Intelligence and Class Structure in American Life"* by (Herrnstein & Murray, 1995), and the paper published as an answer to it by (Cawley, Heckman, & Vytlacil, 1999).

In the book the authors make the case that American society has become more meritocratic in the 20th century, and in particular that social origin lost its preeminent role in determining individuals' social status in favour of cognitive ability. The main driver of this shift, in their opinion, is a more efficient and effective collage system, able to deliver individuals with superior cognitive abilities to firms looking for high-productivity workers. The authors provided an empirical analysis (of dubious academic rigor) in support to their formulation, exploiting published meta-analysis and regressing wages on age, ability and race, using data from the NLSY79 data sample. As a result, they were able to show how cognitive abilities are a better predictor of social status than race, and how social differences actually diminished after controlling for cognitive ability.

As previously said, their conclusions were heavily criticised, and we want to focus in particular on the answer by (Cawley, Heckman, & Vytlacil, 1999), who rejected Herrnstein and Murray's claims and showed that cognitive abilities were not the major predictor of wage premia in the US labour market. To do so, they regressed earnings not just on age, cognitive ability and social status, but also region of residence, unemployment rate, year of the wages and other measures; the results were definitive in proving that cognitive ability explains only a minor fraction of wage variance and that, more in general, cognitive ability and the other human capital variables altogether explain less than a third of the total variance.

The complete results of the regression are available in Appendix A. Here we want to focus, instead, on evaluating the increase in explanatory power of the model after the addiction of cognitive ability measures, both with and without the other human capital variables.

Looking at Table 2 you can see how two alternatives measures of cognitive ability, AFQT and *g*, were used. Both of them are derived from the Armed Services Vocational Aptitude Battery (ASVAB), a kind of test that is used for recruiting purposes by the U.S. Army that is offered broadly to high school students and to whoever is interested in being enlisted. The ASVAB is composed of 10 sections that stem from arithmetic reasoning to mechanical comprehension, and it obviously falls in the category of achievement tests. Now AFQT is simply obtained from a selected subgroup of said sections (putting more emphasis on mathematical skills), while *g* is the first principal component obtained applying Principal Component Analysis (PCA) on the whole set

Table 2 - Contribution of ability to wage determination modelled with and without human capital unconditional on occupation. Elaboration by (Cawley et al., 1999).

CONTRIBUTION OF ABILITY TO WAGE DETERMINATION MODELED WITH AND WITHOUT HUMAN CAPITAL UNCONDITIONAL ON OCCUPATION

	Modeled with background variables only		Modeled with human capital		
Group	AFQT	*g*	AFQT	*g*	Obs.
Black females	0.208 (–0.163) $p = -0.162$	0.244 (–0.166) $p = -0.166$	0.126 (–0.160) $p = -0.171$	0.149 (–0.162) $p = -0.173$	12391
Change in R^2 =	0.172	0.174	0.026	0.027	
Black males	0.157 (–0.117) $p = -0.119$	0.209 (–0.121) $p = -0.117$	0.086 (–0.124) $p = -0.132$	0.123 (–0.126) $p = -0.130$	13674
Change in R^2 =	0.140	0.148	0.013	0.017	
Hispanic females	0.166 (–0.227) $p = -0.179$	0.206 (–0.246) $p = -0.197$	0.086 (–0.186) $p = -0.167$	0.107 (–0.197) $p = -0.176$	8001
Change in R^2 =	0.162	0.165	0.013	0.013	
Hispanic males	0.104 (–0.071) $p = -0.144$	0.189 (–0.081) $p = -0.160$	0.063 (–0.081) $p = -0.137$	0.131 (–0.090) $p = -0.150$	9200
Change in R^2 =	0.147	0.160	0.008	0.014	
White females	0.185 (–0.156) $p = -0.137$	0.238 (–0.163) $p = -0.147$	0.082 (–0.132) $p = -0.131$	0.105 (–0.135) $p = -0.135$	31084
Change in R^2 =	0.188	0.189	0.009	0.010	
White males	0.132 (–0.079) $p = -0.061$	0.208 (–0.092) $p = -0.065$	0.061 (–0.079) $p = -0.069$	0.112 (–0.086) $p = -0.070$	32493
Change in R^2 =	0.186	0.199	0.007	0.011	

Notes: All ability measure standardized by age cohort. Sample includes all valid employed out-of-school observations. OLS regression used with Eicher-White robust standard errors generalized for panel data. Dependent variable is the log of the hourly wage reported for each year in 1990 dollars. Background variables include a linear time variable and indicator variables for local and national unemployment rates. Human capital includes education and potential work experience. Regressions run separately for race-sex groups based on rejection of the hypothesis that coefficients are equal across groups.

of results. As you can see, they perform similarly, with *g* giving only slightly better results.

Now, focusing on the data, you can see that, if one does not control for human capital measures, including *g* increases the value of R^2 between 14.8 and 19.9%, however, if one does control for human capital measures, the increase ranges only between 1.0 and 2.7% (both the scores are slightly lower considering AFQT instead). This suggests that ability is indeed correlated with wages, but it does explain only a minor part of the total variance. Moreover, if we focus on racial differences between groups, it is immediately evident how the wage return to cognitive ability is not uniform, but instead it seems consistently higher for black and Hispanic individuals compared to white ones; this behaviour suggests that there is still something going on in the background, and it does put a dent in the idea of a more meritocratic U.S. pushed by Herrnstein and Murray.

2.4.3 Non-cognitive ability

Detaching from the controversial Bell Curve we now want to tackle the issue of non-cognitive skills, that now are trending topic and are very much considered in the field. For this section we want to present the paper *"the determinants of earnings: a behavioural approach"* by (Bowles, Gintis, & Osborne, 2001), although it's important to say that it would be incorrect to qualify the inclusion of non-cognitive abilities as anything other than a gradual process. Many scholars, in fact, pointed out over the years than something was missing from the Human Capital model, something difficult to measure that accounted for things like motivation and aspiration. However, again, most of the times these kind of researches are driven by the availability of data, and most data samples simply didn't include reliable measures of non-cognitive abilities. Among these farsighted scholars we account even (Griliches, 1977), who also considered the possibility that the ever-sought value of ability was actually far from the measures of cognitive ability used by him, and closer to more primal impulses and drives.

Focusing on (Bowles, Gintis, & Osborne, 2001), they collected the most prominent empirical researches in this field, and they introduced the importance of the so-called soft skills with three examples that we want to summarize here:

1. In a survey of 3,000 employers conducted by the United States Census Bureau in collaboration with the department of Education (Bureau of the Census 1998) recruiters were asked to list the most important drivers which guided their hiring decisions. The most important factor was “attitude”, followed by “communication skills”.

2. In the Employers’ Manpower and Skills Practices Survey of 1,693 British employers reported in (Green, Machin, & Wilkinson, 1998), more than a third of recruiters complained about a shortage of skills among applicants mainly related to “poor attitude, motivation or personality” (62% of the interviews).

3. In a research conducted by James Heckmann on the General Education Development Programme (GED), which is essentially an achievement test of cognitive skills taken by high school dropouts in the US, it was shown that GED recipients perform much worse in the labour market and, more in general, attain lower socio-economic outcomes compared to high school graduates. The author demonstrated how high school dropouts are just as smart as graduates but display a deficit in terms of soft skills (i.e. behavioural and personality issues).

The authors than went on to estimate the augmented human capital model (that takes the name of behavioural model) on two datasets containing slightly different measures of ability:

- The first one is the National Longitudinal Survey of Young Women (NLSYW), which included measures of IQ for cognitive abilities and the Rotter’s score for non-cognitive abilities (it measures the degree with which a person believe that his outcomes are the results of external factors rather than his own fault/merit).

- The second one is the National Child Development Study (NCDS), which includes measures of IQ for cognitive abilities and two measures of aggression and withdrawal obtained through PCA.

Table 3 – Conventional and Behavioral wage equations, elaboration by (Bowles, Gintis, & Osborne, 2001)

	NLSYW		NCDS	
	extended human capital model **A**	**behavioral model** **B**	**extended human capital model** **C**	**behavioral model** **D**
Variable:	*b* (t-stat) *b′*	*b* (t-stat) *b′*	*b* (t-stat) *b′*	*b* (t-stat) *b′*
Years of Education	0.079 (10.647) 0.196	0.071 (6.299) 0.179	0.108 (9.638) 0.204	0.104 (9.264) 0.197
IQ Score	0.066 (4.937) 0.081	0.063 (4.789) 0.077	0.006 (2.996) 0.058	0.014 (2.626) 0.056
"O" Exams Completed*			0.018 (3.258) 0.071	0.0019 (0.861) 0.018
Years of Work Experience	0.0092 (2.399) 0.035	0.0083 (2.172) 0.032		
Parental SES	0.0095 (1.476) 0.025	0.0087 (1.365) 0.023	**	**
Number of Children	-0.073 (-6.278) -0.096	-0.072 (-6.299) -0.094		
Rotter Score		-0.028 (-4.481) -0.067		
Aggression				-0.098 (-3.912) -0.076
Withdrawal				-0.040 (-2.127) -0.033
Adjusted R^2 Observations	0.327 915	0.341 915	0.245 1123	0.259 1123

Table 2: Conventional and Behavioral Wage Equations

Notes: All regressions include a constant and are for white females actively employed in the year that wages are measured (from Osborne 2000).

*"O" level exams indicate the number of completed Ordinary Level Exams prior to age 21.

** Socioeconomic status is also included in the model however, is not reported here because it is not statistically significant in either model.

Some comments could be made on the overall structure of the applied models, that leads to a difference of a few percentage points in returns to education, but, focusing on the impact of non-cognitive abilities, in both cases they are definitely significant and their introduction increases the explanatory power of the respective model. Looking in particular at the NCDS sample, you can see how an increase of a single standard deviation in aggression or withdrawal is associated with a decrease in wages of 7.6% and 3.3% respectively, which is indeed significant.

It is also true that the increase in R^2 is not great in both cases, however there are two further considerations: firstly, there are definitely more rigorous methods to measure non-cognitive abilities; a more exhaustive investigation to assess the best practices in this context is necessary. Secondly, despite being small, the increase in R^2 is comparable to the increase experienced when introducing measures for cognitive abilities (not just in the model shown previously, but in general in the previous literature).

2.4.4 Life cycle skill formation

To conclude this focus on ability we want to focus on the work of (Cunha, Lochner, & Masterov, 2005), who in *"Interpreting the Evidence on Life Cycle Skill Formation"* dig deep on when skills are formed during the life cycle of an individual and which mechanisms regulate these processes.

They identify a multistage process across the life cycle of an individual in which inputs and investments done at a stage produce outputs also for the successive ones, in a deeply intertwined process. They do so because of two features denominated self-productivity (skills acquired in one period persist into the future) and complementarity (skills produced at one stage raise the productivity of investment at subsequent stages); their combined effect is described by the authors as "skill multiplier".

Some stages of life can be more productive in the development of a certain skill (e.g. IQ is more malleable at earlier ages), so they are called "critical" or "sensitive" periods[15], and after such time frames the abilities are crystallized and it becomes very hard to improve them. This implies that, once the crystallization process has completed, the skill multiplier effect simply makes more beneficial to invest in the more able compared to the other ones.

In this context, cognitive and non-cognitive skills are shown to be equally important in determining schooling and the socio-economical success of an individual, however they are both influenced not only by genetic and hereditary factors, but also by early environmental factors such as parental education and maternal ability. Now compensating for eventual adverse family environments becomes even more important in light of what has been just said, since once the early skills crystallize the individual will remain in a condition of disadvantage out of which it is very hard to escape (this is particularly true for cognitive abilities, for which later interventions do not show permanent effects). Moreover, due to the complementary effect, early interventions in cognitive and non-cognitive skills decrease the cost of further investments, thus making them even more efficient.

[15] Stages are called "critical" if the development of a skill can only happen at that point in time. If more than one stages are possible than they are called "sensitive".

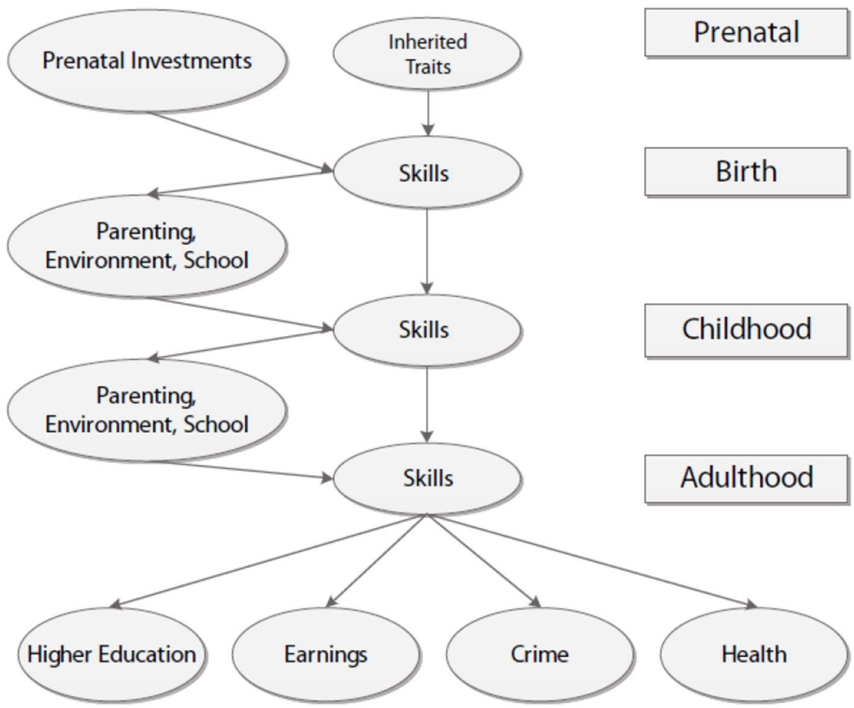


Figure 5 - Framework for understanding skill development, elaboration from (Tim Kautz, James J. Heckman, Ron Diris, Bas ter Weel, & Lex Borghans, 2014)

The object of the authors in these considerations was to guide polities for legislators, ours is to show how deeply connected cognitive and non-cognitive abilities are, and how both are important for the development and the socio-economic success of an individual.

2.5 Instrumental variables

Instrumental variables (from now on IVs) are a powerful econometric tool that can be used to obtain reliable estimates of the returns of endogenous variables (i.e. correlated with the error term). In this situation, in fact, OLS does not provide a good estimate.

The only major problem of IVs is a practical one, since, in order to obtain unbiased estimates, the selected instrument must be compliant with three properties, and finding one is generally not a simple task:

1. The instrument has to be correlated with the independent endogenous variable (the regressor);

2. The instrument has to be uncorrelated with the error term; and
3. The instrument has to influence the dependent variable only through the independent one, not directly.

When these conditions are satisfied, it is possible to reduce or even eliminate the correlation between the dependent variable and the error term, which is mainly due to two reasons:

- *Omitted variables*
  Variables highly correlated with an endogenous regressor generate a persistent bias if they are not included in the model. Introducing a proper IV makes a certain degree of the variation become exogenous, thus reducing the original bias.
- *Measurement error on an explanatory variable*
  If an explanatory variable is measured with additive random errors, then the OLS estimate for that variable will be biased (the higher the proportion of variability due to measurement error, the greater the bias). In this situation, introducing an IV that is uncorrelated with the measurement error and the equation error and correlated with the true value of the variable itself, provides a consistent estimate which converges to the true value when the sample size increases.

It must be underlined that, as a matter of fact, this methodology has a larger standard error compared to OLS, but it permits to obtain a reliable estimation of a troublesome dependent variable, as only the part of its variability that is not correlated with the omitted variables is used. As final note, 2SLS should not be used if the correlation between the endogenous variable and its instrumental variable is weak, since its performances are heavily hindered; there are other, more robust, techniques that can be used in this situation.

2.5.1 Theoretical framework

Over the years, economists have attempted to use different kinds of measures as IVs to obtain a reliable estimation of returns to education, some with more success than the others. As of today, we believe that four families of variables acquired a general positive consensus and popularity: quarter of birth, college proximity, family background and health factors. In the following paragraphs, we will provide a short description of each IV above introduced summarizing the empirical analysis conducted on US data sample.

1. *Quarter of birth*

   Focusing on quarter of birth, the notion that it is related to the individual educational attainment was firstly brought up by (Angrist & Krueger, 1990). In the article, they argue that the relationship is due to the combined effect of school start age policy and compulsory school attendance laws; the idea is that, while all children enter school in the year of their sixth birthday, those individuals born closer to the beginning of the year can drop out earlier, as soon as they are eighteen. In particular, using a US sample of men born from 1930 to 1959, they show that those who were born at the beginning of the year are compelled to attend school for a shorter period of time, so they have slightly less schooling on average compared to individuals who are born later in the year.

   The argument seems compelling and the relevance of the quarter of birth was confirmed multiple times over the years, however the reasoning behind it was later disproven by (Bound & Jaeger, 1996), who argued that the relationship between earnings and quarter of birth is too strong to be due only to a small difference in schooling years, and, moreover, it existed also before the changes in compulsory school attendance laws. They advanced the hypothesis of more underlying factors under the umbrella of the quarter of birth, such as performance at school, regional patterns, race or even personality; however, they were not able to give a definitive answer.

   The subject is still open nowadays, even if an alternative route, introduced by (Buckles & Hungerman, 2013), has gotten more and more popular. They attribute this behaviour to differences in behavioural patterns between women trying to conceive (that show seasonality) and unwanted children (that are uniformly distributed over the year); this phenomenon generates a disproportional amount of births by teenagers and unmarried individuals during winter and in particular at the beginning of the year.

2. *Collage proximity*

   Geographical differences in the accessibility of school have been extensively used in the literature as a potential source of exogenous variation for the educational variable. Card himself was a pioneer in this branch of study and in (Card, David, 1993) he was able to demonstrate the existence of a strong correlation between individuals' educational choices and collage proximity to home, especially in the case of men coming from a disadvantaged family background[16]. These results were later confirmed by the American economist (Kling, 2001) using a broader data sample[17].

   During the last decade, others have tried to go more in depth in the topic and find more precise estimates of the effects of collage proximity on education, also thanks to the higher-quality data samples available (remember that, most of the times, the availability of data is a driving factor in a study). One of the most recent works on the argument has been submitted by (Doyle & Skinner, 2016), who tested different measures of proximity-based measures and showed that the density (rather than the distance) of nearby community collages has a key role in explaining individual educational attainments.

3. *Health Factors*

   The correlation between individuals' education and health has been well detailed in the literature. It has been extensively proven that more educated people are more likely to have better health habits and, consequently, lower mortality rates and/or incidence of chronic diseases. One of the most famous research on this field has been provided by (Farrell, Fuchs, & Fuchs, 1982), who empirically demonstrated the existence of a strong correlation between the two variables. However, it should be clarified that not all health habits can be used as valid instruments for education, as explained in (Evans & Montgomery, 1994); first of all, those health habits which influence individual's productivity must be excluded from the analysis (e.g. heavy drinking), and, secondly, all

[16] He analysed a US sample from the original young men's cohort of the National Longitudinal Survey (NLSYM66), which contains data starting from 1966 on 5,526 men aged 14-24 and continued with follow-up surveys up to 1981, when the numerosity of the sample dropped to 2,037.

[17] National Longitudinal Survey of Youth 1979 (NLSY79).

those health habits which are directly linked to individuals level of earnings must be excluded from the analysis too (e.g. regular check-ups).

Once considered the aforementioned issues, the most used health habit has been “individuals’ smoking behaviour”. One of the most popular empirical analysis on US data sample has been conducted again by (Evans & Montgomery, 1994), who demonstrated that smoking behaviour at age 18 is a statistically valid instrument for education.

4. *Family background*

   Family background is probably the most straightforward and intuitive group of variables among the four, and, as such, economists have tried to include it in a proper model even from the 70s, far earlier than the other two. As outlined in (Card, David, 1999), individuals’ schooling outcomes are very highly correlated with the characteristics of their family, and in particular with parent’s educational level. Looking at the research that has been done on this topic, many parameters of this kind were used, such as parental income and/or education level, number of siblings, size of the house, the (perceived) parental interest on the child’s educational level, and even the spouse’s education level. It is not clear as of today which instrument should be preferred. It must be also underlined that sometimes family background variables are not fully able to provide an exogenous source of variation in educational outcomes due to a direct effect on earnings (e.g. better educated parents could also induce an easier entry in the labour market favouring both better job and better salary). Obviously, results can shift over time and depending on the specificity of the data sample, sometimes even showing unexpected results, but in general its relevance is not put in question.

