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Padova, 21st February 2017

Alessandro Pizzigolotto

## ABSTRACT

Several studies promote vocational education as an effective solution to the school-to-work transition issues, which have become endemic for the most advanced economies. However, individuals choosing this track may face a trade-off among a labour-market advantage at early stage of their individual careers and quicker skills depreciation in the long-run, due to less adaptability and technological change, becoming less competitive than skills provided by academic-based education, in a lifelong learning perspective. Using microdata from the Survey of Household and Income (SHIW) allows to follow individuals over their life-cycle for at least 40 years, to investigate whether this view has empirical support in a borderline country-level labour market, stressing outcomes' differences among school-based vocational education and a more traditional academic-based education at upper-secondary school level. We find strong and robust support to this trade-off, evidencing how a critical labour-market shock as the 2007–08 Financial Crisis has diluted the early advantage of vocational skills. We further address for selectivity in education investigating whether outcomes may vary between cohorts from different decades. Whilst differences in youth employment appears in contrast among birth cohorts, there are no significant results for wages, but it seems clear that vocational skills have weakened moving through years.

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### INTRODUCTION

The main purpose of the following paper is to humbly narrate another small part of the story in the empirical research of economics of education.

In recent times, the attention for this particular field has been amplified for the interest of the most advanced economics to find an effective solution to weak labour-market outcomes of younger adults at the earliest entrance in their working life. Globalisation triggers these issues at a worldwide scale, affecting society both from an economic and a cultural point of view. Approaching the so-called "knowledge society" in a picture of lifelong learning is not enough to find a categorical solution *à tous les niveaux* to the challenging school-to-work transition.

Following the aim of the most recent studies in this field, especially the major work of Hanushek, Woessmann, and Zhang (2011), we develop an empirical model in order to study the effect of individuals' education choices at upper secondary school level along their life-cycle in the labour market, focusing on employment and wages. Our study is embedded in the Italian labour market and education system, ergo the validity of our outcomes may be limited to this institutional framework. Howbeit, it is even more interesting to perform the analysis in this singularly stressed labour market, where we can study differences in outcomes among education types evaluating them into a borderline case, portraying evidences from a particular country in terms of economic and social history.

Aware of the challenging issues of selection bias in these kind of studies, we try to give emphasis to the effect of vocational education at the early stages of the labour market, and to infer its behaviour in later age comparing outcome of pupils whose tracking choices clash on that. To soundly explain these circumstances, we also perform copious robustness checks on our sample.

We are also conscious of the difficult situation the Italian economy and labour market has gone through during the 2007–2008 financial crisis, prolonged by the 2011 sovereign debt crisis, and for this reason we push to the limit our empirical model exploiting differences in labour-market outcomes of different education types in pre-recession and post-recession years. Likewise, in order to go beyond the limit of selectivity in education among different decades, which processes may be influenced either by cultural and economic changes in a between- and within-country context, or by the necessity of a more academic-oriented and broad education, as by repeated and conflicting reform attempts which distress the Italian education system, we try to study separately birth cohorts in the whole sample, extending our model using a difference-in-difference-in-differences approach.

Our paper is organised in the following way. In Section 1.1 we present some background information about the Italian education framework and its Vocational Education and Training structure embedded on it. We also produce a state-of-the-art of the main positions of research in education, as the main challenges in the empirical exploration in Section 1.2. A brief overview of the major studies in education regarding our empirical work is provided in Chapter 2. Section 3.1 describes the data used by the study and Section 3.2 defines the models constructed for the identification strategy. The main empirical results are presented in Chapter 4 for employment over the life-cycle and Chapter 5 for wages among education types. Conclusions follow.

#### CHAPTER

### **BACKGROUND INFORMATION**

#### **1.1 VET in the Italian Education Framework**

Before going deep with an overview of research in education and the most relevant literature of this mostly unexplored subject, it is wise to give a formal definition to what the termino-logy *vocational education* deals with.

Vocational Education and Training (in the acronym, VET) is defined as «the knowledge, know-how, skills, and/or competences required in particular occupations or more broadly on the labour market» (European Centre for the Development of Vocational Training (CEDEFOP), 2014a, p. 292). Hence, from an European perspective the term Education and Training comprises all types and levels of general and education, where VET is just a modest part of it which can take place at secondary, post-secondary or tertiary level in formal education and training, or in non-formal settings including active labour-market measures. In other terms, education can be either school-based, company-based or combining school and company-based learning defining it as "apprenticeship".



Figure 1.1: Diagram of the Italian Education System on the basis of the ISCED 2011 international classification. Source: Organisation for Economic Co-operation and Development (OECD), 2016, reshaped by the author for illustrative purposes.

In Figure 1.1 we have a comprehensive view of the Italian Education System embedded in the International Standard Classification of Education (ISCED, United Nations Educational Scientific and Cultural Organization (UNESCO), 2012). On the basis of the current framework, all people have the right/duty to pursue their education and training for at least 12 years before reaching age 18. The aim is that young people should not leave education and

training without a qualification (see European Centre for the Development of Vocational Training (CEDEFOP), 2014b, p. 22). However, compulsory education lasts 10 years, up to 16, and includes the first two years of upper secondary education or VET.

Pupils finish lower secondary education (ISCED 2) at age 14, at which level they sit a state exam to acquire a certificate which grants admission to upper secondary school level, where tracking between general education and VET. Pupils can self-select in either different tracks, because admission into public high schools does not depend on past performance and all applicants are typically eligible for every track. Thus, tracking in education type happens quite early, *e.g.* earlier than Nordic countries but later than the German well-known "dual-system". At the upper secondary school level, school-based VET is provided by technical school programmes (in Italian, *istituti tecnici*), where learners can acquire the knowledge (ISCED 3), skills and competences to carry out technical and administrative tasks (European Centre for the Development of Vocational Training (CEDEFOP), 2014b), and by vocational school programmes (in Italian *istituti professionali*), which provide students specific theoretical and practical preparation, forming them to carry out qualified tasks in production fields of national interest (*e.g.* craftsmanship). The certificate provided by these schools depends on the branch and the length of the studies:

- students enrolled in vocational education can obtain either a three-years certificate of vocational qualification around age 17, when compulsory school ends, or a four-years professional diploma. These certificates are not recognised as high school diploma, thus individuals with this type of education are not eligible for tertiary education studies.
- students registered in technical school programmes and five-years vocational school programmes obtain a upper secondary school diploma at the end of the studies, which allows individuals to enrol in further tertiary studies or enter in the labour market for a early occupation.

General upper secondary schools (in Italian, *licei*) provide an academic-based education, and they traditionally prepare students for the university. They are mainly focused on humanities (*licei classici*) or on the sciences (*licei scientifici*), but nowadays other general education offers have been introduced, *e.g.* artistic, linguistic, human sciences, music and dance strands.

Within the artistic strand, learners can specialise in figurative arts, architecture and environment, design, audiovisual and multimedia, graphics or stage design in the second period after the first two years in upper secondary education. Therefore, tracking does not bound individuals in the chosen path for the most of the cases.

Beside the normal tertiary education program, which adopts the division provided by the Bologna process except for peculiar subjects (*e.g.* Surgery and Law), there are also post-secondary vocational programmes, reorganised in 2008 with the main goal of developing professional specialisations at post-secondary level to meet the requirements of the labour market in the public and private sectors. There are two different options:

- higher technical education and training programmes (*istruzione e formazione tecnica superiore*, IFTS);
- programmes at the higher technical institutes (istituti tecnici superiori, ITS).

They are both planned and organised at regional level, in the context of the territorial plans adopted every three years, and their provision varies across regions. These programs are worthy of note, but we do not consider them in our analysis, stopping at upper secondary school level for empirical purposes.

In our analysis, we will focus mainly on upper secondary education programs, either in vocational or general tracks.

#### **1.2 Education Matters**

Research of Education has received emphasis in the last decade, since the academic world has been recognised its importance and its correlation with other main issues within the modern economies. For example, Green (2002) considers what we may call the main socio-economic triggers for this trend.

 Population ageing has driven a unprecedented demographic change, making individuals in older age in need of more specific education, in order to maintain their skills longer competitive in the labour-market. Solution in this sense may be lifelong learning policies for the elderly of today and the subsequent elders, and more formal schoolbased education policies providing a good contents in academic subjects. This arises a first question about the weakening of vocational education in favour of more heterogeneous studies supported by lifelong learning.

- Globalisation and global economic restructuring have brought new economic situations. It have caused reduced job opportunities for young people and continuing high levels of youth unemployment, which means that people are staying in school longer and gaining stable employment later. As a consequence, they also marry and have their first child later. This is a another point in favour of the increasing trend in the selection into general education for younger age cohorts in most countries (and also in our data from Section 3.1.1), as they are more oriented in general education looking at a tertiary education.
- Cultural globalisation has created a knowledge society, where education cannot be finalised only at the first stage of life. In this environment, globalisation has put developed countries in competition also for the education market, to face the threat of lower labour-market costs in developing countries providing increased skills given by staying longer time in education (see the recent studies by Lavy (2015) and Rivkin and Schiman (2015)).

Two main concepts emerge from these statements. Lifelong learning may be a plug-and-play solution in the knowledge society, representing one of the main topic of research in education, and «it implies that learning should take place at all stages of the life-cycle (from the "cradle" to the "grave") and, in more recent versions, that it should be life-wide, that is embedded in all life contexts from the school to the workplace, the home and the community, in the context of a learning society» Green (2002, p. 613). Lifelong learning is most informal, it guarantees more flexibility, lower costs, and it is faster to meet increasing learning demands in the learning society pictured by Green (2002) than slower response of formal schooling. This is a strong point in favour of a more general learning path, but we would rather concentrate on the school-to-work transition and its current effects on the labour-market outcomes. School-to-work transition can be asserted as «the period between the end of compulsory schooling and the attainment of a full-time, stable employment» Ryan (2001, p. 35). Nowadays, there is empirical evidence that the school-to-work transition has become long and perilous due to economic restructuring, unlike the short and more direct routes available to previous generations, where traditionally education has mattered less.

School-to-work transition issues vary at country-level, as proposed education systems bring up heterogeneous characteristics. For example, considering the general overview made by Green (2002), Mediterranean states (Italy included) remain relatively centralised, national and comprehensive, keeping the work of a fairly traditional education paradigm. Germanspeaking countries have tended to be more federalised, with strong social partnership models of governance and regulation, but they are generally more oriented to academic selection and curricular specialisation than the Mediterranean colleagues. They also offer consolidated VET systems based on "apprenticeship systems" (as analysed by Hanushek, Schwerdt, Woessmann, and Zhang (2017), we are talking about Germany, Austria and Switzerland), very different from the school-based vocational programs offered by Mediterranean countries where "apprenticeship is a largely residual phenomenon. On the other hand, United Kingdom and The Netherlands have moved towards a quasi-market model, with high levels of diversification and autonomy from the centralised institutions, and in UK continuing preference for curricula specialisation.

This direction has been also taken by Nordic states, but they are still careful embarking a local public control joint with structural and curricula integration in the country overall. These countries have a unique tendency to combine primary and lower secondary education in a single institution, under the name of comprehensive school, moving up the tracking age. Nordic states also tend to have an exceptional wide participation in lifelong learning education and training. School-to-work transition may be correlated with higher youth unemployment rate and weak youth labour-market outcomes. For example, there is a strong evidence of a post-1970s deterioration of youth labour-market outcomes in United States, detected by the study of Levy and Murnane (1992), which can be applied virtually to all OECD countries. Hence, two main policies are suggested by Ryan (2001), who takes a divergent view from the lifelong learning focused policies arisen by Green (2002), to eliminate school-to-work transition issues and thus the relative problems in the labour market:

- direct and planned school-to-work transition, which in a built-in system put firms in the situation to choose new employers directly from the newest graduates from schools, as in the Japanese case;
- "apprenticeship" systems in the German-speaking countries fashion, which implement

direct links with the corporate sector in which they are well-formed to fit the required job positions.

Evidences in these countries' labour markets prove that these systems equip an advantage to early movers, making possible the school-to-work transition of school-leavers to employment and work-based training, and they still have the lowest rate of youth unemployment. Moreover, vocationalism is able to catch many of whom would otherwise drop out of the studies falling in youth unemployment.

On the other hand, other studies detect that vocational education has empirically higher costs in terms of policy, it discourages youth turnover tying a young person and an employer for many years (at least three years in the German case), giving extensive knowledge to the other reducing the asymmetric information that otherwise would have been exploited by the employee in its favour. At support of this view, enrolment in vocational education has been declining because of lower labour market rewards in the long term, becoming less attractive in the knowledge society with individuals seeing the big picture.

Indeed, a theoretical education is typically viewed emphasising abilities which improve the ability to learn and allows to better adapt in a uncertain labour market over time, controlling for the probability of higher education.

A man-in-the-middle solution can be found in full-time schooling vocational programs combined with upgraded curricula and work experience for all types of students (Italy has moved in this direction with the "Buona Scuola" reform, while in the other direction with the previous one).

Exploring these topics, research in education plays a crucial role to analyse the impact of policy with a cross-country point of view, studying a worldwide education market in a international context, where borders does not exist anymore. However, this appears to be more tricky than expected. The persevered absence of a uniform regulation in education, especially for vocational programs, does not allow researchers to study differences in educational institutions' structures and labour-market outcomes in a cross-country fashion. The most important example in cross-country longitudinally data comes from the basic study of our analysis by Hanushek, Woessmann, and Zhang (2011), but we are far from the goodness in panel cross-country data as they have to rely on strong assumptions and cross-section analyses. On the other hand, research using Treatment Effect (TE) approach implies to study micro-data

in education starting from case studies, as in our case, which can be put together or a better comprehension of the phenomenon all-round, but for the intrinsic identification strategy of these analyses there is a lack of external validity, whereas national studies are embedded within an institutional structure common only to the analysed educational programs.

The lack of natural experiments with random assignment on the treatment arises an endemic problem of selection bias for all the major studies. Withal, the limited availability of social experiments matters more for youth, the main focus of these analyses, than for adults. As an example, state dependence in the comparison between vocational and general programs raises up systematically when upstream experiences in schooling or the youth labour market have downstream the effects in working life.

To face these issues, Heckman two-step procedures, Fixed Effect Models and Instrumental Variables are necessary to control the unseen selection processes, making the evaluation of results really difficult. Only time can provide us more availability of sound longitudinal datasets, improving the prospects of removing selection bias when studying causal links.

#### CHAPTER

2

### LITERATURE REVIEW

After a brief introduction of what means researching in education, in the following paragraphs we would like to show some case studies supporting the idea that vocational education has strong impact on lowering youth unemployment. Foremost, we would like to present some empirical studies in favour of the goodness of vocational education in the early stage of the labour market.

Hasanefendic, Heitor, and Horta (2016) produce a case study using qualitative data collecting for three different non-university higher education programs (more specifically in The Netherlands, Germany and South Portugal), which gives an empirical evidence of the power of vocational education in the school-to-work transition, providing problem solving and training that meets the employers' needs.

Blinova, Bylina, and Rusanovskiy (2015) perform an empirical analysis using regression models of the factors affecting the reduction of youth unemployment in the regions of Russia, where this is an endemic issue (as well as in European countries), and to determine the impact of vocational education on the reduction of youth employment.Blinova et al. (2015) take into account economic, demographic and social parameters, clustering on the basis of

those different geographical regions. The considered sample is made by unemployed individuals aged between 20 and 29 with different levels of education, exploiting the data obtained from the Federal State Statistics Service of the Russian Federation (Rosstat). They find that the most significant factor affecting the reduction of youth employment is the growth of the number of people with secondary vocational education and the reduction of the number of those having secondary general education on the labour market, giving a practical importance of how fostering vocational education programs in Russia may alleviate the youth unempoyment.

Riphahn and Zibrowius (2016) study the returns to apprenticeship and vocational training (AVET) at age 15 (at upper secondary school level) for three early labour market outcomes all measured at age 25 for East and West German youths (non-employment in terms of un-employment or out of the labour force, permanent full-time employment, and wages). Within this study they find empirical support to the policy suggestions of Ryan (2001), for which Germany has an international outstanding record in lowering youth unemployment. Empirically, vocational training generates strong positive returns on various dimensions at the early labour market entry. Individuals with AVET experience a lower risk of being inactive, have a higher chance of permanent full-time employment and earn higher wages than their peers who entered the labour market without investing in vocational training in Germany and minor differences between East and West Germany and between males and females. However, this study is strongly oriented to prove the goodness of vocational education at early age, without considering the effect of obsolescence on vocational education with respect to peers with other qualifications.

Moving on, the main theoretical foundation of the future empirical and quantitative work for government education policies, with a sound link with education policies of US and Europe in the last decades, has been developed by D. Krueger and Kumar (2004b). This model has been influenced the more recent studies on the comparison between the effects of general education versus vocational education at life-cycle level, and thus also our empirical study. Indeed, from the background data analysed by D. Krueger and Kumar (2004b), in the 1970s Germany (2.6 percent) and Italy (3.1 percent) has higher annualised per capita GDP growth then in the United States (2.1 percent), when the technological level in firms was lower. In

the 1980s, US grew at the faster rate of 2.3 percent compared to 2.0 percent and 2.2 percent for Germany and Italy (similar patterns can be seen for other European countries). The path is emphasised by a convergence in productivity level of US firms with a lower productivity than European firms until 1980s and it has diverged since then.

D. Krueger and Kumar (2004b) build a model of technology adoption and economic growth in which households optimally obtain either a concept-based general education or a skillspecific vocational education. Firms also are free to adopt either high-level or low-level technology, and a benevolent Ramsey government has the role to subsidise education in this environment. General education in this framework results more costly to obtain, both for individuals and for firms, but it allows individuals to adapt to technological changes, while vocational education makes economy to grow at a slower pace.

The most important outcome of the theoretical model can be found in Figure 2.1. It emerges that a benevolent Ramsey-fashioned government should choose higher subsidies for general education, and the quantity of this optimal subsidy depends crucially on the marginal growth obtainable without higher subsidies for general education. Traditionally, European education subsidies are more readily available for low ability students than in the US. On the basis of this model, if low ability students succeed in education, this may lead to higher skill-risk for new technologies and growth for Europe, with a mean-preserving increase in spread of those in the united states. However, the actual situation is that quality of US education is higher, because data shows that there is a mean-preserving increase in spread in Europe with US.

Under the assumption of  $\bar{s}(\lambda) \ge 1$ , which is the lowest quantity of optimal subsidy for general education in order to generate growth, it is optimal for the benevolent government to provide greater incentives for obtaining general education in order to generate growth.

When the growth rate of technological change is low, as in 1960s—1970s, it might have been the case that United States over-subsidised general education, whereas European policy was optimal. An increase in  $\lambda$ , which realistically has been steeply started in 1980s, has taken United States education policy at optimal level, *ceteris paribus*, while European policy fell in a situation of under-subsidisation for general education. For the authors, the traditional tendency to invest more in vocational education of European countries should be viewed as a metaphor for the rigidity and inflexibility of European upper- and post-secondary education, affecting growth without the required adaptability of workers to work with new technologies as Information and Communication Technologies (ICTs), with respect a more general and flexible education policy framework for the US labour market. To give some numbers, data for EU in 1995 shows 72 percent of individuals in Italy enrolled in vocational or apprenticeship programs, while in West Germany the percentage is 77%, and for the whole Europe 57.6%.



Figure 2.1: Optimal Subsidy *s* for general education in Ramsey government objective function against the relative subsidy, under the underlined assumption that the social discount factor  $\beta$  exceeds the threshold  $\overline{\beta}$  in D. Krueger and Kumar, 2004b, p. 195. Source: D. Krueger and Kumar (2004b, p. 196).

This sound theoretical model has been extended by D. Krueger and Kumar (2004a) to assess the quantitative importance of education policy introducing labour market rigidities and product market regulation, which may be other possible causes of the growth gap between United States and Europe other than education policy's choices. In a calibrated version of the former model, the role of education may still be significant, but it is difficult to theoretically explain the perfect relationship between education and labour market.

From now on, we address the main considered studies focused on differences in labourmarket outcomes among general and vocational education. In this sense, tracking – *i.e.* the level of age at which the choice amid education type is performed – provides great performances to run natural experiments, reducing the selection bias arisen by the analyses in this branch. Across OECD countries there is great diversity regarding the age at which tracking in education type is done. For example, some countries (*e.g.* United States, Spain and Italy as in Section 1.1) do not almost track students across schools, and there is always the possibility to change track in higher level of education, while some countries (*e.g.* German-speaking countries) separate students into different types of schools already at age of 10 (see Riphahn and Zibrowius (2016, p. 4) for further details about tracking in German education system). Countries also differ for the number of tracks available in the education market.

Tracking matters for later outcomes in the labour market, as educational systems with early age tracking are exposed to the risk of students ending up in the wrong track, and it may be difficult to anticipate future education performance at an early point of the education career. Moreover, the willingness to proceed up with the studies may not yet be formed. Effects of selecting in the wrong track for students should be mitigated when all all tracks enable students to continue to higher education, and this even more effective talking about students whose parents have low education, who are more oriented to end up in vocational education without exploiting their abilities all-round.

We introduce some case studies exploiting a policy change on tracking, moving from a more vocational-focused path to one with increased academic contents: in the fashion of the theorised model by D. Krueger and Kumar (2004b), the empirical work by Golsteyn and Stenberg (2015) and the thought of Green (2002), this are evidences of how policymakers may face the need for a broader education in working life, as well as the desire to make everyone eligible to university studies changing the track in education. A classic study in this context is developed by Oosterbeek and Webbink (2007), who investigate the effect of a Dutch reform in 1975 that elongated former three-year vocational tracks with an additional year of general education. They use difference-in-differences approach to estimate the effects, where students already in the former track did not change length serve as control group. Oosterbeek and Webbink (2007) find no positive effect of the extra year of schooling on the vocational students' long-term wages.

Pischke and von Wachter (2008) use a similar policy in German school reform that increased of one year the compulsory schooling in the lowest education track between 1950s and 1970s. They search for changes in long-term wages as well, but they do not find any evidence. Malamud and Pop-Eleches (2010) evaluates a Romanian reform which delayed tracking of students in either vocational or general programs. To do so, they use a regression discontinuity design, failing to find effects of this reform on enrolment in higher education, employment or earnings.

An influent study by Hall (2012) analyses a policy change in Sweden, introduced in order to bring a higher quality of education and increase flexibility of the upper second school system by introducing more academic subjects. The reform reduced the gap in academic content between general and vocational education, concentrating upon vocational education by extending it from two-year to three-year programs. That was implemented by adding, together with Swedish (which was the only former academic subject included in vocational programs), English, Social Studies and an eligible academic course, which was most likely to be Math. The effect of this reform was also to make individuals with vocational education eligible for university.

Reform was progressively introduced among different municipalities from 1988 to 1990. Since only 68 percent of municipalities offered vocational tracks, and the number remained so after the reform, students residing in other municipalities had to attend school in nearby municipalities if they wanted to acquire a vocational education. Hence, the author applies an IV identification strategy where individuals' exposure to the pilot is used as instrument for the selection in three-year rather the former two-year vocational track in order to study different outcomes, and this exposure is measured as the share of available three-year vocational tracks nearby the municipalities at upper secondary education. This instrument results potentially exogenous to the unobserved component of the outcomes of interests, as proved by F-tests provided by the author, and it holds for the monotonicity assumption to obtain Local Average Treatment Effects (LATE).

Controlling for individuals' characteristics (as GPA), family and immigration background, on the basis of different merged datasets provided by Swedish Statistics, IV estimates suggest that enrolling in a three-year track has no effect with respect to enrolling in the former track on the probability of starting or completing a university degree (opposite to the findings of Bianchi (2016) based on Italian micro-data), neither on earnings over life-cycle except for the normal pattern of entering one year soon in the labour market for the two-year vocational track. This is a sound effect in favour of the absence of the initial negative effect on

labour-market outcomes of more vocational education. However, studies from Nordström Skans (2004) based on almost the same data, find that being unemployed the year after upper secondary school's graduation had negative effects on earning and employment during the subsequent five years talking about life-time outcomes in the labour market. However the negative effect seems to decrease over time and is not significantly different from zero six years after graduation, thus around age 25.

The same author keeps the good work in Hall (2016), where she fully investigates, on the basis of the same data, whether acquiring more general education reduces the risk of future unemployment. To do so, Hall (2016) examine students' labour market experiences during the 2008-2010 recession which affected Sweden, as in 1990s when the change of tracking was made, at which time the considered individuals they had reached their late 30s. She applies the same identification strategy by using IV and a linear probability model where the dependent variable is an indicator equal to one if individuals was unemployed for respectively 90, 180 or 360 days during the period 2008-2010.

IV estimates in Hall (2016) suggest that the probability of unemployment by raising academic contents and years of education in the treatment group is not significantly different from zero, thus a different track in more general vocational education does not affect employment in the whole sample. By dividing the sample in gender subgroups and distinguishing between all, low GPA and high GPA, Hall (2016) detects an increased risk of unemployment concentrated on male individuals for 360 days and among man, to those who finished compulsory education with lower grades. However, for this last group Hall (2012) findings suggest that this effect may be related to the increased probability in dropping out from the longer and more general vocational program when the GPA was lower in compulsory education. Hence, the lack of a complete degree may cause worse labour market outcomes among weaker students, and not the increased general content of their education.

All these previous studies on policy changes affecting tracking suggests that a gap between general and vocational education programs in labour-market outcomes is not significantly different from zero.

Furthermore, it is worth to cite the paper by Pekkarinen, Uusitalo, and Kerr (2009), as Hall (2012) may be interpreted as its twin country-based research, studying the effect of the Finnish Comprehensive School reform but focusing on intergenerational income mobility.

The Finnish education reform detained the choice of education type amid academic and vocational tracks from age 11 to age 16, leading to an increase in the whole academic content in the pre-tracking curriculum and the quality of the peer group for those students who would have attended the vocational track in the old system, especially for pupils from a poor background, whose parental preferences are more likely to determine education choices at such early age. The common point with Hall is the gradual implementation of the reform, at different times and different municipalities in a six-year period from 1972 to 1977, starting with Lapland where access to education were most limited.

Using data from Finnish Longitudinal Census by Statistics Finland, with personal identity codes to merge information from different administrative registers, they use a difference-indifferences approach in order to estimate the intergenerational earnings elasticity between fathers' and sons' lifetime earnings, including region fixed effects, cohort dummies and an indicator variable equalling to 1 if the reform had taken place in the municipality by the time the son was eligible for comprehensive school. They find that reform reduced intergenerational earnings elasticity compared by 23 percent compared to the pre-reform level, which means that, with care for external validity, policies which expand the access to academic secondary education and widening the academic content of compulsory education my significantly enhance intergenerational earnings mobility with respect to early-tracking education systems and vocational-oriented.

Few studies consider the evolution of labour-market outcomes over the life-cycle among education type in a strict sense, which makes the empirical foundation of our research for its relevance in this small and still not adequately treated topic. In this sense, Golsteyn and Stenberg (2015) provides a unique case study for Sweden. They use a panel from Upper Secondary School Application Records 1971-1979 (which provides a unique identification number to merge the data with Statistics Sweden) of Swedish siblings who enrolled in the former different 2-year upper secondary school programs with tracking at age 15, for both sex, controlling for GPA (ability) and family fixed effects (family background), following wages trajectories from age 15-23 to age 48-56 from 1978 to 2011. They find that vocational education is associated with an initial relative earnings advantage, but this is transformed into a relative earnings disadvantagege of around 2-3 percent after ten years for males (at age 28) and 2-3 years for female (at age 20), converging at the same level around age 35 and over-

lapping the initial gap in earnings between general and vocational. Contrary to Hanushek, Woessmann, and Zhang (2011) and our analysis, they do not consider tertiary education. The lead study of Hanushek, Woessmann, and Zhang (2011), which put the ground of our analysis, assess whether relative labour-market advantage of vocational education decreases with age, and this comes in line with the D. Krueger and Kumar (2004b) theoretical model where the propensity to use intensive skills-related education against academic-oriented education in Europe that may be the underlying cause of growth rate differential between US and Europe.

Hanushek, Woessmann, and Zhang (2011) provides the soundest empirical evidence to the Ryan (2001) possible trade-off between short-term and long-term costs and benefits for both individuals and the entire society, for which the skills generated by vocational education may facilitate the transition into the labour market but it may later on become obsolete at a faster rate than a more academic education. This is a unique study in terms of information type and its widespread goodness, because only few studies consider cross-country differences in education type and the whole trajectories of the labour-market outcomes over the lifecycle, without focusing only on youth's, although the analysis is more problematic and it comes with strong assumptions. Hanushek, Woessmann, and Zhang (2011) uses IALS data, which contains unique information about respondents' years of schooling and whether they completed a vocational or a general education program in secondary and post-secondary education, for a representative sample of adults between age 16 and 65, as well as extensive data on other individuals employment-related characteristics including age, gender, years of schooling, earnings, employment status and adult training, where the last three are the main analysed outcomes. Information is available for 18 countries: 15 EU Countries (including Italy) and US, New Zealand and Chile. IALS dataset provides also a unique information about a series of assessments of cognitive skills (i.e. "literacies"), which are comparable within and across countries and used as instruments for individuals' ability.

Classification of education type is harmonised at cross-country level, considering at upper secondary school level general education if education program is academic or college preparatory, while vocational education if the program is business, trade and vocational, while at tertiary education level a general program is one that leads to a university degree (BA/BS) and a vocational program is one that does not lead to a university degree. They also exclude females from the sample, because male individuals have more stable aggregate labour-force participation patterns in prime-age groups across countries, and they take individuals with at least upper secondary education.

Hanushek, Woessmann, and Zhang (2011) primarily uses a difference-in-differences identification strategy, which inspires our empirical model in Section 3.2.1, to mature the initial employment probability of those with general education relative to the with vocational education, and the differential impact of a general relative to a vocational on employment with each year of age. General findings of the applied linear probability model controlling for age, age-squared, literacy scores, percentages completing general and vocational education in each country for each age cohort and average literacy scores says that, while individuals with a general education are initially 7.5 percentage points less likely to be employment than those with vocational education at cross-country level, the gap in employment rates is reduced by 1.6 percentage points over ten years, then around age 60 individuals completing general education are more likely to be employed than individuals completing a vocational education. Similar results are obtained also considering propensity score-matching techniques.

Since this sample is heterogeneous and not well-defined, Hanushek, Woessmann, and Zhang (2011) distinguish countries in the IALS data by the distribution of upper secondary students between general together with Education At a Glance (EAG, Organisation for Economic Cooperation and Development (OECD), 2010) 1996 and 2007 reports, obtaining a macro-group of vocational countries (Belgium, Czech Republic Denmark, Finland, Germany, Hungary, Netherlands, Poland, Switzerland, Norway and Slovenia), a small subgroup of "apprentice-ship" countries (Denmark, Germany, and Switzerland), where the share in combined school and work-based programs in vocational programs exceeds 40 percent, and non-vocational countries (Chile, Italy, New Zealand and United States) on the basis of these criteria. Using these groups, Hanushek, Woessmann, and Zhang (2011) obtain results separately for each vocational countries, reporting that all three countries belonging to the "apprentice-ship" countries display a clear age-employment pattern for "apprenticeship" countries may be adult training, as they test for the impact of education type on adult education, resulting that in all the three "apprenticeship" countries individuals with general education are more likely to receive career-related education, and to receive more hours as if they become older. Hanushek, Woessmann, and Zhang (2011) also seek the existence of possible age-related differences in earnings patterns by education type, as a straightforward extension of a Mincer earnings function. It emerges that Finland is the only country where individuals completing general education can earn significantly less in early age being caught up with those with a vocational education over time (but it is biased for small sample size patterns). Using estimates of the initial employment losses from general education, Hanushek, Woessmann, and Zhang (2011) also calculate the present value of lifetime employment for workers with different education type in the apprenticeship countries and they weigh employment at each age by the average earnings for each age cohort by schooling type. It emerges that, German workers with a general education over the lifetime will have 24 percent higher earnings than peers with vocational education, while Danish workers with general education will see six percent higher earnings. Switzerland presents an opposite situation, because the higher present value goes to those with vocational education, and this for the authors can be interpreted as clear empirical evidence of the theory shaped by D. Krueger and Kumar (2004b): in faster growing societies with faster technological change, as Denmark and Germany with respectively a 2.1 and 2.2 percent growth rate in GDP per capita in the period 1970-2000, general education is more adaptive together with added adult employment to yield advantages to the workers, while in societies with staler growth, as for Switzerland with a 1.1 percent growth rate per capita for the same period, vocational education on average may perform better. In addition to the initial study, Hanushek et al. (2017) provides further robustness to the main findings using the cross-section sample limiting the IALS dataset to the only vocational education group of countries. Other than IALS, it considers micro data from two of the most apprenticeships countries in EU, which are German Microcensus and Austrian Security Social Data. For the German Microcensus, they find the same pattern using a much larger and more recent sample of the trade-off between general and vocational education by including also non-linearities not included in the wider sample analysis, while for the Austrian data (which are not previously included in the IALS dataset), analysing the effect of a plant closure with a brand new difference-in-differences model, the relative employment rates of displace blue-collar workers, with more vocational training, are above those of white-collar workers at younger ages, but below them at age 50.

An innovative study in this field has been conducted by Brunello and Rocco (2015). To analyse the short-lived labour market benefits of vocational education, they start from Hanushek, Woessmann, and Zhang (2011) studying the effect freeing the empirical strategy from the strong assumptions of this study and embracing the option that it is more likely that contents of vocational and academic education have changed over time and across cohorts in several developed countries. In order to take into account these differences in selectivity on education, the empirical strategy of Brunello and Rocco (2015) considers only within-cohort variation in labour-market outcomes. They perform the analysis by exploiting two longitud-inal cohort studies in United Kingdom, from age 23 to 55 in case of the older cohort born in 1958, from age 26 to age 42 for the younger cohort born in 1970. In this way, it allows authors to follow individuals for at least 16 years in the labour market.

As UK is not considered a "vocational" country, as vocational-oriented courses are elective within the normal education path, they distinguish between "dominant" and "non-dominant" vocational education evaluating its intensity from the distance in National Vocational Qualification (NVQ) Levels between the highest vocational qualification and the highest academic qualification. They also distinguish two levels for two levels of education on the basis of whether individuals highest attained qualification belongs to upper secondary education or tertiary education level. The selection bias originated by the identification of economic costs and benefits of education types' causal effects, is addressed by estimating separately the effects of time invariant education type on employment and wages at the initial available age by using the AIPW (augmented inverse probability weighted) estimator, and the changes in these effects by Fixed Effects (FE) estimator as individuals remain in the labour market.

Empirical estimates are obtained simulating average employment and earnings profiles by age and computing expected lifetime earnings for each education type, or discontinued sum of expected earnings from the first age to the final available age. Results from this empirical strategy indicate there is a significant early advantage for vocational education at the higher education and it lasts until individuals are in their early 30s: anyway, no trade-off between early employment advantages and later disadvantages can be detected, contrary to Hanushek, Woessmann, and Zhang (2011) in the cross-country study.

Replicating the analysis for wages, Brunello and Rocco (2015) find that, while for employment there are no significant differences between cohorts in the life-cycle of employment, cross-cohort differences are sharper considering net real wages, making individuals with vocational education wealthier at early age, but they shift over time and age into long-term disadvantages with respect to individuals with general education. Considering expected long-term earnings, vocational education is associated to lower earnings for lower-educated individuals with vocational education in the older cohort and higher-educated with vocational education in the younger-cohort.

To conclude this review, albeit it excludes a lot of relevant works, other two studies are briefly worth of a mention. Hotchkiss (1993) studies the effects of vocational education on employment and wages in the United States academic-oriented framework, within high school graduates in 1980, finding no returns to vocational for training-related occupation choice, whereas Dearden, McIntosh, Myck, and Vignoles (2002) compare wages among vocational and general education in United Kingdom stating that, while returns to academic education are the highest, individuals with vocational education perceive higher wages relative to those with no vocational qualification, especially compared to low achieving school leavers as in Hall (2016).

#### CHAPTER

3

### DATA AND IDENTIFICATION

#### **3.1 Data**

To investigate about the effect of our primary hypothesis on education type, we require exhaustive data about those variables, patterns in the labour market over the life-cycle and, more than that, sufficient qualitative information about individuals in the labour market, in order to understand the individual selection in schooling and the effect of the parental back-ground on it.

The Survey on Household Income and Wealth (hereafter, SHIW) by Bank of Italy provides a unique source of information about individuals in the country-level labour market. The SHIW started in 1965 in order to gather data on incomes and savings of Italian households, and over the years it has grown in scope including qualitative information about individuals, wealth and all other aspects' of households' economic and financial behaviour, including for instance the payment methods employed. The survey results are published regularly in the Bank of Italy's Supplements to the Statistical Bulletin and the datasets are freely available in the Bank of Italy's Website (Bank of Italy, 2017) for further research and analysis. Starting from 1987, the Survey on Household Income has tried to provide longitudinal data about households, following individuals for more than one wave, but the creation of a consistent panel is still far from being uniform. Since 2010, the survey has provided the data for Italy for the Eurosystem's Household Finance and Consumption Survey (HFCS, Eurosystem Household Finance and Consumption Network (2013)), coordinated by the European Central Bank, and for a number of years the Bank of Italy has been taking part in projects for the harmonization of income and wealth data (Luxembourg Income Study and Luxembourg Wealth Study).

We consider the SHIW because it is the only source of data which keeps the information about upper secondary education type and tertiary education type together with labourmarket variables. When harmonized with other sources of data from the European countries which participates in the Household Finance and Consumption Survey, the Italian sample has got the older information about education through waves, without being affected by oversampling issues on wealthy individuals (Tiefensee & Grabka, 2016). The only valid alternative to the Survey on Household Income and Wealth could be the European Union Statistics on Income and Living Conditions (EU-SILC) with data gathered by EuroStat, but it still needs to be developed collecting more waves of analysis.

For the analysis we consider different versions of the SHIW:

- The Historical Database (from now on, HD) of the Survey of Italian Household Budgets from 1977 to 2014 (Bank of Italy, 2015), realized in 2015 for the 50<sup>th</sup> anniversary of the Survey. It provides a unique source of information with harmonized variables through the different surveying methodologies, providing more homogeneous variables than the single annual waves for our purposes: this is taken as our main dataset in our analysis.
- The Annual Waves of the Survey of Household Income and Wealth, to acquire qualitative variables about individuals, including the education type, and merge them in the Historical Database for the same individuals.

It is possible to merge these different datasets using the common primary keys in both sources: nquest, which identifies households, nord, to sort individuals in the household

(with nord = 1 as the head of household), and anno for the wave. On the basis of these information, we realize a dataset of longitudinal data from starting from 1987, the first year of panel collection, to 2014, expanding the main idea of Baldi and Pellizzari (2005) script. In this way, we can follow individuals for more waves, being sure they have the same background characteristics. However, it should be said that there is a significant issue in these dataset: together with a *massive measurement error* upon variables overall (Biancotti, D'Alessio, & Neri, 2008), education type starts to be recorded in 1995, and until 2008 it is saved only for the highest education achieved, such as a degree: hence, in case of graduate individuals, we lose the information about upper secondary school education type until 2008.

Therefore, our research is focused on high school diplomas (ISCED 3 in Figure 1.1): we are not able to make a clear separation between vocational and general education at highest degree level as in Hanushek et al. (2017) or Brunello and Rocco (2015), rather following Golsteyn and Stenberg (2015), because at graduate level the indicator variable of degree's type in the dataset (tipolau) merges too many different fields of study together, also without tracking post-secondary vocational education and making impossible to discriminate between vocational and general education tracks.

To stem these issues, we carry out a script with a *top-down* iteration across waves to fill missing values in qualitative variables that should not vary all over the waves, upper secondary education type included. For example, if the upper secondary school diploma is achieved, it is supposed to be that remains the same over time. Starting from 2014 wave, we check the value of each variable affected by this issue, comparing it with the n - 1 wave: if the value is missing or, for parents' educational attainment and other similar variables, it is inconsistently higher than the previous wave, we copy the value under wisdom assumptions on age and other qualitative information, and we continue downwards until 1987 wave. After this first iteration, the script repeats the same technique *bottom-up*, to fill missing values from the oldest to the closest wave, in order to complete the job of the previous cycle.

After the creation of this longitudinal dataset, we have to keep only the individuals where education type information is not missing, and we remove all the individuals flagged as inconsistent. An exploratory table about panel size is given by Table 3.1: as we can see, attrition does not permit us to achieve an acceptable panel size to run a "true" longitudinal analysis,

longitudinal waves															
		1987	1989	1991	1993	1995	1998	2000	2002	2004	2006	2008	2010	2012	2014
starting year	1987	4101 59	937 71	277 79	160 97	126 110	84 76	66 61	48 46	36 34	30 30	26 26	21 21	13 13	9 9
	1989		6389 432	1709 488	879 551	750 624	565 481	417 362	325 294	230 219	169	149 149	121	95 95	52 52
	1991			4990 1094	2099 1256	1682 1415	1212 1061	855 775	650 614	513 499	447 447	390 390	343 343	302 302	197 197
	1993				3480 703	947 794	587 509	379 335	251 235	186 182	165 165	149 149	139 139	123 123	93 93
	1995					3870 3216	387 341	255 234	172 164	121 117	98 98	74 74	64 64	55 55	38 38
	1998						4564 3816	2048 1781	1247 1145	851 809	670 670	573 73	454 454	400 400	281 281
	2000							3688 3014	944 844	629	468	391 391	330	278	182
	2002							5014	3634	957 884	625	500	402	331	204
	2004								5009	3732	1222	948 948	402 747	636	423
	2006									3180	3453	1062	843	696	423 466
	2008										3453	1062 3346	842 1097	696 839	466 475
	2010											3346	1097 3469	839 1189	475 688
	2012												3468	1189 3333	688 1571
	2012													3333	1571 3445
	2014														3445

and this will determine the choice of our identification strategy in Section 3.2.

Table 3.1: Frequencies of longitudinal data in the sample. The table describes the number of individuals which are followed for more than one wave with at least upper secondary education. In the first row for each year, the number indicates the frequency of individuals with upper secondary education in that wave which comes from the previous wave, whereas the frequency of individuals with available education type's information is in the second row. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015).

To avoid further measurement error issues on vital statistics, we exclude waves before 2000 which are also weak in size. Moreover, we exclude all individuals still in education, which does not participate in the labour market at the time of the survey, in order to seek for the most genuine effect of the education type on labour-market outcomes. Thus, it is reasonable to consider a sample of individuals starting from age 20, when theoretically they should have finished the upper secondary education cycle, excluding from the sample a small number of untimely workers who attended a vocational school (*"istituto professionale"*) which ends up around age 17.

This strategy does not follow the same sample division of Hanushek, Woessmann, and Zhang (2011), which includes individuals from age 16 because, looking at the wider sample and including younger people than 20, only a residual part (8%) appears to be employed, while the remaining are still in education for the most.
After this sample restriction, it is also safe for the goodness of our analysis to keep only male individuals: female labour force's participation results passively in the Italian labour market (Crepaldi, Pesce, & Samek Ludovici, 2014) and, keeping this part of the population, it may assemble further bias in the estimation's processes.

In the SHIW (Bank of Italy, 2017), upper secondary education type indicator distinguishes six groups combined with the education highest level indicator, following the same outline of Figure 1.1: vocational school as previously referred, technical school (*istituto tecnico industriale* or *istituto tecnico commerciale*), academic school-*lyceum* (as *linguistic, humanistic* or *scientific* studies), art (*liceo artistico* and *istituto d'arte* before 2011), normal school (formerly *magistrali* before 1992, currently *liceo delle scienze umane*), and other types of upper secondary education. For the purposes of our analysis, we consider with vocational education individuals who graduated in vocational tracks (three-, four- or five-years), technical and normal schools. We also pick up normal school as vocational because, whilst they are assigned as human lyceums now, until 2002 it has qualified graduates to teach in primary and early childhood education (ISCED 0-1), training those individuals for a specific job. On the other hand, we consider with general education more traditionally individuals who graduated in art and academic school. Furthermore, we provide a different category for "other" education programs, in order to clean the true effect on the other two macro-categories.

## **3.1.1 Descriptive Patterns**

With the aim to describe our sample, in Table 3.2 we have frequencies and percentage of education type by age cohorts of five years. As we can see from the tables, the selected sample includes 25,173 male individuals between age 20 and 65, and they have to be considered vocational-oriented in line with our definition of vocational education: for the pooled waves, 76.51% graduated in vocational education programs at upper secondary school, while only 22.11% graduated in general education programs (if we sum the two values we do not reach the unit value because of individuals with "other" education). Even if we are dealing with school-based vocational programs, our data are in contrast with the cross-country sample approached by Hanushek, Woessmann, and Zhang (2011) where, for the International Adult Literacy Survey (IALS, Organization for Economic Co-operation and Development (OECD), 1997) the level of general education for the Italian sub-sample is much higher than

in the selected part of the SHIW dataset. Conducting statistics over the entire SHIW database the results are in analogy with our subset.

age cohort	2000	2002	2004	2006	2008	2010	2012	2014	Total (cohort)
20 — 24	29.24%	30.35%	29.35%	28.07%	33.96%	34.51%	34.19%	33.11%	31.60%
	69.09%	67.82%	69.35%	70.52%	64.40%	64.08%	65.38%	66.22%	67.11%
	537	491	460	424	427	426	465	450	3,680
25 — 29	23.86%	24.59%	25.12%	27.21%	26.68%	31.08%	32.53%	33.70%	28.10%
	75.10%	73.29%	74.16%	71.81%	71.88%	67.67%	67.47%	65.74%	70.89%
	482	423	418	408	416	399	372	359	3,277
30 — 34	16.81%	15.99%	18.18%	21.35%	17.86%	20.71%	26.62%	32.58%	21.26%
	82.05%	81.98%	80.19%	76.61%	81.25%	78.64%	73.38%	66.67%	77.60%
	351	344	308	342	336	309	308	267	2,565
35 — 39	16.12%	11.54%	17.89%	19.57%	20.47%	22.03%	22.29%	22.30%	19.03%
	82.24%	87.06%	80.51%	77.21%	76.56%	75.93%	76.75%	76.62%	79.11%
	304	286	313	373	337	295	314	278	2,500
40 — 44	16.24%	13.94%	14.33%	23.48%	23.47%	23.40%	20.11%	22.12%	19.64%
	81.48%	84.55%	84.08%	74.86%	74.93%	73.65%	77.75%	75.15%	78.31%
	351	330	314	362	375	406	373	330	2,841
45 — 49	17.85%	19.13%	20.00%	23.14%	20.67%	20.91%	21.29%	20.00%	20.37%
	81.14%	78.19%	78.13%	75.76%	76.82%	78.02%	77.36%	78.86%	78.03%
	297	298	320	363	358	373	371	350	2,730
50 — 54	10.61%	14.78%	17.73%	22.44%	26.04%	25.32%	26.20%	20.00%	20.39%
	88.48%	83.16%	80.94%	75.96%	72.49%	74.42%	73.05%	79.00%	78.44%
	330	291	299	312	338	391	397	400	2,758
55 — 59	13.16%	10.83%	13.43%	16.41%	20.38%	22.05%	25.68%	27.30%	18.65%
	85.09%	88.33%	86.22%	82.37%	78.68%	76.40%	73.72%	71.81%	80.33%
	228	240	283	329	319	322	331	337	2,389
60 — 65	17.13%	16.24%	17.94%	22.41%	20.00%	22.28%	21.09%	22.41%	19.94%
	80.66%	82.74%	80.27%	76.21%	79.35%	76.94%	77.96%	76.18%	78.79%
	181	197	223	290	310	386	422	424	2,433
Total (wave)	17.89% 80.59% 3061	17.49% 80.79% 2900	19.33% 79.32% 2938	22.67% 75.70% 3203	23.28% 75.15% 3216	24.70% 73.97% 3307	25.56% 73.65% 3353	25.95% 72.92% 3195	22.11% 76.51% 25,173

Table 3.2: Percentage of education type by age cohorts. Sample includes all males who finished at least secondary education aged from 20 to 65. Age cohorts are grouped by five years. Secondary education is classified as general for academic (*liceo*) and art tracks, vocational for professional (*istituto professionale*), technical (*istituto tecnico*) and normal (*magistrali*) education paths and other for undefined programs. In the first row of each age cohort we have the relative frequencies of general education, while in the second row relative frequencies for vocational education. Observations' numbers are in the third row. Years of Analysis: from 2000 to 2014, every two years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015).

As we anticipated in Section 1.2, the intensity of general education differs by age cohorts, and it varies with waves: from descriptive statistics in Table 3.2 it emerges that younger cohorts, especially the youngest between age 20 and 24, are more in general education than the oldest, and closer waves encounter higher frequencies of general education than the farer, but percentages keep to be in favour of vocational education. In Figures 3.1 we have a graphical description of what we observe from Table 3.2.

The goals of our analysis are employment and wages patterns over the life-cycle. Table 3.4



(a) Descriptive patters for general education by age cohorts, pooled sample

(b) Descriptive patterns for general education by wave and age cohorts



Figure 3.1: Descriptive patterns for general education type discriminating by age cohorts grouped by five years. See caption in Table 3.2 for data source, sample and definition of education type.

shows the percentage employment of males with different education types across the entire sample for age cohorts grouped by five years, where unemployment includes all the categories illustrated by Table 3.3: thus, above all, first-job seekers, home-makers, well off individuals, retired and students. As we can state from Table 3.4, the pattern is not uniform across waves, and until 30 to 34 years old individuals with vocational education are more likely to be employed than those with general education. This difference is huge especially for the youngest cohort, where from Table 3.3 we can see that a large percentage of individuals among these ages with general education are still studying: this is the reason why we exclude the youngest cohort from the sample in Section 4.1.4.2 in order to drop the effect of this cohort on unemployment rates as robustness check. Figure 3.2 illustrates the behaviour of employment rates over the sample drawn by Table 3.4 in graphical terms: we will better describe this behaviour going on with our analysis.

Unemployment Status	Employed	First-Job Seeker	Homemaker	Well Off	Pensioner	Unemployed	Student	Other Unemployed	Total
20 — 24	9.12% 1,184	15.28% 707	0.00% 2	0.00% 1	14.29% 7	4.49% 89	58.32% 1,629	16.39% 61	32.09% 3,680
25 — 29	17.80% 2,051	40.00% 470	50.00% 2		14.29% 7	12.24% 147	59.76% 589	63.64% 11	28.44% 3,277
30 — 34	18.01% 2,077	39.21% 227	0.00% 1	33.33% 3	29.41% 17	15.79% 133	65.38% 104	3	21.75% 2,565
35 — 39	19.95% 2,266	33.82% 68	_	0.00% 1	33.33% 15	16.15% 130	52.94% 17	66.67% 3	20.48% 2,500
40 — 44	21.02% 2,698	59.26% 27	_	66.67% 3	9.09% 11	24.21% 95	66.67% 6	0.00% 1	21.58% 2,841
45 — 49	22.15% 2,605	14.29% 7	_	0.00% 3	19.23% 26	22.35% 85	100.00% 1	66.67% 3	22.16% 2,730
50 — 54	24.11% 2,534	0.00% 3	0.00% 1	80.00% 5	13.13% 99	14.16% 113	100.00% 1	50.00% 2	23.42% 2,758
55 — 59	25.50% 1,737	0.00% 1	0.00% 4	50.00% 6	12.81% 531	13.46% 104	0.00% 1	60.00% 5	22.23% 2,389
60 — 65	35.03% 8,25		0.00% 1	85.71% 7	19.28% 1,546	25.53% 47		14.29% 7	24.91% 2,433
Total	21.06% 17,977	28.15% 1,510	9.09% 11	55.17% 29	17.57% 2,259	15.69% 943	58.99% 2,348	27.08% 96	24.57% 25,173

Table 3.3: Percentage of general education by unemployment status and age cohort. Unemployed individuals are divided by eight classes. Table 3.2 for data source, sample and definition of general education.

In Figure 3.1 we also consider the percentage of general education in the sample excluding self-employed individuals. Indeed, self-employment in Italy has been related to issues of tax evasion and the structure of the labour market, developing a large number of atypical contractual arrangements, such as apprenticeships, fixed-term contracts, collaborators, agency

work and project work, characterized by low social security protection, among standard employment contracts with high social security protection (Berloffa, Modena, & Villa, 2015). With these contracts, thanks to a reduced regime of compulsory pension contributions, and to lower labour costs compared to regular employees (the most of the time without representation by trade unions), any employers, mostly in tertiary sector (including the public administrations), use them extensively, making this form of self-employment more similar to temporary contracts, appearing as self-employed but, at the end of the day, working as normal employees: this is a peculiarity of the Italian job market (Ballarino et al., 2014). We observe that, excluding self-employed individuals from the sample, the percentage of general education increases for youngest age cohorts and decreases for older cohorts, remaining at the same level for the oldest.

age cohort	2000	2002	2004	2006	2008	2010	2012	2014	Total (cohort)
20 — 24	9.55%	10.74%	8.89%	7.56%	9.66%	10.88%	6.29%	8.72%	9.05%
	42.59%	40.84%	43.89%	47.49%	49.09%	44.32%	39.47%	35.57%	42.80%
25 — 29	29.57%	38.46%	47.62%	52.25%	46.85%	37.10%	35.54%	31.40%	39.58%
	72.10%	72.90%	70.65%	79.18%	72.58%	69.26%	69.72%	64.41%	71.60%
30 — 34	71.19%	56.36%	66.07%	80.82%	76.67%	73.44%	59.76%	62.07%	68.10%
	88.19%	86.17%	88.66%	83.59%	86.08%	86.42%	77.43%	73.60%	84.34%
35 — 39	93.88%	96.97%	87.50%	87.67%	88.41%	87.69%	84.29%	87.10%	88.47%
	95.60%	92.77%	94.05%	93.06%	91.09%	86.61%	89.21%	84.98%	91.14%
40 — 44	94.74%	93.48%	95.56%	92.94%	95.45%	91.58%	88.00%	89.04%	92.38%
	99.30%	96.77%	98.11%	96.68%	98.58%	94.98%	92.41%	88.71%	95.76%
45 — 49	100.00%	100.00%	98.44%	97.62%	93.24%	96.15%	97.47%	85.71%	95.89%
	95.44%	97.42%	95.20%	96.73%	96.00%	94.16%	94.77%	93.12%	95.30%
50 — 54	97.14%	93.02%	94.34%	98.57%	97.73%	94.95%	93.27%	92.50%	95.10%
	88.70%	90.08%	89.67%	91.56%	95.51%	92.10%	92.76%	88.92%	91.09%
55 — 59	56.67%	80.77%	76.32%	81.48%	83.08%	92.96%	91.76%	89.13%	84.82%
	54.12%	57.55%	59.02%	67.53%	68.13%	80.08%	81.15%	85.12%	69.64%
60 — 65	22.58%	43.75%	42.50%	38.46%	54.84%	54.65%	51.69%	72.63%	51.80%
	21.92%	23.93%	21.23%	28.05%	23.98%	28.96%	32.83%	40.87%	29.20%
Total	51.54%	53.94%	59.12%	66.62%	65.62%	64.54%	60.76%	61.40%	61.03%
(wave)	74.98%	74.34%	74.17%	76.58%	76.03%	74.82%	73.11%	71.50%	74.45%

Table 3.4: Percentage of employment by education type, age cohort and wave. In the first row for each age cohort we have employment rates for individuals with general education, while in the latter for individuals with vocational education. See caption in Table 3.2 for data source, sample, definition of education type.

Looking at Figure 3.2a, we see that individuals with vocational education perform higher employment rates at the beginning of their working life while they suffer a lack of employment near their retirement age, and this path introduces us to the main goal of our analysis: we expect an advantage of vocational education in the earliest ages and a loss in the oldest.

## CHAPTER 3 - DATA AND IDENTIFICATION

age cohort	2000	2002	2004	2006	2008	2010	2012	2014	Total (cohort)
20 — 24	2,938.64	5,010.71	3,651.61	3,475.22	5,082.14	5,700.93	3,377.78	4,629.17	4,227.47
	7,590.90	8,579.83	8,869.43	9,219.66	10,869.67	9,672.13	8,643.11	8,556.14	8,959.58
	228	184	190	189	185	164	160	150	1,450
25 — 29	6,441.30	9,001.94	8,017.54	9,828.03	10,691.64	10,330.91	8,800.38	9,316.19	9,162.07
	9,193.31	9,683.74	10,946.88	11,770.13	11,386.63	11,061.55	10,873.71	10,388.89	10,625.28
	317	292	290	307	293	254	237	214	2,204
30 — 34	8,785.51	8,836.28	10,357.90	13,686.80	11,461.94	13,476.47	12,159.07	12,030.24	11,597.65
	10,598.18	10,117.53	11,840.38	13,181.43	12,693.61	12,113.17	11,901.54	11,693.59	11,728.99
	307	294	267	292	293	278	236	206	2,173
35 — 39	10,108.57	8,920.19	13,984.31	12,007.65	14,499.80	11,654.17	15,940.68	14,040.26	12,912.12
	11,697.54	12,709.09	13,664.42	13,952.97	12,399.41	13,462.15	14,153.42	12,825.91	13,109.63
	297	272	298	348	320	270	285	250	2,340
40 — 44	12,339.91	13,203.20	16,023.86	19,817.30	16,317.52	17,802.07	15,555.22	15,530.30	16,200.14
	12,825.08	12,553.67	13,096.70	14,660.45	15,794.67	15,134.53	14,296.76	15,749.30	14,245.90
	347	325	311	355	373	392	357	308	2,768
45 — 49	12,947.48	15,243.86	15,933.28	17,758.30	21,464.55	21,551.69	21,519.62	18,988.70	18,528.46
	13,918.19	14,363.42	16,099.91	15,520.69	16,066.06	16,118.37	17,299.48	14,888.80	15,586.50
	296	298	315	361	354	367	367	341	2,699
50 — 54	17,836.95	16,152.09	13,947.36	18,704.16	19,599.61	22,369.33	20,959.80	18,050.00	19,106.45
	13,210.93	14,118.36	14,451.87	15,375.75	16,806.39	15,585.98	15,381.38	16,288.93	15,160.10
	329	289	296	307	337	387	392	391	2,728
55 — 59	6,992.83	15,109.65	20,281.58	16,857.04	19,186.99	21,146.62	23,234.59	22,088.68	19,602.59
	7,194.35	7,918.40	10,299.65	13,574.53	11,997.59	13,462.40	14,255.87	15,858.57	12,031.15
	226	238	281	327	318	320	330	333	2,373
60 — 65	2,083.84	5,734.81	7,369.50	8,954.06	13,225.97	10,641.18	10,828.09	14,691.83	10,438.56
	2,867.17	2,464.31	2,195.79	3,866.90	3,116.38	3,592.98	4,781.53	6,041.72	3,895.96
	181	197	222	290	310	384	420	420	2,424
Total (wave)	9,484.55 10,463.92 2,528	11,261.20 10,710.18 2,389	12,510.38 11,679.92 2,470	14,472.14 12,637.16 2,776	15,703.22 12,515.33 2,783	16,228.11 12,378.09 2,816	16,208.36 12,520.96 2,784	15,653.42 12,721.03 2,613	14,417.61 11,962.96 21,159

Table 3.5: Percentage of net wages and salaries by education type, age cohort and wave, with frequencies. In the first row for each age cohort we have net wages for individuals with general education, while in the second for individuals with vocational education. See caption in Table 3.2 for data source, sample, definition of education type.

Figure 3.3a shows descriptive paths of employment rates by waves, and we can see that the effect of general versus vocational education is not uniform across waves but, among age 35 and 54, the employment paths for the two groups follow almost the same level. The heterogeneity of the pattern amongst waves leads us to consider later two different samples while pooling them together: as we will see in Section 4.1.5, we split the pooled sample in prerecession years, from 2000 to 2008 included, and post-recession years, from 2010 to 2014, in order to partial out the effect of 2007-08 and recession crisis and 2011 *ex post* in the Italian labour market. In Figure 3.2b we can see that for wages the situation is more heterogeneous and the difference among the two groups is cancelled earlier in age, at descriptive level in line with Hall (2012), with different means across waves. Hence, our analysis is based on



these differences, trying to infer a statistical justification to them.

(a) Descriptive patterns for employment, pooled sample

(b) Descriptive patterns for net wages, pooled sample



Figure 3.2: Descriptive patterns for labour-market outcomes by education type on the pooled sample. Sample for wages includes the same individuals in Table 3.2 who perceived a wage in the considered waves. See caption in Table 3.2 for data source, sample and definition of education type.



#### (a) Descriptive patterns for employment, by wave

(b) Descriptive patterns for net wages, by wave



Figure 3.3: Descriptive patterns for labour-market outcomes by education type for the single waves. Sample for wages includes the same individuals in Table 3.2 who perceived a wage in the considered wave. See caption in Table 3.2 for data source, sample and definition of education type.

# 3.2 Methodology

In our research we are interested on how labour-market outcomes (more specifically, employment and wages) evolve for individuals over the life-cycle with respect to education type in the Italian labour market, with a preference for vocational education, and whether there is a relationship among those different outcomes. Our main hypothesis, in the fashion of Hanushek et al. (2017) and the major studies that supports this view enunciated in Chapter 2, is that individuals with vocational education are early movers in the labour market: vocational-oriented education might facilitate the school-to-work transition, providing an advantage on labour-market outcomes than those individuals with general-oriented education. However, we expect that this difference decreases over time because of a lack of adaptability of vocational education to the main labour-market shocks and obsolescence due technological changes, turning in a positive effect for general education after a cut-off age in later years. In order to find an answer to the research question in the most exhaustive way, we do consider the main model in Section 3.2.1 and an extension of it.

# 3.2.1 Main Model for Quasi-Longitudinal Data

In order to verify our main hypothesis, we consider a main model inspired by Hanushek, Woessmann, and Zhang (2011). The model is built over a difference-in-differences (hereinafter, DD) framework, but this is not the archetypical DD design used in applied econometrics, where the two considered dimensions are a *trigger policy* which builds up two difference groups, and a time variable which splits the sample to study pre- and post-policy outcomes, as in the classic paper of Card and Krueger (1994). Rather, we use a more general DD setup, more similar to Angrist and Evans (1999) to study the effect of changes in state abortion laws on teen pregnancy using variation of state and year of birth, or rather to Autor (2003) who implements the Granger test investigating the effect of employment protection policy on firms' use of temporary help for lags of more years than in a before-after strategy. Without considering a "true" trigger policy to run our DD configuration, we apply the treatment in a continuous and subsequent levels of age, starting from a fixed baseline age to a hypothetical and broad retirement age, which represents our individuals' life-cycle in the SHIW dataset. The treatment is general education at upper secondary school level, while individuals with vocational (and "other", taken as given) education fall into the control group. The main differences with the Hanushek, Woessmann, and Zhang (2011) derive from the availability of information in our dataset built from SHIW waves, as illustrated in Section 3.1, which gives us more information than the source of Hanushek, Woessmann, and Zhang (2011) using IALS-97 dataset (Organization for Economic Co-operation and Development (OECD), 1997) only with cross-section data, exploiting a DD regression for only one wave of analysis. More waves of analysis allows us to partially intercept the impact of selectivity in education through individuals born in different decades, who took the treatment in different periods of time: for this reason, we pool information from different waves of the survey together, taking into account age-invariant wave effects, represented by the coefficients  $\delta_s$  in Equation (3.1), where we use the notation of Wooldridge (2010) and Angrist and Pischke (2009).

$$y_{i} = \alpha_{0} + \alpha_{1} \cdot age_{i} + \alpha_{2} \cdot age_{i}^{2} + \beta_{0} \cdot g_{i} + \beta_{1} \cdot g_{i} \cdot age_{i} + \beta_{2} \cdot g_{i} \cdot age_{i}^{2} + \sum_{s} (\delta_{s} \cdot s_{i}) + X_{i} \cdot \gamma + \varepsilon_{i}$$

$$(3.1)$$

In Equation (3.1),  $y_i$  is the labour-market outcome of interest for the *i*<sup>th</sup> individual, age and age-squared capture the normal age-y pattern in economy without treatment,  $g_i$  is an indicator variable equalling 1 if the  $i^{\text{th}}$  individual has general education type as specified and zero otherwise, identifying treatment and control group,  $s_i$  is an indicator variable equalling 1 if the *i*<sup>th</sup> individual belongs to wave *s*, and  $\varepsilon_i$  is simply the the unobserved error term.  $X_i$  is a vector of control variables for the  $i^{th}$  individual including  $o_i$ , which is an indicator variable equalling 1 if individual i has "other" education type and zero otherwise, regional and municipality fixed effects to eliminate overall differences between regional and municipal microlabour markets, and various measures of individual influencing labour-market skills (other than education type), such as education level (including tertiary education), time-invariant birth family background and current household factors. We will look in depth at these controls in Section 3.2.3. Therefore, in the same fashion of Brunello and Rocco (2015) we use ageing as a synonymous of time, as we do not explicitly distinguish between age and time effects in our empirical study because waves are used only for pooling. Furthermore, in contrast with Hanushek, Woessmann, and Zhang (2011) and in line with German Microcensus 2006 data of Hanushek et al. (2017), we propose non-linearities in terms of quadratic effects

of age over the education type, in order to better identify the trajectory of the linear ageing effect over the life-cycle discriminating for education type, and the intensity over time of the differential impact between general and vocational education. This is possible because the pooled sample has sufficient power to look at them.

The configuration of the main model in Equation (3.1) varies on the basis of the y labourmarket outcome's choice, as the coefficients' interpretation.

- Considering employment as labour-market outcome, we obtain a linear probability model (hereafter, LPM) where the dependent variable is a Bernoulli random variable  $emp_i = 1$  indicating the response probability of employment (Wooldridge, 2010, pp. 562-565): this is obtained starting from the variable nonoc in the SHIW (Bank of Italy, 2015), which equals to zero if individuals is employed and > 0 if individual is unemployed for the categories shown by Table 3.3. The interpretation of coefficients is quite straightforward in terms of employment probability:  $\kappa \cdot 100$  is the impact of a unit increase of the level variable x at which this coefficient is assigned on the probability of employment in percentage points.
- for wage patterns over the life-cycle, we consider the net wages and salaries extracted from the SHIW yl1 aggregate indicator of the compensation of employees in their jobs (Bank of Italy, 2015), and reshaped in natural logarithm form, pushed into a linear regression model. This transformation is applied in empirical labour economics' researches for several reasons:
  - to deal with monetary values;
  - to smooth sample outliers without facing other attrition issues;
  - to interpret coefficients as the *semi-elasticity* of wages in a *log-level* model, for which the parameter on a level variable x has to be approximately interpreted as the percentage change in y resulting from a one-unit change in x,  $100 \cdot \kappa_x = 100 \cdot \frac{\partial \ln E[y|x,z,...]}{\partial x}$ , conditional on all covariates (Wooldridge, 2010, pp. 15-19).

