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From the Cradle to the Grave: The Influence of Family Background on the Career Path of Italian Men*

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Abstract

Using a longitudinal data set that contains detailed information on working histories of Italian men, we investigate the relationship between parental background and sons' earnings profiles. We find that the parental influence on sons' earnings persists over the career and that the direct influence controlling for sons' education is large and grows during the working career. After twenty years of experience, our baseline specification indicates that an additional year of parental education is associated with a 2.0% increase in sons' wages, while an additional year of son's education is associated with a 4.8% increase. We use educational mobility between parents and sons to disentangle this influence into a glass ceiling effect – a premium for well-off children who have high educational attainments – and a parachute effect – a premium for well-off children who acquire less education than their parents. We find that both effects contribute to explain the steeper earnings profiles of the well-off sons, consistently with the idea that family ties play a crucial allocative role in the Italian labour market.

I. Introduction

Two well-known empirical regularities in the literature on earnings' dynamics are that wages grow with experience and that the steepness of the experience-earnings profile is heterogeneous across different workers' groups. Existing research finds that high-skilled workers have a steeper profile than low-skilled ones, using education as a proxy for skills (Rubinstein and Weiss, 2006). While this evidence is potentially relevant to the literature on intergenerational inequality because education and skills depend on parental background

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(Holmlund, Lindahl and Plug, 2011), no research has attempted to investigate directly how the experience-earnings profiles depend on family background.[1]

Clearly, the positive correlation between education and parental background should produce steeper earnings profiles for well-off children, but this is not the only channel through which family background can affect the steepness of the experience-earnings profile. Indeed, education being equal, a more advantaged family background is likely to directly affect the returns to experience, because a better background might be associated with both additional workers' skills (cognitive and soft skills) and connections useful to find a better job match in the labour market.

This paper fills a gap in the literature by documenting the persistency of these direct channels of inequality transmission over the children's working career. In particular, we provide new evidence on the heterogeneity in the experience-earnings profiles depending on parental background. We then propose a simple methodology to disentangle the mechanisms that could explain the persistency in the direct influence of parental background along the children's careers.

Our paper takes advantage of a unique longitudinal data set that contains information on family background, educational attainment and detailed career histories of cohorts of Italian men who entered the labour market between 1975 and 2000. The impressive length of our panel allows us to estimate the influence of parental background – measured using parental education – on children's earnings conditional on children's education and effective experience since the entry in the labour market.

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 public education system (Checchi, Ichino and Rustichini, 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 joining top occupational groups (particularly in liberal professions; Pellizzari *et al.*, 2011; Aina and Nicoletti, 2014; Mocetti, 2016).[2] In recent comparisons across EU countries, the relatively low social mobility of Italy is partially explained by a wage premium to children of well-off parents (e.g. according to their occupation) who end up in low- and medium-paid occupations, compared to those holding the same occupation but coming from less advantaged families (Raitano and Vona, 2015a).

Our empirical analysis reveals that the influence of family background on children earnings persists over their careers. Our baseline estimate suggests that, controlling for the influence of children's education, a one-year increase in parental education is associated with a 2.0% increase in children's earnings after twenty years of work experience. Importantly, approximately 3/4 of this effect is formed during the working career rather than in the first job.

[1] An exception is the short paper of Hudson and Sessions (2011). The literature on intergenerational inequality has only indirectly dealt with this issue when computing the life-cycle bias in the estimate of the intergenerational elasticity between children's and parents' incomes. See section II for a detailed review.

[2] For the UK (another country characterized by low social mobility), Crawford *et al.* (2016) document a large earnings advantage for well-off children within the group of tertiary graduates, while Macmillan, Tyler and Vignoles (2015) and Gutierrez, Micklewright and Vignoles (2014) find that parental networks are important to attain top managerial and professional jobs. However, Gutierrez *et al.* (2014) do not find a clear direct influence of some proxies of parental networks on wages.

The main problem to interpret these estimates as causal is that the dynamic influence of parental background depends on unobservable abilities that are correlated with both parental background and experience. While solving this issue is crucial to understand the mechanisms underlying the persistency in the influence of family background on wages, the key policy question is whether the influence of parental background on the slope of the experience-earnings profiles depends on unobservable innate abilities and skills, or on family ties used in finding better jobs and in getting promotions within the same job.

We address this question exploiting information on educational mobility between parents and children to infer knowledge about children's abilities. Our working assumption is that, considering two children who achieved the same education (e.g. upper secondary), the child who studied relatively less compared to his parents should not be endowed with higher innate abilities and unobservable skills than the child of less educated parents. Accordingly, as explained in detail in section V, educational mobility between the parents and the child allows us to construct ability-background pairs that helps us to disentangle, even if not in a causal way, whether the influence of parental education is mainly attributable to unobservable skills or to networks (see Raitano and Vona, 2015a).

We find that a *glass ceiling effect* (i.e. a steeper experience-earnings profile for highly educated children of highly educated parents, compared to highly educated children of less educated parents) and a *parachute effect* (i.e. a steeper earning experience profile for 'low' educated children of highly educated parents, compared to children with the same education and less educated parents) both contribute in explaining the persistent influence of parental background on children's earnings. Although this evidence is not causal in the strict sense, absent an exogenous shock that asymmetrically affects abilities and family connections, our findings suggest that the intergenerational transmission process cannot be merely attributed to human capital accumulation, but it is also explained by family connections and nepotism.

The remainder of the paper is organized as follows. The next section reviews the literature to which this paper contributes. Section III presents the data. Section IV shows new evidence on heterogeneous experience-earnings profiles depending on both parents' and children's education. Section V describes our strategy to disentangle the two mechanisms at work and the main results on *glass ceiling* and *parachute effects*. Section VI briefly concludes.

II. Related literature

This paper contributes to two independent strands of the literature that have studied the sources of the heterogeneity in individual experience-earnings profiles. The first analyses the relationship between workers' skills and earnings growth; the second measures how the influence of parental background varies with the children's age.

With regards to the first strand, theoretical and empirical research agrees that: (i) wages grow with labour market experience; (ii) experience-earnings profiles are steeper for highly skilled workers. On the theoretical side, several models have been proposed to explain the positive effect of skills on life-cycle wage growth. Rubinstein and Weiss (2006) group these models into three broad categories. First, in models of human capital investment over the life-cycle, skilled workers become more productive, and thus better paid, because they are more likely to receive firm-specific training or to learn on-the-job. The second explanation is related to worker's mobility and postulates that the probabilities of a successful job match increases with both worker's experience and ability. Finally, in the presence of asymmetric information, worker's productivity is revealed to the employer gradually procrastinating the emergence of returns to highly talented workers. On the empirical side, the identification of the importance of these channels is problematic because both on-the-job skill formation and job-to-job mobility are fundamentally endogenous (e.g., Connolly and Gottschalk, 2006; Heckman, Lochner and Todd, 2008). In general, empirical studies agree that steeper returns to experience for highly skilled workers can be explained by both endogenous workers' mobility and differences in on-the-job learning capacity between skilled and unskilled workers.

The second strand of the literature relates experience-earnings profiles to worker's parental background, but only indirectly. Early influential studies have assessed the bias in the point in time estimate of the intergenerational income elasticity β between children's and parents' incomes when lifetime parents' and children's incomes are not available (e.g. Jenkins, 1987; Grawe, 2006; Haider and Solon, 2006). These studies provided compelling evidence of a life-cycle bias in the estimate of β: because children's annual earnings do not fully reflect lifetime earnings, the estimated β is downward biased if too young children are observed.[3] To deal with this issue, the usual rule of thumb in empirical analyses is to choose an age at which the difference between the annual and lifetime income is minimized, that is approximately around 35–40 years for males, while for females no general rule emerges (Bohlmark and Lindquist, 2006; Haider and Solon, 2006). However, a recent study of Nybom and Stuhler (2016) has shown that approximating lifetime earnings with annual earnings at a certain age does not remove the life-cycle bias because systematic idiosyncratic deviations from average profiles emerge and these deviations might be correlated with family background. Therefore, point in time estimates of the intergenerational elasticity remain sensitive to the age at which children's earnings are observed and panel data are required to account for the heterogeneity in experience-earnings profiles depending on family background.