2.5.2 Empirical results

In this section we’ll provide an empirical overview of IV estimation methodology considering each instrument above described. Among the papers discussed in the theoretical framework section, we selected four (one for each family of instruments); we summarized their main results in Table 4.

As you can see, despite the value of returns to educations estimated through IVs being always bigger than the corresponding counterpart estimated through OLS, there

Table 4 - Returns to education using different Instrumental Variables and data samples; we report point estimate and standard deviation (in brackets). Angrist & Krueger's model has a quadratic term in age, use quarter of birth interacted with year of birth as instrument and controls for race, marital status and living in a city. Card's model for collage proximity uses a dummy variable for the presence of a nearby 4-years collage as instrument and controls for race, region and parental education. Evans & Montgomery's model has a quadratic term in age, uses a dummy variable for smoking at age 18 as instrument and controls for race, union status, region and living in a city. Card's model for parental background has a cubic term in age, uses mother's education as instrument and controls for race, year and region

Instrument	Author	Data sample	Schooling coefficients	
			OLS	IV
Quarter of birth	Angrist & Krueger	US Data Census (Men), 1920-1929 cohort in 1970	0.070 *(0.000)*	0.101 *(0.033)*
		US Data Census (Men), 1930-1939 cohort in 1980	0.063 *(0.000)*	0.06 *(0.030)*
		US Data Census (Men), 1940-1949 cohort in 1980	0.052 *(0.000)*	0.078 *(0.030)*
College proximity	David Card	NLS Young Men, 1966 cohort	0.073 *(0.004)*	0.132 *(0.049)*
Health Factors	Evans & Montgomery	1987 NMES	0.066 *(0.003)*	0.073 *(0.013)*
Parental Background	David Card	GSS of adult household 1974-1996 (Men)	0.067 *(0.003)*	0.106 *(0.007)*
		GSS of adult household 1974-1996 (Women)	0.113 *(0.004)*	0.110 *(0.011)*

seems to be no convergence on the results. The outcomes seem to be model and data sample dependent, in particular IV's estimates vary from 7.3% to 11%.

In general, the usage of IV estimation methodology in this field has been subject to studies and critiques by economists. In particular, (Card, David, 1999) and (Card, 2001) proposed some reasonable hypotheses which could explain these outcomes. First, he observed that IV estimates might be further upward biased than OLS estimates due to a possible correlation between the adopted instruments and the unobserved factors. Another reason to explain IV and OLS estimates gap could be measurement error, which might induce a downward bias of the OLS estimates. Finally, he observed that, in case of sample heterogeneity, the instruments may affect just a subgroup of the population. In this case, even an instrumental variable compliant with the three properties previously described will not necessarily yield a consistent estimate of the average marginal return to education. Specifically, in case returns to education vary across individuals, IVs estimate a sort of weighted average of the marginal return to educations in the population, where the weights reflect the relative incidence of the selected instrument on each subgroup. The parameter estimated by IV under this condition is known as the Local Average Treatment Effect or LATE. For example, if we consider the extreme situation where the selected instrument affect just one subgroup of the population, the IV estimator will exhibit just the marginal return to education for that subgroup which, of course, cannot be considered valid for the entire population.

This issue could also explain the reason why there is not a convergence on results concerning returns to education whenever different instruments are considered.

2.6 Twins analysis

Studies on twins are a staple methodology used in behavioural economics to estimate a variety of socioeconomic variables. The underlying idea is that, since twin brothers share both genetic traits and a common growing environment, the difference in performance in a specific topic (like wage) will only be due to characteristics which are unique among them. Knowing this, by comparing the results achieved by the twins, it becomes possible to obtain a precise estimate of the effect of said unique elements, ignoring many aspects which may surely be relevant, but that are not differentials (e.g. cultural background, access to financial resources, influences from school and the community); note that this peculiarity of the methodology is especially useful when the non-differential aspects are troublesome to be observed and/or measured. It is important to say, however, that the assumption that a variable is differential or not is a strong one and it needs to be thoroughly checked, otherwise it will surely lead to biased results.

A further clarification on the sample is needed before going on. Until now we have glossed over the fact that twins can be identical/monozygotic (MZ), sharing the 100% of their genes, or fraternal/dizygotic (DZ), sharing only 50%. The letter case is particularly useful when studying of a physical trait present in only one sibling, however, estimating returns to education does not fall in this category, and for this reason mostly MZT[18] samples are used.

2.6.1 Theoretical framework

The first recorded usage of twins in this field actually dates as far back as 1932, with the pioneering work of Donald Gorseline, which was rudimentary but innovative in considering a common family environment.

[18] MonoZygotic Twins.

In recent years, the reference model that has been used the most is the one introduced by (Ashenfelter & Krueger, 1994) and (Ashenfelter & Rouse, 1998), who analysed a sample of twins from the editions of 1991 to 1993 of the annual twins day festival in Twinsburg, Ohio, the largest annual gathering of twins in the world. The core of the model is a system of slightly modified Mincerian equations one for each twin[19]:

$$W_{1j} = \mathrm{A_j} + b_j \mathrm{S_{1j}} + d\mathrm{X_j} + \varepsilon_{1j} \tag{35}$$

$$W_{2j} = \mathrm{A_j} + b_j \mathrm{S_{2j}} + d\mathrm{X_j} + \varepsilon_{2j} \tag{36}$$

W_{ij} is the annual wage of twin i (i=1,2) in family j, A_j, is an "unobservable family component" of family *j* (a combination of innate/inherited ability, family environment and other unobserved skill and may be correlated to the achieved level of education), b_j is the return to education that we want to estimate, S_{ij} is the level of schooling in years, X_j is a vector of other shared characteristics between the twins and ε_{ij} is the error term.

In the formulation of the model, ability plays an important role and influences annual earnings directly though A_j and indirectly through b_j, but, as you can see, in both cases it is considered as non-differential between families (although it is important to say that they are not claimed to be a comprehensive measure of ability). A_j is also referred to as "absolute advantage" (earnings are increased by a fixed amount that does not depends on schooling), while b_j is referred as "comparative advantage" (the increase is proportional to the actual level of schooling of the individual).

If A_j is actually correlated with the level of schooling and uncorrelated with the vector of other shared variables X_j, we can write:

$$A_j = \gamma \frac{S_{1j} + S_{2j}}{2} + v_j \tag{37}$$

Where γ is the correlation between the family's absolute ability level and the observed schooling level of the twins and v_j is an error term. At this point, (Ashenfelter & Rouse, 1998) present two different formulations of the model depending on the heterogeneity of returns to education:

[19] Only couples of twins are considered, triplets (or more) are discarded.

1. If returns to education are assumed to be homogeneous ($b_j = b$) then equation (37) is simply substituted inside (35) and (36), and we can apply generalized least squares (GLS):

$$W_{1j} = bS_{1j} + \gamma \frac{S_{1j} + S_{2j}}{2} + dX_j + v_j + \varepsilon_{1j} \tag{38}$$

$$W_{2j} = bS_{2j} + \gamma \frac{S_{1j} - S_{2j}}{2} + dX_j + v_j + \varepsilon_{2j} \tag{39}$$

Alternatively, it is possible to compute the difference between the two revenues and estimate the parameters through a fixed-effects model (FE), even if doing so we cannot evaluate the correlation between ability and schooling, since the (non-differential) ability component is removed completely:

$$\mathrm{W_{2j}} - \mathrm{W_{1j}} = b\left(S_{2j} - S_{1j}\right) + \varepsilon_{2j} - \varepsilon_{1j} \tag{40}$$

2. If returns to educations (b_j) are allowed to be heterogenous between families, considering the correlation with the family unobservable ability (A_j) it is possible to write them as:

$$b_j = b_0 + b_1 A_j \tag{41}$$

With b_1 expected to be positive, since individuals living in a "more able" environment should be able to capture higher marginal returns.
Including equation (41) in the process shown above, the model becomes:

$$W_{1j} = b_0 S_{1j} + b_1 \gamma \frac{S_{1j} + S_{2j}}{2} S_{1j} + \gamma \frac{S_{1j} + S_{2j}}{2} + dX_j + \varepsilon_{1j} \tag{42}$$

$$W_{2j} = b_0 S_{2j} + b_1 \gamma \frac{S_{1j} + S_{2j}}{2} S_{2j} + \gamma \frac{S_{1j} + S_{2j}}{2} + dX_j + \varepsilon_{1j} \tag{43}$$

And the difference becomes:

$$\mathrm{W_{2j}} - \mathrm{W_{1j}} = b_0\left(S_{2j} - S_{1j}\right) + b_1 \gamma \left[\frac{S_{2j} + S_{1j}}{2}\left(S_{2j} - S_{1j}\right)\right] + \varepsilon_{2j} - \varepsilon_{1j} \tag{44}$$

Before applying either of these formulations to the data, (Ashenfelter & Krueger, 1994) introduce a correction for measurement errors in schooling, that will otherwise lead to downward biased results. To do so, in the sample interview the individuals are asked to report not only his own schooling level, but also its twin; given this, it is possible to write the difference between the two schooling levels as following (we write as S_{ij}^{k} the report by twin k of twin i's schooling level):

$$\Delta S_j^* = S_{1,j}^1 - S_{2,j}^1 = \Delta S_j + \Delta v_j^* \tag{45}$$

$$\Delta S^{**}{}_j = S_{1,j}^2 - S_{2,j}^2 = \Delta S_j + \Delta v_j^{**} \tag{46}$$

where ΔS_j refers to the true schooling difference, while Δv_j represent measurement error. It is possible to eliminate schooling estimate biasedness by adopting IV methodology and in particular by using equation (45) and (46) one as an instrument for the other.

2.6.2 Empirical results

In Table 5 we report the empirical results obtained by (Ashenfelter & Rouse, 1998). The first three columns show estimates of equation (36) controlling for age, age squared[20], race and sex; in column 1 the results are obtained adopting generalized least squares (GLS) and without controlling for ability, in column 2 they do control for ability and in column 3 they use 3SLS[21] to also control also for measurement error. Estimate of equation (38) (the FE model) are instead showed in columns 4 and 5 (in the latter they also control for measurement error). The procedure is then replicated by including the following additional independent variables: union, marital status, and job tenure (from column 6 to 10).

If the ability effect is not considered (as in column 1), the economic return to schooling is estimated to be around 10.2%, while in case we do consider the ability effect the economic return to schooling estimates range from 6.6% (2) to 9.1% (3), and from 7.0% (4) to 8.8% (5) when the FE model is used. This pattern indicates the existence of a positive influence of the ability component on the return to schooling estimates implying an upward biasedness in the traditional cross sectional estimates.

[20] There are no explicit measures of lifetime work experience available in the dataset, so they use age as a proxy.

[21] Similar to 2SLS, but with a system of equations instead of just one.

Table 5 - Returns to schooling under the hypothesis of homogeneity (elaboration by (Ashenfelter & Rouse, 1998))

GLS, 3SLS, and Fixed-Effects Estimates of the (Mean) Return to Schooling for Identical Twins

	Without Other Covariates					Controlling for Other Covariates				
	GLS (1)	GLS (2)	3SLS (3)	First-difference (4)	First-diff. by IV (5)	GLS (6)	GLS (7)	3SLS (8)	First-difference (9)	First-diff. by IV (10)
Own education	0.102 (0.010)	0.066 (0.018)	0.091 (0.024)	0.070 (0.019)	0.088 (0.025)	0.113 (0.010)	0.074 (0.017)	0.106 (0.022)	0.078 (0.018)	0.100 (0.023)
Avg. education $[(S_1+S_2)/2]$		0.051 (0.022)	0.033 (0.028)				0.055 (0.021)	0.031 (0.025)		
Age	0.104 (0.013)	0.103 (0.013)	0.103 (0.013)			0.092 (0.013)	0.088 (0.013)	0.087 (0.013)		
Age^2 (÷100)	-0.107 (0.015)	-0.104 (0.015)	-0.104 (0.015)			-0.106 (0.015)	-0.101 (0.015)	-0.100 (0.015)		
Female	-0.315 (0.049)	-0.309 (0.049)	-0.306 (0.049)			-0.239 (0.048)	-0.228 (0.048)	-0.226 (0.049)		
White	-0.106 (0.090)	-0.105 (0.091)	-0.101 (0.091)			-0.094 (0.086)	-0.096 (0.087)	-0.094 (0.087)		
Covered by a union						0.109 (0.044)	0.106 (0.043)	0.109 (0.043)	0.085 (0.055)	0.087 (0.055)
Married						0.066 (0.050)	0.087 (0.050)	0.101 (0.050)	0.044 (0.073)	0.052 (0.073)
Tenure (years)						0.022 (0.003)	0.023 (0.003)	0.023 (0.003)	0.024 (0.003)	0.024 (0.003)
Sample size	680	680	680	340	340	666	666	666	333	333
R^2	0.262	0.264	0.267	0.039		0.352	0.351		0.177	

Standard errors are in parentheses. Cols. (1)-(3) and (6)-(8) include a constant; cols. (2)-(5) and (7)-(10) assume correlated measurement errors. For the GLS and IV estimates, one twin's reports of twin 1 and twin 2's education are used as regressors and the other twin's reports of the two measures are used as instruments. For the fixed-effects estimates, the difference in education is the difference between twin 1's report of twin 1's own education and twin 1's report of twin 2's education; the instrument used is the difference between twin 2's report of twin 1's education and twin 2's report of twin 2's own education.

Results are almost similar also in case other additional covariates are considered (column 6 to 10).

Instead, if returns to education are allowed to be heterogeneous, varying with individuals' ability level, we observe that both the returns and the heterogeneity component appear not to be statistically significant, as you can see from Table 7 and Table 6.

Table 6 - Estimates of the heterogeneity in returns to schooling (elaboration by (Ashenfelter & Rouse, 1998))

Estimates of Heterogeneity in the Return to Schooling

	Column of Table IVa upon which estimates are based	
	GLS (1)	3SLS (2)
Estimate of the heterogeneity in the return to schooling (b_1)	-0.133 (0.112)	-0.041 (0.040)

Estimated asymptotic standard errors are in parentheses.[20]

Twins' estimation methodology is based on the assumption that the ability factors which bias the original OLS estimates have a pure genetic component. As explained above, it's an intra-family factor which is shared among family members or at list among MZT. But, If MZT are considered as "identical", they should also have same schooling years and wages, but that's not what empirical analysis outlined. That's the main issue which raised the first doubts among economists for what concerns the validity Twins' based estimation. (Griliches, 1979) was among the first ones which started conducting research on this topic, later supported by (Neumark, 1999) and (Bound & Solon, 1999).

They explained that, despite MZT have some sort of visible similarities and share similar environments for a great part of their lives, it's not actually true to treat them as

Table 7 - Returns to schooling under the hypothesis of heterogeneity (elaboration by (Ashenfelter & Rouse, 1998))

Table IVa

GLS, 3SLS, and Fixed-Effects Estimates of the Returns to Schooling by the Average of the Twins' Schooling Levels for Identical Twins

	GLS (1)	3SLS (2)	First-difference (3)	First-diff. by IV (4)
Own education	-0.041	0.141	-0.030	0.167
$[S_1]$	(0.088)	(0.113)	(0.196)	(0.329)
Avg. education	-0.056	0.080		
$[(S_1+S_2)/2]$	(0.089)	(0.114)		
Own*avg. educ.	0.007	-0.003	0.007	-0.005
$[S_1*((S_1+S_2)/2)]$	(0.006)	(0.008)	(0.013)	(0.023)
Age	0.102	0.103		
	(0.013)	(0.013)		
Age^2 (÷100)	-0.104	-0.105		
	(0.015)	(0.015)		
Female	-0.312	-0.305		
	(0.049)	(0.049)		
White	-0.111	-0.098		
	(0.091)	(0.091)		
Sample size	680	680	340	340
R^2	0.266		0.040	

Standard errors are in parentheses. Estimates assume correlated measurement errors. Cols. (1) and (2) include a constant. For the GLS and IV estimates, one twin's reports of twin 1 and twin 2's education are used as the regressors and the other twin's reports of the two measures are used as instruments. For the fixed-effects estimates, the difference in education is the difference between twin 1's report of twin 1's own education and twin 1's report of twin 2's education; the instrument used is the difference between twin 2's report of twin 1's education and twin 2's report of twin 2's own education.

identical individuals. MZT are shaped by different experiences which can occur randomly (e.g. one twin could accidentally break hers arm and the other one doesn't) or systematically (e.g. twins are commonly separated during the schooling path), and even occur before their birth due to some complications. Birth weights are a clear example *of this case; (Miller, Mulvery, & Martin, 1995)* demonstrated that 69% of the twin pairs had birth weights differences by at least four ounces while 48% had birth weights differences by at least eight ounces. In the last decade, numerous studies had demonstrated the existence of a correlation between birth weights and ability. Among the most famous ones, it is worth to mention (Hack et al., 2002), who demonstrated that very low birth weight had lower mean IQ and lower academic performances, and (Black, Devereux, & Salvanes, 2007), who demonstrated that birth weight does matter in explaining adult outcomes such as adult height, IQ, earnings and education.

As a result, ability bias is not completely removed by analysing twins' sample. Nevertheless, as explained and demonstrated by (Griliches, 1979) and (Neumark), estimates bias could be even exacerbated with in twins-based sample.

2.7 Alternatives to the Human Capital Theory

As abundantly explained in the previous chapter, the Human Capital Theory, pioneered by (Schultz, 1961) and (Becker, Gary, 1965), has tempted to explain and measure the relationship between education and wage. Up to here, the models built have assumed that wages rise in response to education because of an enhancing productivity effect which is mainly due to education. In other words, individuals' level of capabilities is improved during schooling years.

Among the other theories have been developed in order to explain the correlation between education and earnings, the most popular one is the signalling theory. The essence of this interpretation, pioneered by (Spence, 1973) and later reviewed by (Riley, 2001), is that education not only enhances productivity, but also signals individuals' innate level of abilities. Despite both the human capital theory and the signalling theory imply that earnings increase with education, signalling theory identify education as a sort of "screening device", a means by which individuals with different level of innate ability can be distinguished.

Different approaches have been used in order to test the validity of the screening assumption and almost all these attempts are based on the assumption that screening hypothesis is determinant in specific types of jobs. One of the most used methodologies has been proposed by (Psacharopoulos, 1979). The author relaxed the initial concept of the signalling theory and tested two different versions of the screening hypotheses:

- *Strong screening hypothesis (SSH)*
  Productivity is immutable with schooling, which is just a signal for employers;
- *Weak screening hypothesis (WSH)*
  The primary role of schooling is to signal inherent productivity, but it may also augment skills.

In order to test the validity of the above-mentioned hypothesis, Psacharopolous identified two sectors of the economy, the competitive/unscreened/private sector and the uncompetitive/screened/public sector, and he estimated the relative earnings functions and compared the rates of return to education. Under SSH only screened workers invest in education, as unscreened workers have no need to signal their inherent ability; so for this reason return to education are expected to be significantly different from zero only in case of screened workers. Under WSH, instead, all workers invest in education; the unscreened workers invest only to augment their productivity while the screened workers also invest to signal their inherent productivity. For these reasons, WSH implies a higher return to education for the screened compared to the unscreened sector (where should be significantly different from zero anyway).

Using a UK data sample, the author found evidence which supported the validity of WSH, in particular he showed that rates of return to education were significantly different from zero in both two sectors, but returns were significantly higher in the competitive (or screened) sector.

The same methodology has also been replicated by other authors which exploited different data samples, one of the most recent ones has been proposed by (Brown & Sessions, 1999) using an Italian data sample (Survey Household Income and Wealth issued by Banca d'Italia). In particular, Brown and Sessions identified two main subsamples, "self-employed" and "employed" workers, that constitute, respectively, the unscreened sector and the screened sector. They then estimated, in both cases, the following standard Mincerian earnings function

$$\ln W = \alpha + \beta_1 c + \beta_2 x + \beta_3 x^2 + \beta_4 d + \varepsilon \tag{47}$$

Where W is hourly earnings, c is a vector of dummies for the levels of schooling education (primary education or less, intermediate education, high education and university/degree), x is age, d is a vector of control dummy variables contain region, marital status and industrial sector.

