# School tracking and equality of opportunity

## SUMMARY

*This paper investigates whether the interaction between family background and secondary school tracking affects human capital accumulation. A widely shared view is that more tracking reinforces the role of parental privilege, and thereby reduces equality of opportunities. This may occur for several reasons, including peer effects (more talented students are gathered together), teacher sorting (better teachers prefer teaching better students), differences in curricula (academic oriented schools – like the German gymnasium, the French lycée, the British grammar school or the Italian liceo – teach abilities that increase the probability of entering college) and/or differences in resource endowment. Compared to the current literature, which focuses on early outcomes, such as test scores at 13 and 15 years old, we look at later outcomes, including literacy, dropout rates, college enrolment, employability and earnings. While we do confirm the common view that school tracking reinforces the impact of family background when looking at educational attainment and labour market outcomes, we do not confirm the same results when studying its impact on literacy and on-the-job training. Overall school tracking has an ambiguous effect in our sample of countries. On the one hand, and consistently with the previous literature, tracking has a detrimental impact on educational attainment, because it prevents some individuals from further progressing to the tertiary level of education (the diversion effect). On the other hand, the curricula offered in vocational schools seem more effective in promoting further training and adult competences (the specialization effect), thereby reducing the impact of parental background on these two outcomes. Thus, reducing the extent of student tracking, either by raising the age of first selection or by reducing the number of tracks available, may be appropriate for increasing intergenerational mobility in educational attainment, but may increase social exclusion for people from disadvantaged backgrounds.*

*— Giorgio Brunello and Daniele Checchi*

Economic Policy October 2007 Printed in Great Britain

# Does school tracking affect equality of opportunity? New international evidence

Giorgio Brunello and Daniele Checchi

Università Padova, CESifo and IZA; Università Milano and IZA

## 1. INTRODUCTION

'Postponing the point in the educational career at which children enter different tracks and where educational decisions have to be made will improve the ability to anticipate future educational performance. The future to be anticipated is shorter and more experience with past educational performance is available to form respective expectations for the future. The working class should profit more from such measures because the upper classes will have better knowledge about educational requirements and more confidence to fulfil them from the beginning.' (Breen *et al.*, 2005, p. 9)

'vocational training is likely to be two-edged in its appeal, as both incentives and diversion effects are simultaneously apparent in our results. . . . On the one hand, vocational training

This paper was prepared for the October Panel Meeting of *Economic Policy* in Helsinki (October 2006). We are grateful to the participants at the Turin conference on 'Institutional Configuration, Schooling Choices, Labor and Financial Markets' and at the 2nd CSEF-IGIER Symposium on 'Economics and Institutions' for comments. We would like to thank our discussants Christian Gollier and Omar Moav, one anonymous referee, Andreas Ammermüller, Gabriele Ballarino, Giuseppe Bertola, Norberto Bottani, Bruno Losito, Lorenzo Rocco and Fabian Waldinger for helpful comments, and Ludger Wößmann for a useful discussion. Virginia Maestri provided competent research assistantship. This paper was prepared during visits at IZA-Bonn (Daniele Checchi) and Collegio Carlo Alberto in Moncalieri (Giorgio Brunello), which provided generous hospitality. The usual disclaimer applies.

The Managing Editor in charge of this paper was Paul Seabright.

Economic Policy October 2007 pp. 781–861 Printed in Great Britain

> might contribute to increased training participation among those who would otherwise not continue into upper secondary education. On the other, young people in vocational training are less likely to invest any more in education and training than those in more general tracks.' (Gangl *et al.*, 2003, p. 296)

> 'the model of comprehensive schooling that grew up in the 1960s and 1970s is simply inadequate for today's needs . . . the keys are diversity not uniformity'. (Morris quoted in Gorard and Smith, 2004, p. 17)

The quotes from the eminent social scientists reported above summarize well the views on school tracking that have emerged after two decades of studies in the sociology of education.[1] A key concept developed in this literature is school stratification, an obstacle to educational achievement because it introduces fictitious barriers to further education and reinforces the intergenerational persistence in educational achievement across different social classes (Mare, 1981).

Tracking can induce school stratification. A school system is characterized by tracking when pupils are allocated, at some stage of their career between primary and tertiary school, to different tracks, which usually differ in the curriculum offered as well as in the average cognitive talent of enrolled students. While in the North-American context tracking is mainly ability grouping or streaming within a fully comprehensive schooling structure, in the European context tracking takes the form of well-defined separate segments in the education process, typically specializing in general and vocational education. Insofar that allocation to tracks is non-random, school tracking introduces selection in the schooling process, which may take several forms, ranging from self-selection to admission based on a test or on teachers' recommendations. In most cases, selection is affected, directly or indirectly, by family background. For instance, better-educated parents are more likely to enrol their offspring in a general track, which leads more naturally to university. On the other hand, blue-collar families may enrol an equally talented child in a more vocational curriculum. Even when the allocation is based on a formal test, pupils from better-educated families are more likely to enter the academic track, either because cognitive ability is in the genes or because it is the product of the environment.[2]

Concern about equality of opportunity in schools has been voiced also by economists. Hanushek and Wößmann (2006), Ammermüller (2005), and Schuetz *et al.* (2005), for instance, have recently investigated the role of family background in school systems characterized by tracking and have found that early tracking accentuates the

[1] While initial studies focused mainly on secondary education, recent literature extends the analysis to school stratification to the tertiary level (Arum *et al.*, 2004).

[2] There are additional dimensions along which students can be selected by ability. For instance, most European countries have introduced the possibility of having students repeat the same class if they are considered unfit for the next level (Goux and Maurin, 2006). The mere existence of final examinations can induce self-selection by ability (Dee and Jacob, 2006), which can be also generated by the presence of private schools, especially when the public sector provides uniform standards of education for everyone (Stiglitz, 1974), but recent empirical evidence on this is controversial (Vandenberghe and Robin, 2004).

impact of family background and increases the dispersion of student achievement.[3] This empirical literature relies on samples of students from international surveys, which measure literacy and numeracy at relatively early ages (13 or 15). This choice of data makes good sense when tracking effects concentrate around or shortly after the time of selection and remain stable afterwards. However, if these effects are either temporary or cumulate over time, then relatively early observation points could substantially over-estimate or under-estimate the overall impact of tracking on schooling and labour market outcomes.[4]

Since family background is a circumstance beyond individual control, its influence on school outcomes can affect equality of opportunity. For many, parental background is not itself open to policy influence in the short and medium run. The government can try to compensate poor background with publicly provided education, especially in the early stages of individual life. Another potential factor affecting schooling outcomes, which is potentially more amenable to policy influence, is school design. By school design we mean the institutional set-up that characterizes compulsory and post-compulsory education, starting from primary and ending with tertiary education. School design can affect outcomes directly, and can interact with parental background in determining individual choice. In this paper, we focus on school tracking as a key feature of school design.[5]

The policy question we ask in this paper is whether the influence of parental background on educational and labour market outcomes can be affected by the design of the schooling system, and in particular by school tracking. Suppose that comprehensive schooling can reduce the influence of family background on educational outcomes. Then government policy which aims at increasing equality before labour market entry should prefer this system to a system which tracks students into different schools. The wave of comprehensive school reforms which have taken place in Europe since the early 1960s – first in the UK and Italy, then in Scandinavia and most recently in Spain – was apparently motivated by the need to reduce the influence of privilege in schools.