In Equation (3.1), the coefficient  $\beta_0$  measures the time-invariant (at age = 0) employment probability, or percentage variation on wages, of those with general education G relative to

those with vocational education v (and "other" education, but hereafter we refer only to vocational education taking this smaller group as given) at the entrance of labour market.

$$\beta_{0} = \underbrace{E[y_{i} \mid g = 1, age = 0, s, X]}_{\text{time-invariant probability of employment}} - \underbrace{E[y_{i} \mid g = 0, age = 0, s, X]}_{\alpha_{0}} = \overline{y}_{G,0|s,X} - \overline{y}_{V,0|s,X}, \quad \forall age. \qquad (3.2)$$

As Hanushek, Woessmann, and Zhang (2011) state, we cannot say the overall difference in employment probabilities and wages between general education and vocational education reflected in  $\beta_0$  adequately identifies the impact of general education, because this parameter implicitly involves any elements of selectivity in the completion on different types of schooling which are not captured by  $X_i$ , raising an omitted variable bias, and it is difficult to control for any factor of congestion in the labour market at country level, especially for what matters the closest waves of analysis affected by the financial crisis (Crepaldi et al., 2014). Withal, it is doubtful that the quantified effects on employment found from our datasets fully capture the systematic differences across schooling groups, and this is also a common issue on the datasets considered by the literature in Chapter 2. Hence, the key parameters of interest are:

β<sub>1</sub>, the DD estimator, which captures the differential impact of a general relative to a vocational education on the labour-market outcome for each year of age, drawing the divergence in employment patterns by education type over age cohorts, and identifying a cut-off age of convergence between the two paths.

$$\beta_1 \cdot age + \beta_2 \cdot age^2 = \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g = 1 - y_i \mid g = 0) \mid age, s, X]}_{=} + \underbrace{E[(y_i \mid g = 1 - y_i \mid g$$

difference after *age*-lags in the labour-market outcome of a *general* relative to a *vocational* 

$$-\underbrace{E[(y_i|g=1-y_i|g=0)|age=0,s,X]}_{\text{time-invariant difference in the labour-market}} = (3.3)$$

 $=(\bar{y}_{\mathrm{G},age|s,X}-\bar{y}_{\mathrm{V},age|s,X})-(\bar{y}_{\mathrm{G},0|s,X}-\bar{y}_{\mathrm{V},0|s,X}),\quad\forall age.$ 

•  $\beta_2$ , which gives the sensibility of the differential impact among the two groups with respect to ageing. For example, if  $\beta_2$  has a negative direction, it means that the dif-

ferential impact of the labour-market outcome with respect to age for individuals with general education over those with vocational education decreases as age increases.

Therefore, the trajectories of labour-market outcomes over the life-cycle for the two different education groups may have a parabolic shape if the coefficients upon  $age_i^2$  and the interaction term  $g_i \cdot age_i^2$  are significantly different from zero, as the normal age-y pattern in the economy is the control group ageing effect on the labour-market outcome.

$$\alpha_{1} \cdot age + \alpha_{2} \cdot age^{2} = \underbrace{E[y_{i} \mid g = 0, age, s, X]}_{\substack{\text{expected value of the labour-}\\ \text{market outcome after } age-lags}}_{\substack{\text{for vocational}}} - \underbrace{E[y_{i} \mid g = 0, age = 0, s, X]}_{\substack{\alpha_{0} \\ \text{average floor level of the labour-}\\ \text{market outcome in the economy}}} = \overline{y}_{V,age|s,X} - \overline{y}_{V,0|s,X}, \quad \forall age.$$

$$(3.4)$$

However, as in Hanushek, Woessmann, and Zhang (2011) we need a crucial assumption for the identification of the causal impact of education type on changes in labour-market outcome patterns over the life-cycle. The selectivity of people into general and vocational education conditional on all covariates of X should not vary over time, which means we assume that current old people are a *good proxy* for today's young people. This is a strong assumption that allows us to estimate the impact of education type by the divergence in ageemployment and age-wages patterns across the life-cycle. To validate this assumption, we look at the descriptive statistics in Table 3.2: again, we perceive that individuals in youngest cohorts select more in general education than in vocational with respect to older age cohorts over time. As long as the effects of this selectivity are captured by covariates in  $X_i$ , the assumption holds perfectly and we fall in a quasi-random experiment framework, otherwise changes in labour market may reflect also the varying ability of young and old workers in different education categories.

In addiction to this assumption and the classic assumptions for the consistency of the Ordinary Least Squares (OLS) estimator of orthogonality and full rank of the expected outer product matrix of the explanatory variables (see Wooldridge, 2010, pp. 52-53), we need to state the classic parallel trends assumption (Angrist & Krueger, 1999, pp. 1296-1299) for DD models, for which in absence of treatment the trend of individuals in general education treatment group should be the same of the trend of those in vocational education control group or, in other terms, interaction terms are zero in absence of treatment. This key identifying assumption is usually not testable and often undervalued by researchers, although its assertion is crucial.

## **3.2.2** Extension of the Main Model interacting with Birth Cohorts

On the basis of the same information used in the main model for quasi-longitudinal data in the previous step, we are interested to understand how the different labour-market outcomes among education type over the life-cycle may vary between individuals born in different decades, thus addressing differences in education type selectivity on different stages carried by conflicting subsequent education policies at a country-level framework. We approach the research question by using a non-archetypical difference-in-difference-in-differences, or triple differences (hereinafter, DDD) design, in the fashion of other studies applied labour economics (see Yelowitz (1995), who considers three dimensions for grouping (state, time, and age of youngest child in a family), or the more recent Herbst (2017), who estimates the impact of the U.S. Lanham Act of 1940, a heavily- subsidized and universal child care program, on maternal employment using this strategy). Within this framework, we split the sample in two different birth cohorts, before and after a pre-determined year.

$$y_{i} = \alpha_{0} + \theta_{0} \cdot c_{i} + \phi_{0} \cdot g_{i} + \beta_{0}(g_{i} \cdot c_{i}) +$$

$$+ \alpha_{1} \cdot age_{i} + \theta_{1}(c_{i} \cdot age_{i}) + \phi_{1}(g_{i} \cdot age_{i}) + \beta_{1}(g_{i} \cdot c_{i} \cdot age_{i}) +$$

$$+ \alpha_{2} \cdot age_{i}^{2} + \theta_{2}(c_{i} \cdot age_{i}^{2}) + \phi_{2}(g_{i} \cdot age_{i}^{2}) + \beta_{2}(g_{i} \cdot c_{i} \cdot age_{i}^{2}) +$$

$$+ \sum_{s} \delta_{s} \cdot s_{i} + X_{i} \cdot \gamma + \eta_{i}$$
(3.5)

In Equation 3.5,  $y_i$  is the labour-market outcome of interest for the *i*<sup>th</sup> individual, age and age-squared capture the normal age-*y* pattern in the economy for the whole sample,  $g_i$  represents again an indicator variable equalling 1 if individuals has achieved general education or zero otherwise, *c* is an indicator variable equalling 1 if the *i*<sup>th</sup> individual is born after the selected birth year and zero otherwise,  $s_i$  describes an indicator variable equalling 1 if the *i*<sup>th</sup> individual for the *i*<sup>th</sup> individual belongs to wave *s*, and  $\eta_i$  is the unobserved random term. *X* does not vary from Equation (3.1), including both time-invariant effects and interactions with age.

 $\theta_0$  measures fixed effects on labour-market outcome for the *i*<sup>th</sup> individual belonging to the c = 1 birth cohort, with respect to the c = 0 birth cohort, which is also the effect of individu-

als with vocational education *between* the two birth cohorts (before the threshold birth year and after it):  $\theta_0 = \bar{y}_{V,0,c|s,X} - \bar{y}_{V,0,0|s,X}$ .  $\theta_1$  describes the DD estimator of the normal age-y pattern in the economy among c = 1 birth cohort and the latter, where  $\theta_2$  appears for its sensibility over ageing, or simpler how the labour-market outcome for individual with vocational education (and "other" education, but we have already taken them as given) varies for each level of age between pre-*c* and post-*c* birth cohorts:  $\Delta[\alpha_1 age_c + \alpha_2 age_c^2] \cdot 100 \forall$  level of *age* and c = 1.

$$\theta_{1} \cdot age + \theta_{2} \cdot age^{2} = \underbrace{(\bar{y}_{v,age,c|s,X} - \bar{y}_{v,0,c|s,X})}_{\text{normal age-y pattern in the economy within cohort } c} \underbrace{(\bar{y}_{v,age,0|s,X} - \bar{y}_{v,0,0|s,X})}_{\alpha_{1}age + \alpha_{2}age^{2}} \quad \forall age. \quad (3.6)$$

We also include the effect of education type for the older cohort (without interacting for *c*), given by coefficients  $\phi_0$ , the time-invariant labour-market outcome effect on general education individuals over those with vocational education within the older cohort,  $\phi_1$ , the differential impact for each level of age within the older cohort and  $\phi_2$  its sensibility on ageing, as expressed in Equation (3.7).

$$\phi_{1} \cdot age + \phi_{2} \cdot age^{2} = \underbrace{(\bar{y}_{G,age,0|s,X} - \bar{y}_{V,age,0|s,X})}_{\text{effect on labour-market outcome of a general over a vocational after age-lags within the older cohort} - \underbrace{(\bar{y}_{G,0,0|s,X} - \bar{y}_{V,0,0|s,X})}_{\phi_{0}: \text{ time-invariant effect of } y \text{ of a general relative to a vocational within the older cohort}} \forall age. (3.7)$$

Triple differences are deduced interacting the post-*c* birth cohort by education type and age or age-squared.  $\beta_0$  results as the difference in the time-invariant impact on the labourmarket outcome *y* of individuals with general education over those with vocational education *between* birth cohorts described in Equation (3.8), while  $\beta_1$  in Equation (3.9) represents the difference among birth cohorts in the differential impact on the labour-market outcome *y* at each level of age of a general relative to a vocational, whereas  $\beta_2$  measures its sensibility over ages.

$$\beta_{0} = \underbrace{(\bar{y}_{G,0,c|s,X} - \bar{y}_{V,0,c|s,X})}_{\substack{\phi_{0} + \beta_{0} \\ \text{time-invariant effect of a} \\ \textit{vocational within cohort c}} - \underbrace{(\bar{y}_{G,0,0|s,X} - \bar{y}_{V,0,0|s,X})}_{\substack{\phi_{0} \\ \text{time-invariant effect of a} \\ \textit{vocational between cohorts}}} \forall age.$$
(3.8)

$$\beta_{1}age + \beta_{2}age^{2} = \begin{bmatrix} (\bar{y}_{G,age,c|s,X} - \bar{y}_{V,age,c|s,X}) - (\bar{y}_{G,0,c|s,X} - \bar{y}_{V,0,c|s,X}) \end{bmatrix} - \\ \underbrace{ \begin{array}{c} \text{differential effect of a general} \\ \text{relative to a vocational} \\ \text{for each level of } age \text{ within } c \end{bmatrix}}_{qge(\phi_{1}+\beta_{1})+age^{2}(\phi_{2}+\beta_{2})} \\ (3.9) \\ - \begin{bmatrix} (\bar{y}_{G,age,0|s,X} - \bar{y}_{G,age,0|s,X}) \\ \text{differential effect of a general} \\ \text{relative to a vocational for each} \\ \text{level of } age \ between \ cohorts \end{bmatrix}} - \underbrace{ \begin{array}{c} (\bar{y}_{G,0,0|s,X} - \bar{y}_{G,0,0|s,X}) \\ \phi_{0} \\ \text{time-invariant effect of a} \\ general \ relative \ to a \\ vocational \ between \ cohorts \end{bmatrix}} \\ \forall \ age. \\ \end{array}$$

 $\phi_1 age + \phi_2 age^2$ 

# **3.2.3** The Choice of Suitable Covariates

In order to address the correct variation of selectivity into education types, and to smooth the omitted variable bias on  $\beta_0$  or  $\phi_0$  in Equation (3.1) and (3.5), we consider in X a set of control variables which are correlated with the labour-market outcomes and education type in the classic literature of labour economics. Quoting Angrist and Krueger (1999), «because it is typical impossible to adequately control for all relevant variables, it is often desirable to seek situations where it is reasonable where it is reasonable to presume that omitted variables are uncorrelated with variables of interest», but we try to include the best range of control variables we can achieve with the derived dataset.

## 3.2.3.1 Schooling and Birth Family Background

Classical studies gives a straightforward causal effect of education level in terms of years of schooling on labour-market outcomes: a clear review of earlier studies has been drawn up by Angrist and Krueger (1999), and we are interested especially in the classic paper of Angrist and Krueger (1991), where they uses quarter of birth to construct Instrumental Variables (IV) estimates of the economic returns to schooling as endogenous variable, obtaining a positive effect of schooling on earnings in the Two-Stage Least Squares (2SLS) estimates. Hence, we consider years of schooling as control variable for y labour-market outcome, as Hanushek, Woessmann, and Zhang (2011) also includes, deriving them in the dataset from the highest level of educational attainment for each individual i updated at the latest Italian education framework. Empirical results will find positive returns of additional years of schooling both

for wages and employment, with less significance in the last one.

It is a central topic in social science and research that people's educational achievement is positive correlated with their parents' education, or with other indicators of their parents' socio-economic status, or with family background all-round including siblings (Björklund & Salvanes, 2011), and literature in this field has significantly increased during recent decades thanks to better data supplied. Labour economists often consider parents as major actors who invest in children's labour-market outcomes via their educational attainment, but intergenerational transmission of educational attainment could be related to a pure selection story, if the type of parent who has more education and earns higher salary has the type of child who will do so as well, or to causation, if obtaining more education makes individuals a different type of parent, leading to children having higher level of education, too. Besides that, the influence of family background may involve mechanisms which are interlaced with ability and, even if we do not control for ability for the reasons stated in Section 3.2.3.4, we still have characteristics strongly related with it.

Considering causation, the primary effect of family background is that children of advantaged social origin are more likely to perform well in school. This empirical question has been analysed by Black, Devereux, and Salvanes (2005a), finding causal positive effects of parents education on children's education, which moves us to first consider in the fashion of Hanushek, Woessmann, and Zhang (2011) controls for parents' educational attainment in order to avoid omitted variable bias on years of schooling, and their interaction with age to see the differential impact of higher educational attainment of parents over the children's life-cycle. Nevertheless, results of Black et al. (2005a), and Björklund, Lindahl, and Plug (2006), which studies the intergenerational effect of pre- and post-birth factors on earnings and education exploiting unique information on Swedish adoptions, are controversial and the findings are different from other studies. For example, Plug (2004) and Holmlund, Lindahl, and Plug (2011) find little evidences of parents' educational attainment intergenerational transmission to children, stating that main results are related to identification issues in the empirical models. We do not support this vision, and our results in Section 4.1 and 5.1 gives unambiguous evidence about these effects, even if causality can be criticised.

The secondary effect of causation is that, for a given level of performance, these children are also more likely to make more ambitious educational choices than their peers from a less advanced social background, controlling for selectivity in education type (Golsteyn & Stenberg, 2015), which explains the positive correlation between general education and parents' educational attainment provided in Section 4.1.4.1. Hall (2012), Pekkarinen et al. (2009) and the major natural experiments of comparison between outcomes of education types provide affirmative evidences of this effect.

In our dataset, parents' education can be recovered using our panel data algorithm illustrated in Section 3.1, collecting the information from the HD of the SHIW in previous waves and from qualitative data in annual waves, merging information together and isolating the highest education level for parents.

Considering siblings' influence on schooling and education type, contrary to Hanushek, Woessmann, and Zhang (2011), we follow evidences of Björklund, Jäntti, and Lindquist (2009) and Black, Devereux, and Salvanes (2005b) to think about the effect of siblings in education age, which is an asset for labour-market outcomes and education type. However, we cannot extract from the dataset the birth order of siblings in education, so we limit the study to the mere presence of them.

## 3.2.3.2 Current Family Factors

Apart from family background, we also look at current family factors and their influence in labour-market outcomes other than education type. Current marital status is included in the analysis: studies by Chun and Lee (2001) and Skåtun (2004) affirm that there is a married male wage premium against unmarried males, and worker's wage is negatively correlated with the spouse's current income. To conclude, we consider also current household size to partial out its effect on the parameters of interest over labour-market outcomes, and partially on educational attainment for kids still in education in the household which turns in workers in successive waves (Black et al., 2005b).

#### 3.2.3.3 Missing Data Analysis

Previously in Section 3.1 we anticipated that measurement error is widespread on the dataset (Biancotti et al., 2008), not only on our variable of interest, but also on any relevant control for the analysis, which may usually produce smaller fixed estimates on the model (Angrist & Pischke, 2009). Since we cannot afford to face attrition again in the dataset (especially for

what matters net wages and salaries sample) and least of all to correct measurement errors on control variables, we use the simplest applied turnaround in social science to avoid it, which is called *dummy variable adjustment*. Following the advice of Allison (2002, pp. 9-12), we take all controls which suffer of measurement error issues (all controls except for years of schooling, household size and, of course, age) as qualitative indicators. Working on the dataset, we fix the level of each missing value in these covariates to zero, and we add controls for "missing" regressors for each of the affected covariates which equals to 1 if the value for the  $i^{\text{th}}$  individual is missing, zero otherwise.

There are many other techniques to empirically deal with missing data, such as using a Maximum Likelihood Estimator (MLE) to obtain average values of the affected regressors. Despite that, since we are mainly interested on effects of the education type over the labour-market outcomes, we may consider significant estimates on control variables as less relevant as they might appear, because their role is mostly to clean the effect of selectivity in education and the omitted variable bias. This is a statement that has to bear in mind along the whole analysis.

## 3.2.3.4 Missing Controls

We extract more alternatives of control variables for the analysis than the previously identified, but some of them have been excluded during the study for several reasons. We extracted parents' skills, expressed as white-collar dummy variable and corrected with Allison (2002, pp. 9-12) approach but, since it may be close to the effect of parents' educational attainment on education level of children, and the missing values are more consistent than the selected alternative, we decided to drop this variable to avoid collinearity problems. Measurement errors and the dummy variable adjustment produced also collinearity issues with dummies on immigration and current family type. A dearth of our analysis is the lack of an indicator for individuals' ability on labour-market outcomes, as in Hanushek et al. (2017) and the main studies on the subject: during pre-analysis phase, we were not able to construct an instrument for cognitive skills and non-cognitive skills in the SHIW dataset, neither for the HD, nor for the annual waves. The only attractive indicator of ability is the information about the highest education grade for individuals, but we could not find a way to standardise it with individuals coming from different Italian education systems among the years. We considered to obtain from the OECD Programme for the International Assessment of Adult Competencies (Organization for Economic Co-operation and Development (OECD) (2016), PIAAC) the average literacy and numeracy scores for Italy considering different qualitative data in order to compute the mean (educational attainment, age, immigration, etc.) and merge them with our dataset, but the values may be reliable only for wave 2012. This is one of the main weaknesses of our study.

# CHAPTER

4

# EFFECTS OVER LIFE-TIME EMPLOYMENT

# 4.1 Main Model for Quasi-Longitudinal Data

In the first place of empirical results, we address the research question for employment considering the pooled waves of the SHIW dataset built as in Section 3.1, from wave 2000 to 2014, using the identification strategy described in Section 3.2.1.

## 4.1.1 Basic Results

The most basic specification, a Linear Probability Model (LPM) where employment is a function of age, age squared, wave controls and education type, considers the whole sample of male individuals between age 20 and 65 (hereinafter, AC20). Estimates are obtained using Ordinary Least Squares (from now on, OLS) Estimators with Robust Standard Errors (Robust-SE), to correct the intrinsic heteroskedasticity of the error term in LPMs (Wooldridge,

2010, pp. 562-563). In contrast with the classic model of Hanushek, Woessmann, and Zhang (2011), we do not subtract to age in order to start the analysis with a baseline age to zero, this to have a more straightforward interpretation of the results and the graphs.

As anticipated in Section 3.2.1, we would like to refine this simple model adding also the effect of completing an "other" upper secondary school program, with its interaction with age and age-squared, in order to exclude from the estimates of the parameters of interest individuals neither with general education nor with vocational education, as they are not distinguishable in the SHIW dataset between treatment and control group (see Section 3.1). However, the impact of "other" education programs is not so wide on the main estimates considering waves individually, because of the meagre size this sub-sample. We involve controls for "other" education type for each specification as taken.

As announced in Section 3.1.1, we start with a sample including 25, 173 individuals in eight waves, every two years, with a sample size that varies among them, between 2,900 observations in 2002 and 3,353 in 2012 which is the most populated wave in the built dataset (we refer to Table 3.2 for descriptive statistics). We exclude from the wave dummies the indicator variable for the first wave (2000), which falls into the constant term, to avoid any collinearity issues. As described in Section 3.1, we do not consider the highest degree to determine education type, unlikely of Hanushek, Woessmann, and Zhang (2011), because in our dataset we cannot distinguish at the bachelor's level between the typical BS/BA and the *diploma universitario*, a vocational-oriented tertiary education introduced in Italy in the 90s for several fields of study.



(a) Male employment by age and education type, pooled sample





Figure 4.1: Smoothed scatterplots of employment rates using locally weighted regressions (*lowess*, Cleveland (1979)). Sample includes all male individuals who finished upper secondary education from age 20 to 65. Years of analysis: from 2000 to 2014, every two years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015).

For a preliminary impression of the trajectories of employment rates over the selected sample, we use a Locally Weighted Scatterplot Smoothing regression (hereafter, LOWESS), following the technique implemented by Cleveland (1979). This produces unconditional estimates in a neighbourhood, producing approximative employment paths over the sample. In Figure 4.1a we can observe that, for the pooled sample from age 20 to 65, employment rate generally increases with age with a parabolic path, consistently with the estimates drawn for *age* in Table 4.1, and decreasing after reaching a peak at different ages between individuals with vocational and general education, respectively at age 42 for the first and 46 for the latter. Figure 4.1b shows smoothing for each wave of analysis and we can see that different outcomes are obtained with this technique through the waves.

A summary view of the results from the basic model is given by Table 4.1, while detailed results can be found at Column 1 in Tables of Section A.1.1 of Appendix A. Estimates of the normal age-employment pattern in the economy for the pooled sample gives that ageing makes individuals (in the control group) 12.4 percentage points more likely to be employed each more year. Given the Conditional Expectation Function (hereafter, CEF) of Equation (3.1),

$$E[y_i|g, age, s, X] = \hat{\alpha}_0 + \hat{\alpha}_1 \cdot age_i + \hat{\alpha}_2 \cdot age_i^2 + \hat{\beta}_0 \cdot g_i + \hat{\beta}_1 \cdot g_i \cdot age_i + \hat{\beta}_2 \cdot g_i \cdot age_i^2 + \sum_s (\hat{\delta}_s \cdot s_i) + X_i \cdot \hat{\gamma}$$

$$(4.1)$$

$$E[\varepsilon_i|g, age, s, X] = E[\varepsilon_i] = 0$$

and the partial derivative for age of  $\hat{y}_i$  fitted values in Equation (4.2a) and (4.2b) either for general or different education,

$$\frac{\partial E[y_i|g=1, age, s, X]}{\partial age} = (\hat{\alpha}_1 + \hat{\beta}_1) + 2 \cdot age_i \cdot (\hat{\alpha}_2 + \hat{\beta}_2)$$
(4.2a)

$$\frac{\partial E[y_i|g=0, age, s, X]}{\partial age} = \hat{\alpha}_1 + 2 \cdot age_i \cdot \hat{\alpha}_2$$
(4.2b)

estimates on age-squared coefficient on employment rates allow us to find the turnaround point of the positive linear effect from the normal age-employment pattern (and of the estimated trajectories for vocational education), which equals to 42 as obtained in Equation (4.3) equalling the partial derivative of the CEF conditional on g = 0 in Equation (4.2b) to zero. After this level, the estimated effect in  $\hat{\alpha}_1$  is decreased by 0.149 percentage points for each more year after the turning point.

$$age^* \mid g = 0 \quad \approx \quad \left[ \left| \frac{\hat{\alpha}_1}{2 \cdot \hat{\alpha}_2} \right| \right]$$

$$(4.3)$$

Given that, the most important estimates are upon the parameters of interest on education type and its interaction with age and age-squared, respectively  $\beta_0$ ,  $\beta_1$  and  $\beta_2$  in Equation (3.1).

	age	$age^2$	General	General × age	$\frac{General}{\times age^2}$	Obs.	$R^2$
AC20	0.124***	-0.00149*** (1.82e.05)	-0.747***	0.0205***	-8.49e-05**	25,173	0.337
AC25	0.123***	-0.00148***	-0.937***	0.0293***	-0.000182***	21,493	0.261
AC20 NOSELF	(0.00212) $0.133^{***}$	(2.37e-05) -0.00161***	(0.0968) -0.617***	(0.00454) 0.0128***	(5.19e-05) 1.14e-05	20,803	0 352
AC 20	(0.00159) 0.137***	(1.85e-05) -0.00166***	(0.0564) -0.962***	(0.00312) 0.0289***	(3.96e-05) -0.000165***	20,893	0.332
AC25 NOSELF	(0.00225)	(2.46e-05)	(0.104)	(0.00492)	(5.63e-05)	17,345	0.297

Table 4.1: Summary results of the most basic model specification for Employment. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 20 (*A*C20) or 25 (*A*C25) to 65 with at least upper secondary education, including or excluding self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

*Ceteris paribus*, the estimate of the time-invariant employment probability on those with general education relative to peers with vocational education suggests that the treatment group is 74.7 percentage points less likely to be employed than the control group at early age. It should be remembered that, from Section 3.2.1, we might not say general education has a *causal effect* on employment, because we are not able to deal with any element of selectivity in the completion of different types of schooling, raising omitted variable bias. The employment gap between the treatment group of individuals with general education is filled by 2.05 percentage points each more age, with a positive effect of 20.5 percent over ten years, *ceteris paribus*. Unlike estimates on  $\beta_0$ ,  $\hat{\beta}_1$  should be considered as the causal impact of education type on changes in employment patterns over the life-cycle, as long as the

selectivity assumption into education type asserted in Section 3.2.1 holds. Estimates on  $\beta_2$  gives us the sensitivity of the linear effect of age over those with general education, together with  $\alpha_2$ : given a negative effect on the quadratic interaction of general education type with age-squared, it means that the positive differential impact of a general relative to a vocational education on employment probability for each year of age decreases after a turning level of age at 46, which is obtained equalling the partial derivative in Equation (4.2a) conditional on g = 1 to zero.

$$age^* \mid g = 1 \quad \approx \quad \left[ \mid \frac{\hat{\alpha}_1 + \hat{\beta}_1}{2 \cdot (\hat{\alpha}_2 + \hat{\beta}_2)} \mid \right]$$

$$(4.4)$$

From these estimates, we can derive a cut-off age of employment between individuals with general education and those with vocational education at 45, when the advantage of vocational education disappears corroborating the main hypothesis. The meeting age is calculated as in Equation 4.5, equalling the CEF in Equation (4.1) expressed for general education (g = 1) with the same expressed for vocational education (g = 0).

$$#\#_{age} = \left[ \frac{-\hat{\beta}_1 + \sqrt{\hat{\beta}_1^2 - 4 \cdot \hat{\beta}_0 \cdot \hat{\beta}_2}}{2 \cdot \hat{\beta}_2} \right]$$
(4.5)

During the analysis, we have run the model with and without controlling for "other" upper secondary education type and its interaction with age: generally, these estimates for individuals with "other" education type are not significant, so we are not sure of the employment trajectory of this part of the sample. However, we rather use these individuals as controls to "clean" estimates on the parameters of interest, which generally decreases with respect to the model specification without the "other" education type, but the magnitude is not so strong due to the small number of individuals in this sample. From now on, we consider controls for "other" education type and its interaction with age as taken for all model specifications. In Figure 4.2 we have a graphical description of what we have just found, with a plot of the linear fitted values of employment for the most basic specification separating plots between treatment and control group and excluding "other" education type for a better interpretation. The level of the curves at the intersection is given by the time-invariant effect on employment by education type (conditional on the other covariates), which are  $\hat{\alpha}_0$  for vocational education and  $\hat{\alpha}_0 + \hat{\beta}_0$  for general education, shifted by  $\hat{\alpha}_1 + 2 \cdot 20 \cdot \hat{\alpha}_2$  for the first group and

 $(\hat{\alpha}_1 + \hat{\beta}_1) + 2 \cdot 20 \cdot (\hat{\alpha}_2 + \hat{\beta}_2)$  for the latter, since for the AC20 sample individuals are considered from the baseline age of 20. The slope for the two groups is given by Equation (4.2b) for individuals with vocational education and by Equation (4.2a) for individuals with general education. While using *lowess* we fit the sample values of employment in the neighbourhood of each age, the fitted values in Figure 4.2 are obtained as prediction of the considered LPM, conditioned on all other covariates (*ceteris paribus* holds).

From these outcomes, it is consolidated the main hypothesis: at whole sample level, individuals with vocational education at upper secondary school has an employment advantage relative to the peers in general education at the access to the labour market, *ceteris paribus*, and this advantage is erased forever by general education, but only in later age when the position in the labour market should have been consolidated. This is in line with results of Hanushek, Woessmann, and Zhang (2011) for the single wave IALS-97 dataset with a crosscountry sample, even considering non-linearities in regressors. Whilst the base specification may give interesting results for policy, it is reasonable to account, as introduced by Section 3.2.3 before, for potential biases from unmeasured ability, from decision-driving and other possible influences on employment, which may change or not over time affecting the life-cycle of employment.

Starting from the basic specification, we add control for years of schooling, including the effect of a higher level of education than the mere high school diploma on employment rates over the life-cycle. For this labour-market outcome analysis, schooling is poorly significant, but we can say that from the estimates on more year of schooling makes individuals 0.229 percentage points more likely to be employed. The effect of education level increases in magnitude while moving on further model specifications adding more control variables. At the last specification, one more year of schooling comes to make individuals 0.455 percentage points more likely to be employed. Detailed results are provided at Column 2 in Tables of Section A.1.1 of Appendix A.



Figure 4.2: Linear prediction plots of the model's basic specification for Employment. See caption in Table 4.1 for data source, sample and model specification.

# 4.1.2 Controlling for Family Background

Keeping up with the analysis, we add controls for parents' educational attainment and their interaction with age, using a dummy for each parent education level higher than middle school: these dummies are adjusted for missing values with the dummy variable adjustment method introduced by Allison (2002, pp. 9-12) (illustrated in Section 3.2.3.3), in order to keep a reliable sample size to the detriment of unbiased estimates on these controls.

Therefore, we use these these control variables only to produce more reliable estimates on the key parameters. They produce smoothed estimates on key parameters. For individuals with general education are 61.3 percentage points less likely to be employed than those with vocational education, and this gap is filled by 1.59 percentage points each more age, *ceteris paribus*. The quadratic effect of age on the differential impact is not significantly different from zero at this specification. Complete results are observable at Column 3 in Tables of Section A.1.1 of Appendix A.

Keeping in mind the previous statements about missing data on these covariates, mother's

educational attainment is most likely to have a significant impact on employment rates at this specification of the model: *ceteris paribus*, mother's higher education has a time-invariant negative effect on employment rates of 15.2 percentage points, and a differential impact over individuals with less-educated mother of 0.298 percentage points each more age. Mother's education significance maintains at 1% for each successive specification both for the time-invariant effect and the interaction with age, with more or less the same magnitude.

Father's educational attainment does not seem to have the same weight as mother's education has, in line with the statements of Björklund et al. (2006): *ceteris paribus*, it has a time-invariant negative effect on employment rates of 10.4 percentage points, and a differential impact over individuals with less-educated father of 0.258 percentage points each more age. The magnitude of these estimates decreases in the following specifications.

We control for the presence of siblings in education age of individuals and its interaction with age, applying dummy variable adjustment on the copious missing values of this control as before. Siblings are not particularly relevant in terms of employment labour-market outcome, being not significantly different from zero in the estimates, but we decide to keep the control: we will see that at the last specification, siblings have a positive time-invariant impact on employment of 7.17 percentage points and a differential impact over only-child individuals of 0.128 for each level of age. Detailed results are at Column 4 in Tables of Section A.1.1 of Appendix A.

## 4.1.3 Controlling for Regional and Current Family Factors

Thanks to the dataset we built, it seems reasonable to control for regional and municipality effects, and their interaction with age, in order to partial out the effects on employed rates created by the behaviour and the size of the labour market at local level. We add to the previous specification a dummy for each regional cohort and for different municipality size from less than 5,000 to higher than 200,000 inhabitants. We exclude dummies of Piedmont (first cohort in the dataset) and municipalities with less than 5,000 inhabitants to avoid collinearity, which effects fall into the constant term, significantly lower than before in its estimate. These controls significantly increase  $R^2$  from 0.344 with the previous controls to 0.378, which is a sign of the goodness of regional controls. Individuals with general education achieve a time-invariant negative effect of 64.8 over those with vocational education, filling

the gap by 1.78 each more age, *ceteris paribus*, reaching convergence at age 46 calculated from the significant estimate on  $\beta_2$ . Individuals with vocational education reach the maximum employment level at age 39, while those in general education at age 43. It is possible to examine results at Column 5 in Tables of Section A.1.1 of Appendix A.

	age	$age^2$	General	$\frac{General}{\times age}$	$\frac{General}{\times age^2}$	Obs.	<i>R</i> <sup>2</sup>
AC20	0.0996*** (0.00252)	-0.00131*** (2.47e-05)	-0.694*** (0.0542)	0.0205*** (0.00286)	-0.000112*** (3.59e-05)	25,173	0.387
AC25	0.0945*** (0.00279)	-0.00127*** (2.75e-05)	-0.867*** (0.0953)	0.0283*** (0.00446)	-0.000198*** (5.10e-05)	21,493	0.317
AC20 NOSELF	0.105*** (0.00269)	-0.00141*** (2.60e-05)	-0.587*** (0.0576)	0.0142*** (0.00311)	-3.08e-05 (3.92e-05)	20,893	0.410
AC25 NOSELF	0.104*** (0.00302)	-0.00141*** (2.90e-05)	-0.886*** (0.102)	0.0279*** (0.00481)	-0.000182*** (5.50e-05)	17,345	0.364

Table 4.2: Summary results of the last model specification for Employment. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 20 (AC20) or 25 (AC25) to 65 with at least upper secondary education, including or excluding self-employed individuals. Omitted education type is vocational. Controlling for age, age-squared, schooling, family background, regional controls, municipality size, birth origin, current marital status and household's size. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

Keep talking of regional controls, birth in Southern Italy is also taken into account, and its interaction with age: this area traditionally has a slightly different labour market architecture, with territorial gaps between North and South that are the widest in Europe in terms of labour market-outcomes and education structure (Crepaldi et al., 2014). Missing values are washed out with the same technique applied for the other controls. Southern-native individuals are originally 7.54 percentage points more likely to be employed from the sample, but this advantage decreases by 0.187 percentage points each more age compared to their counterparts. Ending up, for the most complete specification we control also for the current marital status, suggested by Chun and Lee (2001) and Skåtun (2004), and the household size, in the fashion of Black et al. (2005b): detailed results are observable at Column 7 in Tables of Section A.1.1 of Appendix A and illustrated by Figure 4.3. A summary view of the estimates is provided by Table 4.2 As we can see, comparing estimates of this last specification with Table 4.1 for the AC20 sample, the time-invariant negative effect in general education compared with vocational education is reduced by 5.4 percentage points, while the positive differential impact of a general relative to a vocational education on employment for each year of age maintains at the same level and the coefficient on the interaction with age-squared and education type

narrows to zero in terms of magnitude. More precisely, individuals with general education are 69.4 percentage points less likely to be employment at early age, *ceteris paribus*, and this gap is filled by 2.05 percentage points for each year of age over those with vocational education reaching their level at age 45. These are at the same levels of the basic specification. The positive differential impact for general education starts to decrease after age 42, at which level employment rates reach the peak for the treatment group, while for vocational education the peak is reached at level 38. These results seem to be consistent with the effects estimated by Hanushek, Woessmann, and Zhang (2011) and Hanushek et al. (2017), using a 16–65 age cohort in a sample of eleven countries from IALS-97 Data (Organization for Economic Co-operation and Development (OECD), 1997), without considering cognitive skills, measured as mean literacy scores over individuals.



Figure 4.3: Linear prediction plots of the last model specification for Employment. Sample includes males from age 20 to 65 (*AC*20) with at least upper secondary education, *including* self-employed individuals. See caption in Table 4.2 for data source and model specification.

## 4.1.4 Robustness Checks

#### 4.1.4.1 Covariates Collinearity Analysis with Education Type

In order to assess the degree to which there is varying selection into education types by age cohort, it could be useful to investigate the correlates of education type with the other covariates. Equation (4.6) describes a linear probability model on education type where  $g_i$  is an indicator variable equalling 1 if the *i*<sup>th</sup> individual has general education and zero otherwise, age and age-squared capture the general education pattern in the sample,  $s_i$  is an indicator variable equalling 1 if the *i*<sup>th</sup> individual is analysed in the wave s,  $X_i$  is a vector for the *i*<sup>th</sup> individual of control variables which interact with age previously cited,  $Z_i$  is a vector of missing dummies and years of schooling, which does not interact with age, and  $\zeta_i$  is the unobserved error term.

$$g_{i} = \pi_{0} + \sum_{s} (\delta_{s} \cdot s_{i}) + \pi_{1} age_{i} + \pi_{2} age_{i}^{2} + \pi_{3} X_{i} + \pi_{4} \cdot X_{i} \cdot age_{i} + Z_{i} \cdot \pi_{5} + \zeta_{i}$$

$$X_{i}^{'} = \begin{pmatrix} m_{i}^{educ} & d_{i}^{educ} & sibs_{i} & south_{i} \end{pmatrix}$$

$$Z_{i}^{'} = \begin{pmatrix} educ_{i} & miss\_m_{i}^{educ} & miss\_d_{i}^{educ} & miss\_sibs_{i} & miss\_south_{i} \end{pmatrix}$$

$$(4.6)$$

Results of the linear probability model reported in Table 4.3 indicate that individuals with additional years of schooling and more favourable social background are more likely to select into general education at upper secondary school level, in line with Golsteyn and Stenberg (2015) and the main literature on tracking and education type. Hence, estimates on  $\beta$ s key parameters at the last specification in Table 4.2 are controlled for the higher selectivity in education type addressed by well-educated parents. Moreover, we observe that mother's education matters more than father's in pupils' tracking choices in favour of general education. Separate estimates made by the author using a linear regression model on schooling also find that there is a primary effect in the sample of parents' education whereas a negative correlation of father's education. The trend of parents' educational attainment varies with age, as the differential impact of those on general education type.

Correlates between education and siblings in education age, as for Southern Italy natives,

are not significant, but we believe that they still matter in the analysis for their economical meaning in terms of labour-market outcomes as for regional controls. Moreover, this lack of significance could be attributed at the dummy variable adjustment for measurement errors in these variables.

g = 1 if <i>i</i> has general education	(1)
age	-0.0131***
	(0.00143)
$(222)^2$	0.000154***
(age)	(1.54e-05)
Veers of Schooling	0.0735***
rears of Schooling	(0.00132)
Mather has High School Diploma	0.244***
Mother has high School Dipiolna	(0.0204)
Mather has High School Diploma V aga	-0.00222***
Mother has high School Dipioina × age	(0.000520)
Fother has High School Dinlama	0.185***
rather has high School Dipiona	(0.0215)
Eather has High School Dinlama V ago	-0.00166***
Famer has high School Diploma × age	(0.000534)
Siblings in Education A go	0.0146
Sibilings in Education Age	(0.0172)
Siblings in Education A go X ago	-0.000190
Sibilings in Education Age × age	(0.000430)
Porn in Southarn Italy	-0.0140
Bom in Soutien nary	(0.0159)
Porn in Southarn Italy, y ago	0.000695*
Bom m Southern nary × age	(0.000355)
Constant	-0.586***
	(0.0359)
Observations	24,827
$R^2$	0.267

Table 4.3: Correlates of General Education Type. Linear Probability Models. Dependent Variable: 1 = education type of individual is *general*, *vocational* otherwise. Sample includes male individuals aged 20 to 65 with at least upper secondary education, *including* self-employed individuals (AC20); individuals with "other" education type excluded. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

## 4.1.4.2 Excluding the Youngest Cohort from the Sample

From descriptive statistics based on this sample in Table 3.3 we perceive that, dividing the sample in five-years age cohorts, in the youngest section from 20 to 24 almost 45% of individuals are still in education, appearing as not-employed in the previous analysis from Section 4.1.1. Furthermore, these individuals have the highest percentage in general education of the whole pooled sample (32.09%) which is influenced precisely by those students.

Hence, we would try to exclude a portion of it assuming age 25 as baseline age, since the youngest cohort, in this case between age 25 and 29, has only the 18% of individuals still at school, in order to deeper describe the overall youth population. As suggested by Table 3.2, the sample drops at 21,493 observations, varying among waves with 2,409 individuals in 2002 and 2,888 in 2012. Main results of the analysis on employment using this pooled sample between 25 and 65 (hereafter, AC25) can be found in Table 4.1 for the basic specification and Table 4.2 applying all the previous controls, while in Figure 4.4 there are the linear prediction plots for the model for both the basic and last specification. These estimates are always obtained by including controls for "other" education type and its interaction with age and age-squared. Complete results can be examined in Tables of Section A.1.1 of Appendix A.

In primis, estimates confirm the direction of the previous obtained including the youngest cohort, having a negative time-invariant effect of individuals with general education on employment rates over peers with vocational education at upper secondary school, positive differential impact of the treatment over the control group for each year of age and negative sensitivity of this impact over age. While estimates of the normal age-employment pattern in the economy does not significantly vary in magnitude, we find stronger effects on  $\beta$ s: this is symptomatic of the influence of the youngest cohort on the treatment group and employment. Looking at the results of the basic model where employment is a function of age, age squared, wave and education type for AC25 sample in Table 4.1, individuals with general education are 93.7 percentage points less likely to be employed relative to those with vocational education at early age, and this gap narrows by 2.93 percentage points by ageing, *ceteris paribus*, reaching the level of employment of peers in the control group around age 44, similar to the previous sample results. The turning level of age in the parabolic trajectory of employment of individuals with vocational education is again around age 42 rounding at unit level, as the turning age for those in general education happens around age 46.

Looking at the last specification in Table 4.2 for the AC25 sample, the situation on the key parameters does not change: individuals with general education have a negative time-invariant effect on employment of 86.7 percentage points relative to those with general education, and a positive differential impact of 2.83 percentage points by ageing, with turning level of employment at age 37 for vocational education and 42 for general education, meet-

ing at age 44. Looking at the main controls, estimates gives similar effect with an increase in magnitude for education level and a lack of significance for father's educational attainment. Summing up, the main idea stood out by the previous analysis is confirmed, albeit different amplitudes in estimates: *ceteris paribus*, individuals with general education are weakened at the doors of the labour market, even after age 20, but their education progressively helps to reach same employment rates of people with a more vocational education in later age, maintaining the positive differential impact at a slower pace after a turning age, confirming our hypothesis.



Figure 4.4: Linear prediction plots on Employment. Sample includes males from age 25 to 65 (AC25) with at least upper secondary education, *including* self-employed individuals. See caption in Table 4.2 for data source and model specification.

## 4.1.4.3 Excluding Self-Employment from the Sample

For the reasons enunciated in Section 3.1.1, and to harmonise the characteristics of the sample with the one we will use for the life-time wages analysis in the next chapter in which the treated issue is most relevant, we run another robustness check on the selected sample excluding self-employed individuals.

Considering the last model specification and its recap in Table 4.2 for the 20–65 self-employed omitted age cohort (hereafter, AC20 NOSELF), and comparing the results with for the wider AC20 sample, we notice that the sample drops to 20,893 observations in eight waves, while  $R^2$  slightly increases. The main hypothesis is confirmed also for this sample: the key parameters persist in the same direction, but we lose significance on  $\beta_2$  estimate.

Ceteris paribus, the estimate of the time-invariant employment probability on those with gen-

eral education relative to their counterparts with vocational education convey that the treatment group is 58.7 less likely to be employed than the control group, an impact smoothed more than 10 percentage points with respect to the AC20 sample. The employment gap of a general relative to a vocational education is filled by 1.42 percentage points each year, converging in employment around age 46. Turning point in employment is reached respectively at age 38 for those in vocational education and age 42 for peers with general education. Years of schooling becomes less significant, while the magnitude of the other estimates remains almost stable. In Figure 4.5c we have a graphical representation of the estimates with linear prediction plots of the employment model.

Furthermore, we exclude the youngest cohort also for this sample, for the same reason enunciated in Section 4.1.4.2. Comparing estimates of the last specification excluding the youngest cohort considering or avoiding self-employed individuals, we find that results are close to the AC25 sample, and a dropped sample to 17,345 observations with a  $R^2$  of 0.364 at the last specification. *Ceteris paribus*, the normal age-employment pattern in the economy for this sample gives that ageing makes individuals 10.4 percentage points likely to be employed each more year of age as in the AC20 NOSELF sample, while individuals with general education are 88.6 less likely to be employed at early age than those with vocational education, and the employment gap is reduced by 2.79 percentage points for each level of age. As Figure 4.5d describes, with these estimates the turning point in employment for individuals with vocational education is at age 37, while for those with general education at age 41, and they meet in employment at age 45.


(a) Basic specification, AC20 NOSELF pooled sample (b) Basic specification, AC25 NOSELF pooled sample

(c) Last specification, AC20 NOSELF pooled sample (d) Last specification, AC25 NOSELF pooled sample



Figure 4.5: Linear prediction plots on Employment. Sample includes males from age 20 or 25 to 65, with at least upper secondary education, *excluding* self-employed individuals. See caption in Table 4.1 and 4.2 for data source and model specification.

#### 4.1.4.4 Wave-by-Wave Analysis

In order to give further robustness to our pooled sample analysis, we run the main model in Equation (3.1) for each wave included in the quasi-longitudinal sample, to observe if the main hypothesis is still valid for the single waves. We run the linear probability model for each single wave by progressively including all the considered controls and including also "other" education type control. Exhaustive results can be found in Tables of Section A.1.2 of Appendix A, but we provide a resume for the parameters of interest in Table 4.4 for the last specification, including all controls.

	age	age <sup>2</sup>	General	$\frac{General}{\times age}$	$\frac{General}{\times age^2}$	Obs.	<i>R</i> <sup>2</sup>
2000 2002 2004 2006 2008 2010 2012	0.113*** 0.104*** 0.0967*** 0.0953*** 0.105*** 0.0997*** 0.100***	-0.00151*** -0.00143*** -0.00139*** -0.00133*** -0.00127*** -0.00125***	-0.896*** -0.590*** -0.663*** -1.114*** -0.661*** -0.785*** -0.670***	0.0315*** 0.0156* 0.0196** 0.0447*** 0.0181** 0.0229*** 0.0186**	-0.000265** -5.13e-05 -0.000106 -0.000422*** -6.70e-05 -0.000120 -9.21e-05	3,061 2,900 2,938 3,203 3,216 3,307 3,353	0.448 0.432 0.420 0.402 0.414 0.380 0.401
2012	0.100***	-0.00120***	-0.287*	0.000121	0.000117	3,195	0.361

(a) 20-65 age cohort, all male individuals

(b) 25-65 age cohort, all male individuals

	age	$age^2$	General	$\frac{\textit{General}}{\times \textit{age}}$	$\frac{General}{\times age^2}$	Obs.	$R^2$
2000 2002 2004 2006 2008 2010 2012 2014	0.103*** 0.0947*** 0.0976*** 0.0889*** 0.111*** 0.104*** 0.0972***	-0.00139*** -0.00132*** -0.00138*** -0.00129*** -0.00146*** -0.00132*** -0.00125***	-1.837*** -1.233*** -0.698** -0.856*** -0.187 -0.830*** -0.811***	0.0748*** 0.0452*** 0.0212 0.0333*** -0.00238 0.0249** 0.0251**	-0.000742*** -0.000378** -0.000124 -0.000307** 0.000142 -0.000144 -0.000164 2.660.05	2,524 2,409 2,478 2,779 2,789 2,881 2,888 2,745	0.394 0.370 0.371 0.347 0.367 0.316 0.332 0.277

(c) 20-65 age cohort, without self-employed individuals

	age	$age^2$	General	$\frac{General}{\times age}$	$\frac{General}{\times age^2}$	Obs.	$R^2$
2000	0.119***	-0.00164***	-0.676***	0.0177**	-7.97e-05	2,517	0.476
2002	0.109***	-0.00153***	-0.382**	0.00296	0.000114	2,386	0.454
2004	0.104***	-0.00150***	-0.500***	0.00941	3.10e-05	2,456	0.444
2006	0.0977***	-0.00138***	-1.059***	0.0416***	-0.000384***	2,655	0.430
2008	0.108***	-0.00143***	-0.701***	0.0197**	-7.83e-05	2,662	0.440
2010	0.106***	-0.00137***	-0.655***	0.0159*	-2.87e-05	2,729	0.410
2012	0.107***	-0.00135***	-0.515***	0.0108	3.77e-06	2,809	0.422
2014	0.106***	-0.00129***	-0.235	-0.00243	0.000146	2,679	0.372

(d) 25-65 age cohort, without self-employed individuals

	age	$age^2$	General	$\frac{\textit{General}}{\times \textit{age}}$	$\frac{General}{\times age^2}$	Obs.	<i>R</i> <sup>2</sup>
2000	0.113***	-0.00157***	-1.855***	0.0726**	-0.000688***	2,001	0.453
2002	0.105***	-0.00147***	-1.131***	0.0383**	-0.000283	1,910	0.425
2004	0.106***	-0.00152***	-0.801**	0.0232	-0.000121	2,016	0.418
2006	0.0925***	-0.00136***	-0.989***	0.0384**	-0.000356**	2,250	0.393
2008	0.117***	-0.00155***	-0.179	-0.00308	0.000156	2,251	0.413
2010	0.117***	-0.00149***	-0.709**	0.0185	-6.42e-05	2,316	0.374
2012	0.107***	-0.00139***	-0.774***	0.0226*	-0.000125	2,359	0.453
2014	0.110***	-0.00130***	-0.494*	0.00938	1.47e-05	2,242	0.307

Table 4.4: Summary results of the last specification of Employment for each wave of analysis. Linear Probability Models. Dependent variable: individual is employed. Sample includes males aged 20 or 25 to 65 with at least upper secondary education, *including* or *excluding* self-employed individuals. Omitted education type is vocational. Controlling for age, age-squared, schooling, family background, regional controls, municipality size, birth origin, current marital status and household's size. Years of analysis: from 2000 to 2014, every two years. Data source: Survey on Household Income and Wealth (SHIW), Bank of Italy. Significant at \*\*\*1% \*\*5% \*10%.

A first comment to the results in the last specification is that estimates of the sensibility of the differential impact of a general relative to a vocational occur significant only for few waves, more exactly 2000 and 2006 waves for AC20 and AC25 NOSELF restricted samples, only 2006 for AC20 NOSELF sample and 2000, 2002, 2006 waves for the AC25 sample. To be sure about significance of the interaction term of education type with age-squared, we run the model excluding the this term: as result, estimates over the remaining  $\beta_0$  and  $\beta_1$  parameters for waves where the quadratic interaction is not significant are not different from estimates obtained including the non-significant quadratic interactions, while for waves where there is significance in the quadratic interactions. Hence, the quadratic interaction has to be included, otherwise we may have functional form misspecification, but not all the waves have enough power to detect non-linearities on this term.

After this preliminary consideration, we observe that normal age-employment patterns are really close on average to the estimates for the whole sample, also considering each sample restriction, varying in magnitude throughout the waves: for the AC20 sample individuals are on average around 10% more likely to be employed for each level of age, with the highest level of 11.3 percentage points in 2000 and the lowest of 9.53 percentage points for 2006 wave, ceteris paribus. Looking at the same sample, individuals with vocational education, on the basis of  $\alpha_2$  estimates, on average reach the turning level of employment around age 38, in line with the whole sample, and varying across waves. These effects decreases excluding the youngest cohort and increases excluding self-employed individuals, but they keep the same direction Moving interest on our key parameters, we observe that  $\hat{\beta}$ s are on average in line with the whole sample analysis, calculating that individuals with general education are for the AC20 sample 70.8 percentage points less likely to be employed than those with vocational education, but in some waves they are much higher than others, also overstepping the unit interval [0, |1|]: this may be an important issue to take into account, because these results could not be interpreted as probability changes on the dependent variable by identification of the linear probability model. This is a known limit of the LPM: we ignore this problem at this phase of analysis, as we are running a sensibility test of the main results, but we suggest to deal with situation using propensity score matching in order to develop the weights for a true Weighted Least Squares estimator instead of only using Robust-SE.

As for estimates on  $\alpha_1$  and  $\alpha_2$ ,  $\beta_1$  is consistent with the whole sample, and on average the differential impact of a general relative to a vocational is of 2.14 percentage points for each level of age for the AC20 sample. The age of convergence in employment varies through the waves but on average falls between age 44 and 45. The amplitude of these estimates are also in line with the whole sample restrictions. In Figure 4.6 we have the linear prediction plots for the last specification of the wave-by-wave analysis upon the AC20 sample, to have a graphical description of the analysis.



Figure 4.6: Linear prediction plots of the last model specification for Employment. Sample includes all male individuals from age 20 to 65 (*AC*20).See caption in Tables 4.4 for data source and model specification.

## 4.1.5 Splitting the Sample for the 2007–08 Financial Crisis

From summary patterns in Figure 3.3a we are afraid of the heterogeneity in employment amongst waves, which may be caused by the 2007–28 financial crisis, when Italy has been one of the EU28 Member States worst hit by the crisis, due to its structural weaknesses aggravated by the economic and financial crisis (Crepaldi et al., 2014). For that reason, as anticipated in Section 3.1.1, we split the pooled sample in pre-recession years, with waves from 2000 to 2008 included, and post-recession years, with waves from 2010 to 2014, keeping valid the main model identified by Equation (3.1). To keep the good work, we start analysing the AC20 sample for both portions of the pooled sample, and we perform again our sensitivity tests on the sample excluding self-employed individuals and the youngest cohort from age 20 to 24.

(a) Basic specification, pre-recession years

	age	$age^2$	General	$\frac{General}{\times age}$	$\frac{General}{\times age^2}$	Obs.	$R^2$
AC20	0.130*** (0.00195)	-0.00158*** (2.32e-05)	-0.838*** (0.0679)	0.0257*** (0.00369)	-0.000152*** (4.76e-05)	15,318	0.358
AC25	0.129*** (0.00263)	-0.00158*** (2.96e-05)	-0.989*** (0.125)	0.0329*** (0.00590)	-0.000232*** (6.84e-05)	12,979	0.292
AC20 <sup>NOSELF</sup>	0.139*** (0.00200)	-0.00171*** (2.34e-05)	-0.712*** (0.0719)	0.0179*** (0.00399)	-5.25e-05 (5.14e-05)	12,676	0.374
AC25 NOSELF	0.143*** (0.00278)	-0.00176*** (3.07e-05)	-1.041*** (0.132)	0.0335*** (0.00629)	-0.000225*** (7.25e-05)	10,428	0.330

(b) Basic specification, post-recession years

	age	$age^2$	General	General × age	$\frac{General}{\times age^2}$	Obs.	<i>R</i> <sup>2</sup>
AC20	0.119***	-0.00139***	-0.627***	0.0148***	-2.26e-05	9,855	0.320
1025	(0.00252) 0.121***	(2.94e-05) -0.00142***	(0.0834) -0.836***	(0.00444) 0.0244***	(5.52e-05) -0.000127	8 514	0 235
AC 23	(0.00359)	(3.93e-05)	(0.153)	(0.00713)	(8.04e-05)	0,314	0.235
AC20 NOSELF	0.12/*** (0.00260)	$-0.00151^{***}$ (3.01e-05)	-0.490*** (0.0899)	0.00703 (0.00491)	(6.15e-05)	8,217	0.331
AC25 NOSELF	0.136***	-0.00160***	-0.811***	0.0221***	-9.17e-05	6.917	0.268
AC 25	(0.00383)	(4.12e-05)	(0.165)	(0.00778)	(8.82e-05)	-,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	0.200

Table 4.5: Summary results of the most basic model specification for Employment. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 20 (*AC20*) or 25 (*AC25*) to 65 with at least upper secondary education, including or excluding self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2008 for pre-recession years, from 2010 to 2014 for post-recession years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

Tables 4.5 resume the basic results of Equation (3.1) applied to pre-recession years and post-

recession years. Starting from the AC20 sample, for pre-recession years we count 15,318 observations, while for post-recession years individuals are 9,855. We are going to compare the results over the two sub-samples to fully answer to the research question discriminating for periods pre- and post- crisis.

Starting from normal age-employment pattern in the economy, for the pre-recession years the probability of employment is 13 percentage points higher for each level of age, and the turning point for individuals with vocational education happens around age 41, against age 42 for the whole sample, while for post-recession years probability of employment is fixed at a lower pace around 11.9 percentage points, with a turning level of employment at 43, *ceteris paribus*. Hence, the crisis may affect the normal age-employment pattern pushing away the age of maximum level of employment of two years.



(c) Last specification, pre-recession years



(d) Last specification, post-recession years



Figure 4.7: Linear prediction plots on Employment. Sample includes males from age 20 to 65 (*AC20*) with at least upper secondary education, *including* self-employed individuals. See caption in Tables 4.5 and 4.6 for data source and model specification.

Looking at the key parameters, the time-invariant advantage of vocational education at the base of labour market is significantly steeper in pre-recession years than in post-recession ones. Individuals with general education in pre-recession years are 83.8 percentage points less likely to be employed than those with vocational education, while in post-recession years the time-invariant effect is of -62.7%. The difference in the two constant term estimates may hide a shift in favour of general education in the labour market, with vocational education becoming less favourable at the baseline after 2010. This is reflected by a higher selection of general education reforms to reduce the number of working hours per week in technical and professional schools, making education in vocational-oriented schools more general (Ministero dell'Istruzione, dell'Università e della Ricerca, 2008). It comes together with the main hypotheses on the need of a more academic-oriented education in the modern market, and the higher adaptability of this education type to labour-market shocks.

Furthermore, these evidences are reflected also by the differential impact of a general relative to a vocational education on employment: in pre-recession years the ageing impact is stronger in favour of general education, with general 2.57 percentage points more likely to be employment than a vocational for each level of age and convergence around age 44, while in post-recession years we have a smoother ageing effect at 1.48 percentage points each level of age. The turning point in employment for individuals with general education in pre-recession years happens at age 45, one year earlier than in the whole sample. Estimates on the coefficient of the interaction of education type with age-squared are not significantly different from zero.

Looking at the last specification with all controls in Tables 4.6, differences between the two sub-samples still persist. While normal age-employment patterns are very similar, fixing higher probability of employment of 10 percentage points for each level of age, the negative sensitivity of the normal ageing impact on employment is sightly higher in pre-recession years, making the reduction of the positive effect of age on employment much stronger after the turning age relative to post-recession years. For the first sub-sample, turning level of employment for individuals with vocational education appears at age 36, anticipated by the higher  $\alpha_2$  estimate, while for the latter the profile's inversion happens at age 40.

Looking at key DD parameters, individuals with general education are 78.9 percentage points

	age	$age^2$	General	$\frac{General}{\times age}$	$\frac{General}{\times age^2}$	Obs.	$R^2$
AC20	0.130*** (0.00195)	-0.00158*** (2.32e-05)	-0.838*** (0.0679)	0.0257*** (0.00369)	-0.000152*** (4.76e-05)	15,318	0.358
AC25	0.129*** (0.00263)	-0.00158*** (2.96e-05)	-0.989*** (0.125)	0.0329*** (0.00590)	-0.000232*** (6.84e-05)	12,979	0.292
AC20 NOSELF	0.139*** (0.00200)	-0.00171*** (2.34e-05)	-0.712*** (0.0719)	0.0179*** (0.00399)	-5.25e-05 (5.14e-05)	12,676	0.374
AC25 NOSELF	0.143*** (0.00278)	-0.00176*** (3.07e-05)	-1.041*** (0.132)	0.0335*** (0.00629)	-0.000225*** (7.25e-05)	10,428	0.330

(a) Basic specification, pre-recession years

(b) Basic specification, post-recession years

	age	$age^2$	General	General × age	$\frac{General}{\times age^2}$	Obs.	$R^2$
AC20	0.119***	-0.00139*** (2.94e-05)	-0.627*** (0.0834)	0.0148*** (0.00444)	-2.26e-05 (5.52e-05)	9,855	0.320
AC25	0.121*** (0.00359)	-0.00142*** (3.93e-05)	-0.836*** (0.153)	0.0244*** (0.00713)	-0.000127 (8.04e-05)	8,514	0.235
AC20 NOSELF	0.127*** (0.00260)	-0.00151*** (3.01e-05)	-0.490*** (0.0899)	0.00703 (0.00491)	7.23e-05 (6.15e-05)	8,217	0.331
AC25 NOSELF	0.136*** (0.00383)	-0.00160*** (4.12e-05)	-0.811*** (0.165)	0.0221*** (0.00778)	-9.17e-05 (8.82e-05)	6,917	0.268

Table 4.6: Summary results of the last model specification for Employment. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 20 (*AC*20) or 25 (*AC*25) to 65 with at least upper secondary education, including or excluding self-employed individuals. Omitted education type is vocational. Controlling for age, age-squared, schooling, family background, regional controls, municipality size, birth origin, current marital status and household's size. Waves of analysis: pooled sample, from 2000 to 2008 for pre-recession years, from 2010 to 2014 for post-recession years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

less likely to be employed than those with vocational in pre-recession years, while the same effect is 57.6 post-recession years, and the differential impact of a general relative to a vocational education on employment probability makes the first more likely to be employed than the latter for each year of age of 2.62 percentage points in pre-recession years and 1.37 in post-recession. The quadratic interaction for post-recession years is still not significantly different from zero also at the last specification. In Figures 4.7 we have a graphical description of our findings, while detailed results are in Tables of Section A.1.3 of Appendix A.

Considering the main controls, while education level lose significance in pre-recession years, in post-recession years makes individuals with one more year of schooling 0.66 percentage points more likely to be employed. We lose significance on almost all the other control variables in the analysis except for mother's educational attainment, which estimates in prerecession years are really similar to the whole sample analysis, while for post-recession years the effects are smoother than in the other sub-sample. This last control is kept significant for all considered samples in the pooled analysis.



Figure 4.8: Linear prediction plots on Employment. Sample includes males from age 25 to 65 (*AC*25) with at least upper secondary education, *including* self-employed individuals. See caption in Tables 4.5 and 4.6 for data source and model specification.

In Tables 4.5 and 4.6 we also have results for the main model on the two sub-samples excluding the youngest cohort and self-employed individuals, to check if the main results found with the wider sample are still valid as in Section 4.1.4.2. For post-recession years, we have no significant estimate on  $\beta_2$  for each considered sample for robustness check, as in the wider AC20 sample. Looking at the last specification for different sample restrictions, we realise that estimates keep the same differences between pre-recession and post-recession years, varying in the same way as we apply restrictions as in the whole sample. These findings give support to our main hypothesis: vocational education still gives an advantage at the entrance of the labour market, both in pre-recession and post-recession case, with a lower deficiency for general education in post-recession years, and this gap between the two groups is still absorbed at a certain age of convergence, when general education overlaps vocational at a lower pace after a turning age in the trajectory of employment for general education.

(a) Basic specification, AC20 NOSELF, pre-recession (b) Basic specification, AC20 NOSELF, post-recession years



(c) Last specification, AC20 NOSELF, pre-recession (d) Last specification, AC20 NOSELF, post-recession years



Figure 4.9: Linear prediction plots on Employment. Sample includes males from age 20 to 65 with at least upper secondary education, *excluding* self-employed individuals. See caption in Tables 4.5 and 4.6 for data source and model specification.

(a) Basic specification, AC25 NOSELF, pre-recession (b) Basic specification, AC25 NOSELF, post-recession years



(c) Last specification, AC25 NOSELF, pre-recession (d) Last specification, AC25 NOSELF, post-recession years



Figure 4.10: Linear prediction plots on employment. Sample includes males from age 25 to 65 with at least upper secondary education, *excluding* self-employed individuals ( $AC25^{NOSELF}$ ). See caption in Tables 4.5 and 4.6 for data source and model specification.

# 4.2 Main Model interacting with Birth Cohorts

The obtained dataset after the data management described by Section 3.1 gives us the information about the birth year of each individual and its age, together with all the other variables of interest. Using the birth year information, we pool waves of the SHIW as in the main model of Section 4.1 splitting the sample for a selected year in only two parts to avoid collinearity issues by selecting further cohorts, and we run the model in Equation (3.5) of Section 3.2.2. By that, we select the two birth cohorts using c. In all specifications, we always control for "other" education type in its interactions with age and age-squared and triple interactions including the birth cohort indicator variable. In this way, we may delete part of the bias caused by different returns of education during the years and with different reforms in the Italian education environment. On the other hand, we are also aware that age tracking differs between birth cohorts, and we may fall into overtaking of the treatment in the control birth cohort, thus we are not willing to emphasise time-invariant estimates of the effects on the labour-market outcome among education types.

anasc: year of birth, year									
Percentiles		Smallest	Smallest						
1%	1940	1935							
5%	1945	1935							
10%	1948	1935	Obs	25173					
25%	1956 1935		Sum of Wgt.	25173					
500	1067		Mean	1966.56					
30%	1907	Largest	Std. Dev.	13.56308					
75%	1978	1994							
90%	1985	1994	Variance	183.9571					
95%	1988	1994	Skewness	0538549					
99%	1992	1994	Kurtosis	2.033027					

Table 4.7: Summary Statistics for variable anasc, birth year. Sample includes males from age 20 to 65 (AC20) with at least upper secondary education, *including* self-employed individuals. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015).

