

Intergenerational Mobility and Schooling Decisions In Italy and Germany

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Abstract

Intergenerational mobility in income and education is affected by the influence of parents on children's school choices. Our focus is on the role played by different school systems in reducing or magnifying the impact of parents on children's school choices and therefore on intergenerational mobility in general. We compare two apparently similar educational systems, Italy and Germany, to see how the common feature of the presence of separate track at Secondary School level may produce different impacts on children destinies. Using data from cross-country surveys (PISA 2003), we study the impact of parental education on track choice, showing that the greater flexibility of the Italian system (where parents are free to choose the type of track) translates into greater dependence from parental background. These effects are reinforced when moving to post-secondary education, where the aspiration to go to college is affected not only by the school type but also (in the case of Italy only) by parental education. We then move to country-specific data sets to study actual college choices in nationally representative sample, and we find that parental education still play an independent role on student choices.

1 Introduction

In a recent paper, Hanushek and Wößmann (2005) have reviewed cross-country empirical evidence on the effect of school tracking, questioning a common view about the existence of a trade-off between equality and efficiency. According to their differences-in-differences analysis, countries characterized by early tracking present greater inequality and lower mean performance in students' achievement tests, as measured at the age of fifteen. However, student tracking can be based on different observables (student ability, parental education, family wealth, not to speak of race or religion), and this may also have consequences in terms of (intertemporal) efficiency. If we consider intergenerational mobility as one dimension of intertemporal efficiency (because more mobile societies are characterized by better allocation of talent and/or higher intertemporal welfare - Dardanoni 1993), then different tracking systems can be ranked according to their impact on intergenerational mobility in educational levels. In addition, different degrees of intergenerational mobility in education are also correlated with (across cohorts) inequality measures of educational attainments. Using data for the adult population in 20 countries in the mid-nineties, Chevalier, Denny and McMahon (2005) show that intergenerational mobility and education inequality are positively correlated: as long as educational attainments of the sons are less dependent from the educational attainments of the corresponding fathers, this greater equality of opportunities translates into reduced differences in education within the same generation. Following these inputs for the literature, in the present paper we analyze different systems of student tracking, discussing their consequences in terms of intergenerational mobility. After presenting some descriptive evidence on institutional differences between two countries, Germany and Italy, characterized by tracked secondary school systems in the next section, we introduce a simple model in section 3. Here two polar cases are considered, where student tracking is either based on perfectly observable ability or on family background (as predictor for unobservable ability); some implications in terms of efficiency and mobility are consequently derived. We then move to the empirical analysis in section 4, where we use microdata from international survey on students' achievements (PISA 2003) to assess the impact of family backgrounds on the choice of alternative tracks and on students' aspirations to proceed further in education. In section 5 we use national representative samples of secondary school graduates to evaluate the relative contribution of type of school attended and family background on college enrolments. Section 6 concludes.

2 Different Educational Systems and Descriptive Evidence

Haveman and Wolfe (1995), presenting a survey on children's attainments, conclude that parental choices play a fundamental role in children's attainment and that recent research on the US finds much less mobility across generation than once thought. The role of parental choices is even more intriguing when considered in the European context, since most European countries are characterized by supposedly quite homogenous and egalitarian school system, such as Italy and Germany, which nevertheless experience a low intergenerational mobility in schooling.¹ Part of the explanation may reside in early childhood choices: Esping-Andersen (2004) shows that the impact of family backgrounds attenuates in countries characterized by extensive pre-school day care. A second partial explanation considers the possibility of borrowing constraints (Acemoglu and Pischke 2001). However, the recent literature seems to exclude borrowing constraints explanation as the main channel of the influence of parents on children's school choices even in countries, like the US, where the private cost of schooling is high.²

An approach that studies in more details how institutional features of the school system impact the transmission of parents' decisions seems therefore promising to shed new light on the issue. In comprehensive secondary school system (such as the US and UK) the fundamental decision about how much schooling to acquire is taken at the end of the secondary school level when individuals are about 18/19 years old. In a separate tracks system, different tracks lead to different opportunities in terms of the additional schooling that is possible to acquire. Because of this, the fundamental choice about the final level of schooling is taken at a much earlier age, usually at the end of the primary school. It is incontrovertible that an early decision is more likely to be influenced by parents than a decision at a later stage in life, and therefore that a separate track system may lower intergenerational mobility in schooling.³ However there can be differences in the way in which tracking operates, even independently from the age at which formally the choice about the school type is undertaken.

Figure 1 presents the distribution of literacy skills for 15-year old young students surveyed in 2003 by the PISA assessment for two countries (Germany

¹See Dustmann 2004 and Schnepf 2002 for Germany; Checchi 2003 for Italy. Using ECHP data, Comi 2004 provides estimates of intergenerational mobility in educational attainment, finding that Italy exhibits a quite low level of mobility. On the contrary, Chevalier, Denny and McMahon 2005 using IALS survey ranks Italy high in terms of intergenerational mobility in education, while Germany seems rather immobile.

²For example, Keane and Wolpin 2001 show that even if borrowing constraints are estimated to be binding, their main impact is on consumption behaviour and not on schooling decision. Cameron and Heckman 1998 and 2001 estimate no impact of borrowing constraints once measures of ability are controlled for. Finally, the recent Cameron and Taber 2004 using a new identification strategy also concludes that borrowing constraints are not important in schooling decisions.

³This is the claim put forward by Dustmann 2004 for Germany.

and Italy).⁴ Both countries are characterized by a Secondary School organized in separate tracks, which in principle should sort students according to their academic or vocational orientation. These systems put emphasis on school orientation, which in turn gives importance to the cultural background of families. As long as literacy and mathematical abilities can be taken as proxies for individual cognitive abilities that favours the acquisition of additional schooling (comprising both innate ability and/or family influence in the early stage of child's development)⁵, these distributions suggest that sorting is far from perfect. However there are different degrees of imperfection: looking at the German case, where the sorting seems to be more effective, there is still wide overlapping of the tails of the distributions, suggesting that a significant share of students sorted in one type of schools would have been indistinguishable from students in another type. In order to provide a quantitative assessment of the extent of overlapping, in table 1 we have computed the fraction of population belonging to the overlapping tails. The comparison between the two countries indicates that the extent of overlapping is greater in Italy than in Germany: in Italy more than half on the students in the academic and vocational schools have a comparable level of ability as measured by these test scores, while this is true only for one forth of the students in the German sample. This is an indication that the tracking system as screening device based on ability works differently in the two countries. We believe that understanding the main features of this type of sorting in a country has implications for the analysis of intergenerational mobility within each country. As long as sorting at secondary school level is mainly driven by family observable characteristics, intergenerational persistence is reinforced. On the contrary, whenever school allocation screens students on their innate abilities, being capable of matching students to their most appropriate destinations, opportunities for mobility are enhanced.

⁴The Pisa (Programme for International Student Assessment) is a survey coordinated by OECD and conducted by Canada Statistics (www.pisa.org). The first wave has been run in 2000 in 35 countries, while a second wave was run in 2003 in 48 countries. The aim of the programme is the assessment of student skills (literacy, mathematical, scientific knowledge and problem solving) in a comparable way across countries.

⁵Cunha et al. 2005 claim that human capital investment exhibits both self-productivity (skill attainment at one stage of the life cycle raises skill attainment at later stages of the life cycle) and complementarity (early investment facilitates the productivity of later investment).

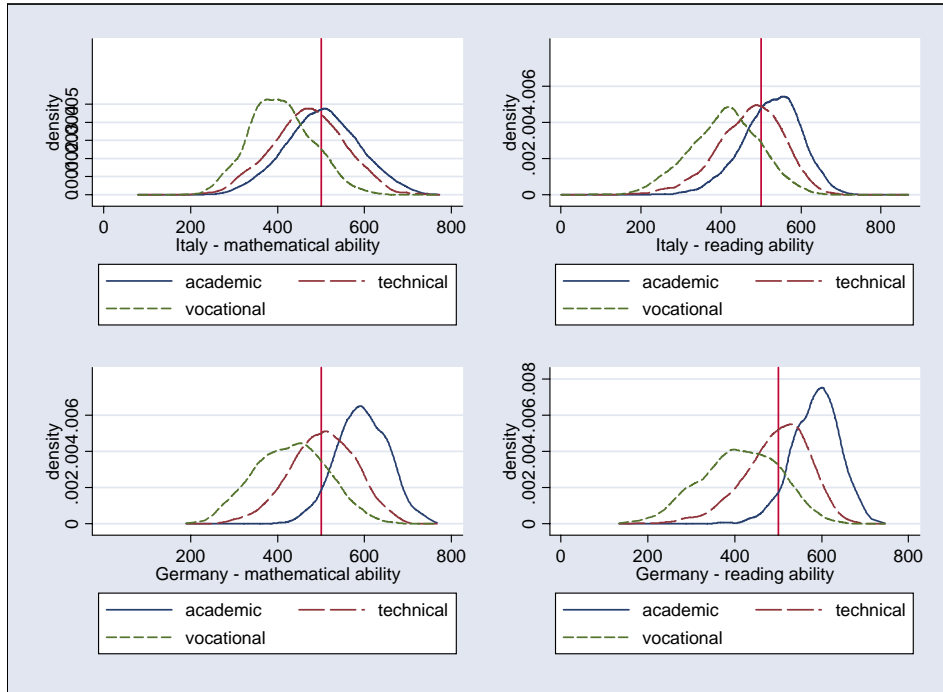


Figure 1 - Kernel estimates of the distribution of mathematical and reading abilities - PISA 2003

While Germany is considered the typical example of a separate track system, less information is available about Italy. Until 1969, Italy was very similar to Germany with only one track granting College admission, another track granting admission only in few fields and the remaining tracks preparing for specific jobs (such as primary school teacher or construction site supervisor). The current system is still characterized by many different tracks (38), but now all of them grant eligibility to College admission. Starting from its earliest stages, this educational system is organized as follows. Kindergarten starts at the age of 3 and ends at the age of 6, and attendance is optional; it is organized and financed either by the central government or by local councils, and as a consequence quality is variable. Compulsory education ranges from 6 to 15 year old, and includes primary school (from 6 to 11, called *scuola primaria*), junior high (from 11 to 14, called *scuola secondaria del primo ciclo*) and the initial year of upper secondary school (which lasts from 14 to 17 or 19, depending on the chosen track).⁶ The upper secondary school (called *scuola secondaria del*