It is not at all obvious, however, that more comprehensive education also fosters efficiency. On the contrary, there could be an equity–efficiency trade-off. One potential merit of tracking is to group pupils into more homogeneous classes, and any teacher knows that her job is much more effective in such an environment. Grouping by ability can foster specialization, and the use of differentiated curricula. Specialization with tracking can be further enhanced by the presence of non-linear peer effects

[3] This could be due to the fact that parental voice is more important for younger students.

[4] Since learning begets learning, initial differences in individual achievement at school due to parental education are likely to widen over time, as documented in a number of papers by Heckman and associates (see, for instance, Carneiro and Heckman, 2003).

[5] We recognize that school design has many other features, including grade repetition, the creation of magnet schools, the development of a private schooling sector and curricula differentiation.

or teacher quality effects, which increase average performance (see Minter-Hoxby, 2000). The relative advantages of specialization could even suggest that it is efficient to track as early as possible. This is not necessarily the case, however. One reason is that the allocation of pupils to tracks is far from noiseless, and that the size of the noise is likely to increase the earlier the allocation occurs (see Brunello *et al.*, 2004; Dustmann, 2004). Therefore, tracking too early could be costly in terms of misallocation of students to tracks. Another reason is that early specialization can reduce versatility: in a rapidly changing economy, lack of versatility in the production of skills can generate relevant economic losses, especially if the labour market has frictions which generate misallocation of workers to jobs (see Ariga *et al.*, 2006).

In summary, optimal school tracking depends both on school and on labour market frictions, and the evaluation of the efficiency costs of deviating from optimality because of concerns with equality of opportunity needs to take these frictions into account. We are aware that an important aspect of a study of the implications of school tracking on equality of opportunity is the exploration of the efficiency versus equity trade-off. As discussed more in detail below, however, the nature of the data at hand do not allow us to pursue this important aspect, and we shall focus hereafter on equality of opportunity.

We are not the first to investigate whether and how school design affects the relationship between parental background and educational outcomes. Our research differs from previous work in two key aspects. First, we study a broad range of individual outcomes that goes beyond early standardized test scores and includes educational attainment, earnings, employment and the literacy of young adults. Depending on the data at hand, we look at individuals in their late teens and early twenties, and compare them with older workers. Our selection of individual outcomes relies on the idea that, if school tracking and family background matter, their effects should unravel more fully at the end of secondary school or in early labour market outcomes than shortly after tracking starts. This strategy follows Card and Krueger (1992), who study the impact of school quality on earnings rather than on test scores, as done for instance by Hanushek (1986).

Second, we add to the standard measures of school tracking – such as the time spent in a tracked school, the age of first selection or the number of available tracks – an additional measure, the share of students enrolled in vocational schools, which captures the presence of asymmetries in the impact of average student ability in the class/track on individual human capital accumulation. Such impact can have several sources, including peer effects, teacher quality, school resources and curricula, and can vary with the selected school track.

We find that the interaction of school tracking with parental background in the determination of educational and labour market outcomes is complex. Whenever tracking reinforces the family background effect, it contributes to reducing intergenerational mobility in educational attainment and fosters inequality. On the one hand, we find that reinforcement occurs both for educational attainment and for the earnings of young adults. On the other hand, there is also evidence that school tracking reduces the impact of parental background on literacy and training. How do we reconcile these findings? Suppose that the earnings of young adults combine the effects of formal education, education on the job (training) and skill development both at school and in the job (literacy). Suppose also that non-cognitive skills matter in the wage generating function. Then the reinforcing effects of tracking on the family background effect on earnings combine the reinforcing effects on formal education and the weakening effects on learning on the job and in the market. Our results suggest that the net outcome of this combination is positive, and that the effects on educational attainment matter the most. By producing specialized skills, early tracking could reduce the influence of privilege on the assignment to training, because of the complementarity between vocational schooling and apprenticeships, and on the development of real skills, such as reading. By reducing the opportunities to enter college, however, tracking may exacerbate the influence of privilege on the highest level of educational attainment, and on high paying college jobs.

The paper is organized as follows. In Section 2 we review the existing literature in the economics of education, which studies tracking and its interactions with parental background. In Section 3 we present a verbal discussion of the theoretical models discussed more in detail in Appendix 1. Section 4 and Section 5 introduce the econometric strategy and the data. Section 6 presents the results. The policy implications are discussed in the final Section 7.

## 2. PREVIOUS RESEARCH

When reviewing the literature on the relationship between school tracking, family background and school outcomes, one needs to recognize that the word 'tracking' means something rather different in Europe and the United States. In Europe tracking refers to the presence of differentiated curricula, usually with an academic and a vocational emphasis, and students are assigned or self-sort into schools that specialize in each curriculum. In the United States, tracking corresponds to ability streaming within a comprehensive school system, open to all American students.

The empirical literature to date on the relationship between school tracking, family background and the production of human capital covers both country specific case studies and cross-country analysis. We briefly review some of these studies in the subsections below. Broadly, the empirical evidence based on country studies does not reject the idea that early tracking reinforces intergenerational persistence in educational attainment. Cross-country analysis also tends to conclude that tracking boosts educational inequality by strengthening the importance of parental background effects. The effects on average school performance appear to be less clear-cut. Overall, the message from this literature is that early school tracking is bad for equal opportunity, because it reinforces the role of household privilege in the quality and quantity of accumulated human capital.