Considering the whole sample with individuals aged from 20 to 65 between 2000 and 2014 waves of the SHIW, we look for the summary statistics in Table 4.7 for birth year. The 50% percentile and the mean both converges to year 1967, and this provides our empirical strategy by grouping for individuals born until 1966 and after it. Hereinafter, we also call the post-1966 the younger birth cohort and the pre-1966 (included) the older birth cohort. Detailed

results are provided in Tables of Section A.1.4 of Appendix A.

We pass over the less explained specifications which does not give significant estimates to analyse our complete specification including all controls used for the main model analysis in Section 4.1, with or without the linear interaction with age as explained in Section 3.2.3.

The age-employment pattern varies among individuals between the birth cohorts. While individuals are 17.6 percentage points more likely to be employed for each level of age in the older cohort, this advantage decreases by 6.9 percentage points for the younger, whose growth stops at age 34 and then starts to decrease, while it keeps growing until 43 in the older one. These levels of age at the steady state for employment rates are obtained with the same technique used in Section 4.1, by partially deriving the CEF of Equation (3.5) for the level of age as in Equation (4.8a) for individuals born after 1966, in Equation 4.8b for those born in the other cohort, equalling the partial derivatives in order to identify the maximum level, obtaining the formulas in Equation 4.9 for post-1966 and Equation 4.10 for pre-1966.

$$E[y_i|g, age, c, s, X] = \hat{\alpha}_0 + \hat{\theta}_0 \cdot c_i + \hat{\phi}_0 \cdot g_i + \hat{\beta}_0(g_i \cdot c_i) + \\ + \hat{\alpha}_1 \cdot age_i + \hat{\theta}_1(c_i \cdot age_i) + \hat{\phi}_1(g_i \cdot age_i) + \hat{\beta}_1(g_i \cdot c_i \cdot age_i) + \\ + \hat{\alpha}_2 \cdot age_i^2 + \hat{\theta}_2(c_i \cdot age_i^2) + \hat{\phi}_2(g_i \cdot age_i^2) + \hat{\beta}_2(g_i \cdot c_i \cdot age_i^2) + \\ + \sum_s \hat{\delta}_s \cdot s_i + X_i \cdot \hat{\gamma}$$

$$(4.7)$$

 $E[\eta_i|g, age, c, s, X] = E[\eta_i] = 0$ 

$$\frac{\partial E[y_i|g=0,c=1,age,s,X]}{\partial age} = (\hat{\alpha}_1 + \hat{\theta}_1) + 2 \cdot age_i \cdot (\hat{\alpha}_2 + \hat{\theta}_2)$$
(4.8a)

$$\frac{\partial E[y_i|g=0, c=0, age, s, X]}{\partial age} = \hat{\alpha}_1 + 2 \cdot age_i \cdot \hat{\alpha}_2$$
(4.8b)

$$age^* \mid g = 0, \ c = 1 \approx \left\lceil \left| \frac{\hat{\alpha}_1 + \hat{\theta}_1}{2 \cdot (\hat{\alpha}_2 + \hat{\theta}_2)} \right| \right\rceil$$
 (4.9)

$$age^* \mid g = 0, \ c = 0 \approx \left[ \left| \frac{\hat{\alpha}_1}{2 \cdot \hat{\alpha}_2} \right| \right]$$
 (4.10)

Nonetheless, the same relationship arises also for general education, for which the steady state is achieved at age 43 in the older cohort whereas 38 in the younger one, calculated as in Equation (4.11b) and (4.11a) and equalling the partial derivatives in order to isolate the steady state age, obtaining the expressions in Equation 4.12 for post-1966 and Equation 4.13 for pre-1966.

$$\frac{\partial E[y_i|g=1, c=1, age, s, X]}{\partial age} = (\hat{\alpha}_1 + \hat{\phi}_1 + \hat{\theta}_1 + \hat{\beta}_1) + 2 \cdot age_i \cdot (\hat{\alpha}_2 + \hat{\phi}_2 + \hat{\theta}_2 + \hat{\beta}_2) \quad (4.11a)$$
$$\frac{\partial E[y_i|g=1, c=0, age, s, X]}{\partial age} = (\hat{\alpha}_1 + \hat{\phi}_1) + 2 \cdot age_i \cdot (\hat{\alpha}_2 + \hat{\phi}_2) \quad (4.11b)$$

$$age^* \mid g = 1, \ c = 1 \approx \left[ \left| \frac{\hat{\alpha}_1 + \hat{\phi}_1 + \hat{\theta}_1 + \hat{\beta}_1}{2 \cdot (\hat{\alpha}_2 + \hat{\phi}_2 + \hat{\theta}_2 + \hat{\beta}_2)} \right| \right]$$
 (4.12)

$$age^* \mid g = 1, \ c = 0 \approx \left\lceil \left| \frac{\hat{\alpha}_1 + \hat{\phi}_1}{2 \cdot (\hat{\alpha}_2 + \hat{\phi}_2)} \right| \right\rceil$$
 (4.13)

Whilst these differences in pre- and post-1966 cohorts may be partially explained by a weakening of the labour market overall, it may be a first signal of how vocational education has lost its bargaining power on being employment, as individuals who invested in this type of education reach the highest level of probability of employment much earlier than those who invested in general education, which offers more interesting and adaptable skills to the market compared with the pre-1966 highest levels.

As we look at estimates on the key parameters of general education type differencing by birth cohorts, we notice that the effect for the older birth cohort finds an opposite effect relative to its counterpart, under which these are in line with the pooled sample analysis using a simpler DD model.

emp = 1 if individual is employed	AC20	AC25	AC20 <sup>NOSELF</sup>	AC25 NOSELF
	0.176***	0.175***	0.193***	0.190***
age	(0.00537)	(0.00542)	(0.00568)	(0.00575)
2	-0.00207***	-0.00207***	-0.00228***	-0.00227***
age-	(5.23e-05)	(5.26e-05)	(5.43e-05)	(5.46e-05)
Down After 1066	1.544***	2.374***	1.991***	2.705***
Bom Aner 1900	(0.152)	(0.202)	(0.166)	(0.230)
Down After 1066 V goo	-0.0690***	-0.139***	-0.0918***	-0.162***
Bom Aner 1900 $\times$ age	(0.00786)	(0.0109)	(0.00849)	(0.0124)
$\mathbf{P}_{a} = \mathbf{A}_{a}^{a} + \mathbf{A}_{a}^{b} + \mathbf{A}_{a}$	0.000506***	0.00147***	0.000782***	0.00175***
Bom Alter 1900 $\times$ age-	(9.95e-05)	(0.000143)	(0.000109)	(0.000165)
Camaral	0.622**	0.660**	-0.138	-0.133
General	(0.313)	(0.315)	(0.371)	(0.369)
Conoral X and	-0.0319**	-0.0334***	-0.00321	-0.00354
General × age	(0.0126)	(0.0127)	(0.0147)	(0.0147)
Concerly $acc^2$	0.000396***	0.000408***	0.000134	0.000135
General × uge	(0.000126)	(0.000126)	(0.000145)	(0.000144)
Canaral $\times$ Born After 1066	-1.373***	-3.575***	-0.254	-2.499***
General × Bolli Alter 1900	(0.344)	(0.454)	(0.403)	(0.525)
Canaral $\times$ Born After 1066 $\times$ aga	0.0547***	0.183***	0.00281	0.135***
General $\times$ Bolli Alter 1900 $\times$ <i>uge</i>	(0.0158)	(0.0232)	(0.0182)	(0.0268)
Canaral $\times$ Born After 1066 $\times aga^2$	-0.000521***	-0.00233***	8.85e-05	-0.00180***
General × Born Arter 1900 × uge	(0.000197)	(0.000308)	(0.000225)	(0.000358)
Observations	25,173	21,493	20,893	17,345
R-squared	0.395	0.332	0.421	0.382

Table 4.8: Summary results of the last model specification for Employment. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 20 (*AC*20) or 25 (*AC*25) to 65 with at least upper secondary education, including or excluding self-employed individuals. Omitted education type is vocational. Triple differences interacting with birth cohort from 1967 to 1994. Controlling for age, age-squared, schooling, family background, regional controls, municipality size, birth origin, current marital status and household's size. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

It appears that individuals with general education in older birth cohorts have an early advantage in probability of being employed relative to those with vocational education by 62.2 percentage points, where the gap decreases by 3.19 percentage points in favour to peers with vocational education, *ceteris paribus*. The early advantage of general education holds until the cut-off age of 33, when the gap turns in favour of vocational education until age 47, at which individuals with general education are again favoured by the labour market in terms of employment. After 1966, the picture is similar to the analysis with the simpler DD model. Individuals with vocational education benefit of their tracking choice at early age, having 75 percentage points higher probability of employment than those who undertook a different path, but the gap with vocational of the latter is reduced by 2.26 percentage points at each level of age, *ceteris paribus*. Convergence in employment among individuals with different education type happens only one time in later age of 43, and after that "generals" keep a higher probability of employment until the end of their days. Meeting ages of employment probability are derived as in Section 4.1, with the difference of expressing it both for c = 1 and c = 0 as respectively in Equation (4.14) and (4.15).

$$#\#_{age} = \left[ \frac{-(\hat{\phi}_1 + \hat{\beta}_1) \pm \sqrt{(\hat{\phi}_1 + \hat{\beta}_1)^2 - 4 \cdot (\hat{\phi}_0 + \hat{\beta}_0) \cdot (\hat{\phi}_2 + \hat{\beta}_2)}}{2 \cdot (\hat{\phi}_2 + \hat{\beta}_2)} \right]$$
(4.14)

$$#\#_{age} = \left[ \frac{-\hat{\phi}_1 \pm \sqrt{\hat{\phi}_1^2 - 4 \cdot \hat{\phi}_0 \cdot \hat{\phi}_2}}{2 \cdot \hat{\phi}_2} \right]$$
(4.15)

Summing up, it seems tricky to give a definitive interpretation to the differences that emerge from this analysis controlling for selectivity in education among birth cohorts. We believe they are partially driven by different tracking ages among birth cohorts, and SHIW do not provide enough reliable waves to perform better. Even though employment profiles among educational choices for individuals born until 1966 are very close, we find no clear early advantage of general education over the skill-oriented school-based counterpart, but rather an advantage in early ages for those who completed the academic track. On the other hand, in the younger birth cohorts vocational education provides an early advantage in employment with respect to general, but its probability reach the maximum level much earlier than in the control birth cohort. Figure 4.11 gives us a graphical and more informative interpretation of the estimates in Table 4.8.

Starting from these considerations, controlling for selection of education among different decades suggests us that there is a clear evidence of obsolescence of the skills provided by vocational education with respect to labour market skills' demand. Hence, there is a strong trade-off between dealing with a higher probability of being unemployed in early age choosing the more comprehensive academic-based education, which provides the skills for a lifelong learning perspective in a internationalised knowledge society of the advanced economies, or reducing likelihood of unemployment in early age choosing the school-based vocational education track in upper secondary school, facing less adaptability in occupation at later age.

There is no unambiguous solution to the trade-off, but these evidences should be considered for policy purposes, together with the fact that retirement age has been increasing in all developed countries which makes necessary for individuals to be competitive in the labour market for longer years, especially for Italy where the retirement age is traditionally one of the earliest worldwide with the other Southern European countries.

To provide a more reliable epilogue for the performance of employment over the life-cycle discriminating by different education patterns, we also perform robustness checks for the triple differences model by excluding the youngest cohort in the sample and excluding self-employed individuals, as in Section 4.1. We obtain significant results only for the AC25 sample, co-opting a lower power of the analysis. For this sample, we have even stronger evidences of the previous phenomenon, but the tracking age is still heterogeneous among birth cohorts.



(a) Last specification for c = 0, 20–65 age cohort

(b) Last specification for c = 1, 20–65 age cohort



Figure 4.11: Linear prediction plots on Employment interacting with birth cohorts. Sample includes males from age 20 to 65 with at least upper secondary education (AC20). See caption in Tables 4.8 for data source and model specification.

## CHAPTER

5

# EFFECTS OVER LIFE-TIME WAGES

## 5.1 Main Model for Quasi-Longitudinal Data

After an exhaustive analysis of the effects of education type on employment rates in the previous chapter, we would like to approach the impact of upper secondary education tracking choices on wages over the life-cycle. In the first instance, we use the same methodology exploited for employment rates and described in Section 3.2.1. As a reminder from Section 3.2, the difference of this analysis with respect to the previous one is on the type of the theoretical composition underlined: while for employment rates we consider a LPM, where the dependent variable *y* is a Bernoulli random variable, here we use net wages and salaries shaped in logarithmic form, assumed as the compensation of employees in their jobs.

### 5.1.1 Modelling with 20–65 age cohort

In the most basic specification we consider a linear regression model as in Equation (3.1) where natural logarithm of net wages and salaries is a function of age, age-squared, wave

controls and education type applied on the whole sample of male individuals between age 20 and 65. Estimates are obtained using OLS Estimators with Robust Standard Errors. As in the employment analysis, we do not subtract the baseline age to the current level to provide a more friendly interpretation of results and graphs. Once again, we consider "other" upper secondary education program with its interaction with age and age-squared for all specifications, in order to exclude individuals we cannot define in general education nor in vocational education from the estimates due to sample issues (see Section 3.1).

As anticipated in Section 3.1.1, to analyse these effects we consider the pooled sample obtained from the SHIW reshaped dataset from wave 2000 to wave 2014 removing self-employed individuals. We might be suspicious on the information about self-employed income, because it could be biased and may not include other sources of income for individuals to be considered as primary wages. However, within this sample we have huge differences with the sample for employment excluding self-employed: here, the sample size is dropped without choice in about one half for each wave for attrition, since information about net wages and salaries is available only for employed individuals and a small part of unemployed, interpreted as temporary workers. This issue may compromise the goodness of our analysis. For the 20–65 age cohort sample excluding self-employed individuals, we keep 13,886 observations in eight waves, every two years, with the highest number of individuals in wave 2006 (1,855) and the lowest in wave 2002 (1,560).

Taking the other considerations about the selection of education type and wave dummies in Section 4.1.1 as given, we use a LOWESS, following the technique implemented by Cleveland (1979), to have a first unconditioned profile of the path of wages over the whole sample. From Figure 5.1a it emerges that ln wages generally increase with age as for employment rates in Section 4.1.1 but, while individuals with general upper secondary education reach a maximum level around age 57 and then wages start to slowly decrease, for individuals with vocational education the path obtained with LOWESS does not decrease, starting a steady trend at a lower level with respect to the treatment group. Furthermore, in Figure 5.1b we find LOWESS regression for each wave of analysis, which suggests different trends for all waves.



(a) Male employment by age and education type, pooled sample





Figure 5.1: Smoothed scatterplots of wages using locally weighted regressions (*lowess*, Cleveland (1979)). Sample includes male individuals with wages for the observed waves, not self-employed, who finished upper secondary education from age 20 to 65. Years of analysis: from 2000 to 2014, every two years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015).

A summary view of the results from the basic model is given by Table 5.1, while detailed results can be found at Column 1 in Tables of Section A.2.1 of Appendix A. In this table, we can observe that the estimates on key parameters follow the same direction of what we obtained in Table 4.1 for employment. Estimates on  $\beta_1$  and  $\beta_2$  as in Equation (4.1) (as all other estimates) may be interpreted as percentage changes on the dependent variable without approximation loss, taking all other effects constant, while for  $\beta_0$  it is more safe to interpret estimates by taking the true value as  $100 \cdot [\exp(\hat{\beta}_0) - 1]$  to avoid oversized approximation error.

	age	$age^2$	General	General × age	$\frac{General}{\times age^2}$	Obs.	$R^2$
AC20 NOSELF	0.0756*** (0.00329)	-0.000696*** (3.96e-05)	-1.008*** (0.217)	0.0445*** (0.0105)	-0.000395*** (0.000122)	13,886	0.248
AC25 NOSELF	0.0657*** (0.00391)	-0.000587*** (4.60e-05)	-0.951*** (0.247)	0.0423*** (0.0117)	-0.000375*** (0.000135)	12,772	0.182

Table 5.1: Summary results of the model's most basic specification for Wages. Linear Regression Models. Dependent variable: In wages and salaries. Sample includes males from age 20 (AC20) or 25 (AC25) to 65 with wages for the observed waves and at least upper secondary education, *excluding* self-employed individuals (*NOSELF*). Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

While  $\alpha_0$  express the average base level of ln wages in the sample, looking at the normal age-wages pattern of the economy, the effect on the labour-market outcome is slightly lower than in the employment case: *ceteris paribus*, ageing makes individuals with vocational education approximately 7.56% richer each additional year from zero, reaching the maximum level around age 54, calculated as in Equation (4.3). From this last statement, it emerges that employment caps earlier than wages for the control group considering the same sample (41 against 54), in line with a more steady growth over ages for wages.

Considering estimates on the time-invariant difference on wages between individuals with general education and those with vocational education  $\beta_0$  we see that, while the probability of employment drops about 75 percentage points for the treatment group relative to the control, the effect on wages is lower. *Ceteris paribus*, wages for a general are 63.5 percentage points lower than peers with vocational education at early age. It is wise to remember that  $\hat{\beta}_0$  may be biased and oversized because of omitted variable bias caused by the lack of controls for selectivity in education, as also described in Section 4.1.1 for employment. We should

keep in mind this statement while we keep analysing the main results in a sceptical eye.

This gap among different education choices decreases by 4.45 percentage points at each level of age, converging at the same level of wages around age 31 as in Equation (4.5), much earlier than for employment. From these results, we can assert that differences in wages between different tracks are smaller compared to employment, with a thinner gap in early age and making individuals with academic-based education as wealthy as their counterparts with skill-based education faster than achieving the same level of occupation.

Steady state age for wages in the general education group is calculated as in Equation (4.4) around age 55 thanks to significant estimates on  $\beta_2$ , the sensibility of the different impact on the labour-market outcome for each level of age of a general relative to a vocational. It means that the highest level of wages for both education types is reached in later age near to the end of the considered life-cycle, when they are likely to have achieved the highest position in their career, whereas the highest probability of employment is reached earlier, and even earlier for individuals with vocational education. In Figure 5.2 we sum up the results for the most basic specification of Equation (3.1) on ln wages by plotting linear prediction plots for both treatment and control group, excluding "other" education type for a better interpretation. Same considerations of employment about the interpretation of trajectories of ln wages in Section 4.1.1 can be applied.

To sum up these basic results, the main hypothesis is also valid for wages, but with some differences. Individuals with vocational education at upper secondary school have a smaller advantage relative to peers with general education in early age, and this advantage is covered by general education in a small window of time, much smaller than the time needed to converge in employment. Furthermore, looking at the turning age in wages we achieve that capabilities provided by vocational education perish mainly for the likelihood to be employed, as both groups reach the cap around the same level of age. Hanushek et al. (2017), in their last version of the study, apply a similar model on the cross-section data of the IALS-97 (Organization for Economic Co-operation and Development (OECD), 1997) and German Microcensus 2006. They discover that the gap between a general relative to a vocational on wages at the beginning of time is less relevant than the employment gap looking at estimates for Germany, but it also turns in favour of general in a shorter time (also around age 30). To keep the good work, as in the other analyses, we progressively add other covariates in



Figure 5.2: Linear prediction plots of the basic specification for Wages. See caption in Table 5.1 for data source, sample and model specification.

order to take into account for other potential biases from unmeasured ability, from decision driving and other possible influences on wages, in analogy with employment rates, which may change over time or not, affecting the life-cycle level of wages.

	age	$age^2$	General	$General \\ \times age$	$\frac{General}{\times age^2}$	Years of Schooling	Obs.	<i>R</i> <sup>2</sup>
AC20 NOSELF	0.0739*** (0.00328)	-0.000680*** (3.94e-05)	-1.080*** (0.215)	0.0440*** (0.0103)	-0.000406*** (0.000120)	0.0423*** (0.00224)	13,886	0.270
AC25 NOSELF	0.0668*** (0.00389)	-0.000602*** (4.56e-05)	-1.098*** (0.245)	0.0449*** (0.0116)	-0.000418*** (0.000133)	0.0441*** (0.00225)	12,772	0.211

Table 5.2: Summary results of the main model for wages. See caption in Table 5.1 for data source, sample and model specification. Controlling for age, age-squared and schooling. Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

Starting from the basic specification, we add control for years of schooling and higher education than upper secondary school. While for the analysis this control has a side effect, it becomes a crucial effect in the determination of wages over the life-cycle, and this is the reason why we resume results in Table 5.2. Indeed, more time in education means on average less time in working activities. This control remains significant and unbiased at 1% from the first specification it is introduced and it raises wages by 4.23 percentage points for each additional year of schooling in constant terms, increasing  $R^2$  from 0.248 to 0.270. While this effect is kept around a 4% increase in the labour-market outcome for all specifications, it increases at the first application the age of convergence in wages from age 31 to age 38, keep turning wages around age 54. Detailed results are provided at Column 2 in Tables of Section A.2.1 of Appendix A.



Figure 5.3: Linear prediction plots of the main model for Wages on the pooled sample. See caption in Table 5.2 for data source, sample and model specification.

Proceeding with the ln wages analysis, we try to add controls for family background, regional controls and current family controls. It is worth remembering that controls for parents' educational attainment, siblings in education age and Southern Italy natives are affected by dummy variable adjustments for missing values using the Allison (2002, pp. 9-12), illustrated in Section 3.2.3.3, in order to remove the large amount of missing values and to avoid attrition. As in the employment analysis, we use these controls not for the relevance of the estimates on these parameters, but rather to clean the omitted variables bias on the parameters of interest, which are scaled down from the oversized basic model. Approaching directly the last specification with all controls, resumed in Table 5.3, we observe that  $R^2$  rises up from 0.248 in Table 5.1 to 0.332.

The normal age-wages pattern gives 4.77% higher wages at each level of age, turning the positive trend around age 46 for individuals with vocational education thanks to a significant estimate on  $\alpha_2$ , *ceteris paribus*. Although estimates are appreciably lowered from the basic specification, the maximum level of wages is still meet at a later age compared to the control group in the employment analysis (46 against 37). We face the same behaviour over estimates on  $\beta_0$  and  $\beta_1$ . Individuals with academic-based education have lower wages than peers with skill-based education by 61.79%, but the gap narrows by 4% higher wages for the treatment group relative to the control at each level of age, converging the profiles at age 38, *ceteris paribus*. Even though the meeting age increases with respect to Table 5.1, the advantage of vocational education is still cancelled faster than in the employment analysis, while the turning point in wages for general education happens at age 49, near to the one for individuals with vocational education but three years later.

Taking a quick look at the main control variables, we observe that fathers' educational attainment oversteps mother's educational attainment in the magnitude of these effects on wages, even they are close, both for the time-invariant effect and the differential impact for each level of age: this response is opposite of what we found for employment, where mother's education seems more important than father's. Having a more-educated father makes individuals decreases wages of 12% and increases them by 0.413 percentage points with respect to individuals with less-educated father, while having a more-educated mother has a lower progressive effect over age (+0.33%). Controls on siblings in education age and birth in Southern Italy are not significant.

Figure 5.4 exhibit a more straightforward interpretation of the results in Table 5.3 for the AC20 sample, while exhaustive results can be found in Tables of Section A.2.2 of Appendix A. Summing up, also with the most complete specification we find a positive reaction to our main hypothesis: albeit vocational education blesses individuals in early age with higher wages, individuals with general education need few years to recover the loss and overwhelm the control group. Despite that, if we look at the trajectories plotted in Figure 5.4 the path is not totally clear: in retirement age, wage profiles of the two groups seem to converge again



Figure 5.4: Linear prediction plots of the last specification for Wages. See caption in Table 5.3 for data source, sample and model specification.

and reaching the same level of the labour-market outcome. Furthermore, comparing effect of wages and employment between the two groups, the main difference is the pace at which the gap is cancelled: probability of employment arrives later at a slower pace, whereas wages are equalled in earlier age and they may converge again in retirement age in favour of vocational education. However, the maximum level of wages is reached later for individuals with vocational education than the maximum probability of employment, and this may be interpreted again as a detriment of vocational skills of their desirability in the labour market.

	age	$age^2$	General	$\frac{General}{\times age}$	$\frac{General}{\times age^2}$	Years of Schooling	Obs.	$R^2$
AC20 NOSELF	0.0477*** (0.00500)	-0.000515*** (5.20e-05)	-0.962*** (0.211)	0.0399*** (0.0101)	-0.000382*** (0.000117)	0.0377*** (0.00230)	13,886	0.332
AC25 NOSELF	0.0337*** (0.00524)	-0.000350*** (5.41e-05)	-1.037*** (0.240)	0.0436*** (0.0113)	-0.000425*** (0.000129)	0.0383*** (0.00232)	12,772	0.285

Table 5.3: Summary results of the model's last specification for wages. See caption in Table 5.1 for data source, sample and model specification. Controlling for age, age-squared, schooling, family background, regional controls, municipality size, birth origin, current marital status and household's size. Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

#### 5.1.2 Excluding the Youngest Cohort from the Sample

As in Section 4.1.4.2 for employment analysis, we run the model by excluding the youngest cohort in the sample for the same reasons. Considering individuals aged between 25 and 65 and excluding self-employed, the sample drops at 12,772 observations, varying between 1,414 individuals in 2002 wave and 1,711 in 2006 wave. Results in Table 5.1 shows that, excluding the 20–24 age cohort reduces the normal age-wages pattern in the economy controlling only for age and age-squared, increasing wages by only 6.57 percentage points for each level of age with respect to 7.56 in the wider sample, reaching the turning point for individuals with vocational education around age 56 against 41 for employment. The time-invariant effect of a general relative to a vocational makes the latter 61.36% richer then the treatment group at the baseline, and this gap is covered by an increase in wages of 4.23 percentage points for each level of age in favour of general education, converging around the same age of the wider sample, and reaching the turning point for generals around age 56, *ceteris paribus*. Albeit the estimates on  $\beta$ s are scaled down in the basic specification using the AC25 NOSELF sample, overall they do not significantly vary from estimates obtained from the wider sample.

Looking at the last specification in Table 5.3 for the AC25 NOSELF sample, the normal agewages pattern remains still lower than the wider sample: wages increase by 3.37 percentage points at each level of age for the control group, interrupting growth at age 48 against 46 in the wider sample and 37 in the employment rates' last specification, *ceteris paribus*. The time-invariant effect increases and makes individuals with vocational education almost 65% richer than those with general education at the baseline, breaking this disadvantage at the pace of 4.36 percentage points for each level of age and converging in wealth at age 37 *ceteris paribus*, almost the same level of the wider sample despite of higher estimates on  $\beta$ s, and still earlier than in the employment case. The turning point for individuals with general education comes at age 50. Checking estimates on the main control variables for the last specification, we see that years of schooling is still significant at 1% and one additional year in education makes individuals 3.83 percentage points wealthier in wages, while we lose significance on the time-invariant effect of parents' educational attainment. Complete results can be examined in Tables of Section A.2.1 of Appendix A.



(a) Basic specification, 25–65 age cohort, pooled sample





Figure 5.5: Linear prediction plots on Wages. Sample includes males from age 25 to 65 (*AC*25) with at least upper secondary education, *excluding* self-employed individuals (NOSELF). See caption in Table 5.3 for data source and model specification.

Figures 5.5 show linear prediction plots for the basic and the last specification of the wages model over the 25–65 age cohort sample. Vocational education keeps advantage in wages for the same amount of time as in the wider sample, confirming the main hypothesis also for this sample restriction, and general education overwhelm individuals with vocational after this meeting age. Anyway, in Figure 5.5b we have two reasonable solutions at Equation (4.5), for both  $\pm \sqrt{\hat{\beta}_1^2 - 4 \cdot \hat{\beta}_0 \cdot \hat{\beta}_2}$ , because it is clear that wage profiles for general and vocational meets again in retirement age at 65.

#### 5.1.3 Wave-by-Wave Analysis

As for Section 4.1.4.4, we apply the main model in Equation (3.1) to each wave to provide further robustness to our quasi-longitudinal sample analysis, to observe if the main hypothesis still holds for the single waves. We run the linear regression model progressively for each single wave while including all the considered controls and "other" education type. Table 5.4 provides a recap of the key parameters for the last specification, exposed in Tables of Section A.2.2 of Appendix A in detail.

Analysing the wider AC20 NOSELF sample, the normal age-wage pattern in the company on average behaves in the same way as for the whole sample, for which individuals become wealthier by 4.77% for each level of age, *ceteris paribus*, capping growth around age 45, which is almost in line with the whole sample taking into account measurement errors. These effects varies throughout the waves, with maximum values reached at the highest level of 56 in 2012 wave and the lowest of 39 in 2006.

Estimates on the key parameters to put general and vocational effects side by side provides significant results only for 2000, 2006 and 2010 waves, where we achieve higher and volatile effects both for  $\beta_0$ ,  $\beta_1$  and  $\beta_2$  than in the whole sample analysis. The highest level is found in 2000 wave, where wages for individuals with vocational education are two times higher than those with general education, followed by a differential impact of 18% higher wages for each level of age in favour of general education *ceteris paribus*, thus the convergence is earlier achieved at age 34, even earlier than in the whole sample for the last specification. Looking at values in mean, the turning age for general education is kept around age 47, with different magnitudes among waves, and average meeting age is found at 37.

On average, results remain in line with the whole sample analysis, but the effects are not

				•				
	age	$age^2$	General	$\frac{General}{\times age}$	$\frac{General}{\times age^2}$	Years of Schooling	Obs.	<i>R</i> <sup>2</sup>
2000	0.0537***	-0.000657***	-3.328***	0.165***	-0.00197***	0.0368***	1,660	0.409
2002	0.0509***	-0.000575***	-0.139	0.00135	6.12e-05	0.0287***	1,560	0.343
2004	0.0556***	-0.000590***	-0.742	0.0255	-0.000187	0.0430***	1,631	0.299
2006	0.0456***	-0.000581***	-1.918**	0.0910**	-0.00102**	0.0274***	1,855	0.305
2008	0.0386***	-0.000406***	-0.112	-0.00528	0.000170	0.0398***	1,830	0.341
2010	0.0564***	-0.000634***	-1.489***	0.0693**	-0.000758**	0.0389***	1,829	0.308
2012	0.0511***	-0.000460***	-0.973*	0.0419*	-0.000394	0.0445***	1,815	0.409
2014	0.0293**	-0.000350**	-0.0294	-0.00599	0.000154	0.0351***	1,706	0.380

(a) 20-65 age cohort, without self-employed individuals

(b) 25-65 age cohort, without self-employed individuals

	age	$age^2$	General	$\frac{General}{\times age}$	$\frac{General}{\times age^2}$	Years of Schooling	Obs.	$R^2$
2000	0.0266*	-0.000349**	-3.222***	0.160***	-0.00190***	0.0380***	1,477	0.327
2002	0.0405***	-0.000464***	-0.711	0.0279	-0.000237	0.0312***	1,414	0.302
2004	0.0331**	-0.000356**	-0.758	0.0273	-0.000215	0.0425***	1,489	0.239
2006	0.0340*	-0.000438**	-1.134	0.0546	-0.000614	0.0273***	1,711	0.253
2008	0.0394***	-0.000389**	-0.301	0.00397	6.02e-05	0.0415***	1,689	0.324
2010	0.0429***	-0.000445***	-1.717**	0.0793**	-0.000864**	0.0384***	1,699	0.254
2012	0.0459***	-0.000380**	-1.285**	0.0548**	-0.000523*	0.0442***	1,697	0.327
2014	0.00682	-9.18e-05	-0.689	0.0238	-0.000172	0.0373***	1,596	0.357

Table 5.4: Summary results of the last specification for each wave of analysis. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived a wage for the observed wave, aged 20 or 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Controlling for age, age-squared, schooling, family background, regional controls, municipality size, birth origin, current marital status and household's size. Years of analysis: from 2000 to 2014, every two years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Linear prediction plots in Figure 5.6 Significant at \*\*\*1% \*\*5% \*10%.

significant and strongly volatile between waves. From AC25 NOSELF sample we can state almost exactly the same conclusions.

## 5.1.4 Splitting the Sample for the 2007–08 Financial Crisis

In the fashion of the analysis in Section 4.1.5, we would like to split the combined sample into two sub-samples, one for pre-recession years from 2000 wave to 2008, and one for post-recession years from 2010 wave to 2014, running the model in Equation (3.1) for both groups, in order to study the heterogeneity among the different waves evidenced by the robustness check in Section 5.1.3. We replicate the study for the main sample including individuals with age between 20 and 65, excluding self-employed as in Section 5.1.1 and dropping the youngest cohort from age 20 to 24 for robustness, as in Section 5.1.2. More detailed



Figure 5.6: Linear prediction plots of the last specification for Wages. Sample includes all male individuals excluding self-employed who perceived a wage for the considered wave, with at least upper secondary education, from age 20 to 65 (*AC*20<sup>*NOSELF*</sup>). See caption in Tables 5.4 for data source and model specification.

results can be found in Tables of Section A.2.3 of Appendix A.

We start the overview of the analysis considering the AC20 sample and a linear regression model where wages are a function of age, age squared, schooling, wave controls and education type. For pre-recession years we count 8,536 observations while for post-recession years individuals are 5,350. We would compare results over the two sub-samples and the whole sample to give a satisfying impression of the wages profiles for periods pre- and post-crisis.

The age-wages pattern in the economy does not significantly vary between the two subsamples. *Ceteris paribus*, in both cases individuals with vocational education experience a 7.5 percentage increase in wages for each level of age, but small differences in  $\alpha_2$  estimates collocate the turning point of the wage path growth at different levels, age 53 in pre-recession (one year earlier than in the whole sample) and 55 in post-recession years (one year later than in the whole sample), which is a first sign of the effect of the crisis in the Italian labourmarket. Once more, these wages reach the highest level quite later than in the employment case, where for the same sample are collocated respectively at age 41 and 42.

	age	$age^2$	General	General × age	$\frac{General}{\times age^2}$	Years of Schooling	Obs.	$R^2$	
AC20 NOSELF	0.0749*** (0.00421)	-0.000704*** (5.17e-05)	-1.277*** (0.301)	0.0550*** (0.0148)	-0.000550*** (0.000177)	0.0383*** (0.00309)	8,536	0.262	
AC25 NOSELF	0.0670*** (0.00506)	-0.000615*** (6.05e-05)	-1.149*** (0.335)	0.0494*** (0.0163)	-0.000493** (0.000192)	0.0406*** (0.00313)	7,780	0.197	
(b) Controls for age and schooling, post-recession years									
	age	$age^2$	General	General × age	$\frac{General}{\times age^2}$	Years of Schooling	Obs.	$R^2$	
AC20 NOSELF	0.0751*** (0.00545)	-0.000677*** (6.35e-05)	-0.899*** (0.312)	0.0350** (0.0147)	-0.000297* (0.000167)	0.0461*** (0.00327)	5,350	0.268	
A GO T NOSELE	0.0697***	-0.000619***	-1.156***	0.0460***	-0.000414**	0.0479***	4.000	0.016	

(a) Controls for age and schooling, pre-recession years

Table 5.5: Summary results of the main model for Wages. Linear Regression Models. Dependent variable: In net
wages and salaries. Sample includes males with wages for the observed waves from age 20 (AC20) or 25 (AC25)
to 65 who finished at least upper secondary education, excluding self-employed individuals (NOSELF). Omit-
ted education type is vocational. Controlling for age, age-squared and schooling. Waves of analysis: pooled
sample, from 2000 to 2008 for pre-recession years, from 2010 to 2014 for post-recession years. Data Source:
Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses.
Significant at ***1% **5% *10%.

(0.0175)

(0.000195)

(0.00329)

4.992 0.216

-1.156\*\*\*

(0.382)

(7.27e-05)

AC25 NOSELF

(0.00638)

Moving our attention on  $\beta$ s estimates, we find higher differences between the sub-samples. In pre-recession years, individuals with vocational education have 70% higher wages of a general in early age, and this gap is quickly covered by an increase of 5.50% in wages in favour of individuals with general education, *ceteris paribus*. However, there are two levels of convergence in the pre-recession sample: there is a first convergence around age 37, almost in line with the pooled sample, when the advantage in wages turns from vocational to general, and a second convergence in retirement age of 63 for elder individuals, when vocational education becomes again more favourable than general education. In post-recession years, where significance upon  $\beta$ s' estimates is lower due to a lower sample size, the situation is different: individuals with vocational education present 60 percentage points higher wages than those with general education at the baseline, but the pace of the differential impact for each level of age in favour of general is also slower, increasing wages by 3.50 percentage points than colleagues with vocational, ceteris paribus.

Convergence appears only in early age, around 38, and the wage surplus turns in favour of general education until the end of the selected age-window (or until age 80 from the calculus). Wages for individuals with general education stop their growing path around age 52 in pre-recession years and age 57 in post-recession years.

The turnout of these results may be the following. In post-recession years, individuals need more time to become wealthy than in the pre-recession ones, and in presence of a huge market shock the early advantage of vocational education is diluted, also by the effect of a school-based vocational education with more academic content (Ministero dell'Istruzione, dell'Università e della Ricerca, 2008). Furthermore, this is also proved by the disappearance of a double convergence, firstly in early age and secondly around the retirement age, presented by pre-recession years, which makes skills provided by vocational education weaker overall. These outcomes are generally in line with the employment analysis in Section 4.1.5.



Figure 5.7: Linear prediction plots on Wages. Sample includes males who perceived a wage for the considered waves, from age 20 to 65 (*AC*20) with at least upper secondary education, *excluding* self-employed individuals (NOSELF). See caption in Tables 5.5 and 5.6 for data source and model specification.

Considering the last specification for wages including all controls, all key parameters are smoothed in their estimates. While including only age and schooling controls vocational individuals may share similar trajectories in wages over the life-cycle, in the last specification the situation is different. While the age-wages pattern makes individuals in both sub-samples approximately 4.8% richer for each level of age, with a small advantage per age for prerecession years (4.93% in pre- against 4.69% in post-recession years), in pre-recession years the steady state of growth in wages for individuals with vocational education falls at age 44, five years earlier than in post-recession years. Differences in steady state age between the two analysed specification does not turn up on individuals with general education among the sub-samples (with turning ages respectively 46 in pre- and 51 in post-recession years). This may be interpreted again as a clear effect of the labour market shock, which makes capabilities provided by vocational education slightly less effective in earlier age.

Looking at the estimates on  $\beta_0$  and  $\beta_1$  differences between the sub-samples in the outcomes of general education with respect to vocational still remains the same with different magnitudes. In pre-recession years, the time-invariant effect of general education relative to peers with vocational gives 66.5% higher wages in favour of vocational as expected, while in postrecession period vocational are 58.7% percentage points wealthier relative to a general. This difference is reduced to a faster pace in pre-recession years than in post-recession as before, and convergence does not vary: we still have double convergence during pre-recession, one in early age and the other in retirement age, validating the previous statements. A graphical description of the phenomenon can be found in Figure 5.7. For sensitivity of the previous

	age	$age^2$	General	$\frac{General}{\times age}$	$\frac{General}{\times age^2}$	Years of Schooling	Obs.	$R^2$	
AC20 NOSELF	0.0493*** (0.00667)	-0.000564*** (7.11e-05)	-1.093*** (0.290)	0.0466*** (0.0142)	-0.000468*** (0.000169)	0.0354*** (0.00318)	8,536	0.324	
AC25 NOSELF	0.0341*** (0.00687)	-0.000392*** (7.31e-05)	-1.023*** (0.320)	0.0436*** (0.0155)	-0.000437** (0.000182)	0.0364*** (0.00322)	7,780	0.276	
(b) Last specification, post-recession years									
	age	$age^2$	General	$\frac{General}{\times age}$	$\frac{General}{\times age^2}$	Years of Schooling	Obs.	<i>R</i> <sup>2</sup>	
AC20 NOSELF	0.0469*** (0.00786)	-0.000480*** (8.01e-05)	-0.874*** (0.313)	0.0363** (0.0146)	-0.000340** (0.000165)	0.0401*** (0.00336)	5,350	0.343	
AC25 NOSELF	0.0371*** (0.00836)	-0.000342*** (8.41e-05)	-1.198*** (0.376)	0.0507*** (0.0172)	-0.000495*** (0.000190)	0.0409*** (0.00338)	4,992	0.303	

(a) Last specification, pre-recession years

Table 5.6: Summary results of the model's last specification for wages, controlling for age, age-squared, schooling, family background, regional controls, municipality size, birth origin, current marital status and household's size. See caption in Table 5.5 for data source, sample and model specification. Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

results, we run the main model for wages over the two sub-samples excluding the youngest cohort from age 20 to 24. Considering the last specification in Table 5.6 for both groups, we observe that while the turning age for individuals both with general and vocational education is kept at the same level in pre-recession years, excluding the youngest sample in post-recession years moves the steady state level of wages for vocational five years higher than in the AC20 sample, which means that individuals with general education reach the highest level of wages earlier than peers with vocational education (52 for general against 54 for the latter). These results give us a sounder overview of the differences after a labour-market shock between the two education types: vocational education is more sensible to issues in labour market than vocational education, making individuals less adaptive in technological changes. However, the early mover advantage for vocational education is still valid, and it exhausts at the same pace in both the sub-samples. A quick overview of the trajectories of wages over the life-cycle excluding the youngest age cohort are given by Figure 5.8 for the model's complete specification.



Figure 5.8: Linear prediction plots on Wages. Sample includes males who perceived a wage for the considered waves, from age 25 to 65 (*AC*25) with at least upper secondary education, *excluding* self-employed individuals (NOSELF). See caption in Table 5.6 for data source and model specification.
### 5.2 Main Model interacting with Birth Cohorts

Recalling the empirical methodology applied for the analysis of employment rates grouping for birth cohorts in Section 4.2, we apply the triple differences model in Equation 3.5 also for wages, splitting the sample by birth year 1966, as selected from Table 4.7. Detailed results are provided in Tables of Section A.2.4 of Appendix A.

In net wages and salaries	AC20 NOSELF	AC25 NOSELF
	0.0366***	0.0386***
age	(0.0105)	(0.0105)
2	-0.000396***	-0.000407***
age-	(0.000107)	(0.000107)
Down After 1066	-1.013***	-0.232
Bom Alter 1900	(0.310)	(0.354)
Porn After 1066 V aga	0.0606***	0.0172
Bom Alter 1900 × age	(0.0149)	(0.0176)
Porn After 1066 $\times aga^2$	-0.000897***	-0.000303
Bolli Alter 1900 × <i>uge</i>	(0.000186)	(0.000226)
Canaral	-2.010**	-2.048**
General	(0.812)	(0.813)
Conoral y aga	0.0829**	0.0843**
General × uge	(0.0329)	(0.0330)
$Gamma = 1 \times aga^2$	-0.000812**	-0.000825**
General × uge	(0.000331)	(0.000332)
General V Born After 1066	0.748	1.071
General × Bolli Alter 1900	(0.999)	(1.132)
Constal V Port After 1066 V age	-0.0234	-0.0414
General $\times$ Bolli Alter 1900 $\times$ <i>uge</i>	(0.0477)	(0.0558)
$G_{anaral}$ × $R_{ara}$ After 1066 × $aaa^2$	0.000117	0.000365
General × Born Aner 1900 × age	(0.000598)	(0.000711)
Observations	13,886	12,772
R-squared	0.334	0.287

Table 5.7: Summary results of the model's last specification for Wages. Linear Regression Models. Dependent variable: In of net wages and salaries. Sample includes males who perceived a wage for the considered waves with at least upper secondary education, from age 20 (AC20) or 25 (AC25) to 65, *excluding* self-employed individuals. Omitted education type is vocational. Triple differences interacting with birth cohort from 1967 to 1994. Controlling for age, age-squared, schooling, family background, regional controls, municipality size, birth origin, current marital status and household's size. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

With an overall lookup of the empirical specifications of the model in Equation 3.5, we should notice that the current analysis does not provide significant estimates on triple interactions parameters for the selected birth cohort. Given that, we start directly analysing the most comprehensive specification of the model including all controls, for which it has been produced a *résumé* of the main estimated parameters in Table 5.7, foremost considering the

analysis over the 20-65 age cohort sample. Looking at estimates the floor level of wages for the two birth cohorts, it is interesting to see that individuals born after 1966 have a lower level of wages than peers born until this year by 63.7%. Keeping an eye on the age-wages pattern in the economy, derived from estimates of  $\alpha_1$  and  $\alpha_2$  for sensibility, we attain a growth path of wages for individuals in pre-1966 birth cohort by 3.66 percentage points for each level of age, ceteris paribus, standing at the steady state for individuals with vocational education born until 1966 around age 46, perfectly in line with the findings of the simpler DD model in Section 5.1 at the last specification. Moving to the same path in the economy for the birth cohort after 1966, they perform 6.06 higher wages than than those born earlier or in 1966, and they cap wages at age 38 against 46 for the pre-1966 cohort and the pooled sample with the simpler DD model, calculated as in Equation (4.9) and (4.10). Comparing these outcomes with employment, also for the latter the turning age is reached earlier, but the economic interpretation is different: while in terms of probability of employment vocational education have the better opportunities earlier, suffering after the turning age, for wages they reach the highest level earlier for the effect of higher wages overall. Thus, individuals become richer at a faster gait whether born after 1966 relative to those born in earlier years in the sample. Looking at  $\phi$ s' estimates, wherewith we have to be careful for age tracking issues inducted by the bounds in birth years of the considered waves, we derive that individuals with vocational education born until 1966 are 86.6 percentage points wealthier than peers with general education in the same birth cohort at early age, filling the gap by 8.21 percentage points for each level of age in favour of "generals", ceteris paribus. Convergence in the older birth cohort happens at age 40 turning into an advantage for general education, and around retirement age of 62 calculated as in Equation (4.15), while the turning age of wages is reached at age 49.



(a) Last specification for c = 0, 20–65 age cohort





Figure 5.9: Linear prediction plots on Wages interacting with birth cohorts. Sample includes males from age 20 to 65 with at least upper secondary education (AC20). See caption in Tables 4.8 for data source and model specification.

## CONCLUSION

In our study, we have investigated the evolution of labour-market outcomes over the lifecycle with respect to education type. For our purposes, we selected a unique sample retrieved from the Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015) embedded in the Italian education and labour market framework. To do so, we followed the approach of Hanushek et al. (2017) for the most, extending it on the basis of our unique dataset. Our estimates generally answer affirmatively to our main hypothesis. Individuals with vocational education provides in the short-run a smoother transition from school to work, in line with the major literature, but at the price of faster depreciation of skills and less adaptability in early age. We provide evidences for employment and wages, with some interesting outcomes. We considered a pooled sample of different SHIW waves, from which we retrieved information on upper secondary school type using the approach illustrated in Section 3.1. From these analyses it becomes visible that vocational education offer better employment prospects at the beginning of an individual career compared with academic-based education, with an approximative 70% higher percentage of employment at early age, and it also provides attractive wages for young adults under a smaller difference (62% higher wages for vocational education). However, as individuals progress in their labour market careers these advantages are rapidly eroded, with a faster pace for wages. Whilst for employment this advantage turns into a long-run disadvantage for vocational education skills after age 45, for wages it turns

at the earlier age of 38 recovering in retirement age.

Studying the profiles for different education choices, we are also allowed to offer an overview of how these outcomes evolve *per sé*. The potential employment is exhausted earlier for individuals with vocation skills than those with academic-based knowledge, whereas we do not find a significant deviation on the time for capping wages, even if general-oriented education provides more wealth.

These outcomes narrate a clear plot. The pupils in their tracking age have a difficult choice to make facing a trade-off between early age employment and higher wages against a labour market uncertainty at the beginning of their labour market career, and employment results the most damaged outcome in the long-run choosing the vocational track.

Whereas this model works really well over the life-cycle for employment, estimates on wages are more volatile introducing further controls, especially considering the highest level of education by years which is most relevant for wages than for employment, as expected from its natural path. A side analysis indicates also that this schooling level is positive affected by having a well-educated mother and negative affected for father's higher education.

Whereas Within this model, we have also investigated the role of social background in terms of parents' education on the self-sorting of individuals into alternative education paths, which has an indirect effect also on labour-market outcomes in this analysis. It happens that, on the basis of our sample, mother's education matters more than father's in children education's choices, and it has a negative effect while interacting for age. This is translated into a negative effect at early age in labour-market outcomes and a positive effect over the life-cycle, where mother's education is more relevant for employment than father's and vice-versa for wages.

We provide several robustness checks to prove the goodness of our analysis. Excluding the younger cohort from the sample, where a significant part of the sample is still in education, we have no relevant changes in the relationship of our parameters. While for employment it increases the gap among different education choices as the pace at which it is filled by general education, for wages it scales down the effect marking the convergence of general with vocational at retirement age.

Studying the outcomes wave-by-wave we understand that our sample has no sufficient power to explain the whole phenomenon, as excluding non-linearities we obtain biased estimates compared to include them. Averaging the results, the effects do not significantly diverge from the previous outcomes.

We stress our model taking into account the most relevant labour market shock in the considered waves caused by the 2007–08 financial crisis and prolonged by the 2011 sovereign debt crisis, to study the behaviour of labour-market outcomes over past education choices' in the most complex situation. Crisis has delayed the peak of the normal age-employment pattern two years later and the advantage in early employment has been significantly diluted at all model's specifications, as the pace at which general education approached to skill-based education profiles. In line with the outcomes of other case studies, we interpreted it as a detriment of the know-how provided by vocational education as a reaction to the labour market shock, becoming obsolete at a faster gait.

The analysis on wages reflects the same differences, delaying the maximum level of wages in post-recession years and neutralising convergence in retirement age, which is approached at age 62 in pre-recession years after an overtaking of general education in wages around age 37.

We gave a try to address the changing contents of vocational and academic education across different birth cohorts of individuals, with a smarter approach to the selection in education among individuals born in different decades. We operated using a fashionable difference-in-difference-in-differences model in the applied research on labour economics. This setting gave us interesting results, especially in terms of employment over the life-cycle, but unclear in the interpretation.

Despite of higher floor probability of employment in the short-run and widespread weakening of employment opportunities in the long-run for individuals born after 1966, which may correspond to a decay in the labour market's health, individuals who selected into skill-based education from the 1980s at age 14 suffer more than peers who selected in the same track and participated to the labour market earlier.

We assess an opposite situation in the behaviour of employment profiles among education types. Academic-based tracks before mid-1980s may provide exclusive skills for the labour market in the short-run, being more competitive than vocational tracks for the smaller number of individuals available with this know-how. It is important to say that vocational tracks in those years had less academic contents than nowadays, and the socio-economic framework

for Italy was different and less-educated. These profiles follow the same trajectories from age 34 to age 47, when the probability of employment of vocational education surpasses the treatment's probability. From late-1980s, the labour-market advantage in the short-run is in line with the main analysis, where vocational tracks perform better for youth employment and in the long-run the higher probability is overtaken by academic tracks. These outcomes provide a clear evidence of weaker skills in the long run offered by vocational tracks, which may have been driven by a wrong policies of this type of education and a change in the labour market background.

Whilst for employment profiles we found significant differences among birth cohorts controlling for different selectivity in education, for wages we cannot say the same, remaining sceptical point of view about the results provided by the analysis. Vocational tracks keep charming individuals with higher wages at the beginning of their individual labour market careers, but this gap among education types is weakened for individuals born after 1966 driven by the effect of lower wages at the baseline overall. However, they also become wealthy faster capping wages earlier. The early age advantage is quickly recovered by the adaptability provided by academic tracks, with no significant differences among cohorts.

We had to face several issues in our analyses, starting from the common problem of selection bias and the normal assumptions for the well-functioning of the DD approach, which cannot be proved. One of the main issues is also the lack of a valid instrument for ability, for which we have no solution because it is a limit of our dataset, and it could be an extension for tomorrow's studies.

We are aware that the copious sensitivity tests we provided all along the analyses are not sufficient to convince about causation of our results, and much more could have been done: for example it may be wise to test sensitivity by using also a Fixed Effects (FE) model clustering standard errors at household's level, a Probit model to make a comparison with the applied linear probability model. We did not perform robustness checks by excluding home-makers and pensioners, or by lowering the retirement age from 65, that we used to remain in line with the cross-country analysis of Hanushek et al. (2017), to earlier age, considering that at 2017 male individuals in Italy retires at the average age of 62.5. We expect that convergence of different education profiles is approached earlier. We ma also check the tricky parallel trends assumption by using a propensity-score matching strategy. We are also aware of the intrinsic measurement errors of the SHIW dataset, keeping a cautious position on the estimates upon the selected control variables. Another limit of our model, which is a structural problem in the Italian education system and of the research in this field, is the absence of a sound reform to study the effects *before-after* obtaining a true grouping estimator (the "impossible" reform). A good proxy for our analysis could have been the 2000 Berlinguer's Reform, but it did not find empirical application in the education system. It could be interesting to apply this research also to the unique dataset made by Bianchi (2016) using information from different tracks in upper secondary schools of Milan, exploiting the 1970s Italian reform that changed the admission requirements for university STEM majors, for which so much old data are not reliable in the SHIW Historical Database.

Together with the major literature, this is only a starting point of what it could be done for research in education. We are confident that in more recent years the HFCS and EU-SILC surveys will provide better cross-country longitudinal datasets and complete information about education choices and cognitive/non-cognitive skills, together with other sources of information.

## REFERENCES

- Allison, P. D. (2002). *Missing Data*. Quantitative Applications in the Social Sciences. Thousand Oaks, CA: SAGE Publications
- Angrist, J. D. & Evans, W. N. (1999). Schooling and Labor Market Consequences of the 1970 State Abortion Reforms. In S. Polachek & K. Tatsiramos (Eds.), *Research in Labor Economics* (Vol. 18, pp. 75–113). Bingley: Emerald Group Publishing
- Angrist, J. D. & Krueger, A. B. (1991). Does Compulsory School Attendance Affect Schooling and Earnings? *Quarterly Journal of Economics*, 106(4), 979–1014
- Angrist, J. D. & Krueger, A. B. (1999). Empirical Strategies in Labor Economics. In O. C. Ashenfelter & D. Card (Eds.), *Handbook of Labor Economics* (Vol. 3, pp. 1277–1366). Amsterdam: North-Holland.
- Angrist, J. D. & Pischke, J.-S. (2009). Mostly Harmless Econometrics: An Empiricist's Companion. Princeton: Princeton University Press.
- Angrist, J. D. & Pischke, J.-S. (2014). *Mastering 'Metrics: The Path from Cause to Effect*. Princeton: Princeton University Press.
- Athey, S. & Imbens, G. W. (2006). Identification and Inference in Nonlinear Difference-in-Differences Models. *Econometrica*, 74(2), 431–497
- Autor, D. H. (2003). Outsourcing at Will: The Contribution of Unjust Dismissal Doctrine to the Growth of Employment Outsourcing. *Journal of Labor Economics*, 21(1), 1–42

- Baldi, S. & Pellizzari, M. (2005). Bank of Italy Survey of Household Income and Wealth: Microdata on Italian Families – Bank of Italy. Retrieved from http://www.frdb.org/ language/eng/page/data/scheda/bank-of-italy-survey-of-households-income-andwealth/doc\_pk/9019
- Ballarino, G., Braga, M., Bratti, M., Checchi, D., Filippin, A., Fiorio, C., ... Scervini, F. (2014). Italy: How Market Policies Can Foster Earnings Inequality. In B. Nolan, D. Checchi, I. Marx, A. McKnight, I. G. Toth, & H. G. Van De Werfhorst (Eds.), *Changing Inequalities and Societal Impacts in Rich Countries: Thirty Countries' Experiences* (1st ed., Chap. 16, pp. 369–392). Oxford: Oxford University Press.
- Bank of Italy. (2015). *Historical Database of the Survey of Italian Household Budgets*, 1977– 2014. Version 9.0. Retrieved from http://www.bancaditalia.it/statistiche/tematiche/ indagini - famiglie - imprese/bilanci - famiglie/documentazione/Legenda\_Archivio\_ Storico2014.pdf
- Bank of Italy. (2017). Survey on Household Income and Wealth: Documentation for the Microdata. Retrieved from http://www.bancaditalia.it/statistiche/tematiche/indagini-famiglie-imprese/bilanci-famiglie/documentazione/index.html
- Berloffa, G., Modena, F., & Villa, P. (2015). Changing labour market opportunities for young people in Italy and the role of the family of origin (Temi di discussione (Economic Working Papers) No. 998). Bank of Italy, Economic Research and International Relations Area. Retrieved from https://www.bancaditalia.it/pubblicazioni/temidiscussione/2015/2015-0998/en\_tema\_998.pdf
- Bianchi, N. (2016). The Indirect Effects of Educational Expansions: Evidence from a Large Enrollment Increase in STEM Majors. Retrieved from http://www.bianchinicola.com/ uploads/2/9/0/9/29094565/bianchi%7B%5C\_%7Deduexp%7B%5C\_%7Dv5.pdf
- Biancotti, C., D'Alessio, G., & Neri, A. (2008). Measurement Error in the Bank of Italy's
  Survey of Household Income and Wealth. *Review of Income and Wealth*, 54(3), 466–493
- Björklund, A., Jäntti, M., & Lindquist, M. J. (2009). Family background and income during the rise of the welfare state: Brother correlations in income for Swedish men born 1932–1968. *Journal of Public Economics*, 93(5), 671–680

- Björklund, A., Lindahl, M., & Plug, E. (2006). The Origins of Intergenerational Associations: Lessons from Swedish Adoption Data. *Quarterly Journal of Economics*, 121(3), 999–1028
- Björklund, A. & Salvanes, K. G. (2011). Education and Family Background: Mechanisms and Policies. In E. A. Hanushek, S. Machin, & L. Woessmann (Eds.), *Handbook of the Economics of Education* (Vol. 3, pp. 201–247). Amsterdam: Elsevier
- Black, S. E., Devereux, P. J., & Salvanes, K. G. (2005a). Why the Apple Doesn't Fall Far: Understanding Intergenerational Transmission of Human Capital. *American Economic Review*, 95(1), 437–449
- Black, S. E., Devereux, P. J., & Salvanes, K. G. (2005b). The More the Merrier? The Effect of Family Size and Birth Order on Children's Education. *Quarterly Journal of Economics*, 120(2), 669–700
- Blinova, T., Bylina, S., & Rusanovskiy, V. (2015). Vocational Education in the System of Determinants of Reducing Youth Unemployment: Interregional Comparisons. *Procedia Social and Behavioral Sciences*, 214(07), 526–534
- Brunello, G. & Rocco, L. (2015). The Labour Market Effects of Academic and Vocational Education Over the Life Cycle: Evidence from Two British Cohorts (tech. rep. No. 9275).
   Institute for the Study of Labor (IZA). Retrieved from http://ftp.iza.org/dp9275.pdf
- Card, D. & Krueger, A. B. (1994). Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania. *American Economic Review*, 84(4), 772–793
- Castagnetti, C. & Rosti, L. (2009). Who skims the cream of the Italian graduate crop? Wage employment versus self-employment. *Small Business Economics*, *36*(2), 223–234
- Chun, H. & Lee, I. (2001). Why do married men earn more: productivity or marriage selection? *Economic Inquiry*, *39*(2), 307–319
- Cleveland, W. S. (1979). Robust locally weighted regression and smoothing scatterplots. Journal of the American Statistical Association, 74(368), 829–836
- Cohen, Y. & Haberfeld, Y. (1991). Why Do Married Men Earn More than Unmarried Men. Social Science Research, 20(1), 29–44

- Crepaldi, C., Pesce, F., & Samek Ludovici, M. (2014). *Social and employment situation in Italy*. European Parliament Think Tank. Retrieved from http://www.europarl.europa. eu/studies
- Dearden, L., McIntosh, S., Myck, M., & Vignoles, A. (2002). The Returns to Academic and Vocational Qualifications in Britain. *Bulletin of Economic Research*, *54*(3), 249–274
- European Centre for the Development of Vocational Training (CEDEFOP). (2014a). *Terminology of European education and training policy*. CEDEFOP Information Series. Luxembourg: Publication Office of the European Union
- European Centre for the Development of Vocational Training (CEDEFOP). (2014b). *Vocational education and training in Italy*. CEDEFOP Information Series. Luxembourg: Publication Office of the European Union
- Eurosystem Household Finance and Consumption Network. (2013). *Eurosystem Household Finance and Consumption Survey: Results from the First Wave* (Statistics Paper Series No. 2). European Central Bank. Retrieved from http://www.ecb.europa.eu/pub/pdf/ other/ecbsp2en.pdf
- Foti, A. & Vivarelli, M. (1994). An econometric test of the self-employment model: The case of Italy. *Small Business Economics*, 6(2), 81–93
- Fritsch, F. N. & Carlson, R. E. (1980). Monotone Piecewise Cubic Interpolation. SIAM Journal on Numerical Analysis, 17(2), 238–246
- Golsteyn, B. H. H. & Stenberg, A. (2015). Comparing Long Term Earnings Trajectories Of Individuals with General and Specific Education. Paper presented at the EALE 2014 Conference.
- Green, A. (2002). The many faces of lifelong learning: recent education policy trends in Europe. *Journal of Education Policy*, *17*(6), 611–626
- Hall, C. (2012). The Effects of Reducing Tracking in Upper Secondary School: Evidence from a Large-Scale Pilot Scheme. *Journal of Human Resources*, 47(1), 237–269
- Hall, C. (2016). Does more general education reduce the risk of future unemployment? Evidence from an expansion of vocational upper secondary education. *Economics of Education Review*, 52, 251–271
- Hanushek, E. A., Machin, S., & Woessmann, L. (Eds.). (2011). *Handbook of the Economics of Education*. Amsterdam: North-Holland.