⁶Only starting from 1999 (law n. 9 20/01/1999), years of compulsory education have been raised from 8 to 9, thus including 5 years of primary school, 3 years of junior high school and the initial year of upper secondary school (obviously conditional on not being failed at any point in the schooling career). Transition rates at the end of compulsory school age are currently above 90%.

secondo ciclo) is currently under reform.⁷ Nevertheless so far (and in the sample data we use in the following section) the upper secondary school could be described as tripartite, with a an academic oriented generalist education provided by high schools (5 years, called *licei*, with further distinctions in humanities, scientific activities, languages, pedagogical sciences), a technical oriented education provided by technical schools (5 years, called *istituti tecnici*, again with further differentiations) and a vocational training offered by local schools organized at regional levels (3 years, called *istituti di formazione professionale*). After a contested reform in 1969, students from any track are entitled to enrol in College and Universities, conditional on having attended 5 years of upper secondary school (even students from vocational schools could enrol if they attend two integrative years). However, each of these tracks still predicts very different outcomes in terms of additional schooling acquired and labour market performance. More than 88% of students who graduate from *Licei* enrol in a University as opposed to 17.8% of the students coming from the vocational track. Transition rates at the end of compulsory education (age fourteen) are close to 90%. The choice on the type of secondary school to be attended is typically taken at the age of 13, during the final year of junior high school. Students and their families are counselled by teachers, in some cases supported by equips of psychologists, using students scores achieved during the compulsory school as one the driving guidelines for orientation. Therefore we may consider the Italian system a de facto early decision tracked system: despite the removal of legal barriers to university admission, attendance of different tracks has different implications for future educational career.

In Germany there are three different tracks at secondary level and only students that graduate from one of them are directly eligible for University admission. The decision of which track to enter is taken at the age of ten.⁸ Compulsory schooling starts at children's age of 6 years in the primary school (*Grundschule*). It generally consists of 4 years schooling in mixed-ability classes after which children are divided into the three main secondary school tracks, (*Hauptschule*, *Realschule* and *Gymnasium*). The *Gymnasium* or high school is the preferred school track taken by the most academically-inclined children and prepares pupils with 8 or 9 years' education ending with the *Abitur*, which is the required degree to enrol in university The *Realschule* or intermediate school is attended by children with medium levels of assessed ability at primary school and lasts 6 years (5th to 10th grade). Pupils with only low average academic

⁷To be more precise, the system has undergone a wave of reforms and counter-reforms in recent years: it was reformed in 2000 by the centre-left government, moving the compulsory requirement at age 16 and unifying the initial two years (Legge quadro n.30 of 10/2/2000). This has been modified in 2002 by the right-wing government in the opposite direction, lowering compulsory age to 15 and promoting the emergence of only two tracks, high schools (including former technical schools) and vocational schools (called *alternanza scuola-lavoro* - Legge quadro n.53 of 28/3/2003).

⁸We draw on Schnepf 2000 and Dustmann 2004 for a description of the German educational system. One has to bear in mind that the German educational system is not fully homogeneous, since the organization is state (Länder) specific. We report what is indicated as the "prevailing" pattern: see Eurydice 2002.

achievement at the primary school generally enrol in the *Hauptschule*, consisting of 5-6 years of schooling. In Germany local educational authorities have more power in orienting students' choice: in some Länder parents are not entitled to choose a track different than the one recommended, while in others they have to pass through consultation before changing the choice.

As a consequence, we expect that the role of parental background being more relevant in Italy than in Germany, given the greater freedom of choice they can exert in the secondary school choice. Looking at the evidence obtainable from the PISA survey conducted in 2003 on 15-year-old students enrolled in secondary school (see table A.1.a and A.1.b), the sorting provides similar outcomes: a little more than one third of students is allocated to academic track (41% in Italy and 34% in Germany), one third to technical schools, that typically qualify for entrance in the labour market in white collar jobs (34% in Italy and 36% in Germany) and the residual fraction is destined to vocational schools.⁹ While PISA data set does not contain direct information on past school performance, we obtain indirect evidence by observing whether a student has already been failed at least one year. The fraction of 15-year-old students who have been failed (probably due to scarce performance at previous stages) in Italy is 19.4% in vocational schools, 10.9% in technical schools and 4.5% in high schools, while comparable figures for Germany are 28.5%, 17.2% and 5.7%. On other dimensions the two samples look rather similar: the average performance of students (that we take as proxy for unobservable abilities) in the two countries is comprised in a standard deviation interval, and therefore Italian and German students are indistinguishable in this respect. As far as family background information, parental education is similar, even if the fraction of at least one graduate parent is lower in Italy, in accordance with aggregate evidence.¹⁰

The overall impression we obtain from this descriptive evidence is that, despite its apparent greater flexibility (parents are free to choose the type of secondary, enrolment at university is independent of the type of secondary school attended) the Italian educational system is less effective in sorting students according to their ability when compared to the German one. One possible reason is related to the overwhelming role of parental background in orienting the destiny of children. In the sequel, we analyze the impact of some measures of family background onto three choice variables, the type of school attended and the intention expressed by 15-year-old to proceed further in education, and the effective proceeding to college education.

⁹For Italy we have classified as academic (high schools) *licei classici*, *licei scientifici* and *licei linguistici*, as technical the *istituti tecnici* and as vocational the *scuole professionali*, the *istituti professionali*, the *licei artistici* and the *scuole d'arte*. For Germany, we have classified as academic the *Gymnasium* (comprehensive), as technical the *Realschule* and the *Gesamtschule* and as vocational the residual (*Hauptschule*, *Koop.Gesamtschule*, *Berufsschule*, *Berufsfachschule*).

¹⁰The fraction of population aged 25-64 with a tertiary degree is 23% in Germany and 10% in Italy (OECD 2004, *Education at a glance*, table A1.1).

3 The Model

We now introduce a simple model, inspired by Checchi, Ichino and Rustichini (1999), aiming to shed light on the role of ability and parental background in school choice. We consider a sequence of non-overlapping generations, where parents optimally select the schools for their children. There is an inherent persistence in ability transmission between generations, and educational choices may reinforce this effect. We consider two polar cases, depending on information available to parents. In the first case, parents directly observe the realisation of ability in their children *before* choosing their school, and given our assumption about skill formation optimally select the type of school. In the second case, parents ignore talent realisation in their offspring, and have to make inference from their own endowment, which is freely observable once they have attended school.

Another interpretation of the same model focus on the timing of tracking. Every school system eventually track students but tracking individuals that are 12 years old is different than tracking individuals that are 18 years old. In the first case the choice is likely to be made by the parents while in the second case the individual is likely to perform a more independent choice. For example: in the first case the student cannot obtain a loan while in the second case it is generally possible. Given this framework, the main argument of imperfect information remain the same: a parent of a 12 years old has less information about the individual ability of the child than the information that the child has about herself when 19 years old.

We will evaluate both cases under two perspectives, allocative efficiency and intergenerational mobility.

The model consists of three elements that describe the information set, the choice variables and the outcome variables. These three elements are the description of individual ability, the schooling/track decision and the labour market. The only link between generations is the transmission of ability and information.

Ability is defined as a realization from two types (or levels) of ability

$$a \in \{H, L\}$$

Intergenerational transmission follows a first-order Markov process

		Son	
		L	H
Father	L	γ	$(1 - \gamma)$
	H	$(1 - \gamma)$	γ

with $1/2 < \gamma < 1$. Persistency in abilities ($\gamma > 1/2$) is motivated by both nature (genetic) and nurture because we will observe ability when children are already socialised. Schooling is divided in two tracks:

$$\tau \in \{A, V\}$$

the choice of a track is the only choice variable. Schooling is essentially a production function that transforms ability in skills. Skills will then have returns in the labor market. Ability and track can be matched differently. The different probability of success in the labour market π_{ij} determines which match (a, τ) is better, i.e. H ability is a better match for the A track because $\pi_{AH} > \pi_{AL}$ while ability L is a better match for V track because $\pi_{VL} > \pi_{VH}$ ¹¹ The track A guarantees an higher ‘quantity’ of skill ($s_A > s_V$) - that may be interpreted as well as more years of schooling - but at an higher cost $k > 0$. There are rational expectations, therefore the realized proportion of success in the population are equal to the expected probabilities. Not a success means that no skill is acquired. From this setting we get the following expectation over skill acquisition:

$$\begin{aligned} E(\text{skill}|A, a) &= s_A \pi_{Aa} - k \\ E(\text{skill}|V, a) &= s_V \pi_{Va} \end{aligned}$$

The labour market is very simple and describes a standard human capital model where skills (or years of schooling) have a positive return determining the following wages:

$$w = rs$$

Note that if no skills are acquired (which occurs with probability $(1 - \pi_{\tau a})$), the wage is (normalized to) zero.

3.1 Case 1: Tracking by Ability

If ability is perfectly observed when choosing τ the decision problem is:

$$\text{Choose } \tau \in \{A, V\} \text{ to maximize } E(w|a)$$

Therefore the optimal decision rule will be the following:

If $a = H$, choose $\tau = A$ when:

$$\begin{aligned} E(w|A, H) &> E(w|V, H) \\ rs_A \pi_{AH} - rk &> rs_V \pi_{VH} \end{aligned}$$

therefore all parents with child’s endowment $a = H$ will choose the A track if the cost differential is low enough:

$$k < s_A \pi_{AH} - s_V \pi_{VH} \equiv k_1^*$$

If $a = L$, choose $\tau = V$ when:

$$\begin{aligned} E(w|V, L) &> E(w|A, L) \\ rs_V \pi_{VL} &> rs_A \pi_{AL} - rk \end{aligned}$$

¹¹Note that “probability of success” here does not simply mean to complete schooling but it means to actually acquire the skills.