The literature on the life-cycle bias deeply examines measurement issues, but does not explicitly studies the sources of the life-cycle bias in the estimation of β. This partially reflects the widely accepted theoretical claim that intergenerational inequality is primarily explained by the effect of parental background on human capital accumulation (Solon, 2004), especially at early ages (Cunha and Heckman, 2007).[4] Steeper earnings profiles for high-skilled workers are thus compatible with models of human capital investments over the life-cycle and, more generally, with the cumulative nature of skill formation (Cunha and Heckman, 2007). If this explanation was valid, we would expect that differences in educational attainment account for the bulk of the relationship between parental

[3] Using several waves of two cohort studies (NCDS and BCS) for the UK, Gregg, Macmillan and Vittori (2016) have recently confirmed that the estimated β grows when older children are observed and, therefore, the lifetime association between parental and children income might be much higher than the association found by point in time estimates at early ages.

[4] Parents influence children's human capital through investment in education and heritability of abilities (e.g. Becker and Tomes, 1979, 1986; Holmlund *et al.*, 2011). The other main channels through which parental background is likely to affect children's human capital accumulation are: educational choices, peer effects, different school quality and extra-school activities, whose influence may be mediated by the educational policies (see, e.g., Benabou, 1996; Dustmann, 2004; Bratsberg *et al.*, 2007; Duncan and Murnane, 2011; Schutz, Ursprung and Woessmann, 2008).

background and experience-earnings profiles. However, since the educational attainment is a poor proxy for the effective worker's skills, empirically we can still observe a significant direct influence of parental background on the returns to experience when controlling for children's education. Indeed, several hardly observable skills – such as innate abilities and more valuable skills, acquired through different educational careers – are positively correlated with both parental background and with the slope of the experience-earnings profile. For instance, school tracking is strongly affected by parental background (e.g. Hanushek and Woessmann, 2006; Checchi and Flabbi, 2013), being the children of the worse-off significantly more likely to be enrolled in vocational schools (directly preparing pupils for specific middle-low skilled jobs) than the children of the well-off which instead are more likely to attend general high-schools (preparing for university education). This (often unobservable) difference in the type of high-school programmes is a primary source of (unobservable) skills differences related to family background.

Parental influence can be also unrelated to children's skills, especially in non-competitive and familistic labour markets, such as the Italian one. In particular, family networks and social ties can be of great help for children to find a good job or to be promoted within the same job (Granovetter, 2005). Discriminating between a human capital and a network explanation of the parental influence is challenging, absent an exogenous shock that asymmetrically affects the two possible sources of background influence.

The seminal paper of Hudson and Sessions (2011) provides the first direct evidence of the positive correlation between experience-earnings profiles and parental education. More in details, they obtain this important result applying a modified Mincerian equation, where labour market experience is interacted with parental education, for a sample of approximately 3,000 US workers. We extend this seminal paper in several ways. First of all, we use longitudinal rather than cross-sectional data and thus we can control for time invariant individual abilities. Second, we measure experience in effective worked weeks rather than in terms of potential experience.[5] Third, taking stock from the literature reviewed above, we allow also child education to have an influence along the working career, while Hudson and Sessions (2011) just control for child education without allowing the effect of child education to vary with experience.[6] Finally, we try to empirically disentangle the sources of this background-related influence on the experience-earnings profiles, while Hudson and Sessions (2011) only suggest possible mechanisms underlying this influence.[7]

III. Data

The availability of a longitudinal data set tracking a large portion of individual working histories and containing information on parental background represents the essential re-

[5] Potential experience is usually computed as the difference between the worker's age and the age when the highest level of education was attained, under the assumption of no career interruptions.

[6] In their empirical specifications, Hudson and Sessions (2011) interact experience with parental background while they do not interact children education with experience.

[7] Hudson and Sessions (2011) argue that the influence of family background on the experience-earning profile may be due to two mechanisms that are very similar to those investigated in our article. First, better educated parents can more effectively supplement the formal education process of children. Second, better educated parents are also likely to be better connected parents, able to secure their children good jobs in firms where they are able to progress rapidly.

quirement to investigate the role played by education and parental background in shaping returns to experience. A recently built data set called AD-SILC (ADministrative Statistics on Income and Living Conditions) satisfies this essential requirement because it tracks Italian workers for an average of 15.2 years and contains information about their educational attainment and parental characteristics.

AD-SILC is the result of a match between the IT-SILC 2005 cross-sectional sample (i.e. the Italian component 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). In particular, the cross-sectional variables collected in the IT-SILC 2005 – that includes information about the worker's educational attainment and a devoted section about intergenerational mobility, where several aspects of family background are recorded in a retrospective fashion (e.g., father's and mother's education and occupation when the interviewee was approximately 14 years old; parental incomes are instead not recorded in IT-SILC) – have been merged with the individual social security records tracking individuals since labour market entry until 2009.[8]

To summarize, AD-SILC contains the detailed working histories of a representative sample of Italian workers (i.e. 'the children') and links these histories to information about time-invariant parental characteristics. Therefore, it represents the ideal data set to analyse the influence of parental background on the children's experience-earnings profiles.[9]

For the purposes of this study, AD-SILC has another remarkable strength because it allows 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. More in detail, because all Italian workers are obliged to enrol in social security, we can reconstruct the whole individuals' working histories. Thus, our panel is free from attrition and we can compute effective experience as the sum of weeks spent working as a private employee, a public employee, or a self-employed or a *parasubordinate* worker (that is a worker formally self-employed, but usually dependent on a single employer).[10]

To the best of our knowledge, AD-SILC is one of the few data sets available in European countries that enrich a longitudinal data set on children's working histories with information on family background. Similar administrative data are available for Scandinavian countries (that are characterized, in international comparisons, by a relatively high degree of social mobility), while UK cohort surveys (i.e. the National Child Development Survey and of the British Cohort Study) allow one to study the time-profile of the association between parents and children incomes as the latter get older (Gregg *et al.*, 2016). However, differently from data collected by administrative sources, these surveys are not free from attrition. Therefore,

[8] More specifically, IT-SILC 2005 has been merged with the several archives managed by INPS that collect information for all types of workers, i.e. employees in the public and in the private sector, *parasubordinate* workers (i.e. workers who are formally self-employed, but are usually dependent on a single employer) and all self-employed categories (i.e. craftsmen, dealers and the various groups of professionals).

[9] When information on parents' incomes are missing, using parents' qualitative characteristics recorded through retrospective interviews is considered a reliable way to study intergenerational inequality (Ermisch, Francesconi and Siedler, 2006).

[10] 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).

AD-SILC is the first data set linking parental background to children careers available for Southern European countries, which are characterized by a relatively low social mobility (Corak, 2013; Raitano and Vona, 2015b).

Our primary estimation sample is selected to minimize the influence of confounding factors that are likely to affect our estimates of the returns to experience. First of all, consistent with the vast majority of existing literature, we consider only males to overcome difficulties associated with the different labour supply behaviours across genders. Second, we only include employees in the private sector because incomes earned by other types of workers are likely to be reported with a systematic measurement error. Unlike earnings of employees in the private sector, self-employed incomes are indeed plagued by a severe underreporting, whereas reliable earnings for employees in the public sector and for *parasubordinate* workers have been available in INPS archives only since 1996. However, it is worth recalling that periods spent working as public employees, *parasubordinate* workers and self-employed are included in the computation of effective experience.[11]

Our primary sample of interest includes the cohorts of males who entered the labour market as employees in the private sector between 1975 and 2000 – including in the measure of experience also the weeks spent in the public sector or as a self-employed before 1975 – and observe their working career up to 2009. We identify the entry year as the first year with an employment spell in the private sector lasting at least 13 weeks at an age between 15 and 34 years. For each year, we consider workers aged 15–64. Because the panel is developed starting from the resident population in 2005, we exclude from the sample individuals who do not have Italian citizenship because the retrospective data set under-represents immigrants in past years.