Empirical research on the implications of school tracking is often bogged down by the lack of adequate data. The ideal dataset that any scholar would be eager to have consists of nationally representative longitudinal samples, collected over a sufficient number of countries and sufficiently long over time to guarantee an adequate number of educational reforms, possibly taking place at different dates. Needless to say, this dataset does not exist, and researchers have to compromise in some way or another. Typically, the studies in this area combine data from different surveys and pursue a difference-in-difference approach. They usually ignore temporal variation, since parental background and student information are collapsed for each country in a single snap-shot.

The papers by Schuetz *et al.* (2005) and Waldinger (2006) are the closest to ours in that they also ask whether cross-country variations in school design can explain the observed cross-country variation in the importance of parental background for schooling outcomes, typically measured by standardized test scores. Because of this, it is useful to consider these papers in some more depth.

Schuetz *et al.* (2005) use as a measure of schooling outcome the test scores of 13-year-old pupils in over 50 countries and investigate whether this measure is significantly affected by the interaction of family background, the number of books available at home, with an indicator of school design, the first age of selection into school tracking, conditional on a set of country dummies and on a number of possible confounding factors. They find that early tracking increases the impact of family background on test scores and exacerbate inequalities.

Waldinger (2006) focuses on the test scores of 15-year-olds and uses a difference-in-difference approach, which consists of comparing outcomes for the treatment group, the 15-year-old students tested in the Programme for International Student Assessment (PISA) experiment, and the control group, the primary school pupils involved in the PIRLS (Progress in International Reading Literacy Study) tests. He finds no evidence that the interaction between school design and family background affects individual outcomes.

While we consider both papers as very valuable contributions to this literature, looking at their potential drawbacks is useful to clarify where the empirical contribution of this paper lies. Both papers focus on the impact of school design on test scores. While this is interesting, it might be somewhat limited when the issue at hand is whether secondary school design affects schooling outcomes. The sample used by Schuetz and co-authors cover the very young 13-year-olds, who have still to start upper secondary education in most countries. With the exception of the countries with a very early tracking system (Germany, Austria, Hungary, Turkey, Czech Republic), tracking usually starts somewhat later, at 14 or 15. Similarly, the PISA sample used by Waldinger covers 15-year-olds, who are in many countries only at the start of a tracking system. By choosing relatively early outcomes, both papers run the risk of not giving tracking enough time to work out its effects. One way to check this is to look at later outcomes, such as for instance completion of secondary school or college.

These papers have also in common the fact that they exploit exclusively the cross-section variation in schooling institutions. This is *prima facie* reasonable, because these institutions vary slowly over time, and necessary with their cross-sectional data. However, the introduction of time variation would help in identifying the effects of schooling institutions on the outcome of interest. This could be done by considering in each country different cohorts of individuals, who have been exposed to school in different periods of time.

## 2.1. Country case studies

**2.1.1. Scandinavia.** Sweden introduced an educational reform in the 1950s, which increased compulsory education age, abolished selection by ability at age 12 and adopted a unified curriculum. Meghir and Palme (2004) use the fact that the reform was gradually implemented across municipalities, adopt a difference-in-difference methodology for two cohorts, control for ability and family background, and show that the reform increased educational attainment and wages for the treated.

A similar reform introduced in Finland in 1972–73 is analysed by Pekkarinen *et al.* (2006). The age when tracking first occurs was shifted in Finland from 10 to 16 and the curriculum was unified. As for Sweden, the gradual introduction of the reform across municipalities allows the authors to use a difference-in-difference approach and estimate the degree of intergenerational mobility in male earnings. They find a significant decline in the autocorrelation coefficient. Since earnings and educational attainment are positively correlated, we interpret this finding as supportive of the view that the educational reform reduced the impact of parental background on educational attainment.[6]

While Norway was already a late tracking country, it extended compulsory education by two years (from 7 to 9) during the 1970s, and unified the curriculum up to that point. Black *et al.* (2005) show that this reform was associated with an increase in educational attainment in the parent generation, but are silent on the potential link in the educational attainment of father and child.

**2.1.2. Germany.** Schnepf (2002) uses data from TIMMS (Trends in International Mathematics and Science Study) 1995 and PISA 2000 to show that the early selection of German boys and girls into different tracks may be responsible for the lower average attainment and the larger variance recorded by Germany in these surveys. She shows that, although ability (proxied by test score) is a key allocation criterion in the tripartite system, educational achievement varies greatly within each school track.

[6] In a related paper, Pekkarinen (2005) explores the impact of the same reform on the gender gap in educational attainment, and finds that postponement of the tracking age increased gender differences in the probability of choosing the academic secondary education and continuing into academic tertiary education. The reform had particularly negative effects on boys with a non-academic family background.

Dustmann (2004) uses the panel component of the German Socio-Economic panel to investigate the correlation between secondary school choice and parental background (father and mother education and occupation). He estimates an ordered probit model for the type of secondary school completed,[7] and shows that the type of school attended affects the entry wage. He also shows that early selection (currently at the age of 10) could generate a poor allocation of talents.

**2.1.3. Great Britain.** Galindo-Rueda and Vignoles (2004) study the gradual transformation of British selective schools into a comprehensive system[8] and document both the increasing role played by parental background in student outcomes, and the decline in the returns to ability. Using the National Child Development Survey, which has information on cognitive ability at ages 7 and 11, and the uneven implementation of the reform across areas, they conclude that comprehensive schools have reduced the school performance of talented students, without substantial changes in the performance of low/middle ability students. According to their study, the desegregation of English secondary schools has reduced the dispersion of educational achievement in the population of students.[9]

Their results have been questioned by Manning and Pischke (2006) on the basis of the pre-existing differences between LEAs that quickly shifted to the comprehensive school system, and LEAs that resisted the reform, the former being systematically poorer and populated by children with lower previous achievement. These authors conclude rather sceptically that we know very little about the effect of comprehensive schooling in Britain.

**2.1.4. Northern Ireland.** Maurin and Macnally (2006) examine the effect of a reform of admission criteria in grammar schools taking place at the end of the 1980s. Forcing elite schools to adopt a less selective policy creates three types of effects: the effect on individuals who otherwise would have not attended a grammar school (the treated); a lowering of the peer quality in elite schools; a similar lowering of the peer quality in non-elite schools. They find a net benefit of widening the access to selective institutions, when measured by the fraction of population attaining qualifications necessary to enrol university. However, they do not evaluate the cost for people attending non-elite institutions (for example, drop-out rates).