therefore all parents with child's endowment $a = L$ will choose the V track if the cost differential is high enough:

$$k > s_A \pi_{AL} - s_V \pi_{VL} \equiv k_1^{**}$$

Note that by definition of probabilities - that is $\pi_{AH} > \pi_{AL}$ and $\pi_{VL} > \pi_{VH}$ - we have:

$$k_1^* > k_1^{**}$$

Therefore we obtain one region of attendance costs that determines a separating equilibrium and two regions that determine a pooling equilibrium. In particular:

if $k_1^{**} < k < k_1^* \Rightarrow$ separating equilibrium: all $a = H$ choose track A , all $a = L$ choose track V with total (net) production equal to:

$$\begin{aligned} W_t &= r s_V \pi_{VL} L_t + (r s_A \pi_{AH} - r k) H_t + 0(1 - \pi_{VL}) L_t + 0(1 - \pi_{AH}) H_t = \\ &= r s_V \pi_{VL} L_t + (r s_A \pi_{AH} - r k) H_t \end{aligned}$$

if $k < k_1^{**} \Rightarrow$ pooling equilibrium: all $a \in \{H, L\}$ choose track A with total production:

$$W_t = r s_A (\pi_{AL} L_t + \pi_{AH} H_t) - r k (L_t + H_t)$$

if $k_1^* < k \Rightarrow$ pooling equilibrium: all $a \in \{H, L\}$ choose track V with total production:

$$W_t = r s_V (\pi_{VL} L_t + \pi_{VH} H_t)$$

Total production in steady state is trivial because the ergodic distribution is $H = L = 0.5$ of the measure one of individuals. In this respect an interesting remark is that there is not an optimal γ in the separating equilibrium case. This is shown by noticing that in steady state distribution an equal proportion of both types is generated, so total net production is:

$$\begin{aligned} W_{SS}(\gamma) &= \frac{r}{2} [\gamma s_V \pi_{VL} + (1 - \gamma)(s_A \pi_{AH} - k) + \gamma(s_A \pi_{AH} - k) + (1 - \gamma) s_V \pi_{VL}] \\ &= \frac{r}{2} [(1 - \gamma + \gamma)(s_A \pi_{AH} - k) + (1 - \gamma + \gamma) s_V \pi_{VL}] \\ &= \frac{r}{2} [(s_A \pi_{AH} - k) + s_V \pi_{VL}] \end{aligned}$$

which is independent from γ : under perfect information γ plays a role only in the transition of abilities. Since however the type of school is optimally selected for all individuals, the possibility of failure in acquiring skill is independent of the degree of intergenerational persistence.

3.2 Case 2: Tracking by Family Background

Now assume that ability is not perfectly observed when choosing τ but that the information set includes wages and τ choices of the previous generation together with full information of the Markov process. From this information set the parent predicts the type of her own child and her expected wages. The problem will then be:

Choose $\tau \in \{A, V\}$ to maximize $E_t(w|a_{t-1})$

Suppose we start from a separating equilibrium: if this is the case, knowing the school choice of the previous generation means knowing parent's ability with probability one. Therefore the optimal decision rule will be.

If $a_{t-1} = H$, choose $\tau = A$ when:

$$\begin{aligned} E_t(w|A, a_{t-1} = H) &> E_t(w|V, a_{t-1} = H) \\ \gamma(rs_A\pi_{AH} - rk) + (1 - \gamma)(rs_A\pi_{AL} - rk) &> \gamma rs_V\pi_{VH} + (1 - \gamma)rs_V\pi_{VL} \end{aligned}$$

therefore all the parent H will choose the A track for their children if the cost differential is low enough:

$$k < s_A [\gamma\pi_{AH} + (1 - \gamma)\pi_{AL}] - s_V [\gamma\pi_{VH} + (1 - \gamma)\pi_{VL}] \equiv k_2^*$$

If $a_{t-1} = L$, choose $\tau = V$ when:

$$\begin{aligned} E_t(w|V, a_{t-1} = L) &> E_t(w|A, a_{t-1} = L) \\ \gamma rs_V\pi_{VL} + (1 - \gamma)rs_V\pi_{VH} &> \gamma[rs_A\pi_{AL} - rk] + (1 - \gamma)[rs_A\pi_{AH} - rk] \end{aligned}$$

therefore all the parents L will choose the V track for their children if the cost differential is high enough:

$$k > s_A [\gamma\pi_{AL} + (1 - \gamma)\pi_{AH}] - s_V [\gamma\pi_{VL} + (1 - \gamma)\pi_{VH}] \equiv k_2^{**}$$

From the definition of the match ability/track we can obtain the following.

Lemma 1 *The set of cost such that a separating equilibrium is sustainable is not empty*

$$k_2^* > k_2^{**}$$

Proof. Again the statement is proved by the ratios of the probabilities of success and by persistency in intergenerational transmission of ability ($1/2 < \gamma < 1$).

$$\begin{aligned} k_2^* &> k_2^{**} \\ s_A [\gamma\pi_{AH} + (1 - \gamma)\pi_{AL} - \gamma\pi_{AL} - (1 - \gamma)\pi_{AH}] &> s_V [\gamma\pi_{HV} + (1 - \gamma)\pi_{LV} - \gamma\pi_{LV} - (1 - \gamma)\pi_{HV}] \\ LHS &= s_A (2\gamma - 1) [\pi_{AH} - \pi_{AL}] > 0 \\ RHS &= s_V (2\gamma - 1) [\pi_{VH} - \pi_{VL}] < 0 \end{aligned}$$

■
It is interesting to consider the limiting case: $\gamma = 1/2$. In this case the two bounds converge and there is no separating equilibrium because children cannot infer any information on their own type from their parent's type. The threshold over k between the two pooling equilibria will then be in this case:

$$\begin{aligned} \bar{k} &= \frac{1}{2}s_A\pi_{AH} + \frac{1}{2}s_A\pi_{AL} - \frac{1}{2}s_V\pi_{HV} - \frac{1}{2}s_V\pi_{LV} \\ &= \frac{1}{2}s_A (\pi_{AH} + \pi_{AL}) - \frac{1}{2}s_V (\pi_{HV} + \pi_{LV}) \end{aligned}$$

obtained as a solution to $k_1^{**} = k_2^{**}$.

Another interesting question to ask is whether the set of cost generating a separating equilibrium under imperfect information is larger or smaller than the set under perfect information. As one may anticipate, the set under imperfect information is smaller as proved in the following.

Lemma 2 *The set of cost such that a separating equilibrium is sustainable is smaller in Case 2 than in Case 1*

$$k_1^{**} < k_2^{**} < k_2^* < k_1^*$$

Proof. Higher upper-bound in Case 1.

$$\begin{aligned} k_1^* &> k_2^* \\ s_A \pi_{AH} - s_V \pi_{VH} &> s_A [\gamma \pi_{AH} + (1 - \gamma) \pi_{AL}] - s_V [\gamma \pi_{HV} + (1 - \gamma) \pi_{LV}] \\ s_A (1 - \gamma) [\pi_{AH} - \pi_{AL}] &> 0 > s_V (1 - \gamma) [\pi_{VH} - \pi_{VL}] \end{aligned}$$

and smaller lower-bound in Case 1.

$$\begin{aligned} k_1^{**} &< k_2^{**} \\ s_A \pi_{AL} - s_V \pi_{VL} &< s_A [\gamma \pi_{AL} + (1 - \gamma) \pi_{AH}] - s_V [\gamma \pi_{VL} + (1 - \gamma) \pi_{VH}] \\ s_V (1 - \gamma) [\pi_{VH} - \pi_{VL}] &< 0 < s_A (1 - \gamma) [\pi_{AH} - \pi_{AL}] \end{aligned}$$

■

An interpretation of this result is that if there is a sense such that the separating equilibrium can be defined as "efficient", then we have proved that Case 2 is worse. This is obvious because we are introducing asymmetric information. Moreover, notice that if $k_2^{**} < k < k_2^*$ then total (net) production in Case 2 is:

$$W_t(2) = r s_V [\gamma \pi_{VL} + (1 - \gamma) \pi_{VH}] L_{t-1} + r \{s_A [\gamma \pi_{AH} + (1 - \gamma) \pi_{AL}] - k\} H_{t-1}$$

But given the same cost, we will also have a separating equilibrium in Case 1 that generates total (net) production:

$$\begin{aligned} W_t(1) &= r s_V \pi_{VL} L_t + (r s_A \pi_{AH} - r k) H_t \\ &= r s_V \pi_{VL} [\gamma L_{t-1} + (1 - \gamma) H_{t-1}] + (r s_A \pi_{AH} - r k) [(1 - \gamma) L_{t-1} + \gamma H_{t-1}] \\ &= r [\gamma s_V \pi_{VL} + (1 - \gamma) (s_A \pi_{AH} - k)] L_{t-1} + r [\gamma (s_A \pi_{AH} - k) + (1 - \gamma) s_V \pi_{VL}] H_{t-1} \\ &> W_t(2) \end{aligned}$$

which is larger than W_t in Case 2.¹²

We can also look at this differential in steady state:

$$\begin{aligned} &W_{SS}(1) - W_{SS}(2) \\ &= \frac{r}{2} [(s_A \pi_{AH} - k) + s_V \pi_{VL}] \\ &\quad - \frac{r}{2} \{s_A [\gamma \pi_{AH} + (1 - \gamma) \pi_{AL}] - k + s_V [\gamma \pi_{VL} + (1 - \gamma) \pi_{VH}]\} \\ &= \frac{r}{2} \{s_A (1 - \gamma) [\pi_{AH} - \pi_{AL}] + s_V (1 - \gamma) [\pi_{VL} - \pi_{VH}]\} > 0 \end{aligned}$$

¹²CHECK Decompose the difference showing that it is all due to "mismatch" of track choices

Again we have a higher net production in Case 1 than in Case 2. Moreover we have shown that Case 2 does not converge to Case 1 in steady state.¹³

Our simple model shows that when sorting by ability is possible, efficient allocation is achieved and output is maximised. On the contrary, under imperfect information on ability, tracking is based on parental education (due to inference on parental abilities), there is misallocation (i.e. people are doing wrong choices with respect to their true abilities ending up in a bad (a, τ) match) and output is reduced.

In the data we have shown in the previous section that misallocation is higher in Italy than in Germany. We interpret this evidence as the result of Germany being closer than Italy to the notion of tracking on ability. As empirical implication from the present model, we should therefore find stronger impact of family background in Italy than in Germany. The following two sections are devoted to study this impact.

4 Impact of Family Background on Secondary Schooling

We essentially consider three sets of variables to estimate the determinants of the choice of the Secondary School track. First, a dependent variable that includes not simply schooling completed or schooling level but a disaggregation by type of schooling tracks. The PISA data set includes such information even if the disaggregation is not homogenous across countries: in the case of Germany and Italy we believe that a tripartite disaggregation is comparable across them, basing on descriptive statistics on test on achievements. Academic schools are the track that typically leads to acquire additional schooling, Technical school leave the option to acquire additional schooling but usually with some constraints and finally Vocational school have mainly the task to teach specific skills to enter the labor market right after completion.