As expressed in Table 8 (columns 1 and 2), the results support the WSH hypothesis. The rates of return to both intermediate and high school education are both significantly different from zero, but the latter ones are significantly higher for the screened workers compared to the unscreened workers. There is not a significant difference among rates of return of the two sample groups considering university education.

The estimation has then been replicated by exploiting a trivariate sample selection, with three subsamples considered instead of just two: the private sector, the self-employed sector (which constitute the unscreened sector) and the public sector (which

Table 8 - Regression on education using dummy variables for levels of educations, age and age squared, elaboration by (Brown & Sessions, 1999)

	Bivariate selection		Multivariate selection		
	All employees	Self-employed	Private sector employees	Public sector employees	Self-employed
Age	0.0329	0.0575	0.0132	0.0061	0.0572
	(3.108)	(2.987)	(0.936)	(0.263)	(3.061)
Age^2	− 0.0003	− 0.0005	− 0.000	0.0001	− 0.0005
	(− 2.052)	(− 2.343)	(− 0.058)	(0.186)	(− 2.346)
Degree	0.6258	0.6311	0.7583	1.1121	0.6299
	(13.019)	(5.807)	(12.299)	(3.657)	(5.860)
High education	0.3481	0.2930	0.4475	0.7489	0.2922
	(9.991)	(3.776)	(10.701)	(2.819)	(3.807)
Intermediate education	0.1458	0.0926	0.1628	0.5334	0.0922
	(4.292)	(1.224)	(4.372)	(2.761)	(1.232)
Lambda	− 0.1013	− 0.0476	− 0.4123	0.6765	− 0.0390
	(− 1.889)	(− 0.782)	(− 3.609)	(2.041))	(− 0.651)
Constant	9.0254	8.7426	9.5811	8.1160	8.7401
	(39.941))	(20.320)	(29.588)	(10.095)	(20.533)
N	853	316	696	153	316
F-statistic	46.649	11.104	45.019	6.581	11.064
	(6846)	(6309)	(6689)	(6150)	(6309)
Log likelihood	− 348.435	− 235.660	− 267.343	− 68.155	− 235.760
R^2 adjusted	0.243	0.161	0.275	0.177	0.161
Mean ln w	10.109	10.379	10.097	10.159	10.379
Lazear H_0:	0.2452	0.2042	0.8841	0.5269	0.1246
	(7846)	(7226)	(7689)	(7150)	(7226)

is the screened sector). The results, shown at columns 3, 4 and 5 of Table 8, are aligned with the previous considerations.

During the last decade, other approaches have been exploited in order to test the signalling theory, the most influent ones has been summarized in (Chevalier, Harmon, Walker, & Zhu, 2004). Nevertheless, the debate is still opened as there is not a general consensus about the validity of the signalling theory. Anyway, in doing empirical analysis, it should be worth to consider both research on human capital and signalling theory. In particular, excluding one theory in favour of the other a priori could be the worst way operating, instead it could be useful to consider each country specific peculiarities (institutions and cultures above all) and provide data sample specific conclusions.

Chapter 3

Application to the Italian case

3.1 Empirical strategy

In the previous sections we detailed the Human capital concept and we analysed the main paths that have been explored in order to measure returns to human capital investments. Starting from the early contributions of (Schultz, 1961), (Becker, 1964) and (Mincer, 1974), we presented the analysis of other famous economists studying labour economics who have later investigated individuals' returns to human capital investments in the labour markets. Empirical analysis had been conducted mainly on US data samples, here used as a benchmark, and, in order to account for endogeneity issues, different strategies had been presented. Three main estimation approaches have been exploited: Instrumental Variable strategy, Ability strategy and Twins based strategy. Unfortunately, as al-ready explained, there is not a general consensus about the approach that should be used in order to obtain reliable estimations, there are instead positive and negative aspects among all the presented methodologies.

For this reason, in this second part, we will try to adopt all the methodologies described in the previous sections with the final aim to obtain reliable estimate of returns to human capital investments in Italy with a focus on macro-regional differences. In order to make results comparable among each model, we will adopt a unique data sample, specifically, we exploit the Programme for the International Assessment of Adult Competencies (PIAAC) also known as the survey of Adult Skills. We decide to go through this specific survey mainly because it gathers information that make both the Instrumental Variable and the Ability path viable. Unfortunately, in the following section we will not go through the twins' estimation methodology because there is no Italian data sample which contains appropriate information for such an analysis

We will apply several models on the Italian subset of PIAAC (2012), with the objective to show the effect of newly introduced explanatory variables and to find the one that best fits the data. In doing so, we follow the path delineated in the previous chapter:

1. The experience-augmented Mincerian equation, whose core elements are years of education and experience;
2. A model including cognitive abilities;
3. A model including both cognitive and non-cognitive abilities;
4. A model including cognitive abilities, non-cognitive abilities and instrumental variables.

All the models presented are obtained through OLS, with the exception of the one including instrumental variables, for which we used 2SLS.

Since we are interested in differences between Italian macro-regions (intended as North, Center and South), we will compute the regressions above both introducing them in the model as dummy variables and restricting the data sample to the specific macro-region. So, for each model there will be four regressions.

Afterwards, using the better performing model we will investigate other points of interests, where we suspect to find statistically significant results:

- Differences between male and female;
- Differences between levels of schooling education;
- Differences between private sector and public sector;
- Differences between full-time workers and part-time workers;
- Model including skill requirements on the job.

3.2 Dataset

As previously stressed, our only source of data for this part is the Programme for the International Assessment of Adult Competencies (PIAAC), which is a study by the Organisation for Economic Co-operation and Development (OECD) made up in order to help policy makers to assess and monitor the development of key aspects of individuals' human capital. In particular, the survey is composed by a background questionnaire which gather information about individuals' labour market status, earnings, education, experience and other demographic characteristics of individuals, and by a cognitive skills survey which asses three domains of skills: numeracy, literacy and problem solving in technology-rich environments. The survey is completed at home through a computer but also through a paper test (if the computer expertise of the interviewed is poor). The different pathways are summarized in figure 6.

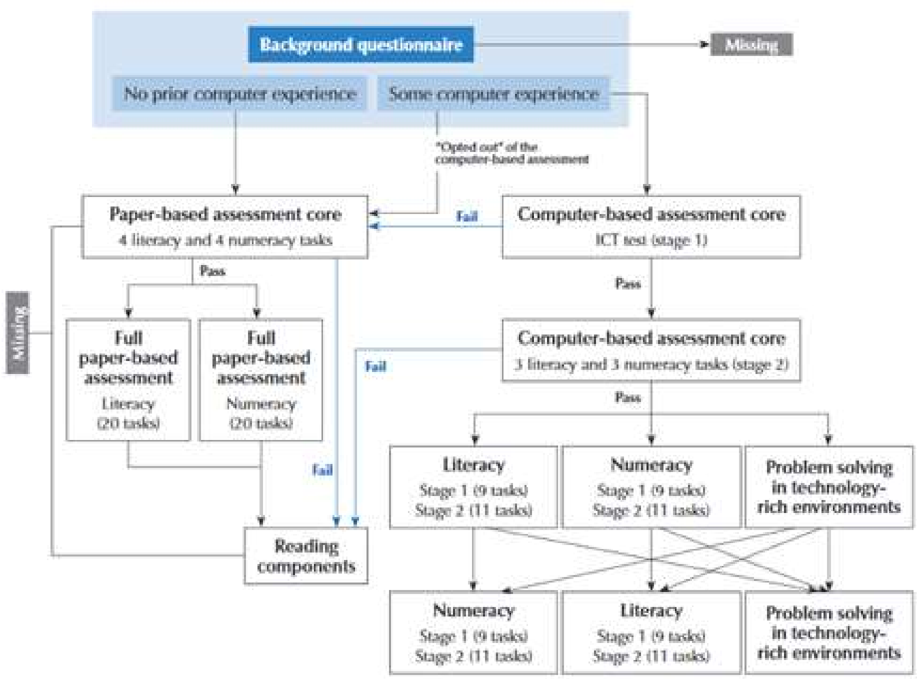


Figure 6 - Flowchart test PIAAC 2012

The fist cycle of data collection (which we will use in this thesis) involved 38 countries in three rounds, carried out in 2011-12[22], 2014-15[23] and 2017[24]. The second cycle will begin in 2021-2022 with the first round involving 33 countries[25] and results being released in 2023; it will include an upgraded background questionnaire and new section regarding non-cognitive skills (which would have been really useful to have in this research!). For each country, the target population consists of all noninstitutionalized adults aged between 16 and 65 years-old residing in the country at the time of data collection regardless of citizenship, nationality or language. Adults in noninstitutional collective dwelling units such as workers' quarters or halfway homes (including adults at school in student group quarters such as dormitory, fraternity or sorority) are included in the target population while adults in institutional collective dwelling units (prisons, hospitals, nursing homes, military barracks and military base) are excluded from the analysis.

Focusing on the Italian PIAAC data, the population of interest has the following hierarchical structure:

- The primary stage units are the 8,094 Italian municipalities;
- The secondary stage units are the households residing in the generic municipality;
- The final stage units are the individuals residing in the household and aged among 16 and 65 years old.

The Italian sampling selection process followed a multistage sampling methodology composed of three stages: in the first stage 260 Italian municipalities were extracted from the total of 8,094 through a probabilistic selection scheme stratified according to the municipality's size; in the second stage 11,592 households were randomly extracted from the 260 primary stage units; in the third and last stage 9,011 eligible households were identified (out of the 11,592 extracted secondary stage units) and one individual for each household was surveyed. The final sample is composed by

[22] Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, Sweden, United Kingdom, United States.

[23] Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Singapore, Slovenia, Turkey.

[24] Ecuador, Hungary, Kazakhstan, Mexico, Peru, United States.

[25] Australia, Austria, Belgium, Canada, Chile, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Netherlands, New Zealand, Norway, Poland, Portugal, Russian Federation, Singapore, Slovak Republic, Spain, Sweden, Switzerland, United Kingdom, United States.

4,621 individuals, almost equally divided between male (48.4%) and female (51.6%). As you can see in Figure 7, instead, the age of the participants is not uniformly distributed, and the data is clustered around the mean.

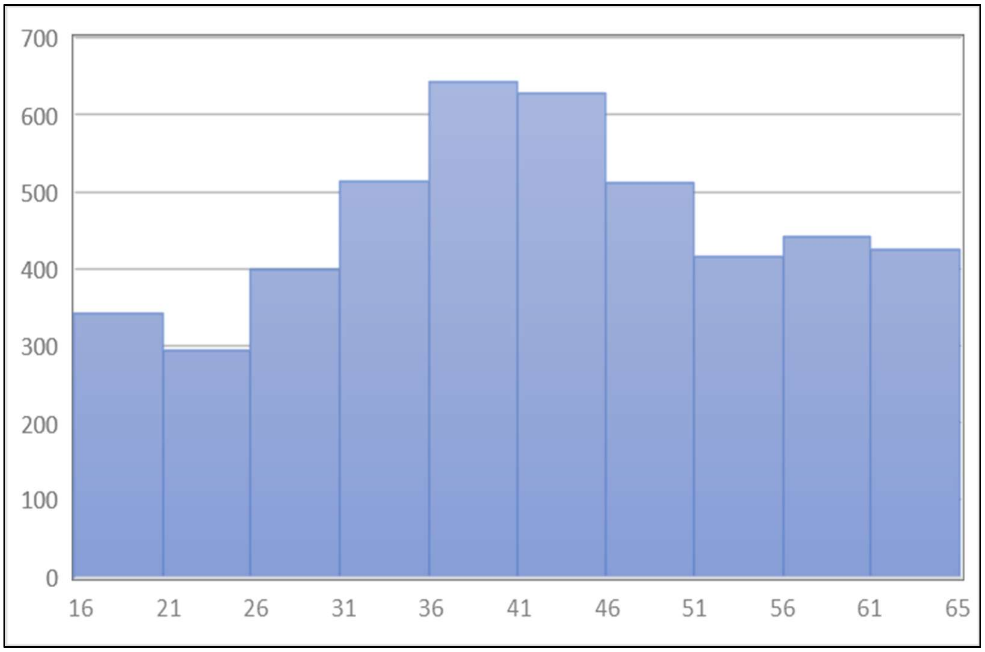


Figure 7 – Histogram of age distribution inside the Italian subsample of PIAAC

It is not an issue per se, but if we want precise estimates the data must reflect the population of the country, and certain resampling techniques are implemented to ensure it. In the case of the Italian subset of PIAAC, the dataset is provided with 80 resampling weights (and a final aggregate one) computed in a 4 stages:

1. Compute the base weights considering the probability of selection;
2. Adjust for nonresponse;
3. Minimal trimming of extreme weights;
4. Adjust to known population total[26].

The weights are then used to simulate multiple samples and guarantee more precise confidence intervals and significance tests, limiting the impact of various kinds of

[26] In total 15 variables were used in the weight adjustment procedures, including age, gender, region, employment status, presence of children at home and so on. For more information see "PIAAC Sample Design, Weights, Variance, and Missing Data" and "Program for the International Assessment of Adult Competencies (PIAAC) 2012: U.S. Main Study Technical Report".

sampling errors. Their usage in the computations is not trivial, so the function REPEST was made available in STATA to handle them with ease.

Two additional remarks need to be made on the Italian subset of PIAAC data: firstly, it does not include information on problem solving in technology-rich environments, whose evaluation, unlike the other skills, was optional. Secondly, it has one extra variable, which is simply the statistical macro-region to which the individual belongs to (North-West, North-East, Center, South or Islands). This variable has been extremely useful, however, for the purpose of the current research, we decided to aggregate the macro-regions: in particular we joined North-West and North-Est ("North") and South and Islands ("South" for convenience, but a more appropriate name would have been "Mezzogiorno").

Figure 8 - Italy divided in its statistical macro-regions

3.3 Model choice

The Italian subsample of PIAAC (2012) contains 4,621 observations before applying constraints. With the aim of obtaining a homogeneous sample with strong labour force commitment, we apply two constraints to the dataset:

- Work full time (at least 30h per week) ;
- Exclude self-employed workers.

In imposing these, we followed the example of (Hanushek, Schwerdt, Wiederhold, & Woessmann, 2013), however, we decided to drop a third constraint limiting the age of the respondents to the range comprised between 35 and 54 years of age. They imposed it because they wanted to focus on prime age workers, but we are interested in a complete picture of the Italian situation. Moreover, this choice has two positive implications: we retain a higher numerosity in the data-sample and the quadratic term in experience is significant (limiting the data to a narrow age range makes the concavity of the earnings function harder to detect).

Ultimately, the numerosity of the sample went down from 4,621 to 1,584 observations, but this number will only decrease in subsequent regressions, creating also some issue. In Table 9 we present the descriptive statistics of the variables we will use in all the subsequent regressions (in order or appearance); they will be

Table 9 - Descriptive statistics of Italian PIAAC data (2012)

*For each variable we report mean and standard deviation (in brackets); the results are obtained in STATA through the command piaacdes, which takes into account sample weights and plausible values. The statistics are categorized according to the different regressions (with different constraints) the reader will go through. Different categories may correspond to different numbers of observations in the data sample. * : NW=1,584, N=785, C=330, S=469. ** : NW=1,580, N=782, C=329, S=469. *** : NW=1,123, N=553, C=252, S=318. **** : NW=1,577, N=779, C=330,S=468. ***** : NW=1,862, N=903, C=385, S=574.*

	Nationwide	**North**	**Center**	**South**
Basic variables				
Hourly earnings *(€)* *	11.40	11.80	11.75	10.25
	(6.91)	*(6.31)*	*(6.91)*	*(7.95)*
Log hourly earnings*	2.32	2.37	2.36	2.18
	(0.46)	*(0.44)*	*(0.43)*	*(0.50)*
Years of schooling* *(years)*	11.39	11.25	11.85	11.29
	(3.71)	*(3.66)*	*(3.76)*	*(3.75)*
Experience* *(years)*	18.37	19.05	19.06	16.29
	(10.52)	*(10.07)*	*(10.82)*	*(10.93)*
Experience^2/1000*	0.45	0.46	0.48	0.38
	(0.43)	*(0.43)*	*(0.47)*	*(0.42)*
PC Foreign*	0.03	0.17	-0.13	-0.13
	(0.82)	*(0.96)*	*(0.59)*	*(0.56)*
Female* *(share)*	0.37	0.38	0.39	0.32
	(0.48)	*(0.49)*	*(0.49)*	*(0.46)*
North* *(share)*	0.53	-	-	-
	(0.50)			
Center* *(share)*	0.22	-	-	-
	(0.41)			
South* *(share)*	0.25	-	-	-
	(0.43)			
Measures of cognitive ability				
Numeracy*	257.03	259.39	268.69	241.65
	(49.75)	*(50.87)*	*(45.45)*	*(47.13)*
Literacy*	255.17	256.94	263.77	243.80
	(45.48)	*(46.89)*	*(42.04)*	*(42.96)*
Self-reported measures of non-cognitive ability				
Cultural engagement**	1.42	1.47	1.41	1.34
	(0.94)	*(0.99)*	*(0.88)*	*(0.90)*
Political efficacy**	2.11	2.10	2.16	2.11
	(1.27)	*(1.25)*	*(1.24)*	*(1.33)*
Social trust (1)**	1.93	1.96	2.01	1.77
	(1.02)	*(1.02)*	*(1.02)*	*(1.02)*
Social trust (2)**	1.91	1.95	2.02	1.73
	(0.97)	*(0.95)*	*(0.97)*	*(0.98)*

Table 9 (continue) - Descriptive statistics of Italian PIAAC data (2012)
*For each variable we report mean and standard deviation (in brackets); the results are obtained in STATA through the command piaacdes, which takes into account sample weights and plausible values. The statistics are categorized according to the different regressions (with different constraints) the reader will go through. Different categories may correspond to different numbers of observations in the data sample. * : NW=1,584, N=785, C=330, S=469. ** : NW=1,580, N=782, C=329, S=469. *** : NW=1,123, N=553, C=252, S=318. **** : NW=1,577, N=779, C=330,S=468. ***** : NW=1,862, N=903, C=385, S=574.*

	Nationwide	**North**	**Center**	**South**
Non-self-reported measures of non-cognitive ability (main test)				
Time per test item*** *(s)*	56.61	58.73	55.98	51.68
	(22.53)	*(21.10)*	*(25.81)*	*(21.24)*
Time per correct test item*** *(s)*	53.52	56.09	51.84	49.63
	(21.33)	*(21.01)*	*(20.22)*	*(22.31)*
Skipped*** *(share)*	0.07	0.07	0.06	0.10
	(0.10)	*(0.10)*	*(0.09)*	*(0.11)*
Not attempted*** *(share)*	0.03	0.03	0.03	0.03
	(0.08)	*(0.08)*	*(0.09)*	*(0.07)*
Actions per test item***	2.55	2.62	2.60	2.32
	(1.07)	*(1.14)*	*(0.97)*	*(0.95)*
Actions per correct test item***	2.53	2.57	2.52	2.43
	(0.98)	*(1.07)*	*(0.86)*	*(0.88)*
Non-self-reported measures of non-cognitive ability (background questionnaire)				
Don't know* *(share)*	0.0007	0.0007	0.0004	0.0010
	(0.0025)	*(0.0027)*	*(0.0017)*	*(0.0028)*
Refused to answer* *(share)*	0.0006	0.0008	0.0002	0.0008
	(0.0026)	*(0.0026)*	*(0.0011)*	*(0.0034)*
Instrumental variables				
Parental education****	0.30	0.33	0.33	0.21
	(0.54)	*(0.56)*	*(0.56)*	*(0.47)*
Dummies for levels of education				
Middle school** *(share)*	0.96	0.97	0.97	0.94
	(0.19)	*(0.17)*	*(0.17)*	*(0.24)*
High school** *(share)*	0.61	0.60	0.66	0.58
	(0.49)	*(0.49)*	*(0.47)*	*(0.49)*
University** *(share)*	0.16	0.16	0.18	0.15
	(0.37)	*(0.36)*	*(0.39)*	*(0.35)*
Dummies for sectors				
Private**** *(share)*	0.74	0.85	0.72	0.71
	(0.44)	*(0.36)*	*(0.45)*	*(0.45)*
Public**** *(share)*	0.25	0.15	0.28	0.28
	(0.43)	*(0.35)*	*(0.45)*	*(0.45)*
Dummies for work situation				
Full time***** *(share)*	0.84	0.84	0.83	0.83
	(0.37)	*(0.36)*	*(0.38)*	*(0.37)*
Part time***** *(share)*	0.16	0.16	0.17	0.17
	(0.37)	*(0.36)*	*(0.38)*	*(0.37)*

explained in full in the relative section. Looking at these numbers, however, we can certainly say that the three macro-regions are more similar than different, and, when significant differences are indeed present, they are focused in Northern or Southern Italy. In particular:

- Hourly earnings are higher in North (11.80€) and Center (11.75€) and lower in the South (10.25€);
- The average number of years at school is higher in the Center (11.85) compared to North (11.25) and South (11.29);
- The average number of years of experience is significantly higher in Northern (19.05) and Central Italy (19.6) compared to the South (16.29);
- First generation immigrants (immigrants either born abroad or born in the country but child of immigrants) are more concentrated in Northern Italy, as expressed by the variable *PC Foreign* (which will be explained more in depth in the following section);
- Cognitive abilities as measured by PIAAC (Numeracy and Literacy), are higher on average for Northern (259.39) and Central Italy (268.69), and lower in the South (241.65);
- Parental education and average level of education are lower in the South (especially parental education);
- More people work in the private sector in the North (85%) compared to Center and South (72% and 71% respectively).