- Hanushek, E. A., Schwerdt, G., Woessmann, L., & Zhang, L. (2017). General Education, Vocational Education, and Labor-Market Outcomes over the Life-Cycle. *Journal of Human Resources*, 52(1), 49–88
- Hanushek, E. A. & Welch, F. (Eds.). (2006). *Handbook of the Economics of Education*. Amsterdam: North-Holland.
- Hanushek, E. A., Woessmann, L., & Zhang, L. (2011). General Education, Vocational Education, and Labor-Market Outcomes over the Life-Cycle. National Bureau of Economic Research
- Hasanefendic, S., Heitor, M., & Horta, H. (2016). Training students for new jobs: The role of technical and vocational higher education and implications for science policy in Portugal. *Technological Forecasting and Social Change*, 113, 328–340
- Herbst, C. M. (2017). Universal Child Care, Maternal Employment, and Children's Long-Run Outcomes: Evidence from the U.S. Lanham Act of 1940. *Journal of Labor Economics*, 35(2)
- Holmlund, H., Lindahl, M., & Plug, E. (2011). The Causal Effect of Parents' Schooling on Children's Schooling: A Comparison of Estimation Methods. *Journal of Economic Literature*, 49(3), 615–651
- Hotchkiss, L. (1993). Effects of Training, Occupation, and Training-Occupation Match on Wage. *Journal of Human Resources*, 28(3), 482–496
- Krueger, D. & Kumar, K. B. (2004a). US–Europe differences in technology-driven growth: quantifying the role of education. *Journal of Monetary Economics*, *51*(1), 161–190
- Krueger, D. & Kumar, K. B. (2004b). Skill-Specific rather than General Education: A Reason for US–Europe Growth Differences? *Journal of Economic Growth*, 9(2), 167–207
- Kugler, A., Jimeno, J. F., & Hernanz, V. (2005). Employment Consequences of Restrictive Permanent Contracts: Evidence from Spanish Labor Market Reforms (FEDEA Working Paper 2003-14 No. 3724). Universitat Pompeu Fabra. Barcelona. Retrieved from https://econ-papers.upf.edu/papers/651.pdf
- Lavy, V. (2015). Do Differences in Schools' Instruction Time Explain International Achievement Gaps? Evidence from Developed and Developing Countries. *Economic Journal*, 125(588), F397–F424

- Levy, F. & Murnane, R. J. (1992). U.S. earnings levels and earnings inequality: a review of recent trends and proposed explanations. *Journal of Economic Literature*, *30*(3), 1333–1381
- Malamud, O. & Pop-Eleches, C. (2010). General Education versus Vocational Training:
  Evidence from an Economy in Transition. *Review of Economics and Statistics*, 92(1), 43–60
- Ministero dell'Istruzione, dell'Università e della Ricerca (Ed.). (2008). *Conversione in legge, con modificazioni, del decreto-legge 10 settembre 2008, n. 137, recante disposizioni urgenti in materia di istruzione e università.*
- Nordström Skans, O. (2004). Scarring effects of the first labour market experience: A sibling based analysis. Institute for Labour Market Policy Evaluation (IFAU). Uppsala. Retrieved from http://www.ifau.se/globalassets/pdf/se/2004/wp04-14.pdf
- Oosterbeek, H. & Webbink, D. (2007). Wage effects of an extra year of basic vocational education. *Economics of Education Review*, 26(4), 408–419
- Organisation for Economic Co-operation and Development (OECD). (2010). *Education at a Glance 2010*. Education at a Glance. Paris: OECD Publishing
- Organisation for Economic Co-operation and Development (OECD). (2016). ISCED 2011 in Italy. Retrieved February 14, 2017, from http://gpseducation.oecd.org/
- Organization for Economic Co-operation and Development (OECD). (1997). Literacy Skills for the Knowledge Society: Further Results from the International Adult Literacy Survey. Paris: OECD Publishing.
- Organization for Economic Co-operation and Development (OECD). (2016). Skills Matter: Further Results from the Survey of Adult Skills
- Pekkarinen, T., Uusitalo, R., & Kerr, S. (2009). School tracking and intergenerational income mobility: Evidence from the Finnish comprehensive school reform. *Journal of Public Economics*, 93(7-8), 965–973
- Pischke, J.-S. & von Wachter, T. (2008). Zero Returns to Compulsory Schooling in Germany: Evidence and Interpretation. *Review of Economics and Statistics*, 90(3), 592–598
- Plug, E. (2004). Estimating the Effect of Mother's Schooling on Children's Schooling Using a Sample of Adoptees. *American Economic Review*, 94(1), 358–368

- Riphahn, R. T. & Zibrowius, M. (2016). Apprenticeship, Vocational Training, and Early Labor Market Outcomes — Evidence from East and West Germany. *Education Economics*, 24(1), 33–57
- Rivkin, S. G. & Schiman, J. C. (2015). Instruction Time, Classroom Quality, and Academic Achievement. *Economic Journal*, 125(588), F425–F448
- Ryan, P. (2001). The School-to-Work Transition: A Cross-National Perspective. Journal of Economic Literature, 39(1), 34–92
- Skåtun, J. D. (2004). Behind Every Well Paid Married Man: The Impact of the Partner's Earning Opportunity. Australian Economic Papers, 43(1), 1–9
- Tiefensee, A. & Grabka, M. (2016). Comparing Wealth Data quality of the HFCS. Survey Research Methods, 10(2), 119–142. Retrieved from https://ojs.ub.uni-konstanz.de/ srm/article/view/6305
- United Nations Educational Scientific and Cultural Organization (UNESCO). (2012). The International Standard Classification of Education 2011. UNESCO Institute for Statistics. Retrieved from http://www.uis.unesco.org/Education/Documents/isced-2011en.pdf
- Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data* (2nd ed.).MIT Press Books. Cambridge, MA: The MIT Press.
- Wooldridge, J. M. (2016). Introductory Econometrics: A Modern Approach (6th ed.). Boston: Cengage Learning.
- Yelowitz, A. S. (1995). The Medicaid Notch, Labor Supply, and Welfare Participation: Evidence from Eligibility Expansions. *Quarterly Journal of Economics*, 110(4), 909–939

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### APPENDIX

A

# EMPIRICAL RESULTS (DETAILS)

### A.1 Effects over Life-Time Employment

#### A.1.1 Main Model for Quasi-Longitudinal Data

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	0.124***	0.124***	0.120***	0.117***	0.110***	0.110***	0.0996***
age	(0.00154)	(0.00154)	(0.00159)	(0.00172)	(0.00189)	(0.00189)	(0.00252)
(age) <sup>2</sup>	-0.00149*** (1.82e-05)	-0.00149*** (1.82e-05)	-0.00146*** (1.85e-05)	-0.00144*** (1.88e-05)	-0.00141*** (1.86e-05)	-0.00141*** (1.86e-05)	-0.00131*** (2.47e-05)
Concern Education	-0.747***	-0.740***	-0.613***	-0.611***	-0.648***	-0.650***	-0.694***
General Education	(0.0526)	(0.0528)	(0.0542)	(0.0542)	(0.0545)	(0.0545)	(0.0542)
General Education $\times$ age	0.0205***	0.0200***	0.0159***	0.0158***	0.0178***	0.0179***	0.0205***
2	-8.49e-05**	-8.08e-05**	-5.28e-05	-5.31e-05	-7.85e-05**	-7.90e-05**	-0.000112***
General Education $\times age^2$	(3.59e-05)	(3.60e-05)	(3.62e-05)	(3.61e-05)	(3.62e-05)	(3.61e-05)	(3.59e-05)
Other Education	0.0921	0.0941	0.0926	0.0943	0.176	0.173	0.148
0	-0.00783	-0.00802	-0.00804	-0.00821	-0.0107	-0.0103	-0.00924
Other Education $\times$ age	(0.0117)	(0.0117)	(0.0115)	(0.0115)	(0.0120)	(0.0120)	(0.0121)
Other Education $\times age^2$	0.000118	0.000120	0.000120	0.000124	0.000137	0.000133	0.000123
0	(0.000140)	(0.000140) 0.00229*	(0.000139) 0.00306**	(0.000139) 0.00313**	(0.000144) 0.00411***	(0.000144) 0.00395***	(0.000145) 0.00455***
Years of Schooling		(0.00122)	(0.00124)	(0.00124)	(0.00123)	(0.00123)	(0.00122)
Mother has High School Diploma			-0.152***	-0.158***	-0.153***	-0.152***	-0.157***
			(0.0217)	(0.0218)	(0.0214)	(0.0214)	(0.0213)
Mother has High School Diploma $\times$ age			(0.000531)	(0.000534)	(0.000528)	(0.000528)	(0.000527)
Father has High School Diploma			-0.104***	-0.0989***	-0.0954***	-0.0947***	-0.0846***
r under mas ringin benoor Diproma			(0.0221)	(0.0222)	(0.0220)	(0.0220)	(0.0219)
Father has High School Diploma $\times$ age			(0.000533)	(0.000536)	(0.000534)	(0.000535)	(0.000533)
Siblings in Education Age			(,	-0.00163	0.0591***	0.0562***	0.0717***
Sibilings in Education Age				(0.0191)	(0.0190)	(0.0190)	(0.0191)
Siblings in Education Age $\times$ age				(0.000487)	(0.000120	(0.000485)	(0.000491)
Born in Southern Italy				(	(,	0.0754**	0.0667*
bon in Soutien hary						(0.0370)	(0.0369)
Born in Southern Italy $\times$ age						-0.00187***	-0.00176***
Voor 2002	-0.000816	-0.00109	-0.000163	0.000101	-0.000651	-0.000489	0.00234
Teal 2002	(0.00937)	(0.00937)	(0.00932)	(0.00932)	(0.00909)	(0.00909)	(0.00903)
Year 2004	0.00252	0.00207	0.00343	0.00319	-0.00110	-0.000684	0.00286
Veer 2006	0.0227**	0.0213**	0.0237***	0.0238***	0.0189**	0.0194**	0.0241***
Teal 2000	(0.00911)	(0.00914)	(0.00909)	(0.00910)	(0.00887)	(0.00888)	(0.00883)
Year 2008	0.0223**	0.0208**	0.0231**	0.0236***	0.0220**	0.0230***	0.0278***
No 2010	0.0141	0.0124	0.0155*	0.00549	0.0114	0.0124	0.0222**
fear 2010	(0.00916)	(0.00921)	(0.00925)	(0.00940)	(0.00918)	(0.00920)	(0.00918)
Year 2012	0.00304	0.00129	0.00574	-0.00721	0.000465	0.00160	0.0134
N 0014	-0.000181	-0.00180	0.00418	-0.0117	-0.00660	-0.00534	0.0112
Year 2014	(0.00962)	(0.00967)	(0.00965)	(0.0101)	(0.00987)	(0.00988)	(0.00988)
Constant	-1.581***	-1.608***	-1.508***	-1.471***	-1.221***	-1.226***	-0.859***
	(0.0525)	(0.0551)	(0.0505)	(0.0405)	(0.0342)	(0.0342)	(0.0001)
Observations	25,173	25,173	25,173	25,173	25,173	25,173	25,173
K <sup>2</sup> Vears of Schooling	0.337	0.337	0.342	0.344 x	0.378	0.379	0.387
Parents' Educational Attainment		~	x	x	x	x	x
Presence of Siblings in Education Age				x	x	x	x
Regional Controls Municipality Size					x	x	x
Born in Southern Italy					А	X	x
Current Marital Status							x
Household Size							x

Table A.1: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 20 to 65 with at least upper secondary education. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	0.123***	0.123***	0.119***	0.116***	0.108***	0.108***	0.0945***
age	(0.00212)	(0.00212)	(0.00215)	(0.00225)	(0.00239)	(0.00239)	(0.00279)
(age) <sup>2</sup>	-0.00148***	-0.00148***	-0.00145***	-0.00143***	-0.00139***	-0.00139***	-0.0012/***
	-0.937***	-0.948***	-0.835***	-0.830***	-0.847***	-0.849***	-0.867***
General Education	(0.0968)	(0.0967)	(0.0977)	(0.0976)	(0.0957)	(0.0957)	(0.0953)
General Education $\times$ age	0.0293***	0.0293***	0.0259***	0.0257***	0.0268***	0.0269***	0.0283***
2	-0.000182***	-0.000183***	-0.000164***	-0.000163***	-0.000178***	-0.000179***	-0.000198***
General Education $\times age^2$	(5.19e-05)	(5.18e-05)	(5.18e-05)	(5.18e-05)	(5.12e-05)	(5.12e-05)	(5.10e-05)
Other Education	0.0490	0.0455	0.0259	-0.000979	-0.00350	-0.00146	-0.0470
	-0.00638	-0.00654	-0.00570	-0.00463	-0.00340	-0.00320	-0.00122
Other Education $\times$ age	(0.0180)	(0.0181)	(0.0180)	(0.0181)	(0.0185)	(0.0185)	(0.0185)
Other Education $\times age^2$	0.000106 (0.000201)	0.000108 (0.000202)	9.89e-05 (0.000201)	9.00e-05 (0.000201)	6.46e-05 (0.000207)	6.12e-05 (0.000206)	4.16e-05 (0.000206)
Years of Schooling		0.00638***	0.00716***	0.00725***	0.00779***	0.00760***	0.00781***
		(0.00123)	-0.182***	-0.186***	-0.180***	-0.180***	-0.187***
Mother has High School Diploma			(0.0288)	(0.0290)	(0.0283)	(0.0283)	(0.0281)
Mother has High School Diploma $\times$ age			0.00352***	0.00362***	0.00346***	0.00346***	0.00366***
			-0.0863***	-0.0829***	-0.0634**	-0.0633**	-0.0455
Father has High School Diploma			(0.0298)	(0.0299)	(0.0293)	(0.0294)	(0.0292)
Father has High School Diploma $\times$ age			0.00219***	0.00212***	0.00178***	0.00176***	0.00138**
			(0.000677)	(0.000679)	(0.000672)	(0.000673)	(0.000669)
Siblings in Education Age				(0.0234)	(0.0230)	(0.0230)	(0.0229)
Siblings in Education Age $\times$ age				0.000377	-0.000672	-0.000560	-0.00167***
				(0.000547)	(0.000545)	(0.000545)	(0.000545)
Born in Southern Italy						(0.0426)	(0.0424)
Born in Southern Italy $\times$ age						-0.00133	-0.00125
	00160	0.000975	0.000804	0.00151	0.00207	(0.000936)	(0.000931)
Year 2002	(0.00981)	(0.00981)	(0.00977)	(0.00976)	(0.00954)	(0.00954)	(0.00946)
Vear 2004	0.00340	0.00195	0.00203	0.00220	-0.00464	-0.00412	0.000477
Tem 2004	(0.00978)	(0.00978)	(0.00976)	(0.00974)	(0.00951)	(0.00951)	(0.00945)
Year 2006	(0.0228***	(0.018/~~	(0.00943)	(0.0200***	(0.0023)	(0.00925)	(0.0209**
Veen 2008	0.0196**	0.0149	0.0163*	0.0169*	0.0145	0.0157*	0.0223**
Teat 2008	(0.00940)	(0.00942)	(0.00940)	(0.00941)	(0.00918)	(0.00921)	(0.00916)
Year 2010	(0.00957)	0.00828	0.00989	-0.000209 (0.00985)	0.00298	0.00415	0.0168*
Van 2012	0.00904	0.00341	0.00675	-0.00659	-0.00264	-0.00111	0.0139
Teat 2012	(0.00970)	(0.00976)	(0.00977)	(0.0101)	(0.00992)	(0.00994)	(0.00988)
Year 2014	0.00923	0.00407	0.00929	-0.00698	-0.00262	-0.00100	0.0198*
Constant	-1.567***	-1.649***	-1.541***	-1.515***	-1.193***	-1.196***	-0.762***
Constant	(0.0469)	(0.0484)	(0.0495)	(0.0529)	(0.0669)	(0.0669)	(0.0758)
Observations	21,493	21,493	21,493	21,493	21,493	21,493	21,493
$R^2$	0.261	0.262	0.266	0.269	0.305	0.306	0.317
Years of Schooling		х	x	x	x	x	x
Presence of Siblings in Education Age			х	x x	x x	x	x x
Regional Controls					x	x	x
Municipality Size					х	х	х
Born in Southern Italy Current Marital Status						х	x
Household Size							x

Table A.2: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 25 to 65 with at least upper secondary education. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	0.133***	0.133***	0.129***	0.126***	0.119***	0.119***	0.105***
age	(0.00159)	(0.00159)	(0.00164)	(0.00180)	(0.00197)	(0.00198)	(0.00269)
(age) <sup>2</sup>	-0.00161***	-0.00161***	-0.00158***	-0.00156***	-0.00153***	-0.00153***	-0.00141*** (2.60e-05)
Construction	-0.617***	-0.617***	-0.486***	-0.485***	-0.526***	-0.528***	-0.587***
General Education	(0.0564)	(0.0567)	(0.0581)	(0.0580)	(0.0584)	(0.0584)	(0.0576)
General Education $\times$ age	0.0128***	0.0128***	0.00846***	0.00848***	0.0107***	0.0107***	0.0142***
2 151 1 2	1.14e-05	1.14e-05	4.24e-05	4.06e-05	1.33e-05	1.28e-05	-3.08e-05
General Education $\times age^2$	(3.96e-05)	(3.98e-05)	(4.00e-05)	(3.98e-05)	(3.97e-05)	(3.97e-05)	(3.92e-05)
Other Education	0.266	0.266	0.270	0.279	0.370	0.361	0.331
	-0.0170	-0.0170	-0.0174	-0.0178	-0.0210*	-0.0203	-0.0190
Other Education $\times$ age	(0.0123)	(0.0123)	(0.0122)	(0.0122)	(0.0127)	(0.0127)	(0.0128)
Other Education $\times age^2$	0.000233	0.000233	0.000238	0.000244*	0.000267*	0.000259*	0.000247
	(0.000148)	1.22e-05	0.00133	0.00147)	0.00232	0.00217	0.00270*
Years of Schooling		(0.00143)	(0.00146)	(0.00146)	(0.00143)	(0.00144)	(0.00142)
Mother has High School Diploma			-0.151***	-0.160***	-0.152***	-0.152***	-0.156***
			0.00228)	0.00298***	0.00226)	0.00226)	0.00225)
Mother has High School Diploma $\times$ age			(0.000578)	(0.000581)	(0.000575)	(0.000575)	(0.000573)
Father has High School Diploma			-0.0983***	-0.0924***	-0.0987***	-0.0988***	-0.0879***
0 1			(0.0233)	(0.0235)	(0.0232) 0.00232***	(0.0232) 0.00232***	(0.0230) 0.00211***
Father has High School Diploma $\times$ age			(0.000573)	(0.000578)	(0.000575)	(0.000575)	(0.000570)
Siblings in Education Age				0.000253	0.0684***	0.0672***	0.0860***
				(0.0203)	(0.0200)	(0.0200)	(0.0202)
Siblings in Education Age × age				(0.000525)	(0.000518)	(0.000519)	(0.000524)
Born in Southern Italy						0.0389	0.0261
						(0.0385)	(0.0383)
Born in Southern Italy $\times$ age						(0.000855)	(0.000853)
Year 2002	0.000861	0.000859	0.00233	0.00251	0.00256	0.00274	0.00642
	(0.0107)	(0.0107)	(0.0107)	(0.0107)	(0.0104)	(0.0104)	(0.0103)
Year 2004	(0.0107)	(0.0107)	(0.0106)	(0.0106)	(0.0103)	(0.0103)	(0.0102)
Year 2006	0.0330***	0.0330***	0.0358***	0.0356***	0.0303***	0.0307***	0.0362***
	(0.0104)	(0.0105)	(0.0104)	(0.0104)	(0.0101)	(0.0101)	(0.0100)
Year 2008	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0101)	(0.0101)	(0.0100)
Year 2010	0.0193*	0.0193*	0.0229**	0.0127	0.0185*	0.0193*	0.0312***
1011 2010	(0.0105)	(0.0105)	(0.0106)	(0.0107)	(0.0104)	(0.0104)	(0.0104)
Year 2012	(0.0105)	(0.0105)	(0.0105)	(0.0108)	(0.0105)	(0.0106)	(0.0105)
Year 2014	0.00240	0.00240	0.00937	-0.00694	-0.00100	-9.75e-05	0.0204*
1011 2011	(0.0109)	(0.0110)	(0.0110)	(0.0114)	(0.0111)	(0.0111)	(0.0111)
Constant	(0.0335)	(0.0373)	(0.0389)	(0.0433)	(0.0576)	(0.0576)	(0.0732)
Observations	20,893	20,893	20,893	20,893	20,893	20,893	20,893
<i>R</i> <sup>2</sup>	0.352	0.352	0.356	0.359	0.399	0.399	0.410
Years of Schooling		х	x	x	x	x	x
Presence of Siblings in Education Age			х	x x	x x	x	x x
Regional Controls				-	x	x	x
Municipality Size					х	x	х
Born in Southern Italy Current Marital Status						x	X x
Household Size							x

Table A.3: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 20 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	979	0.137***	0.137***	0.133***	0.130***	0.121***	0.121***	0.104***
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	age	(0.00225)	(0.00225)	(0.00229)	(0.00241)	(0.00257)	(0.00257)	(0.00302)
$\begin{array}{c} (2.400-05) & (2.400-05) $	(age) <sup>2</sup>	-0.00166***	-0.00166*** (2.46e-05)	-0.00163***	-0.00160***	-0.00156***	-0.00156***	-0.00141*** (2.90e-05)
General Education $(0.104)$ $(0.104)$ $(0.105)$ $(0.105)$ $(0.103)$ $(0.103)$ $(0.102)$ General Education $\times$ age $0.0289^{***}$ $0.0259^{***}$ $0.0254^{***}$ $0.0262^{***}$ $0.0262^{***}$ $0.0262^{***}$ $0.0262^{***}$ $0.0262^{***}$ $0.0262^{***}$ $0.0262^{***}$ $0.0279^{***}$ General Education $\times$ age <sup>2</sup> $-0.000165^{***}$ $-0.000147^{***}$ $-0.000147^{***}$ $-0.000158^{***}$ $-0.000182^{***}$ Other Education $age^2$ $(5.63e-05)$ $(5.62e-05)$ $(5.63e-05)$ $(5.61e-05)$ $(5.55e-05)$ $(5.56e-05)$ $(5.0e-05)$	Convert Education	-0.962***	-0.972***	-0.857***	-0.852***	-0.864***	-0.865***	-0.886***
General Education $\times$ age         0.0289***         0.0258***         0.0254***         0.0262***         0.0262***         0.0279***           General Education $\times$ age <sup>2</sup> (0.00492)         (0.00491)         (0.00493)         (0.00492)         (0.00485)         (0.00486)         (0.00481)           General Education $\times$ age <sup>2</sup> -0.000165***         -0.000167***         -0.000147***         -0.000158***         -0.00158***         -0.000158***         -0.000158***         -0.00163         -0.00163         -0.00163         -0.0163         -0.0163         -0.0163         -0.00173         -0.0122         -0.0107         -0.00836         -0.00173         -0.00173         -0.00163         0.000139         (0.00220)         (0.00220)         (0.000220)         (0.000220)         (0.000220)         (0.000220) </td <td>General Education</td> <td>(0.104)</td> <td>(0.104)</td> <td>(0.105)</td> <td>(0.105)</td> <td>(0.103)</td> <td>(0.103)</td> <td>(0.102)</td>	General Education	(0.104)	(0.104)	(0.105)	(0.105)	(0.103)	(0.103)	(0.102)
$(0.00492)$ $(0.00492)$ $(0.00492)$ $(0.00492)$ $(0.00492)$ $(0.00481)$ $(0.00481)$ $(0.00481)$ General Education $\times age^2$ $(0.00150^{***})$ $(0.00147^{***})$ $(0.00147^{***})$ $(0.00147^{***})$ $(0.00147^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00153^{***})$ $(0.00143^{***})$ $(0.00143^{***})$ $(0.00153^{***})$ $(0.00143^{***})$ $(0.00153^{***})$ $(0.00143^{***})$ $(0.00153^{***})$ $(0.00143^{***})$ $(0.00143^{**})$ $(0.00143^{**})$ $(0.00143^{**})$ $(0.00143^{**})$ Other Education $\times age^2$ $(0.00230)$ $0.000232$ $0.000225$ $0.000217)$ $0.00726^{***}$ $0.00726^{***}$ $0.00726^{***}$ $0.00726^{***}$ $0.00726^{***}$ $0.00724^{***}$ $0.00726^{***}$ $0.00724^{***}$ $0.00724^{***}$ $0.00724^{***}$ <td< td=""><td>General Education <math>\times</math> age</td><td>0.0289***</td><td>0.0289***</td><td>0.0255***</td><td>0.0254***</td><td>0.0262***</td><td>0.0262***</td><td>0.0279***</td></td<>	General Education $\times$ age	0.0289***	0.0289***	0.0255***	0.0254***	0.0262***	0.0262***	0.0279***
General Education $\times age^2$ (5.63e-05)         (5.63e-05)         (5.63e-05)         (5.63e-05)         (5.56e-05)         (5.56e-05)         (5.50e-05)           Other Education         0.235         0.231         0.210         0.187         0.144         0.120         0.0678           Other Education         (0.426)         (0.428)         (0.427)         (0.429)         (0.434)         (0.433)           Other Education $\times age$ -0.0163         -0.0157         -0.0147         -0.0122         -0.0107         -0.00836           Other Education $\times age$ 0.000230         0.000232         0.000225         0.000217         0.000138         0.000139           Other Education $\times age^2$ 0.000214)         (0.001215)         (0.000215)         (0.000216)         (0.000220)         (0.000220)         (0.000220)           Years of Schooling         0.0058***         0.00692***         0.0077***         0.00726***         0.00726***         0.00724***           Mother has High School Diploma         -0.197         -0.193***         -0.193***         -0.193***         -0.1072***         -0.203***	2	-0.000165***	-0.000167***	-0.000147***	-0.000147***	-0.000158***	-0.000159***	-0.000182***
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	General Education $\times age^2$	(5.63e-05)	(5.62e-05)	(5.63e-05)	(5.61e-05)	(5.55e-05)	(5.56e-05)	(5.50e-05)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Other Education	0.235	0.231	0.210	0.187	0.144	0.120	0.0678
Other Education × age         (0.0194)         (0.0194)         (0.0195)         (0.0194)         (0.0198)         (0.0013)         (0.0013)         (0.00220)         (0.00210)         (0.00214)         (0.0014)         (0.0014)         (0.0014)         (0.0014)         (0.0014)         (0.0014)         (		(0.426)	(0.428)	(0.427)	(0.429)	(0.434)	(0.434)	(0.433)
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Other Education $\times$ age	(0.0194)	(0.0195)	(0.0194)	(0.0195)	(0.0198)	(0.0198)	(0.0198)
Outer has High School Diploma         (0.000214)         (0.000215)         (0.000215)         (0.000220)         (0.000220)         (0.000220)           Years of Schooling         0.00558***         0.00692***         0.00707***         0.00726***         0.00724**           Mother has High School Diploma         0.00146)         (0.00149)         (0.00149)         (0.00146)         (0.00147)         (0.00145)           Mother has High School Diploma         0.0317         (0.0311)         (0.0311)         (0.0311)         (0.0318)	Other Education $\times age^2$	0.000230	0.000232	0.000225	0.000217	0.000180	0.000163	0.000139
Years of Schooling         0.0032 (0.00146)         0.00102 (0.00146)         0.00146 (0.00147)         0.00124 (0.00124)           Mother has High School Diploma         -0.195***         -0.203***         -0.193***         -0.193***         -0.193***         -0.200***	Ouler Education × uge	(0.000214)	(0.000215)	(0.000215)	(0.000216)	(0.000220)	(0.000220)	(0.000220)
Mother has High School Diploma         -0.195***         -0.203***         -0.193***         -0.192***         -0.203***           (0.0317)         (0.0317)         (0.0319)         (0.0311)         (0.0308)	Years of Schooling		(0.00146)	(0.00149)	(0.00149)	(0.00146)	(0.00147)	(0.00145)
$(0.0317) \qquad (0.0319) \qquad (0.0311) \qquad (0.0308)$	Mother has High School Diploma		. ,	-0.195***	-0.203***	-0.193***	-0.192***	-0.200***
	Moner has riigh benoor Dipionia			(0.0317)	(0.0319)	(0.0311)	(0.0311)	(0.0308)
Mother has High School Diploma × age 0.00054400 0.00534000 0.00549000 0.00549000 0.00549000 0.00599000 0.00059000 0.000715)	Mother has High School Diploma $\times$ age			(0.00354***	(0.000730)	(0.00349 *** (0.000719))	(0.00347***	(0.00369***
-0.0762** -0.0717** -0.0624* -0.0639** -0.0630*	Eather has High School Dialoma			-0.0762**	-0.0717**	-0.0624*	-0.0639**	-0.0430
Patient has Figh School Dipionia         (0.0329)         (0.0331)         (0.0322)         (0.0319)	Famer has High School Dipionia			(0.0329)	(0.0331)	(0.0322)	(0.0322)	(0.0319)
Father has High School Diploma × age 0.00182** 0.00173** 0.00161** 0.00164** 0.00120* (0.000743) (0.000735) (0.000735) (0.000720)	Father has High School Diploma $\times$ age			0.00182**	0.00173**	0.00161**	0.00164**	0.00120*
				(0.000745)	0.0382	0.110***	0.110***	0.114***
Siblings in Education Age (0.0257) (0.0250) (0.0250) (0.0249)	Siblings in Education Age				(0.0257)	(0.0250)	(0.0250)	(0.0249)
Siblings in Education Age × age 0.000645 -0.000652 -0.000610 -0.00193***	Siblings in Education Age $\times$ age				0.000645	-0.000652	-0.000610	-0.00193***
(0.00054) (0.00054) (0.00054) (0.00056) (0.00056) (0.00054)					(0.000393)	(0.000380)	-0.00618	-0.0169
Born in Southern Italy (0.0452) (0.0450)	Born in Southern Italy						(0.0452)	(0.0450)
Born in Southern Italy × age 0.000120 0.000237	Born in Southern Italy $\times$ age						0.000120	0.000237
0.000980 (0.000980) (0.000980) (0.000980) (0.000980) (0.000980) (0.000980) (0.000980) (0.000980) (0.000927) (0.00112)	, e	0.00318	0.00255	0.00302	0.00380	0.000135	(0.000985)	(0.000980) 0.00412
Year 2002 (0.0116) (0.0115) (0.0115) (0.0111) (0.0111) (0.0110)	Year 2002	(0.0116)	(0.0116)	(0.0115)	(0.0115)	(0.0111)	(0.0111)	(0.0110)
Year 2004 0.0120 0.0108 0.0115 0.0116 0.00388 0.00428 0.00963	Year 2004	0.0120	0.0108	0.0115	0.0116	0.00388	0.00428	0.00963
$(0.0114)  (0.0114)  (0.0114)  (0.0114)  (0.0110)  (0.0109) \\ 0.035^{+++}  0.032^{+++}  0.032^{+++}  0.032^{+++}  0.056^{++}  0.036^{+++} \\ 0.032^{+++}  0.032^{++++}  0.032^{++++}  0.032^{++++}  0.038^{++++}  0.038^{+++++}  0.038^{+++++}  0.038^{+++++}  0.038^{++++++}  0.038^{++++++}  0.038^{+++++++}  0.038^{++++++++++}  0.038^{++++++++++++++++++++++++++++++++++++$		(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0110)	(0.0110)	(0.0109)
Year 2006 (0.0111) (0.0111) (0.0111) (0.0111) (0.0107) (0.0107) (0.0106)	Year 2006	(0.0111)	(0.0111)	(0.0111)	(0.0111)	(0.0107)	(0.0107)	(0.0106)
Year 2008 0.0310*** 0.0271** 0.0293*** 0.0296*** 0.0267** 0.0279*** 0.0352***	Year 2008	0.0310***	0.0271**	0.0293***	0.0296***	0.0267**	0.0279***	0.0352***
(0.0110) (0.0110) (0.0110) (0.0110) (0.0107) (0.0107) (0.0106) 0.01852 0.0141 0.0152 0.0550 0.0752 0.00752 0.00752	104 2000	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0107)	(0.0107)	(0.0106)
Year 2010 (0.0112) (0.0113) (0.0113) (0.0113) (0.0112) (0.0112) (0.0112) (0.0111)	Year 2010	(0.0112)	(0.0113)	(0.0113)	(0.0115)	(0.0112)	(0.0112)	(0.0111)
Ver 2012 0.0164 0.0119 0.0163 0.00223 0.00510 0.00642 0.0247**	Vear 2012	0.0164	0.0119	0.0163	0.00223	0.00510	0.00642	0.0247**
(0.0113) (0.0113) (0.0114) (0.0118) (0.0114) (0.0113) (0.0113) (0.0116) (0.0117) (0.0017) (0.	Teat 2012	(0.0113)	(0.0113)	(0.0114)	(0.0118)	(0.0114)	(0.0114)	(0.0113)
Year 2014 0.0133 0.00913 0.0156 -0.00136 0.00397 0.00529 0.0308** (0.0119) (0.0119) (0.0119) (0.0122) (0.0122) (0.0122) (0.0122)	Year 2014	(0.0133	(0.00913	(0.0156	-0.00136 (0.0125)	(0.00397	(0.0122)	(0.0308**
$-1.873^{***} - 1.944^{***} - 1.836^{***} - 1.805^{***} - 1.469^{***} - 1.469^{***} - 0.926^{***}$	Constant	-1.873***	-1.944***	-1.836***	-1.805***	-1.469***	-1.469***	-0.926***
Constant         (0.0507)         (0.0528)         (0.0541)         (0.0580)         (0.0740)         (0.0740)         (0.0837)	Constant	(0.0507)	(0.0528)	(0.0541)	(0.0580)	(0.0740)	(0.0740)	(0.0837)
Observations 17.345 17.345 17.345 17.345 17.345 17.345 17.345	Observations	17.345	17.345	17,345	17.345	17,345	17,345	17.345
<i>R</i> <sup>2</sup> 0.297 0.298 0.302 0.306 0.350 0.351 0.364	$R^2$	0.297	0.298	0.302	0.306	0.350	0.351	0.364
Years of Schooling x x x x x x x x	Years of Schooling		х	х	х	х	х	х
rarents Educational Attainment X X X X X X X Presence of Siblings in Education Age X Y Y Y	Parents' Educational Attainment Presence of Siblings in Education Age			х	X x	X x	X x	X x
Regional Controls x x x	Regional Controls				~	x	x	x
Municipality Size x x x x	Municipality Size					х	х	х
Born in Southern Italy x x x Current Marital Status	Born in Southern Italy Current Marital Status						х	x
Household Size x	Household Size							x

Table A.4: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

#### A.1.2 Wave-by-Wave Analysis

(a) 20-65 age cohort, all male individuals

(b) 25–65 age cohort, all male individuals

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.139*** (0.00418)	0.139*** (0.00419)	0.136*** (0.00426)	0.133*** (0.00461)	0.128*** (0.00524)	0.128*** (0.00524)	0.113*** (0.00738)	0.134*** (0.00586)	0.134*** (0.00585)	0.131*** (0.00585)	0.129*** (0.00617)	0.118*** (0.00661)	0.118*** (0.00661)	0.103*** (0.00807)
(age) <sup>2</sup>	-0.00171*** (5.09e-05)	-0.00171*** (5.10e-05)	-0.00168*** (5.12e-05)	-0.00168*** (5.15e-05)	-0.00166*** (5.12e-05)	-0.00166*** (5.15e-05)	-0.00151*** (7.43e-05)	-0.00165*** (6.70e-05)	-0.00165*** (6.69e-05)	-0.00163*** (6.66e-05)	-0.00161*** (6.70e-05)	-0.00155*** (6.57e-05)	-0.00155*** (6.57e-05)	-0.00139*** (8.17e-05)
General Education	-0.96/*** (0.142)	-0.96/*** (0.142)	-0.814*** (0.145)	-0.805*** (0.146)	-0.852*** (0.153)	-0.837***	-0.896**** (0.153)	-1.802*** (0.259)	-1.816*** (0.258)	-1.718*** (0.261)	-1.723*** (0.262)	-1.861*** (0.266)	-1.833**** (0.267)	-1.83/*** (0.269)
General Education $\times$ age	0.0328*** (0.00791)	0.0328*** (0.00793)	0.02/1*** (0.00804)	0.0266*** (0.00806)	0.0288*** (0.00834)	0.0277*** (0.00839)	(0.0315*** (0.00834)	(0.0124)	(0.0123)	(0.068/***	0.0688*** (0.0125)	0.0/54*** (0.0127)	(0.0128)	0.0748*** (0.0129)
General Education $\times age^2$	-0.000259** (0.000105)	-0.000259** (0.000105)	-0.000210** (0.000106)	-0.000205* (0.000106)	-0.000229** (0.000109)	-0.000213* (0.000110)	-0.000265** (0.000109)	-0.000689*** (0.000147)	-0.000694*** (0.000146)	-0.000667*** (0.000147)	-0.000670*** (0.000147)	-0.000744*** (0.000149)	-0.000723*** (0.000151)	-0.000742*** (0.000152)
Other Education	0.633 (0.628)	0.633 (0.628)	0.639 (0.612)	0.636 (0.610)	0.525 (0.671)	0.562 (0.675)	0.608 (0.653)	-0.0748 (1.097)	-0.0635 (1.091)	-0.00267 (1.075)	-0.0219 (1.066)	-0.419 (1.076)	-0.385 (1.072)	-0.127 (1.038)
Other Education $\times$ age	-0.0398 (0.0315)	-0.0398 (0.0316)	-0.0406 (0.0309)	-0.0405 (0.0307)	-0.0326 (0.0337)	-0.0343 (0.0338)	-0.0373 (0.0322)	-0.00923 (0.0510)	-0.0103 (0.0507)	-0.0133 (0.0501)	-0.0123 (0.0498)	0.00924 (0.0509)	0.00753 (0.0507)	-0.00511 (0.0482)
Other Education $\times age^2$	0.000577 (0.000383)	0.000577 (0.000383)	0.000586 (0.000377)	0.000587 (0.000373)	0.000472 (0.000407)	0.000492 (0.000408)	0.000544 (0.000382)	0.000261 (0.000573)	0.000275 (0.000571)	0.000307 (0.000565)	0.000294 (0.000562)	2.35e-05 (0.000582)	4.42e-05 (0.000580)	0.000202 (0.000541)
Years of Schooling		-2.29e-05 (0.00478)	0.00168 (0.00493)	0.00229 (0.00496)	0.00454 (0.00499)	0.00434 (0.00500)	0.00532 (0.00496)		0.00994** (0.00473)	0.0107** (0.00487)	0.0119** (0.00491)	0.0128*** (0.00495)	0.0126** (0.00497)	0.0129*** (0.00493)
Mother has High School Diploma			-0.297*** (0.0633)	-0.309*** (0.0636)	-0.264*** (0.0647)	-0.266*** (0.0647)	-0.268*** (0.0646)			-0.309*** (0.0898)	-0.308*** (0.0907)	-0.303*** (0.0905)	-0.306*** (0.0907)	-0.312*** (0.0906)
Mother has High School Diploma $\times$ age			0.00654*** (0.00166)	0.00687*** (0.00166)	0.00580*** (0.00168)	0.00587*** (0.00169)	0.00608*** (0.00168)			0.00683*** (0.00214)	0.00681*** (0.00215)	0.00651*** (0.00218)	0.00658*** (0.00218)	0.00691*** (0.00217)
Father has High School Diploma			-0.00705 (0.0616)	-0.000987 (0.0621)	0.0214 (0.0625)	0.0255 (0.0626)	0.0368 (0.0625)			0.0317 (0.0855)	0.0220 (0.0861)	0.0761 (0.0864)	0.0814 (0.0867)	0.110 (0.0870)
Father has High School Diploma $\times$ age			0.000318 (0.00154)	0.000166 (0.00155)	-0.000220 (0.00157)	-0.000341 (0.00157)	-0.000703 (0.00158)			-0.000625 (0.00199)	-0.000448 (0.00200)	-0.00139 (0.00203)	-0.00153 (0.00203)	-0.00229 (0.00205)
Siblings in Education Age				-0.0557 (0.0586)	0.00937 (0.0594)	0.000545 (0.0595)	-0.0192 (0.0596)				0.0547 (0.0746)	0.118 (0.0748)	0.108 (0.0753)	0.0837 (0.0750)
Siblings in Education Age $\times$ age				0.00244 (0.00160)	0.00135 (0.00162)	0.00165 (0.00162)	0.00122 (0.00161)				0.000295 (0.00185)	-0.000844 (0.00188)	-0.000503 (0.00189)	-0.000856 (0.00187)
Born in Southern Italy						0.159* (0.0945)	0.159* (0.0951)						0.123 (0.112)	0.128 (0.115)
Born in Southern Italy $\times$ age						-0.00407* (0.00222)	-0.00413* (0.00224)						-0.00329 (0.00259)	-0.00343 (0.00264)
Constant	-1.802*** (0.0841)	-1.802*** (0.102)	-1.725*** (0.105)	-1.678*** (0.115)	-1.495*** (0.156)	-1.505*** (0.155)	-1.141*** (0.194)	-1.700*** (0.126)	-1.830*** (0.133)	-1.741*** (0.135)	-1.765*** (0.147)	-1.391*** (0.187)	-1.401*** (0.186)	-1.041*** (0.213)
Observations p2	3,061	3,061	3,061	3,061	3,061	3,061	3,061	2,524	2,524	2,524	2,524	2,524	2,524	2,524
Years of Schooling	0.392	0.392 X	0.400 X	0.400 X	0.438 X	0.440 X	0.448 X	0.550	0.331 X	0.337 X	0.559 X	0.365 X	0.364 X	0.394 X
Parents' Educational Attainment			x	x	x	x	x			x	x	x	x	x
Presence of Siblings in Education Age				x	х	х	x				х	х	х	x
Regional Controls					х	х	х					х	х	х
Municipality Size					х	x	x					х	x	x
Born in Southern Italy Current Marital Status						x	x						х	x
Household Size							X							x

Table A.5: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education. Omitted education type is vocational. Wave of analysis: 2000. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

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emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.135*** (0.00444)	0.135*** (0.00444)	0.130*** (0.00455)	0.128*** (0.00491)	0.118*** (0.00532)	0.118*** (0.00532)	0.104*** (0.00770)	0.129*** (0.00618)	0.129*** (0.00617)	0.126*** (0.00621)	0.124*** (0.00655)	0.112*** (0.00667)	0.112*** (0.00667)	0.0947*** (0.00829)
(age) <sup>2</sup>	-0.00164*** (5.35e-05)	-0.00164*** (5.36e-05)	-0.00160*** (5.41e-05)	-0.00160*** (5.45e-05)	-0.00156*** (5.39e-05)	-0.00156*** (5.41e-05)	-0.00143*** (7.71e-05)	-0.00158*** (7.02e-05)	-0.00158*** (7.01e-05)	-0.00156*** (7.02e-05)	-0.00154*** (7.09e-05)	-0.00150*** (6.92e-05)	-0.00149*** (6.96e-05)	-0.00132*** (8.44e-05)
General Education	-0.617*** (0.156)	-0.623*** (0.157)	-0.465*** (0.163)	-0.463*** (0.164)	-0.541*** (0.169)	-0.543*** (0.169)	-0.590*** (0.169)	-1.206*** (0.291)	-1.208*** (0.291)	-1.038*** (0.295)	-1.034*** (0.297)	-1.241*** (0.296)	-1.247*** (0.297)	-1.233*** (0.297)
General Education $\times$ age	0.0132 (0.00879)	0.0136 (0.00882)	0.00817 (0.00911)	0.00805	0.0127	0.0128 (0.00943)	0.0156*	0.0403***	0.0400***	0.0345** (0.0141)	0.0342** (0.0142)	0.0451***	0.0454***	0.0452***
General Education $\times age^2$	1.01e-05 (0.000116)	6.65e-06 (0.000116)	4.56e-05 (0.000119)	4.60e-05 (0.000120)	-1.64e-05 (0.000123)	-1.75e-05 (0.000124)	-5.13e-05 (0.000123)	-0.000284* (0.000163)	-0.000283* (0.000163)	-0.000246 (0.000165)	-0.000242 (0.000167)	-0.000376** (0.000168)	-0.000378** (0.000168)	-0.000378** (0.000169)
Other Education	-0.202 (0.652)	-0.208 (0.652)	-0.305 (0.636)	-0.296 (0.641)	-0.110 (0.709)	-0.106 (0.710)	-0.188 (0.705)	-0.672 (1.057)	-0.654 (1.060)	-0.743 (1.014)	-0.741 (1.037)	-1.186 (1.089)	-1.119 (1.074)	-1.152 (1.069)
Other Education $\times$ age	0.00375 (0.0349)	0.00417 (0.0350)	0.00998 (0.0343)	0.00955 (0.0347)	0.00281 (0.0384)	0.00259 (0.0385)	0.00773 (0.0381)	0.0254 (0.0517)	0.0242 (0.0518)	0.0301 (0.0497)	0.0302 (0.0508)	0.0530 (0.0545)	0.0500 (0.0539)	0.0528 (0.0536)
Other Education $\times age^2$	3.26e-05 (0.000455)	2.77e-05 (0.000455)	-5.51e-05 (0.000449)	-4.79e-05 (0.000456)	3.91e-06 (0.000504)	7.22e-06 (0.000505)	-6.12e-05 (0.000498)	-0.000206 (0.000625)	-0.000192 (0.000626)	-0.000280 (0.000602)	-0.000280 (0.000614)	-0.000558 (0.000668)	-0.000524 (0.000663)	-0.000564 (0.000660)
Years of Schooling		-0.00209 (0.00457)	-0.000507 (0.00466)	-0.000152 (0.00467)	0.000374 (0.00462)	0.000362 (0.00463)	0.00117 (0.00462)		0.00549 (0.00460)	0.00699 (0.00470)	0.00745 (0.00472)	0.00750 (0.00461)	0.00752 (0.00461)	0.00777* (0.00462)
Mother has High School Diploma			-0.159** (0.0641)	-0.164** (0.0647)	-0.165** (0.0653)	-0.165** (0.0654)	-0.174*** (0.0653)			-0.236*** (0.0899)	-0.235*** (0.0907)	-0.258*** (0.0895)	-0.260*** (0.0896)	-0.265*** (0.0889)
Mother has High School Diploma $\times$ age			0.00350** (0.00163)	0.00365** (0.00165)	0.00355** (0.00168)	0.00357** (0.00168)	0.00379** (0.00168)			0.00496** (0.00209)	0.00497** (0.00211)	0.00527** (0.00212)	0.00533** (0.00212)	0.00552*** (0.00212)
Father has High School Diploma			-0.188*** (0.0639)	-0.186*** (0.0650)	-0.153** (0.0662)	-0.153** (0.0663)	-0.144** (0.0662)			-0.160* (0.0887)	-0.164*	-0.116 (0.0878)	-0.113 (0.0880)	-0.0965 (0.0877)
Father has High School Diploma $\times$ age			0.00453*** (0.00159)	0.00446*** (0.00162)	0.00373** (0.00165)	0.00370** (0.00165)	0.00349** (0.00165)			0.00391* (0.00205)	0.00396*	0.00303 (0.00206)	0.00295	0.00255
Siblings in Education Age				-0.0170 (0.0619)	0.0606 (0.0617)	0.0584 (0.0619)	0.0577 (0.0621)			(	0.0624 (0.0761)	0.122 (0.0748)	0.117 (0.0752)	0.0974 (0.0752)
Siblings in Education Age $\times$ age				0.00154 (0.00164)	0.000121 (0.00164)	0.000201 (0.00165)	-0.000802 (0.00166)				0.000264 (0.00189)	-0.000735 (0.00189)	-0.000585 (0.00190)	-0.00120 (0.00190)
Born in Southern Italy						0.0307 (0.110)	0.0166 (0.109)						0.125 (0.125)	0.108 (0.124)
Born in Southern Italy $\times$ age						-0.000888 (0.00251)	-0.000651 (0.00248)						-0.00280 (0.00283)	-0.00251 (0.00281)
Constant	-1.759*** (0.0897)	-1.732*** (0.105)	-1.614*** (0.109)	-1.596*** (0.122)	-1.217*** (0.151)	-1.220*** (0.151)	-0.798*** (0.200)	-1.636*** (0.133)	-1.708*** (0.140)	-1.616*** (0.142)	-1.631*** (0.155)	-1.213*** (0.177)	-1.216*** (0.177)	-0.726*** (0.213)
Observations	2,900	2,900	2,900	2,900	2,900	2,900	2,900	2,409	2,409	2,409	2,409	2,409	2,409	2,409
K <sup>-</sup> Vears of Schooling	0.370	0.370	0.378	0.378	0.425	0.425	0.432	0.294	0.295	0.303	0.306	0.359	0.360	0.370
Parents' Educational Attainment		X	x	x	x	x	x		A	x	x	x	x	x
Presence of Siblings in Education Age			x	x	x	x	x			x	x	x	x	x
Regional Controls				А	x	x	A X				А	x	A X	x
Municipality Size					x	x	x					x	x	x
Born in Southern Italy					~	x	x					~	x	x
Current Marital Status						~	x						~	x
Household Size							x							x

(a) 20-65 age cohort, all male individuals

Table A.6: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education. Omitted education type is vocational. Wave of analysis: 2002. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

(b) 25–65 age cohort, all male individuals

A.1. Effects over Life-Time Employment

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(b) 25–65 age cohort, all male individuals

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emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.133*** (0.00439)	0.133*** (0.00440)	0.127*** (0.00452)	0.124*** (0.00483)	0.115*** (0.00535)	0.115*** (0.00533)	0.0967*** (0.00755)	0.134*** (0.00607)	0.134*** (0.00607)	0.131*** (0.00616)	0.128*** (0.00646)	0.119*** (0.00681)	0.119*** (0.00678)	0.0976*** (0.00817)
(age) <sup>2</sup>	-0.00163*** (5.21e-05)	-0.00163*** (5.21e-05)	-0.00158*** (5.27e-05)	-0.00157*** (5.30e-05)	-0.00157*** (5.38e-05)	-0.00156*** (5.37e-05)	-0.00139*** (7.55e-05)	-0.00164*** (6.81e-05)	-0.00164*** (6.80e-05)	-0.00161*** (6.83e-05)	-0.00159*** (6.90e-05)	-0.00158*** (7.02e-05)	-0.00158*** (7.00e-05)	-0.00138*** (8.32e-05)
General Education	-0.745*** (0.165)	-0.747*** (0.166)	-0.650*** (0.169)	-0.656*** (0.169)	-0.638*** (0.172)	-0.625*** (0.172)	-0.663*** (0.171)	-0.749** (0.295)	-0.749** (0.295)	-0.695** (0.297)	-0.685** (0.298)	-0.685** (0.297)	-0.671** (0.297)	-0.698** (0.294)
General Education $\times$ age	0.0207** (0.00900)	0.0208** (0.00903)	0.0184** (0.00920)	0.0189** (0.00920)	0.0181* (0.00932)	0.0173* (0.00929)	0.0196** (0.00924)	0.0216 (0.0140)	0.0214 (0.0140)	0.0203 (0.0141)	0.0200 (0.0141)	0.0203 (0.0141)	0.0194 (0.0141)	0.0212 (0.0140)
General Education $\times age^2$	-8.74e-05 (0.000116) 0.320	(0.000116)	-8.58e-05 (0.000118) 0.460	(0.000118) 0.427	-8.64e-05 (0.000119)	(0.000119)	(0.000108)	-0.000104 (0.000163)	-0.000103 (0.000162)	-0.000107 (0.000164)	-0.000105 (0.000164)	-0.000111 (0.000165)	-9.86e-05 (0.000165)	-0.000124 (0.000164)
Other Education	(0.531)	(0.531)	(0.527)	(0.540)	(0.599)	(0.598)	(0.602)	(1.033)	(1.034)	(1.067)	(1.123)	-0.334 (0.983)	-0.321 (0.991)	(1.032)
Other Education $\times$ age	(0.0240)	(0.0240)	(0.0238)	(0.0246)	(0.0227)	(0.0275)	(0.0275)	(0.0438)	(0.0438)	(0.0451)	(0.0477)	(0.0427)	(0.0429)	(0.0323)
Other Education $\times age^2$	-9.19e-05 (0.000277)	-9.37e-05 (0.000277)	-0.000192 (0.000274)	-0.000156 (0.000286)	-0.000239 (0.000319)	-0.000230 (0.000319)	-0.000317 (0.000318)	0.000130 (0.000458)	0.000133 (0.000458)	8.14e-05 (0.000469)	0.000138 (0.000499)	-0.000156 (0.000458)	-0.000147 (0.000460)	-0.000355 (0.000474)
Years of Schooling		-0.00122 (0.00438)	-0.000199 (0.00460)	(0.00461)	(0.00130	(0.00158	(0.00303		0.00328 (0.00446)	0.00321 (0.00469)	0.00351 (0.00471)	0.00411 (0.00456)	0.00432 (0.00456)	0.00556 (0.00455)
Mother has High School Diploma			-0.0824 (0.0642)	(0.0643)	(0.0636)	(0.0637)	(0.0635)			-0.0599 (0.0857)	-0.0625 (0.0866)	-0.0465 (0.0844)	-0.0501 (0.0844)	-0.0598 (0.0837)
Mother has High School Diploma $\times$ age			(0.00165)	(0.00231 (0.00164)	(0.00225	(0.00229	(0.00238			0.00140 (0.00202)	0.00153 (0.00203)	0.00138 (0.00199)	0.00147 (0.00199)	0.00167 (0.00198)
Father has High School Diploma			(0.0641)	-0.256*** (0.0646)	-0.211**** (0.0644)	(0.0642)	(0.0641)			-0.184** (0.0863)	-0.184** (0.0865)	-0.0909 (0.0848)	-0.0857 (0.0845)	-0.0667 (0.0842)
Father has High School Diploma $\times$ age			(0.00160)	(0.00161)	(0.00162)	(0.00161)	(0.00161)			0.00438** (0.00202)	0.00435** (0.00203)	0.00243 (0.00203)	0.00227 (0.00202)	0.00188 (0.00202)
Siblings in Education Age				(0.0611)	(0.0618)	(0.0614)	(0.0619)				0.0786 (0.0762)	0.174** (0.0741)	0.160** (0.0738)	0.134* (0.0738)
Siblings in Education Age $\times$ age				(0.00164)	(0.00140	(0.00165)	(0.00166)				-8.36e-05 (0.00188)	-0.00207 (0.00186)	-0.00162 (0.00185)	-0.00210 (0.00183)
Born in Southern Italy						(0.113)	(0.112)						0.153 (0.121)	0.153 (0.120)
Born in Southern Italy $\times$ age						(0.00254)	(0.00252)						-0.00429 (0.00271)	-0.00427 (0.00270)
Constant	-1.706*** (0.0904)	-1.691*** (0.105)	-1.545*** (0.110)	-1.490*** (0.119)	-1.121*** (0.152)	-1.141*** (0.152)	-0.623*** (0.197)	-1.730*** (0.133)	-1.775*** (0.140)	-1.683*** (0.144)	-1.692*** (0.155)	-1.282*** (0.182)	-1.302*** (0.182)	-0.706*** (0.211)
Observations p <sup>2</sup>	2,938	2,938	2,938	2,938	2,938	2,938	2,938	2,478	2,478	2,478	2,478	2,478	2,478	2,478
Years of Schooling	0.356	0.356 X	0.365 X	0.368 x	0.411 x	0.412 x	0.420 x	0.295	0.295 X	0.299 X	0.303 X	0.339 X	0.500 x	0.371 X
Parents' Educational Attainment			х	x	х	x	x			х	х	х	x	х
Presence of Siblings in Education Age Regional Controls				x	x	x	x				x	x	x	x
Municipality Size					x	x	x					x	x	x
Born in Southern Italy						x	x						x	х
Current Marital Status Household Size							x x							x x

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(a) 20–65 age cohort, all male individuals

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Table A.7: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education. Omitted education type is vocational. Wave of analysis: 2004. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.118*** (0.00446)	0.118*** (0.00446)	0.114*** (0.00457)	0.112*** (0.00484)	0.0983*** (0.00535)	0.0981*** (0.00536)	0.0953*** (0.00696)	0.117*** (0.00580)	0.117*** (0.00580)	0.113*** (0.00580)	0.110*** (0.00604)	0.0955*** (0.00639)	0.0956*** (0.00639)	0.0889*** (0.00739)
(age) <sup>2</sup>	-0.00144*** (5.25e-05)	-0.00144*** (5.26e-05)	-0.00141*** (5.30e-05)	-0.00141*** (5.32e-05)	-0.00136*** (5.27e-05)	-0.00136*** (5.27e-05)	-0.00133*** (6.76e-05)	-0.00143*** (6.53e-05)	-0.00143*** (6.53e-05)	-0.00140*** (6.49e-05)	-0.00139*** (6.57e-05)	-0.00135*** (6.55e-05)	-0.00136*** (6.58e-05)	-0.00129*** (7.39e-05)
General Education	-1.137*** (0.149)	-1.131*** (0.149)	-0.965*** (0.155)	-0.961*** (0.155)	-1.072*** (0.159)	-1.071*** (0.159)	-1.114*** (0.159)	-0.890*** (0.268)	-0.902*** (0.267)	-0.764*** (0.271)	-0.760*** (0.271)	-0.814*** (0.261)	-0.806*** (0.260)	-0.856*** (0.259)
General Education $\times$ age	0.0430*** (0.00779)	0.0425*** (0.00786)	0.0368*** (0.00802)	0.0366*** (0.00803)	0.0420*** (0.00821)	0.0420*** (0.00822)	0.0447***	0.0321***	0.0320** (0.0124)	0.0278** (0.0125)	0.0276**	0.0305** (0.0122)	0.0303**	0.0333***
General Education $\times age^2$	-0.000373*** (9.80e-05)	-0.000369*** (9.85e-05)	-0.000326*** (9.95e-05)	-0.000324*** (9.97e-05)	-0.000388*** (0.000101)	-0.000388*** (0.000102)	-0.000422*** (0.000101)	-0.000259* (0.000142)	-0.000259* (0.000141)	-0.000234* (0.000142)	-0.000232 (0.000142)	-0.000271* (0.000140)	-0.000271* (0.000140)	-0.000307** (0.000139)
Other Education	0.645 (0.748)	0.643 (0.749)	0.602 (0.749)	0.602 (0.748)	1.084 (0.727)	1.101 (0.727)	0.950 (0.743)	1.514* (0.786)	1.473* (0.794)	1.400* (0.794)	1.360* (0.800)	1.592* (0.906)	1.586* (0.892)	1.307 (0.909)
Other Education $\times$ age	-0.0318 (0.0370)	-0.0319 (0.0370)	-0.0306 (0.0370)	-0.0305 (0.0370)	-0.0510 (0.0362)	-0.0522 (0.0362)	-0.0452 (0.0370)	-0.0704* (0.0393)	-0.0690* (0.0396)	-0.0663* (0.0395)	-0.0645 (0.0399)	-0.0739* (0.0444)	-0.0738* (0.0440)	-0.0610 (0.0448)
Other Education $\times age^2$	0.000340 (0.000442)	0.000341 (0.000443)	0.000332 (0.000443)	0.000330 (0.000443)	0.000536 (0.000434)	0.000551 (0.000435)	0.000476 (0.000443)	0.000749 (0.000472)	0.000734 (0.000475)	0.000712 (0.000474)	0.000690 (0.000478)	0.000779 (0.000523)	0.000779 (0.000519)	0.000643 (0.000530)
Years of Schooling		0.00219 (0.00319)	0.00321 (0.00324)	0.00351 (0.00325)	0.00482 (0.00322)	0.00487 (0.00324)	0.00531* (0.00316)		0.00656** (0.00322)	0.00741** (0.00328)	0.00777** (0.00329)	0.00853*** (0.00326)	0.00834** (0.00329)	0.00827*** (0.00320)
Mother has High School Diploma			-0.104 (0.0645)	-0.110* (0.0648)	-0.126** (0.0623)	-0.128** (0.0623)	-0.140** (0.0621)			-0.121 (0.0813)	-0.131 (0.0819)	-0.152* (0.0788)	-0.152* (0.0787)	-0.172** (0.0786)
Mother has High School Diploma $\times$ age			0.00169 (0.00160)	0.00186 (0.00161)	0.00199 (0.00157)	0.00205 (0.00156)	0.00220 (0.00156)			0.00190 (0.00190)	0.00213 (0.00191)	0.00242 (0.00187)	0.00247 (0.00186)	0.00280 (0.00186)
Father has High School Diploma			-0.226*** (0.0658)	-0.222*** (0.0663)	-0.174*** (0.0642)	-0.173*** (0.0644)	-0.157** (0.0638)			-0.237*** (0.0851)	-0.231*** (0.0856)	-0.146* (0.0820)	-0.144* (0.0822)	-0.119 (0.0818)
Father has High School Diploma $\times$ age			0.00531*** (0.00158)	0.00519*** (0.00159)	0.00427*** (0.00155)	0.00427*** (0.00155)	0.00394** (0.00153)			0.00556*** (0.00194)	0.00540*** (0.00195)	0.00373** (0.00189)	0.00371* (0.00190)	0.00320* (0.00188)
Siblings in Education Age				-0.0243 (0.0593)	0.0290 (0.0584)	0.0313 (0.0586)	0.0467 (0.0588)				-0.0208 (0.0688)	0.0307 (0.0689)	0.0412 (0.0694)	0.0371 (0.0693)
Siblings in Education Age $\times$ age				0.00141 (0.00157)	0.000523 (0.00155)	0.000420 (0.00156)	-0.00109 (0.00155)				0.00158 (0.00170)	0.000761 (0.00173)	0.000489 (0.00174)	-0.000706 (0.00172)
Born in Southern Italy						-0.0620 (0.0919)	-0.0845 (0.0911)						-0.191* (0.110)	-0.204* (0.109)
Born in Southern Italy $\times$ age						0.00143 (0.00211)	0.00188 (0.00211)						0.00397 (0.00246)	0.00422* (0.00246)
Constant	-1.419*** (0.0921)	-1.446*** (0.100)	-1.326*** (0.104)	-1.305*** (0.114)	-0.797*** (0.150)	-0.790*** (0.150)	-0.605*** (0.190)	-1.384*** (0.126)	-1.475*** (0.132)	-1.350*** (0.133)	-1.321*** (0.141)	-0.739*** (0.167)	-0.730*** (0.166)	-0.459** (0.195)
Observations	3,203	3,203	3,203	3,203	3,203	3,203	3,203	2,779	2,779	2,779	2,779	2,779	2,779	2,779
R <sup>2</sup>	0.329	0.329	0.337	0.337	0.390	0.390	0.402	0.266	0.267	0.275	0.276	0.329	0.329	0.347
Years of Schooling		х	x	х	х	x	х		x	х	х	х	х	х
Parents' Educational Attainment			х	х	х	х	х			х	х	х	х	х
Presence of Siblings in Education Age				х	х	x	х				х	х	х	х
Regional Controls					х	х	х					х	х	х
Municipality Size					х	х	х					х	х	х
Born in Southern Italy						х	х						х	х
Current Marital Status							х							х
Household Size							х							х

(a) 20-65 age cohort, all male individuals

Table A.8: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education. Omitted education type is vocational. Wave of analysis: 2006. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

A.1. Effects over Life-Time Employment

(b) 25-65 age cohort, all male individuals

	(a) 20–65	age coho	ort, all me	ile indivia	luals			(b) 25–65 age cohort, all male individuals								
emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)		
age	0.125*** (0.00440)	0.125*** (0.00440)	0.122*** (0.00452)	0.120*** (0.00473)	0.115*** (0.00510)	0.114*** (0.00511)	0.105*** (0.00661)	0.134*** (0.00561)	0.134*** (0.00560)	0.130*** (0.00569)	0.127*** (0.00588)	0.122*** (0.00629)	0.122*** (0.00632)	0.111*** (0.00730)		
(age) <sup>2</sup>	-0.00152*** (5.11e-05)	-0.00152*** (5.11e-05)	-0.00150*** (5.18e-05)	-0.00150*** (5.20e-05)	-0.00146*** (5.04e-05)	-0.00145*** (5.06e-05)	-0.00138*** (6.45e-05)	-0.00162*** (6.24e-05)	-0.00162*** (6.23e-05)	-0.00159*** (6.26e-05)	-0.00159*** (6.31e-05)	-0.00155*** (6.05e-05)	-0.00155*** (6.10e-05)	-0.00146*** (7.02e-05)		
General Education	-0.704**** (0.151)	(0.152)	-0.608**** (0.156)	-0.604*** (0.156)	-0.623*** (0.159)	-0.623*** (0.159)	(0.158)	-0.373 (0.278)	-0.370 (0.278)	-0.274 (0.280)	-0.270 (0.279)	-0.166 (0.260)	-0.166 (0.261)	-0.187 (0.260)		
General Education $\times$ age	0.0179** (0.00800)	0.0191** (0.00805)	0.0156* (0.00814)	0.0154* (0.00813)	0.0164** (0.00827)	0.0164** (0.00827)	0.0181** (0.00826)	0.00349 (0.0130)	0.00355 (0.0130)	0.000913 (0.0129)	0.000696 (0.0129)	-0.00342 (0.0123)	-0.00337 (0.0123)	-0.00238 (0.0123)		
General Education $\times age^2$	-4.54e-05 (0.000101)	-5.64e-05 (0.000102)	-3.54e-05 (0.000102)	-3.35e-05 (0.000102)	-4.92e-05 (0.000103)	-4.80e-05 (0.000104)	-6.70e-05 (0.000103)	0.000105 (0.000148)	0.000105 (0.000148)	0.000115 (0.000148)	0.000117 (0.000147)	0.000154 (0.000142)	0.000153 (0.000143)	0.000142 (0.000143)		
Other Education	0.444 (0.647)	0.434 (0.644)	0.495 (0.643)	0.494 (0.642)	0.788 (0.598)	(0.817 (0.599)	0.798 (0.603)	0.482 (0.980)	0.481 (0.975)	0.487 (0.984)	0.453 (0.987)	(1.049	(1.007)	0.991 (1.014)		
Other Education $\times$ age	-0.02/1 (0.0324)	-0.0264 (0.0323)	-0.0293 (0.0323)	-0.0292 (0.0323)	-0.0400 (0.0301)	-0.0417 (0.0301)	-0.0404 (0.0304)	-0.0296 (0.0457)	-0.0294 (0.0455)	-0.0300 (0.0458)	-0.0283 (0.0460)	-0.0531 (0.0458)	-0.0517 (0.0461)	-0.0502 (0.0465)		
Other Education $\times age^2$	(0.000391)	(0.000384	(0.000419	(0.000416)	(0.000379)	(0.000527	(0.000381)	0.000423 (0.000533)	0.000422 (0.000531)	0.000432 (0.000534)	0.000413 (0.000536)	0.000656 (0.000524)	0.000642 (0.000527)	0.000624 (0.000532)		
Years of Schooling		-0.00494 (0.00306)	-0.00485 (0.00313)	-0.004/1 (0.00313)	-0.00399 (0.00308)	-0.00386 (0.00308)	-0.00274 (0.00306)		-0.00189 (0.00309)	-0.00178 (0.00317)	-0.00154 (0.00317)	-0.000777 (0.00311)	-0.000753 (0.00312)	0.000112 (0.00310)		
Mother has High School Diploma			-0.129** (0.0619)	-0.135** (0.0621)	-0.133** (0.0600)	-0.134** (0.0600)	-0.139** (0.0595)			-0.119 (0.0792)	-0.129 (0.0795)	-0.134* (0.0752)	-0.133* (0.0755)	-0.14/* (0.0749)		
Mother has High School Diploma $\times$ age			(0.00215)	(0.00233	(0.00237	(0.00238	(0.00146)			0.00195 (0.00181)	0.00219 (0.00181)	0.00237 (0.00174)	0.00236 (0.00174)	0.00272 (0.00173)		
Father has High School Diploma			-0.0899	-0.0843 (0.0638)	(0.0620)	-0.0978 (0.0621)	-0.0826 (0.0615)			-0.124 (0.0833)	-0.113 (0.0836)	-0.154* (0.0795)	-0.155* (0.0798)	-0.128 (0.0790)		
Father has High School Diploma $\times$ age			0.00272* (0.00154)	0.00257* (0.00155)	0.00275* (0.00152)	0.002/2* (0.00153)	0.00237 (0.00151)			0.00337* (0.00192)	0.00313 (0.00193)	0.00387** (0.00186)	0.00388** (0.00186)	0.00331* (0.00184)		
Siblings in Education Age				-0.0773 (0.0607)	(0.0602)	-0.00131 (0.0604)	(0.0609)				-0.115 (0.0724)	-0.0375 (0.0694)	-0.0360 (0.0698)	-0.0456 (0.0700)		
Siblings in Education Age $\times$ age				(0.00252)	(0.00154)	(0.00155)	-0.000260 (0.00157)				0.00331* (0.00174)	0.00166 (0.00169)	0.00162 (0.00170)	0.000922 (0.00170)		
Born in Southern Italy						(0.102)	(0.101)						-0.0477 (0.119)	-0.0424 (0.118)		
Born in Southern Italy $\times$ age	1.545444	1 402444	1 202444	1.220444	1 01 (1000	-0.00141 (0.00228)	-0.00150 (0.00228)						0.000915 (0.00261)	0.000/05 (0.00261)		
Constant	(0.0924)	(0.0995)	(0.104)	(0.114)	(0.147)	(0.147)	(0.183)	-1./44*** (0.124)	-1./1/*** (0.128)	(0.131)	-1.524*** (0.141)	-1.365*** (0.180)	-1.365*** (0.180)	(0.203)		
Observations p2	3,216	3,216	3,216	3,216	3,216	3,216	3,216	2,789	2,789	2,789	2,789	2,789	2,789	2,789		
Years of Schooling	0.550	0.330 x	0.334 x	0.334 X	0.404 x	0.404 x	0.414 X	0.295	0.295 x	0.299 X	0.300 x	0.550 x	0.550 x	0.507 x		
Parents' Educational Attainment			x	x	x	x	x		A	x	x	x	x	x		
Presence of Siblings in Education Age				х	х	x	х				х	х	х	х		
Regional Controls					х	x	х					х	х	х		
Municipality Size					х	х	х					х	х	х		
Born in Southern Italy Current Marital Status						х	x						x	x		
Household Size							x							x		