The second group of variables we introduce is related to family background. Ideally we would like to have information about earnings, wealth and schooling of the family the students is living and has lived with. The PISA data set provide very detailed information on some psychological and social aspects of the family the student is living with but it does not provide income variables. To accommodate this data constraints we focus on parent's education, provided by a sufficiently disaggregated grade completed variable, and we control for other family background by a Index of Social Status, computed by PISA analysts based on a quite large set of socio-economic questions, and by other potentially relevant variables (such as the number of books in the house).

Finally, on top of the usual demographic controls, we need to know something about the specific ability of the individual. These measures of ability are not our main concern but they are essential to reduce individual heterogeneity when

¹³CHECK: To be completed, showing that intergenerational mobility in educational attainment is higher in Case 1 than in Case 2.

estimating the impact of parents' schooling on the secondary school track chosen for their children. In this respect PISA is probably the best internationally comparable data set that is possible to find. Four different types of cognitive tests are performed, and special care is put to make them comparable across countries. The four types of tests are: a test for mathematical ability, one for reading and writing skills, one for science and one for problem solving. On top of a summary measure of performance on these test we introduce controls for past school experience (failure in any previous grade) and for faster than usual completion of grades.

The empirical specification we will assume is a standard Random Utility Model (RUM) with, at least in the first wave of estimates, extreme value errors. This specification generates a Multinomial Logit (MNL) model, that is the most popular specification when studying discrete choice models with numerosity higher than two. In our case we have three possible choices, denoted by $k \in \{1, 2, 3\}$, that each individual, denoted by $i \in \{1, 2, \dots, N\}$, has to take based on the following expected utility:

$$U_{k,i} = x'_i \beta_k + \varepsilon_{k,i} \quad (1)$$

where $x'_i \beta_k$ denotes the deterministic component and $\varepsilon_{k,i}$ the random component. The optimal strategy is to choose the alternative with the higher expected utility, leading, for example, to the following probability to choose alternative $k = 1$:

$$P(1|\{1, 2, 3\}) = P(U_{1,i} > U_{2,i}, U_{1,i} > U_{3,i}) \quad (2)$$

Under the assumption that $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$ are independently and identically distributed following a standard *Extreme value* (or *Gumbel*) distribution, McFadden 1973 shows that this probability reduces to:

$$P_i(1|\{1, 2, 3\}) = \frac{e^{x'_i \beta_1}}{\sum_{k=1}^3 e^{x'_i \beta_k}} \quad (3)$$

that is the usual logistic form.

This brief review of the model is useful to underline three points. First, identification requires one of the expected utilities to be normalized to zero. This is an immediate consequence of the parametrization (1) and (3): the scale of the utility cannot be identified. Second, it is more interesting to look at the inference on the probabilities than on the expected utilities. Therefore we will focus on the estimated marginal effects and not on the estimated utility parameters $\hat{\beta}_k$. We will call *marginal effect* also the discrete change in probability due to the impact of a dummy variable. Finally, the model and the parametric assumption on the errors lead to the property of *Independence from Irrelevant Alternatives* (IIA) in the choice. This means that we were to shut down one of the available alternative, choices will redistribute in the same proportion over the remaining alternatives. Formally this is shown by the fact that the ratio between two probabilities defined by (3) is independent from the conditioning set of alternatives $\{1, 2, 3\}$. From this property it is possible to obtain a specification

test for the model, developed by Hausman and McFadden 1984. The intuition is simple: consider the ratio over the probabilities to choose two alternatives. If the IIA property holds, then estimating the model including or excluding "irrelevant alternatives", i.e. in this case the third remaining alternative, should not have much of an impact on the estimates for the two alternatives on which we were computing the ratio. The statistic is build as in a standard Hausman test where the *unrestricted* model includes the "irrelevant alternative" and the *restricted* model excludes it¹⁴.

Results of the marginal effects of parent's schooling on the secondary school track chosen by their children are reported in Tables 2a and 2b. The first Table reports estimates on the male sample and the second on the female sample. We have chosen to split the sample by gender because heterogeneity of behavior between men and women seems particularly relevant in this context¹⁵. The marginal effect we focus on is the change in probability due to a father or a mother holding a tertiary level degree (typically College). After estimating by maximum likelihood the MNL model previously described, we compute the change in probability for each individual by:

$$\Delta \hat{P}_i(k|\{1, 2, 3\}, x_i) = \hat{P}_i(k|\{1, 2, 3\}, d_i = 1, x_i) - \hat{P}_i(k|\{1, 2, 3\}, d_i = 0, x_i) \quad (4)$$

where the statement $(d_i = 1, x_i)$ means that the dummy for having a mother or/and a father with College is set to one and all the other regressors are set to the original values for individual i . The other statement $(d_i = 0, x_i)$ is the corresponding statement when the dummy for having a mother or/and a father with College is set to zero. Computed these marginal effects, it is not obvious how give a sense of the average impact in the sample. We have chosen to provide four descriptive measures: the sample mean and the sample standard deviation over $\Delta \hat{P}_i(k|\{1, 2, 3\})$, the marginal effect at the average sample values of the regressors and finally the proportion of individuals i for whom the marginal effect is positive. Notice the difference between the sample mean of the marginal effect:

$$\frac{1}{N} \sum_{i=1}^N \Delta \hat{P}_i(k|\{1, 2, 3\}, x_i) \quad (5)$$

and the marginal effect at the sample mean of the regressors:

$$\Delta \hat{P}(k|\{1, 2, 3\}, \frac{1}{N} \sum_{i=1}^N x_i) \quad (6)$$

The first measure is a good descriptive statistic of the average marginal effect in the sample but it does not provide a clear way to assess the precision of the estimates because a measure of variation of this estimate will include both variation from the estimated values $\hat{\beta}$ and variation from the sample. The second

¹⁴McFadden 1987 shows how to perform the test using a Lagrange Multipliers test strategy.

¹⁵Motivation can be found in the discrimination literature (for example Altonjii and Blank 1999) or in previous works more similar to what we do such as Dustmann 2004.

measure does not have an equally clear interpretation in terms of inference because an individual with all the regressors set at the sample mean is often not the "average individual" one has in mind when looking for descriptive statistics. On the other side, standard errors on (6) are informative and are obtained by bootstrapping.

The third row of Tables 2a and 2b reports the statistic (5) computed for each choice and the fifth row the statistic (6) computed for each choice. Looking at Males in Italy, under the basic specification we estimate that parents' College more than double the average observed probability to choose the Academic track. By this we mean that the average marginal effect (about 0.36 considering the mean and about 0.41 considering the impact at the mean of the regressors) will increase the probability to choose the academic track by a value higher than the observed probability (reported in the first row and equal to about 0.279). As reported in the seventh row, parents' College has a positive effect on the probability to choose the academic track and a negative effect on choosing the Vocational track for every individual in the sample. For about 14.4% of the sample, parents' College has also a positive effect on choosing the Technical track. The variation of these marginal impacts in the sample is quite high, as described by the standard deviation reported in the fourth row, while the estimates are reasonably precise as shown by the standard errors reported in parenthesis on row six. Standard errors are robust to heteroskedasticity due to clusters at school levels.

The previous results are obtained under a Basic Specification that simply includes age (in months) as demographic control, the performance in the mathematical cognitive test as ability control and dummies for three levels of education completed by parents (less than High School; High School; College or more) as family background controls. Dummies on parents' schooling are built by taking the maximum schooling level completed by at least one parent. An additional dummy is included to take into account which of the two parents has the highest education. This Basic Specification is mainly for comparison purposes while a richer Specification includes all the useful variables we can obtain from the PISA data set without losing too many observations due to missing values. The complete specification is reported in Appendix together with complete results from MNL estimates (see tables A2.a and A.2.b). It adds a full array of controls for ability and family background leading to a smaller impact of parents' schooling on track choices. However, the impact is still substantial with an increase in the probability to choose the Academic track of about 50% on average. Again the estimates are reasonably precise, except for the marginal effect on choosing the Vocational track.

Estimates on the male German sample shows a similar picture in terms of the direction of the impact *but the magnitude is always smaller than in Italy*. Parents' College still have a substantial and significant impact in increasing the probability to choose the academic track: the magnitude is about 50% on average under the basic specification and about 30% on average under the richer specification. We find this a very useful comparison to judge the magnitude of these impacts. Previous works have looked at Germany as a typical example

of a country with relatively low intergenerational mobility and at its secondary school tracking system as an important factor in explaining this fact (Dustmann 2004, Schnepf 2002). We confirm this prediction but we also show that in another European country with a milder tracking system this effect is even more pronounced.

The average impact for women is relatively smaller in both countries: the increase in the probability to choose the academic track due to at least one parent with a Tertiary degree is about 70% and 35% on average in the two specifications for Italy and 62% and 32% on average in the two specifications for Germany. Differently from before there is almost no difference in the relative impact between Italy and Germany. This is due to the fact that parents' impact is more important for male children than for female children in Italy while in Germany the impact is quite similar on both subsamples. Therefore the policy implications are sort of gender neutral in Germany while in Italy the major problem seems the inefficient allocation of male students due to a huge impact of parents' education even when controlling for quite detailed measures of ability and for additional family background variables.

In terms of specification, the IIA test does not reject that this property, implied by the MNL model, is valid and therefore does not reject the specification we use. This is true for quite high P-values for all the specifications estimated on both samples on both countries. We just report the results for the test obtained excluding the Technical track choice: this seems the most interesting restriction to impose because it is more likely to be correlated with the Vocational choice. The other IIA tests, not reported, confirm a similar picture. In terms of fit of the model, we just report in the second row the predicted probability at the mean of the sample: this very crude measure of fit shows a better fit on the Italian sample than on the German sample. In particular, we systematically under-predict the choice of the Academic track in Germany.