[7] Dustmann (2004) follows the standard classification, which divides schools into secondary general schools (*Hauptschule*), intermediate schools (*Realschule*), and high schools (*Gymnasium*). In some *Länder* (Berlin is a good example) comprehensive schools (*Gesamtschule*) are important, see the discussion in Schnepf (2002). A similar tripartite system (secondary modern school, technical school, and grammar school) existed in the early postwar period in the UK (see below).

[8] Until the mid 1960s England and Wales were characterized by a tripartite system consisting of college-oriented 'grammar' schools, 'secondary modern' schools and a small and declining number of 'technical' schools. Students were selected into different tracks at the age of 11. The system was gradually reformed during the 1970s.

[9] Sorting by ability has not completely disappeared, especially after the quasi-market reforms introduced in the 1980s, which increased school incentives to attract good students. See the discussion in Noden (2000) and the references therein. Whether England secondary schools can currently be considered a two-tier system *de facto* is discussed in Taylor *et al.* (2005).

**2.1.5. Switzerland.** Bauer and Riphahn (2006) use cantonal variations in the age of tracking interacted with parental education to show that late tracking reduces the relative advantage of privileged children, thus supporting the findings by Dustmann (2004) for Germany.

**2.1.6. The Netherlands.** Oosterbeek and Webbink (2004) investigate the 1975 reform in the Netherlands, which simultaneously increased compulsory education and the length of vocational programmes. While track allocation was formally unaltered, there was a partial de-tracking of schools, because the reform reduced the curricular differences among tracks. The authors find that individuals attending lower vocational programmes did not benefit in terms of better earnings from additional general education.

**2.1.7. Italy.** Students' allocation to different tracks is studied by Checchi and Flabbi (2007), who compare Italy and Germany using the PISA 2003 dataset.[10] These authors argue that, due to the lack of binding restrictions in the access to academic tracks in Italy (contrary to what applies in some German *Länder*), sorting in the former country is driven relatively more by family background (parental education and occupation, books at home) than by ability (test scores, grade repetition, previous marks).

**2.1.8. United States.** A milestone in US research on school tracking is Jeannie Oakes's deeply influential *Keeping Track: How Schools Structure Inequality*, where she provided empirical evidence of the disadvantages endured by students placed in lower tracks. In a similar vein, she revealed that some schools, under orders to desegregate, were promoting internal segregation by disproportionately assigning minority students to lower tracks (see also Oakes, 1992). Overall, Oakes characterized tracking as an elitist practice that perpetuated the status quo by giving students from privileged families greater access to elite colleges and high-income careers. In contrast to this view, Figlio and Page (2002) provide evidence that low achievers may actually benefit from the availability of tracked schools.[11]

## 2.2. Cross-country analysis

Vandenberghe (2006) uses the test scores of 15-year-old students in PISA 2000 and asks whether alternative measures of school stratification (extent of tracking – measured by the percentage of pupils attending vocational and pre-vocational

[10] Upper secondary schools in Italy include vocational (*istituti professionali*), technical (*istituti tecnici*) and academic oriented high schools (*licei*). Differently from Germany, all tracks allow access to university, but transition rates to college varies significantly by track.

[11] Similar results are obtained by Betts and Shkolnik (2000).

programmes; repetition – measured by the percentage of students attending a grade inferior to the modal grade; within school segregation – measured by the standard deviation of school mean scores) affect either the mean or the dispersion of test scores. He concludes that the only measure slightly affecting dispersion is within school segregation.

School segregation is also the focus of the studies conducted by Gorard and Smith (2004) and by Jenkins *et al.* (2006). The first paper is based on PISA 2000 and provides different measures of school dissimilarity indices for 15 EU countries.[12] The second paper extends the analysis to all the countries included in PISA 2000 and PISA 2003. They explore the decomposition of the dissimilarity index in order to account for the differences in segregation that may be attributed to the public/private divide and to the existing degree of parental choice.

Entorf and Lauk (2006) also use PISA data and consider a specific form of social exclusion related to the status of migrant (defined as child of foreign-born parents). They study the group specific peer effect among sub-groups of natives and migrants, and also the spill-over effect among groups (the so-called 'social multiplier'), and find that in early tracking countries (Austria and Germany) group-specific peer effects are stronger than in comprehensive school countries (Scandinavia).[13]

Hanushek and Wößmann (2006), combine six surveys (TIMMS 1995, 1999, 2003; PISA 2000 and 2003; PIRLS 2001) so as to have two observations by country, one before tracking takes place (fourth grade) and the other after it has taken place in countries with early tracking (eighth grade).[14] They measure tracking with a dummy equal to 1 when tracking takes place before or after the eighth grade, and to zero otherwise. After controlling for initial conditions, they find no evidence that tracking affects average performance, and evidence that it increases the dispersion in test scores. They also show that low-performing students are those who are most damaged by early tracking.

Ammermüller (2005) considers four potential sources of inequality in student performance: the number of school tracks available at ninth grade, annual instruction time, the share of students in private schooling and school autonomy (only available for cross-section analysis in PISA). By combining data from two surveys (PISA and PIRLS) he studies whether the correlation between student performance and parental

[12] They compute segregation indices (defined as the 'proportion of disadvantaged students – bottom 10% of the distribution – who would have to exchange schools within the area of the analysis, for there to be an even distribution of this group among the population'), dissimilarity indices and Gini indices by sex, parental occupation, foreign origin and ability. The indices are pairwise highly correlated and give an almost identical ranking of countries; early tracking countries, such as Germany or Belgium, turn out to be among the most segregating educational systems in their sample, while Nordic countries are the least segregated (due to their catchment policy).

[13] They interpret their results in a causal way after showing that the estimated coefficients on peer effects do not change significantly when they exclude the schools where the head of school declares that selection on ability is used for applicants.

[14] The comparability of different surveys (as if they were random draws from the same distribution) is the implicit assumption of this and the following papers (see Fertig, 2004). A comparison of central moments between PISA, PIRLS, TIMMS and IALS suggest that all these surveys give a similar picture in terms of country ranking: see Brown *et al.* (2005).

background (proxied by parental education and social prestige, books available at home and language spoken at home) is affected by one or more measures of school stratification. He finds that the number of tracks has increased inequality since 'the choice of schools seems to benefit socially advantaged students, who have easier access to better schools. This also holds for the size of the private school sector, which is positively linked to the effect of books at home' (Ammermüller, 2005, p. 25).