As shown in Table 1, the final sample is composed of 87,470 longitudinal observations concerning 5,773 individuals (from now on 'the sons'), followed on average for 15.2 years. The longitudinal size of the sample is remarkable: the median number of observations per worker is 16, while 75% of the sample is followed for at least 8 years and 90% is followed for at least 5 years.

Our main variables of interest are measured as follows. The dependent variable is the log of gross weekly wages from employment in the private sector (including personal income taxes and employees' social insurance contributions), computed by dividing the total earnings of the longest working episode of the year as a private sector employee for the associated working weeks. Wages are converted to 2010 constant prices, using the consumer price index. To reduce the effect of outliers, the top and bottom 1% of the weekly wage distribution in each year are dropped.[12] We use weekly wages rather than annual wages because they are a better proxy of a worker's productivity.

Because we do not have information on parental incomes, we use parental education as a proxy of family background. The choice is motivated by the fact that parental education

[11] Focusing on employees in the private sector only could create a selection bias if working in the public sector or as a self-employed is correlated with family background. To investigate this possibility, we run multinomial logit regressions of the probability of working in a given sector on child and parental education. Our results, available upon request for sake of space, show that, compared to the probability of becoming a private employee, parental education is associated with a higher probability to work as a professional (e.g. lawyers, architects), but it is not significantly associated to a higher chance to work in the public sector, to become a *parasubordinate* worker or to be self-employed.

[12] Note that our results are robust to different thresholds of the data trimming.

TABLE 1

Sample descriptive statistics

Son years of education	10.6
	(3.4)
Parental years of education (average both parents)	6.0
	(2.9)
Parental years of education (best parent only)	6.8
	(3.5)
Gap between child and average parental education	4.5
	(3.4)
Gap between child and best parent education	3.8
	(3.7)
Real weekly wage (Euro 2010)	489.7
	(229.4)
Real weekly wage (logs)	6.10
	(0.43)
Age	31.0
	(8.8)
Experience	9.9
	(7.7)
Tenure in the same firm	5.2
	(5.2)
Number of individual obs.	15.2
	(8.7)
Sampled individuals	5,773
Total number of observations	87,470

Note: Mean values, standard deviation in parenthesis.
Source: Elaborations on AD-SILC data.

captures both the parents' earnings potential and their capacity to transfer human capital to children (Chevalier *et al.*, 2013). In our estimates, educational attainments of both parents and sons are converted in years of schooling to be parsimonious and estimate a single coefficient. In particular, we take the average years of schooling of the father and the mother and take only the father's or the mother's education if one parent is missing.

Evidence from our data set confirms that the educational attainment of Italians has clearly improved over the last century (Checchi, Fiorio and Leonardi, 2013). Table 1 shows that, compared to the average parental education, sons' education increased by 4.6 years. Table 2 presents the marginal distribution of the highest parental educational attainment, defined according to the ISCED-97 classification: 60.5% achieved at most primary education (level 1 in ISCED) and 22.8% attained lower secondary education (level 2 in ISCED) whereas only 13.3% and 2.4% attained, respectively, an upper secondary (levels 3 and 4 in ISCED) and a tertiary (levels 5 and 6 in ISCED) educational level. Conversely, the share of those having attained at most primary education reduced to 7.9% in the sons' generation, whereas the shares of upper secondary and tertiary graduates rose, respectively, to 45.4% and 7.7%. Despite such pronounced increase in educational attainment, the association between parental and sons' education remained considerable as evident looking at the diagonal of the transition matrix reported in Table 2.

TABLE 2

Mobility table of highest parental and son's education (row percentages)

Highest parental education	Son education: Less than primary	Primary	Lower secondary	Upper secondary	Tertiary	Total	Parental education
Less than primary	3.1	22.1	51.5	22.1	1.1	100	9.4
Primary	0.4	8.8	46.9	40.3	3.7	100	51.1
Lower secondary	0.2	1.8	34.1	54.8	9.3	100	22.8
Upper secondary	0.3	1.6	14.4	65.8	18.0	100	13.3
Tertiary	0.0	2.1	5.7	45.7	46.4	100	2.4
Son education	0.6	7.3	39.1	45.4	7.7	100	100

Note: Computed on individual observations (i.e. one observation for each individual).
Source: Elaborations on AD-SILC data.

TABLE 3

Average years of education, entry age and average years of experience, by parental education

Highest parental education	Years of education*	Entry age as an employee in the private sector*	Years of experience†
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

Notes: *Computed on individual observations (i.e. one observation for each individual).
†Computed on longitudinal observations.
Source: Elaborations on AD-SILC data.

Table 3 presents descriptive statistics on the sons' career steps according to parental education. Because sons' years of schooling steadily increase with the parental educational attainment (column 1), those coming from a worse background start to work, on average, at a younger age (column 2). However, sons of less educated parents experience more frequent unemployment spells: the gap in effective years of experience in the labour market by parental education is indeed much lower than the gap in the entry age (column 3). For instance, sons of tertiary graduates start to work, on average, 4.5 years later than sons of primary educated parents, but the corresponding mean distance in effective experience shrinks to 1.4 years.

IV. Experience-earnings profiles by parental education

This section provides new evidence on the persistent influence of parental education on the experience-earnings profiles. After presenting in section 'Preliminary evidence' motivational evidence on how the parental influence varies along the working career, section

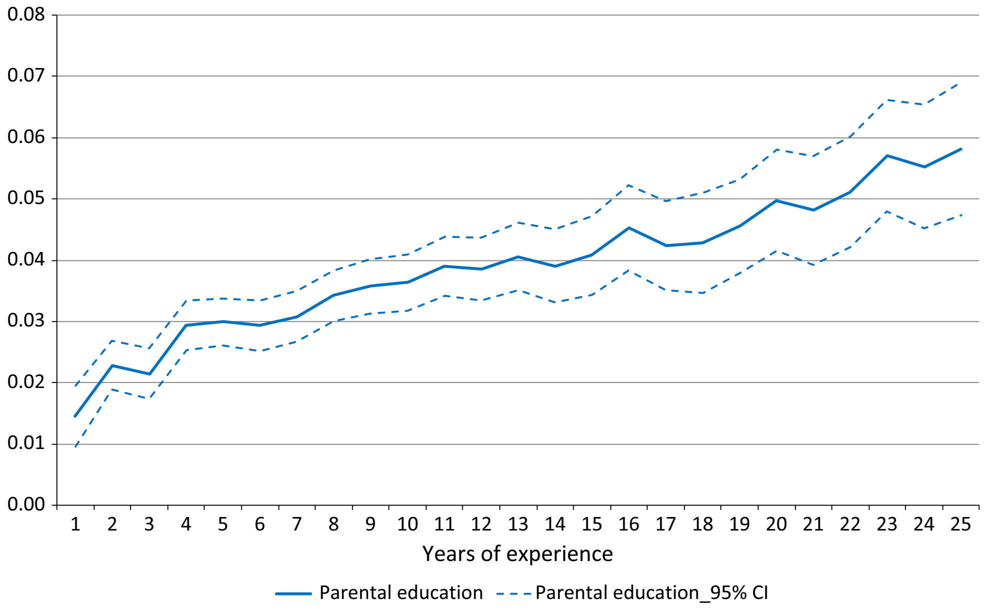

Figure 1. OLS estimated wage returns to parental education by years of experience (not controlling for son's education)
Notes: Estimates are obtained regressing, by each year of experience x (from 1 to 25), log of weekly gross wages (at constant prices) on parental years of education, controlling for time dummies that indicate the year t when the individual i reaches experience x.
Source: Elaborations on AD-SILC data.