5 Impact of Family Background on Post-Secondary Schooling

Before moving to actual choices on post-secondary education, we further exploit the PISA survey by looking at student aspirations. In the questionnaire, surveyed students were asked about the level of educational attainment they expected to complete. The fraction of students expecting to enrol University is clearly different across tracks, but the differences in aspirations are also significant across countries: the 87.9% of students in the Italian academic track aspire to complete tertiary education (ISCED 5A-5B-6), while the same percentage declines to 51.3% among young Germans in the *Gymnasium*. The fraction of students aspiring to university enrolment is lower in technical schools (39.2% in Italy and 24.0% in Germany) and somehow negligible in vocational schools

(24.7% in Italy and 15.7% in Germany).¹⁶ The observation of a larger fraction of students who intend to enrol university in Italy than in Germany is consistent with what we have previously remarked about the screening abilities of these two educational systems, especially when we compare intention with actual behaviours: in 2002 (most recent available data) the 23.6% of the age cohort attained a tertiary degree in Italy, while 29% of Germans in the same cohort achieved a degree.¹⁷

In table 3 we report the estimates for the coefficients of interest in a probit model predicting the aspiration to enrol university (full model estimates are reported in tables A.3.a and A.3.b in the appendix). Two results are surprising: parental education is mostly significant only in Italy, even when fully accounting for ability (extended version), while they are almost insignificant in the German case. In addition, the probability impact of a graduate parent is higher in Italy, and more pronounced for males than for females. *Measured ability does not seem to play any role*, as if aspirations of students were independent of their school performance, conditioning on secondary school tracks. As expected, the type of secondary school attended affect the intention to enrol University: if we compute the odd ratio of a student choosing the academic track compared with the technical track, it ranges between 6.0 and 2.8 in Italy and 2.0 and 0 in Germany. The analysis of students aspirations confirms what we have already found in the case of the secondary school choice: *parental influence is higher in Italy than in Germany, even after controlling for the type of secondary school attended, which in turn plays a role in shaping expectations on the future*. When looking at the full version of the estimated model, we notice that various abilities are more significant in Germany than in Italy, but this result suffer from multicollinearity among these variables; in addition, estimated signs are sometimes negative, thus contradicting theoretical expectations.

We then move to the real objective of the econometrics analysis in this section that is to see whether family influence on post-secondary schooling decision is greatly reduced when we control for secondary school track. If this is the case, *we will claim that one of the main channel by which the family background affects long term schooling decision is the track choice at the secondary school level*. Such a conclusion constitutes only a partial answer to our question if the secondary school system increases or decreases intergenerational mobility in schooling but it will be a clear indication of the direction that policy reforms should take to have a substantial impact.

¹⁶It is worth noticing that almost half (45.3%) of the German students do not answer to this question, and the fraction is highest among students attending vocational schools (76.4%). This suggests that the fraction of students aspiring to university is overestimated in the German sample.

¹⁷Data from OECD 2004, *Education at a glance*, table A3.1. There are differences between countries at tertiary level that may be partially responsible for this difference: while Germany has a well developed technical tertiary education (ISCED 5B), Italy almost completely lacks this type of schools. The 29% of German students achieving a university degree is made of 9.8% from technical universities, 6.5% of students achieving a 3-4 year degree and 12.7% of students attaining a 5-6 year degree. The corresponding figure for Italy are 0.9%, 2.5% and 20.2%.

This strategy is a much more direct test than looking at aspirations but it comes at the cost of losing a data set that is very homogenous across countries, that is we do not have a data set with a structure similar to PISA to study post-secondary school decision. We are then looking at country-specific data sets that can have the information we need.

For Italy we use a Survey conducted by the Italian National Institute of Statistics (ISTAT) on a representative sample of individuals three years after graduation from Secondary School. Individuals were interviewed in 1998. After losing about 5% of the sample due to missing values, the final estimation sample is quite large, with 20929 valid observations. Some descriptive statistics on this sample are reported in Appendix (see Table A.4). For Germany we use the German Socio-Economic Panel Study (SOEP). We try to create a sample that can match the characteristics of the Italian sample. At this stage we have a very preliminary data set in which we extract individuals that are 22 years old, to proxy the three years from graduation condition, in the last available year of SOEP, 2002: we are forced to use 2002 because the question about grades, that we use as controls for ability, has been introduced only in 2001. We are working on a better extraction mechanism in which we actually identify individuals three years after completing secondary school by exploiting the panel structure of the data-set. The numerosity of the sample obtained so far is quite low: 129 valid observations once we consider only individuals with no missing values on all the relevant variables (see Table A.6). Given these constraints we will not provide estimates by gender but we will use only the pooled sample.

Given the different structure of the data we will compare two different specifications for Italy and Germany. More work on SOEP may lead to a more similar common specification. On the Italian sample we will be able to address also the dropped out behavior while on German data we will simply look at College enrollment and we will perform only standard logit.

On the Italian sample we will work with a discrete choice model equal to the one described in the previous section with the difference that now the alternative choices are: (i) Never enrol in College (ii) Drop-out from College, and (iii) Complete College (as proxied by the fact of being still enrolled full-time after three years). Given the extremely high drop-out rate among College students in Italy, it seems particularly interesting to allow the model to capture this behavior. The data are appropriate because they identify individuals that enrolled in College after completing High School and dropped out sometime in the following three years. People still enrolled, then, are a very good proxy of individuals that will actually complete College.¹⁸ These three alternatives, though, have a particular structure because the choices are very likely taken sequentially: first individuals decide if enroll in College or not and later, conditional on this choice, if stay in College or Drop-out. We will therefore focus on a Sequential Logit and we will report a Multinomial Logit as a comparison point. The sequential logit generates the following parametrization of the probability to choose each

¹⁸CHECK We are considering to refine the alternatives by keeping track of measures of performance while in College, such as number of credits earned and class attendance.

alternative:

$$\begin{aligned}
 P_i (\text{Never Enroll}) &= \frac{1}{1 + \exp(x'_i \beta)} \\
 P_i (\text{Dropped-out} \mid \text{Enroll}) &= \frac{1}{1 + \exp(x'_i \alpha)} \frac{\exp(x'_i \beta)}{1 + \exp(x'_i \beta)} \\
 P_i (\text{Enrolled} \mid \text{Enroll}) &= \frac{\exp(x'_i \alpha)}{1 + \exp(x'_i \alpha)} \frac{\exp(x'_i \beta)}{1 + \exp(x'_i \beta)}
 \end{aligned}$$

from which it is possible to identify (α, β) by observing the choices and the regressors. Estimation will be performed by maximum likelihood.

Table 4 reports marginal effects of at least a parent with College on the Italian sample by gender. As in the previous section we use a basic specification and a richer specification. The main difference between the two specifications is about the proxies for ability: in the basic specification we simply control for the grade obtained at the end of lower secondary school (*Scuola Media*) while in the richer specification we build a 16 outcomes variable combining for each individual grades at lower secondary and grades at the end of secondary school. Again as in the previous section we reports the average marginal effects, the marginal effects at the mean of the regressors and the proportion of individuals with a positive impact. For example the third row report the average marginal effect of at least one parent with College computed as in (5) while the fifth row computed as in (6). The main objective of the exercise is to see how the impact of parent's education changes when we control for secondary school tracks: in the Table this means to compare the first three columns with the last three columns.

The sign of the impact is as expected on the Enroll alternative - a positive impact of parents' College - and on the Never Enrolled alternative - a negative impact - while results are mixed on the Drop-out alternative. The magnitude of the impact is huge without controlling for track on the male sample: having at least a parent with College increase the probability to be continuously enrolled in College by more than 100%. On the female sample the impact is relatively lower but still quite high.

When secondary school tracks completed are controlled for the impact is significantly reduced: for both man and women the magnitude of the impact is about 45% lower. This suggests that the secondary school track is an effective channel of the impact of family background on the final level of schooling completed. However, even in the richer specification and with controls for tracks we observe a persistent direct effect of parents' education on College choices.

The estimates are generally precise except for the Drop-out choice. We tentatively interpret this as a composition effect due to the higher heterogeneity of individuals choosing this alternative. In terms of the comparison between the Conditional Logit model and the Multinomial Logit model we observe some difference in the point estimates but similar qualitative results. As expected, the IIA test systematically rejects the independence assumption imposed by the Multinomial Logit model when the alternatives Drop-out and Enrolled are

eliminated.

Table 5 reports very preliminary results for Germany. A simple Logit on the choice of being enrolled in College at age 22 estimates a positive and large impact of a father with at least an *abitur* degree. As found on the Italian sample, this impact is strongly reduced when controlling for the secondary school track. The reduction is relatively larger than on the Italian sample. The remaining direct effect is very imprecisely estimated and it does not suggest a clear inference since the sample size is quite small.

Finally, results can be summarized as follows for Italy: (i) secondary school track controls imply a large and significant reduction of the impact of parents' education on College choices; (ii) the impact of family background is significantly smaller for women in all the specifications; (iii) a significant impact of parents' education on staying in College remains even after controlling for secondary tracks. The tentative inference we draw from these results is consistent with what we have found in the previous section: (i) the secondary school track choice is one of the major channel of the intergenerational persistence in schooling levels but not the only one; (ii) women behavior is more independent from family backgrounds than men behavior. The inference for Germany is very preliminary but it confirms the importance of secondary school tracks.

6 Conclusion

The aim of the present paper is to study the interaction between family background and educational choice in tracked educational systems. The availability of a sorting device represented by different types of secondary schools (academic, technical or vocational) does not necessarily represent a reinforcement of social immobility, this depending on how students are allocated to tracks. At one extreme, one may think at a perfectly meritocratic system, where track allocation is based on pure ability. In this set-up, intergenerational mobility is at the highest, with the only limitation given by the correlation between child ability and parental education (which is typically referred in the literature as "genetic" transmission of ability). At the other extreme, one may think of a perfectly ascriptive system, where track allocation mainly depends on parental background: in this case mobility is lower, because children educational choices replicate parental ones (this has obviously to be interpreted in probabilistic terms: a graduate student is very likely to have studied in an academic track, which is very likely to have been chosen by graduate parents).

We have studied two countries, Italy and Germany, where the educational systems are characterized by a secondary school divided in separate tracks. We have shown that sorting of students across these tracks by ability is more effective in Germany than in Italy, and we have estimated that the role of parental education in selecting the academic track is strongest in Italy. When we bring into the picture post-secondary educational choice, we have shown that, at least in the case of Italy, even if parental background continue to exert a role, family influence on post-secondary schooling decision is greatly reduced

when we control for secondary school track.

Our main policy implication is that tracking can be efficient, in the sense of reducing mismatch and increasing intergenerational mobility, only if it is based on (cognitive) ability and therefore only if the information when the decision is taken is high enough. In this respect any policy that increase information when children are entering the secondary school level is very promising. An alternative or complementary policy to achieve a stronger tracking by ability could be increasing mobility across tracks based on grades or standardized test

If the information when the relevant decision is taken is not enough the risk of mismatch is too high and an elimination of tracks at secondary level seems an appropriate second best. The worse possible system is to keep separate tracks but to eliminate completely any “institutional” tracking-by-ability features. The result of such a system is a strong influence of parents when this early in life decision is taken leading to lower intergenerational mobility and to inefficient lock-in effects. Italy seems closer to such a system than Germany, a country for which some authors have already suggested to integrate the different tracks on efficiency grounds (Dustmann 2004).