Finally, looking broadly at our dataset we can observe that our sample is composed for a great part by full-time workers operating in the private sector and that more than 50% of observations declared to have, at least, a high school educational level.

3.3.1 The experience-augmented Mincerian equation

In this first regression we have inserted only the very basic variables: schooling (*yoe*, years of education) and linear and quadratic terms in experience (*exp* and exp^2). We then control for immigration status (*Foreign*), gender (*Female*) and Italian macro-region (*Center*, *South*). The complete formulation of the model is:

$$\ln Earnhr = \beta_0 + \beta_1 \cdot yoe + \beta_2 \cdot exp + \beta_3 \cdot exp^2 + \beta_4 \cdot Foreign + \beta_5 \cdot Female + \beta_6 \cdot Center + \beta_7 \cdot South \tag{48}$$

The control variable for immigration status (*Foreign*) in particular is not trivial; it is obtained through Polychoric Principal Component Analysis[27] from two dummy variables that indicate the two characteristics which participate in classifying an individual as first generation immigrant:

- *Foreign born*, if the individual was born abroad;
- *Parent foreign born*, if at least one parent of the individual was born abroad.

Our preference, obviously, was to keep both these characteristics independently, but unfortunately the high level of correlation (0.83) caused them to perform badly at macro-regional level (where the number of observations decreases). Moreover, this solution proved to be superior also to the alternative of using a single dummy for first generation immigrant status (born abroad or born in the country but parents were born abroad), we think because it is able to capture the worsening of the individual's situation when both conditions are present. In any case, the results of the Polychoric PCA are reported in Table 10, and, as you can see, by maintaining only the first component we are still able capture a staggering 97.24% of total variability. Furthermore, the estimates are consistently statistically significant, so we can definitely be satisfied with this solution.

Table 10 - Principal Component Analysis (PCA) on Foreign born and Parent foreign born

Component	Eigenvalue	%var	Σ%var
1st component	1.959	97.95%	97.95%
2nd component	0.0410	2.05%	100.00%

	1st component	2nd component
Foreign born		
0	-0.1411	-0.1411
1	1.2302	1.2302
Parent foreign born		
0	-0.1411	0.1411
1	1.2302	-1.2302

[27] A type of Principal Component Analysis that account for variables' discreetness. The "traditional" is not optimal when working with dummy variables.

Now we can finally dive into the first set of regressions. We expect results aligned with those reported in Table 4 (*page 36*) in the OLS column, although returns to schooling should be lower due to the passing of time. This behaviour is due to a well-known phenomenon that has been extensively discussed in the academic literature and it is simply known as "declining returns to education[28]", which is a fancy name for the macroeconomic concept of shifting equilibrium between supply and demand in the market of educated workforce. The idea, in fact, is that the potential earnings and lifestyle of higher levels of education (as well as governmental regulations) draw more individuals towards schooling, increasing the supply of educated labourers and generating a downward pressure on their wages. Now, there are certainly economic sectors and niches in which these macroeconomic forces do not operate like this, and the scarcity of qualified workforce is actually driving wages up, but looking at the economy overall this is certainly true. You can observe this also in Table 4 (again) by looking at returns to education estimated by Angrist and Krueger on consecutive editions of the US Census: the coefficient goes progressively down the more we get close to our days (0.701 > 0.632 > 0.520).

Regarding the elements of the model other than years of education, we expect all of them to be significant, with the quadratic term in experience and the dummy control variables having negative coefficients.

Fortunately, as you can see in Table 10, our expectations for this set of regressions were fulfilled. In particular we want to point out that:

1. All the variables introduced are highly significant both at nationwide and macro-regional level;
2. The overall predictive power of the model is good and aligned with previous results on the topic, although the adjusted R^2 varies significantly among the macro-regions, with a value that is significantly higher for Central Italy (37.34%) compared to North (21.53%) and South (22.95%). This behaviour is surely favoured by the fact that the numerosity of the Central subsample is the lowest among the three, but it also suggests that there are differences among macro-regions not only in the entity of the returns, but also regarding

[28] For further information see (Psacharopoulos & Patrinos, 2004).

Table 10 – Experience-augmented Mincerian model

	Nationwide	North	Center	South
Years of schooling	0.049***	0.046***	0.059***	0.047***
	(0.003)	*(0.005)*	*(0.000)*	*(0.007)*
Experience	0.031***	0.027***	0.030***	0.040***
	(0.003)	*(0.004)*	*(0.000)*	*(0.008)*
$Experience^2/1000$	-0.384***	-0.291***	-0.333***	-0.676***
	(0.071)	*(0.087)*	*(0.003)*	*(0.192)*
PC Foreign	-0.066***	-0.053***	-0.137***	-0.078***
	(0.009)	*(0.012)*	*(0.001)*	*(0.020)*
Female	-0.141***	-0.144***	-0.176***	-0.090*
	(0.016)	*(0.016)*	*(0.001)*	*(0.055)*
Center	-0.055***	-	-	-
	(0.012)			
South	-0.164***	-	-	-
	(0.030)			
Adj R^2	**26.99%**	**21.53%**	**37.34%**	**22.95%**
No. of observations	*1584*	*785*	*330*	*469*

*Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Sample: Employees working at least 30 hours per week. All the explanatory variables are treated as exogenous. *: p-value<=0.10, **: p-value<=0.05, ***: p-value<=0.01.*

the structure of the Human Capital Theory model; now it will be interesting to see if these differences increase or diminish when introducing new variables;

3. The returns to schooling are equal to 4.9% at nationwide level (N=4.6%, C=5.9%, S=4.7%) and they seem to be lower compared to previous results, precisely falling in line with what said before regarding declining returns to education. One could also argue that returns in Northern Italy are lower for the same reason, since the labour market is more competitive, but then why are they so high in Central Italy? We will keep a close look at how the numbers shift in the following models. The results are almost aligned with previous Italian works. One of the most recent research on the topic has been provided by (Fiaschi & Gabbriellini, 2013) that, adopting a similar model, the OLS methodology, and a different dataset (The Survey on Household Income and Wealth issued by Bank of Italy), estimated returns to education that range from 5.1% (1995) to 4.1% (2010) at nationwide level.

4. An additional year of experience is more profitable in Southern Italy, where it grants an increase in earnings of 4.0% (N=2.7%, C=3.0%). This behaviour is

followed also by the quadratic term in experience, which depicts the concavity of earnings profiles over the working life, and its coefficient in the regression for South is more than double those of the other macro-regions;

5. The control variable for immigration is always significant but the coefficient doubles up in Central Italy (NW=-6.6%, N=-5.3%, C=-13.7%, S=-7.8%). These unforeseen results are even more interesting if you consider the data shown in Figure 9: The pie chart shown at top indicates the percentage of individuals born in poor countries, among those born abroad, while the histogram at the bottom describe the number and percentage of individuals born abroad and who have a parent who was born abroad (orange), and those who only have one of those two characteristics (light orange). As you can see, Central Italy holds both the highest percentage of "rich" immigrants and the highest differential in returns, while we would have expected the opposite! Having considered this, we now believe this difference simply to be due to the lower number of immigrants present in the Center (25) compared

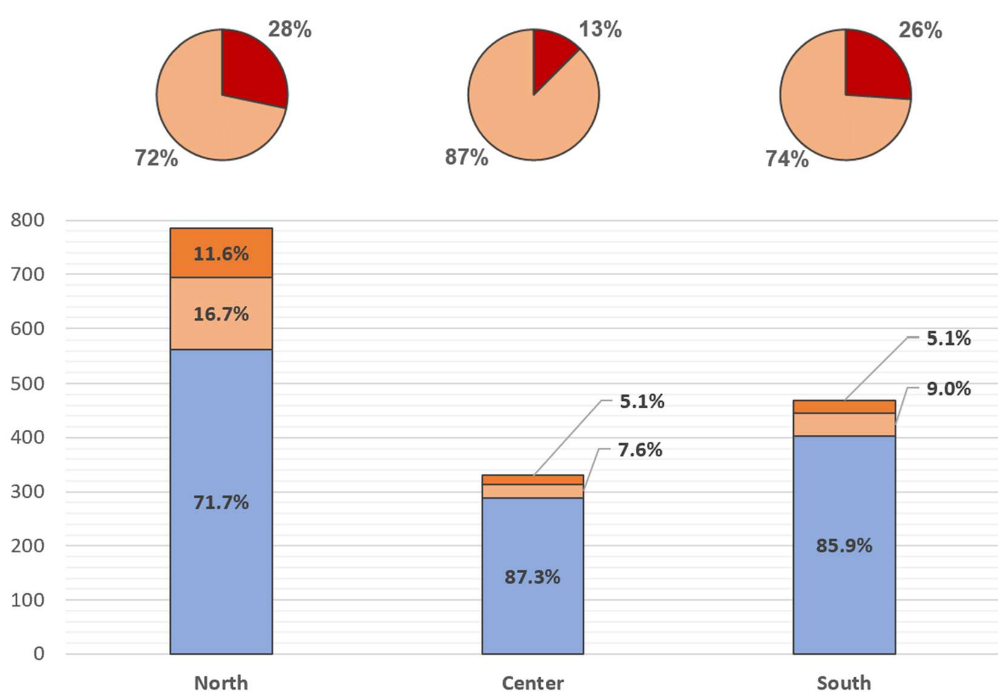


Figure 9 - Focus on the component for immigration
The pie charts at the top shows the percentage of individuals born in poor countries (red) among those respondents who were born in a foreign country. The graph at the bottom provide information on the number of individuals who were either born in a foreign country or have a parent who was born in a foreign country (light orange) or have both these characteristics (dark orange). Results are divided by macro-regions.

to the North (131) and South (42) (the alternative is for it to be a structural characteristic of Central Italy).

On a final note, we want to remind that *pc Foreign* was obtained through polychoric PCA, so it is not a dummy variable and we cannot simply interpret the coefficient as a percentage shift in earnings, however, we can compute said shift by difference. In this case at nationwide level we find out that, if either an individual or his parents were born in a foreign country, she will learn on average 9.1% less than an individual who was born in Italy into a native family with the same years of schooling, experience, gender and living in the same macro-region; and this number goes up to 17.2% if the individual fulfils both characteristics. In Central Italy, instead, these numbers increase again up to 18.8% and 35.6% respectively.

6. Going on, the dummy for gender is always relevant both at nationwide and at macro-regional level, however the coefficient is notably lower (~35%) in the South. This result is very interesting, and we will keep monitoring it in subsequent regressions, to see how it react to the adding of further elements to the model.

   It is important, however, not to confuse these data as evidence for the gender pay gap, which is an ever so important topic nowadays, and deserves appropriate analyses and evaluations. In particular, Blau and Khan (2017) showed how it does exist and it is significant, but you need to control many factors to obtain a correct estimate, such as women forced interruptions from work, hours worked, field and position of work, physical and psychological attributes and even non-cognitive skills (e.g. women on average are more agreeable then men, but less agreeable people make a career more easily!). In this context it is not our aim, nor we have the data, to control for so many factors and give a precise estimation of the gender pay gap, but including the dummy for gender permits us to account for all these differences in the model.

7. The regional dummies in the nationwide regression, as expected, show structurally higher wages in the North compared to Center (-5.6%) and South (-16.4%).’

8. Looking at nationwide level we checked for heteroskedasticity using Breusch-Pagan test and found no issues (H_0=Homoskedasticity, p-value=0.343). We actually fail the test if we use earnings as LHS variable, but it is known that logtransforming the data can solve (or at least reduce) heteroskedasticity.

Overall, the results were in line with what we expected.

3.3.2 Human capital model with cognitive abilities

As previously mentioned, the Italian subset of PIAAC contains measures of skills in two different domains, numeracy and literacy, however they cannot be used concurrently in a single regression model. This is due to the fact that, despite being constructed to measure different dimensions of the skill set of the respondents, their level of correlation is systematically high (0.83), so if used together we obtain not statistically significant (and overall worse) results. We decided to present the evidence obtained using numeracy (*num*), which is the better performing skill among the two (the results using literacy are available in Appendix B).

$$\ln Earnhr = \beta_0 + \beta_1 \cdot yoe + \beta_2 \cdot num + \beta_3 \cdot exp + \beta_4 \cdot exp^2 + \beta_5 \cdot Foreign + \beta_6 \cdot Female + \beta_7 \cdot Center + \beta_8 \cdot South \tag{49}$$

Both the skills are evaluated on a 500-point scale, but, following (Hanushek, Wiederhold, & Woessmann, 2015), we standardized them to have a zero mean and a standard deviation of one. The way in which they are introduced into the regression is also not trivial: they are given using plausible values, a method regularly used in large scale surveys obtain more precise results[29]. Due to this, some non-obvious computations need to be performed on the data, but fortunately the REPEST function present in STATA can handle them automatically.

We expect *Numeracy* to be positive and to improve the predictive power of the model, however this will be paid at the cost of a reduction in returns to schooling (due to the correlation present between *Numeracy* and *Years of schooling* (0.45)). Returns

[29] When measuring cognitive ability (i.e. unobservable continuous variable) through a collection of test scores data (i.e. discrete data) you commit an estimation error. The idea of plausible values is that, instead of computing the unobservable variable directly, you estimate its probability distribution and draw 10 plausible values from it, then the regression is computed 810 times (81 weights x 10 plausible values) and an average point estimate is displayed. For further information on the topic see (OECD, 2009) and (OECD, 2013).

to numeracy should also be lower in North and Center and higher in the South, where there is less competition in the labour market; moreover, the different means in the distributions of numeracy also push in this direction (N=259.39, C=268.69, S=241.65). Finally, we expect the coefficients of the control dummy variables to decrease as we add more and more variables to the model, but it will be interesting to see which of them change the most.

Looking at Table 11 and comparing the results to those in Table 10, we see that, again, the estimates more or less fall in line with what we expected, although there are some differences:

1. The predictive power of the model increased, although the shift had only a minor impact in terms of explained variability (adj. R^2 at nationwide level: 26.99% → 27.54%);
2. The returns to cognitive ability are positive and increase notably going from North to South (NW=4.1%, N=2.3%, C=4.2%, S=8.1%), but, surprisingly, they

Table 11 – Human Capital Model with cognitive abilities as explanatory variable

	Nationwide	**North**	**Center**	**South**
Years of schooling	0.044***	0.043***	0.054***	0.039***
	(0.003)	*(0.005)*	*(0.002)*	*(0.006)*
Numeracy	0.041***	0.023	0.042***	0.081***
	(0.014)	*(0.020)*	*(0.014)*	*(0.024)*
Experience	0.029***	0.026***	0.029***	0.036***
	(0.003)	*(0.004)*	*(0.001)*	*(0.008)*
Experience^2/1000	-0.357***	-0.279***	-0.315***	-0.578***
	(0.072)	*(0.091)*	*(0.013)*	*(0.191)*
PC Foreign	-0.059***	-0.050***	-0.128***	-0.072***
	(0.009)	*(0.013)*	*(0.003)*	*(0.020)*
Female	-0.133***	-0.140***	-0.162***	-0.080
	(0.016)	*(0.016)*	*(0.005)*	*(0.053)*
Center	-0.058***	-	-	-
	(0.012)			
South	-0.148***	-	-	-
	(0.029)			
Adj R^2	**27.54%**	**21.66%**	**37.81%**	**24.82%**
No. of observations	*1584*	*785*	*330*	*469*

Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. All the explanatory variables are treated as exogenous.
** : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

are not even significant in Northern Italy! We did not expect such a clear gap between the macro-regions, even if the behaviour is what we predicted.

3. Returns to education decreased by 10.8% at national level (%ΔN=-7.3%, %ΔC=-8.1%, %ΔS=-16.3%); this is expected and we the differences between these numbers are explained by the differences in returns to cognitive ability.
4. Returns to experience also decreased, even if slightly (%ΔNW=-3.9, %ΔN=-2.6%, %ΔC=-3.3%, %ΔS=-10.0%). We believe that this shift is due to the fact that, even if there is no significant correlation between *experience* and *numeracy*, there is correlation between *experience* and *year of schooling* (-0.31).
5. The coefficient of immigration status decreased by 10.3% at national level and more or less uniformly among the macro-regions (%ΔN=5.7%, %ΔC= 6.6%, %ΔS=7.7%). The coefficient of the gender dummy also reduced, but this time there are manifest regional differences (%ΔNW=-5.7%, %ΔN=-2.8%, %ΔC=-8.0%, %ΔS=-11.1%) and in the South the variables is not even statistically significant anymore. The macro-regional dummies used in the nationwide model also decreased slightly, but the difference is not statistically significant.
6. Still no issues with heteroskedasticity (Breusch-Pagan test, H_0=Homoskedasticity, p-value=0.571).

At this point, we must admit that we did expect cognitive abilities to have a bigger impact on the explanatory capability of the model and individuals' returns in general, instead they were even not statistically significant in Northern Italy. This behaviour was noticed at a European level also by (Hanushek, Schwerdt, Wiederhold, & Woessman, 2015), who pointed out how PIAAC scores seemed to be underperforming compared to the more traditional measures of cognitive ability (e.g. IQ).

3.3.3 Human capital model with cognitive and non-cognitive abilities

Unfortunately, the first cycle of data collection of PIAAC is not comprehensive of direct measures of non-cognitive skills (they will be included from the second cycle onwards, however). Nonetheless, as outlined in (Anghel & Balart, 2017), previous research tried to fill this gap by considering some self-reported and non-self-reported measures based on other questions and the behaviour of the respondent during the test itself.

Considering the first case, recent literature illustrated that the PIAAC background questionnaire includes four exploitable items in order to identify individuals' personality and beliefs. They are measured on a scale from 1 to 5 and they relate to three non-cognitive skill domains:

- *Cultural engagement*
  it examines individuals' frequency in doing voluntary work for a non-profit organisation (from never to every day);
- *Political efficacy*
  it examines individuals' level of self-esteem and/or personal effectiveness by looking at how much he thinks people like him should not have a say in what the government does (from strongly agree to strongly disagree);
- *Social trust*
  it examines individuals' level of optimism and trust in the society by asking if there are only people you can trust (from strongly disagree to strongly agree) and if others will take advantage of you if you are not careful (again, from strongly disagree to strongly agree).

Instead, considering non-self-reported measures, recent literature illustrated three main determinants of non-cognitive skills which are directly related to individuals' own personalities:

- *Missing responses in the background questionnaire*
  (Hedengren & Stratmann, 2012) were among the first who empirically demonstrated that individuals' average non-response rate is directly related to both cognitive ability (you don't know what to answer) and non-cognitive ability (you don't want or don't care to answer). However, as suggested also in (Anghel & Balart, 2017), filling a background questionnaire may be time-consuming but it certainly does not require any cognitive effort, and in fact the correlation between non-response rate and scores in numeracy (used as

proxy of cognitive ability) is very small (-0.05). So, we can consider the non-response rate in the PIAAC background questionnaire as a reliable measure of non-cognitive skills, and we can actually build two variables based on the two possible answer that are accepted as non-response: *don't know* and *refused to answer*. In the computation of these values we actually deviate from (Anghel & Balart, 2017); they simply consider the absolute value of such answers, while we compute the ratio with the total number of valid questions, which is not constant among the respondents.