Analogous conclusions are reached by Schuetz *et al.* (2005). They use data from TIMMS and TIMMS-Repeat to provide an estimate of inequality of opportunity based on the correlation between parental education (proxied by the number of books at home) and student achievement. This measure is correlated with schooling institutions, including the age of first tracking, the duration of pre-primary school and the enrolment in pre-primary education (the latter variable exhibiting an inverted U-shape relationship). Their main results confirm the predictions of their theoretical model:

> 'There is a negative relationship of the FBE [family background effect] with age of first tracking and preschool duration, and an inverted U-shaped relationship between FBE and pre-school enrolment. In the country-level model . . . these features of the education system can together account for 40 percent of the cross-country variation in our estimated FBEs.' (Schuetz *et al.*, 2005, p. 24)

These results have been challenged by Waldinger (2006), who questions the causal link between the selected measure of tracking, parental background and student outcomes. His main argument is that even in comprehensive systems with family choice there may be a spontaneous tendency to self-select according to ability or family background (through residential segregation, use of private sector, choice of subjects). He applies a difference-in-difference approach using PISA 2000, PIRLS 2001, TIMMS 1995 and 1998 surveys, and finds no significant effect of tracking on the relationship between parental background and school outcomes.

### 2.3. Our contribution

Our investigation of the relationship between schooling institutions, parental background and educational outcomes innovates with respect to the previous literature in three directions. First, we look at a much broader list of indicators of school performance, well beyond the standardized test scores taken early on in schooling life. This list includes educational attainment, enrolment in college and literacy, which pertain directly to school outcomes, and also more indirect indicators, which measure early labour market performance, such as employment, training and wages.

Second, we introduce time variation by looking at two different cohorts of individuals, who have been at school at some distance from each other. For each cohort, we have data on schooling outcomes, family background, and schooling institutions, which we reconstruct by going back two decades (mid 1980s and mid

1990s). We believe that by so doing we add to the cross-country variation some genuine temporal variation, which obviously relies on the variation of schooling institutions over time. We are also aware that by so doing we face an important trade-off. If we want to maximize the number of countries, then we should proceed as Schuetz and co-authors (2005), and focus on the standardized test scores of 13- or 15-year-old students. If we want to look at schooling outcomes later on in life, then the number of countries with available data falls dramatically by half, from close to 50 to close to 25. To this we can partially remedy by adding genuine time variation.

Third, we develop theoretical models which justify the inclusion of two indicators of school tracking, the length of time spent in tracked schools and the percentage of students enrolled in vocational tracks. While the former indicator has been used previously, the latter indicator has been ignored, but has potentially interesting implications for the presence – or absence – of non-linear effects running from average student ability in the class or track to individual student performance, which could be driven either by peer effects or by teacher quality or by differences in the curriculum.

## 3. THEORETICAL INSIGHTS

As recently summarized by Manning and Pischke (2006) 'at a theoretical level, there are good arguments for selection as well as for comprehensive education. The main argument for selection or tracking is presumably that it is much easier to teach lower variance classes. Since teachers can focus on the ability level of particular groups of students, students of all ability levels might benefit from selection' (p. 3).

Another argument is peer effects. These effects occur when average student ability in the selected class or track positively affects the production of individual human capital. If peer effects are linear, moving a talented student from the vocational to the academic track reduces human capital in the former track by the same amount as the increase of human capital in the latter track. In this case, average output is unchanged. Peer effects increase efficiency only if they are non-linear and students in the academic track benefit from their better peers more than the amount that students in the vocational track lose from their less talented peers.[15] Quoting Minter-Hoxby and Weingarth (2005) 'if peer effects were linear in means, then regardless of how peers were arranged, society would have the same average level of outcome . . . Moreover, most applications of peer effects . . . need to have non-linear peer effects to generate results that are interesting and that mimic the facts' (p. 3).

There is no consensus in the empirical literature on the existence and/or size of peer group effects. The US evidence to date is mixed, with several studies finding weak or non-existent peer effects. Recent work, including Minter-Hoxby (2000) and

[15] We also need that individual abilities are substitutes in the educational production function (see Appendix 1).

Sacerdote (2001), find evidence of positive peer effects. In a recent study employing Chinese data, Ding and Lehrer (2006), find not only that peer effects exist, but also they are highly non-linear. Using European data, Ammermüller and Pischke (2006) find significant peer effects in the primary school classes of six European countries, even after taking into account self-selection based on family background and measurement errors.[16]

While peer effects may have an important role to play, we hasten to stress that average student ability in the selected class/track can affect individual school performance independently of peer effects. Consider, for instance, teacher quality, and suppose that teachers prefer to teach relatively high ability classes. Assume further that better teachers have priority in the allocation to classes, and that there are no peer effects. Then teacher quality is higher in classes with higher average student ability, but the positive effect of the latter on individual school performance is due to better teachers, not to peer effects. Alternatively, curricula may differ across tracks. When students are assigned to advanced, regular, or basic courses depending on their past performance, as it happens in the United States, students in the advanced tracks may take more advanced material. In this case, the higher average student ability in the class affects individual performance not via peer effects but because of differences in curricula.

Finally, school resources could be higher in academic than in vocational tracks, and this can justify differences in school performance. Using data from the OECD and the UNESCO databases, we have computed for the year 2004 the pupil–teacher ratio in the upper secondary general and vocational schools of four countries with relatively early tracking systems – Germany, Austria, France and Italy. The starkest difference is in Germany, with 11.89 students per teacher in the general track and 21.25 students per teacher in the vocational track. The difference is relatively large in Austria, with ratios equal to 9.05 versus 14.51,[17] and France, with ratios equal to 6.75 and 14.67, but small in Italy (11.17 versus 11.94). These data suggest that academic tracks, which typically attract the students with higher cognitive talents, have also better resources, at least in terms of the number of students per teacher.

The relative variance of student ability differs between tracked and comprehensive schools, and is lower within each track – where selection by ability takes place to some extent – than in classes where ability types are mixed. Following Manning and Pischke, we posit that teaching efficiency is higher in classes with lower ability

[16] Schneeweis and Winter-Ebmer (2005), study the existence of peer effects in the Austrian sample of the PISA 2000 survey, and find a positive contribution of the peer socio-economic background at school level, especially for low-ability students. In the same vein, Goux and Maurin (2006) identify neighbourhood effects produced by teenagers living in close proximity, and find that these effects influence significantly the probability of grade repetition at the end of junior high school.