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Table 1 - Overlapping of ability distributions

	Italy	Germany
Mathematical ability		
Vocational - Technical	0.67	0.65
Vocational - Academic	0.54	0.26
Technical - Academic	0.84	0.52
Reading ability		
Vocational - Technical	0.69	0.61
Vocational - Academic	0.48	0.23
Technical - Academic	0.74	0.50

Note: the figures reported in the table correspond to the overlapping coefficient proposed by Bradley (1985): given two random variables, x_1 and x_2 , and denoting with $f(x_i)$ their density functions (that we estimate through a kernel estimator - see figure 1), the overlapping coefficient is given by $OVL = \sum_{\times} \min [f(x_1) \cdot f(x_2)]$. The OVL coefficient ranges between 0 and 1: a value of 0 implies absence of overlap (disjoint distributions), whereas a value of 1 indicates identical distributions.

Table 2a: Marginal Effect of at least one Parent with College on Secondary School Track Choice. MNL Model - Males

	Italy			Germany		
	Vocational	Technical	Academic	Vocational	Technical	Academic
Basic Specification:						
Observed Distribution	0.273	0.448	0.279	0.357	0.349	0.293
Predicted Distribution	0.241	0.526	0.233	0.374	0.497	0.129
Marginal effects:						
Mean	-0.1307	-0.2252	0.3559	0.0016	-0.1475	0.1459
Standard Deviation	0.0576	0.1607	0.1214	0.0362	0.0800	0.1141
At \bar{x}	-0.1880 (0.0325)	-0.2258 (0.0428)	0.4138 (0.0416)	-0.0061 (0.0517)	-0.1427 (0.0509)	0.1488 (0.0411)
Proportion Positive	0.000	0.144	1.000	0.4683	0.0000	1.0000
IIA Test: P-value						
		0.696			0.7203	
Log-likelihood						
		-4761.3401			-1545.99	
N						
		5517			2018	
Richer Specification:						
Observed Distribution	0.263	0.453	0.284	0.326	0.361	0.314
Predicted Distribution	0.226	0.580	0.195	0.300	0.578	0.122
Marginal effects:						
Mean	-0.0561	-0.0882	0.1443	0.0896	-0.1907	0.1011
Standard Deviation	0.0289	0.0904	0.0789	0.0735	0.0602	0.0912
At \bar{x}	-0.0863 (0.0284)	-0.0843 (0.0394)	0.1706 (0.0394)	0.1375 (0.0575)	-0.2262 (0.0535)	0.0887 (0.0454)
Proportion Positive	0.000	0.256	1.000	0.8689	0.0000	1.0000
IIA Test: P-value						
		0.6386			0.7252	
Log-likelihood						
		-4152.9694			-1268.07	
N						
		5322			1831	

Note: Data from PISA 2000. Standard errors in parentheses robust to clusters at school level. It is reported the impact of father or/and mother completing a tertiary level degree. Estimates are from Multinomial logit weighted by stratification weight reported by PISA. IIA Test is with respect to eliminating the alternative: technical. Complete results in Appendix.

Table 2b: Marginal Effect of at least one Parent with College on Secondary School Track Choice. MNL Model - Females

	Italy			Germany		
	Vocational	Technical	Academic	Vocational	Technical	Academic
Basic Specification:						
Observed Distribution	0.238	0.273	0.489	0.260	0.366	0.374
Predicted Distribution	0.184	0.308	0.508	0.238	0.512	0.250
Marginal effects:						
Mean	-0.1409	-0.2014	0.3422	-0.1147	-0.1157	0.2304
Standard Deviation	0.0505	0.0464	0.0286	0.0459	0.1339	0.1285
At \bar{x}	-0.1517 (0.0256)	-0.2070 (0.0324)	0.3587 (0.0369)	-0.1643 (0.0352)	-0.1697 (0.0552)	0.3340 (0.0631)
Proportion Positive	0.0000	0.0003	1.0000	0.0000	0.2921	1.0000
IIA Test: P-value						
		0.5252			0.3584	
Log-likelihood						
		-5574.72			-1691.27	
N						
		5973			2140	
Richer Specification:						
Observed Distribution	0.236	0.272	0.492	0.229	0.377	0.394
Predicted Distribution	0.178	0.306	0.516	0.190	0.562	0.249
Marginal effects:						
Mean	-0.1167	-0.0549	0.1715	-0.0106	-0.1147	0.1253
Standard Deviation	0.0519	0.0443	0.0363	0.0188	0.0686	0.0846
At \bar{x}	-0.1243 (0.0235)	-0.0756 (0.0316)	0.1999 (0.0352)	-0.0340 (0.0348)	-0.1568 (0.0581)	0.1908 (0.0675)
Proportion Positive	0.0000	0.1313	1.0000	0.2629	0.0000	1.0000
IIA Test: P-value						
		0.7606			0.3101	
Log-likelihood						
		-5189.93			-1430.98	
N						
		5895			1974	

Note: See previous table.

Table 3: Aspirations: marginal effect on intention to proceed further in education

Specification:	Italy		Germany	
	Basic	Richer	Basic	Richer
Males				
highest education in couple upper secondary	0.131 (0.035)	0.073 (0.034)	-0.033 -0.061	-0.08 -0.074
highest education in couple tertiary	0.222 (0.032)	0.116 (0.035)	0.161 (0.057)	0.056 -0.074
mother is highest in education	-0.062 (0.026)	-0.045 -0.028	-0.034 -0.034	0.004 -0.039
ability (mathematics)	0.001 (0.000)	-0.001 0	0.001 0	0 -0.001
attending technical school	0.239 (0.038)	0.22 (0.040)	0.141 (0.058)	0.083 -0.071
attending high school	0.667 (0.024)	0.628 (0.029)	0.295 (0.057)	0.23 (0.073)
N	5341	5168	1094	1012
Pseudo R-squared	0.33	0.35	0.11	0.16
Log likelihood	-2488.11	-2314.41	-654.07	-575.97
Females				
	Basic	Richer	Basic	Richer
highest education in couple upper secondary	0.079 (0.020)	0.02 -0.023	-0.021 -0.069	0.042 -0.075
highest education in couple tertiary	0.158 (0.021)	0.052 -0.027	0.142 (0.072)	0.139 -0.076
mother is highest in education	-0.026 -0.02	-0.002 -0.019	0.078 -0.041	0.083 (0.041)
ability (mathematics)	0.001 (0.000)	0 0	0.001 (0.000)	-0.001 0
attending technical school	0.077 (0.035)	0.077 (0.033)	-0.041 -0.073	-0.086 -0.08
attending high school	0.465 (0.035)	0.435 (0.035)	0.174 (0.068)	0.123 -0.077
N	5866	5759	1356	1279
Pseudo R-squared	0.26	0.29	0.12	0.17
Log likelihood	-2736.95	-2565.82	-784.59	-699.73

Notes: PISA 2003. Robust standard errors in brackets, clustered on schools. * significant at 5%; ** significant at 1%. Weighed using student sample size. Dependent variable=1 if the student declares s/he intends to proceed further to tertiary education. The basic estimates control for age. The richer version controls for foreign, family situation, occupational prestige, availability of books and previous educational career.

Table 4a: Marginal Effect of at least one Parent with College on Post-Secondary School Choice - Male Sample, Italy

	Without Tracks			With Tracks		
	Never Enrolled	Drop-out	Enrolled	Never Enrolled	Drop-out	Enrolled
Sequential Logit						
Basic Specification:						
Observed Distribution	0.6503	0.0580	0.2918	0.6503	0.0580	0.2918
Predicted Distribution	0.6692	0.0655	0.2653	0.6595	0.0713	0.2692
Marginal Effects:						
Mean	-0.4584	0.0119	0.4465	-0.3035	0.0202	0.2833
Standard Deviation	0.0891	0.0261	0.0737	0.0900	0.0245	0.0789
At \bar{x}	-0.5187 (0.0135)	0.0097 (0.0116)	0.5090 (0.0190)	-0.3841 (0.0266)	0.0200 (0.0125)	0.3641 (0.0281)
Proportion Positive	0.0000	0.6837	10.000	0.0000	0.8027	10.000
Log-likelihood		-6707.97			-6269.49	
N		9956			9956	
Richer Specification:						
Observed Distribution	0.6501	0.0579	0.2921	0.6501	0.0579	0.2921
Predicted Distribution	0.6770	0.0661	0.2570	0.6693	0.0728	0.2579
Marginal Effects:						
Mean	-0.4491	0.0069	0.4421	-0.3082	0.0137	0.2945
Standard Deviation	0.0194	0.0124	0.0212	0.0238	0.0116	0.0274
At \bar{x}	-0.3700 (0.0857)	0.0075 (0.0255)	0.3625 (0.0806)	-0.2202 (0.0809)	0.0121 (0.0217)	0.2082 (0.0769)
Proportion Positive	0.0000	0.6305	10.000	0.0000	0.7255	10.000
Log-likelihood		-6813.91			-6270.32	
N		10453			10453	
Multinomial Logit						
Basic Specification:						
Test IIA: P-value	0.4175	0.4164	0.3614	0.1008	0.4633	0.0809
Marginal Effects:						
At \bar{x}	-0.5226 (0.0156)	0.0103 (0.0104)	0.5123 (0.0178)	-0.3860 (0.0228)	0.0214 (0.0131)	0.3646 (0.0239)
Richer Specification:						
Test IIA: P-value	0.8554	0.5009	0.529	0.7656	0.0443	0.3669
Marginal Effects:						
At \bar{x}	-0.4527 (0.0204)	0.0069 (0.0111)	0.4458 (0.0221)	-0.3092 (0.0273)	0.0156 (0.0136)	0.2937 (0.0276)

Notes: Dependent variable =1 if Never Enrolled in College; =2 if Dropped-out; =3 if Still Enrolled after three years. Complete specification in Appendix include controls for: family background, demographic, ability (grades) and secondary school tracks in

the appropriate specification. Bootstrap standard errors in parentheses.