- *Missing responses in the main test*
  (Borghans, Golsteyn, Heckman, & Humphries, 2011), (Duckworth & Kern, 2011) and (Segal, 2012) suggested that achievement tests result not only from individuals' level of cognitive skills, but they are also strongly influenced by non-cognitive skills (e.g. motivation and perseverance). Going on this route, (Hernández & Hershaff, 2014) proposed to assess the respondents' testing behaviour and use it as a proxy for non-cognitive abilities. In particular, they asserted that a good method to do so in a test with no penalty and no time constraints (such as PIAAC), would be to consider skipped questions, since they could be directly related to individuals' low interest in performing well in the test. Also, in this case non-responses can be coded in two different ways, but this time they are defined as *skipped* (if the question was left on the screen for more than 5s) and *not attempted* (vice versa). Again, they are computed as ratio between the number of such items and the total number of valid questions (which may vary between respondents).

- *Time spent and number of actions per item*
  (Anghel & Balart, 2017), always considering a test with no penalties and no time limit, also suggested that time spent and number of actions (clicks) performed before providing a response could be revealing of individuals' non-cognitive ability. In particular, for what concerns the time spent responding the authors asserted that it could be that higher motivated individuals spent more time in providing a response or, vice versa, a longer time could be the consequence of a lack of ability to stay focused. The number of actions performed before responding, instead, could be revealing of low self-confidence or and a lack of ability to decide. For the purpose of our analysis,

we considered not only the average time per test item and the average number of actions per test item, but also the time needed for correct answers and the number of actions needed for correct answers. Unfortunately, the computation of these variables requires the exam to be carried out in its computer-based form, so paper-based scores needed to be dropped and in doing so we lost 30% of the remaining observations (1584 → 1123).

In general, we expect non-cognitive abilities to improve the explanatory capability and to cause a reduction in returns to schooling and cognitive ability (the sign of the coefficient may be positive or negative, depending on the specific variable).

In search of the optimal solution, we examined and compared various models containing the variables described above; we will briefly discuss them here and report for each of them the value of adj. R^2 (the complete regressions are available in Appendix C):

1. *Model containing all the self-reported measures*
   Cultural engagement and the first measure of social trust are consistently not significant; the introduction of these measures decreased the significance of numeracy. The adj. R^2 is 28.44% at nationwide level.

2. *Model containing just political efficacy and the second measure of social trust*
   This is the model we opted for, although the newly introduced measures are still not significant for all the macro-regions and there are important differences in the estimates between them. The adj. R^2 is 28.49% at nationwide level.

3. *Model containing the measures derived from the background questionnaire*
   Although they are mostly statistically significant, the estimates are certainly not consistent, with huge changes in value and even in sign. The adj. R^2 is 27.91% at nationwide level.

4. *Models containing the measures derived from the main test*
   We had to split this case into two due to the existing collinearity between some of the variables (especially *skipped*); in the first model we introduced only *time per test item*, *time per correct test item*, *actions per test item* and *actions per correct test item*, while in the second model we introduced the

remaining *skipped* and *not attempted*. The estimates are neither highly significant nor consistent, with multiple changes also in the sign. The adj. R^2 are respectively 32.62% and 32.58% at nationwide level, but this value is not comparable with the others due to the change in the number of observations; when constraining the estimation to the same sample the adj. R^2 of the second model increases to 33.07%.

5. *Model obtained using PCA on self-reported and non-self-reported measures*
   We apply PCA to the twelve variables described above and retain the first six principal components, containing more than 75% of the total variability (it is impossible to include more in the model due to collinearity issues). The results are not satisfying and most of the introduced variables are not significant. The adj. R^2 is 32.96% at nationwide level, but, like the previous model, cannot be directly compared.

In Table 12 we report the estimates for the second model, which has shown to be the most consistent and better performing one. As non-cognitive ability measures it includes only *political efficacy* (*pe*) and the second measure of *social trust* (*st*).

$$\ln Earnhr = \beta_0 + \beta_1 \cdot yoe + \beta_2 \cdot num + \beta_3 \cdot exp + \beta_4 \cdot exp^2 + \beta_5 \cdot pe + \beta_6 \cdot st + \beta_7 \cdot Foreign + \beta_8 \cdot Female + \beta_9 \cdot Center + \beta_{10} \cdot South \tag{50}$$

The results are close to what we expected:

1. The explanatory capability of the model increases even so slightly (adj. R^2 at nationwide level: 27.72%[30] → 28.49%), but the shift is higher than the one observed with the introduction of cognitive abilities, which is interesting.

2. Returns to non-cognitive abilities are positive and consistent, and the estimated coefficients are coherent with the respective non-cognitive ability. In particular, *political efficacy* (NW=1.6%, N=1.9%, C=1.4%, S=1.6%) measures the level of self-esteem of the individual and *social trust* (NW=3.6%, N=2.6%, C=3.3%, S=4.9%) measures his disingenuousness; we

[30] Value adjusted considering the lower number of observations in the second model, in order to ensure comparability.

Table 12 - Human Capital Model with cognitive and non-cognitive abilities

	Nationwide	**North**	**Center**	**South**
Years of schooling	0.041***	0.040***	0.052***	0.036***
	(0.003)	*(0.006)*	*(0.002)*	*(0.007)*
Numeracy	0.037***	0.021	0.038***	0.073***
	(0.014)	*(0.020)*	*(0.014)*	*(0.025)*
Experience	0.030***	0.027***	0.030***	0.036***
	(0.003)	*(0.004)*	*(0.001)*	*(0.008)*
Experience^2/1000	-0.374***	-0.293***	-0.355***	-0.579***
	(0.074)	*(0.091)*	*(0.013)*	*(0.193)*
Political efficacy	0.016***	0.019**	0.014***	0.016
	(0.005)	*(0.008)*	*(0.001)*	*(0.013)*
Social trust	0.036***	0.026**	0.033***	0.049***
	(0.008)	*(0.013)*	*(0.001)*	*(0.017)*
PC Foreign	-0.060***	-0.049***	-0.138***	-0.069***
	(0.009)	*(0.013)*	*(0.003)*	*(0.020)*
Female	-0.127***	-0.134***	-0.163***	-0.069
	(0.016)	*(0.016)*	*(0.005)*	*(0.054)*
Center	-0.061***	-	-	-
	(0.012)			
South	-0.141***	-	-	-
	(0.029)			
Adj R^2	**28.49%**	**22.21%**	**39.73%**	**25.73%**
No. of observations	*1580*	*782*	*329*	*469*

*Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. All the explanatory variables are treated as exogenous. * : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

believe that both these qualities should indeed be positively correlated to earnings.

3. Returns to schooling decreased slightly a national and macro-regional level as expected; the reason is, like before, the existing correlation between *years of schooling* and *political efficacy* (0.19) and *years of schooling* and *social trust* (0.22). In any case, the differences are not statistically significant.
4. The same can be said for returns to cognitive ability.
5. Returns to experience are stable, without any substantial change even at macro-regional level.
6. The coefficient for immigration status did not shift significantly also, with the exception of Central Italy in which it decreased by 7.8% (remember that it was

abnormally high in that macro-region). The impact of gender instead decreased at nationwide level (-4.5%) and especially in the South (-14.0%), where the coefficient was already low and now is more or less half than the other macro-regions. The dummy variables for macro-region at national level did not show any significant change.

7. Still no issues of heteroskedasticity (Breusch-Pagan test, H_0=Homoskedasticity, p-value=0.664).

In general, the results of this regression were aligned with previous results and our expectations, so we can be satisfied, although we hoped to have a more significant increase in the explaining capability of the model after introducing non-cognitive abilities. Regarding this point, however, there are other considerations to be made. First, as you can see in Table 13, neither the R^2 adj. nor its increments are homogeneous across the macro-regions. The model performed worst in the North, with +1.50% of total increase and 22.21% being the final value; in Central Italy instead it increased by 2.39%, with 39.73% being the final value; lastly, in Southern Italy it increased by 2.78%, with 25.73% being the final value. We certainly expected a better performance in the North and a higher increase, especially considering the fact that its value of R^2 was the lowest at the start; however, we have to consider that the numerosity of its data sample is the largest and its overall performance are not too far from the South (which is the macro-region in which the performance of the model increased the most). It is still Central Italy that seems to be on a different level, even after the including of cognitive and non-cognitive abilities in the model; moreover, the standard deviation of the estimated coefficients is always the lowest, usually by more than one order of magnitude. Mostly, this behaviour is due to the lowest numerosity of

Table 13 – changes in adj. R^2 among macro-regions and across the different models

	Exp-aug		Cognitive		Non-cognitive
Nationwide	26.99%	+ 0.55%	27.54%	+ 0.95%	28.49%
North	21.53%	+ 0.13%	21.66%	+ 0.55%	22.21%
Center	37.34%	+ 0.47%	37.81%	+ 1.92%	39.73%
South	22.95%	+ 1.87%	24.82%	+ 0.91%	25.73%

the data-sample, but at this point the idea that some omitted variables affect North and South more is gaining more weight.

3.3.4 Human capital model with cognitive abilities, non-cognitive abilities and instrumental variables

After having fully exhausted the ability route delineated by (Griliches, 1977) with the variables at our disposal, we are aware that we may have tackled the issue of the endogeneity of schooling, but we were not able to fully solve it (as confirmed later in this chapter by Wu-Hausman's test for endogeneity). In this section we want to go at it from another direction and use instrumental variables, and in doing so we expect to obtain significantly higher returns to education, in line with the results reported in the relative column of Table 4, that range from 6.0% to 13.2%; however, our numbers should be slightly lower due to the "decreasing returns to schooling" phenomenon[31]. In any case, the notion that OLS is downward biased when dealing with education is affirmed in the academic literature of the topic[32].

To choose our candidates for instrumental variables we examined carefully our dataset to select the most promising variables and we considered all the categories previously described: quarter of birth, college proximity, health and family background. Unfortunately, we had no information regarding either quarter of birth and collage proximity, and only one question was asked about the state of health of the individual, but it was tested without success; we had many promising candidates instead regarding family background, such as number of children, people living in the household, parental education, spouse education, working situation of spouse and parents, but unfortunately they were all also tested to no avail except parental education. When computing the model, however, we noticed that cognitive abilities became non-significant in the second stage, while remaining very significant in the first one, so we decided to test them as instrumental variable and, to our surprise, they passed it with wide margin.

We do not believe that in normal conditions cognitive abilities would not be usable as instruments, but the specific characteristics of numeracy may be the cause of this.

[31] This topic has been discussed in section 3.3.1. See (Psacharopoulos & Patrinos, 2004) for further information.

[32] See (Blackburn & Neumark, 1995) for further information.

The idea is that it may be closer to those facets of cognitive abilities that are more useful at school and make the individual a good learner. This theory is also supported by the fact that PIAAC numeracy (and literacy) scores have shown to perform worse than more traditional measures of cognitive ability (e.g. IQ), as noted by (Hanushek, Schwerdt, Wiederhold, & Woessmann, 2015).

Concurrently to this, following (Griliches, 1977) and (Blackburn & Neumark, 1993), we also decided to tackle the issue of experience being endogenous, and we did so by looking at possible instruments for its linear and quadratic terms. At first, we considered variables related to family, but after some experimentation, we concluded that these kinds of variables present in PIAAC's dataset do not perform well in this situation; the only "slight" exception is *Parental Education*, which already is in our set of instruments. Then, by looking at the previous literature on this topic, we observed that one of the most used variables to proxy the experience term is the age term; most of the authors used the latter one as additional covariate instead of adopting experience (especially whenever information on individuals' experience is not available). However, we noticed that age term is both strongly correlated with our experience measure (0.82) and it could impact earnings only through experience. For this reason, we decided to use it as instrument. Finally, focusing on the quadratic term in experience, we looked for specific instrumental variables among the squares of the instrumental variables used for the linear term and their cross products, but only age squared proved to be significative.

The resulting model (2SLS), without taking into account immigration and the dummies for gender and macro-region, is:

$$\begin{aligned}\ln Earnhr = \beta_0 + \beta_1 \cdot yoe + \beta_2 \cdot exp + \beta_3 \cdot exp^2 + \beta_4 \cdot st + \beta_5 \cdot Foreign \\ + \beta_6 \cdot Female + \beta_7 \cdot Center + \beta_8 \cdot South\end{aligned} \tag{51}$$

$$\begin{aligned}yoe = \alpha_{11} \cdot num + \alpha_{12} \cdot ped + \alpha_{13} \cdot age + \alpha_{14} \cdot age^2 + \alpha_{15} \cdot Foreign \\ + \alpha_{16} \cdot Female + \alpha_{17} \cdot Center + \alpha_{18} \cdot South\end{aligned} \tag{52}$$

$$\begin{aligned}exp = \alpha_{21} \cdot num + \alpha_{22} \cdot par + \alpha_{23} \cdot age + \alpha_{24} \cdot age^2 + \alpha_{25} \cdot Foreign \\ + \alpha_{26} \cdot Female + \alpha_{27} \cdot Center + \alpha_{28} \cdot South\end{aligned} \tag{53}$$

$$exp^2 = \alpha_{31} \cdot num + \alpha_{32} \cdot par + \alpha_{33} \cdot age + \alpha_{34} \cdot age^2 + \alpha_{35} \cdot Foreign + \alpha_{36} \cdot Female + \alpha_{37} \cdot Center + \alpha_{38} \cdot South \tag{54}$$

Note that we removed *Political efficacy*, since it does not seem to have an impact on earnings anymore after the changes done to the model. We report the results in Table 14; for the sake of brevity, we do not include the estimates of the first stage, but they are available in full in Appendix D.

Table 14 – Human Capital Model (2SLS) with cognitive abilities, non-cognitive abilities and instrumental variables

	Nationwide	**North**	**Center**	**South**
Years of schooling	0.071***	0.058***	0.087***	0.089***
	(0.006)	*(0.008)*	*(0.005)*	*(0.015)*
Experience	0.043***	0.036***	0.040***	0.060***
	(0.006)	*(0.005)*	*(0.001)*	*(0.019)*
Experience^2/1000	-0.606***	-0.451***	-0.481***	-1.088**
	(0.143)	*(0.129)*	*(0.014)*	*(0.468)*
Social trust	0.026***	0.025**	0.016***	0.025
	(0.008)	*(0.011)*	*(0.004)*	*(0.021)*
PC Foreign	-0.053***	-0.045***	-0.122***	-0.069***
	(0.010)	*(0.012)*	*(0.001)*	*(0.024)*
Female	-0.161***	-0.155***	-0.212***	-0.130
	(0.021)	*(0.019)*	*(0.008)*	*(0.083)*
Center	-0.062***	-	-	-
	(0.014)			
South	-0.141***	-	-	-
	(0.029)			
Wu-Hausman F	**19.20**	**4.62**	**5.86**	**11.79**
p-value	0.000	0.003	0.001	0.000
Cragg-Donald Wald F	**134.50**	**91.68**	**25.59**	**24.64**
Sargan χ^2	**0.26**	**0.40**	**0.40**	**0.08**
p-value	0.609	0.526	0.527	0.779
No. of observations	*1577*	*779*	*330*	*468*

*Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. Schooling is endogenous and instrumented by numeracy and parental education. Experience and Experience^2 are endogenous and instrumented by Age and Age^2 respectively. All other explanatory variables are exogenous. * : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

There are significant differences from the previous estimates:

1. As expected, returns to schooling show a major increase both at nationwide level and macro-regional level (NW=4.1%→7.1%, N=4.0%→5.8%, C=5.2%→8.7%, S=3.6%→8.9%), with an average increase of 73% and a peak of 147% in the South. Now returns to education seems are significantly higher and close in value in Central and Southern Italy, while they lag behind

in Northern Italy. A similar conclusion has also been outlined by Lucifora (1999) adopting different IVs and a different data-set (SHIW).

2. Returns to experience increased both at Nationwide and macroregional level (NW=3.0%→4.3%, N=2.7%→3.6%, C=3.0%→4.0%, S=3.6%→6.0%), with an average growth of 43% and South Italy showing the highest numbers (+67%). The same can be said for the quadratic term, which increased by 62% in absolute value on average. So overall, South Italy shows the highest returns to experience (more or less 1.5 the return of Center and North), but also highest decay of it, as you can see looking at the quadratic term in experience.

3. The impact of social trust, last remaining measure of non-cognitive ability in the model, decreased in Central and Southern Italy, where it also lost statistical significance, but it remained constant in the North (NW=3.6%→2.6%, N=2.6%→2.5%, C=3.3%→1.6%, S=4.9%→2.5%).

4. The coefficient of the component for immigration decreased sensibly only in the Northern subsample, but even there the shift is still not statistically significant. Overall, this variable has been consistently significant in all regressions and macro-regions, but its effect seems to be higher in the Center (-31.7%[33]) compared to the North (-11.7%) and the South (-18.0%).

5. The dummy variable for gender, instead, was majorly affected by the passage from OLS to 2SLS and its coefficient notably increased for all macro-regions (NW=-12.7%→-16.1%, N=-13.4%→15.5%, C=-16.3%→→21.2%, S=-6.9%→-13.0%). In all the regressions we computed, this component has always been relevant at nationwide level, North and Center, while it was weakly significant or not significant at all in the South. We have to note, however, that the standard deviation of the variable in the South is notably higher than the other macro-regions (four times the one for North and more than ten times the one for Center); this suggest that, while on average the difference in wages between men and women is lower in the South, this

[33] This number considers the average differential between an individual who was born in a foreign country and whose parents were born in a foreign country, compared to an individual who was born in Italy into a native family with the same years of schooling, experience, numeracy score, gender, macro-region and parental education.

number spikes up more often than in the North and the South, but at the same time it also becomes non-significant as often.

6. The results for the macroregional dummies fall perfectly in line with the previous results.
7. Still no issues of heteroskedasticity (We used Pagan-Hall general test statistic, H_0=Homoskedasticity, p-value=0.436).

We can be satisfied with these results, especially since the postestimation tests returned no issues. In particular, we used Wu-Hausman's F test to check for endogeneity (H_0 = the variables are exogenous), Cragg-Donald's F statistic to check for weak instruments (we cannot use Stock-Yogo's critical values because we need one more instrument, so we use Staiger and Stock's rule of thumb and reject weakness if the value of the statistic is higher than 10[34]) and Sargan's χ^2 test to check for overidentification (H_0 = the variables are valid).

Overall, these results fall within the range of our expectations, with increased returns to education and experience. We did not forecast such an increase in the dummy for gender, but it is the consequence of accounting for endogeneity in the model, and we can be certain that it is closer to the actual value.

We have arrived at the definitive formulation of the human capital model that we wanted to put together in this thesis, so we believe it is time for some general considerations:

- The Human Capital Model applied to Italy generates returns to education that are in line with those present in the academic literature on the topic, with no major change in the OLS model after the introduction of cognitive and non-cognitive abilities;
- We find evidence that suggest the presence of structural differences among the macro-regions, in particular:
  - Returns to education are lower in Northern Italy by approximately one third. Following (Psacharopoulos, G., & Patrinos, H. A. 2018), we

[34] This rule of thumb has sparked some critics because, when the number of endogenous variables and instruments go up, it is not reliable anymore. If the number of instruments is low, it guarantees a maximum TLSL size distortion of less than 10/20%.

believe that this behaviour is due to the higher GRP of the Northern regions (only 1 out of the first 9 regions with the highest GRP pro-capita is not in Northern Italy[35]). We have to note, however, that these results might be biased by the fact that respondents may not have obtained their schooling in their macro-region of residence; in particular, if we assume that quality of schooling is higher in Northern Italy (as data seems to tell[36]) and the share of workers educated in the North is higher in the North rather than the South (and Center), this would generate a downward bias in the returns to schooling of Northern regions.

- Linear and quadratic returns to experience are higher in absolute value in the South, with estimates that are more or less double the one for North and Center. This trend may be caused by the difference in GRP (again) in conjunction with the different prevailing economic sectors of Southern regions (i.e. agri-food and tourism).
- Returns to non-cognitive abilities (i.e. *social trust*) are not significant in Southern Italy but the value of the coefficient is still aligned with the other macro-regions; returns in the North are slightly higher than in the Center but the difference is not statistically significant.
- Regarding the dummy variable for immigration, Northern Italy (which population-wise is the macro-region with the highest density of immigrants) seems to discriminate the least, while the opposite is true for Central Italy;
- As for the dummy variable for gender, we find an average decrease in earnings of 17.2% for females, with the highest being in Central Italy and the lowest in the South. We also have to note that the variable is almost not statistically significant in the South due to its standard deviation, which is notably higher than the other macro-regions.