'Estimating the influence of parents' education on sons' earnings profiles' presents panel-data estimates of the influence of parental education over the workers' career and section 'Robustness checks' presents some robustness checks.

Preliminary evidence

To give a preliminary idea of the life-long persistency in the correlation between parental education and sons' earnings, we run simple regressions of sons' log weekly wage on parental education in correspondence to different levels of labour market experience. Specifically, we estimate through OLS the following relation separately for each experience level:

$$\log(w_{ij}) = \alpha + \beta_j par\_edu_i + \delta_{ijt} + \varepsilon_i \tag{1}$$

where $\log(w_{ij})$ is log of sons' gross weekly wage at experience level j; par_edu_i is parents' average years of education; β_j is our coefficient of interest and captures the association between parental education and sons' wages at different years of labour market experience j; δ_{ijt} is a set of year dummies denoting the calendar year t when the individual i has reached a given experience level j and ε_i is a standard residual.

In Figure 1, we plot the estimated $\hat{\beta}_j$ that captures, for experience level from 1 year to 25 years, the increase in the log of the son's weekly wage associated with an additional year of parents' education. This Figure clearly shows that: (i) parental background is associated with significantly higher weekly wages, and (ii) $\hat{\beta}_j$ increases steadily with sons' experience.

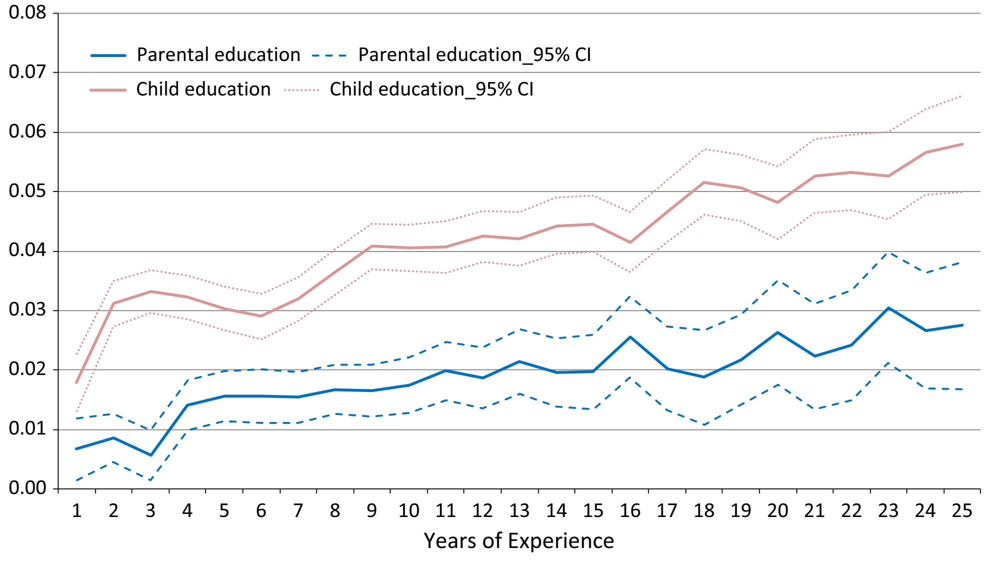

Figure 2. OLS estimated wage returns to son and parental education by years of experience
Notes: Estimates are obtained regressing, by each year of experience x (from 1 to 25), log of weekly gross wages (at constant prices) on son's years of education and parental years of education, controlling for time dummies that indicate the year t when the individual i reaches experience x.
Source: Elaborations on AD-SILC data.

Remarkably, this second finding indicates that the influence of parental background persists and grows over the sons' career.

The cumulative process of skill formation can generate such persistent pattern because, as shown in Tables 2 and 3, the sons' education is strongly dependent on their parents' education. To shed light on the role of education, we re-estimate the β_j augmenting equation (1) for the sons' education son_edu_i, also measured in years. Figure 2 shows that both returns to sons' and parents' education increase with experience. Although returns to parents' education halves compared to the estimates presented in Figure 1, they remain statistically significant at conventional levels and increase along the son's career.

These preliminary results highlight the existence of a *direct* influence of parental background on son's earnings on top of the *indirect* influence through the son's educational attainment.[13] In the next section, we exploit the longitudinal structure of our data to fully reveal the strength of the life-long influence of parental background on sons' earnings.

Estimating the influence of parents' education on sons' earnings profiles

A convenient starting point to assess the overall influence of parental background on wage growth is the empirical model proposed by Hudson and Sessions (2011), whose salient feature is to allow the experience-earnings profile to explicitly depend on parental educa-

[13] Raitano and Vona (2015a,b) find that the emergence of a direct influence of parental background on children earnings when controlling for children's education is a distinct feature of the European countries characterized by a higher level of intergenerational inequality, as Italy and the UK, as opposed to those characterized by a lower intergenerational inequality, as Denmark and Finland.

tion. We take advantage of the longitudinal nature of our data and estimate the following equation:

$$\log(w_{it}) = g(e_{it}) + \beta par\_edu_i \bullet e_{it} + X_{it}'\delta + \mu_i + \varepsilon_{it} \tag{2}$$

where $\log(w_{it})$ is the log of gross weekly wages, $g(e_{it})$ is a third-order polynomial in effective experience e_{it}, i.e. $\sum_{j=1}^{3} \gamma_j e_{it}^j$;[14] $\mathbf{X}_{it}$ is a vector of usual controls in wage equations,[15] μ_i are time-invariant individual effects and ε_{it} is a standard error term.

Our main variable of interest is the interaction between parental education par_edu_i and experience e_{it}, which captures the influence of parental background along the son's working career. Hence, a positive β would indicate that labour market experience is more valuable for those coming from a better family background.

The inclusion of individual effects μ_i in panel fixed-effects estimates mitigates the concern that the influence of unobservable skills, that are correlated with both lifetime earning potential and parents' education, may result in a biased estimation of β. However, a fixed-effects (FE) estimator does not allow us to estimate the influence of time-invariant covariates, in particular the coefficient of parental education at zero years of experience. Therefore, we also present ordinary least square (OLS) estimates of equation (2) that allow us to retrieve the coefficient associated with par_edu_i, that hence captures the association between parental background and the son's wage in the first job.

As a first step in the interpretation of our results, we assess whether the influence of parental background on the experience-earnings profiles is fully mediated by the son's educational attainment or an additional *direct* influence emerges. To this aim, we also estimate through FE equation (3), where the interaction term between the son's education and experience is added to equation (2):

$$\log w_{it} = g(e_{it}) + \vartheta son\_edu_i \bullet e_{it} + \beta par\_edu_i \bullet e_{it} + X_{it}'\delta + \mu_i + \varepsilon_{it} \tag{3}$$

where ϑ captures the returns to son's education along their working career. We also estimate equation (3) through OLS in order to assess the influence on the first job of both son's and parental education.

Table 4 reports the baseline estimates of equations (2) and (3).[16] Specifically, models 'M1' and 'M2' (first and second panel, respectively) present OLS and FE estimates of Equations (2) and (3), respectively. While experience is measured in weeks, we express the estimated coefficient in years (dividing by 52) to make the interpretation easier.

Our results are perfectly in line with those of Figures 1 and 2. Parents' education has a substantial and significant influence on the experience-earnings profiles of Italian males. The point estimates of the interaction between experience and parental education are similar if we use OLS or our preferred FE estimator. Through OLS, we can also estimate the influence of parental education at entry that, not surprisingly, is positive and statistically significant at conventional level.

[14] We include a third-order polynomial on experience because the coefficients of the terms of this polynomial are always significant at the 99.9% level. Detailed results are available upon request.

[15] 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.

[16] In all Tables we present only the coefficients related to sons' and parents' education. Results for the other covariates are provided upon request.

