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Summary

This paper investigates the influence of parental education on the returns to experience of Italian men using a new longitudinal dataset that contains detailed information on individual working histories. Our favourite panel estimates indicate that an additional year of parental education increases sons' weekly wages by 11.7% after twenty years of experience and that 71% of this effect emerges during the career. We show that this effect holds irrespective of individual abilities, and it appears the result of both a glass ceiling effect, due to the complementarity between parental education and son's abilities, and a parachute effect, associated with family labour market connections.

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JEL Classification: J62, J24, J31

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FROM THE CRADLE TO THE GRAVE: THE EFFECT OF FAMILY BACKGROUND ON THE CAREER PATH OF ITALIAN MEN

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Abstract

This paper investigates the influence of parental education on the returns to experience of Italian men using a new longitudinal dataset that contains detailed information on individual working histories. Our favourite panel estimates indicate that an additional year of parental education increases sons' weekly wages by 11.7% after twenty years of experience and that 71% of this effect emerges during the career. We show that this effect holds irrespective of individual abilities, and it appears the result of both a glass ceiling effect, due to the complementarity between parental education and son's abilities, and a parachute effect, associated with family labour market connections.

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1. INTRODUCTION

Intergenerational inequality in socio-economic attainments has usually been studied through the lens of human capital theory. A large body of empirical research has made this view prominent, showing that parental characteristics play a crucial role in the formation of the various skills on which labour market success depends (e.g., Becker and Tomes, 1979 and 1986). Thanks to the availability of new datasets that link parents' characteristics to their children's labour market outcomes, recent research has broadened this view and indicated the existence of other, more direct channels through which parents may influence their children's outcomes, such as job referrals, nepotism and the transmission of employers (e.g., Magruder, 2010; Corak and Piraino, 2011).

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This paper contributes to this growing literature by analysing the lifelong incidence of parental background on children's earnings for cohorts of Italian men who entered the labour market between 1975 and 2000. Italy is an intriguing country for research on intergenerational inequality: on the one hand, it has one of the lowest levels of social mobility among developed countries (Corak, 2013); on the other hand, it has a tuition-free and rather egalitarian educational system (Checchi et al., 1999). In addition, Italy is well known as a country where family connections have a considerable effect on both job finding rates and the probability of achieving prestigious occupations (particularly in liberal professions; Pellizzari et al., 2011; Aina and Nicoletti, 2014). In recent comparisons across EU countries, the relatively low social mobility of Italy and Spain is partially explained by a parachute effect, which ensures a wage premium to well-off individuals who end up in low- and medium-paid occupations (Raitano and Vona, 2015).

To investigate the direct influence of parental background on children's experience-earnings profiles and the mechanisms shaping this influence, this paper resorts to a unique longitudinal dataset that contains information on family background, educational attainment and detailed individual working histories. The impressive length of our panel allows us to estimate the direct influence of parental background conditional on effective experience levels, individual abilities and education. The first contribution of this paper is the use of panel data techniques to unravel the crucial importance of parental background on workers' experience-earning profile. Our favourite estimate shows that after twenty years of experience, the direct effect of parental background on children's earning is 11.7%, and 71% of this effect is formed during the worker's career rather than being dependent on pre-labour market conditions.

However, standard panel data techniques are not enough to disentangle whether the direct influence of parental background on experience-earning profiles passes through better unobservable skills and thus learning capacities or through family ties used in finding better jobs or in getting promotions within the same job. We propose to solve this identification problem using the very general theoretical claim (which is also empirically well grounded; Cunha and Heckman, 2007) that parental background and children's idiosyncratic abilities independent of background are complementary inputs in the formation of individual skills and learning capacity. Operating under this assumption and using quantile regression fixed effects, we expect to observe a stronger parental background effect in the top of the ability distribution, i.e., a glass ceiling effect. In addition, we expect to observe that steeper experience-earning profiles for well-off children are primarily concentrated within the group of highly educated workers, where such ability-background complementarity is magnified. The fact that we observe the coexistence of a glass ceiling effect at the top of the ability distribution and a parachute effect at the bottom (i.e., for people descending the educational ladder relative to their parents) gives empirical substance to the claim that family connections matter in misallocating talents in the Italian labour market. Although this evidence is not conclusive absent an exogenous shock that asymmetrically affects abilities and family connections, our research opens a new avenue to identify the mechanism through which parental background influences children's lifelong outcomes.

It is worth noting that our paper differs from previous research that attempts to identify the influence of family connections in finding good jobs: we do not resort to self-reported measures of relatives' help. Instead, we combine the simple theoretical assumption of ability-background complementarity with the possibility to condition our estimates to individual abilities to disentangle the glass ceiling and parachute effects.

The remainder of the paper is organised as follows. The next section presents the main advantages of our dataset to study the lifelong influence of parental background on children's earnings. Section 3 presents preliminary evidence of how the point estimates of the parental background effect keep increasing along the career path. Section 4 sketches in detail the empirical strategy and the conceptual framework used to disentangle the two mechanisms at work. Section 5 discusses the main results, and Section 6 briefly concludes.

2. DATA

The availability of a longitudinal dataset tracking a large portion of working histories for individuals with different family backgrounds represents the essential requirement to investigate the role played by education and parental background in shaping returns to experience. A recently built dataset called AD-SILC satisfies this essential requirement because it tracks Italian workers for an average of 15.2 years and contains information about children's and parents' education. AD-SILC is the result of a match between the IT-

SILC 2005 cross-sectional sample (i.e., the Italian version of the 2005 wave of the European Union Statistics on Income and Living Conditions - EU-SILC) and the administrative longitudinal records provided by the Italian National Social Security Institute (INPS).[1] In particular, the cross-sectional variables collected in the IT-SILC 2005 have been enriched by the individual social security records since their entry in the labour market up to 2009. In a nutshell, this new dataset enriches the very detailed information on working histories that can be obtained from the social security archives (e.g., earnings and workers' status) with time-invariant characteristics related to family background and education.

For the purpose of this study, AD-SILC has other remarkable strengths. First and foremost, our data allow for a precise reconstruction of workers' effective experience. As shown by Blau and Kahn (2013), relying on effective rather than on potential experience or on survey data responses is crucial to correctly analyse the returns to human capital accumulation.[2] More in detail, because all types of workers are obliged to enrol in social security, we can reconstruct all the individual working histories, distinguishing between inactivity periods and changes in employment status (e.g., employment, self-employment, and unemployment). Thus, our panel is free from any attrition, and it allows us to compute effective experience as the sum of the weeks spent working as a private employee, a public employee or a self-employed worker.[3] In addition, the INPS archives identify the firm for which an individual works, thus allowing us to observe job-to-job transitions, firm changes and firm tenure. In general, AD-SILC allows for a fine-grained decomposition of working histories into several detailed episodes. This advantage will be exploited to disentangle the mechanisms through which parental education affects the experience-earning profile.

To the best of our knowledge, AD-SILC is one of the few datasets available internationally that combines detailed information on working histories and family

[1] IT-SILC 2005 has been merged with the several archives managed by INPS that collect information for all types of workers: private employees, public employees, *parasubordinate* workers (i.e., individuals formally acting as self-employed workers but usually working as employees), farmers and all self-employed categories (i.e., craftsmen, dealers and the various groups of professionals).

[2] Potential experience is computed as the difference between the year of the last graduation and the worker's age, under the assumption that there are no career interruptions. In addition, potential experience is measured in years rather than in weeks.

[3] Consistent with the Italian rules about contractual seniority, effective experience is computed including weeks spent receiving sickness or parental allowances or being temporarily suspended by the firm without being fired (receiving the so-called *Cassa Integrazione* allowance).

characteristics. Similar data are primarily available for highly mobile Scandinavian countries and partially for the UK, as the population sampled in the National Child Development Survey and in the British Cohort Study are getting older (Gregg et al., 2014), but not for the relatively immobile Mediterranean countries.

Our primary estimation sample is selected to minimise the influence of confounding factors that are likely to affect our estimates of the returns to experience and education. First of all, we consider only males to overcome difficulties associated with the different labour supply behaviours across genders. Second, we use only private employees because incomes earned by other categories are likely to be reported with substantial measurement error. Unlike private employees' earnings, self-employed incomes are plagued by underreporting and truncation in the administrative archives, whereas reliable earnings for public employees and *parasubordinate* workers have been available in INPS archives only since 1996. However, it is worth recalling that periods spent working as public employees, *parasubordinates* and self-employed workers are included in the computation of effective experience, which can be hence considered a sufficient statistic of the entire work history.