- We find that the variable for cognitive ability (*numeracy*) can be used as instruments for education. We reiterate that this might be due to the fact that the variable is closer to those facets of cognitive ability that are more useful

[35] Data coming from "Regional GDP in the European Union, 2017" by Eurostat.
[36] See (Abramo, D'Angelo, & Rosati, 2016).

at school; this is also supported by the fact that it performs worse than the more traditional measures used in the HCM.

3.4 Further points of interest

Employing our developed model, we will now investigate specific differences in returns between:

- Genders;
- Levels of schooling education;
- Private sector and public sector;
- Full-time workers and part-time workers.

Finally, we will formulate an alternative model using skills at work.

3.4.1 Differences between genders

In this section we will apply the previously developed model to male and female individuals independently, identifying also possible macroregional differences. Overall, we expect to find greater returns to education for females, as reported by many international and domestic academic papers related to the subject, such as (Dougherty, 2005), (Lucifora, Comi, & Brunello, 2000) and (Cingano, Cipollone, & Ciccone, 2004).

As you can see in Table 15, the situation in Italy is definitely different from the international scene, as well as important regional differences seem to be in place. If we look at nationwide level, returns to education are almost equal between genders, but the situation is very different when looking at macro-regions. In fact, only in the North we can find higher returns to education for females, while the situation is completely reversed in the Center and the South. In particular, in Southern Italy we find the largest gap between genders, with male individuals gaining close to 70% higher returns to education than their female counterparts.

Looking at the other components of the model, we find that for male individuals both the linear and quadratic terms for experience are on average higher in absolute value and more significant, with Central Italy being the only exception. Finally, the

Table 15 - Human Capital Model (2SLS) with cognitive abilities, non-cognitive abilities and instrumental variables. Focus on differences between genders.

	Male				Female			
	Nationwide	**North**	**Center**	**South**	**Nationwide**	**North**	**Center**	**South**
Years of schooling	0.069***	0.049***	0.098***	0.107***	0.072***	0.072***	0.078***	0.063***
	(0.008)	*(0.011)*	*(0.009)*	*(0.017)*	*(0.007)*	*(0.010)*	*(0.007)*	*(0.022)*
Experience	0.052***	0.048***	0.034***	0.067***	0.027***	0.019**	0.049***	0.032
	(0.008)	*(0.006)*	*(0.001)*	*(0.022)*	*(0.008)*	*(0.008)*	*(0.003)*	*(0.024)*
$Experience^2/1000$	-0.803***	-0.728***	-0.327***	-1.238**	-0.202	-0.034	-0.735***	-0.332
	(0.177)	*(0.162)*	*(0.023)*	*(0.511)*	*(0.197)*	*(0.220)*	*(0.057)*	*(0.672)*
Social trust	0.030***	0.035**	-0.011	0.022	0.023*	0.016	0.040***	0.029
	(0.011)	*(0.018)*	*(0.010)*	*(0.018)*	*(0.012)*	*(0.018)*	*(0.001)*	*(0.044)*
PC Foreign	-0.038***	-0.029	-0.173***	-0.025	-0.075***	-0.064***	-0.070***	-0.183***
	(0.014)	*(0.019)*	*(0.002)*	*(0.033)*	*(0.015)*	*(0.020)*	*(0.001)*	*(0.042)*
Center	-0.045***	-	-	-	-0.089***	-	-	-
	(0.017)				*(0.017)*			
South	-0.151***	-	-	-	-0.133**	-	-	-
	(0.030)				*(0.058)*			
Wu-Hausman F	**10.01**	**2.48**	**2.25**	**8.10**	**9.84**	**3.91**	**4.28**	**4.59**
p-value	0.000	0.061	0.084	0.000	0.000	0.009	0.006	0.004
Cragg-Donald Wald F	**83.97**	**70.04**	**12.77**	**14.30**	**51.21**	**27.40**	**11.07**	**7.38**
Sargan χ^2	**0.49**	**1.11**	**0.44**	**0.39**	**0.00**	**0.23**	**0.14**	**0.17**
p-value	0.485	0.291	0.508	0.535	0.982	0.633	0.713	0.683
No. of observations	*913*	*437*	*180*	*296*	*664*	*342*	*150*	*172*

*Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. Schooling is endogenous and instrumented by numeracy and parental education. Experience and $Experience^2$ are endogenous and instrumented by Age and Age^2 respectively. All other explanatory variables are exogenous. * : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

component for immigration (*PC Foreign)* seems to be consistently higher for female individuals, and it was not even statistically significant for male individuals in the North and South. Unfortunately, some very high values are shown for male individuals in the Center and female individuals in the South, but we believe these values to be skewed by the low numerosity of the immigrant population in these subsets, which is never higher than 15.

Overall, it’s safe to say that relevant differences between genders come up from this analysis, but we need more data to be able to be sure and go more in depth. In fact, you can see how the instruments became weaker and weaker the more the numerosity of the sample is reduced, and we also have some issues with endogeneity in Northern and Central Italy for male, where we barely do not pass the test with α=5%.

3.4.2 Differences between levels of schooling education

In this section we try to insert in the model dummy variables for the different levels of schooling (*Primary school*, *Middle school*, *High school* and *University*)[37] instead of the variable *years of schooling*. In doing so, unfortunately our instruments for education become very weak, so we are forced to instrument only experience; this means they our returns on education will probably be downward biased. We also notice that with this formulation *Political efficacy* is significant again, so we include it in the model.

As you can see from Table 16, completing the three levels of schooling gives an individual different pay-outs. *Middle school* does not even give you a premium on the labour market, which makes sense; it probably did years ago, but nowadays everybody has at least completed middle school. We have to note here that it seems to be significant in Central Italy, but we believe this is due to the "overfitting" behaviour that we have signalled multiple times for this data subsample. Going on, *High school* and *University*'s returns instead are statistically significant, with the return for *University* being constantly around four times the one for *High school*. We also note that these pay-outs are more or less consistent between Northern and Southern Italy, only in the Center we see higher values, especially for *University*.

There is not much to say about this model, since most of the remaining estimates are not dissimilar from what we have seen previously. We notice, however, that the dummy variable for gender has notably decreased in absolute value, reverting to the range it showed before correcting for endogeneity. This simply means that education, not experience (for which we have proper instruments), was responsible for its shift.

[37] All the respondents in our dataset completed at least primary school, so this will be our baseline and the corresponding dummy variable will actually not be inserted as regressor in the model (otherwise we suffer from perfect multicollinearity).

If there is one other thing that we can take away from this regression, it is that returns to education may be different depending on the level of schooling education (as the coefficients for the levels of schooling seem to indicate). This hypothesis is supported also by the works of (Cingano, Cipollone, & Ciccone, 2004) and (Lucifora, Comi, & Brunello, 2000) on the topic.

Table 16 - Human Capital Model (2SLS) with cognitive abilities, non-cognitive abilities and instrumental variables. Focus on differences between genders.

	Nationwide	**North**	**Center**	**South**
Middle school	0.028	-0.101	0.261***	0.056
	(0.089)	*(0.165)*	*(0.015)*	*(0.091)*
High school	0.112***	0.111***	0.136***	0.121**
	(0.025)	*(0.029)*	*(0.008)*	*(0.055)*
University	0.337***	0.326***	0.406***	0.283***
	(0.019)	*(0.026)*	*(0.006)*	*(0.046)*
Numeracy	0.048***	0.031	0.049***	0.074***
	(0.014)	*(0.020)*	*(0.013)*	*(0.027)*
Experience	0.043***	0.038***	0.038***	0.057***
	(0.007)	*(0.006)*	*(0.001)*	*(0.022)*
Experience^2/1000	-0.679***	-0.573***	-0.483***	-1.072**
	(0.162)	*(0.151)*	*(0.017)*	*(0.544)*
Political efficacy	0.017***	0.022**	0.015***	0.016
	(0.005)	*(0.009)*	*(0.001)*	*(0.013)*
Social trust	0.039***	0.029**	0.035***	0.049***
	(0.008)	*(0.012)*	*(0.001)*	*(0.018)*
PC Foreign	-0.062***	-0.055***	-0.144***	-0.066***
	(0.010)	*(0.014)*	*(0.004)*	*(0.023)*
Female	-0.121***	-0.130***	-0.152***	-0.052
	(0.017)	*(0.017)*	*(0.005)*	*(0.060)*
Center	-0.050***	-	-	-
	(0.012)			
South	-0.115***	-	-	-
	(0.030)			
Wu-Hausman F	**6.564**	**0.786**	**4.547**	**2.585**
p-value	0.001	0.456	0.011	0.077
Cragg-Donald Wald F	**524.406**	**481.055**	**103.251**	**110.406**
No. of observations	*1580*	*782*	*329*	*469*

*Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. Experience and Experience^2 are endogenous and instrumented by Age and Age^2 respectively. All other explanatory variables are exogenous. * : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

3.4.3 Differences between private sector and public sector

In this section we try to apply the previously developed model distinguishing between individuals who work in the private sector and individuals who work in the public sector.

In doing so we want to find if and how workers are paid differently, as well as check if the Signalling theory, as proposed by Psacharopolous (1979), is applicable with this dataset. In particular we want to check the validity of two hypotheses:

1. Strong screening hypothesis (SSH), schooling has no impact on productivity, it is just a signal for employers and for this reason returns to schooling are close to zero in the unscreened (private) sector;
2. Weak screening hypothesis (WSH), even though schooling is mainly a signal for the employer, it also increases productivity. So, returns to schooling should be higher than zero in the unscreened (private) sector, but they should still be lower than the returns for the screened (public) sector.

In doing this subdivision between public and private we lose only 6 observations[38], but unfortunately, due to the low numerosity of the public sector subsample (395), we cannot properly look for macro-regional differences in this area.

Looking at Table 17, first of all we can say that this time the postestimation tests show no issue, although we notice that the instruments we chose seem to be weaker (but still strong enough) in estimating the returns of the public sector. Regarding the estimated coefficients, there are no major differences but a couple of elements to point out:

- Returns to schooling are 16% higher for individuals working in the private sector (7.1% > 6.1%);
- Returns to experience are significantly higher (+48%) for the public sector (5.9% > 4.0%), but also the decay is twice as fast;
- The difference between genders increases noticeably in the public sector (20.7% > 15.1% in absolute value);
- The differences between macro-regions are not particularly affected.

These results are incompatible with both SSH and WHS, since returns to education in the private sector are different than zero and even higher compared to the public sector. So, under the conditions defined by (Psacharopolous, 1979) we can conclude

[38] These individuals work in non-profit organisations (e.g. charities, professional associations or religious organisations).

Table 17 - Human Capital Model (2SLS) with cognitive abilities, non-cognitive abilities and instrumental variables. Focus on differences between private sector and public sector.

	Private sector	**Public sector**
Years of schooling	0.071***	0.061***
	(0.008)	*(0.016)*
Experience	0.040***	0.059***
	(0.007)	*(0.012)*
Experience^2/1000	-0.529***	-0.967***
	(0.158)	*(0.252)*
Social trust	0.023**	0.034*
	(0.010)	*(0.018)*
PC Foreign	-0.050***	-0.039
	(0.010)	*(0.031)*
Female	-0.151***	-0.207***
	(0.024)	*(0.034)*
Center	-0.065***	-0.077**
	(0.011)	*(0.039)*
South	-0.159***	-0.131***
	(0.033)	*(0.050)*
Wu-Hausman F	**14.12**	**5.76**
p-value	0.000	0.001
Cragg-Donald Wald F	**103.49**	**19.44**
Sargan χ^2	**0.05**	**1.08**
p-value	0.829	0.300
No. of observations	*1174*	*397*

*Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. Schooling is endogenous and instrumented by numeracy and parental education. Experience and Experience^2 are endogenous and instrumented by Age and Age^2 respectively. All other explanatory variables are exogenous. * : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

that schooling's main effect is definitely increasing productivity for individuals and there is no evidence of a signalling effect.

Our findings are aligned instead with (Harmon, Oosterbeek, & Walker, 2003), who say that when productivity matters, education is recognized.

3.4.4 Differences between full-time and part-time workers

In this section we want to investigate if and how much human capital is paid differently when working part-time of full-time. In our opinion, human capital should generally be paid less when working part-time, simply because such working position are usually low-grade in the structure of a company. At the same time however, if such position were a high-grade one it should be paid more, since less people would rather work part-time than full-time; but this is certainly not true for the majority of cases.

In order to correctly evaluate these differences, we had to modify the constraints on the data, and in particular we lowered the minimum weekly working hours from 30 to 10[39]. As a result of this, we retained 1,565 observations related to full time workers and 293 for part time ones.

As you can see from Table 18, both returns to schooling and returns to experience decrease with part-time workers (as we expected), with the latters also becoming non

Table 18 - Human Capital Model (2SLS) with cognitive abilities, non-cognitive abilities and instrumental variables. Focus on differences between full-time workers and part-time workers

	Overall	**Full time**	**Part time**
Years of schooling	0.073***	0.075***	0.060***
	(0.006)	*(0.006)*	*(0.011)*
Experience	0.039***	0.047***	0.014
	(0.006)	*(0.007)*	*(0.011)*
$Experience^2/1000$	-0.489***	-0.640***	-0.055
	(0.145)	*(0.156)*	*(0.294)*
Social trust	0.020***	0.023***	0.004
	(0.008)	*(0.008)*	*(0.020)*
PC Foreign	-0.044***	-0.045***	-0.064***
	(0.010)	*(0.011)*	*(0.016)*
Female	-0.130***	-0.145***	-0.130**
	(0.020)	*(0.021)*	*(0.061)*
Center	-0.050***	-0.049***	-0.072*
	(0.013)	*(0.014)*	*(0.038)*
South	-0.116***	-0.119***	-0.144**
	(0.027)	*(0.028)*	*(0.063)*
Wu-Hausman F	**23.24**	**20.65**	**0.94**
p-value	0.000	0.000	0.420
Cragg-Donald Wald F statistic	**152.23**	**128.56**	**14.48**
Sargan χ^2	**0.69**	**0.02**	**1.47**
p-value	0.406	0.896	0.225
No. of observations	*1862*	*1569*	*293*

*Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 10 hours per week. Schooling is endogenous and instrumented by numeracy and parental education. Experience and $Experience^2$ are endogenous and instrumented by Age and Age^2 respectively. All other explanatory variables are exogenous. * : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

[39] The constraint of weekly hour worked significantly affect the number of part-time workers in the data sample, which increases from 117 to 293 when lowering the minimum amount of hours worked from 30 to 10.

statistically significant anymore. It is also interesting to notice that both the immigration component (*PC Foreign*) and the dummies for macro-region (*Center* and *South*) are higher in absolute value for part-time workers, while the dummy for gender (*Female*) behaves the opposite. Moreover, we notice that the model fails the endogeneity test in the case of part-time workers, and the instruments seem to be weaker; if we account for this in the computation we obtain even lower returns.

These results look very interesting because they seem to indicate that part-time workers' wages are less affected by their human capital. This makes sense from a logical point of view, since, as previously said, part-time jobs are usually low grade; they are not looking for individuals with superior qualifications, only someone with basic skills.

3.4.5 Alternative model with ability on the job

We believe that one crucial element that is missing in our analysis is to account for the different paths and business sectors that characterize the educational and career path of an individual. There are some variables in the dataset that could help going in this direction, but unfortunately the numerosity of the subsamples becomes too scarce to be able to draw any statistical inference.

With this model we try to go around the issue by including variables related to the different skills used at work. In the dataset we have seven indexes that describe this aspect, and they are related to:

- ICT skills;
- Influencing skills;
- Numeracy skills;
- Reading skills;
- Writing skills;
- Task discretion.

The idea is that, instead of inserting precisely the composition of the human capital of an individual, we include the skills required by the agent's line of work, which should reflect it (certainly, we introduce an error in doing so). In any case, we applied Principal Component Analysis (PCA) on these variables and computed the first two principal components, retaining 52% of the total variability (as you can see in Table 19).

Table 19 - Principal Component Analysis (PCA) on skills required at work.

Component	Eigenvalue	%var	Σ%var
1st component	2.4909	35.58%	35.58%
2th component	1.1603	16.58%	52.16%

	1st component	2nd component
Ictwork	**0.4011**	**-0.4294**
influence	**0.4045**	**0.5088**
numwork	**0.3756**	**-0.3557**
planning	**0.3366**	**0.6023**
readwork	**0.4268**	-0.0755
taskdisc	0.1978	0.1269
writwork	**0.4470**	-0.2138

Unfortunately, these variables are not populated for every individual and we lost many observations following this route (1577 → 822). We believe that this could have contributed to the incorrect results for Central and Southern Italy, for which the numerosity of the sample is the lowest; specifically, the tests for the strength of the instrumental variables showed them to be very weak, and this certainly produces biased returns for the endogenous variables. We report the full results in Table 20.

Focusing only at nationwide level for this analysis, we can notice:

- A 22.5% growth in returns to schooling (7.1% → 8.7%), but the standard error doubles too;
- A 9.3% decrease in return to experience (4.3% → 3.9%), although the difference is not statistically significant;
- An increase in the impact of the immigration status (-0.053 → -0.010), gender (-16.1% → -14.9%), Center (-6.2% → -5.0%) and South (-14.1% → -10.7%).

So, correcting for the level of ability required at work produces higher returns to schooling and decreases returns to experience. We believe that this behaviour could be explained by the fact that, if someone does not change profession or career path, he will naturally increase his skills while accumulating experience, while going up in positions that require even more of those skills.

Overall, we believe this model to provide an interesting approach, but it goes without saying that we simply obtain better results using the previously discussed model, which also shows no issues at the postestimation tests (unlike this one, where we have problems of weak instruments in Central and Southern Italy, as well as residual endogeneity and overidentification in Southern Italy).

Table 20 - Human Capital Model (2SLS) with cognitive abilities, non-cognitive abilities, instrumental variables and indicators of the skills used at work.

	Nationwide	**North**	**Center**	**South**
Years of schooling	0.087***	0.055***	0.130***	0.087
	(0.013)	*(0.013)*	*(0.007)*	*(0.093)*
Experience	0.039***	0.046***	0.032***	0.011
	(0.007)	*(0.006)*	*(0.001)*	*(0.026)*
$Experience^2/1000$	-0.388**	-0.539***	-0.232***	0.142
	(0.166)	*(0.142)*	*(0.015)*	*(0.591)*
Social trust	0.029**	0.028*	-0.013**	0.098***
	(0.012)	*(0.014)*	*(0.006)*	*(0.032)*
PC skills-at-work	0.037***	0.062***	0.062***	-0.031
	(0.010)	*(0.012)*	*(0.002)*	*(0.084)*
PC skills-at-work 2	0.046***	0.047**	0.066***	-0.002
	(0.018)	*(0.021)*	*(0.005)*	*(0.028)*
PC Foreign	-0.010	0.011	-0.249***	0.071
	(0.019)	*(0.023)*	*(0.012)*	*(0.084)*
Female	-0.149***	-0.125***	-0.191***	-0.220
	(0.028)	*(0.029)*	*(0.012)*	*(0.220)*
Center	-0.050**	-	-	-
	(0.024)			
South	-0.107**	-	-	-
	(0.045)			
Wu-Hausman F	**13.38**	**4.24**	**3.35**	**1.13**
p-value	0.000	0.006	0.021	0.339
Cragg-Donald Wald F	**23.31**	**24.32**	**2.97**	**1.91**
Sargan χ^2	**2.05**	**0.60**	**0.02**	**15.62**
p-value	0.152	0.440	0.879	0.000
No. of observations	*723*	*391*	*169*	*163*

*Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. Schooling is endogenous and instrumented by numeracy and parental education. Experience and $Experience^2$ are endogenous and instrumented by Age and Age^2 respectively. All other explanatory variables are exogenous. * : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

3.5 Robustness analysis

In order to assess the baseline estimates' accuracy and to investigate any possible bias arising from the IV baseline model estimates, we performed a robustness analysis on the model depicted at equation (51). Additional control variables and alternative measures of the dependent and independent variables have been considered, and, in order to prevent sample selection bias in the wage equation, we also performed the Heckman's selection procedure.