Table A.9: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education. Omitted education type is vocational. Wave of analysis: 2008. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.119*** (0.00440)	0.118*** (0.00442)	0.117*** (0.00455)	0.110*** (0.00490)	0.105*** (0.00545)	0.105*** (0.00546)	0.0997*** (0.00732)	0.124*** (0.00608)	0.123*** (0.00609)	0.121*** (0.00623)	0.113*** (0.00634)	0.110*** (0.00714)	0.110*** (0.00717)	0.104*** (0.00846)
(age) <sup>2</sup>	-0.00142*** (5.14e-05)	-0.00141*** (5.15e-05)	-0.00140*** (5.23e-05)	-0.00136*** (5.38e-05)	-0.00131*** (5.36e-05)	-0.00131*** (5.36e-05)	-0.00127*** (7.14e-05)	-0.00147*** (6.73e-05)	-0.00147*** (6.73e-05)	-0.00144*** (6.80e-05)	-0.00139*** (6.83e-05)	-0.00137*** (6.86e-05)	-0.00137*** (6.86e-05)	-0.00132*** (8.09e-05)
General Education	-0.757*** (0.147)	-0.747*** (0.147)	-0.706*** (0.153)	-0.692*** (0.153)	-0.743*** (0.153)	-0.747*** (0.153)	-0.785*** (0.153)	-0.913*** (0.262)	-0.950*** (0.260)	-0.887*** (0.268)	-0.847*** (0.267)	-0.810*** (0.264)	-0.814*** (0.263)	-0.830*** (0.264)
General Education $\times$ age	0.0214*** (0.00771)	0.0204*** (0.00778)	0.0192** (0.00790)	0.0186**	0.0207*** (0.00788)	0.0209*** (0.00785)	0.0229*** (0.00785)	0.0286** (0.0122)	0.0293**	0.0274**	0.0256**	0.0237*	0.0238*	0.0249**
General Education $\times age^2$	-9.55e-05 (9.62e-05)	-8.74e-05 (9.67e-05)	-8.17e-05 (9.74e-05)	-7.57e-05 (9.74e-05)	-9.41e-05 (9.67e-05)	-9.51e-05 (9.63e-05)	-0.000120 (9.63e-05)	-0.000175 (0.000138)	-0.000186 (0.000137)	-0.000175 (0.000139)	-0.000157 (0.000139)	-0.000131 (0.000138)	-0.000130 (0.000137)	-0.000144 (0.000138)
Other Education	-0.161 (0.517)	-0.145 (0.518)	-0.113 (0.519)	-0.127 (0.525)	-0.208 (0.527)	-0.181 (0.522)	-0.217 (0.522)	-0.217 (1.176)	-0.187 (1.168)	-0.257 (1.168)	-0.556 (1.184)	0.243 (1.137)	0.364 (1.137)	0.398 (1.114)
Other Education $\times$ age	0.000813 (0.0266)	-0.000200 (0.0267)	-0.00200 (0.0268)	-0.00184 (0.0269)	0.00341 (0.0267)	0.00182 (0.0263)	0.00388 (0.0261)	0.00199 (0.0526)	0.000101 (0.0522)	0.00259 (0.0523)	0.0152 (0.0529)	-0.0179 (0.0510)	-0.0237 (0.0507)	-0.0247 (0.0496)
Other Education $\times age^2$	3.94e-05 (0.000334)	5.06e-05 (0.000335)	7.41e-05 (0.000336)	7.56e-05 (0.000337)	3.83e-06 (0.000329)	2.67e-05 (0.000324)	-4.73e-06 (0.000319)	3.77e-05 (0.000577)	5.85e-05 (0.000573)	3.85e-05 (0.000574)	-9.03e-05 (0.000580)	0.000239 (0.000560)	0.000308 (0.000554)	0.000308 (0.000540)
Years of Schooling		0.00560* (0.00297)	0.00554* (0.00302)	0.00594** (0.00301)	0.00561* (0.00299)	0.00539* (0.00300)	0.00569* (0.00299)		0.00957*** (0.00300)	0.00983*** (0.00304)	0.0103*** (0.00303)	0.00940*** (0.00303)	0.00914*** (0.00303)	0.00918*** (0.00302)
Mother has High School Diploma			-0.0414 (0.0573)	-0.0700 (0.0579)	-0.0828 (0.0575)	-0.0829 (0.0574)	-0.0790 (0.0574)			-0.0856 (0.0732)	-0.122* (0.0736)	-0.107 (0.0724)	-0.109 (0.0724)	-0.108 (0.0724)
Mother has High School Diploma $\times$ age			0.000112 (0.00135)	0.000906 (0.00137)	0.00117 (0.00137)	0.00119 (0.00137)	0.00117 (0.00137)			0.000709 (0.00161)	0.00164 (0.00163)	0.00137 (0.00163)	0.00142 (0.00163)	0.00148 (0.00163)
Father has High School Diploma			-0.0308 (0.0610)	-0.00413 (0.0615)	-0.0515 (0.0612)	-0.0472 (0.0612)	-0.0427 (0.0614)			-0.0164 (0.0804)	0.0153 (0.0813)	-0.0205 (0.0805)	-0.0133 (0.0806)	-0.00402 (0.0808)
Father has High School Diploma $\times$ age			0.00142 (0.00144)	0.000718 (0.00146)	0.00173 (0.00146)	0.00160 (0.00146)	0.00154 (0.00146)			0.00125 (0.00180)	0.000466 (0.00183)	0.00124 (0.00182)	0.00103 (0.00182)	0.000861 (0.00183)
Siblings in Education Age				-0.0375 (0.0517)	0.0229 (0.0513)	0.0181 (0.0515)	0.0483 (0.0537)				-0.0672 (0.0646)	-0.0145 (0.0650)	-0.0221 (0.0650)	0.0151 (0.0670)
Siblings in Education Age $\times$ age				0.00288** (0.00126)	0.00199 (0.00127)	0.00216* (0.00127)	0.000648 (0.00134)				0.00366** (0.00143)	0.00269* (0.00145)	0.00292** (0.00145)	0.00121 (0.00153)
Born in Southern Italy						0.0651 (0.107)	0.0463 (0.107)						0.164 (0.123)	0.140 (0.124)
Born in Southern Italy $\times$ age						-0.00243 (0.00234)	-0.00206 (0.00235)						-0.00441* (0.00268)	-0.00393 (0.00268)
Constant	-1.492*** (0.0915)	-1.557*** (0.0977)	-1.515*** (0.103)	-1.427*** (0.111)	-1.260*** (0.158)	-1.268*** (0.158)	-1.027*** (0.203)	-1.603*** (0.134)	-1.728*** (0.139)	-1.664*** (0.144)	-1.544*** (0.147)	-1.385*** (0.209)	-1.404*** (0.210)	-1.131*** (0.241)
Observations R <sup>2</sup>	3,307	3,307	3,307	3,307	3,307	3,307	3,307	2,881	2,881	2,881	2,881	2,881	2,881	2,881
Years of Schooling	0.527	0.528 X	0.529 X	0.555 X	0.574 X	0.574 x	0.580 X	0.238	0.200 X	0.205 X	0.270 x	0.507 x	0.309 X	0.510 X
Parents' Educational Attainment		~	x	x	x	x	x		~	x	x	x	x	x
Presence of Siblings in Education Age				х	х	x	x				х	х	x	х
Regional Controls					х	x	х					х	х	х
Municipality Size					х	х	х					х	х	х
Born in Southern Italy						х	х						х	х
Current Marital Status							x							x
Household Size							х							х

(a) 20-65 age cohort, all male individuals

Table A.10: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education. Omitted education type is vocational. Wave of analysis: *2010*. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

(b) 25–65 age cohort, all male individuals

	(a) <i>20–65</i>	age coho	ort, all me	ile indivia		(b) 25–65 age cohort, all male individuals								
emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.123*** (0.00416)	0.122*** (0.00418)	0.120*** (0.00434)	0.109*** (0.00495)	0.105*** (0.00556)	0.105*** (0.00556)	0.100*** (0.00714)	0.126*** (0.00595)	0.126*** (0.00596)	0.123*** (0.00622)	0.111*** (0.00652)	0.105*** (0.00731)	0.105*** (0.00730)	0.0972*** (0.00826)
(age) <sup>2</sup>	-0.00145*** (4.82e-05)	-0.00144*** (4.84e-05)	-0.00142*** (4.93e-05)	-0.00134*** (5.33e-05)	-0.00129*** (5.32e-05)	-0.00129*** (5.34e-05)	-0.00125*** (6.93e-05)	-0.00148*** (6.48e-05)	-0.00148*** (6.48e-05)	-0.00145*** (6.64e-05)	-0.00136*** (6.83e-05)	-0.00132*** (6.71e-05)	-0.00132*** (6.74e-05)	-0.00125*** (7.86e-05)
General Education	-0.695*** (0.139)	-0.684*** (0.139)	-0.616*** (0.145)	-0.587*** (0.145)	-0.603*** (0.146)	-0.615*** (0.146)	-0.670*** (0.145)	-0.946*** (0.261)	-0.966*** (0.260)	-0.908*** (0.265)	-0.855*** (0.264)	-0.762*** (0.253)	-0.776*** (0.253)	-0.811*** (0.252)
General Education $\times$ age	0.0179** (0.00743)	0.0170** (0.00748)	0.0148* (0.00759)	0.0136* (0.00758)	0.0151** (0.00760)	0.0157** (0.00761)	0.0186** (0.00755)	0.0295** (0.0121)	0.0297** (0.0120)	0.0281** (0.0122)	0.0256** (0.0121)	0.0223* (0.0117)	0.0231** (0.0117)	0.0251** (0.0116)
General Education $\times age^2$	-6.19e-05 (9.28e-05)	-5.39e-05 (9.32e-05)	-3.95e-05 (9.37e-05)	-2.63e-05 (9.35e-05)	-5.13e-05 (9.33e-05)	-5.70e-05 (9.35e-05)	-9.21e-05 (9.27e-05)	-0.000189 (0.000136)	-0.000193 (0.000136)	-0.000184 (0.000136)	-0.000158 (0.000136)	-0.000131 (0.000132)	-0.000138 (0.000132)	-0.000164 (0.000131)
Other Education	-1.035** (0.478)	-1.040** (0.483)	-0.988* (0.512)	-1.053** (0.529)	-1.479** (0.690)	-1.567** (0.695)	-1.553** (0.691)	-2.285 (2.764)	-2.481 (2.786)	-2.483 (2.735)	-3.187 (2.766)	-4.391 (2.765)	-4.604* (2.693)	-4.737* (2.570)
Other Education $\times$ age	0.0366 (0.0274)	0.0367 (0.0276)	0.0343 (0.0286)	0.0377 (0.0291)	0.0522 (0.0344)	0.0573* (0.0345)	0.0543 (0.0341)	0.0864 (0.110)	0.0942 (0.111)	0.0940 (0.109)	0.123 (0.110)	0.169 (0.111)	0.180* (0.108)	0.183* (0.103)
Other Education $\times age^2$	-0.000374 (0.000337)	(0.000340)	-0.000350 (0.000349)	-0.000389 (0.000352)	-0.000512 (0.000398)	-0.000572 (0.000398)	-0.000517 (0.000393)	-0.000859 (0.00107)	-0.000936 (0.00108)	-0.000931 (0.00106)	-0.00122 (0.00107)	-0.00166 (0.00108)	-0.00178* (0.00106)	-0.00178*
Years of Schooling		(0.00392)	(0.00305)	(0.00302)	(0.00303)	(0.00304)	(0.00302)		0.00685** (0.00300)	(0.00715**	0.00740** (0.00304)	0.00785** (0.00305)	0.00732** (0.00306)	0.00722** (0.00305)
Mother has High School Diploma			-0.118** (0.0571)	-0.148*** (0.0573)	-0.145*** (0.0561)	-0.145*** (0.0562)	-0.139** (0.0561)			-0.0875 (0.0756)	-0.124 (0.0753)	-0.109 (0.0736)	-0.109 (0.0735)	-0.108 (0.0735)
Mother has High School Diploma $\times$ age			(0.00134)	(0.00135)	(0.00133)	(0.00133)	(0.00133)			(0.00146)	(0.00240	(0.00194	(0.00163)	(0.00192
Father has High School Diploma			(0.0598)	(0.0255)	-0.00438 (0.0601)	(0.0602)	(0.0600)			-0.0358 (0.0816)	(0.0815)	(0.0796)	(0.0798)	(0.0796)
Father has High School Diploma $\times$ age			(0.00139)	-0.000194 (0.00140)	(0.00140)	(0.00140)	(0.00191 (0.00140)			(0.00178)	(0.00179)	(0.00175)	(0.00176)	-0.000146 (0.00175)
Siblings in Education Age				(0.0514)	(0.0508)	(0.0509)	(0.0528)				(0.0659)	(0.0648)	-0.138** (0.0649)	-0.103 (0.0666)
Siblings in Education Age $\times$ age				(0.00124)	(0.00123)	(0.00124)	(0.00131)				(0.00142)	(0.00142)	(0.00143)	(0.00342**
Born in Southern Italy						(0.114)	(0.113)						(0.123)	(0.123)
Born in Southern Italy $\times$ age	-1 617***	-1 662***	-1 507***	-1 308***	-1 203***	(0.00245)	(0.00244)	1 700***	1 701***	1 700***	1 452***	1 108***	(0.00264)	(0.00263)
Constant	(0.0869)	(0.0923)	(0.0974)	(0.112)	(0.165)	(0.165)	(0.201)	(0.134)	(0.137)	(0.145)	(0.152)	(0.223)	(0.223)	(0.240)
Observations	3,353	3,353	3,353	3,353	3,353	3,353	3,353	2,888	2,888	2,888	2,888	2,888	2,888	2,888
K <sup>2</sup> Years of Schooling	0.345	0.345 x	0.348 x	0.354 x	0.392 x	0.392 x	0.401 x	0.262	0.264 x	0.266 x	0.275 x	0.320 x	0.322 x	0.332 x
Parents' Educational Attainment			x	x	x	x	x			x	x	x	x	x
Presence of Siblings in Education Age				х	х	х	х				х	х	х	х
Regional Controls					х	х	х					х	х	х
Municipality Size					х	x	x					х	x	x
Current Marital Status						А	x						A	x
Household Size							x							x

Table A.11: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education. Omitted education type is vocational. Wave of analysis: 2012. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.115*** (0.00450)	0.114*** (0.00451)	0.109*** (0.00471)	0.0976*** (0.00534)	0.0970*** (0.00576)	0.0973*** (0.00576)	0.100*** (0.00712)	0.115*** (0.00663)	0.115*** (0.00664)	0.108*** (0.00682)	0.0944*** (0.00717)	0.0944*** (0.00766)	0.0947*** (0.00766)	0.0963*** (0.00886)
(age) <sup>2</sup>	-0.00132*** (5.29e-05)	-0.00131*** (5.30e-05)	-0.00127*** (5.43e-05)	-0.00117*** (5.86e-05)	-0.00116*** (5.76e-05)	-0.00116*** (5.78e-05)	-0.00120*** (6.92e-05)	-0.00132*** (7.26e-05)	-0.00132*** (7.26e-05)	-0.00126*** (7.37e-05)	-0.00115*** (7.61e-05)	-0.00113*** (7.38e-05)	-0.00113*** (7.38e-05)	-0.00116*** (8.44e-05)
General Education	-0.426*** (0.147)	-0.393*** (0.149)	-0.249 (0.152)	-0.236 (0.151)	-0.230 (0.152)	-0.245 (0.152)	-0.287* (0.152)	-0.614** (0.274)	-0.640** (0.273)	-0.492* (0.273)	-0.431 (0.271)	-0.374 (0.269)	-0.390 (0.269)	-0.471* (0.269)
General Education $\times$ age	0.00521 (0.00787)	0.00278 (0.00796)	-0.00239 (0.00798)	-0.00312 (0.00793)	-0.00319 (0.00799)	-0.00235 (0.00798)	0.000121 (0.00795)	0.0139 (0.0127)	0.0136 (0.0127)	0.00863 (0.0126)	0.00574 (0.0125)	0.00323	0.00410 (0.0125)	0.00836 (0.0125)
General Education $\times age^2$	8.52e-05 (9.71e-05)	0.000109 (9.78e-05)	0.000150 (9.72e-05)	0.000158 (9.66e-05)	0.000155 (9.73e-05)	0.000147 (9.72e-05)	0.000117 (9.69e-05)	-7.70e-06 (0.000143)	-7.72e-06 (0.000142)	2.84e-05 (0.000141)	6.02e-05 (0.000140)	8.40e-05 (0.000140)	7.55e-05 (0.000140)	2.66e-05 (0.000140)
Other Education	0.327 (0.925)	0.303 (0.943)	0.244 (0.902)	0.144 (0.931)	-0.0683 (0.940)	-0.157 (0.941)	-0.115 (0.939)	-0.485 (1.134)	-0.477 (1.142)	-0.627 (1.169)	-1.068 (1.078)	-1.241 (1.249)	-1.357 (1.240)	-1.384 (1.246)
Other Education $\times$ age	-0.00898 (0.0413)	-0.00813 (0.0421)	-0.00601 (0.0405)	-0.00333 (0.0417)	0.00576 (0.0419)	0.0106 (0.0419)	0.00737 (0.0419)	0.0250 (0.0497)	0.0245 (0.0501)	0.0302 (0.0510)	0.0470 (0.0476)	0.0546 (0.0542)	0.0606 (0.0538)	0.0604 (0.0540)
Other Education $\times age^2$	4.50e-05 (0.000445)	3.45e-05 (0.000453)	1.56e-05 (0.000438)	-1.43e-06 (0.000450)	-0.000101 (0.000451)	-0.000156 (0.000452)	-0.000108 (0.000453)	-0.000297 (0.000523)	-0.000294 (0.000528)	-0.000349 (0.000536)	-0.000506 (0.000505)	-0.000592 (0.000567)	-0.000658 (0.000564)	-0.000641 (0.000566)
Years of Schooling		0.00799** (0.00317)	0.00832*** (0.00322)	0.00812** (0.00321)	0.0108*** (0.00318)	0.00982*** (0.00318)	0.00921*** (0.00321)		0.0117*** (0.00320)	0.0122*** (0.00327)	0.0119*** (0.00325)	0.0143*** (0.00321)	0.0134*** (0.00321)	0.0126*** (0.00324)
Mother has High School Diploma			-0.223*** (0.0627)	-0.240*** (0.0624)	-0.229*** (0.0604)	-0.233*** (0.0604)	-0.249*** (0.0605)			-0.336*** (0.0886)	-0.351*** (0.0875)	-0.316*** (0.0852)	-0.321*** (0.0853)	-0.339*** (0.0855)
Mother has High School Diploma $\times$ age			0.00531*** (0.00145)	0.00581*** (0.00145)	0.00561*** (0.00142)	0.00566*** (0.00142)	0.00604*** (0.00142)			0.00755*** (0.00192)	0.00794*** (0.00190)	0.00730*** (0.00187)	0.00736*** (0.00187)	0.00779*** (0.00187)
Father has High School Diploma			-0.0315 (0.0622)	-0.00912 (0.0623)	-0.0387 (0.0621)	-0.0378 (0.0621)	-0.0238 (0.0621)			0.0316 (0.0876)	0.0518 (0.0868)	0.0172 (0.0851)	0.0119 (0.0852)	0.0265 (0.0855)
Father has High School Diploma $\times$ age			0.000631 (0.00142)	9.82e-05 (0.00142)	0.000609 (0.00143)	0.000548 (0.00143)	0.000265 (0.00143)			-0.000711 (0.00188)	-0.00116 (0.00187)	-0.000528 (0.00185)	-0.000470 (0.00185)	-0.000757 (0.00185)
Siblings in Education Age				-0.159*** (0.0541)	-0.0838 (0.0542)	-0.0908* (0.0541)	-0.0252 (0.0578)				-0.250*** (0.0713)	-0.164** (0.0709)	-0.174** (0.0709)	-0.108 (0.0745)
Siblings in Education Age $\times$ age				0.00423*** (0.00131)	0.00294** (0.00131)	0.00322** (0.00131)	0.00132 (0.00142)				0.00576*** (0.00156)	0.00408*** (0.00157)	0.00442*** (0.00157)	0.00247 (0.00169)
Born in Southern Italy						0.174 (0.107)	0.177* (0.107)						0.155 (0.133)	0.165 (0.134)
Born in Southern Italy $\times$ age						-0.00392* (0.00226)	-0.00406* (0.00227)						-0.00358 (0.00275)	-0.00385 (0.00278)
Constant	-1.540*** (0.0918)	-1.634*** (0.0980)	-1.500*** (0.104)	-1.245*** (0.119)	-1.271*** (0.162)	-1.273*** (0.161)	-1.163*** (0.201)	-1.554*** (0.148)	-1.707*** (0.152)	-1.515*** (0.157)	-1.191*** (0.165)	-1.254*** (0.224)	-1.258*** (0.224)	-1.128*** (0.258)
Observations p <sup>2</sup>	3,195	3,195	3,195	3,195	3,195	3,195	3,195	2,745	2,745	2,745	2,745	2,745	2,745	2,745
Vears of Schooling	0.290	0.297 X	0.502	0.509	0.550	0.555	0.501	0.197	0.200	0.208	0.218	0.205	0.200	0.277
Parents' Educational Attainment	~	x	x	x	x	x			~	x	x	x	x	x
Presence of Siblings in Education Age		A	x	x	x	x				~	x	x	x	x
Regional Controls			~	x	x	x					*	x	x	x
Municipality Size				x	x	x						x	x	x
Born in Southern Italy					x	x							x	x
Current Marital Status						x								х
Household Size						x								х

(a) 20-65 age cohort, all male individuals

Table A.12: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education. Omitted education type is vocational. Wave of analysis: *2014*. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

(b) $25-65$ age cohort	all male	individuals

A.1. Effects over Life-Time Employment

(a) <i>20–65</i>	(a) 20–65 age cohort, male individuals without self-employed										(b) 25–65 age cohort, male individuals without self-employed								
emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)		(1)	(2)	(3)	(4)	(5)	(6)	(7)				
age	0.148*** (0.00429)	0.148*** (0.00429)	0.145*** (0.00437)	0.141*** (0.00482)	0.135*** (0.00546)	0.136*** (0.00546)	0.119*** (0.00798)	= =	0.150*** (0.00628)	0.150*** (0.00630)	0.145*** (0.00627)	0.143*** (0.00666)	0.129*** (0.00713)	0.129*** (0.00712)	0.113*** (0.00890)				
(age) <sup>2</sup>	-0.00184*** (5.16e-05)	-0.00184*** (5.17e-05)	-0.00181*** (5.19e-05)	-0.00180*** (5.22e-05)	-0.00180*** (5.13e-05)	-0.00180*** (5.14e-05)	-0.00164*** (7.89e-05)		-0.00185*** (7.03e-05)	-0.00185*** (7.04e-05)	-0.00181*** (6.98e-05)	-0.00179*** (7.04e-05)	-0.00173*** (6.81e-05)	-0.00173*** (6.81e-05)	-0.00157*** (8.69e-05)				
General Education	-0.732***	-0.734*** (0.153)	-0.578*** (0.155)	-0.576***	-0.618*** (0.163)	-0.610***	-0.676*** (0.161)		-1.803***	-1.826***	-1.723***	-1.744***	-1.875***	-1.858***	-1.855***				
General Education $\times$ age	0.0182** (0.00871)	0.0183** (0.00875)	0.0125	0.0125	0.0141 (0.00910)	0.0135 (0.00915)	0.0177**		0.0690*** (0.0130)	0.0695*** (0.0129)	0.0662*** (0.0130)	0.0671*** (0.0129)	0.0731*** (0.0134)	0.0721*** (0.0135)	0.0726*** (0.0134)				
General Education $\times age^2$	-7.06e-05 (0.000114)	-7.15e-05 (0.000114)	-1.99e-05 (0.000115)	-2.10e-05 (0.000114)	-3.35e-05 (0.000117)	-2.37e-05 (0.000118)	-7.97e-05 (0.000116)		-0.000631*** (0.000153)	-0.000642*** (0.000151)	-0.000615*** (0.000152)	-0.000628*** (0.000151)	-0.000689*** (0.000156)	-0.000676*** (0.000158)	-0.000688*** (0.000157)				
Other Education	0.816 (0.667)	0.815 (0.668)	0.806 (0.651)	0.820 (0.644)	0.652 (0.709)	0.680 (0.711)	0.686 (0.707)		0.122 (1.157)	0.117 (1.148)	0.109 (1.121)	0.139 (1.108)	-0.381 (1.109)	-0.353 (1.105)	-0.149 (1.104)				
Other Education $\times$ age	-0.0488 (0.0349)	-0.0486 (0.0350)	-0.0493 (0.0343)	-0.0500 (0.0337)	-0.0387 (0.0365)	-0.0398 (0.0366)	-0.0406 (0.0364)		-0.0197 (0.0542)	-0.0201 (0.0539)	-0.0206 (0.0529)	-0.0217 (0.0524)	0.00671 (0.0529)	0.00550 (0.0527)	-0.00438 (0.0523)				
Other Education $\times age^2$	0.000670 (0.000439)	0.000669 (0.000440)	0.000687 (0.000432)	0.000694 (0.000422)	0.000529 (0.000451)	0.000538 (0.000450)	0.000563 (0.000446)		0.000379 (0.000620)	0.000386 (0.000618)	0.000400 (0.000608)	0.000409 (0.000602)	4.08e-05 (0.000611)	5.31e-05 (0.000609)	0.000178 (0.000599)				
Years of Schooling		-0.00142 (0.00569)	0.00137 (0.00579)	0.00207 (0.00583)	0.00335 (0.00576)	0.00299 (0.00576)	0.00403 (0.00569)			0.0118** (0.00565)	0.0136** (0.00573)	0.0151*** (0.00579)	0.0150*** (0.00569)	0.0146** (0.00570)	0.0147*** (0.00567)				
Mother has High School Diploma			-0.309*** (0.0658)	-0.321*** (0.0658)	-0.263*** (0.0668)	-0.262*** (0.0668)	-0.265*** (0.0666)				-0.351*** (0.0983)	-0.348*** (0.0990)	-0.330*** (0.0974)	-0.330*** (0.0974)	-0.339*** (0.0974)				
Mother has High School Diploma $\times$ age			0.00671*** (0.00175)	0.00700*** (0.00174)	0.00553*** (0.00175)	0.00553*** (0.00175)	0.00572*** (0.00175)	z			0.00771*** (0.00229)	0.00761*** (0.00230)	0.00689*** (0.00230)	0.00689*** (0.00230)	0.00723*** (0.00231)				
Father has High School Diploma			0.0183 (0.0634)	0.0265 (0.0638)	0.0492 (0.0645)	0.0508 (0.0647)	0.0621 (0.0641)				0.0372 (0.0933)	0.0260 (0.0940)	0.100 (0.0942)	0.103 (0.0946)	0.137 (0.0944)				
Father has High School Diploma $\times$ age			-0.000967 (0.00156)	-0.00117 (0.00158)	-0.00155 (0.00161)	-0.00158 (0.00162)	-0.00191 (0.00160)				-0.00148 (0.00209)	-0.00127 (0.00211)	-0.00261 (0.00214)	-0.00265 (0.00216)	-0.00350 (0.00215)				
Siblings in Education Age				-0.0731 (0.0614)	0.00344 (0.0613)	-0.00130 (0.0615)	-0.0284 (0.0619)					0.0573 (0.0811)	0.131* (0.0791)	0.126 (0.0799)	0.0923 (0.0801)				
Siblings in Education Age $\times$ age				0.00322* (0.00169)	0.00201 (0.00167)	0.00215 (0.00168)	0.00166 (0.00166)					0.000698 (0.00197)	-0.000573 (0.00194)	-0.000421 (0.00196)	-0.000684 (0.00193)				
Born in Southern Italy						0.108 (0.0969)	0.110 (0.0974)							0.0809 (0.119)	0.0870 (0.121)				
Born in Southern Italy $\times$ age						-0.00242 (0.00228)	-0.00249 (0.00230)							-0.00177 (0.00271)	-0.00192 (0.00277)				
Constant	-1.983*** (0.0864)	-1.965*** (0.110)	-1.895*** (0.113)	-1.833*** (0.124)	-1.605*** (0.166)	-1.608*** (0.166)	-1.205*** (0.213)		-2.017*** (0.137)	-2.168*** (0.148)	-2.065*** (0.149)	-2.087*** (0.162)	-1.594*** (0.205)	-1.594*** (0.205)	-1.197*** (0.241)				
Observations	2,517	2,517	2,517	2,517	2,517	2,517	2,517		2,001	2,001	2,001	2,001	2,001	2,001	2,001				
K <sup>2</sup> Vears of Schooling	0.407	0.407	0.416	0.417	0.465	0.466	0.476		0.373	0.375	0.382	0.380	0.442	0.442	0.455				
Parents' Educational Attainment		~	x	x	x	x	x			~	x	x	x	x	x				
Presence of Siblings in Education Age				x	х	х	х					x	х	х	х				
Regional Controls					x	х	x						х	х	х				
Municipality Size					х	х	х						х	х	х				
Born in Southern Italy						х	x							х	x				
Household Size							x								x				
Trousenoid bize							Λ								A				

Table A.13: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education, excluding self-employed individuals. Omitted education type is vocational. Wave of analysis: 2000. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.
emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.146*** (0.00447)	0.146*** (0.00447)	0.141*** (0.00460)	0.139*** (0.00505)	0.130*** (0.00562)	0.130*** (0.00563)	0.109*** (0.00834)	0.148*** (0.00646)	0.148*** (0.00646)	0.144*** (0.00652)	0.142*** (0.00699)	0.130*** (0.00734)	0.130*** (0.00733)	0.105*** (0.00920)
(age) <sup>2</sup>	-0.00179*** (5.28e-05)	-0.00179*** (5.28e-05)	-0.00175*** (5.36e-05)	-0.00175*** (5.40e-05)	-0.00172*** (5.38e-05)	-0.00172*** (5.41e-05)	-0.00153*** (8.10e-05)	-0.00181*** (7.11e-05)	-0.00181*** (7.11e-05)	-0.00179*** (7.14e-05)	-0.00177*** (7.24e-05)	-0.00171*** (7.15e-05)	-0.00171*** (7.18e-05)	-0.00147*** (8.97e-05)
General Education	-0.389** (0.169)	-0.395** (0.170)	-0.239 (0.175)	-0.232 (0.177)	-0.318* (0.184)	-0.318* (0.184)	-0.382** (0.181)	-1.059*** (0.310)	-1.070*** (0.310)	-0.908*** (0.314)	-0.892*** (0.317)	-1.151*** (0.321)	-1.149*** (0.322)	-1.131*** (0.321)
General Education $\times$ age	-0.000315 (0.00974)	9.34e-05 (0.00980)	-0.00528 (0.0100)	-0.00572 (0.0101)	-0.000802 (0.0104)	-0.000832 (0.0105)	0.00296 (0.0103)	0.0314** (0.0149)	0.0315** (0.0149)	0.0265* (0.0150)	0.0255* (0.0152)	0.0388** (0.0155)	0.0386** (0.0156)	0.0383** (0.0155)
General Education $\times age^2$	0.000183 (0.000127)	0.000179 (0.000128)	0.000219* (0.000131)	0.000224* (0.000132)	0.000161 (0.000136)	0.000162 (0.000136)	0.000114 (0.000134)	-0.000167 (0.000174)	-0.000171 (0.000173)	-0.000140 (0.000175)	-0.000127 (0.000177)	-0.000285 (0.000182)	-0.000282 (0.000183)	-0.000283 (0.000182)
Other Education	-0.396 (0.658)	-0.403 (0.659)	-0.492 (0.645)	-0.490 (0.648)	-0.301 (0.736)	-0.300 (0.737)	-0.436 (0.721)	-1.263 (0.983)	-1.232 (0.988)	-1.313 (0.941)	-1.313 (0.984)	-2.012** (0.997)	-1.957** (0.983)	-1.997** (0.963)
Other Education $\times$ age	0.0174 (0.0352)	0.0179 (0.0353)	0.0231 (0.0347)	0.0231 (0.0350)	0.0166 (0.0400)	0.0165 (0.0400)	0.0254 (0.0388)	0.0590 (0.0456)	0.0572 (0.0457)	0.0624 (0.0439)	0.0626 (0.0460)	0.0986** (0.0477)	0.0961** (0.0471)	0.100** (0.0461)
Other Education $\times age^2$	-0.000174 (0.000450)	-0.000179 (0.000451)	-0.000251 (0.000445)	-0.000250 (0.000450)	-0.000206 (0.000519)	-0.000205 (0.000520)	-0.000324 (0.000500)	-0.000649 (0.000524)	-0.000630 (0.000525)	-0.000706 (0.000506)	-0.000704 (0.000532)	-0.00114** (0.000560)	-0.00112** (0.000555)	-0.00118** (0.000542)
Years of Schooling		-0.00269 (0.00543)	-0.000355 (0.00553)	-0.000264 (0.00554)	0.000166 (0.00547)	-2.26e-06 (0.00549)	0.00105 (0.00543)		0.00732 (0.00550)	0.00976* (0.00561)	0.00978* (0.00563)	0.00919* (0.00547)	0.00900 (0.00549)	0.00935* (0.00546)
Mother has High School Diploma			-0.149** (0.0669)	-0.155** (0.0675)	-0.137** (0.0693)	-0.137** (0.0695)	-0.143** (0.0696)			-0.227** (0.100)	-0.231** (0.101)	-0.238** (0.101)	-0.237** (0.101)	-0.240** (0.0997)
Mother has High School Diploma $\times$ age			0.00300* (0.00173)	0.00319* (0.00174)	0.00264 (0.00179)	0.00261 (0.00180)	0.00273 (0.00182)			0.00447** (0.00228)	0.00457** (0.00229)	0.00442* (0.00233)	0.00441* (0.00234)	0.00447* (0.00235)
Father has High School Diploma			-0.174*** (0.0663)	-0.171** (0.0675)	-0.152** (0.0696)	-0.154** (0.0697)	-0.143** (0.0697)			-0.169* (0.0981)	-0.170* (0.0984)	-0.138 (0.0970)	-0.137 (0.0974)	-0.113 (0.0970)
Father has High School Diploma $\times$ age			0.00402** (0.00164)	0.00391** (0.00167)	0.00361** (0.00172)	0.00364** (0.00172)	0.00337* (0.00173)			0.00394* (0.00219)	0.00394* (0.00221)	0.00354 (0.00221)	0.00352 (0.00221)	0.00295 (0.00223)
Siblings in Education Age				-0.0119 (0.0647)	0.0754 (0.0644)	0.0761 (0.0646)	0.0755 (0.0648)				0.0686 (0.0826)	0.150* (0.0798)	0.150* (0.0801)	0.120 (0.0801)
Siblings in Education Age $\times$ age				0.00167 (0.00172)	4.36e-06 (0.00173)	-5.19e-06 (0.00173)	-0.00122 (0.00173)				0.000395 (0.00203)	-0.00116 (0.00200)	-0.00111 (0.00200)	-0.00165 (0.00199)
Born in Southern Italy						-0.00257 (0.116)	-0.0228 (0.114)						0.0920 (0.133)	0.0703 (0.132)
Born in Southern Italy $\times$ age						7.88e-05 (0.00262)	0.000499 (0.00257)						-0.00185 (0.00298)	-0.00139 (0.00294)
Constant	-1.960*** (0.0910)	-1.926*** (0.114)	-1.821*** (0.117)	-1.803*** (0.132)	-1.450*** (0.167)	-1.449*** (0.166)	-0.832*** (0.222)	-2.009*** (0.143)	-2.105*** (0.154)	-2.016*** (0.156)	-2.023*** (0.172)	-1.593*** (0.204)	-1.593*** (0.204)	-0.892*** (0.245)
Observations	2,386	2,386	2,386	2,386	2,386	2,386	2,386	1,910	1,910	1,910	1,910	1,910	1,910	1,910
$R^2$	0.384	0.384	0.391	0.392	0.441	0.441	0.454	0.338	0.339	0.346	0.349	0.410	0.411	0.425
Years of Schooling		х	х	х	х	х	х		х	х	х	х	х	х
Parents' Educational Attainment			х	х	х	х	х			х	х	х	х	х
Presence of Siblings in Education Age				х	х	х	х				х	х	х	х
Regional Controls					х	х	х					х	х	х
Municipality Size					х	х	х					х	х	х
Born in Southern Italy						х	x						х	x
Current Marital Status							х							х
Household Size							х							х

Table A.14: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Wave of analysis: 2002. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*1% \*\*5% \*10%.

(a) 20–65 age cohort, male individuals without self-employed (b) 25–65 age cohort, male individuals without self-employed

(a) <i>20–65</i>	age coho	ort, male i	ndividual	s without	self-empl	loyed			(b) 25-	-65 age c	ohort, all	male indi	viduals	
emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.142*** (0.00447)	0.142*** (0.00447)	0.137*** (0.00465)	0.133*** (0.00504)	0.125*** (0.00559)	0.125*** (0.00557)	0.104*** (0.00805)	0.147*** (0.00634)	0.147*** (0.00632)	0.144*** (0.00645)	0.140*** (0.00686)	0.131*** (0.00727)	0.132*** (0.00726)	0.106*** (0.00869)
(age) <sup>2</sup>	-0.00175*** (5.22e-05)	-0.00175*** (5.22e-05)	-0.00171*** (5.32e-05)	-0.00169*** (5.37e-05)	-0.00170*** (5.35e-05)	-0.00169*** (5.36e-05)	-0.00150*** (7.80e-05)	-0.00180*** (6.94e-05)	-0.00180*** (6.92e-05)	-0.00178*** (6.98e-05)	-0.00175*** (7.09e-05)	-0.00176*** (7.13e-05)	-0.00176*** (7.14e-05)	-0.00152*** (8.51e-05)
General Education	-0.561*** (0.178)	-0.566*** (0.178)	-0.4/3*** (0.181)	-0.4/4*** (0.181)	-0.454** (0.184)	-0.441** (0.184)	-0.500*** (0.181)	-0.90/***	-0.90/*** (0.316)	-0.866*** (0.318)	-0.846**** (0.318)	-0.7/6** (0.323)	-0.767** (0.323)	-0.801** (0.319)
General Education $\times$ age	0.00940 (0.00985)	0.00977 (0.00989)	0.00728 (0.0100)	0.00742 (0.0100)	0.00662 (0.0101)	0.00573 (0.0101)	0.00941 (0.00998)	0.0261* (0.0150)	0.0260* (0.0150)	0.0252* (0.0151)	0.0243 (0.0151)	0.0214 (0.0154)	0.0208 (0.0154)	0.0232 (0.0152)
General Education $\times age^2$	5.59e-05 (0.000126)	5.33e-05 (0.000127)	6.13e-05 (0.000129)	5.74e-05 (0.000129)	6.62e-05 (0.000130)	7.96e-05 (0.000130)	3.10e-05 (0.000128)	-0.000131 (0.000174)	-0.000131 (0.000173)	-0.000133 (0.000175)	-0.000125 (0.000175)	-9.49e-05 (0.000180)	-8.59e-05 (0.000179)	-0.000121 (0.000178)
Other Education	-0.276 (0.522)	-0.283 (0.522)	-0.428 (0.518)	-0.399 (0.525) 0.0176	-0.424 (0.607) 0.0209	-0.415 (0.607)	-0.556 (0.605) 0.0273	0.225 (1.025) 0.0124	(1.026)	(1.070) 0.00750	(1.135) 0.00067	-0.361 (1.005) 0.0170	-0.350 (1.013) 0.0162	-0.780 (1.041) 0.0363
Other Education $\times$ age	(0.0236)	(0.0236)	(0.0235)	(0.0236)	(0.0279)	(0.0280)	(0.0273)	(0.0429)	(0.0429)	(0.0447)	(0.0476)	(0.0434)	(0.0437)	(0.0443)
Other Education $\times age^2$	-9.11e-05 (0.000268)	-9./2e-05 (0.000268)	-0.000198 (0.000268)	-0.000177 (0.000267)	-0.000230 (0.000321)	-0.000216 (0.000322)	-0.000315 (0.000308)	0.000162 (0.000439)	0.000168 (0.000439)	9.80e-05 (0.000457)	0.000122 (0.000486)	-0.000183 (0.000460)	-0.000172 (0.000464)	-0.000408 (0.000460)
Years of Schooling		-0.00271 (0.00507)	-0.000981 (0.00529)	-0.000399 (0.00530)	0.000138 (0.00519)	0.000390 (0.00519)	0.00180 (0.00512)		0.00315 (0.00519)	0.00364 (0.00544)	0.00403 (0.00546)	0.00461 (0.00531)	0.00477 (0.00531)	0.00585 (0.00526)
Mother has High School Diploma			-0.0704 (0.0672)	-0.0912 (0.0673)	-0.0730 (0.0668)	-0.0761 (0.0669)	-0.0825 (0.0669)			-0.0269 (0.0932)	-0.0346 (0.0941)	-0.00548 (0.0925)	-0.00978 (0.0925)	-0.0269 (0.0915)
Mother has High School Diploma $\times$ age			0.000705 (0.00175)	0.00131 (0.00175)	0.00109 (0.00173)	0.00120 (0.00174)	0.00130 (0.00174)			-0.000105 (0.00218)	0.000160 (0.00219)	-0.000304 (0.00217)	-0.000175 (0.00217)	0.000179 (0.00216)
Father has High School Diploma			-0.225**** (0.0673)	-0.214*** (0.0679)	-0.1/1** (0.0672)	-0.1/0** (0.0671)	-0.158** (0.0668)			-0.144 (0.0938)	-0.140 (0.0941)	-0.0365 (0.0904)	-0.0324 (0.0901)	-0.0103 (0.0899)
Father has High School Diploma $\times$ age			0.00554*** (0.00170)	0.00527*** (0.00172)	0.00436** (0.00171)	0.00429** (0.00171)	0.00410** (0.00170)			0.00374* (0.00218)	0.00363* (0.00219)	0.00145 (0.00215)	0.00134 (0.00214)	0.000892 (0.00214)
Siblings in Education Age				-0.0302 (0.0659)	0.0389 (0.0658)	0.0248 (0.0652)	0.0213 (0.0653)				0.0675 (0.0837)	0.180** (0.0805)	0.168** (0.0800)	0.143* (0.0794)
Siblings in Education Age $\times$ age				(0.00182)	(0.00157 (0.00184)	(0.00199 (0.00181)	(0.00179)				(0.00209)	(0.00206)	(0.00203)	-0.00183 (0.00199)
Born in Southern Italy						(0.122)	(0.121)						(0.134)	(0.132)
Born in Southern Italy $\times$ age						(0.00273)	(0.00271)						(0.00259)	(0.00204)
Constant	-1.890*** (0.0926)	-1.856*** (0.111)	-1.734*** (0.117)	-1.687*** (0.129)	-1.337*** (0.166)	-1.353*** (0.166)	-0.755*** (0.215)	-1.985*** (0.141)	-2.029*** (0.151)	-1.967*** (0.156)	-1.958*** (0.170)	-1.544*** (0.204)	-1.560*** (0.204)	-0.847*** (0.231)
Observations	2,456	2,456	2,456	2,456	2,456	2,456	2,456	2,016	2,016	2,016	2,016	2,016	2,016	2,016
R <sup>2</sup> Years of Schooling	0.371	0.371 x	0.378 x	0.382 x	0.432 x	0.433 x	0.444 x	0.331	0.331 X	0.333 X	0.338 X	0.402 x	0.403 X	0.418 X
Parents' Educational Attainment			x	x	x	x	x			x	x	x	x	x
Presence of Siblings in Education Age				x	x	х	х				х	х	х	х
Regional Controls					x	x	x					x	x	x
Nunicipality Size					х	x	x					х	x	x
Current Marital Status						А	x						Λ.	X
Household Size							х							х

Table A.15: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education, excluding self-employed individuals. Omitted education type is vocational. Wave of analysis: 2004. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.127*** (0.00467)	0.127*** (0.00468)	0.122*** (0.00481)	0.120*** (0.00516)	0.106*** (0.00571)	0.106*** (0.00573)	0.0977*** (0.00750)	0.129*** (0.00623)	0.129*** (0.00623)	0.123*** (0.00626)	0.121*** (0.00656)	0.105*** (0.00689)	0.105*** (0.00690)	0.0925*** (0.00802)
(age) <sup>2</sup>	-0.00156*** (5.45e-05)	-0.00156*** (5.45e-05)	-0.00152*** (5.52e-05)	-0.00152*** (5.55e-05)	-0.00146*** (5.51e-05)	-0.00146*** (5.53e-05)	-0.00138*** (7.21e-05)	-0.00158*** (6.89e-05)	-0.00158*** (6.89e-05)	-0.00154*** (6.86e-05)	-0.00153*** (6.95e-05)	-0.00148*** (6.89e-05)	-0.00148*** (6.94e-05)	-0.00136*** (7.90e-05)
General Education	-1.078*** (0.155)	-1.0/9*** (0.156)	-0.891*** (0.161)	-0.884*** (0.161)	-1.011*** (0.167)	-1.011*** (0.168)	-1.059*** (0.166)	-1.042*** (0.285)	-1.053*** (0.284)	-0.899*** (0.289)	-0.895*** (0.289)	-0.951*** (0.280)	-0.937*** (0.279)	-0.989*** (0.277)
General Education $\times$ age	0.0395*** (0.00824)	0.0396*** (0.00832)	0.0330*** (0.00845)	0.0326*** (0.00845)	0.0385*** (0.00871)	0.0385*** (0.00872)	0.0416*** (0.00859)	0.0381*** (0.0132)	0.0381*** (0.0132)	0.0333** (0.0133)	0.0331** (0.0133)	0.0357*** (0.0131)	0.0353*** (0.0131)	0.0384*** (0.0130)
General Education $\times age^2$	-0.000331*** (0.000103)	-0.000332*** (0.000104)	-0.000283*** (0.000104)	-0.000279*** (0.000104)	-0.000346*** (0.000107)	-0.000347*** (0.000107)	-0.000384*** (0.000106)	-0.000317** (0.000149)	-0.000319** (0.000148)	-0.000291* (0.000149)	-0.000289* (0.000149)	-0.000321** (0.000148)	-0.000318** (0.000148)	-0.000356** (0.000147)
Other Education	0.809 (0.790)	0.809 (0.790)	0.776 (0.793)	0.785 (0.792)	1.306* (0.754)	1.338* (0.756)	1.139 (0.776)	1.763* (0.927)	1.719* (0.935)	1.653* (0.939)	1.625* (0.951)	1.682 (1.058)	1.805* (1.074)	1.357 (1.090)
Other Education $\times$ age	-0.0411 (0.0389)	-0.0411 (0.0389)	-0.0401 (0.0392)	-0.0403 (0.0391)	-0.0636* (0.0376)	-0.0656* (0.0377)	-0.0563 (0.0387)	-0.0835* (0.0454)	-0.0819* (0.0457)	-0.0795* (0.0458)	-0.0781* (0.0465)	-0.0807 (0.0512)	-0.0864* (0.0519)	-0.0660 (0.0528)
Other Education $\times age^2$	0.000468 (0.000463)	0.000468 (0.000462)	0.000462 (0.000465)	0.000462 (0.000465)	0.000705 (0.000448)	0.000730 (0.000450)	0.000630 (0.000461)	0.000917* (0.000533)	0.000901* (0.000536)	0.000880 (0.000536)	0.000862 (0.000544)	0.000888 (0.000590)	0.000949 (0.000597)	0.000730 (0.000610)
Years of Schooling		-0.000396 (0.00374)	0.000854 (0.00379)	0.00134 (0.00381)	0.00254 (0.00373)	0.00263 (0.00375)	0.00310 (0.00362)		0.00557 (0.00381)	0.00663* (0.00389)	0.00720* (0.00391)	0.00814** (0.00383)	0.00791** (0.00386)	0.00778** (0.00371)
Mother has High School Diploma			-0.139** (0.0687)	-0.147** (0.0692)	-0.158** (0.0662)	-0.160** (0.0662)	-0.173*** (0.0657)			-0.178** (0.0900)	-0.190** (0.0906)	-0.190** (0.0865)	-0.191** (0.0864)	-0.213** (0.0858)
Mother has High School Diploma $\times$ age			0.00243 (0.00175)	0.00266 (0.00176)	0.00260 (0.00171)	0.00267 (0.00171)	0.00283* (0.00170)			0.00300 (0.00210)	0.00327	0.00309	0.00317 (0.00206)	0.00354*
Father has High School Diploma			-0.221***	-0.215***	-0.182***	-0.181***	-0.160**			-0.213**	-0.207**	-0.119	-0.117	-0.0870
Father has High School Diploma $\times$ age			0.00527***	0.00509***	0.00449***	0.00449***	0.00400** (0.00165)			0.00514**	0.00496**	0.00324	0.00322	0.00254
Siblings in Education Age			(0.000000)	-0.0270	0.0376	0.0400	0.0617			(0.00215)	-0.00574	0.0710	0.0843	0.0788
Siblings in Education Age $\times$ age				0.00193	0.000774	0.000652	-0.00129				0.00174	0.000370	5.76e-06	-0.00142
Born in Southern Italy				(0.00171)	(0.00100)	-0.0352	-0.0727				(0.00107)	(0.0010))	-0.198*	-0.221*
Born in Southern Italy $\times$ age						0.000954	0.00178						0.00416	0.00471*
Constant	-1.595*** (0.0967)	-1.590*** (0.107)	-1.458*** (0.112)	-1.435*** (0.123)	-0.931*** (0.163)	-0.923*** (0.163)	-0.574*** (0.206)	-1.622*** (0.137)	-1.699*** (0.144)	-1.554*** (0.146)	-1.529*** (0.155)	-0.919*** (0.184)	-0.908*** (0.182)	-0.465** (0.214)
Observations	2,655	2,655	2,655	2,655	2,655	2,655	2,655	2,250	2,250	2,250	2,250	2,250	2,250	2,250
$R^2$	0.344	0.344	0.353	0.354	0.414	0.414	0.430	0.297	0.298	0.306	0.308	0.370	0.371	0.393
Years of Schooling		х	х	х	х	х	х		х	х	х	х	х	х
Parents' Educational Attainment			х	х	х	х	х			х	х	х	х	х
Presence of Siblings in Education Age				х	х	х	х				х	х	х	х
Regional Controls					х	х	х					х	х	х
Municipality Size					х	х	х					х	х	х
Born in Southern Italy						х	х						х	х
Current Marital Status							х							х
Household Size							х							х

(a) 20-65 age cohort, male individuals without self-employed

(b) 25–65 age cohort, male individuals without self-employed

Table A.16: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Wave of analysis: 2006. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

(a) <i>20–65</i>	age coho	rt, male i	ndividual	s without	self-empl	loyed		(b) 25–	65 age co	hort, mal	le individi	uals withe	out self-en	nployed
emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.133*** (0.00458)	0.133*** (0.00456)	0.130*** (0.00471)	0.128*** (0.00495)	0.123*** (0.00529)	0.123*** (0.00530)	0.108*** (0.00709)	0.148*** (0.00593)	0.148*** (0.00591)	0.144*** (0.00603)	0.141*** (0.00627)	0.135*** (0.00667)	0.135*** (0.00669)	0.117*** (0.00799)
(age) <sup>2</sup>	-0.00164*** (5.24e-05)	-0.00164*** (5.23e-05)	-0.00162*** (5.32e-05)	-0.00162*** (5.34e-05)	-0.00156*** (5.18e-05)	-0.00156*** (5.21e-05)	-0.00143*** (6.87e-05)	-0.00180*** (6.43e-05)	-0.00180*** (6.42e-05)	-0.00176*** (6.49e-05)	-0.00176*** (6.53e-05)	-0.00171*** (6.27e-05)	-0.00171*** (6.33e-05)	-0.00155*** (7.57e-05)
General Education	-0.699*** (0.158)	-0.732*** (0.159)	-0.619*** (0.165)	-0.610*** (0.165)	-0.622*** (0.169)	-0.621*** (0.169)	-0.701*** (0.168)	-0.386 (0.300)	-0.382 (0.299)	-0.298 (0.301)	-0.288 (0.300)	-0.113 (0.282)	-0.113 (0.283)	-0.179 (0.281)
General Education $\times$ age	0.0167* (0.00862)	0.0192** (0.00873)	0.0156* (0.00885)	0.0151* (0.00884)	0.0156* (0.00905)	0.0155* (0.00905)	0.0197** (0.00896)	0.00324 (0.0141)	0.00364 (0.0141)	0.00143 (0.0141)	0.000869 (0.0140)	-0.00666 (0.0135)	-0.00664 (0.0135)	-0.00308 (0.0134)
General Education $\times age^2$	-2.60e-05 (0.000110)	-5.05e-05 (0.000111)	-2.58e-05 (0.000112)	-2.06e-05 (0.000112)	-2.86e-05 (0.000114)	-2.71e-05 (0.000114)	-7.83e-05 (0.000113)	0.000113 (0.000162)	0.000110 (0.000161)	0.000118 (0.000161)	0.000124 (0.000161)	0.000200 (0.000157)	0.000199 (0.000157)	0.000156 (0.000156)
Other Education	(0.666)	(0.662)	(0.618	0.623 (0.661) 0.0264	(0.614)	(0.615)	(0.622)	(1.062)	(1.045)	(1.057)	(1.058) 0.0277	(1.086)	(1.091)	(1.095)
Other Education $\times$ age	(0.0333)	(0.0332)	(0.0332)	(0.0332)	(0.0309)	(0.0309)	(0.0312)	(0.0491)	(0.0485)	(0.0489)	(0.0490)	(0.0492)	(0.0495)	(0.0497)
Other Education $\times age^2$	0.000503 (0.000415)	0.000490 (0.000415)	0.000521 (0.000415)	0.000521 (0.000415)	0.000641* (0.000386)	0.000660* (0.000385)	0.000643* (0.000389)	0.000546 (0.000566)	0.000545 (0.000560)	0.000555 (0.000564)	0.000542 (0.000565)	0.000785 (0.000552)	0.000764 (0.000557)	0.000752 (0.000559)
Years of Schooling		-0.00918*** (0.00356)	-0.00880** (0.00365)	-0.00864** (0.00366)	-0.00786** (0.00357)	-0.00772** (0.00358)	-0.00665* (0.00353)		-0.00533 (0.00362)	-0.00489 (0.00373)	-0.00465 (0.00374)	-0.00388 (0.00364)	-0.00390 (0.00364)	-0.00320 (0.00360)
Mother has High School Diploma			-0.121* (0.0649)	-0.131** (0.0652)	-0.132** (0.0630)	-0.132** (0.0631)	-0.140** (0.0628)			-0.142 (0.0868)	-0.156* (0.0870)	-0.161* (0.0826)	-0.160* (0.0830)	-0.178** (0.0825)
Mother has High School Diploma $\times$ age			0.00198 (0.00162)	0.00223 (0.00163)	0.00242 (0.00159)	0.00243 (0.00159)	0.00270* (0.00159)			0.00244 (0.00199)	0.00276 (0.00199)	0.00307 (0.00192)	0.00305 (0.00193)	0.00351* (0.00192)
Father has High School Diploma			-0.0952 (0.0676)	-0.0867 (0.0679)	-0.116* (0.0656)	-0.115* (0.0658)	-0.0964 (0.0653)			-0.0995 (0.0929)	-0.0841 (0.0933)	-0.148* (0.0876)	-0.149* (0.0880)	-0.115 (0.0874)
Father has High School Diploma $\times$ age			0.00262 (0.00168)	0.00240 (0.00169)	0.00294* (0.00166)	0.00291* (0.00167)	0.00253 (0.00166)			0.00262 (0.00214)	0.00228 (0.00215)	0.00356* (0.00206)	0.00359* (0.00207)	0.00289 (0.00207)
Siblings in Education Age				-0.0724 (0.0646)	0.00479 (0.0639)	0.00338 (0.0641)	0.0166 (0.0649)				-0.0988 (0.0805)	-0.0232 (0.0760)	-0.0203 (0.0765)	-0.0347 (0.0771)
Siblings in Education Age $\times$ age				(0.00168)	(0.00115)	(0.00116)	-0.000223 (0.00171)				0.00337* (0.00191)	0.00163 (0.00184)	(0.00157)	0.000777 (0.00187)
Born in Southern Italy						(0.105)	(0.105)						-0.0683 (0.125)	-0.0826 (0.124)
Born in Southern Italy $\times$ age						-0.00127 (0.00235)	-0.00106 (0.00237)						0.00132 (0.00274)	0.00151 (0.00274)
Constant	-1.704*** (0.0966)	-1.588*** (0.107)	-1.501*** (0.112)	-1.439*** (0.122)	-1.371*** (0.154)	-1.373*** (0.154)	-0.867*** (0.195)	-2.038*** (0.133)	-1.963*** (0.139)	-1.855*** (0.144)	-1.773*** (0.155)	-1.605*** (0.197)	-1.604*** (0.196)	-1.029*** (0.226)
Observations	2,662	2,662	2,662	2,662	2,662	2,662	2,662	2,251	2,251	2,251	2,251	2,251	2,251	2,251
R <sup>2</sup> Years of Schooling	0.369	0.370 x	0.373	0.375	0.430 x	0.430 x	0.440 x	0.331	0.332	0.335	0.336	0.401 x	0.401 x	0.413 x
Parents' Educational Attainment		A	x	x	x	x	x			x	x	x	x	x
Presence of Siblings in Education Age				х	х	х	x				x	x	x	х
Regional Controls					х	х	х					х	х	х
Municipality Size					х	х	х					х	х	х
Born in Southern Italy						х	x						х	x
Household Size							x							x

Table A.17: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education, excluding self-employed individuals. Omitted education type is vocational. Wave of analysis: 2008. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.129*** (0.00455)	0.128*** (0.00457)	0.126*** (0.00473)	0.119*** (0.00515)	0.113*** (0.00572)	0.113*** (0.00572)	0.106*** (0.00806)	0.142*** (0.00651)	0.142*** (0.00652)	0.138*** (0.00669)	0.130*** (0.00683)	0.125*** (0.00776)	0.126*** (0.00778)	0.117*** (0.00940)
(age) <sup>2</sup>	-0.00155*** (5.24e-05)	-0.00155*** (5.26e-05)	-0.00154*** (5.35e-05)	-0.00149*** (5.55e-05)	-0.00142*** (5.57e-05)	-0.00142*** (5.57e-05)	-0.00137*** (7.81e-05)	-0.00169*** (7.03e-05)	-0.00169*** (7.04e-05)	-0.00166*** (7.13e-05)	-0.00160*** (7.17e-05)	-0.00156*** (7.28e-05)	-0.00156*** (7.29e-05)	-0.00149*** (8.87e-05)
General Education	-0.608*** (0.157)	-0.604*** (0.158)	-0.541*** (0.164)	-0.528*** (0.164)	-0.606*** (0.162)	-0.612*** (0.162)	-0.655*** (0.162)	-0.839*** (0.277)	-0.864*** (0.276)	-0.757*** (0.286)	-0.709** (0.285)	-0.702** (0.275)	-0.708*** (0.274)	-0.709** (0.275)
General Education $\times$ age	0.0127 (0.00847)	0.0123 (0.00856)	0.0103 (0.00868)	0.00976 (0.00865)	0.0132 (0.00848)	0.0135 (0.00848)	0.0159* (0.00843)	0.0236* (0.0130)	0.0240* (0.0130)	0.0205 (0.0132)	0.0184 (0.0132)	0.0178 (0.0128)	0.0181 (0.0127)	0.0185 (0.0128)
General Education $\times age^2$	1.58e-05 (0.000106)	1.90e-05 (0.000107)	3.26e-05 (0.000107)	3.66e-05 (0.000107)	2.54e-06 (0.000104)	-2.72e-07 (0.000104)	-2.87e-05 (0.000104)	-0.000104 (0.000148)	-0.000111 (0.000147)	-8.59e-05 (0.000149)	-6.52e-05 (0.000149)	-5.61e-05 (0.000144)	-5.77e-05 (0.000144)	-6.42e-05 (0.000144)
Other Education	0.107 (0.535)	0.113 (0.535)	0.161 (0.535)	0.139 (0.542)	0.0372 (0.548)	0.0423 (0.545)	-0.000775 (0.544)	0.0484 (1.282)	0.0730 (1.274)	-0.0193 (1.276)	-0.346 (1.295)	0.695 (1.242)	0.746 (1.243)	0.835 (1.214)
Other Education $\times$ age	-0.0149 (0.0280)	-0.0153 (0.0280)	-0.0181 (0.0281)	-0.0172 (0.0282)	-0.0121 (0.0280)	-0.0125 (0.0278)	-0.00989 (0.0274)	-0.0140 (0.0568)	-0.0156 (0.0565)	-0.0126 (0.0566)	0.00141 (0.0574)	-0.0430 (0.0552)	-0.0453 (0.0551)	-0.0483 (0.0537)
Other Education $\times age^2$	0.000252 (0.000352)	0.000256 (0.000352)	0.000291 (0.000354)	0.000282 (0.000354)	0.000223 (0.000344)	0.000229 (0.000341)	0.000188 (0.000334)	0.000256 (0.000615)	0.000273 (0.000612)	0.000251 (0.000614)	0.000105 (0.000621)	0.000560 (0.000598)	0.000587 (0.000595)	0.000603 (0.000578)
Years of Schooling		0.00189 (0.00351)	0.00226 (0.00356)	0.00264 (0.00355)	0.00241 (0.00349)	0.00225 (0.00351)	0.00235 (0.00347)		0.00744** (0.00357)	0.00815** (0.00360)	0.00859** (0.00359)	0.00782** (0.00355)	0.00752** (0.00357)	0.00734** (0.00354)
Mother has High School Diploma			-0.0330 (0.0607)	-0.0677 (0.0615)	-0.0891 (0.0611)	-0.0892 (0.0611)	-0.0851 (0.0611)			-0.0944 (0.0809)	-0.139* (0.0813)	-0.131* (0.0798)	-0.133* (0.0799)	-0.135* (0.0797)
Mother has High School Diploma $\times$ age			-0.000143 (0.00146)	0.000855 (0.00149)	0.00124 (0.00149)	0.00125 (0.00149)	0.00124 (0.00149)			0.000715 (0.00177)	0.00185 (0.00180)	0.00172 (0.00179)	0.00176 (0.00179)	0.00193 (0.00179)
Father has High School Diploma			-0.0644 (0.0657)	-0.0319 (0.0665)	-0.106 (0.0658)	-0.104 (0.0659)	-0.101 (0.0659)			-0.0581 (0.0913)	-0.0185 (0.0926)	-0.105 (0.0894)	-0.101 (0.0897)	-0.0908 (0.0897)
Father has High School Diploma $\times$ age			0.00192 (0.00158)	0.00107 (0.00161)	0.00274* (0.00161)	0.00267* (0.00161)	0.00270* (0.00160)			0.00197 (0.00203)	0.000991 (0.00207)	0.00292 (0.00202)	0.00280 (0.00202)	0.00262 (0.00202)
Siblings in Education Age				-0.0501 (0.0550)	0.0277 (0.0542)	0.0264 (0.0544)	0.0733 (0.0570)				-0.0812 (0.0714)	0.00177 (0.0707)	-0.00155 (0.0708)	0.0587 (0.0731)
Siblings in Education Age $\times$ age				0.00346** (0.00136)	0.00217 (0.00136)	0.00225* (0.00136)	6.56e-05 (0.00145)				0.00440*** (0.00156)	0.00264* (0.00156)	0.00277* (0.00156)	0.000253 (0.00164)
Born in Southern Italy						-0.0151 (0.111)	-0.0380 (0.111)						0.0637 (0.130)	0.0379 (0.129)
Born in Southern Italy $\times$ age						-0.000524 (0.00240)	-5.81e-05 (0.00240)						-0.00212 (0.00277)	-0.00159 (0.00276)
Constant	-1.683*** (0.0950)	-1.704*** (0.103)	-1.655*** (0.109)	-1.554*** (0.118)	-1.363*** (0.167)	-1.365*** (0.167)	-1.029*** (0.223)	-1.985*** (0.146)	-2.079*** (0.152)	-1.993*** (0.158)	-1.860*** (0.161)	-1.693*** (0.233)	-1.705*** (0.233)	-1.326*** (0.270)
Observations	2,729	2,729	2,729	2,729	2,729	2,729	2,729	2,316	2,316	2,316	2,316	2,316	2,316	2,316
$R^2$	0.344	0.344	0.345	0.352	0.402	0.402	0.410	0.299	0.301	0.304	0.312	0.363	0.364	0.374
Years of Schooling		х	х	х	х	х	х		х	х	х	х	х	х
Parents' Educational Attainment			х	х	х	х	х			х	х	х	х	х
Presence of Siblings in Education Age				х	х	х	х				х	х	х	х
Regional Controls					х	х	х					х	х	х
Municipality Size					х	х	х					х	х	х
Born in Southern Italy						х	x						х	x
Current Marital Status							х							х
Household Size							х							х

Table A.18: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Wave of analysis: 2010. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