TABLE 4

Influence of parental education and experience on wages

	M1 model 'Parental education Interacted with experience'		*M2 model 'Parental and child education Interacted with experience'*	
	OLS	*Fixed effects*	*OLS*	*Fixed effects*
Parental education	0.00859***	–	0.00571***	–
	(0.00149)	–	(0.00150)	–
Experience × parental education	0.00165***	0.00153***	0.00073***	0.00078***
	(0.00016)	(0.00014)	(0.00016)	(0.00015)
Son education	–	–	0.01284***	–
	–	–	(0.00143)	–
Experience × son education	–	–	0.00175***	0.00166***
	–	–	(0.00013)	(0.00012)
N	87,465	87,465	87,465	87,465

Notes: 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. Standard errors clustered by individuals in parenthesis. $*P<0.10$; $**P<0.05$; $***P<0.01$.
Source: Elaborations on AD-SILC data.

Importantly, these effects persist when we control for son's education and its interaction with experience: columns (3) and (4) of Table 4 show that parental education *directly* and *indirectly* affects son's earnings over the working career. Although the coefficient of the interaction between parental education and experience more than halves when we control for son's education, it remains statistically significant at 99% level. Again, results barely change using OLS and parental background keeps having a strong *direct* influence on sons' earnings when they enter the labour market.

Table 5 reports the quantified effect of an additional year of son's and parental education at entry and after, respectively, 5, 10 and 20 years of experience. The effects are computed by multiplying the estimated coefficients of Table 4 for the level of experience. Using OLS estimates, after twenty years of experience, and controlling for the influence of son's education (panel A of Table 5, M2 model), the wage premium associated with an additional year of parental education amounts to 2.03% (it amounts to 4.16% when we do not control for son's education) and 71.9% of this premium is formed during the career rather than in the first job. The effect of parental education is also sizeable compared to the cumulative 20-years wage premium associated with an additional year of son's education, which amounts to 4.78% (Table 5, M2 model). Notice that the effect of parental education along the son's career is slightly larger using the FE estimator (panel B), while the effect associated with son's education slightly reduces in the FE specification. In sum, at experience 20, the return to an additional year of parental education represents 47% of the return to an additional year of son's education in the FE specification while it is 42% in the OLS specification.[17]

[17] If we re-express these figures in terms of discrete differences in parental education converting years of education in degrees, according to OLS estimates, sons of tertiary graduates' parents earn in the first job 2.9% more than sons of upper secondary graduates, 5.7% more than sons of lower secondary graduates' ones and 7.4% more than sons of those with just a primary education. These gaps widen dramatically along the career: after 20 years of working

TABLE 5

Quantification of the influence of son and parental education along the career for a one-year increase in child education and in parental education (percentage values)

	M1 model				*M2 model*							
	Parental education				*Son education*				*Parental education*			
	Entry	*Experience 5*	*Experience 10*	*Experience 20*	*Entry*	*Experience 5*	*Experience 10*	*Experience 20*	*Entry*	*Experience 5*	*Experience 10*	*Experience 20*
Panel A: OLS estimates												
Starting salary	0.86	–	–	–	1.28	–		–	0.57	–		–
Effect along the career	–	0.83	1.65	3.30	–	0.88	1.75	3.50	–	0.37	0.73	1.46
Total effect	0.86	1.68	2.51	4.16	1.28	2.16	3.03	4.78	0.57	0.94	1.30	2.03
Panel B: Fixed effects estimates												
Effect along the career	–	0.77	1.53	3.06	–	0.83	1.66	3.32	–	0.39	0.78	1.56

Notes: The quantification is based on estimated coefficients of Table 4.
Source: Elaborations on AD-SILC data.

Robustness checks

We carry out a number of robustness checks to corroborate the main results of this section. Firstly, in order to be sure that results are not driven by younger individuals that are observed for fewer years in our sample, we replicate the analysis of section 'Estimating the influence of parents' education on sons' earnings profiles' considering only the cohort of those who started to work in the 1980–89 period.

Table A1 in Appendix A shows that our findings do not change when we focus on a subsample of workers followed for a similar number of years. Indeed, the coefficient of the interaction between parental education and experience remains statistically significant at 1% level

The sign and the size of the estimated coefficients are also very robust to the inclusion of additional individual and sectorial controls (Tables A2 and A3 in Appendix A).[18]

Results do not change also when parents' and son's education are interacted with the third-order polynomial in experience (see Table A4 in Appendix A). Note also that the coefficients of the interaction terms with the squared and the cubic values of experience are not statistically significant, thus supporting our choice to interact parents' and son's education only with a linear term in experience.

As a final robustness check, we distinguished fathers' and mothers' education, following the assumption that, once controlling for son's education, the former might be more strongly correlated with family networks and labour market nepotism and the latter with unobserved abilities (Altonji and Dunn, 1996; Chen and Feng, 2011). Our results indicate that both fathers' and mothers' educational attainments affect son's earnings during the career and no significant differences between the paternal and the maternal coefficients emerge (see Table A5, run on the subsample of sons living in a two-parent household). However, the extent to which this exercise helps in disentangling network and background-related skill effects is limited because it hinges upon the very strong assumption of a perfect correspondence between paternal influence and family network, on the one hand, and maternal influence and unobservable skills, on the other. Next section proposes a different approach to disentangle these two channels of inequality transmission.

V. Disentangling mechanisms behind the association between parental background and sons' earnings profiles

The panel structure of our data allows us to retrieve a reliable estimate of the parental influence on sons' earnings profiles, but this estimate remains an empty box without additional knowledge of the underlying mechanisms. As pointed out in sections I and II, educational attainment being equal, a more advantaged background may affect sons' earnings profiles both through unobservable skills (which can in turn depend, e.g. on innate ability, educational quality and tracking, early age investments) and to connections useful to find a

experience, sons of tertiary graduates earn 10.2% more than sons of upper secondary graduates, 20.3% more than sons of lower secondary graduates and 26.4% more than sons of parents with just primary education.

[18] In particular, in these 'augmented specifications', we also include sector dummies and the log of firm size (available in the data set since 1987), tenure and other proxies of worker history (namely, white collar dummy and the number of weeks spent in a year, respectively, receiving unemployment benefits or being temporarily suspended by the employer).

better job in the labour market. This section proposes a simple methodology to distinguish these two transmission mechanisms using educational mobility to approximate individual unobservable skills.

A procedure to disentangle the mechanisms

As we already mentioned in section II, parents do not only affect the 'quantity' of formal education, but also the 'quality' of education plus unobservable abilities and skills correlated with earnings On the one hand, parental characteristics (e.g. education, occupation, income and wealth) can hence be considered as good proxies of the unobservable son's skills. On the other hand, especially in a country belonging to the Southern 'familial' welfare regime like Italy, parental characteristics can directly affect the son's labour market outcomes through a network of social relations that could prove extremely useful in finding good jobs and reducing unemployment risk.

An empirical assessment of the relative importance of unobservable skills and networks is extremely difficult in absence of precise measures of these variables. Indeed, as almost all available data sets linking parents and sons, the AD-SILC data set does not contain proxies of family networks and we are able to observe only a limited part of the effective worker's human capital, i.e. educational attainment. We must thus rely on a second-best approach to gauge the incidence of these two mechanisms.

We follow Raitano and Vona (2015a) by assuming that the unobservable part of son's skill endowment is correlated with the improvement or the worsening in the son's educational attainment compared to that of the parents. The idea is that the difference in the educational attainment of the parent and the child may be used to infer, at least in certain cases, the child's unobservable skill endowment and, thus, distinguish the influence of network and skill-related parental effects. The argument can be exemplified as follows.