In this paper, we use the cohorts of males who entered the labour market as private employees between 1975 and 2000 and observe their working career up to the end of 2009.[4] We identify the entry year as the first year with a private employment spell lasting at least 13 weeks and at an age no younger than 15 and no higher than 34. For each year, we consider workers aged 15-64. We exclude from the sample individuals who do not have Italian citizenship because the retrospective dataset has underrepresented immigrants in past years (the panel is developed starting from the resident population in 2005).

The final sample is composed of 88,000 longitudinal observations concerning 5,774 individuals. Table 1 shows that the longitudinal size of the sample is remarkable: the median number of individual observations is 16, while 75% of the sample is followed for at least 8 years, and 90% is followed for at least 5 years. Given the small average firm size, Italian workers experience substantial mobility across firms throughout their career: the mean value of the number of firm changes experienced by the individuals

[4] Note that possible periods spent working as a public employee or a self-employed before 1975 are included in the computation of individual experience.

tracked in our sample is 2.4. As a consequence, tenure in a specific firm is significantly lower than the total experience in the labour market (on average, 5.2 vs. 9.9).

Our main variables of interest are measured as follows. The dependent variable is the log of gross weekly wages from private employment (including personal income taxes and employees' social insurance contributions), computed by dividing the total earnings of the longest working episode as a private employee in a year for the related working weeks. Wages are converted to 2010 constant prices using the consumer price index. To reduce the effect of outliers, the top 0.5% and the bottom 1% of the weekly wage distribution in each year are dropped. We use weekly wages rather than annual wages because they are a better proxy of a worker's productivity. In addition, using weekly wages depurates from the influence of family background on labour supply decisions and on the probability of being unemployed, thus allowing our analysis to be focused on heterogeneity in the returns to experience depending on family background.

Following Hudson and Sessions (2011), we use the average years of education of the father and the mother as proxy of family background. Because a measure of parental earnings is absent in the EU-SILC, education is usually considered the best proxy of parental characteristics (e.g., Chevalier et al., 2013). Although this proxy is less informative than parental income, it is the best way to capture both parental earning potential and the parental capacity to transfer human capital. Educational attainments are converted to years of education to be parsimonious and estimate a single coefficient.

Our sample confirms that in the last century, Italy experienced a clear improvement in its population's educational attainment (Checchi et al., 2013). Compared to the average parental education, sons' education increased by 4.52 years (Table 1). Looking at the marginal distribution of the highest parental degree in Table 2, 60.5% achieved at most a primary degree, whereas only 13.3% and 2.4% attained, respectively, an upper secondary and a tertiary degree. Conversely, the share of those having attained at most a primary degree was reduced to 7.9% in the children's generation, whereas the shares of upper secondary and tertiary graduates rose, respectively, to 45.4% and 7.7%. However, in spite of the increase in educational attainment, the association between parental and children education remains large. Indeed, Table 2 shows that children's education is highly correlated with their parents' education.

Table 3 presents the descriptive statistics on the career steps of children with parents with different education. Because children's years of education steadily increases with parental education (Column 1), those coming from a worse background enter the labour market, on average, at a lower age (Column 2). However, worse-off children experience more frequent employment interruptions, as highlighted by the fact that the gap in effective years of experience in the labour market is much lower than the gap in the entry age. For instance, children of tertiary graduates start to work, on average, 4.5 years later than children of primary educated parents, but the corresponding mean-distance in effective experience shrinks to 1.4 years.

3. EARNINGS GROWTH BY PARENTAL BACKGROUND

As widely recognised in both theoretical and empirical literature, individual wages grow with labour market experience, and most importantly for the aims of this paper, experience-earning profiles are steeper for highly skilled workers.[5] A large fraction of this steeper profile is explained by endogenous workers' mobility and is because, over their career, high-ability workers are more likely to be matched with more productive firms. Likewise, a steeper experience-earnings profile for highly skilled workers reflects differences in learning capacity between skilled and unskilled workers and the cumulative nature of skill formation along the life cycle.

Parental background can cause returns to experience to be highly correlated with unobservable worker skills and the connections useful to find a good job. However, to the best of our knowledge, and with the exception of the short paper of Hudson and Sessions (2011), no studies have directly investigated the effect of parental background on the shape of the experience-earnings profile.

In the empirical literature on intergenerational inequality (Bjorklund and Jantti, 2009; Black and Devereux, 2011; Blanden, 2013), this issue has been addressed indirectly by assessing the potential life-cycle bias in the estimate of the intergenerational elasticity β between children's and parents' incomes. In particular, it has been shown that an estimation bias is likely to emerge because the association between children's current and lifetime income varies over the life cycle when reliable measures of lifetime incomes

[5] See Rubinstein and Weiss (2006) for a literature review of the theoretical mechanism and the empirical evidence and methods.

are difficult to retrieve for both generations (Haider and Solon, 2006; Grawe, 2006).[6] The usual rule of thumb to solve this problem is to choose an age for which the difference between the current and lifetime income is minimised, which is approximately 40 years for males (Haider and Solon, 2006). However, Nybom and Stuhler (2011) have recently shown that approximating lifetime earnings based on annual earnings at a certain age does not remove the lifecycle bias because idiosyncratic deviations from average profiles are correlated with family background. Therefore, as heterogeneity in income profiles is intrinsically dependent on family background, the age at which the gap between annual and lifetime earnings is minimised crucially depends on family background itself, making it exceedingly difficult to reduce the bias in the β.

This paper seeks to fill this gap in the literature and directly investigates the influence of parental background on returns to experience. Before carrying out proper panel estimates (see next sections), it is interesting to provide a preliminary descriptive picture of the association between children's earnings and parental background along the career path. As stated in Section 2, our dataset does not record information on parents' incomes; thus, the β elasticity cannot be properly estimated. However, we mimic these estimates using parents' education as proxy of background. We let the β depend on experience by running a set of OLS estimates at the different years of labour market experience. More precisely, we use our pooled panel and estimate for each level of experience the simple relation:

$$\log(w_{\mathrm{it}}) = \alpha + \beta \cdot par\_edu_i + \delta_{\mathrm{t}} + \varepsilon_{\mathrm{i}}; \quad \forall\ exp(1, 25) \qquad \text{(eq. 1)}$$

where $\log(w_{it})$ is log of gross weekly wage, par_edu_i is parents' average years of education and δ_{t} is a dummy that equals one if the individual *i* has reached experience level *x* at year *t*.

Figure 1 presents the estimates of equation (1) for each experience level. This figure clearly shows that: 1. parental background is associated with significantly higher weekly wages, and 2. the estimated β increases steadily with sons' experience. Remarkably, this second finding indicates that the influence of parental background never declines or

[6] Heterogeneity in earnings growth across individuals is usually considered to be due to the heterogeneity in human capital investment. Indeed, the estimates of the intergenerational elasticities would be biased if young children were observed because earnings profiles are steeper for more educated children and children's education is associated to parental background.

stabilises around a certain value. Rather, it continues to grow during the sons' entire career. The cumulative nature of skill formation can account for this pattern as long as children's education is strongly dependent on their parents' education (Hertz et al., 2007).

To provide preliminary insights on this hypothesis, Figure 2 presents the results of the same regression augmented for the sons' own education, also measured in years. The main result is that the β keeps increasing with children's experience, although at a slower pace than that shown in Figure 1. Also note that in this case, the β_S are always statistically significant. Returns to children's education also increase with experience, confirming the key role of cumulative skill formation (Cunha and Heckman, 2007). In turn, the emergence of a direct effect of parental background when controlling for children's education is a distinct feature of all unequal European countries as opposed to more equal ones (Raitano and Vona, 2015). This direct influence is more difficult to explain and requires further analyses to disentangle whether it depends on unobservable abilities or other mechanisms.

In sum, our preliminary evidence is consistent with the hypothesis of an irreducible heterogeneity in earning profiles, as dependent on both parents' and children's education (Nybom and Stuhler, 2011). In next section, we present a simple conceptual framework to guide structured empirical analyses capable to shed some light on the mechanisms underpinning this persistent influence of parental education on sons' earnings.

4. Empirical Strategy

Human capital accumulation is usually considered the main channel through which parental background influences lifetime earnings (Becker and Tomes, 1979 and 1986; Solon, 2004). Parental background is likely to affect human capital accumulation through different channels (e.g., educational choices, peer effects, different schooling quality; Benabou, 1996; Dustmann, 2004; Bratsberg et al., 2007) whose influence may be mediated by on-going educational policies (Schuetz et al., 2008). To be sure, not only do well-off children remain longer at school on average (Hertz et al., 2007), but they also outperform other children in test scores at a given school level (Fuchs and Woessmann, 2007) and benefit more from extra-schooling activities and parental care (Devereux, 2011). More important, the cumulativeness in skill formation makes early-age investments crucial (Cunha and Heckman, 2007) and thus increases the likelihood that well-off parents have a persistent influence on their children's labour market outcomes through a better learning capacity. This early life influence is particularly important for cognitive skills on which labour market success strongly depends. In addition to core cognitive skills, parental background can affect children's labour market outcomes in other ways. Indeed, well-off parents transfer to their children soft skills and a network of social relations that could prove extremely useful in finding good jobs and reducing the unemployment risk.