[17] Notice, however, that in the case of Austria, the total cost of a student in the academic track is €7.300 in 1999, while the corresponding cost for a student in vocational tracks varies between €7.340 and €14.920 per year, depending on the type of schools (data made available to us from Rudolf Winter-Ebmer – source: Bundesrechnungsabschlüsse, Statistik Austria, BMSG, BMBWK (Schulstatistischen Informationssystem); Berechnungen: IHS in: Lorenz Lassnigg, Peter M. Steiner, Angela Wroblewski, Kosten-Nutzen-Analyse des Bildungssystems, Institut für Höhere Studien (IHS), 2001.

variance, and call it 'the specialization effect'. We show in Appendix 1 that such effect is important not only for efficiency but also for equity, because it influences the relationship between school tracking and the impact of parental background on school and labour market outcomes, which we call the family background effect (FBE), in line with Schuetz and co-authors.

The first model presented in Appendix 1 sets the preliminary stage and in the spirit of Benabou (1996) shows that whether ability types are complements or substitutes in the production of the peer effect is relevant both for average human capital and for the impact of tracking on the FBE. The second model draws from previous work by Brunello *et al.* (2004) and is described at some length in this section – the interested reader can find the technical details in Appendix 1. We consider a schooling system ranging from primary to upper secondary education – college can be fitted in at some additional cost. Depending on the schooling institutions in place, at some stage schools are separated into two tracks, a general and a vocational track. Define tracking length as the percentage of total schooling time spent in a track. The allocation of pupils to tracks depends on a mixture of parental choice, ability testing and recommendation by teachers. A key tenet in this literature is that parental background affects individual ability both directly – because ability is partly in the genes – and indirectly, because households with 'good' parental background are more likely to provide a better environment for the development of talent in the early stages of individual life, and consequently to have their offspring admitted to the general track, which is expected to provide better education. If the children of less privileged households are more likely to end up in vocational tracks, and the quality of the education offered by these tracks is lower than in general tracks, then the gap in schooling performance between these pupils and the pupils of more privileged households is going to increase the longer the time spent in each track.

We assume that individual human capital is produced by combining (a) individual ability; (b) average student ability in the track. The second factor affects individual human capital either via a peer effect, or via teacher quality, or finally because of differences in curricula. The academic track attracts more talented pupils and better teachers. Average student ability and average teacher quality are lower in the vocational track, which is also hampered by fewer resources, at least in terms of the pupil–teacher ratio.

We model parental background as a component of individual ability: the better the background, the higher individual talent. While this is a convenient short-cut, it captures well the important role played by household characteristics in the development of talent in the initial steps of life. We show that FBE depends on tracking length, the specialization effect and on eventual asymmetries in the impact of average student ability in each track on individual human capital. An additional factor affecting FBE is the share of individuals enrolled in the vocational and less prestigious track. The reason for the latter effect is that, while a good background is key for the allocation of the pupil to the academic track, such allocation depends also on the availability of slots. When only a few slots are available in the academic track, even students from privileged households end up in vocational tracks, where average student ability is lower.

The concern for equality of opportunity prompts the following questions: does family background matter more for schooling when tracking is longer? Our answer is that more tracking affects positively the FBE if it generates a specialization effect. Does family background matter less when the share of vocational students is higher? Yes when there are asymmetries in the effect of average student ability on individual school performance, and this effect is larger in the academic than in the vocational track.

Our interest for equality of opportunity in this paper does not imply that we believe that the relative efficiency of school tracking is an issue of second order of importance. If tracking has a positive specialization effect, which improves average school performance, de-tracking increases equity at the expense of efficiency. As anticipated in the introduction, the nature of this trade-off is affected by two factors: (a) misallocation of students to tracks; (b) labour market frictions. Both factors reduce the optimal tracking length and suggest that the efficiency costs of de-tracking schools could be smaller than the costs associated to deviations from optimal tracking when the labour market is perfectly competitive and individual ability can be measured without error.

The trade-off between equity and efficiency raises important questions on the efficiency costs of de-tracking schools. Unfortunately, the nature of our data does not allow us to study efficiency issues in a satisfactory way. To do so we would need measures of individual productivity *in the labour market* rather than at school. These measures are typically not available, and replacing them with earnings is not satisfactory when the labour market is not perfectly competitive. Another reason – which we discuss more at length in the empirical section of this paper – is that the identification of the efficiency effects of tracking is prevented in our data by the fact that our information on tracking varies only across countries and over time, as do many relevant confounding factors, including macroeconomic and institutional effects. Once we properly control for these confounding factors with country by time dummies, there is no room for the identification of the impact of school tracking on average performance at school or in the labour market.

### 3.1. Our measures of school tracking

The empirical literature, which has investigated how parental background and school design affect individual school performance, has used alternative indicators of school tracking. Hanushek and Wößmann (2006), for instance, measure tracking with the age at which tracking takes place. Since performance is measured at the same age (15 for PISA and 13 for TIMMS), the inclusion of the age of first selection in a cross-country set-up captures the length of time spent in a diversified system. Ammermüller

(2005) uses instead the number of tracks of a schooling system when the students are in secondary education. This measure fails to capture how many years a student spends in a track. Waldinger (2006) measures tracking with the minimum school grade at which a significant proportion of students are educated in different types of schools. He then defines an early tracking threshold, which indicates whether a country tracks students early or late.

Our theoretical model implies that the FBE on human capital is affected both by the extent of time spent by an (average) student in a tracked school, and by the share of students allocated to the vocational track. The latter variable matters only when the relationship between average student ability in the class/track and individual school performance varies with the track, signalling the presence of non-linear peer or teacher quality effects. We can think of other confounding variables, which can affect FBE. For instance, where schools are comprehensive, sorting may occur along different dimensions, such as the public-private divide. Family background could also interact with the resources invested in education, such as the share of public expenditure in education over GDP or the student-teacher ratio in secondary education. Following Schuetz *et al.* (2005) we also consider the percentage of the student population enrolled in pre-primary education, which in their model has a non-linear effect on the FBE.[18]

Table 1 reports our main indicators of tracking for the majority of OECD countries at three discrete points of time, 1985, 1995 and 2002 – details on the data sources are in Appendix 2. The age of first selection into tracks (first three columns) has remained unchanged over time in most countries, because the major comprehensive school reforms have taken place in the 1960s and 70s. Important exceptions are Spain, with the LOGSE (Ley de Ordenación General del Sistema Educafivo) reform of 1990, which delayed tracking from 14 to 16,[19] the Czech Republic, which anticipated it from 15 to 11 in the early 1990s by allowing pupils to complete compulsory education using either normal school or the gymnasium, and the Netherlands, which introduced in 1993 an additional year of compulsory education, thereby delaying the separation into tracks at age 13.