Table 4b: Marginal Effect of at least one Parent with College on Post-Secondary School Choice - Female Sample, Italy

	Without Tracks			With Tracks		
	Never Enrolled	Drop-out	Enrolled	Never Enrolled	Drop-out	Enrolled
Sequential Logit						
Basic Specification:						
Observed Distribution	0.5567	0.0525	0.3908	0.5567	0.0525	0.3908
Predicted Distribution	0.5545	0.0591	0.3863	0.5370	0.0632	0.3997
Marginal Effects:						
Mean	-0.4520	0.0007	0.4514	-0.3281	0.0176	0.3105
Standard Deviation	0.1147	0.0206	0.0983	0.1138	0.0212	0.0976
At \bar{x}	-0.4921 (0.0108)	-0.0044 (0.0071)	0.4964 (0.0120)	-0.3868 (0.0205)	0.0112 (0.0107)	0.3755 (0.0217)
Proportion Positive	0.0000	0.4921	10.000	0.0000	0.7259	10.000
Log-likelihood		-8351.27			-7782.38	
N		11527			11527	
Richer Specification:						
Observed Distribution	0.5568	0.0530	0.3903	0.5568	0.0530	0.3903
Predicted Distribution	0.5587	0.0597	0.3816	0.5393	0.0643	0.3963
Marginal Effects:						
Mean	-0.3703	-0.0051	0.3754	-0.2536	0.0069	0.2467
Standard Deviation	0.0968	0.0203	0.0859	0.0936	0.0183	0.0841
At \bar{x}	-0.4293 (0.0176)	-0.0089 (0.0085)	0.4382 (0.0180)	-0.3255 (0.0254)	0.0022 (0.0118)	0.3233 (0.0264)
Proportion Positive	0.0000	0.4112	10.000	0.0000	0.6293	10.000
Log-likelihood		-8731.71			-8094.68	
N		12343			12343	
Multinomial Logit						
Basic Specification:						
Test IIA: P-value	0.5964	0.0067	0.5206	0.0709	0.0639	0.0017
Marginal Effects:						
At \bar{x}	-0.4955 (0.0117)	-0.0048 (0.0084)	0.5004 (0.0139)	-0.3901 (0.0182)	0.0105 (0.0115)	0.3796 (0.0203)
Richer Specification:						
Test IIA: P-value	0.2799	0.1404	0.3969	0.2998	0.2423	0.2021
Marginal Effects:						
At \bar{x}	-0.4333 (0.0158)	-0.0075 (0.0087)	0.4408 (0.0174)	-0.3295 (0.0217)	0.0036 (0.0112)	0.3259 (0.0232)

Notes: see Table 4a.

Table 5: Marginal Effect of a Father with Academic Secondary School degree on Enrolling in College Logit - Germany

	Without Tracks	With Tracks
Observed Distribution	0.2481	0.2481
Predicted Distribution	0.2136	0.1491
Marginal Effect at \bar{x}	0.3426 (0.1209)	0.1838 (0.1280)
Log-likelihood	-63.169	-45.280
N	129	129

Notes: Dependent variable=1 if enrolled in College at age 22. Academic secondary school degree is *Abitur*, i.e. completion of the German academic track (Gymnasium). The specification includes demographics (marital status, gender, immigration status), family background (father secondary school track), ability controls (grade in mathematics in Secondary School) and, in the appropriate specification, secondary school track completed using the Academic, Technical and Vocational definition.

7 Appendix

Table A.1 - Definition of variables in PISA sample

Definition	Variable Name
female	female
age (months)	age
foreign born	foreign
speaking dialect at home	dialect
combined score in mathematical test	combmath
combined score in reading test	combread
combined score in science test	combscie
combined score in problem solving test	combprob
slower than usual in completing grades	regular1
regular in completing grades	regular2
faster than usual in completing grades	regular 3
failed at least once	failed
highest parents completed primary	histedaggr1
highest parents completed secondary	histedaggr2
highest parents completed tertiary	histedaggr3
mother is highest	mhist
parents living together	intact
highest parents socio-economic status	hisei
mother currently housewife	housewife
less than 25 books at home	books1
between 25 and 200 books at home	books2
more than 200 books at home	books3
vocational school	type1
technical school	type2
high school	type3

Tab A.1a: Descriptive Statistics PISA sample - Italy

variable name	full sample		male		female	
	wgh.mean	sd	wgh.mean	sd	wgh.mean	sd
female	0.529	0.499				
age	15.707	0.285	15.699	0.283	15.714	0.287
foreign	0.025	0.157	0.025	0.155	0.026	0.158
dialect	0.154	0.361	0.190	0.392	0.122	0.327
combmath	469.438	89.860	481.162	94.093	459.014	84.575
combread	480.244	91.115	461.358	95.926	497.037	83.090
combscie	491.497	97.081	497.471	102.266	486.186	91.908
combprob	474.505	92.385	475.324	98.990	473.777	86.089
regular1	0.139	0.346	0.187	0.390	0.096	0.295
regular2	0.817	0.387	0.779	0.415	0.850	0.357
regular 3	0.044	0.206	0.034	0.182	0.053	0.225
failed	0.109	0.311	0.150	0.358	0.071	0.258
histedaggr1	0.284	0.451	0.268	0.443	0.299	0.458
histedaggr2	0.364	0.481	0.344	0.475	0.382	0.486
histedaggr3	0.352	0.477	0.388	0.487	0.319	0.466
mhist	0.233	0.423	0.241	0.428	0.226	0.418
intact	0.791	0.407	0.790	0.408	0.791	0.406
hisei	47.093	16.695	47.387	16.926	46.831	16.485
housewife	0.365	0.482	0.349	0.477	0.381	0.486
books1	0.247	0.431	0.265	0.442	0.231	0.422
books2	0.526	0.499	0.501	0.500	0.549	0.498
books3	0.213	0.409	0.217	0.412	0.210	0.407
type1	0.246	0.430	0.282	0.450	0.213	0.410
type2	0.346	0.476	0.415	0.493	0.284	0.451
type3	0.409	0.492	0.303	0.459	0.503	0.500
N	11181		5322		5859	

Table A.1.b - Descriptive Statistics PISA sample - Germany

variable name	full sample		male		female	
	wgh.mean	sd	wgh.mean	sd	wgh.mean	sd
female	0.517	0.500				
age	15.769	0.283	15.777	0.279	15.762	0.287
foreign	0.080	0.271	0.079	0.270	0.081	0.273
dialect	0.000	0.000	0.000	0.000	0.000	0.000
combmth	520.639	91.320	528.516	93.047	513.733	88.665
combread	512.201	91.839	493.870	94.774	529.689	85.358
combscie	522.689	96.135	529.274	98.336	517.124	93.173
combprob	528.354	85.206	527.696	87.817	529.371	82.272
regular1	0.135	0.342	0.157	0.364	0.115	0.319
regular2	0.612	0.487	0.618	0.486	0.280	0.449
regular 3	0.252	0.434	0.224	0.417	0.280	0.449
failed	0.126	0.332	0.138	0.345	0.114	0.318
histedagr1	0.135	0.342	0.144	0.351	0.127	0.333
histedagr2	0.437	0.496	0.408	0.492	0.465	0.499
histedagr3	0.428	0.495	0.449	0.497	0.408	0.492
mhist	0.172	0.377	0.179	0.383	0.165	0.371
intact	0.754	0.431	0.766	0.424	0.744	0.437
hisei	50.041	16.219	50.260	16.341	49.906	16.078
housewife	0.204	0.403	0.200	0.400	0.208	0.406
books1	0.176	0.381	0.195	0.396	0.156	0.363
books2	0.505	0.500	0.503	0.500	0.507	0.500
books3	0.311	0.463	0.293	0.455	0.329	0.470
type1	0.302	0.459	0.351	0.477	0.253	0.435
type2	0.359	0.480	0.350	0.477	0.370	0.483
type3	0.339	0.474	0.299	0.458	0.377	0.485
N	3840		1831		1974	

Table A2a: Choice of Secondary School Track: Complete Results - Male

	Italy				Germany			
	Basic (5517)		Richer (5322)		Basic (2018)		Richer (1831)	
	Log-lik= Coef.	-4761.34 Std. Err.	Log-lik= Coef.	-4152.97 Std. Err.	Log-lik= Coef.	-1545.99 Std. Err.	Log-lik= Coef.	-1268.07 Std. Err.
<i>Technical</i>								
age	0.073	0.171	0.015	0.180	-0.067	0.264	0.299	0.305
foreign			-0.741	0.322			0.836	0.328
dialect			-0.488	0.230				
combmath	0.012	0.002	0.006	0.002	0.013	0.002	0.003	0.003
combread			0.003	0.001			0.008	0.002
combscie			0.001	0.001			0.000	0.002
combprob			0.003	0.002			0.005	0.003
regular1			-0.366	0.649			0.476	0.373
regular2			-0.176	0.629			0.119	0.274
failed			-0.058	0.199			0.146	0.206
histedaggr2	0.132	0.151	-0.019	0.153	-0.196	0.216	-0.365	0.239
histedaggr3	0.435	0.174	0.255	0.168	-0.282	0.230	-0.863	0.263
mhist	0.160	0.133	0.063	0.138	-0.205	0.151	-0.396	0.170
intact			0.441	0.120			0.119	0.177
hisei			0.007	0.005			0.024	0.006
housewife			0.192	0.165			0.195	0.204
books2			-0.048	0.135			0.060	0.183
books3			0.037	0.182			0.755	0.250
constant	-6.550	2.823	-5.824	3.073	-4.888	4.174	-13.455	5.298
<i>Academic</i>								
age	0.349	0.221	0.268	0.249	-0.932	0.330	-0.403	0.455
foreign			-0.852	0.500			1.340	0.593
dialect			-0.882	0.278				
combmath	0.021	0.002	0.004	0.002	0.035	0.002	0.017	0.004
combread			0.008	0.002			0.022	0.003
combscie			0.002	0.002			0.000	0.003
combprob			0.008	0.002			0.004	0.005
regular1			-1.940	0.682			1.379	0.521
regular2			-0.768	0.611			0.502	0.339
failed			-0.111	0.337			-0.511	0.382
histedaggr2	1.190	0.215	0.495	0.239	0.110	0.339	0.069	0.421
histedaggr3	2.440	0.231	1.203	0.235	1.074	0.339	0.251	0.446
mhist	0.587	0.151	0.377	0.165	0.385	0.207	0.069	0.240
intact			0.569	0.195			0.245	0.224
hisei			0.046	0.006			0.052	0.007
housewife			0.367	0.192			0.311	0.277
books2			0.611	0.171			0.094	0.326
books3			0.927	0.232			1.054	0.374
constant	-17.226	3.682	-17.769	4.198	-5.287	5.056	-19.917	7.452

Notes: Estimates are from Multinomial Logit weighted by stratification weights reported by PISA. Standard errors robust to clusters at school level. For variables definition see Table A1. Normalization with respect to Vocational track.