Imagine observing a son coming from a good parental background who achieves an educational attainment lower than his parents. This son underperforms compared to what would be expected given his background-related advantage, which should have made him able to achieve at least the same educational level of his parents. Because unobservable skills and formal education attainment are positively correlated, this indirectly implies that such child is not endowed with high innate abilities and, in general, should have a low level of unobservable skills.[19]

To summarize, our working assumption is that – for a given level of son's education (e.g. secondary education) but a different parental background – the son who studied relatively less compared to his parents should not be endowed with higher unobservable skills than the son of less educated parents.

A caveat is worth making at this point; as mentioned in section II, several mechanisms generate background-related differences in unobservable skills, but in our empirical analysis we are forced to stack them together. Since unobservable skills are also related to school tracking, field of study and educational quality, heterogeneity in such skills should mechanically increase with the level of education. As a result, the capacity of our approach to truly detect skill-related vs. network-related explanations of intergenerational transmis-

[19] A well-established empirical research, usually based on quantile regressions techniques, show that highly educated people are over-represented in top earnings' quantiles and that returns to education are generally increasing with unobservable abilities (e.g. Martins and Pereira, 2004).

sion decreases with sons' educational attainment To put it differently, the unobservable skill differences of sons with basic education should be smaller than those of sons with tertiary education.

To illustrate this point and understand the limits of our procedure, let us consider three possible educational outcomes for both generations: low (L), middle (M) and high (H). We have nine possible son-parent pairs: LL, LM, LH; ML, MM, MH; HL, HM, HH, where the first letter indexes the parent and the second the son.

Consider first the group of sons with low education where identification of the network- and skill-related mechanism is more transparent. In spite of their initial advantage, sons of well-off parents (HL) downgraded with respect to their highly educated parents and were unable to reach a high educational level. Consequently, their inferred unobserved skills and innate abilities should not be better than those of LL (parents and child with low education) and ML (parents with middle education, child with lower education). Therefore, education being equal, a wage premium for HL and ML over LL – a *parachute effect* according to our terminology – can be mostly explained by the influence of family network and nepotism.

A similar argument applies to the group of sons with middle education, although with an important caveat. Indeed, the middle group is composed of sons who attended different types of school, i.e. vocational vs. general education. In this case, observing a *parachute effect* – a wage premium for HM compared to MM and LM– can be associated both with network and with unobserved differences in the attained education (e.g. vocational vs. general high school programmes). However, while certainly our procedure is less reliable for the middle group, we contend that it is hardly plausible that the whole *parachute effect* is explained by unobservable skills of sons that were unable to attain at least the same education of their parents.

Within the group of the highly educated, sons of low and middle educated parents (respectively, LH and MH) substantially improve with respect to their parents and, thus, should have high innate abilities, while we have no information about the quality of their education. For the HH sons, we cannot say anything about their unobservable skills; both innate abilities (as the educational level H is the highest possible) and educational quality are unobservable for this category. The substantial heterogeneity in the quality (e.g. top university or not) and the value (e.g., field of study) of tertiary education makes it exceedingly difficult to compare sons from different parental background within this group. This implies that pairwise comparisons within the 'Child High' group cannot shed light on the underlying mechanisms: an earnings premium for those coming from a better background – i.e. a *glass ceiling effect* according to our terminology – can either reflect a better family network or be associated with higher skills achievable only by well-off sons with high abilities.

Empirical implementation

Practically, we implement this idea by estimating (through both OLS and FE) the following equation:

$$w_{it} = \sum_{j}^{3}\sum_{i}^{3} \alpha_{ji} 1_{\{par\_edu=j\}} 1_{\{son\_edu=i\}} + \sum_{j}^{3}\sum_{i}^{3} \vartheta_{ji} 1_{\{par\_edu=j\}} 1_{\{son\_edu=i\}} \times e_{it} \ldots \\ + g(e_{it}) + X_{it}'\delta + \mu_i + \varepsilon_{it} \tag{6}$$

where the notation is as in equations (2) and (3), and the same control variables are included, and the nine groups mentioned above are captured by the interactions $1_{\{par\_edu=j\}}1_{\{son\_edu=i\}}$, where '*par_edu*' and '*son_edu*' refer, respectively, to parent's and son's education. To link these estimates with the ones of section IV, we allow the experience-earnings profiles to be specific to each of the nine groups, interacting the dummies on the educational pairs between parents and sons with experience e_{it}.

For the sons' generation, we consider three groups: tertiary graduates (H), upper secondary graduates (M) and at most lower secondary graduates (L). To define the three correspondent groups for parents, note that, as shown in Table 2, educational attainments changed dramatically between the two generations, reflecting both changes in the economic structure and reforms in compulsory education. Consistently, we consider as highly educated (H) those parents who have at least an upper secondary degree, lower secondary graduates represent the middle group (M) and those with primary education represent the lowest group (L).

As a final caveat, note that our approach does not allow us to exactly identify structural parameters or causal effects. The approach here proposed is instead useful to better understand the mechanisms behind the intergenerational transmission process. A precise identification of abilities and network effects would actually require an exogenous shock that affects networks and ability asymmetrically.

Estimates of parachute and glass ceiling effects

Table 6 presents estimation results of Equation (6). Estimated coefficients are reported for both OLS and FE models, although they are qualitatively similar.

The main result is that, in correspondence to middle and lower sons' educational attainment, the influence of family background is explained by a *parachute effect* and this effect is amplified along the working career. This implies that 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. Wald tests reported in Table 7 corroborate this interpretation, showing the statistical significance of the pairwise differences in the coefficients associated with the different parent-son combination. In particular, FE estimates show a significant advantage along the career for HM (high parents/mid son) over MM (mid parents/mid son) and over LM (low parents/mid son) and for ML (mid-parents/low son) over LL (low parents/ low son). As previously discussed, the *parachute effect* reveals the strong presence of family related networks in the labour market only for the groups of low educated sons. For the group of upper-secondary graduates, heterogeneity in the quality of school might also matter, especially in terms of school tracking. Therefore, we cannot exclude that, for this group, a *parachute effect* is the consequence of different school choices depending on parental background.

The second result is that the *parachute effect* co-exists with a *glass ceiling effect*, that is also active in different phases of the sons' career. Highly educated sons with highly educated parents (HH) earn significantly more than highly educated sons from less educated parents (i.e. MH or LH; see Tables 6–7). As discussed in section 'A procedure to disentangle the mechanisms', the *glass ceiling effect* is less straightforward to interpret and can be due both to network and ability-background complementarities.

TABLE 6

Influence of experience and educational mobility on wages

		OLS	*Fixed effects*
Son high education × Experience ×…	Parent high education	0.14803***	–
		(0.02660)	–
	Parent middle education	0.05874*	–
		(0.03207)	–
	Parent low education	0.02233	–
		(0.03270)	–
Son middle education × Experience ×…	Parent high education	0.02217	–
		(0.01565)	–
	Parent low education	−0.02189*	–
		(0.01249)	–
Son low education × Experience ×…	Parent high education	−0.04157	–
		(0.02825)	–
	Parent middle education	−0.08012***	–
		(0.01677)	–
	Parent low education	−0.07782***	–
		(0.01224)	–
Son high education × Experience ×…	Parent high education	0.01860***	0.02262***
		(0.00264)	(0.00242)
	Parent middle education	0.01395***	0.01525***
		(0.00287)	(0.00307)
	Parent low education	0.01400***	0.01547***
		(0.00441)	(0.00254)
Son middle education × Experience ×…	Parent high education	0.00434**	0.00317**
		(0.00197)	(0.00158)
	Parent low education	−0.00191	−0.00108
		(0.00141)	(0.00115)
Son low education × Experience ×…	Parent high education	−0.01028***	−0.00630**
		(0.00284)	(0.00276)
	Parent middle education	−0.00610***	−0.00453***
		(0.00184)	(0.00160)
	Parent low education	−0.00977***	−0.00827***
		(0.00133)	(0.00109)
N		87,465	87,465

Notes: Log of weekly gross wage is the dependent variable. Control variables as in 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. Son 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. Omitted categories are 'son middle × parent middle' and 'son middle × experience × parent middle'. Standard errors clustered by individuals in parenthesis. $^{*}P<0.10$; $^{**}P<0.05$; $^{***}P<0.01$.
Source: Elaborations on AD-SILC data.