The empirical identification of the mechanisms through which parental background can affect children's labour market dynamics and earnings is exceedingly difficult, but it can be facilitated through the use of a simple illustrative equation governing the process of skill formation. Under a quite general assumption, such an equation helps distinguish between the two empirically unobservable components through which parental background can influence children's earnings: additional cognitive abilities vs. network and social relations.

Let us assume that individual skills, s_i, are an additive function of family background, b_i, and of an idiosyncratic ability shock orthogonal to background, a_i. A general way to write such a skill production function is:

$$s_i = \delta b_i + \beta a_i + \gamma a_i b_i \qquad \text{(eq.2)}$$

where δ, β, γ are parameters capturing the intensity of, respectively, a pure background effect, an ability effect and the background effect conditional on children's ability. In line with leading research on skill formation (Cunha and Heckman, 2007), Equation 1 assumes that b_i and a_i are complements in the production function of skills and thus that the autonomous effect of parental background on skills is magnified in presence of highly idiosyncratic abilities. When allowing skills to influence earnings dynamically through learning and job changes, the wage of individual *i* at time *t* can be written as:

$$w_{it} = s_i(1 + e_{it}) = (\delta_1 b_i + \delta_2 b_i e_{it}) + (\beta_1 a_i + \beta_2 a_i e_{it}) + (\gamma_1 a_i b_i + \gamma_2 a_i b_i e_{it}) \qquad \text{(eq. 3)}$$

where labour market experience e_{it} is interacted with the three components of the skill vector. The coefficients denoted with "1" capture the influence of skills on earning potential, whereas the coefficients denoted with "2" capture the influence along the working career. The latter typically occurs through on-the-job learning and (voluntary and involuntary) job changes.

Our expectations on the sign of the coefficients in Equation (3) are the following. First, the pure ability effects are reasonably expected to be positive and significant. Second, we should expect to observe a strong complementarity between ability and background in the accumulation of cognitive skills (Cunha and Heckman, 2007). This implies that γ_1 and γ_2 are both expected to be positive and significant. Third, under the assumption of complementarity between background and ability, we should expect the autonomous background effects δ_1 and δ_2 to be near zero and statistically insignificant unless parental background exerts a strong influence on earnings through family connections and inherited social capital.

In Southern European countries, family ties and networks often play a major role (Checchi et al., 1999; Guell et al., 2007), affecting the probability of finding a good job and other labour market outcomes (Granovetter, 2005). For instance, family networks can ensure good jobs to low-ability individuals, even those with poor levels of schooling or abilities (Raitano and Vona, 2015). As a result, the autonomous effect of parents' education on children's earnings is likely to be positive and particularly strong along the workers' career (i.e., $\delta_2 > 0$).[7]

The direct empirical counterpart of Equation (2) is the empirical model proposed by Hudson and Sessions (2011), which has the advantage of allowing the impact of work experience to explicitly depend on parental education. We estimate the following Mincerian equation:

$$\log(w_{it}) = g(e_{it}) + par\_edu_i(\varphi_1 + \varphi_2 e_{it}) + \mathbf{X}_{it}\boldsymbol{\beta} + \mu_i + \varepsilon_{it} \qquad \text{(eq.4)}$$

where $\log(w_{it})$ is the log of weekly wages[8], ε_{it} is a standard error term, $\mathbf{X}_{it}$ is a set of usual controls in wage equations[9], and $g(e_{it})$ is a third-order polynomial in effective

[7] The literature on the influence of family networks in the labour markets is growing fast (e.g., Pellizzari, 2010; Magruder, 2009; Kramarz and Nordstrom Skans, 2013; Aina and Nicoletti, 2014; Corak and Piraino, 2011; Marcenaro Gutierrez et al., 2014). However, this literature usually focuses on the probability of finding a good job through self-reported family help, whereas in this paper, we investigate the effect of family background on earnings.

[8] In the Appendix, we show that our results hold using annual earnings as the dependent variable.

[9] In the baseline model, the vector **X** contains the following variables: age, age squared, number of weeks worked in the year, dummy for part-time work in the week, regional dummies, cohort dummies and year dummies. In augmented specifications, we also include sector dummies and the log of firm size (available in the dataset since 1987), tenure and other proxies of worker history (i.e., white collar dummy, periods spent receiving unemployment subsidies or being temporarily suspended by the employer).

experience (measured in weeks), i.e., $\sum_{j=1}^{3}\gamma_j e_{it}^{j}$. Our main coefficient of interest is that of the interaction between parental background and experience, $\hat{\varphi}_2$. This coefficient captures the labour market effect of parental background, while $\hat{\varphi}_1$ reflects the better earning potential of well-off children, independently of their experience.

The structure of our data allows us to expand upon Hudson and Sessions' specification in two important ways. First, our very accurate measurement of effective experience greatly reduces the measurement error bias that affects the estimates of the interaction between experience and parents' education. Second, we can exploit the panel dimension to include individual effects μ_i. The inclusion of individual effects mitigate the usual concern that the influence of unobservable skills may result in a biased estimation of $\hat{\varphi}_2$ because these unobservable skills are likely to be correlated with lifetime earning potential and parents' education.

As a further departure from Hudson and Sessions' specification, we also estimate Equation (4) including children's education and an interaction term between children's education and experience. This allows us to distinguish between a direct effect and an indirect effect of parents' education, acting through formal education. Because we expect children's education to be more strongly correlated with effective workers' skills than parents' education, this augmented version of Eq. 4 represents a starting point to interpret our coefficients of interest. Alternatively, we distinguish between fathers' and mothers' education under the assumption that the former is more strongly correlated with family networks and labour market nepotism and the latter with abilities (Chen and Feng, 2009). However, although these augmented specifications offer interesting insights, it appears difficult to believe that individual abilities are fully captured by either mothers' or children's education.

Along the lines proposed by Raitano and Vona (2015), a first direct approach to address these issues consists of using the difference in the educational attainments of parents and sons to build groups with different ability-background combinations. The idea is to use intergenerational educational mobility to distinguish between two types of background-related effects. The first type emerges because there is complementarity between ability and parental background, and it implies that well-off children should have a better endowment of unobservable skills in correspondence to high levels of education (a glass ceiling effect). The second type is associated with insurance for the children of well-educated parents who fail in achieving a high qualification (a parachute effect). Our partial identification comes from the fact that a glass ceiling effect is likely to depend on both family networks and abilities (see, e.g., Macmillan et al., 2013). Conversely, it is hard to believe that the parachute effect can be associated with better abilities; hence, in this case, family networks should be of paramount importance. We implement this idea by estimating the following equation:

$$\log(w_{it}) = \sum_{ij}^{K=9} \alpha_k 1_{\{par\ edu=j\}}\, 1_{\{edu=i\}} + \sum_{ij}^{K=9} \vartheta_k\, 1_{\{par\ edu=j\}} 1_{\{edu=i\}} e_{it} \cdots$$

$$+g(exp_{it}) + \mathbf{X}_{it}\boldsymbol{\beta} + \mu_i + \varepsilon_{it} \qquad \text{(eq.5)}$$

where both j (for parents) and i (for children) have three modalities: low education (L), middle education (M) and high education (H). We hence distinguish nine parent-child pairs (HH, HM, HL, MH, MM, ML, LH, LM, and LL) and allow the experience-earning profiles to be pair specific. For sons, the three groups are tertiary qualifications (H), upper secondary qualification (M) and less than upper secondary qualifications (L). To define the three correspondent groups for parents, observe that the mean education attainment changed dramatically between the two generations, reflecting both changes in the economic structure and reforms in compulsory education (see Table 2). Consistently, we consider as highly educated those parents who have at least an upper secondary degree. Lower secondary graduates represent the middle group, and those with primary education represent the lowest group.

Let us make a few examples to understand how these groups can provide insight into the sign and the magnitude of the effects mentioned in Equation 2. Children with LH and MH substantially improve with parent outcomes, and thus, they should have high idiosyncratic abilities a_i and low b_i. For the group HH, instead, ability-background complementarity is expected to be magnified. Finally, for downward movers (i.e., HM, HL, ML), it is primarily parental background b_i that should matter. A reward for downward movers compared to stayers is then likely to reflect better parental networks rather than individual abilities.