(a) 20–65 age cohort, male individuals without self-employed

(b) 25–65 age cohort, male individuals without self-employed

(a) <i>20–65</i>	age coho	rt, male i	ndividual	s without	self-emp	loyed		(b) 25–	65 age co	ohort, ma	le individi	uals withe	out self-en	nployed
emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.132*** (0.00424)	0.132*** (0.00427)	0.129*** (0.00445)	0.117*** (0.00516)	0.113*** (0.00580)	0.113*** (0.00580)	0.107*** (0.00745)	0.138*** (0.00625)	0.138*** (0.00627)	0.135*** (0.00658)	0.121*** (0.00693)	0.115*** (0.00778)	0.115*** (0.00776)	0.107*** (0.00868)
(age) <sup>2</sup>	-0.00157*** (4.85e-05)	-0.00157*** (4.87e-05)	-0.00154*** (4.98e-05)	-0.00145*** (5.45e-05)	-0.00139*** (5.53e-05)	-0.00140*** (5.54e-05)	-0.00135*** (7.18e-05)	-0.00164*** (6.66e-05)	-0.00164*** (6.67e-05)	-0.00160*** (6.87e-05)	-0.00150*** (7.10e-05)	-0.00145*** (6.98e-05)	-0.00146*** (7.00e-05)	-0.00139*** (8.11e-05)
General Education	-0.524*** (0.148)	-0.521*** (0.149)	-0.450*** (0.154)	-0.420*** (0.154)	-0.441*** (0.156)	-0.445*** (0.156)	-0.515*** (0.155)	-0.963***	-0.980*** (0.278)	-0.930*** (0.284)	-0.857***	-0.726*** (0.270)	-0.731**** (0.271)	-0.7/4*** (0.268)
General Education $\times$ age	0.00844 (0.00812)	0.00818 (0.00817)	0.00616 (0.00829)	0.00494 (0.00823)	0.00695 (0.00824)	0.00714 (0.00828)	0.0108 (0.00816)	0.0288** (0.0130)	0.0291** (0.0130)	0.0279** (0.0131)	0.0246* (0.0131)	0.0199 (0.0126)	0.0202 (0.0126)	0.0226* (0.0125)
General Education $\times age^2$	5.3/e-05 (0.000101) 0.775	5.60e-05 (0.000102) 0.776	6.80e-05 (0.000102)	(0.000102) 0.764	4.70e-05 (0.000101)	4.62e-05 (0.000101) 1.210*	3.7/e-06 (0.000100) 1.256*	-0.000166 (0.000147) 6.651	-0.000171 (0.000146) 6 736	-0.000168 (0.000147) 6 723	-0.000133 (0.000147) 7.324	-9.46e-05 (0.000141) 8.442*	-9.59e-05 (0.000142) 8.356*	-0.000125 (0.000140) 8.412*
Other Education	(0.521) 0.0193	(0.523) 0.0194	(0.556) 0.0163	(0.564) 0.0197	(0.727) 0.0328	(0.733) 0.0368	(0.728) 0.0370	(4.793) 0.250	(4.844) 0.253	(4.852) 0.253	(5.081) 0.278	(4.837) 0.320*	(4.917) 0.319*	(4.631) 0.320*
Other Education $\times age^2$	(0.0304) -0.000139	(0.0305) -0.000140	(0.0316) -0.000104	(0.0318) -0.000149	(0.0368) -0.000260	(0.0371) -0.000306	(0.0364) -0.000293	(0.185) -0.00235	(0.187) -0.00238	(0.187) -0.00237	(0.196) -0.00263	(0.187) -0.00302*	(0.190) -0.00302*	(0.179) -0.00302*
Years of Schooling	(0.000375)	(0.000376) 0.00117 (0.00346)	(0.000386) 0.00189 (0.00356)	(0.000387) 0.00236 (0.00351)	(0.000429) 0.00281 (0.00350)	(0.000432) 0.00245 (0.00352)	(0.000423) 0.00259 (0.00349)	(0.00174)	(0.00176) 0.00503 (0.00349)	(0.00176) 0.00567 (0.00360)	(0.00184) 0.00602* (0.00354)	(0.00177) 0.00580 (0.00353)	(0.00180) 0.00524 (0.00355)	(0.00169) 0.00498 (0.00353)
Mother has High School Diploma		(0.00540)	-0.145** (0.0598)	-0.178*** (0.0601)	-0.173*** (0.0588)	-0.172*** (0.0590)	-0.161*** (0.0588)		(0.00549)	-0.102 (0.0818)	-0.141* (0.0817)	-0.119 (0.0793)	-0.117 (0.0794)	-0.115 (0.0791)
Mother has High School Diploma $\times$ age			0.00238 (0.00145)	0.00334** (0.00147)	0.00313** (0.00144)	0.00305** (0.00145)	0.00277* (0.00144)			0.00151 (0.00181)	0.00255 (0.00182)	0.00190 (0.00178)	0.00177 (0.00178)	0.00172 (0.00178)
Father has High School Diploma			0.0250 (0.0627)	0.0521 (0.0628)	-0.00122 (0.0629)	-0.00153 (0.0631)	0.00755 (0.0627)			-0.0122 (0.0884)	0.0328 (0.0884)	0.00993 (0.0856)	0.00647 (0.0859)	0.0160 (0.0855)
Father has High School Diploma $\times$ age			-0.000247 (0.00149)	-0.000947 (0.00150)	0.000252 (0.00149)	0.000267 (0.00150)	0.000118 (0.00149)			0.000432 (0.00193)	-0.000616 (0.00194)	4.02e-05 (0.00189)	0.000119 (0.00190)	-6.05e-05 (0.00189)
Siblings in Education Age				(0.0536)	(0.0529)	(0.0530)	(0.0550)				-0.176*** (0.0708)	-0.114* (0.0693)	-0.118* (0.0694)	-0.0704 (0.0710)
Siblings in Education Age $\times$ age				(0.00132)	(0.00130)	(0.00131)	(0.00138)				(0.00152)	(0.00151)	(0.00152)	(0.00159)
Born in Southern Italy						(0.115) 0.00108	(0.114) 0.000841						(0.126) 0.00186	(0.125) 0.00164
Born in Southern Italy $\times$ age	-1 788***	-1 801***	-1 734***	-1 535***	-1 414***	(0.00250)	(0.00249) -1.103***	-1 043***	-2 000***	-1 025***	-1 660***	-1 373***	(0.00270)	(0.00269)
Constant	(0.0887)	(0.0958)	(0.102)	(0.117)	(0.171)	(0.171)	(0.209)	(0.142)	(0.146)	(0.156)	(0.164)	(0.241)	(0.240)	(0.256)
Observations $R^2$	2,809 0.357	2,809 0.357	2,809 0.360	2,809 0.368	2,809 0.411	2,809 0.412	2,809 0.422	2,359 0.296	2,359 0.297	2,359 0.299	2,359 0.309	2,359 0.366	2,359 0.368	2,359 0.379
Years of Schooling		x	х	х	x	x	х		x	x	х	x	x	х
Parents' Educational Attainment			х	x	x	x	x			х	x	x	x	x
Regional Controls				x	x	x	x				x	x	x	X X
Municipality Size					X	x	X					X	x	X
Born in Southern Italy						x	x						x	x
Current Marital Status Household Size							x x							x x

Table A.19: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Wave of analysis: 2012. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.122*** (0.00469)	0.122*** (0.00471)	0.117*** (0.00495)	0.104*** (0.00570)	0.105*** (0.00611)	0.105*** (0.00611)	0.106*** (0.00763)	0.130*** (0.00715)	0.130*** (0.00717)	0.123*** (0.00746)	0.107*** (0.00793)	0.109*** (0.00838)	0.109*** (0.00839)	0.110*** (0.00981)
(age) <sup>2</sup>	-0.00142*** (5.50e-05)	-0.00141*** (5.51e-05)	-0.00138*** (5.68e-05)	-0.00127*** (6.18e-05)	-0.00125*** (6.09e-05)	-0.00126*** (6.12e-05)	-0.00129*** (7.39e-05)	-0.00150*** (7.73e-05)	-0.00150*** (7.74e-05)	-0.00144*** (7.94e-05)	-0.00130*** (8.27e-05)	-0.00128*** (7.97e-05)	-0.00129*** (7.99e-05)	-0.00130*** (9.27e-05)
General Education	-0.321** (0.161)	-0.294* (0.162)	-0.155 (0.167)	-0.157 (0.165)	-0.164 (0.166)	-0.179 (0.166)	-0.235 (0.166)	-0.555* (0.303)	-0.595** (0.302)	-0.448 (0.302)	-0.402 (0.301)	-0.385 (0.298)	-0.395 (0.298)	-0.494* (0.298)
General Education $\times$ age	-0.000814 (0.00891)	-0.00282 (0.00900)	-0.00775 (0.00906)	-0.00764 (0.00893)	-0.00664 (0.00898)	-0.00584 (0.00897)	-0.00243 (0.00895)	0.0104 (0.0144)	0.0109 (0.0143)	0.00616 (0.0143)	0.00401 (0.0142)	0.00353 (0.0141)	0.00416 (0.0141)	0.00938 (0.0141)
General Education $\times age^2$	0.000156 (0.000111)	0.000175 (0.000112)	0.000215* (0.000112)	0.000214* (0.000110)	0.000196* (0.000110)	0.000188* (0.000110)	0.000146 (0.000110)	3.19e-05 (0.000163)	2.34e-05 (0.000162)	5.70e-05 (0.000161)	8.09e-05 (0.000160)	8.09e-05 (0.000160)	7.50e-05 (0.000160)	1.47e-05 (0.000160)
Other Education	0.556 (0.956)	0.535 (0.972)	0.484 (0.933)	0.401 (0.954)	0.166 (0.972)	(0.971)	(0.972)	-0.0744 (1.196)	-0.0659 (1.205)	-0.214 (1.241)	-0.669 (1.126)	-0.826 (1.293)	-0.935 (1.279)	-1.020 (1.283)
Other Education $\times$ age	-0.0204 (0.0434)	-0.0196 (0.0441)	-0.0178 (0.0427)	-0.0159 (0.0435)	-0.00524 (0.0439)	-0.000682 (0.0439)	-0.00242 (0.0440)	0.00585 (0.0529)	0.00531 (0.0534)	0.0108 (0.0547)	0.0282 (0.0504)	0.0351 (0.0567)	0.0408 (0.0561)	0.0432 (0.0563)
Other Education $\times age^2$	0.000188 (0.000471)	0.000178 (0.000478)	0.000163 (0.000464)	0.000153 (0.000473)	3.33e-05 (0.000476)	-1.78e-05 (0.000476)	1.43e-05 (0.000477)	-7.37e-05 (0.000558)	-7.19e-05 (0.000564)	-0.000123 (0.000575)	-0.000286 (0.000537)	-0.000365 (0.000596)	-0.000427 (0.000590)	-0.000437 (0.000593)
Years of Schooling		0.00708* (0.00373)	0.00769** (0.00383)	0.00750** (0.00381)	0.0105*** (0.00379)	0.00954** (0.00380)	0.00879** (0.00383)		0.0124*** (0.00381)	0.0134*** (0.00393)	0.0130*** (0.00391)	0.0155*** (0.00386)	0.0147*** (0.00388)	0.0136*** (0.00391)
Mother has High School Diploma			-0.168** (0.0670)	-0.189*** (0.0665)	-0.175*** (0.0646)	-0.179*** (0.0647)	-0.187*** (0.0650)			-0.332*** (0.0991)	-0.351*** (0.0977)	-0.313*** (0.0950)	-0.317*** (0.0954)	-0.325*** (0.0960)
Mother has High School Diploma $\times$ age			0.00378** (0.00165)	0.00446*** (0.00164)	0.00411** (0.00162)	0.00414** (0.00162)	0.00427*** (0.00163)			0.00707*** (0.00222)	0.00762*** (0.00220)	0.00682*** (0.00215)	0.00685*** (0.00216)	0.00698*** (0.00218)
Father has High School Diploma			-0.0753 (0.0656)	-0.0488 (0.0658)	-0.0908 (0.0655)	-0.0910 (0.0656)	-0.0792 (0.0657)			0.0190 (0.0961)	0.0455 (0.0952)	-0.00133 (0.0932)	-0.00858 (0.0934)	0.00195 (0.0939)
Father has High School Diploma $\times$ age			0.00147 (0.00156)	0.000814 (0.00156)	0.00160 (0.00157)	0.00156 (0.00157)	0.00139 (0.00158)			-0.000543 (0.00209)	-0.00115 (0.00208)	-0.000238 (0.00206)	-0.000134 (0.00207)	-0.000270 (0.00208)
Siblings in Education Age				-0.152*** (0.0570)	-0.0687 (0.0566)	-0.0742 (0.0565)	-0.00536 (0.0610)				-0.240*** (0.0778)	-0.138* (0.0766)	-0.146* (0.0765)	-0.0777 (0.0810)
Siblings in Education Age $\times$ age				0.00455*** (0.00142)	0.00318** (0.00142)	0.00340** (0.00142)	0.00136 (0.00153)				0.00604*** (0.00171)	0.00410** (0.00171)	0.00438** (0.00171)	0.00234 (0.00184)
Born in Southern Italy						0.115 (0.111)	0.124 (0.111)						0.0788 (0.145)	0.1000 (0.147)
Born in Southern Italy $\times$ age						-0.00196 (0.00237)	-0.00228 (0.00239)						-0.00126 (0.00302)	-0.00180 (0.00305)
Constant	-1.696*** (0.0950)	-1.780*** (0.103)	-1.657*** (0.111)	-1.386*** (0.128)	-1.480*** (0.168)	-1.484*** (0.168)	-1.312*** (0.213)	-1.891*** (0.161)	-2.053*** (0.165)	-1.851*** (0.174)	-1.499*** (0.184)	-1.650*** (0.243)	-1.659*** (0.243)	-1.486*** (0.285)
Observations	2,679	2,679	2,679	2,679	2,679	2,679	2,679	2,242	2,242	2,242	2,242	2,242	2,242	2,242
R <sup>2</sup>	0.302	0.303	0.307	0.316	0.361	0.363	0.372	0.221	0.225	0.231	0.242	0.294	0.296	0.307
Years of Schooling		х	x	x	x	x	x		х	x	x	x	x	x
Parents' Educational Attainment			х	x	x	x	x			х	x	x	x	x
Presence of Siblings in Education Age				х	x	x	x				х	x	x	x
Municipality Size					x	X	A v					X	X	X
Rom in Southern Italy					х	x	X					х	x	X
Current Marital Status						X	A V						X	X
Household Size							A V							A V
riousenolu olize							~							~

(a) 20–65 age cohort, male individuals without self-employed

(b) 25-65 age cohort, male individuals without self-employed

Table A.20: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males age 20 or 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Wave of analysis: 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

## A.1.3 Analysis for the Financial Crisis

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	0.130***	0.130***	0.125***	0.123***	0.114***	0.114***	0.102***
age	(0.00195)	(0.00195)	(0.00200)	(0.00213)	(0.00234)	(0.00234)	(0.00319)
(age) <sup>2</sup>	-0.00158***	-0.00158***	-0.00155***	-0.00154***	-0.00152***	-0.00152***	-0.00140***
(uge)	(2.32e-05)	(2.32e-05)	(2.34e-05)	(2.35e-05)	(2.32e-05)	(2.32e-05)	(3.16e-05)
General Education	-0.838***	-0.841***	-0.702***	-0.700***	-0.749***	-0.746***	-0.789***
	(0.0679)	(0.0081)	(0.0699)	(0.0698)	(0.0/11)	(0.0/11)	(0.0707)
General Education $\times$ age	0.0257***	(0.0259***	(0.00276)	(0.0213***	(0.0239***	(0.0230***	(0.0262***
	-0.000152***	-0.000154***	-0.000124**	-0.000124**	0.00156***	-0.000153***	-0.000186***
General Education $\times age^2$	(4 76e-05)	(4 78e-05)	(4.81e-05)	(4.81e-05)	(4 86e-05)	(4 86e-05)	(4 83e-05)
	0.209	0.207	0.186	0.187	0.346	0.361	0.301
Other Education	(0.289)	(0.289)	(0.287)	(0.288)	(0.303)	(0.303)	(0.307)
Other Education of	-0.0154	-0.0152	-0.0141	-0.0142	-0.0196	-0.0204	-0.0172
Other Education $\times$ age	(0.0145)	(0.0145)	(0.0145)	(0.0145)	(0.0153)	(0.0152)	(0.0154)
Other Education $\times aga^2$	0.000236	0.000234	0.000220	0.000222	0.000261	0.000272	0.000233
Other Education × uge	(0.000179)	(0.000179)	(0.000179)	(0.000180)	(0.000189)	(0.000188)	(0.000191)
Years of Schooling		-0.00124	-0.000318	2.93e-05	0.00110	0.00118	0.00203
		(0.00169)	(0.00173)	(0.00173)	(0.00171)	(0.00171)	(0.00169)
Mother has High School Diploma			-0.151***	-0.160***	-0.149***	-0.149***	-0.156***
6 1			(0.0284)	(0.0286)	(0.0281)	(0.0281)	(0.0280)
Mother has High School Diploma × age			0.00302***	0.00329***	0.00300***	0.00301***	0.0031/***
			(0.000/17)	(0.000/19)	(0.000/11)	(0.000/12)	(0.000709)
Father has High School Diploma			-0.130***	-0.130****	-0.119****	-0.11/****	-0.100****
			0.00381***	0.00365***	0.00298***	0.0292***	0.00267***
Father has High School Diploma $\times$ age			(0.000703)	(0.000708)	(0.00220	(0.000292	(0.000705)
			(0.000705)	-0.0441	0.0248	0.0205	0.0228
Siblings in Education Age				(0.0269)	(0.0268)	(0.0269)	(0.0271)
				0.00212***	0.000815	0.000944	-9.11e-05
Siblings in Education Age × age				(0.000714)	(0.000713)	(0.000715)	(0.000720)
Porn in Southorn Italy						0.0840*	0.0722
Born in Soutiern nary						(0.0455)	(0.0453)
Born in Southern Italy × age						-0.00208**	-0.00186*
Boin in Sounoin haif A age						(0.00103)	(0.00103)
Year 2002	0.000637	0.000785	0.00162	0.00193	0.00108	0.00111	0.00399
	(0.00933)	(0.00933)	(0.00929)	(0.00928)	(0.00904)	(0.00905)	(0.00900)
Year 2004	0.00558	0.00585	0.00708	0.00692	0.00173	0.00100	(0.00010
	(0.00952)	(0.00932)	(0.00928)	(0.00928)	(0.00907)	(0.00908)	(0.00904)
Year 2006	(0.00907)	(0.00913)	(0.00910)	(0.00909)	(0.00888)	(0.00890)	(0.00886)
	0.0276***	0.0285***	0.0301***	0.0300***	0.0281***	0.0277***	0.0331***
Year 2008	(0.00904)	(0.00908)	(0.00907)	(0.00907)	(0.00886)	(0.00890)	(0.00888)
Countrat .	-1.651***	-1.636***	-1.524***	-1.483***	-1.166***	-1.171***	-0.803***
Constant	(0.0403)	(0.0450)	(0.0467)	(0.0515)	(0.0668)	(0.0667)	(0.0849)
Observations	15 210	15 210	15 210	15 210	15 210	15 210	15 210
Observations p <sup>2</sup>	15,518	15,518	15,518	15,318	15,518	15,518	15,518
л Veers of Schooling	0.338	0.558	0.304	0.305	0.403	0.405	0.411
Parents' Educational Attainment		х	x	x	x	x	x
Presence of Siblings in Education Age			~	x	x	x	x
Regional Controls				~	x	x	x
Municipality Size					x	x	x
Born in Southern Italy						x	x
Current Marital Status							x
Household Size							x

Table A.21: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 20 to 65 with at least upper secondary education. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2008 for pre-recession years, every two years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

1 individual is smallened	(1)	(2)	(3)	(4)	(5)	(6)	(7)
emp = 1 individual is employed	0.110***	0.110***	0.116444	0.107***	0.102***	0.104***	0.0000***
age	0.119***	0.118***	0.116***	0.10/***	0.103***	0.104***	0.0999***
	-0.00139***	-0.00139***	-0.00137***	-0.00130***	-0.00126***	-0.00126***	-0.00124***
(age) <sup>2</sup>	(2.94e-05)	(2.95e-05)	(3.00e-05)	(3.17e-05)	(3.14e-05)	(3.15e-05)	(4.00e-05)
	-0.627***	-0.610***	-0.534***	-0.517***	-0.526***	-0.537***	-0.576***
General Education	(0.0834)	(0.0839)	(0.0867)	(0.0865)	(0.0864)	(0.0865)	(0.0862)
General Education $\times$ and	0.0148***	0.0134***	0.0110**	0.0102**	0.0110**	0.0115**	0.0137***
General Education × uge	(0.00444)	(0.00448)	(0.00454)	(0.00452)	(0.00451)	(0.00450)	(0.00449)
General Education $\times age^2$	-2.26e-05	-1.01e-05	6.05e-06	1.35e-05	2.25e-06	-2.54e-06	-2.95e-05
Seneral Education A use	(5.52e-05)	(5.55e-05)	(5.58e-05)	(5.56e-05)	(5.54e-05)	(5.53e-05)	(5.51e-05)
Other Education	-0.135	-0.135	-0.112	-0.167	-0.297	-0.345	-0.338
	(0.408)	(0.410)	(0.404)	(0.408)	(0.410)	(0.408)	(0.408)
Other Education $\times$ age	(0.0103)	(0.0104)	(0.0102)	(0.0103)	(0.0104)	(0.0119	(0.0103)
_	3.869-05	3 720 05	(0.0192)	(0.0193) -3.70e-05	0.0194)	-0.000122	0.0193)
Other Education $\times age^2$	(0.000221)	(0.000222)	(0.000220)	(0.000221)	(0.000223)	(0.000122)	(0.000221)
	(0.000221)	0.00583***	0.00612***	0.00623***	0.00707***	0.00658***	0.00658***
Years of Schooling		(0.00175)	(0.00179)	(0.00177)	(0.00177)	(0.00177)	(0.00177)
		(	-0.115***	-0.137***	-0.138***	-0.139***	-0.138***
Mother has High School Diploma			(0.0342)	(0.0342)	(0.0335)	(0.0335)	(0.0336)
Mathanhaa High Sahaal Dinlama V aga			0.00215***	0.00278***	0.00280***	0.00280***	0.00280***
Mother has High School Dipionia × age			(0.000805)	(0.000807)	(0.000800)	(0.000800)	(0.000801)
Eather has High School Diploma			-0.0271	-0.00553	-0.0415	-0.0396	-0.0324
r aner has riigh benoor Dipionia			(0.0353)	(0.0353)	(0.0352)	(0.0352)	(0.0351)
Father has High School Diploma $\times$ age			0.000948	0.000412	0.00116	0.00109	0.000967
0 1 0			(0.000822)	(0.000825)	(0.000825)	(0.000825)	(0.000823)
Siblings in Education Age				-0.0903***	-0.0299	-0.0351	(0.00000)
				0.00344***	0.00298)	0.00298)	0.00102
Siblings in Education Age × age				(0.000729)	(0.0024)	(0.00203	(0.00102
				(0.000727)	(0.000727)	0.0804	0.0793
Born in Southern Italy						(0.0633)	(0.0633)
						-0.00210	-0.00216
Born in Southern Italy × age						(0.00137)	(0.00137)
Vear 2012	-0.0127	-0.0128	-0.0119	-0.0155*	-0.0148*	-0.0145	-0.0119
Teal 2012	(0.00909)	(0.00909)	(0.00910)	(0.00910)	(0.00890)	(0.00890)	(0.00887)
Year 2014	-0.0173*	-0.0170*	-0.0152	-0.0212**	-0.0226**	-0.0223**	-0.0150
	(0.00945)	(0.00944)	(0.00954)	(0.00970)	(0.00949)	(0.00948)	(0.00949)
Constant	-1.539***	-1.606***	-1.535***	-1.365***	-1.281***	-1.284***	-1.05/***
	(0.0525)	(0.0559)	(0.0589)	(0.0660)	(0.0922)	(0.0923)	(0.115)
Observations	0.855	0.855	0.855	0.855	0.855	0.855	9 855
p2	0.320	0.320	0.322	0.328	0.362	0.363	0.369
Vears of Schooling	0.520	0.520 X	0.522 X	0.520 X	0.502 X	0.505 X	0.509 X
Parents' Educational Attainment		~	x	x	x	x	x
Presence of Siblings in Education Age				x	x	x	x
Regional Controls					х	x	х
Municipality Size					х	х	х
Born in Southern Italy						х	х
Current Marital Status							х
Household Size							х

Table A.22: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 20 to 65 with at least upper secondary education. Omitted education type is vocational. Waves of analysis: pooled sample, from 2010 to 2014 for post-recession years, every two years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.129*** (0.00263)	0.129*** (0.00263)	0.125*** (0.00265)	0.123*** (0.00277)	0.112*** (0.00291)	0.113*** (0.00291)	0.0980*** (0.00345)
(age) <sup>2</sup>	-0.00158*** (2.96e-05)	-0.00158*** (2.96e-05)	-0.00155*** (2.96e-05)	-0.00154*** (2.98e-05)	-0.00150*** (2.93e-05)	-0.00150*** (2.94e-05)	-0.00136*** (3.45e-05)
General Education	-0.989*** (0.125)	-0.992*** (0.125)	-0.885*** (0.126)	-0.886*** (0.126)	-0.962*** (0.124)	-0.961*** (0.124)	-0.972*** (0.124)
General Education $\times$ age	0.0329*** (0.00590)	0.0327*** (0.00589)	0.0296*** (0.00591)	0.0297*** (0.00591)	0.0335*** (0.00587)	0.0334*** (0.00587)	0.0344*** (0.00585)
General Education $\times age^2$	-0.000232*** (6.84e-05)	-0.000232*** (6.82e-05)	-0.000216*** (6.84e-05)	-0.000218*** (6.84e-05)	-0.000263*** (6.82e-05)	-0.000262*** (6.82e-05)	-0.000277*** (6.79e-05)
Other Education	0.178 (0.465)	0.178 (0.466)	0.166 (0.464)	0.171 (0.466)	0.0866 (0.475)	0.0998 (0.474)	0.0171 (0.477)
Other Education $\times$ age	-0.0144 (0.0216)	-0.0147 (0.0216)	-0.0139 (0.0216)	-0.0141 (0.0217)	-0.00856 (0.0223)	-0.00928 (0.0223)	-0.00505 (0.0225)
Other Education $\times age^2$	0.000229 (0.000247)	0.000232 (0.000248)	0.000221 (0.000248)	0.000224 (0.000249)	0.000146 (0.000258)	0.000155 (0.000258)	0.000106 (0.000260)
Years of Schooling		0.00409** (0.00170)	0.00480*** (0.00175)	0.00520*** (0.00176)	0.00581*** (0.00173)	0.00585*** (0.00173)	0.00630*** (0.00172)
Mother has High School Diploma			-0.165*** (0.0379)	-0.172*** (0.0382)	-0.171*** (0.0372)	-0.172*** (0.0372)	-0.182*** (0.0369)
Mother has High School Diploma $\times$ age			0.00329*** (0.000885)	0.00347*** (0.000889)	0.00337*** (0.000877)	0.00339*** (0.000877)	0.00364*** (0.000873)
Father has High School Diploma			-0.134*** (0.0384)	-0.131*** (0.0386)	-0.0745** (0.0378)	-0.0722* (0.0378)	-0.0503 (0.0376)
Father has High School Diploma $\times$ age			0.00327*** (0.000889)	0.00318*** (0.000893)	0.00205** (0.000884)	0.00199** (0.000886)	0.00151* (0.000882)
Siblings in Education Age				0.00509 (0.0329)	0.0783** (0.0325)	0.0747** (0.0327)	0.0594* (0.0327)
Siblings in Education Age $\times$ age				0.00125 (0.000811)	-0.000168 (0.000810)	-5.82e-05 (0.000813)	-0.000770 (0.000811)
Born in Southern Italy						0.0303 (0.0524)	0.0214 (0.0521)
Born in Southern Italy $\times$ age						-0.000980 (0.00118)	-0.000830 (0.00117)
Year 2002	0.00335 (0.00976)	0.00284 (0.00975)	0.00274 (0.00972)	0.00342 (0.00971)	9.74e-05 (0.00948)	3.61e-05 (0.00948)	0.00301 (0.00943)
Year 2004	0.00681 (0.00971)	0.00588 (0.00971)	0.00595 (0.00970)	0.00628 (0.00969)	-0.000829 (0.00946)	-0.000932 (0.00947)	0.00310 (0.00943)
Year 2006	0.0274*** (0.00940)	0.0247*** (0.00945)	0.0255*** (0.00942)	0.0255*** (0.00941)	0.0200** (0.00923)	0.0197** (0.00925)	0.0259*** (0.00919)
Year 2008	0.0250*** (0.00936)	0.0220** (0.00940)	0.0229** (0.00940)	0.0229** (0.00940)	0.0210** (0.00920)	0.0206** (0.00924)	0.0273*** (0.00921)
Constant	-1.637*** (0.0575)	-1.691*** (0.0599)	-1.592*** (0.0610)	-1.574*** (0.0659)	-1.179*** (0.0794)	-1.183*** (0.0793)	-0.755*** (0.0913)
Observations	12,979	12,979	12,979	12,979	12,979	12,979	12,979
R <sup>2</sup> Verse of Schooling	0.292	0.293	0.297	0.299	0.339	0.339	0.350
Parents' Educational Attainment		х	X	x	x	x	x
Presence of Siblings in Education Age			х	x	x	x	x
Regional Controls				^	x	x	x
Municipality Size					x	x x	x x
Born in Southern Italy					~	x	x
Current Marital Status							x
Household Size							x

Table A.23: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 25 to 65 with at least upper secondary education. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2008 for pre-recession years, every two years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.121*** (0.00359)	0.121*** (0.00359)	0.117*** (0.00370)	0.107*** (0.00384)	0.104*** (0.00421)	0.104*** (0.00421)	0.0982*** (0.00487)
(age) <sup>2</sup>	-0.00142*** (3.93e-05)	-0.00142*** (3.94e-05)	-0.00139*** (4.00e-05)	-0.00131*** (4.08e-05)	-0.00128*** (4.01e-05)	-0.00128*** (4.02e-05)	-0.00124*** (4.64e-05)
General Education	-0.836*** (0.153)	-0.864*** (0.153)	-0.783*** (0.156)	-0.739*** (0.155)	-0.696*** (0.151)	-0.707*** (0.151)	-0.739*** (0.151)
General Education $\times$ age	0.0244*** (0.00713)	0.0247*** (0.00711)	0.0223*** (0.00716)	0.0203*** (0.00714)	0.0186*** (0.00701)	0.0191*** (0.00700)	0.0210*** (0.00699)
General Education $\times age^2$	-0.000127 (8.04e-05)	-0.000133* (8.01e-05)	-0.000119 (8.03e-05)	-9.71e-05 (8.02e-05)	-8.13e-05 (7.90e-05)	-8.66e-05 (7.89e-05)	-0.000110 (7.88e-05)
Other Education	-0.314 (0.763)	-0.318 (0.763)	-0.372 (0.774)	-0.712 (0.752)	-0.424 (0.797)	-0.489 (0.802)	-0.478 (0.804)
Other Education $\times$ age	0.0105 (0.0331)	0.0103 (0.0332)	0.0124 (0.0336)	0.0261 (0.0328)	0.0140 (0.0347)	0.0177 (0.0349)	0.0162 (0.0349)
Other Education $\times age^2$	-0.000105 (0.000349)	-0.000104 (0.000350)	-0.000122 (0.000354)	-0.000258 (0.000346)	-0.000139 (0.000367)	-0.000181 (0.000368)	-0.000154 (0.000369)
Years of Schooling		0.00925*** (0.00177)	0.00967*** (0.00181)	0.00974*** (0.00179)	0.0102*** (0.00178)	0.00964*** (0.00179)	0.00937*** (0.00179)
Mother has High School Diploma			-0.144*** (0.0457)	-0.171*** (0.0455)	-0.155*** (0.0442)	-0.157*** (0.0442)	-0.159*** (0.0442)
Mother has High School Diploma $\times$ age			0.00264*** (0.00100)	0.00333*** (0.00100)	0.00301*** (0.000989)	0.00303*** (0.000988)	0.00311*** (0.000988)
Father has High School Diploma			-0.0232 (0.0480)	0.00541 (0.0480)	-0.0175 (0.0470)	-0.0178 (0.0470)	-0.00732 (0.0470)
Father has High School Diploma $\times$ age			0.000864 (0.00105)	0.000206 (0.00105)	0.000711 (0.00104)	0.000681 (0.00104)	0.000482 (0.00104)
Siblings in Education Age				-0.143*** (0.0384)	-0.0807** (0.0380)	-0.0874** (0.0380)	-0.0407 (0.0390)
Siblings in Education Age $\times$ age				0.00447*** (0.000841)	0.00335*** (0.000842)	0.00358*** (0.000842)	0.00173* (0.000885)
Born in Southern Italy						0.0953 (0.0731)	0.0952 (0.0733)
Born in Southern Italy $\times$ age						-0.00245 (0.00156)	-0.00253 (0.00156)
Year 2012	-0.00688 (0.00952)	-0.00725 (0.00951)	-0.00590 (0.00952)	-0.0104 (0.00953)	-0.0102 (0.00933)	-0.00971 (0.00933)	-0.00671 (0.00929)
Year 2014	-0.00841 (0.00996)	-0.00807 (0.00994)	-0.00526 (0.0101)	-0.0119 (0.0103)	-0.0111 (0.0101)	-0.0106 (0.0101)	-0.00209 (0.0101)
Constant	-1.602*** (0.0801)	-1.725*** (0.0824)	-1.626*** (0.0859)	-1.408*** (0.0893)	-1.292*** (0.125)	-1.296*** (0.125)	-1.021*** (0.141)
Observations	8,514	8,514	8,514	8,514	8,514	8,514	8,514
R <sup>2</sup> Years of Schooling	0.235	0.237	0.240 x	0.248 x	0.284 x	0.285 x	0.293 x
Parents' Educational Attainment		~	x	x	x	x	x
Presence of Siblings in Education Age				х	х	х	х
Regional Controls					х	х	х
Municipality Size					х	х	х
Born in Southern Italy						х	х
Current Marital Status Household Size							x x

Table A.24: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 25 to 65 with at least upper secondary education. Omitted education type is vocational. Waves of analysis: pooled sample, from 2010 to 2014 for post-recession years, every two years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.139***	0.139***	0.134***	0.132***	0.123***	0.123***	0.107***
(age) <sup>2</sup>	-0.00171***	-0.00171***	-0.00167***	-0.00167***	-0.00164***	-0.00164***	-0.00149***
General Education	-0.712***	-0.721***	-0.579***	-0.575***	-0.628***	-0.626***	-0.684***
General Education $\times$ age	0.0179***	0.0186*** (0.00403)	0.0138***	0.0136***	0.0162*** (0.00413)	0.0160*** (0.00413)	0.0196***
General Education $\times age^2$	-5.25e-05 (5.14e-05)	-5.84e-05 (5.17e-05)	-2.43e-05 (5.20e-05)	-2.35e-05 (5.19e-05)	-5.43e-05 (5.26e-05)	-5.15e-05 (5.27e-05)	-9.60e-05* (5.17e-05)
Other Education	0.319	0.313	0.293	0.296	0.461	0.474	0.414
Other Education $\times$ age	-0.0206	-0.0201	-0.0192	-0.0192	-0.0250	-0.0258	-0.0226
Other Education $\times age^2$	0.000296	0.000290	0.000279	0.000279	0.000323	0.000332	0.000294
Years of Schooling	(,	-0.00368* (0.00198)	-0.00217 (0.00202)	-0.00173 (0.00203)	-0.000897 (0.00198)	-0.000817 (0.00198)	4.79e-05 (0.00195)
Mother has High School Diploma		. ,	-0.156*** (0.0299)	-0.168*** (0.0300)	-0.150*** (0.0295)	-0.150*** (0.0295)	-0.160*** (0.0294)
Mother has High School Diploma $\times$ age			0.00296*** (0.000771)	0.00325*** (0.000773)	0.00283*** (0.000764)	0.00283*** (0.000765)	0.00306*** (0.000762)
Father has High School Diploma			-0.140*** (0.0299)	-0.133*** (0.0302)	-0.109*** (0.0299)	-0.108*** (0.0299)	-0.0943*** (0.0296)
Father has High School Diploma $\times$ age			0.00328*** (0.000746)	0.00309*** (0.000752)	0.00260*** (0.000750)	0.00256*** (0.000752)	0.00225*** (0.000744)
Siblings in Education Age				-0.0431 (0.0285)	0.0338 (0.0283)	0.0304 (0.0283)	0.0338 (0.0285)
Siblings in Education Age $\times$ age				0.00254*** (0.000769)	0.00107 (0.000763)	0.00116 (0.000765)	-0.000132 (0.000765)
Born in Southern Italy						0.0666 (0.0473)	0.0457 (0.0471)
Born in Southern Italy $\times$ age						-0.00152 (0.00107)	-0.00111 (0.00107)
Year 2002	0.00202 (0.0107)	0.00242 (0.0107)	0.00394 (0.0106)	0.00444 (0.0106)	0.00462 (0.0103)	0.00464 (0.0103)	0.00842 (0.0102)
Year 2004	0.0122 (0.0106)	0.0130 (0.0106)	0.0152 (0.0106)	0.0150 (0.0106)	0.00991 (0.0103)	0.00988 (0.0103)	0.0143 (0.0102)
Year 2006	0.0374*** (0.0104)	0.0395*** (0.0105)	0.0419*** (0.0104)	0.0415*** (0.0104)	0.0364*** (0.0101)	0.0360*** (0.0101)	0.0422*** (0.0100)
Year 2008	0.0372*** (0.0104)	0.0396*** (0.0104)	0.0421*** (0.0104)	0.0419*** (0.0104)	0.0406*** (0.0101)	0.0402*** (0.0101)	0.0467*** (0.0101)
Constant	-1.835*** (0.0417)	-1.790*** (0.0482)	-1.685*** (0.0500)	-1.643*** (0.0554)	-1.335*** (0.0718)	-1.338*** (0.0717)	-0.845*** (0.0918)
Observations p <sup>2</sup>	12,676	12,676	12,676	12,676	12,676	12,676	12,676
л Years of Schooling	0.374	0.374 x	0.380 x	0.382 x	0.425	0.425 x	0.430 x
Parents' Educational Attainment		~	x	x	x	x	x
Presence of Siblings in Education Age			~	x	x	x	x
Regional Controls					х	x	х
Municipality Size					x	х	х
Born in Southern Italy						х	х
Current Marital Status Household Size							x x

Table A.25: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 20 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2008 for pre-recession years, every two waves. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.127*** (0.00260)	0.127*** (0.00261)	0.124*** (0.00271)	0.114*** (0.00306)	0.111*** (0.00333)	0.112*** (0.00334)	0.106*** (0.00438)
(age) <sup>2</sup>	-0.00151*** (3.01e-05)	-0.00151*** (3.02e-05)	-0.00149*** (3.08e-05)	-0.00141*** (3.29e-05)	-0.00137*** (3.27e-05)	-0.00137*** (3.28e-05)	-0.00134*** (4.23e-05)
General Education	-0.490*** (0.0899)	-0.481*** (0.0905)	-0.395*** (0.0935)	-0.384*** (0.0929)	-0.403*** (0.0927)	-0.410*** (0.0928)	-0.460*** (0.0922)
General Education $\times$ age	0.00703 (0.00491)	0.00624 (0.00496)	0.00357 (0.00502)	0.00317 (0.00498)	0.00453 (0.00494)	0.00488 (0.00494)	0.00774 (0.00490)
General Education $\times age^2$	7.23e-05 (6.15e-05)	7.94e-05 (6.18e-05)	9.79e-05 (6.21e-05)	0.000101 (6.16e-05)	8.06e-05 (6.09e-05)	7.74e-05 (6.09e-05)	4.29e-05 (6.05e-05)
Other Education	0.128 (0.424)	0.128 (0.425)	0.162 (0.419)	0.109 (0.422)	-0.0350 (0.423)	-0.0847 (0.422)	-0.106 (0.421)
Other Education $\times$ age	-0.0113 (0.0204)	-0.0114 (0.0205)	-0.0133 (0.0203)	-0.0114 (0.0203)	-0.00594 (0.0204)	-0.00299 (0.0203)	-0.00276 (0.0202)
Other Education $\times age^2$	0.000155 (0.000235)	0.000156 (0.000236)	0.000179 (0.000234)	0.000161 (0.000234)	0.000109 (0.000235)	7.43e-05 (0.000234)	7.89e-05 (0.000233)
Years of Schooling		0.00340* (0.00206)	0.00417** (0.00210)	0.00435** (0.00209)	0.00508** (0.00207)	0.00465** (0.00208)	0.00449** (0.00207)
Mother has High School Diploma			-0.104*** (0.0361)	-0.130*** (0.0361)	-0.134*** (0.0354)	-0.135*** (0.0354)	-0.130*** (0.0354)
Mother has High School Diploma $\times$ age			0.00167* (0.000882)	0.00246*** (0.000885)	0.00250*** (0.000877)	0.00249*** (0.000877)	0.00236*** (0.000878)
Father has High School Diploma			-0.0429 (0.0374)	-0.0178 (0.0375)	-0.0706* (0.0373)	-0.0700* (0.0373)	-0.0647* (0.0372)
Father has High School Diploma $\times$ age			0.00111 (0.000893)	0.000480 (0.000899)	0.00163* (0.000898)	0.00161* (0.000899)	0.00156* (0.000894)
Siblings in Education Age				-0.0854*** (0.0316)	-0.0152 (0.0312)	-0.0183 (0.0312)	0.0328 (0.0326)
Siblings in Education Age $\times$ age				0.00372*** (0.000783)	0.00253*** (0.000775)	0.00264*** (0.000777)	0.000589 (0.000821)
Born in Southern Italy						0.0226 (0.0652)	0.0223 (0.0653)
Born in Southern Italy $\times$ age						-0.000365 (0.00141)	-0.000485 (0.00142)
Year 2012	-0.0116 (0.0104)	-0.0116 (0.0104)	-0.0105 (0.0104)	-0.0147 (0.0104)	-0.0134 (0.0101)	-0.0133 (0.0101)	-0.00989 (0.0100)
Year 2014	-0.0192* (0.0108)	-0.0191* (0.0108)	-0.0167 (0.0109)	-0.0236** (0.0110)	-0.0234** (0.0107)	-0.0232** (0.0107)	-0.0140 (0.0107)
Constant	-1.710*** (0.0543)	-1.749*** (0.0588)	-1.681*** (0.0623)	-1.501*** (0.0700)	-1.428*** (0.0962)	-1.429*** (0.0963)	-1.134*** (0.123)
Observations	8,217	8,217	8,217	8,217	8,217	8,217	8,217
R <sup>2</sup> Vears of Schooling	0.331	0.331	0.333	0.341	0.380	0.380	0.388
Parents' Educational Attainment		~	x	x	x	x	x
Presence of Siblings in Education Age				x	x	x	x
Regional Controls					х	х	х
Municipality Size					x	х	х
Born in Southern Italy						х	х
Current Marital Status Household Size							X X
11040enolu bize							A

Table A.26: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 20 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2010 to 2014 for post-recession years, every two waves. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.143***	0.143***	0.139***	0.136***	0.125***	0.125***	0.105***
c	(0.00278)	(0.00278)	(0.00281)	(0.00297)	(0.00313)	(0.00313)	(0.003/3)
(age) <sup>2</sup>	(3.07e-05)	(3.06e-05)	(3.07e-05)	(3.10e-05)	(3.02e-05)	(3.03e-05)	(3.62e-05)
a 181 i	-1.041***	-1.043***	-0.936***	-0.937***	-1.011***	-1.011***	-1.025***
General Education	(0.132)	(0.132)	(0.134)	(0.134)	(0.133)	(0.133)	(0.131)
Conoral Education V and	0.0335***	0.0334***	0.0303***	0.0303***	0.0338***	0.0338***	0.0351***
General Education × age	(0.00629)	(0.00628)	(0.00631)	(0.00631)	(0.00631)	(0.00631)	(0.00623)
General Education $\times age^2$	-0.000225***	-0.000225***	-0.000208***	-0.000209***	-0.000250***	-0.000250***	-0.000269***
Seneral Education A use	(7.25e-05)	(7.24e-05)	(7.26e-05)	(7.26e-05)	(7.30e-05)	(7.30e-05)	(7.21e-05)
Other Education	0.255	0.254	0.244	0.251	0.0755	0.0821	-0.000692
	(0.510)	(0.512)	(0.510)	(0.513)	(0.517)	(0.517)	(0.518)
Other Education $\times$ age	-0.0185	-0.0185	-0.0179	-0.0180	-0.00867	-0.00900	-0.00485
	0.000276	0.000279	0.000271	0.000271	0.000153	0.000157	0.000109
Other Education $\times age^2$	(0.000274)	(0.000274)	(0.000275)	(0.000276)	(0.000281)	(0.000282)	(0.000283)
	(,,	0.00321	0.00451**	0.00501**	0.00541***	0.00546***	0.00574***
Years of Schooling		(0.00201)	(0.00207)	(0.00207)	(0.00202)	(0.00202)	(0.00199)
Mathanhar II'sh Cahaal D'alama			-0.183***	-0.193***	-0.184***	-0.184***	-0.199***
Mother has High School Diploma			(0.0418)	(0.0420)	(0.0408)	(0.0408)	(0.0404)
Mother has High School Diploma × age			0.00348***	0.00370***	0.00343***	0.00344***	0.00380***
would has frigh School Dipionia × age			(0.000969)	(0.000973)	(0.000957)	(0.000957)	(0.000952)
Father has High School Diploma			-0.115***	-0.110***	-0.0576	-0.0564	-0.0284
			(0.0422)	(0.0424)	(0.0412)	(0.0412)	(0.0408)
Father has High School Diploma $\times$ age			0.00268***	0.00256***	0.00154	0.00150	0.000880
0 1 0			(0.000965)	(0.000971)	(0.000956)	(0.000958)	(0.000949)
Siblings in Education Age				0.0114	0.0984***	(0.0252)	(0.0252)
				(0.0501)	-0.000122	(0.0555)	-0.000897
Siblings in Education Age × age				(0.00139)	(0.000122)	(0.000874)	(0.000865)
				(0.000000)	(0.000071)	0.00570	-0.0123
Born in Southern Italy						(0.0555)	(0.0551)
						-0.000284	5.20e-05
Born in Southern Italy $\times$ age						(0.00124)	(0.00123)
Voor 2002	0.00456	0.00420	0.00479	0.00580	0.00285	0.00276	0.00637
Teal 2002	(0.0115)	(0.0115)	(0.0114)	(0.0114)	(0.0111)	(0.0111)	(0.0110)
Year 2004	0.0156	0.0148	0.0158	0.0162	0.00872	0.00858	0.0133
	(0.0113)	(0.0113)	(0.0113)	(0.0113)	(0.0110)	(0.0110)	(0.0109)
Year 2006	0.0402***	0.0383***	0.0397***	0.0396***	0.0332***	0.0329***	0.0400***
	(0.0110)	(0.0111)	(0.0110)	(0.0110)	(0.0107)	(0.0108)	(0.0107)
Year 2008	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0107)	(0.0107)	(0.0107)
	-1 937***	-1 980***	-1 882***	-1 861***	-1 437***	-1 439***	-0.862***
Constant	(0.0621)	(0.0656)	(0.0669)	(0.0725)	(0.0880)	(0.0879)	(0.101)
	(,	(	(,	(	(,	(,	(,
Observations	10,428	10,428	10,428	10,428	10,428	10,428	10,428
$R^2$	0.330	0.330	0.335	0.337	0.385	0.385	0.399
Years of Schooling		х	х	х	х	х	х
Parents' Educational Attainment			х	х	х	х	х
Presence of Siblings in Education Age				х	х	х	x
Regional Controls					x	x	x
Nunicipality Size					х	x	x
Current Marital Status						х	x
Household Size							x
Trousenoid Size							~

Table A.27: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2008 for pre-recession years, every two years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.136***	0.136***	0.132***	0.120***	0.117***	0.117***	0.110***
(age) <sup>2</sup>	-0.00160*** (4.12a.05)	-0.00160*** (4.130.05)	-0.00157*** (4.21a.05)	-0.00147*** (4.32a.05)	-0.00144*** (4.24a.05)	-0.00144*** (4.242.05)	-0.00139*** (4.07a.05)
General Education	-0.811***	-0.839***	-0.749***	-0.702***	-0.660***	-0.666***	-0.702***
General Education $\times$ age	0.0221***	0.0225***	0.0199**	0.0178**	0.0163**	0.0167**	0.0188**
General Education $\times age^2$	-9.17e-05	-9.89e-05	-8.34e-05	-6.20e-05	-5.03e-05	-5.35e-05	-7.90e-05
Other Education	-0.0129 (0.820)	-0.0133 (0.820)	-0.0879 (0.831)	-0.449 (0.804)	-0.101 (0.864)	-0.183	-0.202
Other Education $\times$ age	-0.00637 (0.0354)	-0.00662 (0.0355)	-0.00406 (0.0359)	0.0108 (0.0349)	-0.00436 (0.0375)	0.000309 (0.0376)	0.000573 (0.0377)
Other Education $\times age^2$	0.000113 (0.000371)	0.000114 (0.000372)	9.30e-05 (0.000376)	-5.52e-05 (0.000367)	9.93e-05 (0.000394)	4.52e-05 (0.000394)	4.91e-05 (0.000395)
Years of Schooling		0.00819*** (0.00209)	0.00910*** (0.00214)	0.00919*** (0.00212)	0.00945*** (0.00210)	0.00891*** (0.00211)	0.00840*** (0.00210)
Mother has High School Diploma			-0.146*** (0.0502)	-0.176*** (0.0498)	-0.162*** (0.0483)	-0.163*** (0.0484)	-0.163*** (0.0483)
Mother has High School Diploma $\times$ age			0.00237** (0.00112)	0.00318*** (0.00111)	0.00287*** (0.00110)	0.00285*** (0.00110)	0.00286*** (0.00110)
Father has High School Diploma			-0.0340 (0.0530)	-0.000439 (0.0530)	-0.0490 (0.0514)	-0.0510 (0.0515)	-0.0419 (0.0513)
Father has High School Diploma $\times$ age			0.000942 (0.00116)	0.000165 (0.00117)	0.00125 (0.00114)	0.00128 (0.00115)	0.00114 (0.00114)
Siblings in Education Age				-0.139*** (0.0418)	-0.0613 (0.0409)	-0.0654 (0.0409)	-0.00492 (0.0421)
Siblings in Education Age $\times$ age				0.00481*** (0.000910)	0.00327*** (0.000901)	0.00344*** (0.000902)	0.00113 (0.000948)
Born in Southern Italy						0.00625 (0.0769)	0.0105 (0.0771)
Born in Southern Italy $\times$ age						-0.000117 (0.00163)	-0.000315 (0.00164)
Year 2012	-0.00358 (0.0110)	-0.00387 (0.0110)	-0.00198 (0.0110)	-0.00714 (0.0111)	-0.00621 (0.0107)	-0.00591 (0.0107)	-0.00200 (0.0107)
Year 2014	-0.00860 (0.0116)	-0.00841 (0.0116)	-0.00455 (0.0117)	-0.0119 (0.0119)	-0.00764 (0.0116)	-0.00721 (0.0116)	0.00355 (0.0116)
Constant	-1.921*** (0.0866)	-2.027*** (0.0894)	-1.922*** (0.0937)	-1.687*** (0.0978)	-1.583*** (0.137)	-1.584*** (0.137)	-1.242*** (0.155)
Observations	6,917	6,917	6,917	6,917	6,917	6,917	6,917
R <sup>-</sup> Vears of Schooling	0.268	0.269	0.272	0.281	0.326	0.327	0.336
Parents' Educational Attainment		А	x	x	x	x	A X
Presence of Siblings in Education Age			A.	x	x	x	x
Regional Controls					x	x	x
Municipality Size					х	х	х
Born in Southern Italy						x	х
Current Marital Status							х
Household Size							х

Table A.28: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2010 to 2014 for post-recession years, every two years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

## A.1.4 Main Model interacting with Birth Cohorts

emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2004	0.190***	0.189***	0.184***	0.181***	0.179***	0.179***	0.176***
age	(0.00516)	(0.00517)	(0.00533)	(0.00533)	(0.00536)	(0.00535)	(0.00537)
(age) <sup>2</sup>	-0.00214*** (5.14e-05)	-0.00214*** (5.14e-05)	-0.00209*** (5.26e-05)	-0.00208*** (5.25e-05)	-0.00210*** (5.21e-05)	-0.00209*** (5.21e-05)	-0.0020/*** (5.23e-05)
D 10//	1.544***	1.541***	1.487***	1.459***	1.593***	1.587***	1.918***
Born After 1966	(0.152)	(0.152)	(0.157)	(0.157)	(0.154)	(0.154)	(0.165)
Born After 1966 $\times$ age	-0.0572***	-0.0573***	-0.0550***	-0.0532***	-0.0584***	-0.0580***	-0.0690***
2	0.000444***	0.000446***	0.000416***	0.000384***	0.000432***	0.000427***	0.000506***
Born After $1966 \times age^2$	(9.45e-05)	(9.44e-05)	(9.73e-05)	(9.70e-05)	(9.42e-05)	(9.42e-05)	(9.95e-05)
General Education	0.166	0.176	0.334	0.390	0.619*	0.610*	0.622**
	(0.317)	(0.317)	(0.319)	(0.318)	(0.317)	(0.317)	(0.313)
General Education $\times$ age	(0.0128)	(0.0128)	(0.0128)	(0.0128)	(0.0128)	(0.0127)	(0.0126)
General Education $\times age^2$	0.000268**	0.000271**	0.000308**	0.000328***	0.000403***	0.000400***	0.000396***
General Education / age	(0.000127)	(0.000127)	(0.000127)	(0.000127)	(0.000127)	(0.000127)	(0.000126)
General Education $\times$ Born After 1966	(0.350)	(0.350)	(0.351)	(0.350)	(0.348)	(0.348)	(0.344)
General Education $\times$ Born After 1966 $\times$ and	0.0330**	0.0312*	0.0296*	0.0324**	0.0463***	0.0459***	0.0547***
General Education × Born Arter 1900 × uge	(0.0162)	(0.0162)	(0.0162)	(0.0161)	(0.0160)	(0.0160)	(0.0158)
General Education $\times$ Born After 1966 $\times$ age <sup>2</sup>	-0.000272 (0.000203)	-0.000245	-0.000211 (0.000203)	-0.000243 (0.000202)	-0.000398** (0.000199)	-0.000393** (0.000199)	-0.000521*** (0.000197)
Other Education	1.042	1.028	1.021	1.021	0.820	0.851	1.502*
Outer Education	(0.872)	(0.875)	(0.876)	(0.877)	(0.884)	(0.883)	(0.907)
Other Education $\times$ age	-0.0441	-0.0436	-0.0435	-0.0427	-0.0324	-0.0338	-0.0575
	0.000460	0.000455	0.000454	0.000443	0.000321	0.000335	0.000549
Other Education $\times age^2$	(0.000375)	(0.000377)	(0.000378)	(0.000378)	(0.000382)	(0.000381)	(0.000389)
Other Education × Born After 1966	-1.655	-1.631	-1.598	-1.521	-1.170	-1.210	-1.765
	0.0835	0.0823	0.0804	0.0747	0.0584	0.0603	0.0774
Other Education $\times$ Born After 1966 $\times$ age	(0.0522)	(0.0524)	(0.0523)	(0.0522)	(0.0532)	(0.0532)	(0.0538)
Other Education $\times$ Born After 1966 $\times age^2$	-0.00109	-0.00107	-0.00104	-0.000960	-0.000789	-0.000812	-0.000925
	(0.000690)	0.00333***	0.00367***	(0.000688)	0.00474***	(0.000702) 0.00464***	(0.000704) 0.00519***
Years of Schooling		(0.00121)	(0.00124)	(0.00124)	(0.00123)	(0.00123)	(0.00122)
Mother has High School Diploma			-0.156***	-0.163***	-0.157***	-0.157***	-0.162***
			0.00301***	(0.0217) 0.00321***	0.00307***	0.00307***	0.00322***
Mother has High School Diploma $\times$ age			(0.000528)	(0.000531)	(0.000525)	(0.000525)	(0.000524)
Father has High School Diploma			-0.110***	-0.104***	-0.101***	-0.0996***	-0.0882***
			(0.0220) 0.00276***	(0.0221) 0.00262***	(0.0219) 0.00257***	(0.0219) 0.00253***	(0.0218) 0.00230***
Father has High School Diploma $\times$ age			(0.000530)	(0.000533)	(0.000531)	(0.000532)	(0.000529)
Siblings in Education Age				-0.0135	0.0480**	0.0455**	0.0673***
				(0.0192) 0.00112**	0.00190)	0.00208	-0.00121**
Siblings in Education Age $\times$ age				(0.000486)	(0.000483)	(0.000483)	(0.000488)
Born in Southern Italy						0.0775**	0.0702*
,						(0.0369)	(0.0367)
Born in Southern Italy $\times$ age						(0.000819)	(0.000815)
Year 2002			-0.00246	-0.00210	-0.00312	-0.00303	-0.00136
104 2002			(0.00935)	(0.00935)	(0.00911)	(0.00911)	(0.00905)
Year 2004			(0.00941)	(0.00941)	(0.00919)	(0.00919)	(0.00914)
Vear 2006			0.0226**	0.0230**	0.0174*	0.0175*	0.0182**
Teal 2000			(0.00930)	(0.00931)	(0.00907)	(0.00908)	(0.00902)
Year 2008			0.0245***	0.0256***	0.0233** (0.00915)	0.0237***	0.0241*** (0.00912)
Vear 2010			0.0209**	0.0107	0.0162*	0.0166*	0.0229**
Teat 2010			(0.00968)	(0.00979)	(0.00956)	(0.00957)	(0.00954)
Year 2012			0.01//*	0.00460	0.0120	0.0125	0.0212**
V 2014			0.0222**	0.00626	0.0112	0.0118	0.0254**
Tear 2014			(0.0104)	(0.0107)	(0.0105)	(0.0105)	(0.0105)
Constant	-3.198***	-3.231***	-3.083***	-3.033***	-2.918***	-2.921***	-2.745***
	(0.120)	(0.127)	(0.151)	(0.152)	(0.150)	(0.150)	(0.155)
Observations	25,173	25,173	25,173	25,173	25,173	25,173	25,173
κ Years of Schooling	0.343	0.343 x	0.348 x	0.350 x	U.386 x	0.386 x	0.395 x
Parents' Educational Attainment		~	x	x	x	x	x
Presence of Siblings in Education Age				х	x	х	х
Regional Controls Municipality Size					x	x	x
Born in Southern Italy					л	x	x
Current Marital Status							х
Household Size							х

Table A.29: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 20 to 65 with at least upper secondary education. Omitted education type is vocational. Triple differences interacting with birth cohort from 1967 to 1994. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

	(1)	(2)	(2)	(4)	(5)	(6)	(7)
emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
302	0.190***	0.189***	0.183***	0.181***	0.179***	0.179***	0.175***
	(0.00516) -0.00214***	(0.00516) -0.00213***	(0.00535) -0.00209***	(0.00536) -0.00207***	(0.00542)	(0.00541) -0.00210***	(0.00542)
(age) <sup>2</sup>	(5.14e-05)	(5.14e-05)	(5.28e-05)	(5.27e-05)	(5.23e-05)	(5.23e-05)	(5.26e-05)
Born After 1966	2.374***	2.351***	2.295***	2.325***	2.521***	2.513***	3.159***
Deven Africa 1077 co	-0.105***	-0.104***	-0.101***	-0.103***	-0.111***	-0.110***	-0.139***
Born After 1966 $\times$ age	(0.0104)	(0.0104)	(0.0106)	(0.0106)	(0.0103)	(0.0103)	(0.0109)
Born After 1966 $\times age^2$	0.00111***	0.00110***	0.00106***	0.00107***	0.00116***	0.00115***	0.00147***
General Education	0.166 (0.317)	0.186 (0.317)	0.364 (0.320)	0.414 (0.318)	0.653** (0.318)	0.645** (0.318)	0.660**
General Education $\times$ age	-0.0158	-0.0170	-0.0228*	-0.0248*	-0.0336***	-0.0333***	-0.0334***
	(0.0128) 0.000268**	(0.0128) 0.000274**	(0.0128) 0.000317**	0.000335***	(0.0128) 0.000414***	0.000412***	(0.0127) 0.000408***
General Education $\times$ age <sup>2</sup>	(0.000127)	(0.000127)	(0.000127)	(0.000127)	(0.000127)	(0.000127)	(0.000126)
General Education $\times$ Born After 1966	-2.979***	-2.968***	(0.469)	-3.0/9***	-3.41/***	-3.408***	-3.575***
General Education $\times$ Born After 1966 $\times$ age	0.156**** (0.0242)	0.154*** (0.0242)	0.155**** (0.0241)	0.159*** (0.0239)	0.1/3*** (0.0235)	0.173*** (0.0235)	0.183*** (0.0232)
General Education $\times$ Born After 1966 $\times$ $age^2$	-0.00202*** (0.000324)	-0.00200*** (0.000323)	-0.00199*** (0.000322)	-0.00204*** (0.000319)	-0.00220*** (0.000313)	-0.00219*** (0.000313)	-0.00233*** (0.000308)
Other Education	1.042 (0.872)	1.014 (0.878)	1.009 (0.880)	1.016 (0.881)	0.742 (0.893)	0.761 (0.893)	1.461 (0.916)
Other Education $\times$ age	-0.0441 (0.0366)	-0.0431 (0.0368)	-0.0431 (0.0370)	-0.0426 (0.0370)	-0.0291 (0.0375)	-0.0300 (0.0375)	-0.0556 (0.0383)
Other Education $\times age^2$	0.000460	0.000450	0.000450	0.000440	0.000286	0.000295	0.000527
Other Education × Dom After 1066	(0.000376) -2.659*	(0.000378) -2.593*	(0.000380) -2.747*	(0.000380) -2.637*	(0.000386) -2.213	(0.000386) -2.213	(0.000393) -2.703*
	(1.516) 0.138*	(1.531) 0.134*	(1.542) 0.144*	(1.537) 0.136*	(1.580) 0.116	(1.579) 0.116	(1.574) 0.129
Other Education $\times$ Born After 1966 $\times$ age	(0.0798) -0.00181*	(0.0807) -0.00177	(0.0815) -0.00190*	(0.0811) -0.00179	(0.0835) -0.00159	(0.0833) -0.00158	(0.0825) -0.00162
Other Education $\times$ Born After 1966 $\times$ age <sup>2</sup>	(0.00107)	(0.00108)	(0.00110)	(0.00109)	(0.00112)	(0.00112)	(0.00110)
Years of Schooling		(0.00122)	(0.00126)	(0.00126)	(0.00125)	(0.00125)	(0.00124)
Mother has High School Diploma			-0.186*** (0.0287)	-0.193***	-0.186*** (0.0281)	-0.186*** (0.0281)	-0.196***
Mother has High School Diploma $\times$ age			0.00355*** (0.000652)	0.00372*** (0.000655)	0.00354*** (0.000647)	0.00355*** (0.000646)	0.00382*** (0.000642)
Father has High School Diploma			-0.0978*** (0.0298)	-0.0923*** (0.0298)	-0.0728** (0.0292)	-0.0721** (0.0293)	-0.0510* (0.0290)
Father has High School Diploma $\times$ age			0.00249*** (0.000673)	0.00237*** (0.000675)	0.00203*** (0.000668)	0.00200*** (0.000669)	0.00156** (0.000665)
Siblings in Education Age				0.0150 (0.0234)	0.0763***	0.0741***	0.0806***
Siblings in Education Age $\times$ age				0.000770	-0.000293	-0.000202	-0.00146***
Born in Southern Italy				(	(	0.0490	0.0423
Born in Southern Italy $\times$ age						-0.00136	-0.00131
Year 2002			-0.000694	-5.32e-06	-0.00409	-0.00401	-0.00188
Voor 2004			(0.00979) 0.000209	(0.00979) 0.000200	(0.00955) -0.00763	-0.00731	-0.00548
15ai 2004			(0.00987) 0.0213**	(0.00986) 0.0215**	(0.00962)	(0.00962)	(0.00954)
Year 2006			(0.00969)	(0.00969)	(0.00948)	(0.00949)	(0.00941)
Year 2008			0.0213** (0.00981)	0.0221** (0.00982)	0.0182* (0.00957)	0.0189** (0.00959)	0.0212** (0.00952)
Year 2010			0.0197* (0.0102)	0.00866 (0.0104)	0.0107 (0.0101)	0.0113 (0.0101)	0.0211** (0.0101)
Year 2012			0.0241** (0.0105)	0.00955 (0.0108)	0.0126 (0.0105)	0.0135 (0.0105)	0.0259** (0.0105)
Year 2014			0.0328*** (0.0111)	0.0153 (0.0116)	0.0187* (0.0114)	0.0197* (0.0114)	0.0371*** (0.0113)
Constant	-3.198*** (0.128)	-3.267*** (0.127)	-3.107*** (0.132)	-3.089*** (0.133)	-2.928*** (0.139)	-2.928*** (0.139)	-2.710*** (0.138)
Observations	21,493	21,493	21,493	21,493	21,493	21,493	21,493
Years of Schooling	0.271	0.272 X	0.277 X	0.201 X	0.318 X	0.318 X	0.352 X
Parents' Educational Attainment			х	x	х	x	x
Presence of Siblings in Education Age Regional Controls				х	x	X	x
Municipality Size					X	X	x
Born in Southern Italy						х	x
Current Marital Status Household Size							x
HOUSCHOID SIZE							х