To gauge the economic magnitude of our estimates, we plot the OLS estimated effect along the working career (Figures 3–5). For expositional clarity, we plot estimates separately for sons with, respectively, high, middle and low educational attainment and the plots represent the advantage for sons with high and middle educated parents compared to sons with low educated parents (the omitted category). Figures 3–5 clearly indicate that both the *glass ceiling* and the *parachute effect* are sizeable. For instance, Figure 3 shows that, after 15 years of experience, the HH group has an earnings advantage of 15.9

TABLE 7

P-values of Wald tests of the estimated coefficients of the influence of experience and educational mobility on wages

	OLS	*Fixed effects*
Par. H – Son H = Par. M – Son H	0.021**	
Par. H – Son H = Par. L – Son H	0.001***	
Par. M – Son H = Par. L – Son H	0.400	
Par. H – Son M = Par. M – Son M	0.157	
Par. H – Son M = Par. L – Son M	0.002***	
Par. M – Son M = Par. L – Son M	0.080*	
Par. H – Son L = Par. M – Son L	0.188	
Par. H – Son L = Par. L – Son L	0.179	
Par. M – Son L = Par. L – Son L	0.873	
Par. H – Son H × Exp = Par. M – Son H × Exp	0.181	0.042**
Par. H – Son H × Exp = Par. L – Son H × Exp	0.343	0.025**
Par. M – Son H × Exp = Par. L – Son H × Exp	0.990	0.953
Par. H – Son M × Exp = Par. M – Son M × Exp	0.028**	0.050**
Par. H – Son M × Exp = Par. L – Son M × Exp	0.000***	0.004***
Par. M – Son M × Exp = Par. L – Son M × Exp	0.177	0.346
Par. H – Son L × Exp = Par. M – Son L × Exp	0.153	0.539
Par. H – Son L × Exp = Par. L – Son L × Exp	0.845	0.455
Par. M – Son L × Exp = Par. L – Son L × Exp	0.015**	0.007***

Notes: Wald tests of the estimated coefficients of Table 8. *$P<0.10$; **$P<0.05$; ***$P<0.01$.
Source: Elaborations on AD-SILC data.

and 19.5 percentage points over, respectively, the MH and LH group. Figure 4 reports the *parachute effect* for the group of the high school graduates (M-sons). After 15 years of working experience, the wage premium of HM is 13.8 percentage points with respect to LM and 8.7 percentage points with respect to MM. Finally, as shown in Figure 5, a sizeable *parachute effect* emerges even within sons with at most lower secondary education, even if a significant advantage over worse-off sons characterizes only sons of medium educated parents, as shown by the 95% confidence intervals: indeed, sons of less educated parents (LL) experience an earning penalty of 5.3 percentage points after 15 years of work compared to sons belonging to the ML group.

Moreover, these effects are lower at the beginning of the career than in the following years. For instance, with regard to the *glass ceiling effect*, the initial premium of HH over MH is 9.0 p.p. and increases up to 15.9 p.p. after 15 years and, likewise, as concerns the *parachute effect*, the initial premium of HM over MM amounts to 2.2 p.p. and becomes 8.7 p.p. after 15 years.

VI. Conclusions

This paper provides new evidence on the influence of parental background on 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 sons' fixed effects. Our baseline estimate indicates that an additional year

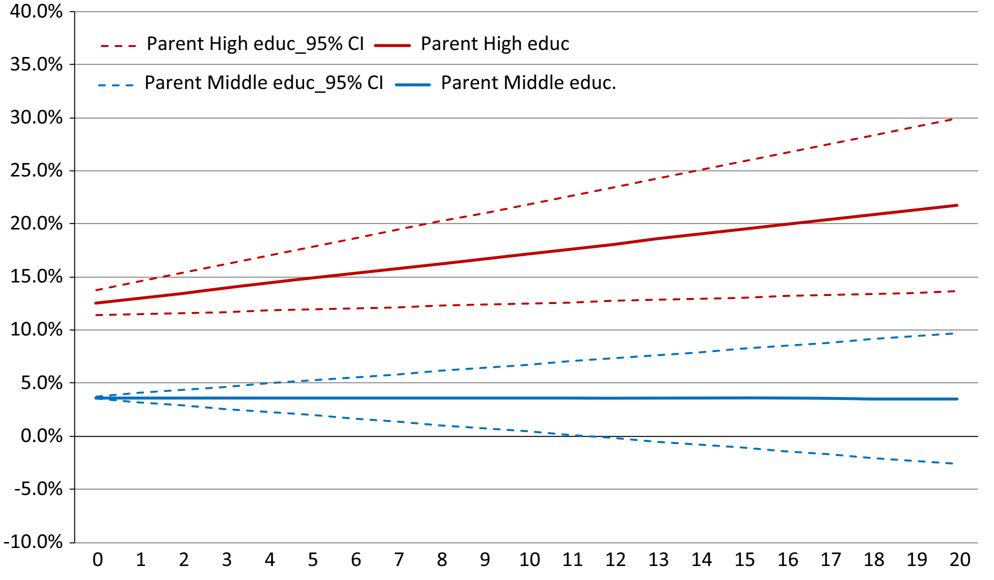

Figure 3. Quantification of the wage gap along the career for sons with a tertiary degree (H) by parental education (percentage points; Reference category 'Parents with a Low education'). OLS estimates
Note: Predicted values of estimated coefficients of Table 7.
Source: Elaborations on AD-SILC data.

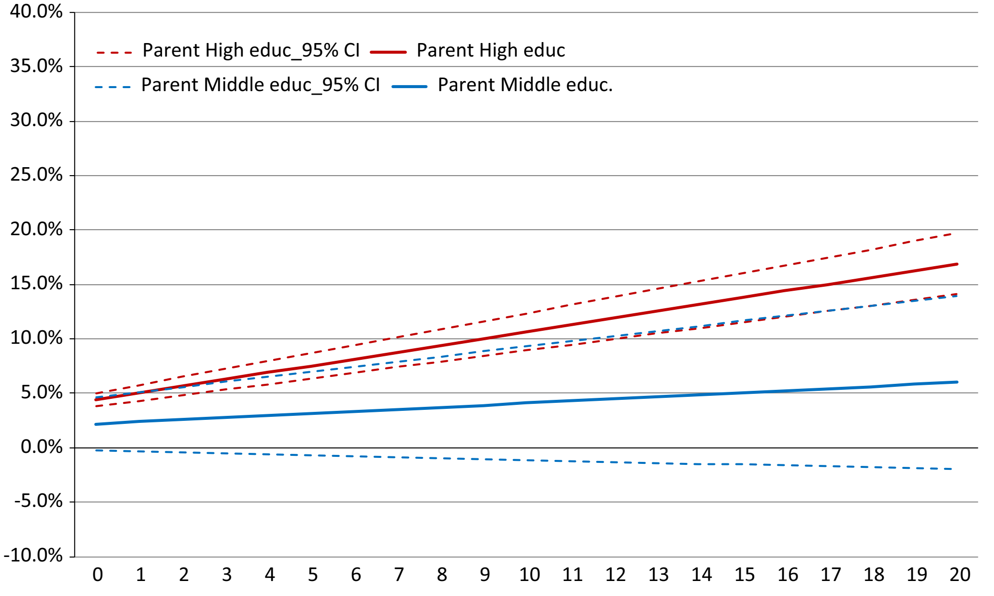

Figure 4. Quantification of the wage gap along the career for sons with a high-school degree (M) by parental education (percentage points; Reference category 'Parents with a Low education'). OLS estimates
Note: Predicted values of estimated coefficients of Table 7.
Source: Elaborations on AD-SILC data.