A second and more conventional approach to disentangle the two background-related effects consists of conditioning the estimated coefficients on ability. Quantile regressions allow the effects of interest to vary depending on individual abilities. We estimate

Equation (3) using the quantile fixed effect approach proposed by Canay (2011). Using this approach, not only is our main effect of interest (i.e., φ_2) allowed to depend on abilities, but we can also account for time-invariant unobservable skills. Although this specification does not consent to directly recollecting the structural coefficients of Equation (2), it provides indirect evidence of the importance of the various mechanisms at work. The coefficients associated with the polynomial in experience fully capture the interaction between idiosyncratic abilities and experience. In turn, the estimated coefficient $\hat{\varphi}_{2;a_i}$ is the sum of the structural parameters δ_2 and γ_2. Inspecting the shape of the function $\hat{\varphi}_{2;a_i}$, we can infer the relative magnitude and the statistical significance of these two coefficients. If a positive and significant $\hat{\varphi}_{2;a_i}$ is observed in correspondence to low values of a_i, it is likely that family connections ensure a parachute to low-ability individuals with good family background. If $\hat{\varphi}_{2;a_i}$ is increasing with a_i, a glass ceiling effect for high-ability individuals with good background gradually emerge along the career path. Recall that if networks matter, their effects should be displayed particularly during the working career, and hence, $\hat{\varphi}_{2;a_i}$ is expected to be positive and significant along the entire ability distribution.

In the final step of our empirical analysis, we investigate whether the bulk of the effect of parental education on the earning-experience profile depends on learning-by-doing as opposed to endogenous job mobility. This exercise represents another way to disentangle the mechanisms at work. By way of example, if well-off children can benefit from better connections, they are either more likely to find better jobs during their career or to reduce the harmful consequences of involuntary displacement. However, our data do not allow us to distinguish between voluntary and involuntary job changes by exploiting some source of exogenous worker displacements, such as firm closure (Dustmann and Meghir, 2005), and thus, the result of this exercise should be interpreted with caution. Bearing in mind these limitations, we re-estimate Equation (4) including the interactions of parental background with experience, number of firm changes and previous unemployment spells. The new interactions of parents' education with past unemployment and number of firm changes allow us to distinguish the influence of parents' education on the job opportunities faced after an involuntary change and after a voluntary change, respectively.

5. Estimation Results

The organisation of the results section reflects the two goals of this paper. The first part is devoted to providing new evidence of the relationship between parental education and experience. Our main novelty is the use of panel data techniques to unravel the crucial importance of family background on workers' experience-earning profile. Our estimates question the reliability of empirical specifications that neglect the influence of family background along the workers' entire career. The second part is novel in that it represents the first attempt to disentangle the mechanisms that lead to a positive effect of parental background on experience-earning profiles. To focus on the main message of the paper, we will present tables with only the coefficients of parental background variables.[10]

5.1 Influence of Parents' Education along the Career Path

Table 4 reports the estimates of Equation (3). Column 1 presents a simple benchmark model that is estimated without including the interaction between parents' education and experience. We estimate Equation (3) using either a random (Column 2) or a fixed (Column 3) effect model. The former approach allows us to recollect the time-invariant effect of parents' education and to compare it with the effect of parents' education after labour market entry. The latter approach is more general in that it relaxes the assumption of independence between covariates and individual effects. For these reasons, we will keep comparing the RE and the FE model throughout this section. In columns 4 and 5, we restrict our estimates to the cohort of people who started to work in the decade 1980-1989 (and had at least twenty years of experience in 2009). This restriction reassures us that the results are not driven by young individuals with low experience levels.

The first notable result is that parents' education has a substantial and significant effect on the experience-earning profiles of Italian males. The effect is particularly stable across specification, decreasing by only 6.5% when considering the restricted cohort. The point estimate is quite large; a 1 year increase in both experience and parents'

[10] Results for other covariates can be provided by the authors upon request.

education generates a 0.16% earning advantage, which corresponds to 13.2% of the autonomous effect of parental background (see Table 5).[11] However, the relative magnitude of the two effects changes as experience grows. In panel 1 of Table 5, it is evident that a 5-year increase in parental education leads to a 22.2% earnings increase when the child reaches 20 years of experience. Of this effect, only 27.3% can be attributed to the time-invariant component of the parental education effect.

The second result is that the autonomous effect of parents' education on the earning potential remains positive and statistically significant at a conventional level when including the interaction between parents' education and experience. This result corroborates our claim that parental background plays a role on both phases of the children's life-cycle, pre- and post-labour market entry.

Less obvious is the third result, which emerges from the comparison of the FE and RE model. Remarkably, both the FE and the RE model deliver nearly identical estimates of the effect of parents' education on the earnings profile. Therefore, the RE model can be safely used in comparing the magnitude of the parental background effect at different stages of the working career.

This set of results has two important implications for the literature on intergenerational income elasticity and social mobility in general. First, it raises serious concerns on the reliability of empirical models that assume the influence of parental background to be independent of labour market histories. Second, it lends support to the finding of Nybom and Stuhler (2011) that life-cycle biases in estimations of intergenerational elasticities are unlikely to be minimised in correspondence to any specific point of the working career because deviations from average profiles are correlated with family background.

The first four Columns of Table 6 replicate the analysis of Table 4, including among the covariates son's education and the interaction between son's education and experience. This allows us to distinguish between a direct and an indirect effect of parents' education on earnings. Noteworthy is that the direct effects of parental education halve but remain positive and statistically significant at the 99% level when we control for son's education. In addition, returns to experience are significantly higher for highly educated sons. The quantifications presented in Table 5 highlight that a one-year increase in both children's and parents' education leads to a sizeable wage increase of

[11] Recall that experience is measured in weeks.

7.3% (5% for children's education vs. 2.3% for parents' education), whereas the corresponding increase estimated in Model 1 for parental education is 4.4%.

In last two columns of Table 6, we distinguish between mothers' and fathers' influence on their children's earnings. Recent literature suggests that fathers' education stands for family ties useful to find a good job; thus, it is a candidate proxy for b_i in eq. 2. Mothers' education appears to be a good proxy of children's unobservable ability once controlling for formal education (e.g., Altonji and Dunn, 1996). Our results indicate that both fathers' and mothers' educational attainments have a significant effect on children's working careers, and no significant differences among paternal and maternal coefficients emerge. The paternal and maternal effects are significant for earning potential and in making returns to experience steeper. In spite of its intrinsic interest, the extent to which this exercise is capable of identifying network and background-related ability effects is limited because it hinges upon the strong assumption of a perfect correspondence between paternal and maternal influences, on the one hand, and these two mechanisms, on the other.

As a corollary of this first set of results, it is worth noticing the size of the estimated effects is very robust to the inclusion of additional individual and sectorial controls, interacting both parents' and children's education with the third-order polynomial in experience or using annual earnings as a dependent variable. Tables 1A, 2A and 3A in the Appendix contain these results in full detail.

5.2 Disentangling the mechanisms

The second part of this section seeks to disentangle the sources of the lifetime effect of parents' education more rigorously. Following our empirical strategy, we report the estimation results for Equation 4 in Table 7. Estimated coefficients are reported for both the FE and the RE models, which again are very similar. The results contained in Table 7 clearly indicate the co-existence of a parachute and a glass ceiling effect. Furthermore, remarkably, both components of the parental background effect are active in different phases of the children's career.

Let us first observe what happens for highly educated sons where the glass ceiling effect emerges. Highly educated sons with highly educated parents (HH) earn significantly more than highly educated sons from less advantaged family backgrounds parents, i.e., those with middle (MH) or lower parental education (LH); this group shows not significant advantage with respect to the reference group MM. The advantage of the HH group over the other two groups is statistically significant, as shown by the Wald tests in Table 8. The overall magnitude of the glass ceiling effect is large: at twenty years of experience, the HH group had earned 20.6 and 27.4 percentage points more than, respectively, the MH and LH group. The emergence of a glass ceiling effect is in line with the existence of a complementarity between parental background and ability, which previous research has shown to be widespread across eight European countries representative of different welfare regimes (Raitano and Vona, 2015).

The parachute effect is observed in correspondence of both middle (M) and lower (L) educational levels, and it is clearly amplified along the working career. The well-off sons still gain a significant earning advantage over the worse-off sons, in spite of the fact that they achieve a lower (adjusted for structural change) educational level than their parents. In the group of high school graduates, for instance, the earning advantage of HM at twenty years of experience is 14.7 percentage points with respect to LM and 9.4 percentage points with respect to reference group MM. Note that the two corresponding effects at zero experience were considerably smaller: 4.7 and 2.3 percentage points, respectively. The parachute effect emerges even for sons with primary or lower secondary education. There, sons of less educated parents (LL) experience an earning penalty of approximately 8 percentage points after twenty years of work compared to sons with more educated parents (ML and HL). Therefore, although the parachute effect seems slightly smaller than the glass ceiling effect, it still creates a substantial wedge in the career prospects of individuals with different parental backgrounds.