The second group of three columns reports the length of school tracking, which measures the percentage of time in primary and secondary school spent in a tracking regime, which ranges between zero and one.[20] Finally, the third group of three columns

[18] We have also collected data on other dimensions of student sorting, such as the age of the start and at the end of compulsory education, the share of students in tracked lower secondary schools, the repetition rate at the secondary level of education, the number of tracks available at secondary and tertiary level, the share of students in tertiary vocational education (ISCED 5-B), but the number of missing values and/or the high correlation with other selected variables have led us to exclude these additional variables from the empirical analysis.

[19] We are grateful to Laura Romero for helping us with the Spanish institutional set-up.

[20] This variable is constructed as the ratio of $(t - s)$, where $t$ is the age at the end of upper secondary education and $s$ is the age of first selection (column 1 to 3), to $(t - p)$, where $p$ is the age when primary education starts. One may object that $t$ varies across countries, and that we are not comparing countries on the same basis (as it would be if $t$ were set equal to 18 for all countries). However, the actual variation is limited, and in the mid 1990s the end of secondary school ranged from 17.5 (Ireland, the Netherlands and Russian Federation) to 19.5 (Denmark, Switzerland).

**Table 1. School design across countries**

| | Age of first selection into tracks mid 80s | Age of first selection into tracks mid 90s | Age of first selection into tracks 2002 | Percentage primary + secondary education in tracking mid 80s | Percentage primary + secondary education in tracking mid 90s | Percentage primary + secondary education in tracking 2002 | Share of students in upper secondary vocational mid 80s | Share of students in upper secondary vocational mid 90s | Share of students in upper secondary vocational 2002 |
|---|---|---|---|---|---|---|---|---|---|
| Australia | 16 | 16 | 16 | 0.167 | 0.167 | 0.154 | 0.306 | 0.648 | 0.630 |
| Austria | 10 | 10 | 10 | 0.680 | 0.680 | 0.667 | 0.754 | 0.774 | 0.723 |
| Belgium | 12 | 12 | 12 | 0.500 | 0.500 | 0.500 | 0.487 | 0.676 | 0.701 |
| Brazil | . | . | . | . | . | . | . | 0.408 | 0.140 |
| Bulgaria | 14 | 14 | 14 | 0.417 | 0.417 | 0.364 | . | . | . |
| Canada | 18 | 18 | 18 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.072 |
| Chile | 14 | 13 | 13 | 0.333 | 0.417 | 0.417 | . | 0.420 | 0.396 |
| Czech Republic | 15 | 11 | 11 | 0.250 | 0.615 | 0.615 | 0.540 | 0.844 | 0.802 |
| Denmark | 16 | 16 | 16 | 0.280 | 0.280 | 0.250 | 0.653 | 0.541 | 0.530 |
| Finland | 16 | 16 | 16 | 0.250 | 0.250 | 0.250 | 0.531 | 0.522 | 0.572 |
| France | 16 | 15 | 15 | 0.167 | 0.250 | 0.250 | 0.580 | 0.534 | 0.563 |
| Germany | 10 | 10 | 10 | 0.692 | 0.692 | 0.692 | 0.789 | 0.765 | 0.630 |
| Greece | 14.5 | 14.5 | 15 | 0.280 | 0.280 | 0.250 | 0.328 | 0.293 | 0.400 |
| Hong Kong (China) | . | . | . | . | . | . | . | 0.572 | 0.433 |
| Hungary | 10 | 10 | 11 | 0.667 | 0.667 | 0.667 | 0.757 | 0.731 | 0.269 |
| Iceland | . | . | 16 | . | . | 0.286 | . | 0.363 | 0.370 |
| Indonesia | . | . | . | . | . | . | . | 0.390 | 0.355 |
| Ireland | 12 | 12 | 15 | 0.478 | 0.478 | 0.182 | 0.245 | 0.208 | 0.237 |
| Israel | . | . | . | . | . | . | . | 0.462 | 0.348 |
| Italy | 14 | 14 | 14 | 0.385 | 0.385 | 0.385 | 0.680 | 0.724 | 0.268 |
| Japan | 15 | 15 | 15 | 0.280 | 0.250 | 0.250 | 0.293 | 0.277 | 0.249 |
| Korea | 14 | 14 | 14 | 0.429 | 0.429 | 0.333 | . | 0.432 | 0.321 |
| Latvia | 16 | 16 | 16 | 0.182 | 0.250 | 0.250 | . | . | . |
| Luxembourg | 12 | 12 | 13 | 0.538 | 0.538 | 0.462 | 0.644 | 0.640 | 0.640 |
| Macao (China) | . | . | . | . | . | . | . | 0.572 | 0.433 |
| Mexico | 12 | 12 | 12 | 0.500 | 0.500 | 0.455 | . | 0.174 | 0.114 |
| Netherlands | 12 | 13 | 13 | 0.440 | 0.360 | 0.500 | 0.521 | 0.704 | 0.692 |
| New Zealand | 18 | 18 | 16 | 0.000 | 0.000 | 0.154 | 0.215 | 0.380 | 0.372 |
| Norway | 16 | 16 | 16 | 0.250 | 0.231 | 0.167 | 0.567 | 0.552 | 0.580 |
| Poland | 15 | 15 | 15 | 0.360 | 0.360 | 0.385 | 0.746 | 0.703 | 0.609 |
| Portugal | 15 | 15 | 15 | 0.250 | 0.250 | 0.250 | 0.102 | 0.244 | 0.288 |
| Russian Federation | 15 | 15 | 15 | 0.273 | 0.238 | 0.217 | 0.436 | 0.419 | 0.329 |
| Slovakia | 10 | 10 | 11 | 0.667 | 0.692 | 0.615 | . | . | 0.764 |
| Slovenia | 15 | 15 | 15 | 0.333 | 0.308 | 0.333 | . | . | . |
| Spain | 14 | 16 | 16 | 0.360 | 0.167 | 0.167 | 0.416 | 0.398 | 0.380 |
| Sweden | 16 | 16 | 16 | 0.250 | 0.250 | 0.250 | 0.771 | 0.560 | 0.496 |
| Switzerland | 15.5 | 15.5 | 15 | 0.296 | 0.296 | 0.273 | 0.756 | 0.693 | 0.646 |
| Thailand | . | . | . | . | . | . | . | 0.280 | 0.240 |
| Tunisia | . | . | . | . | . | . | . | . | 0.041 |
| Turkey | 12 | 12 | 11 | 0.500 | 0.500 | 0.545 | 0.407 | 0.436 | 0.394 |
| United Kingdom | 16 | 16 | 16 | 0.154 | 0.154 | 0.154 | 0.443 | 0.579 | 0.721 |
| United States | 18 | 18 | 18 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Uruguay | . | . | . | . | . | . | . | 0.203 | 0.192 |

*Sources:* See Appendix 2.

shows the percentage of students enrolled in vocational upper secondary education, which ranges from 0 in the United States and Canada, where schools are entirely comprehensive,[21] to more than 70% in Austria and Germany.[22]

[21] However, ability streaming within comprehensive institutions is widespread in the US.