First of all, three alternative measures of earnings have been considered. In particular, we adopted *log gross hourly wages including bonus*, *log gross monthly wages excluding bonus* and *log gross monthly wages including bonus*. As expressed in Table 21, returns to schooling differences among the four models tend to be relatively modest, estimates range from 6.5% to 7.9%. It is worth to notice that the gender indicator has instead slightly decreased in all the three new models. This trend could be explained by two main facts: female work for a lower amount of hours per weeks compared to male (on average 3.01 hours less) and they earn a lower bonus

Table 21 – Robustness analysis, alternative measures of earnings

	Hourly Wage	**Hourly Wage + Bonus**	**Monthly Wage**	**Monthly Wage + Bonus**
Years of schooling	0.071***	0.079***	0.065***	0.079***
	(0.006)	*(0.007)*	*(0.007)*	*(0.007)*
Experience	0.043***	0.045***	0.038***	0.038***
	(0.006)	*(0.007)*	*(0.005)*	*(0.005)*
$Experience^2/1000$	-0.606***	-0.630***	-0.519***	-0.488**
	(0.143)	*(0.154)*	*(0.118)*	*(0.121)*
Social trust	0.026***	0.024***	0.015*	0.013
	(0.008)	*(0.009)*	*(0.008)*	*(0.009)*
PC Foreign	-0.053***	-0.059***	-0.053***	-0.053***
	(0.010)	*(0.010)*	*(0.012)*	*(0.012)*
Female	-0.161***	-0.188***	-0.227***	-0.258***
	(0.021)	*(0.021)*	*(0.020)*	*(0.020)*
Center	-0.062***	-0.054***	-0.088***	-0.082***
	(0.014)	*(0.016)*	*(0.013)*	*(0.016)*
South	-0.141***	-0.174***	-0.124***	-0.178***
	(0.029)	*(0.032)*	*(0.030)*	*(0.035)*
Wu-Hausman F	**19.20**	**18.37**	**9.19**	**15.69**
p-value	0.000	0.000	0.000	0.000
Cragg-Donald Wald F	**134.50**	**125.66**	**134.50**	**125.66**
Sargan χ^2	**0.26**	**1.29**	**1.44**	**1.47**
p-value	0.609	0.256	0.230	0.225
No. of observations	*1577*	*1468*	*1577*	*1468*

*Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. Schooling is endogenous and instrumented by numeracy and parental education. Experience and $Experience^2$ are endogenous and instrumented by Age and Age^2 respectively. All other explanatory variables are exogenous. * : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

(-8.1% on average considering hourly salary and 12.8% considering the monthly one), while being accounting for 42% of the individuals who achieve a benefit (avg. share of women in the dataset: 38%).

Subsequently, we adopt Literacy and two separate variables, which account for the individual's father and mother educational level, as alternative measure for, respectively, numeracy and parental education. As show in Table 22, there are not any statistically significant differences between the new estimates and the baseline case.

Table 22 - Robustness analysis, alternative measures of cognitive abilities and parental education

	Baseline model	**Literacy**	**Mother and Father education**
Years of schooling	0.071***	0.069***	0.073***
	(0.006)	*(0.007)*	*(0.006)*
Experience	0.043***	0.043***	0.042***
	(0.006)	*(0.006)*	*(0.006)*
$Experience^2/1000$	-0.606***	-0.607***	-0.571***
	(0.143)	*(0.142)*	*(0.144)*
Social trust	0.026***	0.027***	0.024***
	(0.008)	*(0.008)*	*(0.008)*
PC Foreign	-0.053***	-0.053***	-0.051***
	(0.010)	*(0.010)*	*(0.010)*
Female	-0.161***	-0.159***	-0.164***
	(0.021)	*(0.022)*	*(0.021)*
Center	-0.062***	-0.061***	-0.063***
	(0.014)	*(0.014)*	*(0.014)*
South	-0.141***	-0.141***	-0.142***
	(0.029)	*(0.029)*	*(0.030)*
Wu-Hausman F	**19.20**	**15.24**	**19.03**
p-value	0.000	0.000	0.000
Cragg-Donald Wald F	**134.50**	**125.67**	**111.19**
Sargan χ^2	**0.26**	**1.18**	**0.25**
p-value	0.609	0.277	0.881
No. of observations	*1577*	*1577*	*1577*

*Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy and Literacy are estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. Schooling is endogenous and instrumented by numeracy/literacy and parental education/mother and father education. Experience and $Experience^2$ are endogenous and instrumented by Age and Age^2 respectively. All other explanatory variables are exogenous. * : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

Finally, we investigated whether sample selectivity bias, caused by to the adoption of non-random data sample, applies in our analysis. Sample selection bias could arise because, for example, individuals with high level of schooling not only have higher potential earnings, but also an higher probability to be selected in the labour market, or, in other words, to choose to work; individuals with low levels of schooling, instead, are less likely to find a job, as their accumulated human capital isn't necessary enough to grant them the minimum wage. Unfortunately, the human capital theory doesn't consider the probability of individuals to be selected into the working sample, leading to a possible bias in the final estimates. Moreover, it can be claimed that our initial hypothesis to focus just on those workers with more than 30 hours per week could exacerbate this issue; in order to protect our final estimations from sample selection bias and work out a reliable analysis on a sample representative of the entire population, it should be necessary to extend the analysis also to part-time workers (individuals who work less than 30 hours) and, more important, also to the non-employed individuals. Unfortunately, it is not so immediate to do that, as, for example, non-employed earnings information are by definition considered as missing. To overcome this issue, we followed Heckman's selection procedure proposed by James Heckmann. We fit the following model:

$$\begin{aligned}\ln Earnings = \beta_0 + \beta_1 \cdot Yoe + \beta_2 \cdot Exp + \beta_3 \cdot Exp^2 + \beta_4 \cdot ST + \beta_5 \\ \cdot Foreign + \beta_6 \cdot Female + \beta_7 \cdot Center + \beta_8 \cdot South + u\end{aligned} \tag{55}$$

$$\begin{aligned}\gamma_0 + \gamma_1 \cdot yoe + \gamma_2 \cdot exp + \gamma_2 \cdot exp^2 + \gamma_3 \cdot st + \gamma_4 \cdot Foreign + \gamma_5 \cdot Female \\ + \gamma_6 \cdot Center + \gamma_7 \cdot South + \gamma_8 \cdot Living\ with\ partner\ + \gamma_9 \\ \cdot Partner\ working\ situation + \gamma_{10} \cdot No.of\ children\ > 0\end{aligned} \tag{56}$$

$$\begin{aligned}Yoe = \alpha_{10} + \alpha_{11} \cdot \mathrm{ST} + \alpha_{12} \cdot Num + \alpha_{13} \cdot PE + \alpha_{14} \cdot Age + \alpha_{15} \cdot Age^2 \\ + \alpha_{16} \cdot Foreign + \alpha_{17} \cdot Female + \alpha_{18} \cdot Center + \alpha_{19} \cdot South \\ + \varepsilon_1\end{aligned} \tag{57}$$

$$\begin{aligned}Exp = \alpha_{20} + \alpha_{21} \cdot \mathrm{ST} + \alpha_{22} \cdot Num + \alpha_{23} \cdot PE + \alpha_{24} \cdot Age + \alpha_{25} \cdot Age^2 \\ + \alpha_{26} \cdot Foreign + \alpha_{27} \cdot Female + \alpha_{28} \cdot Center + \alpha_{29} \cdot South \\ + \varepsilon_2\end{aligned} \tag{58}$$

$$\begin{aligned}Exp^2 = \alpha_{30} + \alpha_{31} \cdot \mathrm{ST} + \alpha_{32} \cdot Num + \alpha_{33} \cdot PE + \alpha_{34} \cdot Age + \alpha_{35} \cdot Age^2 \\ + \alpha_{26} \cdot Foreign + \alpha_{27} \cdot Female + \alpha_{28} \cdot Center + \alpha_{29} \cdot South \\ + \varepsilon_3\end{aligned} \tag{59}$$

The outcome equation (55) includes the logarithm of hourly earnings (*ln Earnings*) as dependent variable, and all the variables used in the baseline model as covariates[40]. The selection equation (56) (which determines whether the dependent variable in the outcome equation is observed), instead, uses the same RHS[41] variables and three additional dummies, which add information on whether or not the respondent lives with her spouse (*Living with spouse*), the working situation of the spouse (*Partner working situation*) and the individual's number of children (*Number of children*).

Moreover, since education and experience are endogenous variables, we followed (Schwiebert, 2015) and included, both in the main equation and in the selection equation, the residuals from the first stage reduced form equations (57), (58), (59) as additional control variables. As shown in Appendix E, the coefficient associated to ρ (which measure the correlation between the errors in the outcome and selection equations u and v) is not statistically significant[42]. As a consequence, we can conclude that our model does not suffer from selectivity bias (the same outcome is obtained estimating the same model for male and female separately).

[40] Years of schooling (*Yoe*), experience (*Exp* and *Exp*^{2}), social trust (*ST*), an immigrant status indicator (*Foreign*), dummies for gender (*Female*) and macro-region (*Center* and *South*).

[41] Right Hand Side (explanatory variables).

[42] The model has been computed without REPEST due to technical issues (conformability error). The estimation has been performed only using the final weight SPFWT0 and the average value of Numeracy.

Chapter 4

Conclusion

The aim of this thesis was to tackle the Italian situation regarding the impact of education, a founding element of modern society. Our analysis returned a picture of a country whose macro-regions are certainly more alike than not, but with still important differences in place.

Our analysis starts from the Human Capital Theory, the most renowned and widely accepted theory on the topic. First, we present a state-of-the-art review starting to its inception to the most recent developments, among which the inclusion of measures of non-cognitive abilities seems to be the most trending one. Afterwards, we build and propose a two stages (2SLS) model using new Italian data coming from PIAAC (2012), a recent international study by the OECD that was never previously used in estimating Italian macro-regional differences. Moreover, in the model we include measures of non-cognitive ability that, to the best of our knowledge, were hardly used in previous estimates.

Applying our model, we find that returns to schooling are significantly lower in Northern Italy compared to Center and South (N=5.8%, C=8.7%, S=8.9%). This difference is easily explainable simply because returns to education are notoriously higher in low-income countries, and Northern Italy definitely outperforms the other macro-regions in this specific category (only 1 out of the first 9 regions with the highest GRP pro-capita is not in Northern Italy).

Furthermore, we find that returns to experience are more or less 50% higher in Southern Italy, but with a decay (concavity due to experience^2) more than 100% faster, too. We believe this behaviour may be due to the differences in prevailing economic sector in the macro-region, with Southern Italy being more focused on agri-food and tourism. Finally, we find evidence of a gender pay gap both at a nationwide level and considering each macro-region and estimates show that gender differences exacerbates in Central Italy.

We applied our model to different subgroups of individuals, and obtained the following findings:

- We did not find significant differences in return to schooling estimates at national level between male and female individuals. If we focus on macro-regions, we find instead that returns to schooling are higher for females in Northern Italy. The opposite is true for Center and South. These results deviate from other researches on the topic and thus we think they need further analysis that we leave for future research. In particular (Cingano, Cipollone, & Ciccone, 2004) provide evidence of higher returns to schooling for females at national levels, while (Lucifora, Comi, & Brunello, 2000) found similar results also at macro-regional level. International results also show higher returns for females due to different reasons (e.g. male individuals drop out of school with higher frequency while female workers tend to choose jobs where education is more rewarded; see (Dougherty, 2005) for more information).
- Returns to schooling may vary according to the schooling level and, in particular, returns may increase in higher levels of schooling education. The same trend has also been identified by (Cingano, Cipollone, & Ciccone, 2004) and (Lucifora, Comi, & Brunello, 2000).
- We find higher returns to schooling when working in the private sector compared to the public sector. With these results we can reject the Signalling theory for education, which claims that education has no real effect on increasing productivity but only signals the innate level of ability of the individual, acting as a sort of screening tool for employers.
- Returns to schooling are lower for part-time workers and the terms in experience are not significant at all. This is coherent with the low-grade position that is usually associated with part-time jobs.

Although we are satisfied with our results, we think that further analysis is needed on the topic. In particular, we suggest including in the PIAAC some basic data that simply was missing and some other measures for variables that proved to be troublesome. As for the first category, we wondered to have more information on households' financial position (especially during the individual's schooling years), school's quality, its closeness to home and its macro-region (we do not actually know if an individual in the dataset moved at some point in his life for either school or work). Regarding the second category, instead, we suggest adding more traditional measures of cognitive ability (i.e. IQ), so that it is possible to compare them to PIAAC's specific measures of cognitive ability (i.e. numeracy, literacy and problem solving in technology-rich environments).

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Appendix

Appendix A

Table 23 - Log wages regression with traditional human capital variables and ASVAB results processed through PCA, divided by demographic group. Elaboration by (Cawley, Heckman & Vytlacil, 1999).

LOG WAGE REGRESSION
UNCONDITIONAL ON OCCUPATION
Eicker-White standard errors appear in parentheses

Variable	Black Females	Black Males	Hispanic Females	Hispanic Males	White Females	White Males
1st Principal Component (g)	0.1565 (0.0151) p = 0.0000	0.1191 (0.0139) p = 0.0000	0.1124 (0.0190) p = 0.0000	0.1376 (0.0194) p = 0.0000	0.1090 (0.0103) p = 0.0000	0.1027 (0.0106) p = 0.0000
2nd Principal Component	-0.0415 (0.0109) p = 0.0001	-0.0022 (0.0109) p = 0.8406	0.0255 (0.0136) p = 0.0612	0.0308 (0.0133) p = 0.0208	0.0706 (0.0081) p = 0.0000	0.0045 (0.0080) p = 0.5743
3rd Principal Component	0.0107 (0.0112) p = 0.3395	-0.0024 (0.0107) p = 0.8213	0.0336 (0.0134) p = 0.0122	0.0718 (0.0154) p = 0.0000	-0.0046 (0.0074) p = 0.5322	0.0741 (0.0077) p = 0.0000
4th Principal Component	-0.0072 (0.0111) p = 0.5180	0.0320 (0.0115) p = 0.0056	0.0035 (0.0127) p = 0.7800	0.0338 (0.0149) p = 0.0231	0.0169 (0.0078) p = 0.0311	0.0109 (0.0077) p = 0.1575
5th Principal Component	-0.0016 (0.0104) p = 0.8791	0.0327 (0.0108) p = 0.0025	-0.0191 (0.0125) p = 0.1275	0.0348 (0.0134) p = 0.0097	-0.0052 (0.0074) p = 0.4803	0.0419 (0.0074) p = 0.0000
6th Principal Component	-0.0120 (0.0112) p = 0.2857	0.0024 (0.0108) p = 0.8209	-0.0137 (0.0129) p = 0.2884	0.0041 (0.0138) p = 0.7675	-0.0170 (0.0074) p = 0.0206	0.0012 (0.0072) p = 0.8730
7th Principal Component	-0.0151 (0.0104) p = 0.1465	-0.0161 (0.0099) p = 0.1050	0.0190 (0.0129) p = 0.1416	0.0194 (0.0151) p = 0.1970	0.0119 (0.0072) p = 0.0979	0.0043 (0.0072) p = 0.5450
8th Principal Component	-0.0072 (0.0109) p = 0.5080	0.0173 (0.0106) p = 0.1042	-0.0122 (0.0128) p = 0.3405	0.0120 (0.0141) p = 0.3943	0.0044 (0.0069) p = 0.5233	0.0197 (0.0075) p = 0.0089
9th Principal Component	0.0039 (0.0099) p = 0.6951	0.0024 (0.0108) p = 0.8255	-0.0058 (0.0122) p = 0.6331	-0.0096 (0.0141) p = 0.4979	-0.0152 (0.0072) p = 0.0346	-0.0006 (0.0071) p = 0.9344
10th Principal Component	-0.0012 (0.0110) p = 0.9101	0.0091 (0.0103) p = 0.3778	-0.0047 (0.0135) p = 0.7294	0.0160 (0.0145) p = 0.2720	-0.0027 (0.0072) p = 0.7104	0.0048 (0.0074) p = 0.5167
Grades Completed	0.0822 (0.0058) p = 0.0000	0.0776 (0.0054) p = 0.0000	0.0691 (0.0065) p = 0.0000	0.0597 (0.0063) p = 0.0000	0.0848 (0.0035) p = 0.0000	0.0722 (0.0034) p = 0.0000
Potential Experience	0.0265 (0.0020) p = 0.0000	0.0284 (0.0019) p = 0.0000	0.0247 (0.0024) p = 0.0000	0.0436 (0.0023) p = 0.0000	0.0232 (0.0013) p = 0.0000	0.0381 (0.0013) p = 0.0000
Region of Residence: North Central	-0.1634 (0.0291) p = 0.0000	-0.1327 (0.0293) p = 0.0000	-0.1936 (0.0521) p = 0.0002	-0.1164 (0.0471) p = 0.0135	-0.1346 (0.0162) p = 0.0000	-0.1064 (0.0156) p = 0.0000
Region of Residence: South	-0.1721 (0.0215) p = 0.0000	-0.1402 (0.0238) p = 0.0000	-0.1673 (0.0277) p = 0.0000	-0.1716 (0.0295) p = 0.0000	-0.1254 (0.0151) p = 0.0000	-0.0739 (0.0147) p = 0.0000
Region of Residence: West	-0.0496 (0.0338) p = 0.1421	0.0441 (0.0372) p = 0.2356	-0.0928 (0.0274) p = 0.0007	-0.0355 (0.0274) p = 0.1951	-0.0225 (0.0184) p = 0.2234	-0.0115 (0.0182) p = 0.5258
Local Unemployment Rate: 6-9%	-0.0544 (0.0131) p = 0.0000	-0.0685 (0.0116) p = 0.0000	-0.0486 (0.0175) p = 0.0056	-0.0872 (0.0154) p = 0.0000	-0.0815 (0.0090) p = 0.0000	-0.0560 (0.0088) p = 0.0000
Local Unemployment Rate: Over 9%	-0.0906 (0.0198) p = 0.0000	-0.0949 (0.0187) p = 0.0000	-0.1396 (0.0215) p = 0.0000	-0.2103 (0.0207) p = 0.0000	-0.1266 (0.0126) p = 0.0000	-0.1185 (0.0133) p = 0.0000
National Unemployment Rate: 6-9%	-0.0163 (0.0102) p = 0.1083	-0.0208 (0.0102) p = 0.0420	-0.0314 (0.0133) p = 0.0187	-0.0002 (0.0115) p = 0.9871	-0.0081 (0.0074) p = 0.2704	-0.0324 (0.0069) p = 0.0000
National Unemployment Rate: Over 9%	-0.0189 (0.0189) p = 0.3154	-0.0688 (0.0183) p = 0.0002	-0.0327 (0.0213) p = 0.1257	0.0199 (0.0200) p = 0.3205	-0.0009 (0.0119) p = 0.9420	-0.0365 (0.0120) p = 0.0023
Year	-0.0032 (0.0010) p = 0.0010	-0.0083 (0.0009) p = 0.0000	0.0036 (0.0011) p = 0.0011	-0.0061 (0.0010) p = 0.0000	0.0087 (0.0006) p = 0.0000	0.0036 (0.0006) p = 0.0000
R-squared	$R^2 = 0.2219$	$R^2 = 0.1888$	$R^2 = 0.2036$	$R^2 = 0.2156$	$R^2 = 0.2433$	$R^2 = 0.2483$
Number of Observations	12391	13674	8001	9200	31084	32493

Appendix B

Table 24 - Human Capital Model with cognitive abilities as explanatory variable

	Nationwide	**North**	**Center**	**South**
Years of schooling	0.046***	0.044***	0.054***	0.043***
	(0.003)	*(0.005)*	*(0.001)*	*(0.006)*
Literacy	0.029**	0.014	0.051***	0.043
	(0.012)	*(0.018)*	*(0.008)*	*(0.029)*
Experience	0.030***	0.026***	0.028***	0.038***
	(0.003)	*(0.004)*	*(0.000)*	*(0.008)*
$Experience^2/1000$	-0.366***	-0.284***	-0.300***	-0.633***
	(0.072)	*(0.089)*	*(0.009)*	*(0.199)*
PC Foreign	-0.059***	-0.050***	-0.128***	-0.072***
	(0.010)	*(0.014)*	*(0.003)*	*(0.020)*
Female	-0.140***	-0.145***	-0.171***	-0.087
	(0.016)	*(0.015)*	*(0.003)*	*(0.053)*
Center	-0.056***	-	-	-
	(0.012)			
South	-0.154***	-	-	-
	(0.029)			
Adj R^2	**27.26%**	**21.55%**	**38.18%**	**23.43%**
No. of observations	*1584*	*785*	*330*	*469*

Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Literacy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. All the explanatory variables are treated as exogenous.
** : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