Figure 3 displays the results of the quantile fixed effect regressions, which represent a more conventional method to disentangle the different mechanisms at work. We estimate both Model 1 and Model 2 to compare how the inclusion of children's education affects the coefficients of parents' education along the ability distribution. The results fully confirm our previous findings. In both Models, returns to experience are steeper for well-off children with high abilities. However, the estimated coefficients are statistically significant along the entire distribution, suggesting that parents' education also has an influence on the earning prospects of low-ability individuals. In line with previous findings, the relative size of the parental education effect is reduced by half when we include the interaction between experience and children's education. Note that for both models, the effects at the median are perfectly in line with those estimated using standard panel data techniques. Overall, we find clear support for our main finding of a widespread effect of parents' education on the earning-experience profile, irrespective of sons' abilities.

A final caveat is in order at this point. Although the results of this sub-section indicate family connections as main candidate explanation to account for the influence of parental background at the bottom of the ability distribution, we cannot fully discharge the role played by occupation-specific skills in the transmission of occupational status across generations.[12] However, we can be confident that this role has a minor influence at least on the parachute effect. First, we do not consider self-employed workers for whom the transmission of occupational-specific skills and experience plays a major role. Second, the parachute effect occurs by definition in low- and medium-paid occupations where human capital (included specific human capital) is relatively less important. As a result, although the glass ceiling effect may partially capture the intergenerational transfer of specific skills in certain occupations, the same is difficult to say for the intergenerational influence at the bottom of the ability distribution, where those performing low-paid occupations are arguably concentrated.

A further way to investigate the avenues through which parental background improves children's lifetime prospects is to decompose the workers' histories into three different events: unemployment spells, firm changes and total work experience. Unemployment spells are defined as periods of consecutive unemployment longer than three months and are hence a proxy of involuntary displacement (our sample is composed of prime-age men, who typically have high participation rates), whereas job-to-job changes are a proxy of voluntary job changes. We then enrich our basic specification of Model 2, including the interaction of parents' education with, respectively, the number of job changes and a dummy when an unemployment spell occurs. Arguably, a well-connected parent is likely to be more successful in helping his/her son to find a better job rather than to ensure better career prospects within the same job. Therefore, the influence of

[12] In the EU-SILC, we have information on the main two-digit ISCO occupation performed by both parents (20 in total). However, such detailed occupational categories are available for sons only in 2005 and thus are unreliable to identify the main job performed throughout the career.

family networks should be well-approximated by the interaction between job change and parental background. In turn, once depurated from these new terms, the interaction between parents' education and experience can be interpreted as a proxy of on-the-job learning.

Table 9 shows a descriptive picture of the way in which parental background influences these two labour market outcomes. The number of firm changes depends on parents' and children's education; it is higher for less educated child from disadvantaged family backgrounds. The same pattern can be observed for the share of weeks in unemployment since the entry in the labour market, which is considerably higher for less educated individuals from disadvantaged backgrounds (Columns 3-4). One can hence conclude that as expected, parental background affects children's probabilities of being unemployed and of finding a new job.

Table 10 lends support to this interpretation. In Columns 1 (RE) and 3 (FE), the positive interaction between the number of firm changes and parental background indicates that well-off children change firms less frequently, but at the same time, they have more success in finding better jobs. The same result holds for children's education, and it is likely to reflect the better outside options of high-ability individuals. Notably, the usual interaction term between experience and parents' education decreases by only 25% with respect to our previous estimates. This finding implies that both an endogenous job change effect and a learning effect are active in shaping the steeper returns to experience of well-off sons. The inclusion of the interaction between the unemployment dummy and experience discards the importance of this additional channel. Whereas children of parents with higher education have a higher likelihood of being employed conditional on their own education, this condition does not significantly affect the wage gains or losses that follow a long period out of the workforce. The opposite cannot be said for children's own education, which worsen the wage losses associated with an unemployment spell.[13]

Overall, this additional empirical exercise indicates that job-to-job transitions are an important channel of intergenerational persistency. This evidence is clearly not conclusive on the relative importance of family networks and learning in the process of

[13] Our findings do not change if we distinguish experiences as private employees or other types of work (e.g., self-employed or public employees) and interact both types of experiences with children's and parents' education (see Table A.4 in the Appendix).

intergenerational transmission. However, when combined with the previous results of this section, we can be more confident in interpreting the positive job change effect for well-off sons as dependent, at least partially, on family networks rather than uniquely on unobservable abilities.

6. CONCLUSIONS

This paper provides new evidence on the influence of parental background along their sons' working career. We find that parental background continues to exert a significant direct influence on sons' earnings after twenty-five years of their career and even when we condition our estimates to both the observable and unobservable characteristics of sons. Our favourite point estimates indicate that the parental background effect at twenty years of experience ranges between 11.7% (when controlling for sons' education) and 22.2%. More than 2/3 of this effect is formed on the labour market rather than being dependent on an initial advantage. We also show that parental background shifts upward the experience-earnings profiles through two mechanisms: a glass ceiling effect for high-ability individuals, due to the complementarity between background and son's idiosyncratic abilities, and a parachute effect for low-ability individuals, associated with better labour market connections.

Whereas the glass ceiling effect is, to a certain extent, an unavoidable consequence of the process of skill formation, the parachute effect may indicate a distortion in the way in which the Italian labour market allocates talents to jobs. The perceived unfairness that results from this imperfect functioning of the labour market can discourage human capital investments of disadvantaged children, and thus, it is likely to have harmful consequences for economic growth. Future research is required to investigate these channels in greater detail, for example, exploiting labour and product market liberalisations that have arguably changed sectorial quasi-rents and thus returns to abilities as opposed to family connections.

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TABLES AND FIGURES

Tab. 1: Sample descriptive statistics[1]

Child years of education	10.55
	[3.40]
Parental years of education (average both parents)	6.03
	[2.89]
Parental years of education (best parent only)	6.78
	[3.51]
Gap between child and average parental education	4.52
	[3.39]
Gap between child and best parent education	3.77
	[3.73]
Real weekly wage (Euro 2010)	495.6
	[247.8]
Real weekly wage (logs)	6.10
	[0.44]
Age	31.1
	[8.8]
Experience	9.9
	[7.7]
Tenure	5.2
	[5.2]
Number of firm changes	2.4
	[2.3]
Number of individual obs.	15.2
	[8.8]
Sampled individuals	5,774
Total number of observations	*88,000*

[1]Mean values, standard deviation in parenthesis.
Source: elaborations on AD-SILC data

Tab. 2: Mobility table of highest parental and child education (row percentages)[1]

	Child education						
Highest parental education	Less than primary	Primary	Lower sec.	Upper sec.	Tertiary	Total	*Parental educ.*
Less than primary	3.1	22.1	51.5	22.1	1.1	100.0	*9.4*
Primary	0.4	8.8	46.9	40.3	3.7	100.0	*51.1*
Lower secondary	0.2	1.8	34.1	54.8	9.3	100.0	*22.8*
Upper secondary	0.3	1.6	14.4	65.8	18.0	100.0	*13.3*
Tertiary	0.0	2.1	5.7	45.7	46.4	100.0	*2.4*
Child educ.	*0.6*	*7.3*	*39.1*	*45.4*	*7.7*	*100.0*	*100.0*