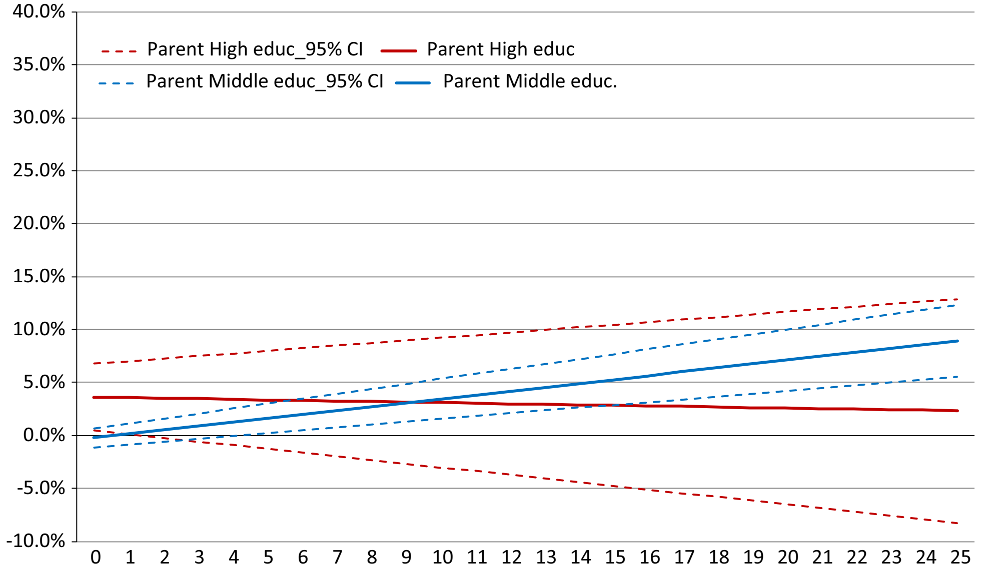

Figure 5. Quantification of the wage gap along the career for sons with Low education (L) by parental education (percentage points; Reference category 'Parents with a Low education'). OLS estimates
Note: Predicted values of estimated coefficients of Table 7.
Source: Elaborations on AD-SILC data.

of parental education is associated with an increase in sons' earnings at twenty years of experience that ranges between 2.0% (when controlling for the influence of sons' education on the earnings profile) and 4.2% (when not controlling for the influence of sons' education). Moreover, approximately 3/4 of the influence of parental education on sons' earnings 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 that advantage those coming from a better background: a *glass ceiling effect* for high-ability individuals and a *parachute effect* for low-ability individuals, that is likely associated with better labour market connections and nepotism.

These results have three important implications for the literature on intergenerational inequality and earnings' dynamics. First, they raise serious concerns on the reliability of empirical models that assume that the influence of parental background occurs only through education. Second, life-cycle biases in estimations of intergenerational elasticities are unlikely to be minimized in correspondence to any specific point of the working career because deviations from average profiles are clearly correlated with family background. Third, both *glass ceiling effect* and *parachute effect* contrast with the concept of equality of opportunity, because these effects benefit sons with better parental 'circumstances' (Roemer, 1998). However, from a normative standpoint, whereas the evidence of a *glass ceiling effect* is, to a certain extent, an unavoidable consequence of the process of skill formation and may not be at odds with economic efficiency, the existence of a *parachute effect*, being likely unrelated to individual abilities, is less acceptable from an equality of opportunity perspective (Jencks and Tach, 2006) and may also indicate a distortion in the way in which the labour market allocates talents to jobs. The perceived unfairness that results from this imperfect functioning of the labour market can further discourage human capital investments of disadvantaged sons and, thus, it is likely to have harmful impacts on economic growth.

Appendix A: Additional Results

Tables A1–A5.

TABLE A1

Influence of parental education and experience on wages. Sample restricted to those entered in employment in the period 1980–89

	M1 model 'Parental education also interacted with experience'		*M2 model 'Parental and child education also interacted with experience'*	
	OLS	*Fixed effects*	*OLS*	*Fixed effects*
Parental education	0.00908***	–	0.00707***	–
	(0.00222)	–	(0.00221)	–
Experience × parental education	0.00147***	0.00140***	0.00064***	0.00068***
	(0.00021)	(0.00019)	(0.00021)	(0.00020)
Son education	–	–	0.00957***	
	–	–	(0.00204)	
Experience × son education	–	–	0.00190***	0.00180***
	–	–	(0.00019)	(0.00016)
N	42,889	42,889	42,889	42,889

Notes: 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. Standard errors clustered by individuals in parenthesis. $^{*}P<0.10$; $^{**}P<0.05$; $^{***}P<0.01$.
Source: Elaborations on AD-SILC data.

TABLE A2

Influence of child education, parental education and experience on wages. Fixed effects estimates: variants of the M1 model with additional controls

	S1	*S2*	*S3*
	Job features	*S1 plus firms features*	*S2 for post-1987 entrants*
Experience × parental education	0.00143***	0.00141***	0.00174***
	(0.00014)	(0.00014)	(0.00022)
N	86,366	72,513	31,833

Notes: 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 because sectorial variables are available in our data set only since that year. Standard errors clustered by individuals in parenthesis. $^{*}P<0.10$; $^{**}P<0.05$; $^{***}P<0.01$.
Source: Elaborations on AD-SILC data.

TABLE A3

Influence of child education, parental education and experience on wages. Fixed effects estimates: variants of the M2 model with additional controls

	S1	*S2*	*S3*
	Job features	*S1 plus firms features*	*S2 for post 1987 entrants*
Experience × parental education	0.00076*** (0.00014)	0.00080*** (0.00015)	0.00116*** (0.00023)
Experience × son education	0.00152*** (0.00012)	0.00148*** (0.00012)	0.00158*** (0.00022)
N	86,366	72,513	31,833

Notes: 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 because sectorial variables are available in our data set only since that year. Standard errors clustered by individuals in parenthesis. $^{*}P<0.10$; $^{**}P<0.05$; $^{***}P<0.01$.
Source: Elaborations on AD-SILC data.

TABLE A4

M2 model plus interactions with a third order polynomial on experience

	'Third order' model†	
	OLS	*Fixed effects*
Parental education	0.00377**	–
	(0.00183)	–
Experience × parental education	0.00137**	0.00175***
	(0.00065)	(0.00059)
Experience^2/1,000 × parental education	−0.03787	−0.06416
	(0.05922)	(0.04897)
Experience^3/100,000 × parental education	0.04955	0.10318
	(0.14857)	(0.11495)
Son education	0.01245***	–
	(0.00176)	–
Experience × son education	0.00223***	0.00122**
	(0.00060)	(0.00052)
Experience^2/1,000 × son education	−0.06142	0.02715
	(0.05272)	(0.04188)
Experience^3/100,000 × son education	0.17363	−0.03948
	(0.12614)	(0.09617)
$(Par.educ. \times exp + Par.educ. \times exp^2 + Par.educ. \times exp^3) = 0$	*11.27****	*11.32****
N	87,465	87,465

Notes: †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.

TABLE A5

Influence of father and mother education and experience on wages

	'Father and mother' model	
	OLS	*Fixed effects*
Son education	0.01233***	–
	(0.00150)	–
Experience × son education	0.00177***	0.00167***
	(0.00014)	(0.00013)
Father education	0.00264*	–
	(0.00152)	–
Mother education	0.00434***	–
	(0.00168)	–
Experience × father education	0.00042***	0.00033**
	(0.00016)	(0.00014)
Experience × mother education	0.00035*	0.00051***
	(0.00018)	(0.00016)
Father education = Mother education	*0.4087*	
Experience × father education = Experience × mother education	*0.7952*	*0.5034*
N	81,353	81,353

Notes: Control variables as in M2 model. 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.

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