Table A2b: Choice of Secondary School Track: Complete Results - Female

	Italy				Germany			
	Basic (5973)		Richer (5859)		Basic (2140)		Richer (1974)	
	Log-lik= Coef.	-5574.72 Std. Err.	Log-lik= Coef.	-5189.93 Std. Err.	Log-lik= Coef.	-1691.2 Std. Err.	Log-lik= Coef.	-1430.98 Std. Err.
<i>Technical</i>								
age	-0.033	0.248	-0.211	0.251	-0.350	0.261	-0.336	0.330
foreign			0.507	0.348			0.933	0.388
dialect			0.019	0.288				
combmath	0.007	0.002	0.003	0.002	0.011	0.002	0.004	0.003
combread			0.004	0.002			0.007	0.002
combscie			0.002	0.001			-0.001	0.003
combprob			0.000	0.002			0.004	0.003
regular1			-0.688	0.579			-0.014	0.378
regular2			-0.241	0.501			-0.211	0.241
failed			0.431	0.236			0.517	0.250
histedaggr2	0.200	0.160	0.427	0.149	0.100	0.187	-0.120	0.222
histedaggr3	0.206	0.190	0.540	0.192	0.420	0.206	-0.106	0.223
mhist	-0.109	0.156	0.089	0.164	0.145	0.171	0.063	0.196
intact			0.156	0.170			0.161	0.176
hisei			-0.002	0.006			0.017	0.005
housewife			0.504	0.173			0.066	0.196
books2			-0.349	0.143			0.264	0.198
books3			-0.672	0.238			0.560	0.267
constant	-2.214	3.794	-0.551	4.040	0.250	4.125	-2.047	5.528
<i>Academic</i>								
age	0.194	0.214	-0.005	0.220	-0.923	0.294	-0.044	0.462
foreign			0.079	0.454			1.367	0.453
dialect			-0.087	0.391				
combmath	0.011	0.002	0.002	0.002	0.031	0.002	0.017	0.003
combread			0.009	0.002			0.024	0.003
combscie			0.002	0.001			-0.003	0.003
combprob			-0.001	0.002			0.003	0.004
regular1			-1.414	0.542			1.550	0.514
regular2			-0.425	0.429			0.746	0.305
failed			0.381	0.273			-0.268	0.373
histedaggr2	0.981	0.167	0.780	0.148	0.718	0.310	0.313	0.355
histedaggr3	1.668	0.203	1.172	0.182	1.973	0.324	0.905	0.369
mhist	0.282	0.143	0.394	0.157	0.571	0.220	0.381	0.255
intact			0.095	0.159			0.315	0.228
hisei			0.016	0.006			0.047	0.008
housewife			0.402	0.168			-0.289	0.260
books2			0.247	0.175			-0.103	0.282
books3			0.493	0.258			0.324	0.346
constant	-8.169	3.296	-6.562	3.610	-2.509	4.627	-23.984	7.853

**Table A.3.a: Aspirations (intention to proceed further in education)
- Probit - Italy**

	males basic	males extended	females basic	females extended
age	0.001 [0.039]	-0.036 [0.041]	0.038 [0.028]	0.016 [0.029]
ability(mathematics)	0.001 [0.000]**	-0.001 [0.000]	0.001 [0.000]**	0 [0.000]
attending technical school	0.239 [0.038]**	0.22 [0.040]**	0.077 [0.035]*	0.077 [0.033]*
attending high school	0.667 [0.024]**	0.628 [0.029]**	0.465 [0.035]**	0.435 [0.035]**
highest education in the couple (secondary)	0.131 [0.035]**	0.073 [0.034]*	0.079 [0.020]**	0.02 [0.023]
highest education in the couple (tertiary)	0.222 [0.032]**	0.116 [0.035]**	0.158 [0.021]**	0.052 [0.027]
mother is highest in education	-0.062 [0.026]*	-0.045 [0.028]	-0.026 [0.020]	-0.002 [0.019]
foreign born		0.078 [0.068]		0.074 [0.060]
ability(reading)		0.001 [0.000]		0.001 [0.000]*
ability(science)		0.001 [0.000]**		0 [0.000]
ability(problem solving)		0 [0.000]		0 [0.000]
earlier in age of enrolment		-0.264 [0.074]**		-0.34 [0.071]**
regular in age of enrolment		-0.187 [0.060]**		-0.148 [0.032]**
failed		-0.042 [0.065]		0.016 [0.040]
intact family		-0.011 [0.029]		0.021 [0.023]
socio-economic index (highest in the couple)		0.003 [0.001]**		0.003 [0.001]**
26-200 books at home		0.051 [0.030]		0.086 [0.018]**
more than 200 books at home		0.166 [0.038]**		0.159 [0.020]**
Observations	5341	5168	5866	5759
PseudoR-squared	0.33	0.35	0.26	0.29
Loglikelihood	-2488.11	-2314.41	-2736.95	-2565.82

**Table A.3.b: Aspirations (intention to proceed further in education)
- Probit - Germany**

	males basic	males extended	females basic	females extended
age	0 [0.054]	0 [0.081]	0.074 [0.046]	0.028 [0.065]
ability(mathematics)	0.001 [0.000]	0 [0.001]	0.001 [0.000]**	-0.001 [0.000]
attending technical school	0.141 [0.058]*	0.083 [0.071]	-0.041 [0.073]	-0.086 [0.080]
attending high school	0.295 [0.057]**	0.23 [0.073]**	0.174 [0.068]*	0.123 [0.077]
highest education in the couple (secondary)	-0.033 [0.061]	-0.08 [0.074]	-0.021 [0.069]	0.042 [0.075]
highest education in the couple (tertiary)	0.161 [0.057]**	0.056 [0.074]	0.142 [0.072]*	0.139 [0.076]
mother is highest in education	-0.034 [0.034]	0.004 [0.039]	0.078 [0.041]	0.083 [0.041]*
foreign born		0.127 [0.080]		0.145 [0.065]*
ability(reading)		-0.001 [0.001]		-0.001 [0.000]*
ability(science)		0.004 [0.001]**		0.004 [0.001]**
ability(problem solving)		-0.002 [0.001]**		-0.001 [0.001]*
earlier in age of enrolment		0.048 [0.100]		-0.035 [0.078]
regular in age of enrolment		-0.015 [0.055]		-0.062 [0.044]
failed		-0.091 [0.065]		-0.028 [0.083]
intact family		-0.059 [0.042]		0.026 [0.034]
socio-economic index (highest in the couple)		0.001 [0.001]		0.002 [0.001]*
26-200 books at home		-0.012 [0.071]		-0.045 [0.055]
more than 200 books at home		0.088 [0.073]		-0.025 [0.055]
Observations	1094	1012	1356	1279
PseudoR-squared	0.11	0.16	0.12	0.17
Loglikelihood	-654.07	-575.97	-784.59	-699.73

Table A.4: Descriptive Statistics ISTAT Sample

	Mean	Std. Dev.
Vocational	0.386	0.487
Technical	0.443	0.497
Academic	0.171	0.376
Father Schooling:		
Compulsory or less	0.637	0.481
High School	0.299	0.458
College or more	0.063	0.244
Mother Schooling:		
Compulsory or less	0.679	0.467
High School	0.269	0.443
College or more	0.053	0.223
Lower Secondary grade:		
Sufficient	0.450	0.497
Good	0.276	0.447
Very Good	0.148	0.355
Excellent	0.126	0.332
Demographic		
Woman	0.535	0.499
NorthWest	0.227	0.419
NorthEast	0.154	0.360
Center	0.195	0.396
South	0.425	0.494
Single	0.969	0.173
#obs		20929

Table A.5: Impact of Parents Schooling on Post-Secondary Schooling: Complete Results from MNL

Specification:	Family, Ability, and Secondary School Track		Family and Ability	
	Coefficients	St. Error	Coefficients	St. Error
Dropped-out				
Vocational	0.4905	0.0710		
Academic	1.7014	0.1133		
fach2	0.3332	0.0742	0.4225	0.0736
fach3	0.6486	0.1674	0.9452	0.1629
mosch2	0.4992	0.0760	0.6076	0.0752
mosch3	0.7234	0.1820	1.0562	0.1773
good	0.2436	0.0714	0.3081	0.0703
very good	0.5385	0.0898	0.7635	0.0873
woman	0.0455	0.0631	0.1072	0.0626
NE	-0.1340	0.1085	-0.2052	0.1079
C	0.2356	0.0939	0.1878	0.0933
S	0.1558	0.0820	0.1614	0.0815
single	0.3720	0.1901	0.3888	0.1895
cons	-3.6517	0.2091	-3.4352	0.2058
Enrolled				
Vocational	1.0015	0.0419		
Academic	3.3093	0.0672		
fach2	0.4264	0.0426	0.6643	0.0384
fach3	1.1339	0.1002	1.8258	0.0883
mosch2	0.5021	0.0442	0.7726	0.0396
mosch3	1.0617	0.1099	1.7985	0.0970
good	0.1105	0.0415	0.1425	0.0378
very good	0.5616	0.0517	0.9794	0.0462
woman	0.3876	0.0366	0.5664	0.0334
NE	0.0196	0.0604	-0.1538	0.0543
C	0.1229	0.0564	0.0077	0.0506
S	0.2479	0.0472	0.1983	0.0425
single	1.2116	0.1352	1.3171	0.1277
cons	-3.6460	0.1460	-3.0571	0.1354
N	20,929		20,929	
Loglikelihood	-13,811.961		-15478.644	

Table A.6: Descriptive Statistics GSOEP Sample

Variable	Mean	Std. Dev.
college	0.2481	0.4336
single	0.9535	0.2114
woman	0.4651	0.5007
immigrant	0.0620	0.2421
fathtrackd1	0.2326	0.4241
fathtrackd2	0.2713	0.4464
fathtrackd3	0.4961	0.5019
grademathd1	0.1163	0.3218
grademathd2	0.3411	0.4759
grademathd3	0.4031	0.4924
grademathd4	0.1395	0.3479
trackd1	0.3488	0.4785
trackd2	0.4341	0.4976
trackd3	0.2171	0.4138
N	129	