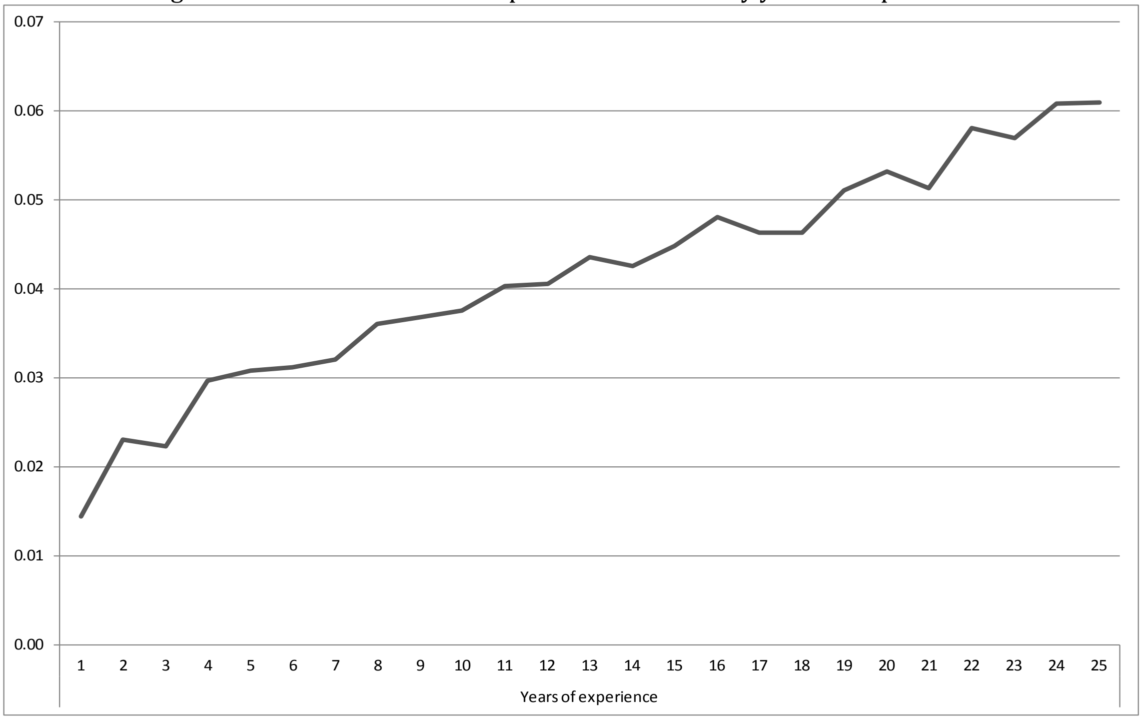
[1] Computed on individual observations (i.e. one observation for each individual).
Source: elaborations on AD-SILC data

Tab. 3: Average years of education, entry age and average years of experience, by parental education

Highest parental education	Years of education[1]	Entry age as a private employee[1]	Years of experience[2]
Less than primary	8.2	21.5	10.2
Primary	9.8	20.3	10.5
Lower secondary	11.4	21.0	9.1
Upper secondary	12.8	22.4	8.8
Tertiary	14.5	24.8	9.1
Total	10.6	21.0	9.9

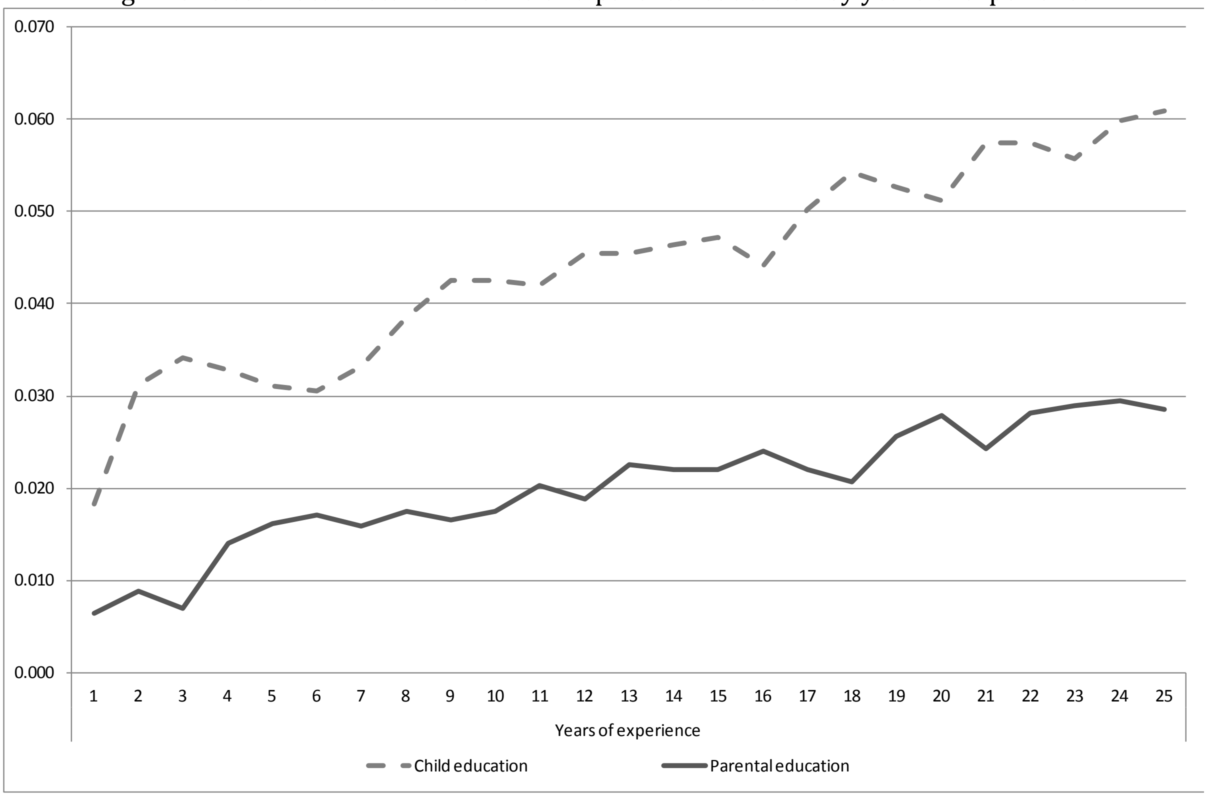
[1] Computed on individual observations (i.e. one observation for each individual). [2] Computed on longitudinal observations. Source: elaborations on AD-SILC data

Fig. 1: OLS estimated returns to parental education by years of experience[1]



[1] Log of weekly gross wage (at constant prices) is the dependent variable. Estimates are obtained controlling for a set of dummies that are equal one if the individual *i* has reached experience *x* at year *t*. Source: elaborations on AD-SILC data.

Fig. 2: OLS estimated returns to child and parental education by years of experience[1]



[1] Log of weekly gross wage (at constant prices) is the dependent variable. Estimates are obtained controlling for a set of dummies that are equal one if the individual *i* has reached experience *x* at year *t*. Source: elaborations on AD-SILC data.

Tab. 4: Association between wages, parental education and experience (not controlling for child education)[1]

	M0	M1		M1 (restricted sample)[2]	
	Random effects	*Random effects*	*Fixed effects*	*Random effects*	*Fixed effects*
Par. educ.	0.024005***	0.012112***	.	0.012590***	.
	[0.001519]	[0.001454]	.	[0.002233]	.
Exp.*Par. educ.		0.000031***	0.000031***	0.000029***	0.000029***
		[0.000003]	[0.000003]	[0.000004]	[0.000004]
N	88,000	88,000	88,000	43,178	43,178

[1] Log of weekly gross wage (at constant prices) is the dependent variable. Control variables are age, age squared, dummy for part-time, third order polynomial on effective experience (in weeks) and fixed effects for region of work, year and cohort of entry into employment. [2] The sample is restricted to those entered in employment in the period 1980-1989. Standard errors clustered by individuals in parenthesis. * p<0.10; ** p<0.05; *** p<0.01. Source: elaborations on AD-SILC data

Tab. 5: Quantification of the impact of child and parental education along the career

	M1 model			M2 model					
	Parental educ.			Child educ.			Parental educ.		
	Exp. 0	Exp. 1	Exp. 20	Exp. 0	Exp. 1	Exp. 20	Exp. 0	Exp. 1	Exp. 20
1 year of educ.									
Starting salary	1.21%	.	.	1.44%	.	.	0.67%	.	.
Growth effect	.	0.16%	3.22%	.	0.18%	3.54%		0.08%	1.66%
Total effect	1.21%	1.37%	4.43%	1.44%	1.62%	4.98%	0.67%	0.75%	2.33%
5 years of educ.									
Starting salary	6.06%	.	.	7.20%	.	.	3.33%	.	.
Growth effect	.	0.81%	16.12%	.	0.88%	17.68%	.	0.42%	8.32%
Total effect	6.06%	6.87%	22.18%	7.20%	8.08%	24.88%	3.33%	3.75%	11.65%

Source: elaborations on AD-SILC data

Tab. 6: Association between wages, child and parental education and experience[1]