Appendix C

1. Model containing all the self-reported measures for non-cognitive ability

Table 25 - Human Capital Model with all the self-reported non-cognitive abilities as explanatory variable

	Nationwide	North	Center	South
Years of schooling	0.041***	0.039***	0.052***	0.036***
	(0.003)	*(0.006)*	*(0.002)*	*(0.007)*
Numeracy	0.037***	0.019	0.035**	0.071***
	(0.014)	*(0.020)*	*(0.014)*	*(0.025)*
Experience	0.030***	0.027***	0.030***	0.035***
	(0.003)	*(0.004)*	*(0.001)*	*(0.008)*
$\text{Experience}^2/1000$	-0.375***	-0.300***	-0.348***	-0.570***
	(0.073)	*(0.089)*	*(0.012)*	*(0.191)*
Cultural engagement	0.007	0.011	-0.012***	0.018
	(0.006)	*(0.009)*	*(0.002)*	*(0.016)*
Political efficacy	0.017***	0.021**	0.018***	0.014
	(0.005)	*(0.009)*	*(0.001)*	*(0.013)*
Social trust (1)	-0.009	-0.017	-0.018***	0.009
	(0.010)	*(0.014)*	*(0.002)*	*(0.024)*
Social trust (2)	0.042***	0.036*	0.045***	0.042**
	(0.011)	*(0.019)*	*(0.002)*	*(0.020)*
PC Foreign	-0.059***	-0.047***	-0.138***	-0.070***
	(0.010)	*(0.013)*	*(0.003)*	*(0.018)*
Female	-0.127***	-0.136***	-0.167***	-0.069
	(0.016)	*(0.016)*	*(0.005)*	*(0.054)*
Center	-0.060***	-	-	-
	(0.012)			
South	-0.140***	-	-	-
	(0.029)			
Adj R^2	**28.44%**	**22.15%**	**39.51%**	**25.53%**
No. of observations	*1580*	*782*	*329*	*469*

Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. All the explanatory variables are treated as exogenous.
** : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

2. Model containing a selected subsample of self-reported measures of non-cognitive ability (Political efficacy and the second measure of Social trust)

Table 26 - Human Capital Model with a selected subsample of self-reported non-cognitive abilities as explanatory variable (Political efficacy and Social trust)

	Nationwide	**North**	**Center**	**South**
Years of schooling	0.041***	0.040***	0.052***	0.036***
	(0.003)	*(0.006)*	*(0.002)*	*(0.007)*
Numeracy	0.037***	0.021	0.038***	0.073***
	(0.014)	*(0.020)*	*(0.014)*	*(0.025)*
Experience	0.030***	0.027***	0.030***	0.036***
	(0.003)	*(0.004)*	*(0.001)*	*(0.008)*
$Experience^2/1000$	-0.374***	-0.293***	-0.355***	-0.579***
	(0.074)	*(0.091)*	*(0.013)*	*(0.193)*
Political efficacy	0.016***	0.019**	0.014***	0.016
	(0.005)	*(0.008)*	*(0.001)*	*(0.013)*
Social trust	0.036***	0.026**	0.033***	0.049***
	(0.008)	*(0.013)*	*(0.001)*	*(0.017)*
PC Foreign	-0.060***	-0.049***	-0.138***	-0.069***
	(0.009)	*(0.013)*	*(0.003)*	*(0.020)*
Female	-0.127***	-0.134***	-0.163***	-0.069
	(0.016)	*(0.016)*	*(0.005)*	*(0.054)*
Center	-0.061***	-	-	-
	(0.012)			
South	-0.141***	-	-	-
	(0.029)			
Adj R^2	**28.49%**	**22.21%**	**39.73%**	**25.73%**
No. of observations	*1580*	*782*	*329*	*469*

Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. All the explanatory variables are treated as exogenous.
** : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

3. *Model containing non-self-reported measures derived from the background questionnaire*

Table 27 - Human Capital Model with non-self-reported non-cognitive abilities obtained from the background questionnaire as explanatory variable

	Nationwide	**North**	**Center**	**South**
Years of schooling	0.045***	0.043***	0.054***	0.040***
	(0.003)	*(0.005)*	*(0.002)*	*(0.006)*
Numeracy	0.041***	0.023	0.043***	0.074***
	(0.013)	*(0.020)*	*(0.014)*	*(0.023)*
Experience	0.030***	0.028***	0.029***	0.036***
	(0.003)	*(0.004)*	*(0.001)*	*(0.008)*
Experience^2/1000	-0.363***	-0.310***	-0.317***	-0.581***
	(0.072)	*(0.089)*	*(0.014)*	*(0.197)*
Don't know	-2.837	0.865***	13.074***	-15.408**
	(4.462)	*(5.200)*	*(0.294)*	*(6.256)*
Refused to answer	-11.789***	-13.714***	-9.907***	-5.436*
	(1.601)	*(2.015)*	*(1.294)*	*(3.281)*
PC Foreign	-0.061***	-0.053***	-0.127***	-0.070***
	(0.010)	*(0.014)*	*(0.003)*	*(0.021)*
Female	-0.134***	-0.142***	-0.162***	-0.082
	(0.016)	*(0.016)*	*(0.005)*	*(0.052)*
Center	-0.067***	-	-	-
	(0.012)			
South	-0.147***	-	-	-
	(0.029)			
Adj R^2	**27.91%**	**22.10%**	**37.74%**	**25.44%**
No. of observations	*1584*	*785*	*330*	*469*

Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. All the explanatory variables are treated as exogenous.
** : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

1. *Models containing non-self-reported measures derived from the background questionnaire*

Table 28 - Human Capital Model with non-self-reported non-cognitive abilities obtained from the main test as explanatory variable (1)

	Nationwide	**North**	**Center**	**South**
Years of schooling	0.044***	0.043***	0.054***	0.043***
	(0.003)	*(0.005)*	*(0.001)*	*(0.007)*
Numeracy	0.046**	0.018	0.037**	0.135***
	(0.019)	*(0.024)*	*(0.017)*	*(0.044)*
Experience	0.031***	0.027***	0.037***	0.031***
	(0.004)	*(0.005)*	*(0.001)*	*(0.010)*
$Experience^2/1000$	-0.309***	-0.193	-0.470***	-0.281
	(0.104)	*(0.149)*	*(0.014)*	*(0.222)*
Skipped	-0.197	-0.614***	-0.132**	0.560
	(0.148)	*(0.195)*	*(0.072)*	*(0.364)*
Not attempted	0.367	0.977**	-0.057**	-0.532**
	(0.300)	*(0.450)*	*(0.026)*	*(0.209)*
PC Foreign	-0.044***	-0.030	-0.154***	-0.045*
	(0.016)	*(0.023)*	*(0.003)*	*(0.024)*
Female	-0.140***	-0.105***	-0.191***	-0.178***
	(0.016)	*(0.019)*	*(0.005)*	*(0.047)*
Center	-0.087***	-	-	-
	(0.016)			
South	-0.150***	-	-	-
	(0.027)			
Adj R^2	**32.58%**	**28.93%**	**37.78%**	**31.65%**
No. of observations	*1123*	*553*	*252*	*318*

Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. All the explanatory variables are treated as exogenous.
** : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

Table 29 - Human Capital Model with non-self-reported non-cognitive abilities obtained from the main test as explanatory variable (2)

	Nationwide	**North**	**Center**	**South**
Years of schooling	0.045***	0.045***	0.054***	0.041***
	(0.003)	*(0.006)*	*(0.001)*	*(0.007)*
Numeracy	0.049***	0.029	0.045***	0.103***
	(0.016)	*(0.021)*	*(0.012)*	*(0.036)*
Experience	0.031***	0.026***	0.039***	0.030***
	(0.004)	*(0.006)*	*(0.001)*	*(0.010)*
$Experience^2/1000$	-0.304***	-0.181	-0.508***	-0.268
	(0.101)	*(0.145)*	*(0.018)*	*(0.228)*
Time per test item	0.002***	0.002*	0.003***	0.001
	(0.000)	*(0.001)*	*(0.000)*	*(0.001)*
Time per correct test item	-0.002***	-0.003***	-0.003***	0.000
	(0.001)	*(0.001)*	*(0.000)*	*(0.001)*
Actions per test item	-0.031***	-0.043***	-0.017***	-0.006
	(0.012)	*(0.013)*	*(0.003)*	*(0.051)*
Actions per correct test item	0.021**	0.023**	0.036***	-0.002
	(0.009)	*(0.012)*	*(0.003)*	*(0.045)*
PC Foreign	-0.041***	-0.028	-0.151***	-0.038
	(0.015)	*(0.020)*	*(0.002)*	*(0.024)*
Female	-0.142***	-0.116***	-0.191***	-0.169***
	(0.016)	*(0.019)*	*(0.006)*	*(0.049)*
Center	-0.089***	-	-	-
	(0.017)			
South	-0.159***	-	-	-
	(0.031)			
Adj R^2	**32.62%**	**27.09%**	**38.32%**	**30.28%**
No. of observations	*1123*	*553*	*252*	*318*

Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. All the explanatory variables are treated as exogenous.
** : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

2. *Model obtained using PCA on self-reported and non-self-reported measures*

Table 30 - Principal Component Analysis (PCA) on Foreign born and Parent foreign born

	Eigenvalue	%var	Σ%var
1st component	2.787	23.22%	23.22%
2nd component	1.823	15.19%	38.41%
3rd component	1.246	10.38%	48.79%
4th component	1.195	9.96%	58.75%
5th component	1.025	8.54%	67.29%

	1st component	2nd component	3rd component	4th component	5th component
Cultural engagement	0.059	0.173	-0.122	-0.145	0.240
Political efficacy	0.109	**0.390**	0.044	0.033	0.122
Social trust (1)	0.126	**0.609**	0.105	0.073	-0.106
Social trust (2)	0.129	**0.606**	0.096	0.085	-0.096
Time per test item	**0.474**	-0.108	**0.323**	**-0.309**	0.146
Time per correct test item	**0.367**	-0.131	**0.579**	-0.293	0.060
Skipped	**-0.359**	-0.066	**0.459**	0.107	-0.175
Not attempted	**-0.345**	0.036	**0.471**	0.211	-0.191
Actions per test item	**0.466**	-0.136	-0.151	**0.421**	-0.075
Actions per correct test item	**0.325**	-0.162	0.127	**0.635**	-0.214
Don't know	-0.069	-0.011	0.046	0.291	**0.699**
Refused to answer	-0.131	0.030	0.222	0.252	**0.525**

Table 31 - Human Capital Model with Principal Component Analysis (PCA) applied to the 12 proposed measures of non-cognitive abilities

	Nationwide	**North**	**Center**	**South**
Years of schooling	0.042***	0.042***	0.052***	0.041***
	(0.003)	*(0.005)*	*(0.001)*	*(0.007)*
Numeracy	0.048***	0.031	0.035**	0.094**
	(0.018)	*(0.024)*	*(0.014)*	*(0.041)*
Experience	0.031***	0.026***	0.037***	0.031***
	(0.004)	*(0.005)*	*(0.001)*	*(0.010)*
$Experience^2/1000$	-0.320***	-0.183	-0.494***	-0.302
	(0.102)	*(0.149)*	*(0.015)*	*(0.230)*
PC1	0.001	-0.017	0.026***	0.012
	(0.010)	*(0.016)*	*(0.003)*	*(0.014)*
PC2	0.030***	0.031***	0.027***	0.031***
	(0.007)	*(0.010)*	*(0.001)*	*(0.010)*
PC3	0.000	-0.005	0.010***	0.012
	(0.011)	*(0.018)*	*(0.002)*	*(0.021)*
PC4	-0.003	0.007	0.017***	-0.020
	(0.011)	*(0.017)*	*(0.003)*	*(0.015)*
PC5	-0.022***	-0.004	-0.001	-0.048***
	(0.009)	*(0.010)*	*(0.001)*	*(0.016)*
PC Foreign	-0.041***	-0.030	-0.158***	-0.041*
	(0.015)	*(0.022)*	*(0.002)*	*(0.022)*
Female	-0.135***	-0.107***	-0.182***	-0.167***
	(0.015)	*(0.019)*	*(0.005)*	*(0.045)*
Center	-0.086***	-	-	-
	(0.017)			
South	-0.141***	-	-	-
	(0.030)			
Adj R^2	**33.03%**	**27.11%**	**38.30%**	**32.13%**
No. of observations	*1121*	*551*	*252*	*318*

Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. All the explanatory variables are treated as exogenous.
** : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

Appendix D

Table 32 - Human Capital Model (2SLS) with cognitive abilities, non-cognitive abilities and instrumental variables

	Nationwide				North			
	(II)	(I) Schooling	(I) Exp	(I) Exp^2/1000	(II)	(I) Schooling	(I) Exp	(I) Exp^2/1000
Years of schooling	0.071***	-	-	-	0.058***	-	-	-
	(0.006)				*(0.008)*			
Experience	0.043***	-	-	-	0.036***	-	-	-
	(0.006)				*(0.005)*			
Experience^2/1000	-0.606***	-	-	-	-0.451***	-	-	-
	(0.143)				*(0.129)*			
Social trust	0.026***	0.488***	-0.427***	-0.012***	0.025**	0.471***	-0.309**	-0.005
	(0.008)	*(0.072)*	*(0.099)*	*(0.004)*	*(0.011)*	*(0.118)*	*(0.142)*	*(0.006)*
Numeracy	-	1.338***	0.031	-0.002	-	1.447***	-0.254	-0.01
		(0.065)	*(0.150)*	*(0.006)*		*(0.107)*	*(0.209)*	*(0.009)*
Parental education	-	2.031***	-1.674***	-0.062***	-	1.975***	-2.139***	-0.077***
		(0.138)	*(0.180)*	*(0.006)*		*(0.225)*	*(0.271)*	*(0.010)*
Age	-	0.034	0.400***	-0.038***	-	0.081	0.632***	-0.036***
		(0.048)	*(0.066)*	*(0.003)*		*(0.076)*	*(0.082)*	*(0.003)*
Age^2	-	-0.001	0.006***	0.001***	-	-0.002*	0.003***	0.001***
		(0.001)	*(0.001)*	*(0.000)*		*(0.001)*	*(0.001)*	*(0.000)*
PC Foreign	-0.053***	-0.165**	-0.737***	-0.038***	-0.045***	-0.162*	-1.004***	-0.049***
	(0.010)	*(0.070)*	*(0.170)*	*(0.006)*	*(0.012)*	*(0.086)*	*(0.229)*	*(0.009)*
Female	-0.161***	1.552***	-2.798***	-0.113***	-0.155***	1.284***	-2.014***	-0.092***
	(0.021)	*(0.108)*	*(0.233)*	*(0.006)*	*(0.019)*	*(0.175)*	*(0.245)*	*(0.011)*
Center	-0.062***	0.304***	-1.536***	-0.059***	-	-	-	-
	(0.014)	*(0.085)*	*(0.140)*	*(0.008)*				
South	-0.141***	0.984***	-4.944***	-0.183***	-	-	-	-
	(0.029)	*(0.145)*	*(0.388)*	*(0.016)*				
Wu-Hausman F	**19.20**				**4.62**			
p-value	0.000				0.003			
Cragg-Donald Wald F statistic	**134.50**				**91.68**			
Sargan χ^2	**0.26**				**0.40**			
p-value	0.609				0.526			
No. of observations	*1577*				*779*			

*Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. Schooling is endogenous and instrumented by numeracy and parental education. Experience and Experience^2 are endogenous and instrumented by Age and Age^2 respectively. All other explanatory variables are exogenous. * : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*

Table 30 (continue) - Human Capital Model (2SLS) with cognitive abilities, non-cognitive abilities and instrumental variables

	Center				South			
	(II)	(I) Schooling	(I) Exp	(I) $Exp^2/1000$	(II)	(I) Schooling	(I) Exp	(I) $Exp^2/1000$
Years of schooling	0.087***	-	-	-	0.089***	-	-	-
	(0.005)				*(0.015)*			
Experience	0.040***	-	-	-	0.060***	-	-	-
	(0.001)				*(0.019)*			
$Experience^2/1000$	-0.481***	-	-	-	-1.088**	-	-	-
	(0.014)				*(0.468)*			
Social trust	0.016***	0.503***	-0.767***	-0.025***	0.025	0.495***	-0.273	-0.010
	(0.004)	*(0.031)*	*(0.029)*	*(0.001)*	*(0.021)*	*(0.127)*	*(0.251)*	*(0.011)*
Numeracy	-	1.453***	0.343	0.011	-	1.011***	0.501	0.009
		(0.079)	*(0.227)*	*(0.010)*		*(0.133)*	*(0.384)*	*(0.015)*
Parental education	-	1.769***	-1.573***	-0.056***	-	2.378***	-0.445	-0.014
		(0.072)	*(0.086)*	*(0.004)*		*(0.219)*	*(0.346)*	*(0.012)*
Age	-	0.000	0.319***	-0.048***	-	0.031	0.048	-0.042***
		(0.036)	*(0.014)*	*(0.001)*		*(0.077)*	*(0.172)*	*(0.007)*
Age^2	-	0.000	0.007***	0.001***	-	-0.001	0.009***	0.001***
		(0.000)	*(0.000)*	*(0.000)*		*(0.001)*	*(0.002)*	*(0.000)*
PC Foreign	-0.122***	-0.053	0.479***	0.008***	-0.069***	-0.153	-0.583	-0.009
	(0.001)	*(0.041)*	*(0.061)*	*(0.003)*	*(0.024)*	*(0.234)*	*(0.380)*	*(0.011)*
Female	-0.212***	2.024***	-2.706***	-0.121***	-0.130	1.715***	-4.548***	-0.143***
	(0.008)	*(0.093)*	*(0.028)*	*(0.001)*	*(0.083)*	*(0.361)*	*(0.837)*	*(0.033)*
Center	-	-	-	-	-	-	-	-
South	-	-	-	-	-	-	-	-
Wu-Hausman F	**5.86**				**11.79**			
p-value	0.001				0.000			
Cragg-Donald Wald F statistic	**25.59**				**24.64**			
Sargan χ^2	**0.40**				**0.08**			
p-value	0.527				0.779			
No. of observations	*330*				*468*			

*Notes: least squares regression weighted by sampling weights. Dependent variable: log hourly wage. Numeracy is estimated using 10 plausible values. Sample: Employees working at least 30 hours per week. Schooling is endogenous and instrumented by numeracy and parental education. Experience and $Experience^2$ are endogenous and instrumented by Age and Age^2 respectively. All other explanatory variables are exogenous. *: p-value<=0.10, **: p-value<=0.05, ***: p-value<=0.01.*

Appendix E

Table 33 - Robustness analysis, Heckman model

	Outcome equation	Selection equation
Years of schooling	0.069***	0.065***
	(0.009)	*(0.020)*
Experience	0.041***	0.081***
	(0.010)	*(0.019)*
$Experience^2/1000$	-0.566**	-1.590***
	(0.234)	*(0.455)*
Social trust	0.029**	0.075**
	(0.014)	*(0.043)*
PC Foreign	-0.054***	-0.046
	(0.017)	*(0.046)*
Female	-0.154**	-0.595***
	(0.059)	*(0.088)*
Center	-0.041	-0.164*
	(0.034)	*(0.099)*
South	-0.127*	-0.438***
	(0.068)	*(0.113)*
Residuals (Years of schooling)	-0.024***	0.030
	(0.008)	*(0.023)*
Residuals (Experience)	-0.023**	0.006
	(0.010)	*(0.023)*
Residuals ($Experience^2$)	0.379*	0.875*
	(0.217)	*(0.526)*
Living with partner	-	-0.168
		(0.118)
Partner working situation	-	0.176*
		(0.105)
Number of children	-	-0.087*
		(0.044)
LR test of indep. Eqns. (ρ=0) $\chi^2(1)$	**0.39**	
p-value	0.530	
No. of observations	*2505*	
Censored observations	*616*	
Uncensored observations	*1889*	

*Notes: Heckman selection model estimated adopting one sampling weight (spfwt0). Dependent variable of the main equation: log hourly wage. Numeracy is estimated using by using the average between the 10 plausible values. Sample: Employees and non-employed individuals. Schooling is endogenous and instrumented by numeracy and parental education. Experience and $Experience^2$ are endogenous and instrumented by Age and Age^2 respectively. All other explanatory variables are exogenous. * : p-value<=0.10, ** : p-value<=0.05, *** : p-value<=0.01.*