Table A.30: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 25 to 65 with at least upper secondary education. Omitted education type is vocational. Triple differences interacting with birth cohort from 1967 to 1994. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

mp = 1 individual is compleyed         (1)         (2)         (3)         (4)         (3)         (6)         (7)           age         0.0005151 0.0005517 0.0002517**         0.000551 0.000257**         0.000057**         0.00077**         0.000057***         0.000057***         0.000057***         0.000057***         0.000057****         0.000057****         0.000057******         0.000057********************************								
age $0.209^{++}$ $0.202^{++}$ $0.190^{++}$ $0.190^{++}$ $0.190^{++}$ $0.190^{++}$ $0.190^{++}$ $0.190^{++}$ $0.190^{++}$ $0.190^{++}$ $0.190^{++}$ $0.190^{++}$ $0.190^{++}$ $0.022^{++}$ $0.0022^{++}$ $0.0002^{++}$ $0.0002^{++}$ $0.0002^{++}$	emp = 1 individual is employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)
mg         0.39***         0.39***         0.39***         0.19***         0.19***         0.19***         0.19***         0.19***         0.0055*           lap2 <sup>2</sup> 0.0055*         0.0055*         0.0055*         0.0055*         0.0055*         0.0055*         0.0055*           Ben Ahre 196         1.99***         1.55***         1.55***         1.55***         1.55***         1.55***         1.55***         1.55***         1.55***         1.55***         1.55***         1.55***         1.55***         1.55***         1.55***         1.55***         1.55***         1.55***         1.55****         1.55****         1.55***         1.55***         1.55*****         1.55*************         1.55*******         1.55*****								
"""         0.00551)         0.00550         0.00570         0.00570         0.00570         0.00570         0.00570         0.00570         0.00570         0.00570         0.00570         0.00570         0.00570         0.00050         0.000731         0.000135         0.0000135         0.0000135 <td>2002</td> <td>0.209***</td> <td>0.209***</td> <td>0.202***</td> <td>0.198***</td> <td>0.196***</td> <td>0.196***</td> <td>0.193***</td>	2002	0.209***	0.209***	0.202***	0.198***	0.196***	0.196***	0.193***
insp?         10.22.07         0.02.200         0.002.000         0.002.000         0.002.000         0.002.000         0.002.000         0.002.000         0.002.000         0.002.000         0.002.000         0.002.000         0.002.000         0.002.000         0.002.000         0.002.000         0.002.000         0.002.0000         0.0000.000         0.0000000         0.0000000         0.0000000         0.00000000000000000000000000000000000	age	(0.00551)	(0.00553)	(0.00569)	(0.00569)	(0.00569)	(0.00569)	(0.00568)
Image         1091+*1         1090+**         1090+**         1090+**         1000***         1000***         1000***         1000***         1000***         1000***         1000***         1000***         1000***         1000***         1000***         1000***         1000***         1000***         1000***         1000**** <th100****< th="">         1000****         <th< td=""><td>(age)<sup>2</sup></td><td>-0.00237*** (5.35e-05)</td><td>-0.00237*** (5.37e-05)</td><td>-0.00231*** (5.50e-05)</td><td>-0.00229*** (5.48e-05)</td><td>-0.00230*** (5.41e-05)</td><td>-0.00230*** (5.41e-05)</td><td>-0.00228*** (5.43e-05)</td></th<></th100****<>	(age) <sup>2</sup>	-0.00237*** (5.35e-05)	-0.00237*** (5.37e-05)	-0.00231*** (5.50e-05)	-0.00229*** (5.48e-05)	-0.00230*** (5.41e-05)	-0.00230*** (5.41e-05)	-0.00228*** (5.43e-05)
John Altre 1986         (0.166)         (0.166)         (0.177)         (0.177)         (0.177)         (0.177)         (0.177)         (0.177)         (0.0778)         (0.0773)         (0.0773)         (0.0773)         (0.0773)         (0.0773)         (0.0713)	P 10 1077	1.991***	1.990***	1.895***	1.855***	1.965***	1.964***	2.366***
Barn Alter 1966 × ege         0.00814***         0.0073****         0.0073***         0.0073***         0.008250         0.0073***         0.008550           Born Alter 1966 × ege <sup>2</sup> 0.000105         0.000125         0.000125         0.000170         0.000107         0.000170         0.0000170	Born After 1966	(0.166)	(0.166)	(0.171)	(0.170)	(0.167)	(0.167)	(0.178)
Control of the second	Born After 1966 $\times$ age	-0.0814***	-0.0815***	-0.0777***	-0.0748***	-0.0787***	-0.0785***	-0.0918***
Bon         Mon (196)         0.000(116)		(0.00803)	(0.00803)	(0.00824)	(0.00820)	(0.00796)	(0.00797)	(0.00849)
General Education         0.349         0.379         0.349         0.022         0.0515         0.0573         0.0373           General Education × age         0.00512         0.0290         0.00513         0.00813         0.01813         0.0193         0.0193         0.00814         0.00814         0.00814         0.00814         0.00814         0.00823         0.008234	Born After 1966 $\times age^2$	(0.000105)	(0.000105)	(0.000108)	(0.000107)	(0.000103)	(0.000103)	(0.000109)
Octam Lakanan         (0.397)         (0.0011)         (0.0011)         (0.0011)         (0.0011)         (0.0011)         (0.113)         (0.113)         (0.113)         (0.113)         (0.113)         (0.113)         (0.113)         (0.113)         (0.113)         (0.113)         (0.113)         (0.113)         (0.113)         (0.113)         (0.113)         (0.113)         (0.114)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)         (1.141)	Conoral Education	-0.340	-0.337	-0.184	-0.122	-0.0515	-0.0573	-0.138
General Education × age         0.0012         0.00216         0.00216         0.000153         0.000172         0.000171         0.000170           General Education × ge <sup>2</sup> 0.000153         0.000153         0.000153         0.000172         0.000171         0.000170           General Education × Bon Ahrt 1966         0.430         0.433         0.0433         0.0429         0.01176         0.4167         0.4167         0.0453           General Education × Bon Ahrt 1966 × age         0.01033         0.01933         0.00183         0.01833 <td< td=""><td>General Education</td><td>(0.397)</td><td>(0.397)</td><td>(0.400)</td><td>(0.397)</td><td>(0.387)</td><td>(0.386)</td><td>(0.371)</td></td<>	General Education	(0.397)	(0.397)	(0.400)	(0.397)	(0.387)	(0.386)	(0.371)
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	General Education $\times$ age	0.00312	0.00290	-0.00216	-0.00451	-0.00694	-0.00674	-0.00321
General Education × ge*         (0.000152)         (0.000153)         (0.000152)         (0.000145)         (0.000145)           General Education × Bon After 1966 × age         (0.0113)         (0.0133)         (0.0133)         (0.0133)         (0.0122)         (0.000145)         (0.000145)           General Education × Bon After 1966 × age         (0.00023)         (0.00032)         (0.00032)         (0.00032)         (0.00023)         (0.00043)         (0.00040)	2	9.45e-05	9.54e-05	0.000132	0.000153	0.000172	0.000170	0.000134
General Education × Born After 1966         0.00738         0.0213         0.0572         0.00310         0.1173         0.1475         0.1483         0.04185           General Education × Born After 1966 × age         0.01133         -0.0123         -0.0123         -0.0129         -0.01482         -0.0183         0.01835           General Education × Born After 1966 × age*         0.0002399         0.00002399         0.00002390         0.0000330         0.0001330         0.0001330         0.0001330         0.0001330         0.0001330         0.0001330         0.0001330         0.0001330         0.0001330         0.0001330         0.0001330         0.0001330         0.0001330         0	General Education $\times age^2$	(0.000152)	(0.000152)	(0.000152)	(0.000152)	(0.000149)	(0.000149)	(0.000145)
$ \begin{array}{c} (0.430) & (0.430) & (0.430) & (0.430) & (0.429) & (0.418) & (0.418) & (0.013) \\ (0.0192) & (0.0192) & (0.0192) & (0.0188) & (0.0123) \\ (0.0192) & (0.0192) & (0.0188) & (0.0123) \\ (0.0192) & (0.0192) & (0.0188) & (0.0123) \\ (0.00023) & (0.00023) & (0.00023) & (0.00023) \\ (0.00023) & (0.00023) & (0.00023) & (0.00023) \\ (0.00023) & (0.00023) & (0.00023) & (0.00023) \\ (0.00023) & (0.00023) & (0.00023) & (0.00023) \\ (0.00023) & (0.00023) & (0.00023) & (0.00023) \\ (0.00023) & (0.00023) & (0.00023) & (0.00023) & (0.00023) \\ (0.00023) & (0.00023) & (0.00023) & (0.00023) & (0.00023) & (0.00023) \\ (0.00023) & (0.0003) & (0.0003) & (0.0003) & (0.00023) & (0.00023) & (0.00023) \\ (0.00142) & (0.0012) & (0.0023) & (0.0003) & (0.00030)$	General Education × Born After 1966	0.00738	0.0218	0.0572	-0.00310	-0.176	-0.167	-0.254
General Education × Born After 1966 × age         -0.0113 0.00239         -0.00123 0.000239         -0.00123 0.000239         -0.000239 0.000239         0.000239 0.000239         0.000338         0.00079         0.000363         0.00039         0.00039         0.00039         0.000363         0.000924	Scherar Education × Born Arter 1900	(0.430)	(0.430)	(0.433)	(0.429)	(0.419)	(0.418)	(0.403)
	General Education $\times$ Born After 1966 $\times$ age	-0.0113	-0.0123	-0.0153	-0.0129	-0.00422	-0.00466	0.00281
General Bubustion × Born After 1966 × age <sup>2</sup> (0.000239)         (0.000239)         (0.000230)         (0.000231)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00141)         (0.00141)         (0.00141)         (0.00142)         (0.00131)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00031)         (0.00144)         (0.00144)         (0.00144)         (0.00144)         (0.00144)         (0.00144)         (0.00144)         (0.00144)         (0.00144)         (0.00144)         (0.00144)         (0.00144)		0.000275	0.000290	0.000342	0.000318	0.000209	0.000215	8.85e-05
Other Education         1.274         1.266         1.214         1.272         1.279         1.830           Other Education × age         0.0157         4.01555         0.01553         0.01553         0.01553         0.01553         0.01553         0.01553         0.01553         0.001593         0.000233         0.000234         0.000234         0.000234         0.000234         0.000234         0.000234         0.000234         0.000234         0.000345         0.000134         0.000143         0.000143         0.000144         0.000144         0.000144 </td <td>General Education <math>\times</math> Born After 1966 <math>\times</math> age<sup>2</sup></td> <td>(0.000239)</td> <td>(0.000239)</td> <td>(0.000239)</td> <td>(0.000236)</td> <td>(0.000231)</td> <td>(0.000231)</td> <td>(0.000225)</td>	General Education $\times$ Born After 1966 $\times$ age <sup>2</sup>	(0.000239)	(0.000239)	(0.000239)	(0.000236)	(0.000231)	(0.000231)	(0.000225)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Other Education	1.274	1.266	1.265	1.314	1.272	1.279	1.830
Other Education × age         0.0452)         0.0452)         0.0453)         0.0464)         0.0464)         0.04640)         0.04640)           Other Education × age <sup>2</sup> 0.000590         0.000556         0.000557         0.000580         0.000560)         0.000570         0.000540)         0.000640)         0.000640)         0.000640)         0.000640)         0.000719           Other Education × Bon After 1966         (1.279)         (1.281)         (1.285)         (1.285)         (1.285)         0.00523         0.00253         0.00234         0.00134         0.00134         0.00134         0.00134         0.00134         0.00134         0.00134         0.00146         0.00234         0.00134         0.00234         0.00134         0.00234         0.00146         0.00234         0.00134         0.00234         0.00124         0.00124         0.00124         0.00124         0.00124         0.00124         0.00124         0.00124         0.00124         0.00124 </td <td></td> <td>(1.104)</td> <td>(1.106)</td> <td>(1.111)</td> <td>(1.116)</td> <td>(1.125)</td> <td>(1.125)</td> <td>(1.169)</td>		(1.104)	(1.106)	(1.111)	(1.116)	(1.125)	(1.125)	(1.169)
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Other Education $\times$ age	(0.0452)	(0.0452)	(0.0455)	(0.0457)	(0.0460)	(0.0460)	(0.0475)
Outle Education × 2ge*         (0.000457)         (0.000457)         (0.000457)         (0.000457)           Other Education × Born After 1966         (1.279)         (1.281)         (1.285)         (1.285)         (1.285)         (1.285)         (1.285)         (1.285)         (1.285)         (1.285)         (0.0619)         (0.0625)         (0.0025)         (0.0035)	Other Education V and	0.000599	0.000596	0.000597	0.000598	0.000535	0.000538	0.000719
Other Education × Born After 1966         -1.858         -1.846         -1.769         -1.474         -1.497         -1.908         -1.999           Other Education × Born After 1966 × age         0.0957         0.0951         0.0961         0.0663         0.0726         0.0732         0.00865           Other Education × Born After 1966 × age         0.00120         -0.00120         -0.00121         0.00169         0.00857         0.00869         0.000807         0.000807         0.000807         0.000807         0.000807         0.000807         0.000807         0.000807         0.000807         0.000807         0.000807         0.000147         0.00142	Other Education × age-	(0.000452)	(0.000453)	(0.000455)	(0.000457)	(0.000460)	(0.000460)	(0.000473)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Other Education × Born After 1966	-1.858	-1.846	-1.769	-1.744	-1.497	-1.508	-1.969
Other Education × Born After 1966 × age <sup>2</sup> (0.0619)         (0.0627)         (0.0617)         (0.0623)         (0.0623)         (0.0623)           Other Education × Born After 1966 × age <sup>2</sup> (0.000805)         (0.000807)         (0.000805)         (0.000315**         0.0112**         (0.0023**)         (0.0023**)         (0.0023**)         (0.0023**)         (0.0023**)         (0.0023**)         (0.0023**)         (0.0023**)         (0.00035**)         (0.00035**)         (0.00035**)         (0.00035**)         (0.0023**)         (0.0005**)         (0.0005**)		0.0957	0.0951	0.0901	0.0863	0.0726	0.0732	0.0866
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Other Education $\times$ Born After 1966 $\times$ age	(0.0619)	(0.0620)	(0.0621)	(0.0619)	(0.0625)	(0.0625)	(0.0636)
None is account of boor days         (0.000805)         (0.000805)         (0.000805)         (0.000805)         (0.000805)         (0.000805)         (0.000805)         (0.000815**           Years of Schooling         (0.00141)         (0.00145)         (0.00145)         (0.00145)         (0.00145)         (0.00145)         (0.00145)         (0.00145)         (0.00142)         (0.00142)         (0.00142)         (0.00141)         (0.00145)         (0.00145)         (0.00145)         (0.00145)         (0.00141)         (0.00141)         (0.00141)         (0.00141)         (0.00141)         (0.00155***         (0.0025****         (0.0025***)         (0.00055)         (0.00055**)         (	Other Education $\times$ Born After 1966 $\times age^2$	-0.00126	-0.00126	-0.00118	-0.00112	-0.000953	-0.000962	-0.00103
Years of Schooling         0.00130         0.00240         0.001420         0.001420         0.001420         0.001420         0.001420         0.001420         0.001420         0.001420         0.001420         0.001420         0.001420         0.001420         0.001420         0.001420         0.001420         0.001420         0.001420         0.002241         0.002241         0.002241         0.002241         0.002241         0.002241         0.00235***         0.00235***         0.00235***         0.00235***         0.00235***         0.00235***         0.00255*         0.00255* <td>Such Education &amp; Born Frich 1900 &amp; uge</td> <td>(0.000805)</td> <td>(0.000807)</td> <td>(0.000808)</td> <td>(0.000800)</td> <td>(0.000805)</td> <td>(0.000805)</td> <td>(0.000812)</td>	Such Education & Born Frich 1900 & uge	(0.000805)	(0.000807)	(0.000808)	(0.000800)	(0.000805)	(0.000805)	(0.000812)
Mother has High School Diploma         -0.167***         -0.161***         -0.161***         -0.161***         -0.161***         -0.161***         -0.161***         -0.161***         -0.161***         -0.161***         -0.161***         0.0023**         0.0023***         0.0023***         0.0023***         0.0023***         0.0025***         0.0025***         0.0025***         0.0025***         0.0025***         0.0025*         0.000557         (0.000567)         (0.000567)         (0.000567)         (0.000567)         (0.000557)         (0.000567)         (0.000557)         (0.000557)         (0.000557)         (0.000557)         (0.000515)         (0.000515)         (0.000515)         (0.000515)         (0.000557)         (0.00156)         (	Years of Schooling		(0.00141)	(0.00230)	(0.00145)	(0.00348)	(0.00142)	(0.00140)
Moder has High School Diploma         (0.0227)         (0.0229)         (0.0224)         (0.0224)         (0.0224)           Mother has High School Diploma × age         (0.000573)         (0.000576)         (0.000569)         (0.000569)         (0.000569)           Father has High School Diploma × age         (0.0231)         (0.0233)         (0.0230)         (0.0223)         (0.0223)           Father has High School Diploma × age         (0.000576)         (0.0005770)         (0.0005677)         (0.0005677)         (0.0005677)         (0.0005677)         (0.0005677)         (0.0005677)         (0.0005677)         (0.0005677)         (0.0005677)         (0.000577)         (0.00077)         (0.000577)         (0.0	Mathankaa High Sahaal Dinlama		(0.000 1.17)	-0.157***	-0.168***	-0.161***	-0.161***	-0.166***
Mother has High School Diploma × age         0.00281***         0.00295***         0.00295***         0.00295***         0.000567)           Father has High School Diploma         -0.017***         -0.007***         0.00257***         0.000257***         0.00255***         0.00255***         0.00255***         0.00255***         0.00225***         0.00255***         0.00255***         0.00255***         0.00255***         0.00255***         0.00255***         0.00255***         0.00255***         0.00255***         0.00255***         0.00255***         0.00255***         0.00255***         0.000550         0.0000507         0.00000507         0.00000507         0.0000507         0.0000550         0.0000550         0.000250***         0.00155         0.0000507         0.00000507         0.00000507         0.0000507         0.00000507         0.00000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000077         0.001617         0.0001617         0.0001617         0.000517         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507         0.0000507 </td <td>Would has frigh School Diploma</td> <td></td> <td></td> <td>(0.0227)</td> <td>(0.0229)</td> <td>(0.0224)</td> <td>(0.0224)</td> <td>(0.0223)</td>	Would has frigh School Diploma			(0.0227)	(0.0229)	(0.0224)	(0.0224)	(0.0223)
Hole has High School Diploma         -0.107**         -0.0003/10         -0.0005/10         -0.0005/10         -0.00005/10         -0.00005/10         -0.00005/10         -0.000010         -0.000120**         -0.00013         -0.000120**         -0.00013         -0.00013:         -0.00013:         -0.00013:	Mother has High School Diploma $\times$ age			0.00281***	0.00313***	0.00295***	0.00295***	0.00311***
Father has High School Diploma       (0.023)       (0.0230)       (0.0230)       (0.0230)       (0.0230)         Father has High School Diploma × age       (0.00057)       (0.00057)       (0.000567)       (0.000515)       (0.00051)       (0.0016)       (0.0103)       (0.0103)       (0.0103)       (0.0103)       (0.0103)       (0.0103)       (0.0103)       (0.0				-0.107***	-0.0993***	-0.106***	-0.106***	-0.0929***
Father has High School Diploma × age         0.00237****         0.00235***         0.00225***         0.000567)         0.00000000         0.0000000         0.0000000         0.00000000         0.00000000         0.00000000         0.00000000         0.000000010         0.000000010         0.000000010         0.000000010         0.000000010         0.000000010         0.00000000         0.00000000         0.00000000         0.00000000         0.00000000         0.00000000         0.00000000         0.00000000         0.00000000         0.00000000         0.00000000         0.00000000         0.00000000         0.000000000         0.00000000         0.00000000         0.00000000         0.00000000000000000000000000000000000	Father has High School Diploma			(0.0231)	(0.0233)	(0.0230)	(0.0230)	(0.0229)
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Father has High School Diploma × age			0.00257***	0.00239***	0.00255***	0.00255***	0.00229***
Siblings in Education Age       -0.0204       0.0484**       0.00400*       0.00200       0.00200       0.00200       0.00200       0.00200       0.00200       0.00200       0.00200       0.00200       0.00200       0.00200       0.00200       0.00200       0.0000515       0.00				(0.000565)	(0.000570)	(0.000567)	(0.000567)	(0.000562)
Siblings in Education Age × age       0.00162***       0.000401       -0.00120**         Born in Southern Italy       0.000522       (0.000515)       (0.000517)       (0.000518)         Born in Southern Italy × age       0.000806       0.00166       0.000836       0.000912       (0.000818)         Year 2002       0.00107       (0.0107)       (0.0107)       (0.01038)       (0.0107)         Year 2004       0.00107       (0.0107)       (0.0103)       (0.0103)       (0.0103)         Year 2006       0.00381***       0.03381***       0.0320***       0.0319***       0	Siblings in Education Age				(0.0204	$(0.0484^{++})$	$(0.0470^{333})$	(0.0202)
Shiftings in Education Age × age         (0.000522)         (0.000515)         (0.00151)         (0.00151)	Siblings in Education Age v age				0.00162***	0.000481	0.000491	-0.00120**
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Siblings in Education Age × age				(0.000522)	(0.000515)	(0.000515)	(0.000519)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Born in Southern Italy						0.0397	0.0290
$\begin{array}{l c c c c c c c c c c c c c c c c c c c$							(0.0385)	-0.000611
Year 2002       0.000806       0.00107       (0.0107)       (0.0103)       (0.0103)       (0.0103)         Year 2004       0.0107)       (0.0107)       (0.0103)       (0.0103)       (0.0103)         Year 2006       0.0381***       0.0383***       0.0320***       (0.0103)       (0.0103)       (0.0103)         Year 2006       (0.0106)       (0.0106)       (0.0106)       (0.0103)       (0.0103)       (0.0103)         Year 2008       (0.0106)       (0.0106)       (0.0103)       (0.0103)       (0.0103)         Year 2010       0.0356***       0.0209**       0.0216**       0.0228**       0.0320***       (0.0107)       (0.0107)       (0.0107)         Year 2012       0.0356***       0.0110)       (0.0107)       (0.0107)       (0.0107)       (0.0107)       (0.0107)         Year 2014       0.0313***       0.0148       0.0206*       0.0206*       0.0359***         Constant       -3.604***       -3.621***       -3.444**       -3.344**       -3.284**       -3.283**       -3.063***         Observations       20,893       20,893       20,893       20,893       20,893       20,893       20,893       20,893       20,893       20,893       20,893       20,893       20,	Born in Southern Italy $\times$ age						(0.000852)	(0.000848)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Vear 2002			0.000806	0.00106	0.000836	0.000912	0.00290
Year 2004 $0.01017$ $0.00973$ $0.00464$ $0.00470$ $0.00270$ Year 2006 $0.01077$ $(0.0107)$ $(0.0107)$ $(0.0103)$ $(0.0103)$ $(0.0103)$ Year 2008 $0.0392^{***}$ $0.0383^{***}$ $0.0320^{***}$ $0.0318^{***}$ $0.0318^{***}$ Year 2010 $0.0106$ $(0.0106)$ $(0.0103)$ $(0.0103)$ $(0.0103)$ Year 2010 $0.0315^{***}$ $0.0209^{*}$ $0.0261^{**}$ $0.0242^{**}$ $0.0328^{***}$ Year 2012 $0.0306^{***}$ $0.0167$ $0.0244^{**}$ $0.0243^{**}$ $0.0339^{***}$ Year 2014 $0.0110)$ $(0.0110)$ $(0.0116)$ $(0.0116)$ $(0.0116)$ Constant $-3.604^{***}$ $-3.621^{***}$ $-3.344^{***}$ $-3.280^{***}$ $-3.063^{***}$ Years of SchoolingxxxxxxYears of SchoolingxxxxxxYears of SchoolingxxxxxxxPresence of Siblings in Education AgexxxxxxxxxxxMunicipality Sizexxx<	10a 2002			(0.0107)	(0.0107)	(0.0103)	(0.0103)	(0.0102)
Year 2006 $(0.310^{++})$ $(0.318^{++})$ $(0.318^{++})$ $(0.318^{++})$ $(0.319^{++})$ $(0.319^{++})$ $(0.319^{++})$ $(0.319^{++})$ $(0.319^{++})$ $(0.319^{++})$ $(0.319^{++})$ $(0.319^{++})$ $(0.319^{++})$ $(0.319^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.310^{++})$ $(0.0103)$ $(0.0107)$ $(0.0107)$ $(0.0107)$ $(0.0107)$ $(0.0107)$ $(0.0107)$ $(0.0107)$ $(0.0107)$ $(0.0107)$ $(0.0107)$ $(0.0107)$ $(0.0116)$	Year 2004			(0.0101)	(0.00983	(0.00464	(0.00470)	(0.0103)
Year 2006       (0.0106)       (0.0103)       (0.0103)       (0.0102)         Year 2008       (0.0106)       (0.0106)       (0.0103)       (0.0103)       (0.0102)         Year 2010       (0.0106)       (0.0106)       (0.0103)       (0.0103)       (0.0103)         Year 2012       (0.0109)       (0.0110)       (0.0107)       (0.0107)       (0.0107)         Year 2014       (0.0116)       (0.0116)       (0.0116)       (0.0116)       (0.0116)       (0.0116)         Year 2014       (0.0116)       (0.0116)       (0.0116)       (0.0116)       (0.0116)       (0.0116)         Year 2014       (0.0116)       (0.0116)       (0.0116)       (0.0116)       (0.0116)       (0.0116)         Constant $-3.604^{***}$ $-3.621^{***}$ $-3.444^{***}$ $-3.384^{***}$ $-3.280^{***}$ $-3.283^{***}$ $-3.063^{***}$ Constant $(0.139)$ (0.139)       (0.143)       (0.147)       (0.147)       (0.145)         Observations       20.893       20.893       20.893       20.893       20.893       20.893       20.893       20.893       20.893       20.893       20.893       20.893       20.893       20.893       20.893       20.893       20				0.0381***	0.0383***	0.0320***	0.0319***	0.0318***
Year 2008 $0.392^{***}$ $0.0403^{***}$ $0.0381^{***}$ $0.0391^{***}$ $0.0381^{***}$ $0.0391^{***}$ $0.0391^{***}$ $0.0391^{***}$ $0.0391^{***}$ $0.0301^{***}$ $0.0301^{***}$ $0.0301^{***}$ $0.0103$ $(0.0103)$ $(0.0103)$ Year 2010 $0.0315^{***}$ $0.0209^{*}$ $0.0261^{**}$ $0.0262^{**}$ $0.0228^{***}$ $0.0262^{**}$ $0.0238^{***}$ $0.0261^{**}$ $0.0262^{**}$ $0.0328^{***}$ $0.0317^{***}$ $0.0209^{*}$ $0.0261^{**}$ $0.0262^{**}$ $0.0238^{***}$ $0.0306^{***}$ $0.0107$ $(0.0107)$ $(0$	Year 2006			(0.0106)	(0.0106)	(0.0103)	(0.0103)	(0.0102)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Year 2008			0.0392***	0.0403***	0.0381***	0.0381***	0.0379***
Year 2010 $(0.0109)$ $(0.0107)$ $(0.0107)$ $(0.0107)$ $(0.0107)$ Year 2012 $(0.0109)$ $(0.0107)$ $(0.0107)$ $(0.0107)$ $(0.0107)$ Year 2014 $(0.0116)$ $(0.0116)$ $(0.0116)$ $(0.0109)$ $(0.0109)$ Constant $-3.604^{***}$ $-3.621^{***}$ $-3.444^{***}$ $-3.384^{***}$ $-3.280^{***}$ $-3.283^{***}$ $-3.063^{***}$ Observations $20.893$ </td <td></td> <td></td> <td></td> <td>(0.0106)</td> <td>(0.0106)</td> <td>(0.0103)</td> <td>(0.0103)</td> <td>(0.0103)</td>				(0.0106)	(0.0106)	(0.0103)	(0.0103)	(0.0103)
Year 2012 $0.0306^{***}$ $0.0167$ $0.0244^{**}$ $0.0233^{***}$ $0.0339^{***}$ Year 2014 $0.0313^{***}$ $0.0110$ ) $(0.0110)$ $(0.0110)$ $(0.0109)$ $(0.0109)$ Constant $-3.604^{***}$ $-3.621^{***}$ $-3.344^{***}$ $-3.384^{***}$ $-3.283^{***}$ $-3.283^{***}$ $-3.663^{***}$ Observations $20.893$ <td< td=""><td>Year 2010</td><td></td><td></td><td>(0.0109)</td><td>(0.0110)</td><td>(0.0107)</td><td>(0.0107)</td><td>(0.0107)</td></td<>	Year 2010			(0.0109)	(0.0110)	(0.0107)	(0.0107)	(0.0107)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Vear 2012			0.0306***	0.0167	0.0244**	0.0243**	0.0339***
Year 2014 $(0.0148$ $0.0206^{*}$ $0.0205^{*}$ $0.01205^{*}$ $0.01205^{*}$ $0.01205^{*}$ $0.01205^{*}$ $0.01205^{*}$ $0.01205^{*}$ $0.01205^{*}$ $0.01205^{*}$ $0.01205^{*}$ $0.01205^{*}$ $0.01205^{*}$ $0.01205^{*}$ $0.01205^{*}$ $0.01205^{*}$ $0.01165$ $(0.0116)$ $(0.0147)$ $(0.147)$ $(0.147)$ $(0.147)$ $(0.147)$ $(0.147)$ $(0.147)$ $(0.147)$ $(0.147)$ $(0.147)$ $(0.288)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.893)^{2}$ $(0.8$	10al 2012			(0.0110)	(0.0112)	(0.0109)	(0.0110)	(0.0109)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Year 2014			0.0313***	0.0148	0.0206*	0.0206*	0.0359***
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	_	-3.604***	-3.621***	-3.444***	-3.384***	-3.280***	-3.283***	-3.063***
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Constant	(0.139)	(0.139)	(0.143)	(0.143)	(0.147)	(0.147)	(0.145)
Observations         20,695 <th2< td=""><td>Observations</td><td>20.802</td><td>20.802</td><td>20.802</td><td>20.802</td><td>20.802</td><td>20.802</td><td>20.802</td></th2<>	Observations	20.802	20.802	20.802	20.802	20.802	20.802	20.802
x         x	$R^2$	20,893	20,893	20,893	20,893	20,893	20,893	20,893
Parents' Educational Attainment         x <t< td=""><td>Years of Schooling</td><td>0.500</td><td>x</td><td>x</td><td>X</td><td>X X</td><td>X X</td><td>X</td></t<>	Years of Schooling	0.500	x	x	X	X X	X X	X
Presence of Siblings in Education Age         x	Parents' Educational Attainment			x	x	x	x	x
Regional Controls         x	Presence of Siblings in Education Age				х	х	х	x
Municipanty Size     x     x     x     x       Born in Southern Italy     x     x     x       Current Marital Status     x     x       Household Size     x     x	Regional Controls					х	х	х
Unrent Marital Status X X Household Size X X	Municipality Size					х	x	x
Household Size x	Current Marital Status						х	x X
	Household Size							x

Table A.31: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 20 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Triple differences interacting with birth cohort from 1967 to 1994. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
emp = 1 individual is employed	(1)	(2)	(0)	(1)	(0)	(0)	(/)
age	0.209***	0.208***	0.200***	0.197***	0.195***	0.195***	0.190***
	(0.00551) -0.00237***	(0.00552) -0.00236***	(0.00573) -0.00230***	(0.00573) -0.00228***	(0.00576) -0.00230***	(0.00576) -0.00230***	(0.00575) -0.00227***
(age) <sup>2</sup>	(5.36e-05)	(5.37e-05)	(5.52e-05)	(5.50e-05)	(5.45e-05)	(5.45e-05)	(5.46e-05)
Born After 1966	2.705***	2.685*** (0.230)	2.596*** (0.235)	2.623*** (0.234)	2.798***	2.794***	3.606*** (0.241)
Born After 1966 $\times$ age	-0.122***	-0.122***	-0.118***	-0.119***	-0.126***	-0.126***	-0.162***
2	0.00120)	0.00120)	(0.0122) 0.00128***	(0.0122) 0.00128***	0.00134***	0.00134***	0.00124)
Born After 1966 $\times age^2$	(0.000161)	(0.000161)	(0.000164)	(0.000163)	(0.000158)	(0.000158)	(0.000165)
General Education	(0.397)	(0.396)	-0.152 (0.401)	(0.396)	-0.0477 (0.384)	(0.384)	(0.369)
General Education $\times$ age	0.00312	0.00239	-0.00345	-0.00537	-0.00723	-0.00725	-0.00354
Conoral Education × aga <sup>2</sup>	(0.0150) 9.45e-05	(0.0150) 9.76e-05	0.000141	0.000158	0.000173	0.000173	0.000135
General Education × uge	(0.000152)	(0.000152)	(0.000153)	(0.000152)	(0.000149)	(0.000149)	(0.000144)
General Education × Born After 1966	(0.565)	(0.564)	(0.565)	(0.558)	(0.542)	(0.542)	(0.525)
General Education $\times$ Born After 1966 $\times$ age	0.120***	0.118***	0.116*** (0.0288)	0.119*** (0.0284)	0.126***	0.126***	0.135***
General Education $\times$ Born After 1966 $\times age^2$	-0.00161***	-0.00158***	-0.00154***	-0.00156***	-0.00165***	-0.00165***	-0.00180***
General Education × Bonn Anter 1966 × age	(0.000387)	(0.000386)	(0.000384)	(0.000379)	(0.000368)	(0.000368)	(0.000358)
Other Education	(1.104)	(1.110)	(1.117)	(1.124)	(1.142)	(1.142)	(1.182)
Other Education $\times$ age	-0.0557 (0.0452)	-0.0547 (0.0454)	-0.0553 (0.0458)	-0.0570 (0.0460)	-0.0506 (0.0466)	-0.0502	-0.0719 (0.0480)
Other Education $\times age^2$	0.000599	0.000588	0.000595	0.000603	0.000515	0.000511	0.000708
	(0.000452) -2.940*	-2.893	(0.000459) -2.979*	-2.958	-2.763	-2.759	-3.225*
Other Education × Born After 1966	(1.778)	(1.792)	(1.809)	(1.802)	(1.834)	(1.834)	(1.845)
Other Education $\times$ Born After 1966 $\times$ age	(0.0926)	(0.0934)	(0.0946)	(0.0937)	(0.0950)	(0.0950)	(0.0947)
Other Education $\times$ Born After 1966 $\times age^2$	-0.00204	-0.00201	-0.00207	-0.00200	-0.00189	-0.00188	-0.00194
Years of Schooling	(0.00124)	0.00618***	0.00664***	0.00680***	0.00731***	0.00723***	0.00742***
Mather has High School Diploma		(0.00144)	(0.00148) -0.201***	(0.00148) -0.212***	(0.00145) -0.203***	(0.00146) -0.202***	(0.00143) -0.215***
			(0.0315) 0.00361***	(0.0317) 0.00388***	(0.0308) 0.00367***	(0.0308) 0.00366***	(0.0305) 0.00400***
Mother has High School Diploma $\times$ age			(0.000719)	(0.000723)	(0.000711)	(0.000712)	(0.000705)
Father has High School Diploma			(0.0327)	(0.0329)	(0.0320)	(0.0320)	(0.0316)
Father has High School Diploma $\times$ age			0.00220*** (0.000736)	0.00204*** (0.000740)	0.00194*** (0.000727)	0.00195*** (0.000728)	0.00143** (0.000720)
Siblings in Education Age				0.0119 (0.0257)	0.0852*** (0.0249)	0.0852*** (0.0250)	0.0948***
Siblings in Education Age $\times$ age				0.00126**	-5.81e-05	-4.63e-05	-0.00155***
Born in Southern Italy				(0.0000000)))	(0.0000001)	-0.00184	-0.0120
Born in Southern Italy $\times$ age						5.18e-05	0.000159
Year 2002			0.00238	0.00310	-0.00115	-0.00111	0.00129
Veen 2004			(0.0115) 0.0117	(0.0115) 0.0115	(0.0111) 0.00267	(0.0111) 0.00281	(0.0110) 0.00459
fear 2004			(0.0115)	(0.0115)	(0.0111)	(0.0111)	(0.0110)
Year 2006			(0.0113)	(0.0113)	(0.0110)	(0.0110)	(0.0109)
Year 2008			0.0381*** (0.0114)	0.0387*** (0.0114)	0.0339*** (0.0110)	0.0343*** (0.0110)	0.0360*** (0.0109)
Year 2010			0.0312*** (0.0118)	0.0195 (0.0120)	0.0198* (0.0116)	0.0201* (0.0116)	0.0310*** (0.0115)
Year 2012			0.0402***	0.0245**	0.0262**	0.0266**	0.0408***
Year 2014			0.0459***	0.0272**	0.0316**	0.0321**	0.0525***
Constant	-3.604***	-3.663***	-3.462***	-3.437***	(0.0129) -3.281***	(0.0130) -3.278***	(0.0129) -3.013***
Constant	(0.139)	(0.139)	(0.144)	(0.145)	(0.151)	(0.151)	(0.149)
Observations R <sup>2</sup>	17,345	17,345	17,345 0.315	17,345	17,345	17,345	17,345
Years of Schooling	2.200	x	x	x	x	x	x
Parents' Educational Attainment Presence of Siblings in Education Age			х	x x	x x	x x	x x
Regional Controls					x	x	x
Born in Southern Italy					х	x	x x
Current Marital Status Household Size							x
Household Size							А

Table A.32: The Effect of Education Type on Employment over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males from age 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Triple differences interacting with birth cohort from 1967 to 1994. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

# A.2 Effects over Life-Time Wages

#### A.2.1 Main Model for Quasi-Longitudinal Data

In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.0756***	0.0739***	0.0712***	0.0657***	0.0593***	0.0612***	0.0477***
-	-0.000696***	-0.000680***	-0.000662***	(0.00346)	-0.000627***	-0.000646***	-0.000515***
(age) <sup>2</sup>	(3.96e-05)	(3.94e-05)	(3.91e-05)	(3.97e-05)	(4.02e-05)	(4.03e-05)	(5.20e-05)
General Education	-1.008***	-1.080***	-0.970***	-0.967***	-1.001***	-0.988***	-0.962***
General Education	(0.217)	(0.215)	(0.213)	(0.213)	(0.212)	(0.212)	(0.211)
General Education $\times$ age	0.0445***	0.0440***	0.0397***	0.0396***	0.0412***	0.0410***	0.0399***
0	(0.0105)	(0.0103)	(0.0102)	(0.0102)	(0.0102)	(0.0102)	(0.0101)
General Education $\times age^2$	(0.000122)	(0.000120)	(0.000119)	(0.000119)	(0.000119)	(0.000119)	(0.000117)
Other Education	0.162	0.214	0.192	0.163	0.238	0.0696	0.0421
Other Education	(0.531)	(0.527)	(0.530)	(0.529)	(0.527)	(0.526)	(0.527)
Other Education $\times$ age	-0.0134	-0.0183	-0.0172	-0.0160	-0.0196	-0.00892	-0.00762
	(0.0255)	(0.0253)	(0.0254)	(0.0254)	(0.0254)	(0.0252)	(0.0251)
Other Education $\times age^2$	(0.000190	(0.000231	(0.000238	(0.000227	(0.000273	(0.000140	(0.000120)
	(0.000298)	0.0423***	0.0385***	0.0386***	0.0396***	0.0377***	0.0377***
Years of Schooling		(0.00224)	(0.00231)	(0.00231)	(0.00233)	(0.00233)	(0.00230)
Mother has High School Diploma			-0.0944**	-0.113***	-0.105**	-0.102**	-0.108**
Moulei has frigh School Dipionia			(0.0428)	(0.0433)	(0.0426)	(0.0426)	(0.0424)
Mother has High School Diploma × age			0.00337***	0.00383***	0.00335***	0.00318***	0.00333***
			(0.00103)	(0.00105)	(0.00104)	(0.00104)	(0.00103)
Father has High School Diploma			(0.0491)	(0.0496)	(0.0500)	(0.0500)	(0.0498)
			0.00555***	0.00525***	0.00436***	0.00445***	0.00413***
Father has High School Diploma × age			(0.00119)	(0.00120)	(0.00121)	(0.00121)	(0.00119)
Siblings in Education Age				-0.0805**	-0.0401	-0.0440	-0.0307
				(0.0371)	(0.0365)	(0.0366)	(0.0370)
Siblings in Education Age $\times$ age				(0.00296***	(0.00271***	(0.00314****	(0.000978
				(0.000939)	(0.000920)	0.0350	0.0217
Born in Southern Italy						(0.0738)	(0.0726)
Born in Southern Italy × age						-0.00199	-0.00181
Bolli lii Bouuleili luuly × uge						(0.00165)	(0.00163)
Year 2002	0.052/***	0.0490***	0.0482***	0.0487***	0.0470***	0.0476***	0.0534***
	(0.0156)	(0.0156)	(0.0155)	(0.0155)	(0.0151)	(0.0151)	(0.0150)
Year 2004	(0.0164)	(0.0162)	(0.0162)	(0.0162)	(0.0158)	(0.0158)	(0.0158)
V	0.167***	0.145***	0.145***	0.144***	0.137***	0.144***	0.154***
Year 2006	(0.0162)	(0.0161)	(0.0160)	(0.0160)	(0.0157)	(0.0157)	(0.0156)
Year 2008	0.197***	0.173***	0.172***	0.172***	0.170***	0.180***	0.192***
	(0.0156)	(0.0155)	(0.0154)	(0.0154)	(0.0151)	(0.0151)	(0.0149)
Year 2010	(0.0161)	(0.0160)	(0.0160)	(0.0162)	(0.0159)	(0.0159)	(0.0157)
X 2012	0.152***	0.122***	0.123***	0.106***	0.118***	0.130***	0.155***
Year 2012	(0.0165)	(0.0163)	(0.0163)	(0.0168)	(0.0164)	(0.0162)	(0.0161)
Year 2014	0.161***	0.133***	0.133***	0.115***	0.122***	0.134***	0.167***
Iou Dolt	(0.0166)	(0.0165)	(0.0164)	(0.0174)	(0.0171)	(0.0171)	(0.0170)
Constant	(0.0666)	/.226***	/.345***	/.464***	/./55***	(0.0921)	8.199***
	(0.0000)	(0.070))	(0.0712)	(0.0701)	(0.0)20)	(0.0)21)	(0.124)
Observations	13,886	13,886	13,886	13,886	13,886	13,886	13,886
$R^2$	0.248	0.270	0.277	0.279	0.312	0.317	0.332
Years of Schooling		х	x	x	x	x	x
Presence of Siblings in Education Age			х	x	x	x	x
Regional Controls				~	x	x	x
Municipality Size					x	x	x
Born in Southern Italy						х	x
Current Marital Status							х
Household Size							x

Table A.33: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males with at least upper secondary education who perceived wages, from age 20 to 65 *excluding* self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)
200	0.0657***	0.0668***	0.0640***	0.0582***	0.0496***	0.0512***	0.0337***
age	(0.00391)	(0.00389)	(0.00388)	(0.00410)	(0.00425)	(0.00425)	(0.00524)
(age) <sup>2</sup>	(4.60e-05)	(4.56e-05)	(4.53e-05)	(4.62e-05)	(4.63e-05)	(4.62e-05)	(5.41e-05)
General Education	-0.951***	-1.098***	-1.002***	-1.012***	-1.077***	-1.047***	-1.037***
	0.0423***	(0.245) 0.0449***	0.0411***	0.0416***	0.0447***	0.0438***	0.0436***
General Education $\times$ age	(0.0117)	(0.0116)	(0.0115)	(0.0115)	(0.0115)	(0.0114)	(0.0113)
General Education $\times age^2$	-0.0003/5***	-0.000418***	-0.000393***	-0.000399***	-0.000438***	-0.000428*** (0.000131)	-0.000425*** (0.000129)
Other Education	0.0387	0.0533	0.0786	-0.00786	-0.107	-0.301	-0.384
	(0.784)	(0.763)	(0.768)	(0.762)	(0.776)	(0.778)	(0.786)
Other Education $\times$ age	(0.0360)	(0.0350)	(0.0353)	(0.0351)	(0.0357)	(0.0356)	(0.0358)
Other Education $\times age^2$	0.000116 (0.000403)	0.000162 (0.000393)	0.000170 (0.000397)	0.000132 (0.000395)	9.40e-05 (0.000400)	-5.62e-05 (0.000399)	-9.87e-05 (0.000399)
Years of Schooling		0.0441***	0.0401***	0.0403***	0.0408***	0.0387***	0.0383***
Mother has High School Diploma		(0.00225)	-0.102**	-0.120**	-0.112**	-0.107**	-0.118**
Mother has frigh School Dipiona			(0.0467)	(0.0472)	(0.0469)	(0.0470)	(0.0464)
Mother has High School Diploma $\times$ age			(0.00111)	(0.00112)	(0.00112)	(0.00112)	(0.00110)
Father has High School Diploma			-0.137***	-0.122**	-0.0804	-0.0930*	-0.0690
			(0.0530) 0.00468***	(0.0539) 0.00437***	(0.0538) 0.00323**	(0.0538) 0.00350***	(0.0531) 0.00302**
Father has High School Diploma $\times$ age			(0.00126)	(0.00129)	(0.00129)	(0.00128)	(0.00127)
Siblings in Education Age				-0.0466	-0.00876	-0.0100	-0.0126
Siblings in Education Assay and				0.00239**	0.00220**	0.00263***	0.000631
Siblings in Education Age × age				(0.000992)	(0.000983)	(0.000978)	(0.000989)
Born in Southern Italy						(0.0817)	(0.0804)
Born in Southern Italy $\times$ age						-0.00259	-0.00244
	0.0320**	0.0283*	0.0273*	0.0276*	0.0253*	(0.00181) 0.0258*	(0.00178) 0.0321**
Year 2002	(0.0157)	(0.0155)	(0.0155)	(0.0155)	(0.0150)	(0.0150)	(0.0148)
Year 2004	0.0870***	0.0796***	0.0782***	0.0767***	0.0725***	0.0763***	0.0864***
Veen 2006	0.153***	0.129***	0.128***	0.127***	0.118***	0.126***	0.138***
Tear 2000	(0.0161)	(0.0160)	(0.0159)	(0.0159)	(0.0155)	(0.0155)	(0.0153)
Year 2008	(0.0156)	(0.0154)	(0.0153)	(0.0153)	(0.0148)	(0.0148)	(0.0146)
Year 2010	0.165***	0.132***	0.134***	0.121***	0.127***	0.139***	0.163***
	(0.0160) 0.143***	(0.0157) 0.110***	(0.0158) 0.110***	(0.0159) 0.0928***	(0.0156) 0.102***	(0.0155) 0.116***	(0.0153) 0.143***
Year 2012	(0.0164)	(0.0161)	(0.0161)	(0.0165)	(0.0161)	(0.0159)	(0.0157)
Year 2014	0.150***	0.119***	0.119***	0.0993***	0.106***	0.120***	0.158***
Constant	7.946***	7.372***	7.496***	7.604***	7.943***	7.924***	8.482***
Constant	(0.0810)	(0.0850)	(0.0854)	(0.0927)	(0.107)	(0.107)	(0.132)
Observations	12.772	12.772	12.772	12.772	12.772	12.772	12.772
$R^2$	0.182	0.211	0.219	0.222	0.258	0.266	0.285
Years of Schooling Parents' Educational Attainment		x	x	x	X	X	x
Presence of Siblings in Education Age			А	X	л Х	л Х	A X
Regional Controls					х	х	х
Municipality Size Born in Southern Italy					х	x	x
Current Marital Status						А	A X
Household Size							х

Table A.34: The Effect of Education Type on Wages over the Life-Cycle. Linear Probability Models. Dependent variable: individual is employed. Sample includes males with at least upper secondary education who perceived wages, from age 25 to 65 *excluding* self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

#### A.2.2 Wave-by-Wave Analysis

(a) 20–65 age cohort, male individuals without self-employed

(b) 25–65 age cohort, male individuals without self-employed

CHAPTER A -

EMPIRICAL RESULTS (DETAILS)

In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.0911*** (0.0102)	0.0905*** (0.0103)	0.0845*** (0.00999)	0.0834*** (0.0105)	0.0723*** (0.0117)	0.0743*** (0.0117)	0.0537*** (0.0161)	0.0635*** (0.0110)	0.0650*** (0.0110)	0.0610*** (0.0109)	0.0577*** (0.0111)	0.0443*** (0.0115)	0.0461*** (0.0115)	0.0266* (0.0150)
(age) <sup>2</sup>	-0.000875*** (0.000127)	-0.000872*** (0.000127)	-0.000821*** (0.000124)	-0.000831*** (0.000124)	-0.000862*** (0.000129)	-0.000879*** (0.000129)	-0.000657*** (0.000166)	-0.000559*** (0.000134)	-0.000581*** (0.000133)	-0.000548*** (0.000133)	-0.000550*** (0.000134)	-0.000549*** (0.000130)	-0.000569*** (0.000130)	-0.000349** (0.000157)
General Education	-3.341*** (0.704)	-3.489*** (0.700)	-3.333**** (0.697)	-3.325*** (0.696)	-3.455*** (0.680)	-3.411*** (0.683)	-3.328*** (0.675)	-2.971***	-3.249*** (1.009)	-3.125*** (1.010)	-3.136*** (1.011)	-3.386*** (0.958)	-3.343*** (0.961)	-3.222*** (0.960)
General Education $\times$ age	0.163*** (0.0346)	0.169*** (0.0342)	0.163*** (0.0338)	0.163*** (0.0338)	0.172*** (0.0332)	0.169*** (0.0333)	0.165*** (0.0327)	0.147*** (0.0478)	0.159*** (0.0474)	0.154*** (0.0472)	0.154*** (0.0472)	0.168*** (0.0450)	0.165*** (0.0450)	0.160*** (0.0447)
General Education $\times age^2$	-0.00187*** (0.000418)	-0.00197*** (0.000412)	-0.00192*** (0.000405)	-0.00192*** (0.000405)	-0.00205*** (0.000400)	-0.00201*** (0.000402)	-0.00197*** (0.000392)	-0.00171*** (0.000554)	-0.00187*** (0.000548)	-0.00182*** (0.000543)	-0.00182*** (0.000544)	-0.00200*** (0.000520)	-0.00197*** (0.000520)	-0.00190*** (0.000511)
Other Education	1.185** (0.509)	1.205** (0.516)	1.322** (0.567)	1.329** (0.568)	1.416* (0.757)	1.513** (0.751)	1.370* (0.722)	0.00140 (0.806)	-0.102 (0.848)	0.0653 (0.827)	0.0607 (0.834)	-0.498 (1.071)	-0.567 (1.069)	-0.661 (1.050)
Other Education $\times$ age	-0.0526* (0.0288)	-0.0558* (0.0290)	-0.0629** (0.0311)	-0.0631** (0.0311)	-0.0689* (0.0400)	-0.0731* (0.0399)	-0.0638* (0.0385)	0.00145 (0.0396)	0.00303 (0.0413)	-0.00572 (0.0407)	-0.00510 (0.0409)	0.0183 (0.0519)	0.0211 (0.0519)	0.0295 (0.0513)
Other Education $\times age^2$	0.000550 (0.000346)	0.000597* (0.000348)	0.000696* (0.000371)	0.000696* (0.000372)	0.000816* (0.000478)	0.000858* (0.000478)	0.000730 (0.000462)	-4.31e-05 (0.000442)	-4.12e-05 (0.000457)	7.03e-05 (0.000454)	5.84e-05 (0.000456)	-0.000140 (0.000585)	-0.000171 (0.000586)	-0.000300 (0.000584)
Years of Schooling		0.0337*** (0.00886)	0.0321*** (0.00869)	0.0320*** (0.00871)	0.0374*** (0.00861)	0.0360*** (0.00858)	0.0368*** (0.00853)		0.0390*** (0.00921)	0.0355*** (0.00901)	0.0357*** (0.00913)	0.0395*** (0.00890)	0.0382*** (0.00884)	0.0380*** (0.00876)
Mother has High School Diploma			0.0232 (0.156)	0.00744 (0.159)	7.01e-05 (0.157)	-0.00189 (0.157)	0.00721 (0.157)			0.0158 (0.169)	-0.0111 (0.171)	-0.0540 (0.161)	-0.0564 (0.162)	-0.0588 (0.162)
Mother has High School Diploma $\times$ age			0.000453 (0.00377)	0.000813 (0.00384)	0.000550 (0.00381)	0.000578 (0.00381)	0.000413 (0.00382)			0.000485	0.00105	0.00175 (0.00390)	0.00177 (0.00392)	0.00190 (0.00392)
Father has High School Diploma			-0.488*** (0.162)	-0.479*** (0.165)	-0.422** (0.168)	-0.429** (0.168)	-0.428** (0.169)			-0.284* (0.171)	-0.261	-0.230	-0.237	-0.202 (0.168)
Father has High School Diploma $\times$ age			0.0129*** (0.00384)	0.0127*** (0.00390)	0.0110***	0.0113*** (0.00397)	0.0113*** (0.00399)			0.00823**	0.00779*	0.00679*	0.00708*	0.00627
Siblings in Education Age			(,	-0.0972	-0.0398	-0.0538	-0.0996			(0.000.00_)	-0.147	-0.0996	-0.0990	-0.132
Siblings in Education Age $\times$ age				0.00241 (0.00332)	0.00225 (0.00326)	0.00291 (0.00332)	0.00289 (0.00344)				0.00412 (0.00287)	0.00405 (0.00302)	0.00442 (0.00301)	0.00377 (0.00317)
Born in Southern Italy						0.159 (0.208)	0.162 (0.211)						-0.00151 (0.233)	0.0112 (0.239)
Born in Southern Italy $\times$ age						-0.00573 (0.00495)	-0.00584 (0.00505)						-0.00233 (0.00548)	-0.00260 (0.00563)
Constant	7.422*** (0.199)	7.011*** (0.216)	7.184*** (0.215)	7.246*** (0.239)	7.715*** (0.308)	7.686*** (0.309)	8.139*** (0.413)	8.002*** (0.218)	7.481*** (0.231)	7.623*** (0.236)	7.735*** (0.252)	8.270*** (0.298)	8.257*** (0.299)	8.736*** (0.385)
Observations	1,660	1,660	1,660	1,660	1,660	1,660	1,660	1,477	1,477	1,477	1,477	1,477	1,477	1,477
R <sup>2</sup>	0.308	0.316	0.325	0.326	0.399	0.402	0.409	0.187	0.201	0.209	0.210	0.310	0.315	0.327
Parents' Educational Attainment		х	x	x	x	x	x		x	x	x	x	x	x
Presence of Siblings in Education Age			~	x	x	x	x			~	x	x	x	x
Regional Controls				~	x	x	x				~	x	x	x
Municipality Size					x	x	x					x	x	x
Born in Southern Italy						х	х						х	х
Current Marital Status							x							x
Household Size							х							х

Table A.35: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived a wage on the considered wave, aged 20 or 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Wave of analysis: 2000. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

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In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.0793*** (0.00889)	0.0791*** (0.00889)	0.0776*** (0.00884)	0.0734*** (0.00891)	0.0707*** (0.00924)	0.0732*** (0.00923)	0.0509*** (0.0121)	0.0765*** (0.0118)	0.0776*** (0.0118)	0.0780*** (0.0120)	0.0734*** (0.0121)	0.0636*** (0.0121)	0.0671*** (0.0121)	0.0405*** (0.0138)
(age) <sup>2</sup>	-0.000754*** (0.000110)	-0.000755*** (0.000110)	-0.000744*** (0.000109)	-0.000741*** (0.000110)	-0.000768*** (0.000111)	-0.000792*** (0.000110)	-0.000575*** (0.000134)	-0.000720*** (0.000140)	-0.000736*** (0.000140)	-0.000737*** (0.000141)	-0.000727*** (0.000142)	-0.000696*** (0.000143)	-0.000724*** (0.000143)	-0.000464*** (0.000155)
General Education	(0.516)	-0.558 (0.513)	-0.235 (0.507)	(0.503)	(0.496)	-0.174 (0.492)	(0.489)	-0.684 (0.693)	-0.812 (0.687)	-0.729 (0.679)	-0.684 (0.684)	-0.805 (0.676)	-0.754 (0.666)	-0.711 (0.663)
General Education $\times$ age	(0.0266)	(0.0263)	(0.0259)	(0.0255)	(0.0252)	(0.0251)	(0.0250)	(0.0338)	(0.0337)	(0.0283	(0.0257	(0.0320)	(0.0324)	(0.0279
General Education $\times age^2$	-3.96e-05 (0.000324)	-7.37e-05 (0.000320)	-3.63e-06 (0.000312)	3.61e-05 (0.000307)	3.39e-05 (0.000303)	3.16e-05 (0.000301)	6.12e-05 (0.000302)	-0.000243 (0.000395)	-0.000311 (0.000389)	-0.000240 (0.000382)	-0.000207 (0.000382)	-0.000290 (0.000379)	-0.000268 (0.000377)	-0.000237 (0.000379)
Other Education	-0.300 (1.505)	-0.260 (1.472)	-0.197 (1.474)	-0.106 (1.469)	-0.287 (1.443)	-0.338 (1.501)	-0.540 (1.525)	-0.723 (3.138)	-0.581 (3.098)	-0.329 (3.099)	-0.182 (3.116)	-0.145 (2.633)	-0.458 (2.772)	-0.671 (2.805)
Other Education $\times$ age	0.0150 (0.0808)	0.0127 (0.0786)	0.00843 (0.0788)	0.00272 (0.0783)	0.00932 (0.0765)	0.0104 (0.0792)	0.0238 (0.0811)	0.0370 (0.158)	0.0295 (0.156)	0.0153 (0.156)	0.00681 (0.157)	0.00152 (0.133)	0.0156 (0.140)	0.0293 (0.142)
Other Education $\times age^2$	-0.000205 (0.00103)	-0.000187 (0.000997)	-0.000122 (0.00100)	-3.59e-05 (0.000993)	-7.05e-05 (0.000966)	-7.21e-05 (0.000997)	-0.000261 (0.00102)	-0.000475 (0.00192)	-0.000399 (0.00189)	-0.000207 (0.00189)	-8.78e-05 (0.00189)	3.08e-05 (0.00161)	-0.000127 (0.00169)	-0.000315 (0.00172)
Years of Schooling		0.0263*** (0.00800)	0.0208** (0.00835)	0.0211** (0.00836)	0.0291*** (0.00875)	0.0286*** (0.00874)	0.0287*** (0.00861)		0.0306*** (0.00798)	0.0238*** (0.00839)	0.0242*** (0.00842)	0.0325*** (0.00873)	0.0315*** (0.00872)	0.0312*** (0.00860)
Mother has High School Diploma			-0.0411 (0.118)	-0.0608 (0.118)	-0.0574 (0.117)	-0.0643 (0.119)	-0.0659 (0.119)			0.184 (0.120)	0.158 (0.119)	0.173 (0.125)	0.178 (0.127)	0.176 (0.124)
Mother has High School Diploma $\times$ age			8.73e-05 (0.00287)	0.000576 (0.00282)	0.000185 (0.00286)	0.000296 (0.00287)	0.000136 (0.00289)			-0.00459* (0.00276)	-0.00398 (0.00272)	-0.00480* (0.00287)	-0.00493* (0.00291)	-0.00506* (0.00288)
Father has High School Diploma			-0.102 (0.121)	-0.0990 (0.125)	-0.0612 (0.126)	-0.0704 (0.126)	-0.0500 (0.127)			-0.0831 (0.138)	-0.0781 (0.144)	-0.00823 (0.141)	-0.0296 (0.142)	0.00142 (0.142)
Father has High School Diploma $\times$ age			0.00543* (0.00300)	0.00537* (0.00306)	0.00431 (0.00308)	0.00448 (0.00307)	0.00401 (0.00311)			0.00471 (0.00330)	0.00462 (0.00340)	0.00283 (0.00336)	0.00327 (0.00336)	0.00255 (0.00337)
Siblings in Education Age				-0.0912 (0.110)	0.00526 (0.116)	0.00384 (0.121)	0.00448 (0.120)				-0.0853 (0.137)	0.00455 (0.140)	0.00461 (0.145)	-0.0171 (0.143)
Siblings in Education Age $\times$ age				0.00424 (0.00289)	0.00289 (0.00303)	0.00339 (0.00315)	0.00141 (0.00317)				0.00396 (0.00346)	0.00277 (0.00353)	0.00324 (0.00367)	0.00159 (0.00366)
Born in Southern Italy						-0.269 (0.244)	-0.291 (0.240)						-0.228 (0.302)	-0.259 (0.300)
Born in Southern Italy $\times$ age						0.00239 (0.00553)	0.00291 (0.00547)						0.00147 (0.00677)	0.00219 (0.00675)
Constant	7.724*** (0.173)	7.397*** (0.194)	7.498*** (0.195)	7.583*** (0.205)	7.680*** (0.226)	7.640*** (0.226)	8.281*** (0.295)	7.780*** (0.241)	7.371*** (0.255)	7.428*** (0.260)	7.521*** (0.274)	7.826*** (0.271)	7.756*** (0.273)	8.517*** (0.324)
Observations	1,560	1,560	1,560	1,560	1,560	1,560	1,560	1,414	1,414	1,414	1,414	1,414	1,414	1,414
$R^2$	0.243	0.250	0.257	0.259	0.317	0.326	0.343	0.180	0.190	0.199	0.202	0.269	0.280	0.302
Years of Schooling		х	х	х	х	х	х		х	х	х	х	х	х
Parents' Educational Attainment			х	х	х	х	х			х	х	х	х	х
Presence of Siblings in Education Age				х	х	х	х				х	х	х	х
Regional Controls					х	х	х					х	х	х
Municipality Size					х	х	х					х	х	х
Born in Southern Italy						х	х						х	х
Current Marital Status							х							х
Household Size							х							х

(a) 20–65 age cohort, male individuals without self-employed

Table A.36: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived a wage on the considered wave, aged 20 or 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Wave of analysis: 2002. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

(b) 25–65 age cohort, male individuals without self-employed

(a) 20–65 age cohort, male individuals without self-employed							(b) 25–65 age cohort, all male individuals							
In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.0759*** (0.0100)	0.0759*** (0.00996)	0.0751*** (0.0101)	0.0714*** (0.00992)	0.0655*** (0.0102)	0.0673*** (0.0103)	0.0556*** (0.0132)	0.0556*** (0.0107)	0.0593*** (0.0107)	0.0575*** (0.0108)	0.0531*** (0.0108)	0.0471*** (0.0116)	0.0494*** (0.0116)	0.0331** (0.0144)
(age) <sup>2</sup>	-0.000730*** (0.000123)	-0.000737*** (0.000122)	-0.000727*** (0.000122)	-0.000722*** (0.000123)	-0.000691*** (0.000123)	-0.000698*** (0.000122)	-0.000590*** (0.000149)	-0.000502*** (0.000131)	-0.000549*** (0.000130)	-0.000536*** (0.000130)	-0.000525*** (0.000133)	-0.000506*** (0.000139)	-0.000508*** (0.000137)	-0.000356** (0.000159)
General Education	-0.821 (0.549)	-0.858 (0.544)	-0.791 (0.540)	-0.790 (0.539)	-0.786 (0.534)	-0.778 (0.537)	-0.742 (0.538)	-1.131 (0.782)	-1.197 (0.780)	-1.031 (0.776)	-1.073 (0.778)	-0.886 (0.782)	-0.818 (0.792)	-0.758 (0.803)
General Education $\times$ age	0.0329 (0.0275)	0.0325 (0.0270)	0.0282 (0.0268)	0.0281 (0.0268)	0.0278 (0.0267)	0.0276 (0.0268)	0.0255 (0.0271)	0.0477 (0.0372)	0.0485 (0.0368)	0.0401 (0.0367)	0.0420 (0.0368)	0.0334 (0.0372)	0.0306 (0.0377)	0.0273 (0.0385)
General Education $\times age^2$	-0.000257 (0.000329)	-0.000279 (0.000322)	-0.000229 (0.000320)	-0.000228 (0.000320)	-0.000222 (0.000319)	-0.000218 (0.000321)	-0.000187 (0.000326)	-0.000427 (0.000426)	-0.000461 (0.000420)	-0.000369 (0.000420)	-0.000390 (0.000421)	-0.000292 (0.000428)	-0.000260 (0.000434)	-0.000215 (0.000446)
Other Education	-5.126* (2.852)	-5.010* (2.835)	-5.061* (2.864)	-5.012* (2.884)	-4.711* (2.622)	-4.738* (2.614)	-4.974* (2.645)	-4.074* (2.179)	-4.050* (2.066)	-4.215** (2.092)	-4.214** (2.100)	-4.565** (2.169)	-4.522** (2.152)	-4.965** (2.159)
Other Education $\times$ age	0.259* (0.136)	0.249* (0.135)	0.253* (0.137)	0.249* (0.138)	0.233* (0.128)	0.235* (0.127)	0.247* (0.129)	0.213* (0.110)	0.207** (0.105)	0.216** (0.107)	0.215** (0.107)	0.230** (0.111)	0.229** (0.109)	0.250** (0.110)
Other Education $\times age^2$	-0.00310* (0.00159)	-0.00296* (0.00157)	-0.00302* (0.00160)	-0.00296* (0.00161)	-0.00275* (0.00152)	-0.002/8* (0.00151)	-0.00293* (0.00153)	-0.00261* (0.00135)	-0.00251* (0.00129)	-0.00265** (0.00132)	-0.00261** (0.00132)	-0.00275** (0.00137)	-0.00275** (0.00136)	-0.00300** (0.00136)
Years of Schooling		0.0486*** (0.00746)	0.0435*** (0.00775)	0.0438*** (0.00776)	0.0433*** (0.00820)	0.0423*** (0.00818)	0.0430**** (0.00816)		0.0497*** (0.00765)	0.0456*** (0.00802)	0.0460*** (0.00804)	0.0437*** (0.00853)	0.0422*** (0.00849)	0.0425*** (0.00847)
Mother has High School Diploma			(0.122)	(0.122)	-0.0134 (0.127)	-0.0109 (0.128)	-0.0221 (0.127)			-0.0452 (0.136)	-0.0679 (0.138)	-0.0826 (0.139)	-0.0755 (0.140)	-0.0974 (0.138)
Mother has High School Diploma $\times$ age			(0.00314)	(0.00311)	(0.00325)	(0.00328)	(0.00329)			(0.00212	(0.00263	(0.00281)	(0.00269	(0.00316
Father has High School Diploma			-0.0672 (0.126)	(0.125)	(0.134)	-0.00344 (0.134)	(0.134)			-0.119 (0.125)	-0.105 (0.125)	-0.0451 (0.127)	-0.0613 (0.127)	-0.0340 (0.126)
Father has High School Diploma $\times$ age			(0.00306)	(0.00283	(0.00142)	(0.00137 (0.00321)	(0.00320)			(0.00304)	(0.00302)	(0.00247	(0.00306)	(0.00302)
Siblings in Education Age				(0.109)	(0.109)	(0.110)	(0.109)				(0.123)	-0.0415 (0.126)	(0.126)	(0.125)
Siblings in Education Age $\times$ age				(0.00277)	(0.00285)	(0.00407 (0.00286)	(0.00285)				(0.00395)	(0.00285)	(0.00321)	(0.00318)
Born in Southern Italy						(0.189) -0.00805*	(0.187)						(0.209)	(0.207)
Born in Southern Italy $\times$ age	7 875***	7 260***	7 321***	7 417***	7 627***	(0.00451) 7.588***	(0.00448) 8.019***	8 305***	7 500***	7 687***	7 800***	8 067***	(0.00493)	(0.00488)
Constant	(0.195)	(0.211)	(0.212)	(0.216)	(0.256)	(0.257)	(0.321)	(0.210)	(0.226)	(0.225)	(0.232)	(0.279)	(0.281)	(0.353)
Observations $R^2$	1,631 0,203	1,631 0.225	1,631 0.230	1,631 0.231	1,631 0.286	1,631 0.290	1,631 0,299	1,489 0.127	1,489 0.155	1,489 0.161	1,489 0.162	1,489 0.220	1,489 0.226	1,489 0.239
Years of Schooling		x	х	х	x	х	x		x	х	х	х	x	x
Parents' Educational Attainment			х	х	х	х	х			х	х	х	х	х
Presence of Siblings in Education Age				х	х	х	х				х	х	х	х
Regional Controls Municipality Size					x	x	x					x	x	x
Born in Southern Italy					x	x	x					X	x	x
Current Marital Status						~	x						~	x
Household Size							х							х