	M2		M2 (restricted sample)[2]		"Father and mother" model[3]	
	Random effects	Fixed effects	Random effects	Fixed Effects	Random Effects	Fixed effects
Child educ.	0.014390***	.	0.009960***	.	0.013843***	.
	[0.001433]	.	[0.002029]	.	[0.001504]	.
Par. educ.	0.006658***	.	0.008639***	.		
	[0.001483]	.	[0.002277]	.		
Exp*Child ed.	0.000034***	0.000034***	0.000037***	0.000037***	0.000034***	0.000034***
	[0.000002]	[0.000002]	[0.000003]	[0.000003]	[0.000002]	[0.000003]
Exp*Par. ed..	0.000016***	0.000016***	0.000014***	0.000014***		
	[0.000003]	[0.000003]	[0.000004]	[0.000004]		
Father ed..					0.003625**	.
					[0.001470]	.
Mother ed..					0.003526**	.
					[0.001672]	.
Exp*Fath. ed..					0.000007**	0.000007**
					[0.000003]	[0.000003]
Exp*Moth. ed.					0.000010***	0.000010***
					[0.000003]	[0.000003]
Fath.ed..= Moth.ed.					*0.9712*	
*Exp*Fath.ed.= Exp*Moth.ed.*					*0.4545*	*0.4756*
N	88,000	88,000	43,178	43,178	81,873	81,873

[1] Log of weekly gross wage (at constant prices) is the dependent variable. Control variables are age, age squared, dummy on part-time, third order polynomial on effective experience (in weeks) and fixed effects for region of work, year and cohort of entry into employment. [2] The sample is restricted to those entered in employment in the period 1980-1989. [3]Dependent and control variables as in M2 model; parental education is split in father and mother education. P-values of Wald tests are presented to test the equality of the estimated coefficients related to father and mother education. Standard errors clustered by individuals in parenthesis. * p<0.10; ** p<0.05; *** p<0.01. Source: elaborations on AD-SILC data.

Tab. 7: Association between wages, experience and educational mobility

	Random effects	Fixed effects
Parent H - Child H	0.148404***	.
	[0.024430]	.
Parent M - Child H	0.068624**	.
	[0.032730]	.
Parent L - Child H	0.001025	.
	[0.033604]	.
Parent H - Child M	0.02252	.
	[0.014883]	.
Parent L - Child M	-0.024715**	.
	[0.012066]	.
Parent H - Child L	-0.063553**	.
	[0.027819]	.
Parent M - Child L	-0.084207***	.
	[0.016175]	.
Parent L-Child L	-0.098511***	.
	[0.012128]	.
Parent H - Child H * Exp	0.000444***	0.000448***
	[0.000047]	[0.000047]
Parent M - Child H * Exp	0.000323***	0.000322***
	[0.000065]	[0.000066]
Parent L - Child H * Exp	0.000322***	0.000304***
	[0.000056]	[0.000055]
Parent H - Child M * Exp	0.000069**	0.000065**
	[0.000032]	[0.000033]
Parent L - Child M * Exp	-0.000028	-0.000026
	[0.000023]	[0.000023]
Parent H - Child L * Exp	-0.000127**	-0.000123**
	[0.000053]	[0.000055]
Parent M - Child L * Exp	-0.000094***	-0.000094***
	[0.000031]	[0.000031]
Parent L - Child L * Exp	-0.000163***	-0.000164***
	[0.000021]	[0.000022]
N	88,000	88,000

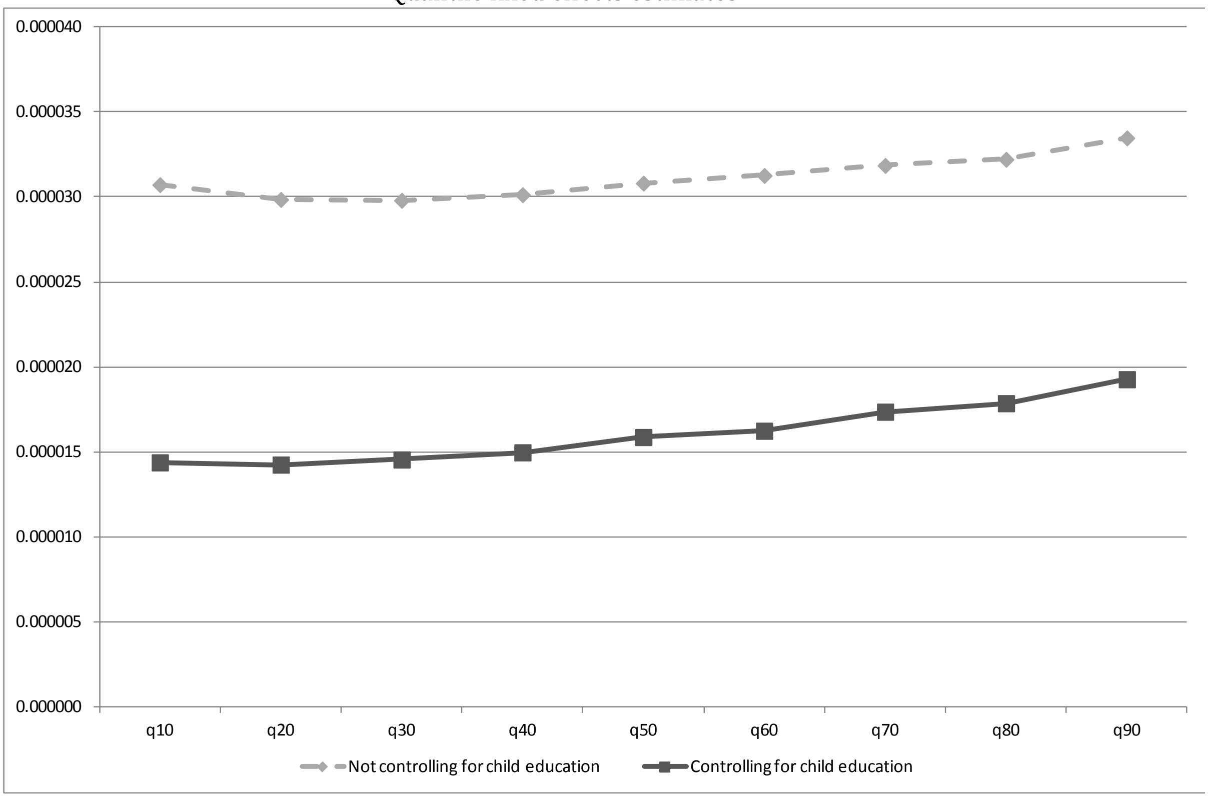
[1] Log of weekly gross wage is the dependent variable. Control variables as in M1 and M2 models. Parental education is L when average years of education are at most 5, M when they are between 5 and 8 years, H when they are higher than 8 years. Child education is L when years of education are at most 8, M when they are between 8 and 18, H when they are at least 18. Standard errors clustered by individuals in parenthesis. *p<0.10; ** p<0.05; *** p<0.01. Source: elaborations on AD-SILC data.

Tab. 8: P-values of Wald tests of the estimated coefficients of the association between wages, experience and educational mobility in Table 7

	Random effects	Fixed effects
Par. H -Ch. H = Par. M-Ch. H	*0.035 (**)*	
Par. H -Ch. H = Par. L-Ch. H	*0.000 (***)*	
Par. M -Ch. H = Par. L-Ch. H	*0.099 (*)*	
Par. H -Ch. M = Par. M-Ch. M	*0.130*	
Par. H -Ch. M = Par. L-Ch. M	*0.000 (***)*	
Par. M -Ch. M = Par. L-Ch. M	*0.041 (**)*	
Par. H -Ch. L = Par. M-Ch. L	*0.474*	
Par. H -Ch. L = Par. L-Ch. L	*0.192*	
Par. M -Ch. L = Par. L-Ch. L	*0.306*	
*Par. H -Ch. H *Exp = Par. M-Ch. H *Exp*	*0.101 (*)*	*0.0954 (*)*
*Par. H -Ch. H *Exp = Par. L-Ch. H *Exp*	*0.069 (*)*	*0.0298 (**)*
*Par. M -Ch. H *Exp = Par. L-Ch. H *Exp*	*0.990*	*0.8245*
*Par. H -Ch. M *Exp = Par. M-Ch. M *Exp*	*0.033 (**)*	*0.046 (**)*
*Par. H -Ch. M *Exp = Par. L-Ch. M *Exp*	*0.001 (***)*	*0.0023 (***)*
*Par. M -Ch. M *Exp = Par. L-Ch. M *Exp*	*0.222*	*0.260*
*Par. H -Ch. L *Exp = Par. M-Ch. L *Exp*	*0.551*	*0.6095*
*Par. H -Ch. L *Exp = Par. L-Ch. L *Exp*	*0.481*	*0.4230*
*Par. M -Ch. L *Exp = Par. L-Ch. L *Exp*	*0.009 (***)*	*0.0084 (***)*

* p<0.10; ** p<0.05; *** p<0.01. Source: elaborations on AD-SILC data.

Fig. 3: Association between wages, parental education and experience along the wage distribution. Quantile fixed effects estimates.



[1] Log of weekly gross wage is the dependent variable. Control variables as in M1 and M2 models of Tables 4-5. Source: elaborations on AD-SILC data

Tab. 9: Mean number of firm changes and ratio between unemployment and working weeks since the entry in the labour market, by child and highest parental education

	Number of firm changes		Share of unemployment weeks	
	Child education	Parental education	Child education	Parental education
Primary	3.6	3.1	13.8%	11.7%
Lower secondary	3.2	2.8	13.3%	12.5%
Upper secondary	2.6	2.6	10.5%	10.8%
Tertiary	2.5	2.2	7.7%	7.8%
Total	2.9	2.9	11.7%	11.7%

Source: elaborations on AD-SILC data.

Tab. 10: Association between wages, child education, parental education and experience[1], controlling for firm changes and unemployment spells[2]

	Random effects		Fixed effects	
	Firm changes	*Firm changes and unemp. spells*	*Firm changes*	*Firm changes and unemp. spells*
Child educ.	0.013905***	0.016403***	.	.
	[0.001496]	[0.001677]	.	.
Par. educ.	0.006395***	0.005866***	.	.
	[0.001569]	[0.001763]	.	.
Exp*Child educ.	0.000031***	0.000030***	0.000030***	0.000029***
	[0.000003]	[0.000003]	[0.000003]	[0.000003]
Exp*Par. educ.	0.000012***	0.000012***	0.000011***	0.000011***
	[0.000003]	[0.000003]	[0.000004]	[0.000004]
Child educ.*changes	0.001784**	0.001547**	0.002326***	0.002078***
	[0.000707]	[0.000704]	[0.000752]	[0.000752]
Par. educ.*changes	0.001465*	0.001542*	0.001995**	0.002131**
	[0.000870]	[0.000870]	[0.000931]	[0.000939]
Child educ.*unemp.		-0.005986***		-0.004654***
		[0.001664]		[0.001722]
Par. educ.*unemp.		0.001098		0.001907
		[0.001847]		[0.001938]
N	88,000	88,000	88,000	88,000

[1] Log of weekly gross wage is the dependent variable. Control variables as in M2 model of Table 5, plus the number of firm changes, and dummies for periods spent in a year as unemployed or receiving CIG. [2]Firm changes are expressed by the (time varying) number of previous changes along the career. An unemployment spell is identified in case of at least 13 weeks not worked in a year. Standard errors clustered by individuals in parenthesis. * p<0.10; ** p<0.05; *** p<0.01. Source: elaborations on AD-SILC data

APPENDIX

Tab. A1: Association between wages, child education, parental education and experience. Fixed effects estimates: further specifications of the M1 model[1]

	S1	S2	S3	S4	S5
	Job features	*S1 plus firms features*	*S2 for post 1987 entrants*	*M2 on log annual earnings*	*S2 on log annual earnings*
Exp.*Par. educ.	0.000029***	0.000029***	0.000034***	0.000028***	0.000030***
	[0.000003]	[0.000003]	[0.000004]	[0.000004]	[0.000003]
N	86,825	72,891	31,925	87,479	72,522

[1] Log of weekly gross wage is the dependent variable in S1-S3; log of annual gross earnings is the dependent variable in S4-S5. Control variables as in M1 model of Table 4.[2] Additional controls in S1 are a third order polynomial on tenure and dummies on occupation, on periods spent in a year as unemployed or receiving CIG. Additional controls in S2 are the same as in S1 plus firm's sector and size. S3 is restricted to cohorts entered in employment since 1987. Standard errors clustered by individuals in parenthesis. * p<0.10; ** p<0.05; *** p<0.01. Source: elaborations on AD-SILC data.

Tab. A2: Association between wages, child education, parental education and experience. Fixed effects estimates: further specifications of the M2 model[1]

	S1	S2	S3	S4	S5
	Job features	*S1 plus firms features*	*S2 for post 1987 entrants*	*M2 on log annual earnings*	*S2 on log annual earnings*
Exp*ch. ed.	0.000031***	0.000030***	0.000032***	0.000037***	0.000036***
	[0.000002]	[0.000002]	[0.000004]	[0.000003]	[0.000003]
Exp*par. ed.	0.000016***	0.000016***	0.000022***	0.000011***	0.000015***
	[0.000003]	[0.000003]	[0.000004]	[0.000004]	[0.000003]
N	86,825	72,891	31,925	87,479	72,522

[1] Log of weekly gross wage is the dependent variable in S1-S3; log of annual gross earnings is the dependent variable in S4-S5. Control variables as in M1 model of Table 4.[2] Additional controls in S1 are a third order polynomial on tenure and dummies on occupation, on periods spent in a year as unemployed or receiving CIG. Additional controls in S2 are the same as in S1 plus firm's sector and size. S3 is restricted to cohorts entered in employment since 1987. Standard errors clustered by individuals in parenthesis. * p<0.10; ** p<0.05; *** p<0.01. Source: elaborations on AD-SILC data.

Tab. A3: M2 model plus interactions with a third order polynomial on experience.

	"Third order" model[1]	
	Random effects	Fixed effects
Child educ.	0.01519423***	.
	[0.00177025]	.
Exp*Child educ.	0.00002820***	0.00002461**
	[0.00001005]	[0.00001015]
$Exp^2/1000$*Child educ.	0.00000617	0.00001242
	[0.00001586]	[0.00001566]
$Exp^3/100000$*Child educ.	-0.00000015	-0.00000042
	[0.00000071]	[0.00000069]
Parental educ.	0.00413558**	.
	[0.00183421]	.
Exp* Par. educ.	0.00003362***	0.00003420***
	[0.00001121]	[0.00001143]
$Exp^2/1000$*Par. Educ.	-0.00002116	-0.00002153
	[0.00001820]	[0.00001829]
$Exp^3/100000$*Par. Educ.	0.00000058	0.00000059
	[0.00000083]	[0.00000082]
*(Par. educ*exp +Par.educ.*exp²+ Par.educ*exp³)=0*	*11.27 (***)*	*11.32 (***)*
N	88,000	88,000

[1] Dependent and control variables as in M2 model plus a third order polynomial on experience interacted with both child and parental education. Standard errors clustered by individuals in parenthesis. F tests of joint nullity of interacted polynomial of experience and parental education are reported. * p<0.10; ** p<0.05; *** p<0.01.
Source: elaborations on AD-SILC data

Tab. A4: Association between wages, child education, parental education and experience[1], controlling for firm changes and unemployment spells and distinguishing experience as private employees or other types of works[2]

	Random effects		Fixed effects	
	Firm changes	*Firm changes and unemp. spells*	*Firm changes*	*Firm changes and unemp. spells*
Child educ.	0.013491***	0.015966***	.	.
	[0.001488]	[0.001668]	.	.
Par. educ.	0.006230***	0.005611***	.	.
	[0.001561]	[0.001751]	.	.
Pr. Emp. Exp*child educ.	0.000031***	0.000030***	0.000030***	0.000029***
	[0.000003]	[0.000003]	[0.000003]	[0.000003]
Pr. Emp. Exp *par. educ.	0.000016***	0.000016***	0.000014***	0.000014***
	[0.000003]	[0.000004]	[0.000004]	[0.000004]
Oth. Exp*child educ.	0.000032***	0.000031***	0.000031***	0.000030***
	[0.000004]	[0.000004]	[0.000005]	[0.000005]
Oth. Exp *par. educ.	0.000003	0.000004	0.000002	0.000003
	[0.000006]	[0.000006]	[0.000006]	[0.000006]
Child educ.*changes	0.001800**	0.001567**	0.002336***	0.002091***
	[0.000705]	[0.000702]	[0.000749]	[0.000750]
Par. educ.*changes	0.001535*	0.001623*	0.002076**	0.002220**
	[0.000871]	[0.000872]	[0.000931]	[0.000939]
Child educ.*unemp.		-0.005920***		-0.004609***
		[0.001667]		[0.001726]
Par. educ.*unemp.		0.001325		0.002042
		[0.001830]		[0.001919]
N	88,000	88,000	88,000	88,000

[1] Log of weekly gross wage is the dependent variable. Control variables as in M2 model of Table 5, plus the number of firm changes, and dummies for periods spent in a year as unemployed or receiving CIG. [2] The total experience is split in periods spent as a private employee or a self-employed and both types of experiences are included among the covariates (instead that the total experience) as a third order polynomial and interacted with child and parental education. Firm changes is expressed by the (time varying) number of previous changes along the career. An unemployment spell is identified in case of at least 13 weeks not worked in a year. Standard errors clustered by individuals in parenthesis. * p<0.10; ** p<0.05; *** p<0.01. Source: elaborations on AD-SILC data

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