Table A.37: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived a wage on the considered wave, aged 20 or 25 to 65 with at least upper secondary education, excluding self-employed individuals. Omitted education type is vocational. Wave of analysis: 2004. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.0720*** (0.00878)	0.0715*** (0.00883)	0.0698*** (0.00880)	0.0638*** (0.00976)	0.0522*** (0.0103)	0.0527*** (0.0104)	0.0456*** (0.0175)	0.0659*** (0.0117)	0.0687*** (0.0118)	0.0674*** (0.0118)	0.0610*** (0.0129)	0.0434*** (0.0130)	0.0443*** (0.0132)	0.0340* (0.0181)
(age) <sup>2</sup>	-0.000658*** (0.000108) 2.183**	-0.000656*** (0.000108) 2.211**	-0.000650*** (0.000108) 2.043**	-0.000615*** (0.000109) 2.087**	-0.000640*** (0.000114) 2.088***	-0.000644*** (0.000115) 2.079***	-0.000581*** (0.000180)	-0.000589*** (0.000138)	-0.000624*** (0.000138)	-0.000622*** (0.000138)	-0.000564*** (0.000141)	-0.000525*** (0.000144)	-0.000534*** (0.000146)	-0.000438** (0.000188)
General Education	(0.873)	(0.867)	(0.852)	(0.855)	(0.800)	(0.801)	(0.788)	-1.248 (0.792)	(0.795)	(0.794)	(0.797)	(0.766)	(0.762)	(0.720)
General Education $\times$ age	(0.0430)	0.105** (0.0427)	(0.0421)	(0.0423)	(0.0399)	(0.0400)	(0.0389)	(0.0632)	(0.0635)	(0.0399)	(0.0588 (0.0402)	(0.0384)	(0.0383)	(0.0546)
General Education $\times age^2$	-0.00115** (0.000511)	-0.00115** (0.000508)	-0.00110** (0.000502)	-0.00113** (0.000505)	-0.00113** (0.000480)	-0.00112** (0.000481)	-0.00102** (0.000463)	-0.000687 (0.000488)	-0.000703 (0.000488)	-0.000643 (0.000484)	-0.000681 (0.000487)	-0.000732 (0.000466)	-0.000721 (0.000465)	-0.000614 (0.000430)
Other Education	(1.134)	(1.103)	(1.131)	(1.133)	(1.097)	(1.084)	1.448 (1.056)	3.098** (1.395)	2.815** (1.335)	3.131** (1.393)	3.064** (1.338)	2.866** (1.403)	2.921** (1.420)	2.520* (1.397)
Other Education $\times$ age	-0.0573 (0.0581)	-0.0558 (0.0570)	-0.0609 (0.0580)	-0.0589 (0.0582)	-0.0875 (0.0573)	-0.0860 (0.0565)	-0.0785 (0.0554)	-0.152** (0.0717)	-0.140** (0.0690)	-0.155** (0.0713)	-0.152** (0.0694)	-0.144** (0.0723)	-0.145** (0.0726)	-0.126* (0.0715)
Other Education $\times age^2$	0.000692 (0.000691)	0.000675 (0.000678)	0.000735 (0.000688)	0.000719 (0.000691)	0.00105 (0.000687)	0.00103 (0.000677)	0.000942 (0.000665)	0.00171** (0.000857)	0.00159* (0.000824)	0.00174** (0.000847)	0.00172** (0.000833)	0.00166* (0.000862)	0.00167* (0.000861)	0.00146* (0.000847)
Years of Schooling		0.0313*** (0.00623)	0.0257*** (0.00644)	0.0268*** (0.00645)	0.0282*** (0.00624)	0.0282*** (0.00637)	0.0274*** (0.00639)		0.0323*** (0.00622)	0.0262*** (0.00639)	0.0275*** (0.00639)	0.0290*** (0.00621)	0.0285*** (0.00635)	0.0273*** (0.00640)
Mother has High School Diploma			-0.133 (0.115)	-0.146 (0.116)	-0.0891 (0.117)	-0.0863 (0.117)	-0.113 (0.117)			-0.183 (0.131)	-0.191 (0.130)	-0.125 (0.129)	-0.120 (0.130)	-0.156 (0.128)
Mother has High School Diploma $\times$ age			0.00475 (0.00289)	0.00498* (0.00290)	0.00355 (0.00291)	0.00345 (0.00293)	0.00390 (0.00292)			0.00586* (0.00316)	0.00596* (0.00316)	0.00442 (0.00313)	0.00431 (0.00316)	0.00490 (0.00311)
Father has High School Diploma			-0.173 (0.136)	-0.166 (0.137)	-0.0640 (0.133)	-0.0628 (0.133)	-0.0310 (0.132)			-0.0804 (0.138)	-0.0862 (0.142)	0.0358 (0.144)	0.0361 (0.144)	0.0872 (0.142)
Father has High School Diploma $\times$ age			0.00642** (0.00321)	0.00631* (0.00323)	0.00323 (0.00315)	0.00317 (0.00314)	0.00251 (0.00310)			0.00434 (0.00325)	0.00450 (0.00334)	0.00101 (0.00339)	0.000978 (0.00339)	-9.91e-05 (0.00331)
Siblings in Education Age				-0.0150 (0.119)	-0.0143 (0.118)	-0.0196 (0.119)	-0.0268 (0.120)				0.101 (0.135)	0.0830 (0.132)	0.0869 (0.137)	0.0524 (0.138)
Siblings in Education Age $\times$ age				0.00279 (0.00335)	0.00317 (0.00340)	0.00342 (0.00344)	0.00159 (0.00344)				0.000403 (0.00366)	0.00104 (0.00368)	0.00109 (0.00377)	-0.000297 (0.00375)
Born in Southern Italy						0.0760 (0.188)	0.0432 (0.183)						-0.0781 (0.226)	-0.0927 (0.220)
Born in Southern Italy $\times$ age						-0.00242 (0.00430)	-0.00166 (0.00423)						0.000850 (0.00504)	0.00123 (0.00496)
Constant	7.967*** (0.172)	7.572*** (0.186)	7.695*** (0.187)	7.762*** (0.216)	8.278*** (0.250)	8.262*** (0.251)	8.588*** (0.411)	8.099*** (0.242)	7.618*** (0.255)	7.735*** (0.255)	7.762*** (0.289)	8.421*** (0.305)	8.408*** (0.306)	8.802*** (0.427)
Observations	1,855	1,855	1,855	1,855	1,855	1,855	1,855	1,711	1,711	1,711	1,711	1,711	1,711	1,711
$R^2$	0.211	0.223	0.233	0.238	0.291	0.291	0.305	0.139	0.154	0.167	0.174	0.232	0.232	0.253
Years of Schooling		х	х	х	х	х	х		х	х	х	х	х	х
Parents' Educational Attainment			х	х	х	х	х			х	х	х	х	х
Presence of Siblings in Education Age				х	х	х	х				х	х	х	х
Regional Controls					х	х	х					х	х	х
Municipality Size					х	х	х					х	х	х
Born in Southern Italy						х	х						х	х
Current Marital Status							х							х
Household Size							х							х

(a) 20–65 age cohort, male individuals without self-employed

(b) 25–65 age cohort, male individuals without self-employed

Table A.38: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived a wage on the considered wave, aged 20 or 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Wave of analysis: 2006. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

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(b) 25–65 age cohort, male individuals without self-employed

(a) 20–65 age cohort	, male individuals	without self-employed
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In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.0595*** (0.00908)	0.0577*** (0.00887)	0.0563*** (0.00889)	0.0526*** (0.00896)	0.0463*** (0.00929)	0.0485*** (0.00941)	0.0386*** (0.0133)	0.0628*** (0.0114)	0.0648*** (0.0111)	0.0616*** (0.0106)	0.0576*** (0.0109)	0.0510*** (0.0114)	0.0535*** (0.0115)	0.0394*** (0.0146)
(age) <sup>2</sup>	-0.000522*** (0.000112)	-0.000507*** (0.000109)	-0.000496*** (0.000108)	-0.000491*** (0.000108)	-0.000487*** (0.000110)	-0.000511*** (0.000112)	-0.000406*** (0.000143)	-0.000559*** (0.000136)	-0.000586*** (0.000131)	-0.000560*** (0.000127)	-0.000546*** (0.000129)	-0.000514*** (0.000126)	-0.000538*** (0.000127)	-0.000389** (0.000151)
General Education	(0.390)	-0.0821 (0.382)	-0.0583 (0.378)	-0.0721 (0.378)	-0.238 (0.381)	-0.174 (0.380)	-0.112 (0.376)	-0.223 (0.481)	-0.285 (0.468)	-0.217 (0.467)	-0.244 (0.467)	-0.430 (0.476)	-0.352 (0.475)	-0.301 (0.468)
General Education $\times$ age	-0.00605 (0.0194)	-0.00679 (0.0189)	-0.00721 (0.0185)	-0.00684 (0.0185)	0.000400 (0.0188)	-0.00164 (0.0186)	-0.00528 (0.0184)	0.00478 (0.0230)	0.00173 (0.0222)	0.000116 (0.0219)	0.00110 (0.0219)	0.00967 (0.0225)	0.00691 (0.0224)	0.00397 (0.0220)
General Education $\times age^2$	0.000197 (0.000233)	0.000199 (0.000225)	0.000181 (0.000220)	0.000178 (0.000220)	0.000101 (0.000225)	0.000118 (0.000222)	0.000170 (0.000221)	8.32e-05 (0.000267)	0.000111 (0.000257)	9.77e-05 (0.000252)	8.72e-05 (0.000251)	-8.93e-06 (0.000261)	1.73e-05 (0.000258)	6.02e-05 (0.000254)
Other Education	0.902 (0.609)	1.052* (0.604)	1.095* (0.604)	1.124* (0.603)	1.413** (0.694)	1.195* (0.676)	1.081 (0.672)	0.464 (1.086)	0.658 (1.081)	0.702 (1.069)	0.708 (1.067)	1.439 (1.103)	1.309 (1.088)	1.116 (1.074)
Other Education $\times$ age	-0.0505 (0.0324)	-0.0602* (0.0320)	-0.0628** (0.0319)	-0.0644** (0.0319)	-0.0755** (0.0358)	-0.0629* (0.0350)	-0.0558 (0.0348)	-0.0318 (0.0503)	-0.0438 (0.0496)	-0.0464 (0.0491)	-0.0470 (0.0490)	-0.0772 (0.0517)	-0.0686 (0.0508)	-0.0578 (0.0503)
Other Education $\times age^2$	0.000596 (0.000393)	0.000709*	0.000745* (0.000382)	0.000/64** (0.000381)	0.0008/4** (0.000423)	0.000/26* (0.000415)	0.000627 (0.000413)	0.000404 (0.000553)	0.000544 (0.000536)	0.000580 (0.000532)	0.000590 (0.000531)	0.000893 (0.000569)	0.000788 (0.000561)	0.000649 (0.000556)
Years of Schooling		(0.00522)	(0.00544)	(0.00545)	(0.00550)	(0.00550)	(0.00541)		0.0486*** (0.00533)	0.0438*** (0.00557)	0.0442*** (0.00558)	0.0428*** (0.00556)	0.0412*** (0.00555)	0.0415*** (0.00546)
Mother has High School Diploma			-0.0802 (0.0983)	-0.0953 (0.0988)	-0.0625 (0.0997)	-0.0426 (0.0995)	-0.0720 (0.0979)			-0.185 (0.120)	-0.202* (0.120)	-0.161 (0.119)	-0.132 (0.118)	-0.175 (0.115)
Mother has High School Diploma $\times$ age			(0.00322)	(0.00354)	(0.00250)	(0.00188	(0.00246)			0.00541* (0.00282)	0.00577** (0.00283)	0.00436 (0.00285)	0.00362 (0.00282)	0.00451 (0.00274)
Father has High School Diploma			-0.0263 (0.105)	-0.0120 (0.105)	-0.00741 (0.100)	-0.0184 (0.100)	0.00896 (0.0985)			-0.0491 (0.125)	-0.0264 (0.126)	-0.0452 (0.122)	-0.0619 (0.123)	-0.0205 (0.121)
Father has High School Diploma $\times$ age			0.00269 (0.00259)	0.00241 (0.00259)	0.00194 (0.00251)	0.00221 (0.00251)	0.00173 (0.00244)			0.00315 (0.00299)	0.00270 (0.00299)	0.00280 (0.00293)	0.00320 (0.00294)	0.00242 (0.00286)
Siblings in Education Age				-0.0466 (0.0956)	-0.0767 (0.0981)	-0.0727 (0.0980)	-0.0314 (0.101)				-0.00320 (0.115)	0.00391 (0.114)	0.0135 (0.116)	0.0270 (0.118)
Siblings in Education Age $\times$ age				0.00327 (0.00257)	0.00485* (0.00263)	0.00518** (0.00262)	0.00187 (0.00270)				0.00249 (0.00293)	0.00310 (0.00293)	0.00330 (0.00294)	0.000583 (0.00299)
Born in Southern Italy						-0.114 (0.149)	-0.150 (0.141)						-0.112 (0.171)	-0.140 (0.163)
Born in Southern Italy $\times$ age						(0.000762)	0.00146 (0.00314)						0.000777 (0.00374)	0.00132 (0.00357)
Constant	8.257*** (0.177)	7.691*** (0.188)	7.784*** (0.189)	7.837*** (0.192)	8.074*** (0.224)	8.052*** (0.224)	8.493*** (0.323)	8.184*** (0.231)	7.511*** (0.243)	7.656*** (0.233)	7.693*** (0.243)	7.896*** (0.288)	7.859*** (0.288)	8.386*** (0.370)
Observations p <sup>2</sup>	1,830	1,830	1,830	1,830	1,830	1,830	1,830	1,689	1,689	1,689	1,689	1,689	1,689	1,689
Years of Schooling	0.209	0.243 x	0.230 x	0.239 x	0.313 x	0.319 x	0.341 x	0.175	0.219 X	0.231 X	0.255 X	0.295 X	0.501 x	0.524 X
Parents' Educational Attainment		~	x	x	x	x	x		~	x	x	x	x	x
Presence of Siblings in Education Age				х	х	х	х				х	х	х	х
Regional Controls					х	х	х					х	х	х
Municipality Size					х	х	х					х	х	х
Born in Southern Italy						х	х						х	х
Current Marital Status							X							x
Household Size							A							X

Table A.39: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived a wage on the considered wave, aged 20 or 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Wave of analysis: *2008*. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.0764*** (0.00946)	0.0724*** (0.00939)	0.0689*** (0.00895)	0.0550*** (0.00948)	0.0465*** (0.00988)	0.0490*** (0.00998)	0.0564*** (0.0144)	0.0638*** (0.0106)	0.0632*** (0.0103)	0.0604*** (0.0104)	0.0475*** (0.0113)	0.0385*** (0.0117)	0.0410*** (0.0116)	0.0429*** (0.0148)
(age) <sup>2</sup>	-0.000722*** (0.000111) 1.134**	-0.000679*** (0.000110) 1.216**	-0.000660*** (0.000106)	-0.000557*** (0.000108) 1.150**	-0.000530*** (0.000111) 1.477***	-0.000550*** (0.000111) 1.481***	-0.000634*** (0.000153)	-0.000584*** (0.000123)	-0.000578*** (0.000119)	-0.000560*** (0.000119)	-0.000467*** (0.000124)	-0.000404*** (0.000126)	-0.000422*** (0.000124)	-0.000445*** (0.000155)
General Education	(0.564)	(0.558)	(0.568)	(0.564)	(0.566)	(0.562)	(0.566)	-1.250* (0.725)	-1.434** (0.719)	(0.716)	(0.711)	-1.085*** (0.717)	-1.085*** (0.705)	(0.711)
General Education $\times$ age	(0.0274)	(0.0272)	(0.0274)	(0.0271)	(0.0272)	(0.0270)	(0.0272)	(0.0341)	(0.0338)	(0.0336)	(0.0332)	(0.0334)	(0.0329)	(0.0332)
General Education $\times age^2$	-0.000566* (0.000322)	-0.000543* (0.000319)	-0.000533* (0.000318)	-0.000552* (0.000314)	-0.000/33** (0.000315)	-0.000740** (0.000312)	-0.000/58** (0.000314)	-0.000631 (0.000389)	-0.000648* (0.000385)	-0.000667* (0.000380)	-0.000682* (0.000376)	-0.000822** (0.000376)	-0.000832** (0.000371)	-0.000864** (0.000374)
Other Education	(1.142)	(1.136)	(1.069)	(1.090)	(1.129)	(1.143)	(1.141)	-0.869 (2.582)	-0.935 (2.415)	(2.330)	-1.242 (2.358)	-0.846 (2.867)	-0.894 (3.059)	-0.593 (3.138)
Other Education $\times$ age	-0.0606 (0.0504)	-0.0634 (0.0507)	-0.0586 (0.0486)	-0.0489 (0.0490)	(0.0513)	-0.0401 (0.0509)	-0.0486 (0.0509)	(0.111)	(0.104)	(0.101)	(0.102)	(0.123)	0.0246 (0.130)	(0.133)
Other Education $\times age^2$	(0.000555)	(0.000561)	(0.000550)	(0.000550)	(0.000769	(0.000568)	(0.000720	(0.00116)	(0.00109)	(0.00107)	(0.00108)	(0.00128)	(0.00135)	(0.00139)
Years of Schooling		(0.00587)	(0.00609)	(0.00604)	(0.00625)	(0.00630)	(0.00627)		(0.00594)	(0.00618)	(0.00613)	(0.00635)	(0.00640)	(0.00636)
Mother has High School Diploma			(0.119)	(0.124)	(0.121)	(0.120)	(0.119)			(0.122)	-0.140 (0.129)	(0.136)	-0.141 (0.134)	(0.133)
Mother has High School Diploma $\times$ age			(0.00306)	(0.00325)	(0.00326)	(0.00324)	(0.00319)			(0.00314)	(0.00338)	(0.00357)	(0.00353)	(0.00348)
Father has High School Diploma			(0.160)	(0.162)	(0.155)	(0.155)	(0.155)			(0.180)	(0.186)	(0.187)	(0.185)	(0.185)
Father has High School Diploma $\times$ age			(0.00401)	(0.00409)	(0.00391)	(0.00391)	(0.00254 (0.00387) 0.242**			(0.00333 (0.00442)	(0.00457)	(0.00456)	(0.00452)	(0.00449)
Siblings in Education Age				(0.103)	(0.104)	(0.104)	(0.105)				(0.117)	-0.210* (0.117)	(0.115)	-0.198* (0.116)
Siblings in Education Age $\times$ age				(0.00255)	(0.00253)	(0.00251)	(0.00260)				(0.00739111	(0.00276)	(0.00271)	(0.00278)
Born in Southern Italy						(0.216)	(0.218)						(0.229)	(0.231)
Born in Southern Italy $\times$ age	7 000***	7 425***	7 563***	7 880***	8 211***	(0.00479)	(0.00481) 8 159***	9 197***	7 600***	7 705***	7 000***	9 792***	(0.00503)	(0.00505)
Constant	(0.193)	(0.205)	(0.196)	(0.212)	(0.252)	(0.254)	(0.351)	(0.220)	(0.234)	(0.239)	(0.266)	(0.301)	(0.299)	(0.374)
Observations	1,829	1,829	1,829	1,829	1,829	1,829	1,829	1,699	1,699	1,699	1,699	1,699	1,699	1,699
$R^2$	0.200	0.229	0.237	0.245	0.287	0.294	0.308	0.134	0.172	0.180	0.189	0.227	0.236	0.254
Years of Schooling		х	х	х	х	х	х		х	х	х	х	х	х
Parents' Educational Attainment			х	х	х	х	х			х	х	х	х	х
Presence of Siblings in Education Age				х	х	х	х				х	х	х	х
Regional Controls					х	х	х					х	х	х
Municipality Size					х	х	х					х	х	х
Born in Southern Italy						х	х						х	х
Current Marital Status							х							х
Household Size							х							х

(a) 20-65 age cohort, male individuals without self-employed

(b) 25–65 age cohort, male individuals without self-employed

Table A.40: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived a wage on the considered wave, aged 20 or 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Wave of analysis: *2010*. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

(a) 20–65 <i>age cohort</i> ,	male individuals	without sel	f-employed
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(3)

(4)

(5)

(6)

(2)

(1)

0.280

0.315

х

0.323

х

х

0.324

х

х

х

0.368

х

х

х

х

х

In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.0854***	0.0811***	0.0744***	0.0675***	0.0645***	0.0648***	0.0511***	0.0827***	0.0810***	0.0738***	0.0691***	0.0633***	0.0634***	0.0459***
(age) <sup>2</sup>	-0.000776*** (0.000119)	-0.000731*** (0.000118)	-0.000684*** (0.000117)	-0.000628*** (0.000120)	-0.000588*** (0.000117)	-0.000597*** (0.000116)	-0.000460*** (0.000136)	-0.000745*** (0.000141)	-0.000729*** (0.000140)	-0.000671*** (0.000140)	-0.000635*** (0.000143)	-0.000556*** (0.000139)	-0.000562*** (0.000135)	-0.000380** (0.000148)
General Education	-1.024* (0.558)	-1.160** (0.552)	-0.878 (0.543)	-0.885 (0.539)	-0.827 (0.557)	-0.931* (0.551)	-0.973* (0.550)	-0.947 (0.634)	-1.217* (0.626)	-1.073* (0.612)	-1.088* (0.611)	-1.154* (0.620)	-1.244** (0.609)	-1.285** (0.609)
General Education $\times$ age	0.0448* (0.0259)	0.0456* (0.0254)	0.0352 (0.0249)	0.0353 (0.0247)	0.0339 (0.0255)	0.0397 (0.0251)	0.0419* (0.0250)	0.0415 (0.0290)	0.0480* (0.0284)	0.0431 (0.0277)	0.0436 (0.0276)	0.0471* (0.0281)	0.0524* (0.0275)	0.0548** (0.0275)
General Education $\times age^2$	-0.000365 (0.000289)	-0.000387 (0.000282)	-0.000306 (0.000276)	-0.000306 (0.000274)	-0.000307 (0.000282)	-0.000368 (0.000276)	-0.000394 (0.000276)	-0.000332 (0.000320)	-0.000414 (0.000311)	-0.000385 (0.000304)	-0.000388 (0.000303)	-0.000437 (0.000309)	-0.000495 (0.000301)	-0.000523* (0.000301)
Other Education	-6.676*** (0.758)	-6.522*** (0.809)	-6.837*** (0.803)	-7.049*** (0.797)	-7.199*** (0.788)	-8.217*** (0.775)	-8.366*** (0.769)	3.129 (4.450)	4.685 (4.173)	4.163 (4.167)	3.930 (4.070)	1.756 (4.645)	2.634 (3.639)	2.228 (3.535)
Other Education $\times$ age	0.266*** (0.0420)	0.257*** (0.0448)	0.272*** (0.0443)	0.281*** (0.0438)	0.288*** (0.0422)	0.349*** (0.0408)	0.354*** (0.0405)	-0.140 (0.186)	-0.208 (0.175)	-0.184 (0.175)	-0.174 (0.171)	-0.0815 (0.197)	-0.0984 (0.154)	-0.0833 (0.150)
Other Education $\times age^2$	-0.00265*** (0.000552)	-0.00254*** (0.000584)	-0.00270*** (0.000573)	-0.00282*** (0.000565)	-0.00289*** (0.000535)	-0.00365*** (0.000515)	-0.00369*** (0.000512)	0.00150 (0.00190)	0.00222 (0.00178)	0.00195 (0.00179)	0.00184 (0.00176)	0.000872 (0.00203)	0.000904 (0.00160)	0.000756 (0.00156)
Years of Schooling		0.0502*** (0.00553)	0.0495*** (0.00578)	0.0496*** (0.00579)	0.0495*** (0.00575)	0.0450*** (0.00566)	0.0445*** (0.00554)		0.0513*** (0.00556)	0.0500*** (0.00583)	0.0501*** (0.00585)	0.0497*** (0.00578)	0.0449*** (0.00570)	0.0442*** (0.00558)
Mother has High School Diploma			-0.264** (0.109)	-0.288*** (0.109)	-0.282*** (0.106)	-0.289*** (0.105)	-0.277*** (0.106)			-0.235** (0.112)	-0.250** (0.113)	-0.250** (0.113)	-0.245** (0.111)	-0.245** (0.111)
Mother has High School Diploma $\times$ age			0.00661*** (0.00254)	0.00726*** (0.00256)	0.00652** (0.00254)	0.00637** (0.00250)	0.00614** (0.00252)			0.00622** (0.00264)	0.00663** (0.00265)	0.00605** (0.00268)	0.00559** (0.00263)	0.00564** (0.00263)
Father has High School Diploma			-0.270** (0.130)	-0.241* (0.132)	-0.266** (0.131)	-0.249* (0.132)	-0.236* (0.130)			-0.184 (0.134)	-0.155 (0.138)	-0.179 (0.137)	-0.183 (0.136)	-0.168 (0.132)
Father has High School Diploma $\times$ age			0.00714** (0.00313)	0.00642** (0.00317)	0.00690** (0.00316)	0.00651** (0.00315)	0.00626** (0.00308)			0.00521 (0.00322)	0.00453 (0.00330)	0.00495 (0.00329)	0.00504 (0.00325)	0.00473 (0.00314)
Siblings in Education Age				-0.154 (0.102)	-0.132 (0.100)	-0.162 (0.100)	-0.132 (0.106)				-0.139 (0.112)	-0.142 (0.111)	-0.164 (0.109)	-0.122 (0.114)
Siblings in Education Age $\times$ age				0.00379 (0.00238)	0.00392* (0.00230)	0.00533** (0.00228)	0.00278 (0.00251)				0.00321 (0.00256)	0.00381 (0.00247)	0.00514** (0.00244)	0.00206 (0.00265)
Born in Southern Italy						0.103 (0.204)	0.1000 (0.204)						0.191 (0.211)	0.186 (0.210)
Born in Southern Italy $\times$ age						-0.00390 (0.00481)	-0.00385 (0.00484)						-0.00582 (0.00495)	-0.00577 (0.00496)
Constant	7.595*** (0.199)	7.027*** (0.207)	7.233*** (0.206)	7.402*** (0.222)	7.432*** (0.335)	7.485*** (0.334)	7.954*** (0.373)	7.651*** (0.251)	7.008*** (0.258)	7.223*** (0.262)	7.346*** (0.271)	7.426*** (0.395)	7.487*** (0.387)	8.040*** (0.409)
Observations	1,815	1,815	1,815	1,815	1,815	1,815	1,815	1,697	1,697	1,697	1,697	1,697	1,697	1,697

0.409

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0.344

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X

0.365

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х

(7)

(1)

(2)

(3)

(b) 25–65 age cohort, male individuals without self-employed

(4)

(5)

(6)

(7)

Table A.41: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived a wage on the considered wave, aged 20 or 25 to 65 with at least upper secondary education, excluding self-employed individuals. Omitted education type is vocational. Wave of analysis: 2012. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

0.393

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х

х

х

х

 $R^2$ 

Years of Schooling

Regional Controls

Municipality Size

Born in Southern Italy Current Marital Status Household Size

Parents' Educational Attainment

Presence of Siblings in Education Age

In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.0768*** (0.00916)	0.0744*** (0.00918)	0.0717*** (0.00956)	0.0504*** (0.0107)	0.0480*** (0.0109)	0.0499*** (0.0109)	0.0293** (0.0138)	0.0673*** (0.0109)	0.0671*** (0.0109)	0.0631*** (0.0111)	0.0434*** (0.0117)	0.0335*** (0.0121)	0.0340*** (0.0119)	0.00682 (0.0148)
(age) <sup>2</sup>	-0.000674*** (0.000104)	-0.000652*** (0.000103)	-0.000628*** (0.000105)	-0.000436*** (0.000114)	-0.000510*** (0.000118)	-0.000531*** (0.000119)	-0.000350** (0.000139)	-0.000574*** (0.000121)	-0.000576*** (0.000120)	-0.000542*** (0.000121)	-0.000367*** (0.000125)	-0.000344*** (0.000127)	-0.000349*** (0.000125)	-9.18e-05 (0.000145)
General Education	(0.488)	(0.484)	(0.478)	(0.475)	(0.481)	(0.479)	(0.476)	(0.635)	-0.826 (0.628)	(0.627)	(0.620)	(0.583)	-0.724 (0.578)	(0.573)
General Education $\times$ age	(0.0230)	(0.0225)	(0.0222)	(0.0221)	(0.0223)	-0.00413 (0.0222)	(0.0221)	(0.0223	(0.0281)	(0.0237	(0.0259	(0.0258	(0.0242	(0.0258
General Education $\times age^2$	3.06e-05 (0.000262)	2.39e-05 (0.000255)	5.12e-05 (0.000251)	5.0/e-05 (0.000250)	0.000132 (0.000252)	0.000142 (0.000251)	0.000154 (0.000250)	-0.000128 (0.000317)	-0.000199 (0.000309)	-0.000163 (0.000306)	-0.000184 (0.000304)	-0.000167 (0.000292)	-0.000168 (0.000290)	-0.000172 (0.000289)
Other Education	0.332 (1.800)	0.456 (1.776)	0.238 (1.778)	0.0898 (1.860)	-0.669 (1.893)	-0.954 (1.898)	-1.053 (1.883)	-2.211 (3.126)	-2.031 (3.103)	-2.414 (3.044)	-2.954 (2.913)	-3.867 (2.860)	-4.243 (2.916)	-4.551 (2.826)
Other Education $\times$ age	-0.0136 (0.0793)	-0.0218 (0.0774)	-0.00953 (0.0772)	-0.00637 (0.0807)	0.0236 (0.0836)	0.0403 (0.0833)	0.0428 (0.0824)	0.0974 (0.135)	0.0864 (0.134)	0.106 (0.131)	0.126 (0.125)	0.165 (0.124)	0.186 (0.126)	0.198 (0.122)
Other Education $\times age^2$	0.000153 (0.000859)	0.000255 (0.000836)	0.000102 (0.000827)	9.46e-05 (0.000862)	-0.000185 (0.000905)	-0.000381 (0.000897)	-0.000391 (0.000883)	-0.00102 (0.00143)	-0.000884 (0.00141)	-0.00111 (0.00138)	-0.00130 (0.00132)	-0.00168 (0.00131)	-0.00193 (0.00133)	-0.00203 (0.00128)
Years of Schooling		0.0436*** (0.00555)	(0.03/5***	0.0372*** (0.00573)	0.0374*** (0.00587)	0.0348*** (0.00580)	0.0351*** (0.00568)		0.0468*** (0.00552)	0.0407*** (0.00563)	0.0407*** (0.00567)	0.0406*** (0.00582)	0.0374*** (0.00573)	0.0373*** (0.00560)
Mother has High School Diploma			-0.0743 (0.142)	-0.112 (0.140)	-0.0275 (0.142)	-0.0594 (0.142)	-0.0219 (0.144)			-0.0560 (0.165)	-0.0809 (0.164)	-0.0399 (0.155)	-0.0727 (0.154)	-0.0121 (0.156)
Mother has High School Diploma $\times$ age			0.00357 (0.00302)	0.00449 (0.00301)	0.00256 (0.00304)	0.00312 (0.00305)	0.00233 (0.00307)			0.00350 (0.00345)	0.00408 (0.00346)	0.00285 (0.00333)	0.00341 (0.00332)	0.00220 (0.00333)
Father has High School Diploma			-0.102 (0.146)	-0.0674 (0.145)	-0.0282 (0.148)	-0.0448 (0.148)	-0.0644 (0.148)			-0.190 (0.175)	-0.164 (0.174)	-0.158 (0.168)	-0.198 (0.167)	-0.238 (0.166)
Father has High School Diploma $\times$ age			0.00441 (0.00319)	0.00359 (0.00318)	0.00286 (0.00327)	0.00308 (0.00326)	0.00341 (0.00326)			0.00590 (0.00373)	0.00532 (0.00372)	0.00532 (0.00367)	0.00602* (0.00364)	0.00672* (0.00362)
Siblings in Education Age				-0.372*** (0.119)	-0.293** (0.120)	-0.306** (0.119)	-0.234* (0.126)				-0.383*** (0.131)	-0.292** (0.126)	-0.307** (0.125)	-0.233* (0.128)
Siblings in Education Age $\times$ age				0.00819*** (0.00268)	0.00713*** (0.00264)	0.00783*** (0.00264)	0.00425 (0.00283)				0.00813*** (0.00285)	0.00696** (0.00275)	0.00775*** (0.00273)	0.00408 (0.00286)
Born in Southern Italy						0.148 (0.239)	0.186 (0.237)						0.220 (0.238)	0.276 (0.236)
Born in Southern Italy $\times$ age						-0.00340 (0.00485)	-0.00458 (0.00479)						-0.00496 (0.00485)	-0.00656 (0.00480)
Constant	7.771*** (0.196)	7.259*** (0.203)	7.386*** (0.216)	7.892*** (0.246)	8.338*** (0.281)	8.315*** (0.281)	9.021*** (0.375)	7.994*** (0.240)	7.390*** (0.245)	7.561*** (0.250)	8.033*** (0.269)	8.603*** (0.321)	8.609*** (0.318)	9.435*** (0.416)
Observations p2	1,706	1,706	1,706	1,706	1,706	1,706	1,706	1,596	1,596	1,596	1,596	1,596	1,596	1,596
K <sup>2</sup> Veers of Schooling	0.245	0.272	0.283	0.295	0.347	0.357	0.380	0.189	0.226	0.240	0.252	0.312	0.327	0.357
Parants' Educational Attainment		х	x	x	x	x	x		х	x	x	x	x	x
Presence of Siblings in Education Age			A	X X	X X	A V	x			A	X X	x	x	x
Regional Controls				А	x	x	A X				А	x	x	x
Municipality Size					x	x	x					x	x	x
Born in Southern Italy					~	x	x					~	x	x
Current Marital Status						~	x						~	x
Household Size							x							x

(a) 20-65 age cohort, male individuals without self-employed

(b) 25-65 age cohort, male individuals without self-employed

Table A.42: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived a wage on the considered wave, aged 20 or 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Wave of analysis: *2014*. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

### A.2.3 Analysis for the Financial Crisis

In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	0.0756***	0.0740***	0.0720***	0.0690***	0.0610***	0.0627***	0.0402***
age	(0.00422)	(0.00/49****	(0.00/29***	(0.00426)	(0.0010***	(0.00455)	(0.0493***
-	(0.00423)	(0.00421)	(0.00420)	(0.00430)	(0.00433)	(0.00433)	(0.00007)
(age) <sup>2</sup>	-0.000707****	-0.000704****	-0.000090****	-0.000081***	-0.000080****	-0.000700****	-0.000304
	(3.216-03)	(3.178-03)	(3.140-03)	(3.160-03)	(3.278-03)	(3.290-03)	(7.110-03)
General Education	-1.213***	-1.277****	-1.164****	-1.162***	-1.190***	-1.1/4****	-1.095****
	(0.505)	(0.501)	(0.297)	(0.298)	(0.293)	(0.293)	(0.290)
General Education $\times$ age	(0.0150)	(0.0148)	(0.0312+++	(0.0147)	(0.0145)	(0.0144)	(0.0142)
	0.000520***	(0.0146)	0.000524***	(0.0147)	(0.0143)	(0.0144)	0.000468***
General Education $\times age^2$	-0.000329	-0.000330***	-0.000324	-0.000324	-0.000551***	-0.000323	-0.000408
	(0.000175)	0.000177)	(0.000174)	0.210	0.000175)	0.412	0.252
Other Education	(0.551)	(0.547)	(0.555)	(0.553)	(0.543)	(0.540)	(0.535)
	0.0150	0.0100	0.0218	0.0215	0.0288	0.0242	0.0207
Other Education $\times$ age	(0.0276)	(0.0274)	(0.0218	(0.0213	(0.0288	(0.0245)	(0.0207
	0.000175	0.000224	0.000260	0.000260	0.000352	0.000202	0.000247
Other Education $\times age^2$	(0.000334)	(0.000234)	(0.000200	(0.000200	(0.000342)	(0.000232)	(0.000247
	(0.000554)	0.0383***	0.033/***	0.0340***	0.0361***	0.0352***	0.0354***
Years of Schooling		(0.00200)	(0.00210)	(0.00210)	(0.00220)	(0.00221)	(0.00218)
		(0.00309)	-0.0376	-0.0548	-0.0597	-0.0529	-0.0692
Mother has High School Diploma			(0.0543)	(0.0545)	(0.0545)	(0.0546)	(0.0543)
			0.00105	0.00222*	0.00212	0.00101	0.00222*
Mother has High School Diploma $\times$ age			(0.00133)	(0.00233)	(0.00212	(0.00134)	(0.00223)
			-0.178***	0.160***	-0.111*	-0.115*	0.00133
Father has High School Diploma			(0.0597)	(0.0601)	(0.0609)	(0.0610)	(0.0608)
			0.00621***	0.00602***	0.00/39***	0.00446***	0.00396***
Father has High School Diploma × age			(0.001/12)	(0.00144)	(0.0045)	(0.00146)	(0.00144)
			(0.00145)	-0.0737	-0.0311	-0.0357	-0.0270
Siblings in Education Age				(0.0517)	(0.0515)	(0.0522)	(0.0527)
				0.00343**	0.00316**	0.00358**	0.00158
Siblings in Education Age × age				(0.00138)	(0.00139)	(0.00141)	(0.00142)
				(0.00150)	(0.00157)	0.0204	0.000315
Born in Southern Italy						(0.0870)	(0.0853)
						-0.00218	-0.00176
Born in Southern Italy $\times$ age						(0.00210)	(0.00196)
	0.0540***	0.0506***	0.0491***	0.0499***	0.0472***	0.0469***	0.0518***
Year 2002	(0.0156)	(0.0155)	(0.0155)	(0.0155)	(0.0151)	(0.0151)	(0.0150)
	0.105***	0.0982***	0.0964***	0.0958***	0.0945***	0.0963***	0.103***
Year 2004	(0.0163)	(0.0162)	(0.0162)	(0.0162)	(0.0158)	(0.0158)	(0.0158)
	0.171***	0.150***	0.149***	0.149***	0.142***	0.146***	0.154***
Year 2006	(0.0162)	(0.0160)	(0.0160)	(0.0160)	(0.0156)	(0.0157)	(0.0155)
	0.202***	0.180***	0.178***	0.178***	0 174***	0.179***	0.189***
Year 2008	(0.0156)	(0.0155)	(0.0155)	(0.0155)	(0.0152)	(0.0151)	(0.0150)
_	7.741***	7.276***	7.388***	7.462***	7.791***	7.763***	8.202***
Constant	(0.0835)	(0.0902)	(0.0904)	(0.0976)	(0.111)	(0.111)	(0.160)
	· · · ·	· · · ·					
Observations	8,536	8,536	8,536	8,536	8,536	8,536	8,536
$R^2$	0.246	0.262	0.268	0.270	0.309	0.312	0.324
Years of Schooling		х	х	х	х	х	х
Parents' Educational Attainment			х	х	х	х	х
Presence of Siblings in Education Age				х	х	х	х
Regional Controls					х	х	х
Municipality Size					х	х	х
Born in Southern Italy						х	х
Current Marital Status							х
Household Size							х

Table A.43: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived a wage for the considered waves, from age 20 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2008 for pre-recession years, every two waves. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.0787*** (0.00547)	0.0751*** (0.00545)	0.0708*** (0.00541)	0.0576*** (0.00583)	0.0527*** (0.00624)	0.0546*** (0.00623)	0.0469*** (0.00786)
(age) <sup>2</sup>	-0.000713*** (6.39e-05)	-0.000677*** (6.35e-05)	-0.000646*** (6.28e-05)	-0.000534*** (6.51e-05)	-0.000526*** (6.55e-05)	-0.000546*** (6.52e-05)	-0.000480*** (8.01e-05)
General Education	-0.784** (0.315)	-0.899*** (0.312)	-0.752** (0.313)	-0.775** (0.312)	-0.859*** (0.314)	-0.878*** (0.313)	-0.874*** (0.313)
General Education $\times$ age	0.0354** (0.0149)	0.0350** (0.0147)	0.0296** (0.0147)	0.0305** (0.0146)	0.0345** (0.0147)	0.0360** (0.0146)	0.0363** (0.0146)
General Education $\times age^2$	-0.000293* (0.000171)	-0.000297* (0.000167)	-0.000261 (0.000166)	-0.000270 (0.000165)	-0.000318* (0.000166)	-0.000332** (0.000165)	-0.000340** (0.000165)
Other Education	-0.345 (1.445)	-0.272 (1.436)	-0.429 (1.437)	-0.598 (1.460)	-0.918 (1.454)	-1.345 (1.459)	-1.312 (1.475)
Other Education $\times$ age	0.00471 (0.0633)	-0.000974 (0.0628)	0.00713 (0.0629)	0.0140 (0.0638)	0.0265 (0.0637)	0.0518 (0.0636)	0.0480 (0.0642)
Other Education $\times age^2$	6.10e-05 (0.000681)	0.000132 (0.000675)	3.36e-05 (0.000676)	-3.59e-05 (0.000684)	-0.000157 (0.000683)	-0.000462 (0.000681)	-0.000402 (0.000686)
Years of Schooling		0.0461*** (0.00327)	0.0437*** (0.00338)	0.0437*** (0.00339)	0.0437*** (0.00343)	0.0405*** (0.00342)	0.0401*** (0.00336)
Mother has High School Diploma			-0.158** (0.0703)	-0.192*** (0.0709)	-0.169** (0.0696)	-0.181*** (0.0693)	-0.172** (0.0693)
Mother has High School Diploma $\times$ age			0.00502*** (0.00165)	0.00597*** (0.00167)	0.00518*** (0.00166)	0.00528*** (0.00165)	0.00513*** (0.00165)
Father has High School Diploma			-0.185** (0.0846)	-0.146* (0.0850)	-0.141* (0.0846)	-0.139* (0.0847)	-0.134 (0.0844)
Father has High School Diploma $\times$ age			0.00514** (0.00201)	0.00420** (0.00203)	0.00406** (0.00201)	0.00396** (0.00201)	0.00393** (0.00200)
Siblings in Education Age				-0.240*** (0.0604)	-0.204*** (0.0604)	-0.220*** (0.0603)	-0.178*** (0.0625)
Siblings in Education Age $\times$ age				0.00598*** (0.00141)	0.00584*** (0.00139)	0.00662*** (0.00138)	0.00384*** (0.00147)
Born in Southern Italy						0.134 (0.133)	0.134 (0.132)
Born in Southern Italy $\times$ age						-0.00357 (0.00286)	-0.00373 (0.00285)
Year 2012	-0.0287* (0.0166)	-0.0295* (0.0163)	-0.0311* (0.0162)	-0.0368** (0.0162)	-0.0343** (0.0159)	-0.0331** (0.0157)	-0.0292* (0.0155)
Year 2014	-0.0213 (0.0168)	-0.0209 (0.0165)	-0.0232 (0.0165)	-0.0317* (0.0170)	-0.0338** (0.0167)	-0.0338** (0.0165)	-0.0206 (0.0165)
Constant	7.792*** (0.113)	7.266*** (0.118)	7.419*** (0.119)	7.728*** (0.130)	7.988*** (0.168)	7.978*** (0.168)	8.327*** (0.210)
Observations	5,350	5,350	5,350	5,350	5,350	5,350	5,350
Years of Schooling	0.237	0.208 x	0.273 x	0.280 x	0.313 x	0.528 x	0.343 x
Parents' Educational Attainment		A	x	x	x	x	x
Presence of Siblings in Education Age				х	x	х	х
Regional Controls					х	x	х
Municipality Size					х	х	х
Born in Southern Italy						x	х
Current Marital Status Household Size							x x

Table A.44: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived a wage for the considered waves, from age 20 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2010 to 2014 for post-recession years, every two waves. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.0648*** (0.00509)	0.0670*** (0.00506)	0.0651*** (0.00504)	0.0604*** (0.00522)	0.0501*** (0.00529)	0.0519*** (0.00532)	0.0341*** (0.00687)
(age) <sup>2</sup>	-0.000585*** (6.10e-05)	-0.000615*** (6.05e-05)	-0.000602*** (6.01e-05)	-0.000581*** (6.10e-05)	-0.000560*** (6.09e-05)	-0.000574*** (6.11e-05)	-0.000392*** (7.31e-05)
General Education	-1.044*** (0.336)	-1.149*** (0.335)	-1.045*** (0.332)	-1.055*** (0.332)	-1.137*** (0.328)	-1.099*** (0.328)	-1.023*** (0.320)
General Education $\times$ age	0.0474*** (0.0164)	0.0494*** (0.0163)	0.0449*** (0.0161)	0.0453*** (0.0161)	0.0490*** (0.0159)	0.0476*** (0.0159)	0.0436*** (0.0155)
General Education $\times age^2$	-0.000453** (0.000194)	-0.000493** (0.000192)	-0.000457** (0.000189)	-0.000464** (0.000190)	-0.000507*** (0.000188)	-0.000491*** (0.000187)	-0.000437** (0.000182)
Other Education	0.234 (0.801)	0.260 (0.782)	0.348 (0.796)	0.305 (0.794)	0.146 (0.792)	0.0700 (0.793)	-0.0769 (0.784)
Other Education $\times$ age	-0.0137 (0.0382)	-0.0175 (0.0373)	-0.0218 (0.0382)	-0.0200 (0.0380)	-0.0130 (0.0382)	-0.00785 (0.0381)	-0.000172 (0.0377)
Other Education $\times age^2$	0.000151 (0.000441)	0.000201 (0.000430)	0.000252 (0.000443)	0.000234 (0.000442)	0.000173 (0.000447)	0.000106 (0.000445)	1.37e-05 (0.000438)
Years of Schooling		0.0406*** (0.00313)	0.0354*** (0.00323)	0.0360*** (0.00323)	0.0378*** (0.00324)	0.0367*** (0.00324)	0.0364*** (0.00322)
Mother has High School Diploma			-0.0683 (0.0604)	-0.0884 (0.0605)	-0.0996* (0.0601)	-0.0882 (0.0603)	-0.115* (0.0593)
Mother has High School Diploma $\times$ age			0.00260* (0.00144)	0.00302** (0.00144)	0.00299** (0.00145)	0.00267* (0.00145)	0.00323** (0.00142)
Father has High School Diploma			-0.120* (0.0626)	-0.109* (0.0633)	-0.0330 (0.0628)	-0.0420 (0.0630)	-0.00349 (0.0622)
Father has High School Diploma $\times$ age			0.00487*** (0.00149)	0.00465*** (0.00150)	0.00262* (0.00149)	0.00282* (0.00149)	0.00199 (0.00147)
Siblings in Education Age				-0.0506 (0.0570)	-0.00668 (0.0572)	-0.00669 (0.0585)	-0.0210 (0.0585)
Siblings in Education Age $\times$ age				0.00312** (0.00147)	0.00279*	0.00314** (0.00152)	0.00146 (0.00152)
Born in Southern Italy						0.00153 (0.101)	-0.0161 (0.0990)
Born in Southern Italy $\times$ age						-0.00184 (0.00228)	-0.00148 (0.00224)
Year 2002	0.0329**	0.0295*	0.0278*	0.0285*	0.0260*	0.0255*	0.0306**
Year 2004	0.0889***	0.0820***	0.0795***	0.0788***	0.0752***	0.0769***	0.0848***
Year 2006	0.156***	0.133***	0.132***	0.132***	0.123*** (0.0154)	0.127***	0.137***
Year 2008	0.174***	0.150***	0.148***	0.149***	0.142***	0.148***	0.160***
Constant	7.984*** (0.103)	7.430*** (0.109)	7.543*** (0.109)	7.619*** (0.117)	8.007*** (0.128)	7.977*** (0.128)	8.527*** (0.166)
Observations	7,780	7,780	7,780	7,780	7,780	7,780	7,780
$R^2$	0.175	0.197	0.205	0.208	0.254	0.258	0.276
Years of Schooling		х	х	х	х	х	х
Parents' Educational Attainment			х	х	х	х	х
Presence of Siblings in Education Age				х	х	х	х
Regional Controls					х	х	х
Municipality Size					х	х	х
Born in Southern Italy						х	х
Current Marital Status Household Size							x x

Table A.45: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived a wage for the considered waves, from age 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2000 to 2008 for pre-recession years, every two years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

age 0.0705*** 0.0697*** 0.0651*** 0.0534*** 0.0477*** 0.0491*** 0.0 (0.00642) (0.00642) (0.00641) (0.00641) (0.00722) (0.00717) (0.00717)	71*** 0836) )342***
(0.00043) $(0.00038)$ $(0.00042)$ $(0.00081)$ $(0.00732)$ $(0.00717)$ $(0.00717)$	)342***
$ (age)^2 \qquad \begin{array}{c} -0.000625^{***} & -0.000619^{****} & -0.000583^{***} & -0.000485^{***} & -0.000447^{***} & -0.000460^{***} & -0.000619^{***} & -0.000485^{***} & -0.000447^{***} & -0.000460^{***} & -0.000619^{***} & -0.000619^{***} & -0.000485^{***} & -0.000485^{***} & -0.000485^{***} & -0.000460^{***} & -0.000619^{***} & -0.000619^{***} & -0.000485^{***} & -0.0008^{***} & -0.0008^{**} & -0.00085^{***} & -0.00085^{***} & $	1e-05)
$ \begin{array}{c} -0.913^{**} & -1.156^{***} & -1.063^{***} & -1.096^{***} & -1.176^{***} & -1.195^{**} & -1.195^{**} & -1.195^{**} & -1.195^{**} & -1.195^{**} & -1.195^{**} & -1.195^{**} & -1.195^{**} & -1.195^{**} & -1.195^{**} & -1.195^{*$	98*** .376)
General Education × age $0.0412^{**}$ $0.0460^{***}$ $0.0429^{**}$ $0.0441^{**}$ $0.0483^{***}$ $0.0499^{***}$ $0.050^{***}$ (0.0178)(0.0175)(0.0174)(0.0173)(0.0174)(0.0171)(0.0171)	07*** 0172)
$ \begin{array}{c} \text{General Education} \times age^2 \\ \hline 0.000199 \\ \hline 0.000199 \\ \hline 0.000195 \\ \hline 0.000193 \\ \hline 0.0$	)495*** )0190)
Other Education         -1.071         -1.015         -1.135         -1.493         -1.595         -2.037         -2           (2.095)         (2.030)         (2.030)         (1.981)         (2.083)         (2.169)         (2	.006 .271)
Other Education $\times$ age         0.0364         0.0312         0.0380         0.0530         0.0572         0.0835         0.00000000000000000000000000000000000	0798 0966)
Other Education $\times age^2$ -0.000273 (0.000940)         -0.000207 (0.000911)         -0.000294 (0.000913)         -0.000447 (0.000891)         -0.000488 (0.000933)         -0.000806 (0.000965)         -0.00000000000000000000000000000000000	00747 0101)
Years of Schooling         0.0479***         0.0452***         0.0454***         0.0450***         0.0416***         0.04           (0.00329)         (0.00340)         (0.00340)         (0.00346)         (0.00344)         (0.0	.09*** (0338)
Mother has High School Diploma         -0.125*         -0.154**         -0.135*         -0.151**         -0.00000000000000000000000000000000000	147* 0752)
Mother has High School Diploma × age $0.00458^{***}$ $0.00535^{***}$ $0.00456^{**}$ $0.00474^{***}$ $0.00$ $(0.00175)$ $(0.00177)$ $(0.00180)$ $(0.00178)$ $(0.0178)$	472*** 0177)
Father has High School Diploma         -0.184**         -0.143         -0.138         -0.150         -0           (0.0931)         (0.0944)         (0.0936)         (0.0932)         (0.	.148 0923)
Father has High School Diploma × age $0.00488^{**}$ $0.00395^{*}$ $0.00382^{*}$ $0.00401^{*}$ $0.0$ $(0.00218)$ $(0.00220)$ $(0.00219)$ $(0.0219)$ $(0.00219)$ $(0.00219)$	0403* 10217)
Siblings in Education Age         -0.216***         -0.183***         -0.200***         -0.           (0.0659)         (0.0654)         (0.0647)         (0.	150** 0658)
Siblings in Education Age × age $0.00548^{***}$ $0.00541^{***}$ $0.00626^{***}$ $0.006000000000000000000000000000000000$	315** 0152)
Born in Southern Italy         0.227*         0.           (0.137)         (0	228* .137)
Born in Southern Italy × age $-0.00554^*$ $-0.0$ $(0.00295)$ $(0.00295)$ $(0.00295)$	0573* 0294)
Year 2012 $-0.0221$ $-0.0225$ $-0.0246$ $-0.0308^*$ $-0.0298^*$ $-0.0287^*$ $-0.00087^*$ <	0248 0156)
Year 2014 $-0.0165$ $-0.0157$ $-0.0193$ $-0.0281^*$ $-0.0287^*$ $-0.0279^*$ $-0.00000000000000000000000000000000000$	0137 0164)
Constant         7.973***         7.358***         7.521***         7.787***         8.017***         8.014***         8.4.           (0.136)         (0.141)         (0.154)         (0.199)         (0.195)         (0	54*** 229)
Observations $4,992$	992
X         0.1/0         0.210         0.224         0.227         0.200         0.255         0           Years of Schooling         x	x
Parents' Educational Attainment x x x x	x
Presence of Siblings in Education Age x x x	x
Regional Controls x x	х
Municipality Size x x	х
Born in Southern Italy x	х
Current Marital Status Household Size	x x

Table A.46: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived a wage for the considered waves, from age 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Waves of analysis: pooled sample, from 2010 to 2014 for post-recession years, every two years. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

A.2.4	Main	Model	interacting	with	Birth	Cohorts
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In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.0811***	0.0807***	0.0552***	0.0498***	0.0441***	0.0425***	0.0366***
uge	(0.0105)	(0.0104)	(0.0105)	(0.0106)	(0.0106)	(0.0105)	(0.0105)
(age) <sup>2</sup>	(0.000109)	(0.000107)	(0.000108)	(0.000108)	(0.000107)	(0.000106)	(0.000107)
Dame After 1066	-0.267	-0.160	-0.837***	-0.854***	-0.951***	-1.060***	-1.013***
Born After 1966	(0.298)	(0.295)	(0.299)	(0.299)	(0.293)	(0.291)	(0.310)
Born After 1966 $\times$ age	0.0251*	0.0178	0.0450***	0.0462***	0.0538***	0.0588***	0.0606***
2	-0.000429**	-0.000325*	-0.000628***	-0.000652***	-0.000775***	-0.000834***	-0.000897***
Born After 1966 $\times age^2$	(0.000181)	(0.000179)	(0.000181)	(0.000181)	(0.000178)	(0.000177)	(0.000186)
General Education	-2.026**	-1.968**	-1.959**	-1.918**	-1.959**	-1.965**	-2.010**
	(0.858)	(0.840)	(0.831)	(0.831)	(0.828)	(0.822)	(0.812)
General Education $\times$ age	(0.0349)	(0.0341)	(0.0337)	(0.0337)	(0.0336)	(0.0334)	(0.0329)
General Education $\times aaa^2$	-0.000799**	-0.000783**	-0.000782**	-0.000770**	-0.000805**	-0.000803**	-0.000812**
General Education × uge	(0.000351)	(0.000343)	(0.000339)	(0.000339)	(0.000338)	(0.000335)	(0.000331)
General Education × Born After 1966	(1.054)	(1.036)	(1.025)	(1.024)	(1.012)	(1.011)	(0.999)
Consul Education & Dom After 1066 & and	0.00104	-0.0114	-0.0220	-0.0241	-0.0272	-0.0246	-0.0234
General Education $\times$ Born After 1966 $\times$ <i>age</i>	(0.0503)	(0.0495)	(0.0490)	(0.0489)	(0.0482)	(0.0482)	(0.0477)
General Education $\times$ Born After 1966 $\times age^2$	-0.000238	-4.90e-05	9.74e-05	0.000137	0.000181	0.000148	0.000117
-	0.0452	-0.0566	0.128	0.0515	0.0846	-0.0583	0.686
Other Education	(1.786)	(1.710)	(1.662)	(1.659)	(1.631)	(1.625)	(1.633)
Other Education $\times$ age	-0.0141	-0.0116	-0.0185	-0.0141	-0.0112	-0.00434	-0.0318
	(0.0735)	(0.0702)	(0.0684)	(0.0683)	(0.0671)	(0.0669)	(0.0669)
Other Education $\times age^2$	(0.000751)	(0.000716)	(0.000697)	(0.000697)	(0.000685)	(0.000684)	(0.000679)
Other Education × Born After 1966	-0.563	-0.312	-0.552	-0.403	-0.187	-0.0873	-0.763
Outer Education × Bonn Aner 1900	(2.104)	(2.047)	(2.017)	(2.012)	(2.002)	(1.985)	(1.995)
Other Education $\times$ Born After 1966 $\times$ age	(0.0416	(0.0289	(0.0397	(0.0304	(0.0152	(0.00904	(0.0322
	-0.000622	-0.000474	-0.000602	-0.000476	-0.000288	-0.000158	-0.000355
Other Education $\times$ Born After 1966 $\times$ age-	(0.00120)	(0.00119)	(0.00120)	(0.00119)	(0.00120)	(0.00118)	(0.00118)
Years of Schooling		0.0449***	0.0383***	0.0384***	0.0394***	0.0373***	0.0371***
		(0.00224)	-0.0984**	-0.118***	-0.110***	-0.107**	-0.112***
Mother has High School Diploma			(0.0427)	(0.0432)	(0.0425)	(0.0425)	(0.0422)
Mother has High School Diploma $\times$ age			0.00347***	0.00395***	0.00348***	0.00330***	0.00344***
0 1 0			(0.00103)	(0.00105)	(0.00104)	(0.00103)	(0.00103)
Father has High School Diploma			(0.0490)	(0.0496)	(0.0498)	(0.0499)	(0.0496)
Father has High School Diploma × age			0.00558***	0.00527***	0.00439***	0.00447***	0.00415***
r anter has riigh benoor Diptoina // age			(0.00118)	(0.00120)	(0.00120)	(0.00120)	(0.00119)
Siblings in Education Age				(0.0372)	(0.0366)	(0.0366)	(0.0371)
Siblings in Education Age v age				0.00304***	0.00279***	0.00320***	0.000944
Storings in Education Age × age				(0.000941)	(0.000928)	(0.000925)	(0.000947)
Born in Southern Italy						0.0424	0.0330
						-0.00218	-0.00208
Born in Southern Italy $\times$ age						(0.00166)	(0.00163)
Year 2002			0.0491***	0.0498***	0.0472***	0.0479***	0.0522***
			0.0969***	0.0960***	0.0931***	0.0965***	0.103***
Year 2004			(0.0165)	(0.0165)	(0.0161)	(0.0161)	(0.0161)
Year 2006			0.149***	0.149***	0.140***	0.146***	0.153***
			(0.0165)	(0.0165)	(0.0162)	(0.0162)	(0.0160)
Year 2008			(0.0161)	(0.0161)	(0.0157)	(0.0157)	(0.0156)
Year 2010			0.164***	0.152***	0.157***	0.167***	0.183***
			(0.0169)	(0.0171)	(0.0168)	(0.0167)	(0.0166)
Year 2012			(0.0175)	(0.0179)	(0.0175)	(0.0173)	(0.0172)
X 2014			0.156***	0.140***	0.145***	0.156***	0.185***
Icai 2014			(0.0182)	(0.0191)	(0.0187)	(0.0187)	(0.0186)
Constant	/.621***	(0.249)	(0.253)	/.869***	8.131***	8.192***	8.451***
	(0.255)	(0.249)	(0.255)	(0.255)	(0.258)	(0.250)	(0.255)
Observations	13,886	13,886	13,886	13,886	13,886	13,886	13,886
R <sup>2</sup> Veers of Schooling	0.238	0.263	0.278	0.280	0.314	0.319	0.334
Parents' Educational Attainment		х	x x	x	x	x x	x
Presence of Siblings in Education Age				x	x	x	x
Regional Controls					х	х	х
Municipality Size Born in Southern Italy					х	x	x
Current Marital Status							x
Household Size							х

Table A.47: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived wages in the considered waves, from age 20 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Triple differences interacting with birth cohort from 1967 to 1994. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.

In net wages and salaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.0811***	0.0807***	0.0576***	0.0530***	0.0472***	0.0456***	0.0386***
( )2	-0.000717***	-0.000725***	-0.000530***	-0.000502***	-0.000497***	-0.000480***	-0.000407***
(age) <sup>2</sup>	(0.000109)	(0.000107)	(0.000108)	(0.000108)	(0.000108)	(0.000106)	(0.000107)
Born After 1966	0.00755	0.0203	-0.481	-0.428	-0.436	-0.567*	-0.232
P 10.1077	0.00922	0.00718	0.0255	0.0230	0.0251	0.0315*	0.0172
Born After 1966 $\times$ age	(0.0173)	(0.0172)	(0.0173)	(0.0173)	(0.0169)	(0.0167)	(0.0176)
Born After 1966 $\times age^2$	-0.000206	-0.000174	-0.000364	-0.000337	-0.000382*	-0.000458**	-0.000303
	-2.026**	-1.966**	-1.969**	-1.937**	-1.997**	-2.002**	-2.048**
General Education	(0.858)	(0.840)	(0.831)	(0.830)	(0.830)	(0.823)	(0.813)
General Education $\times$ age	0.0856**	0.0810**	0.0804**	0.0793**	0.0826**	0.0828**	0.0843**
	-0.000799**	-0.000783**	-0.000784**	-0.000775**	-0.000819**	-0.000817**	-0.000825**
General Education $\times age^2$	(0.000351)	(0.000343)	(0.000339)	(0.000339)	(0.000339)	(0.000336)	(0.000332)
General Education × Born After 1966	1.038	0.943	1.046	1.060	1.141	1.129	1.071
	-0.0380	-0.0366	-0.0410	-0.0427	-0.0476	-0.0465	-0.0414
General Education $\times$ Born After 1966 $\times$ age	(0.0584)	(0.0575)	(0.0568)	(0.0566)	(0.0565)	(0.0566)	(0.0558)
General Education $\times$ Born After 1966 $\times age^2$	0.000309	0.000306	0.000365	0.000396	0.000461	0.000449	0.000365
	(0.000745) 0.0452	-0.0613	(0.000723) 0.109	0.0544	(0.000/19) 0.0743	-0.0796	(0.000/11) 0.699
Other Education	(1.786)	(1.708)	(1.666)	(1.662)	(1.644)	(1.642)	(1.651)
Other Education $\times$ age	-0.0141	-0.0115	-0.0179	-0.0142	-0.0111	-0.00370	-0.0325
	(0.0735)	(0.0701)	(0.0684)	(0.0683)	(0.0676)	(0.0675)	(0.0675)
Other Education $\times age^2$	(0.000751)	(0.000714)	(0.000697)	(0.000697)	(0.000688)	(0.000688)	(0.000684)
Other Education × Born After 1966	-2.680	-2.331	-2.562	-2.499	-2.682	-2.718	-3.522
ould Education / Dom Ther 1900	(2.916)	(2.877)	(2.877)	(2.857)	(2.890)	(2.851)	(2.895)
Other Education $\times$ Born After 1966 $\times$ age	(0.148)	(0.143)	(0.138)	(0.131	(0.149)	(0.146)	(0.149)
Other Education $\times$ Born After 1966 $\times agg^2$	-0.00233	-0.00211	-0.00224	-0.00218	-0.00233	-0.00230	-0.00258
Olici Education × Born Ander 1900 × uge	(0.00191)	(0.00192)	(0.00194)	(0.00192)	(0.00195)	(0.00190)	(0.00194)
Years of Schooling		(0.00226)	(0.00233)	(0.00233)	(0.00235)	(0.00235)	(0.00232)
Mother has High School Diploma		(···· · · /	-0.105**	-0.124***	-0.117**	-0.112**	-0.124***
Motier has high School Diploma			(0.0468)	(0.0473)	(0.0470)	(0.0470)	(0.0464)
Mother has High School Diploma $\times$ age			(0.00111)	(0.00112)	(0.00112)	(0.00112)	(0.00111)
Father has High School Diploma			-0.139***	-0.124**	-0.0829	-0.0946*	-0.0704
ranci has riigh School Dipionia			(0.0530)	(0.0539)	(0.0538)	(0.0538)	(0.0531)
Father has High School Diploma $\times$ age			(0.00127)	(0.00128)	(0.00129)	(0.00128)	(0.00127)
Siblings in Education Age				-0.0564	-0.0170	-0.0177	-0.0171
Sibilitys in Education Age				(0.0405)	(0.0401)	(0.0401)	(0.0402)
Siblings in Education Age $\times$ age				(0.000995)	$(0.00239^{**})$	(0.000981)	(0.000993)
Porn in Southarn Italy				(0.000)/2)	(0.000307)	0.0620	0.0523
Bolii în Soutierii nary						(0.0818)	(0.0803)
Born in Southern Italy $\times$ age						-0.00269	-0.00259 (0.00178)
X 2002			0.0288*	0.0292*	0.0262*	0.0269*	0.0317**
Tear 2002			(0.0157)	(0.0157)	(0.0152)	(0.0152)	(0.0150)
Year 2004			0.0815***	0.0804***	0.0750***	0.0787***	0.0862***
N. 2007			0.134***	0.133***	0.123***	0.130***	0.138***
Year 2006			(0.0165)	(0.0165)	(0.0161)	(0.0161)	(0.0159)
Year 2008			0.151***	0.152***	0.146***	0.156***	0.165***
			0.146***	0.134***	0.139***	0.149***	0.169***
Year 2010			(0.0168)	(0.0169)	(0.0165)	(0.0165)	(0.0163)
Year 2012			0.128***	0.111***	0.119***	0.131***	0.154***
			(0.0174) 0.142***	(0.0177) 0.124***	(0.01/3) 0.130***	(0.01/1) 0.142***	(0.0169) 0.175***
Year 2014			(0.0180)	(0.0188)	(0.0184)	(0.0184)	(0.0182)
Constant	7.621***	7.049***	7.680***	7.766***	8.025***	8.084***	8.379***
	(0.253)	(0.249)	(0.253)	(0.256)	(0.260)	(0.258)	(0.258)
Observations	12,772	12,772	12,772	12,772	12,772	12,772	12,772
$R^2$	0.171	0.204	0.220	0.223	0.260	0.268	0.287
rears of Schooling Parents' Educational Attainment		х	x x	x x	x x	x x	x x
Presence of Siblings in Education Age			~	x	x	x	x
Regional Controls					x	x	х
Municipality Size					х	x	x
Current Marital Status						х	x
Household Size							x

Table A.48: The Effect of Education Type on Wages over the Life-Cycle. Linear Regression Models. Dependent variable: In net wages and salaries. Sample includes males who perceived wages in the considered waves, from age 25 to 65 with at least upper secondary education, *excluding* self-employed individuals. Omitted education type is vocational. Triple differences interacting with birth cohort from 1967 to 1994. Waves of analysis: pooled sample, from 2000 to 2014. Data Source: Survey on Household Income and Wealth (SHIW, Bank of Italy, 2015). Robust standard errors in parentheses. Significant at \*\*\*1% \*\*5% \*10%.