[22] We were forced to group together 'pre-vocational' and 'vocational' secondary school enrolment, because our OECD data source merged the two definitions into one around mid 1990s.

**Table 2. Pairwise correlation of school system indicators – mid 1980s and mid 1990s**

| | Share of students in tracked schools – secondary education | Share of students in upper secondary vocational education | Enrolment in pre-primary education | Share of upper secondary school students in private schools | Public expenditure in education over GDP | Student-teacher ratio in upper secondary school |
|---|---|---|---|---|---|---|
| Share of students in tracked schools – secondary education | 1.0000<br>*68* | | | | | |
| Share of students in upper secondary vocational education | 0.5900*<br>*57* | 1.0000<br>*66* | | | | |
| Enrolment in pre-primary education | 0.3699*<br>*57* | 0.4262*<br>*66* | 1.0000<br>*66* | | | |
| Share of upper secondary school students in private schools | 0.0590<br>*58* | −0.0640<br>*65* | −0.0653<br>*65* | 1.0000<br>*66* | | |
| Public expenditure in education over GDP | −0.1614<br>*56* | 0.2171<br>*55* | 0.3416*<br>*55* | −0.0815<br>*55* | 1.0000<br>*57* | |
| Student-teacher ratio in upper secondary schools | −0.1460<br>*50* | −0.1145<br>*50* | −0.2434<br>*50* | 0.1204<br>*50* | −0.2538<br>*49* | 1.0000<br>*52* |

*Notes:* Figures in italics report the number of observations.
* indicates statistical significance at 5%.

*Source:* See Appendix 2.

Table 2 reports pairwise correlations of our selected variables. On the one hand, time spent in tracked curricula is correlated with the share of students in the vocational track; on the other hand, both variables positively correlate with pre-primary enrolment. In addition, pre-primary schooling is positively correlated with public expenditure in education. Overall, the low level of correlation between these variables is reassuring that we are capturing different features of educational systems in the countries included in our sample.

## 3.2. Advantages and limits of our measures

There are two potential problems in our research strategy. The first is the classification of institutions. To the best of our knowledge, there is no official data source providing institutional information that is consistently comparable across countries and years.[23] Especially for the initial years in our sample – remember that we want

[23] Eurydice (www.eurydice.org) is a rich source of information on institutional details about educational systems, but unfortunately covers only European countries, and in some cases lacks retrospective information. The UNESCO World Higher Education Database (http://www.unesco.org/iau/onlinedatabases/index.html) has a larger country coverage, but it spans only 7 years. The well-known OECD publication *Education at a Glance* was started only in 1996, and is not very rich on institutional details.

information on educational systems to go back at least to the mid 1980s – we are forced to use paper sources, and to reconstruct institutional details either from country specific information or by visual inspection of charts, which describe different educational systems. The risk of measurement errors due to arbitrary classification is clearly high. The second problem is school participation data. In some cases, we have found different numbers for secondary school participation in different sources.[24] For reasons of comparability we have decided to stick to a unique data source, the OECD Education Database, which ensures the largest country/year coverage. However, the inspection of the data suggests that changes in definitions have occurred both between the first and the second period for a few countries (notably the definition of vocational education in Belgium in 1991 and Australia in 1993) and between the second and the third period for other countries (vocational education in Hungary in 1998 and in Italy in 2000). We believe that the net benefits in terms of comparability of using alternative national data sources rather than an international dataset are negative, especially since we always control in our regressions for country/year fixed effects. Therefore, our data on pre-primary education, vocational enrolment and private school participation are all extracted from the same OECD dataset.

## 4. THE ECONOMETRIC APPROACH

It is very difficult to evaluate the impact of changes in educational systems – most notably school reforms – on individual outcomes. As argued by Palme and Meghir (2005), these reforms are implemented nationally and often at once, which implies that one should rely on before and after comparisons that may confound the effects of policies with other country and cohort effects. We start from the baseline specification:

$$Y_{ijk} = \delta_{jk} + \alpha X_{ijk} + \beta_1 FB_{ijk} + \gamma FB_{ijk} T_{jk} + \varepsilon_{ijk} \quad (1)$$

where $Y$ is the outcome of interest, $\delta$ are dummies (country ($k$) × cohort ($j$)), $X$ is a vector of individual controls, $FB$ is the indicator of family background, and $T$ is the vector of school tracking indicators. This specification omits the direct effect of school tracking on individual outcomes, which are affected by a host of country by cohort confounding factors, such as macroeconomic effects. Since our school tracking indicators vary across country and over cohorts, we cannot hope with the data at hand to be able to tell apart the influence of tracking from the influence of country by cohort confounders. By focusing instead on the impact of schooling institutions on the slope of the relationship between $Y$ and $FB$, we reduce the bias attributable to omitted country-specific variables, the impact of which is captured by unrestricted

[24] For example, according to Eurostat the share of students in vocational secondary education in Belgium in 1985 is 64.8, while in the OECD database the same number is 48.7; similarly, corresponding figures for Greece are 28.3 and 32.8, for the Netherlands 66.1 and 52.1, and for Portugal 27.0 and 10.2.

country × cohort dummies.[25] The underlying idea is that the structure of schooling can alter the relationship between household characteristics and individual outcomes, or the FBE.

As discussed in the theoretical section of this paper, tracking can alter the FBE on individual school performance because of: (a) the positive relationship between average student ability in the track and individual school performance; (b) the specialization effect originated by the lower ability variance in tracked schools. The former relationship can be induced by peer effects, teacher quality effects, or by curriculum effects, but our empirical estimates do not pretend to distinguish between these alternative sources.

An important consequence of this empirical set-up is that our data are informative on the consequences of school tracking for equality of opportunity, but are not informative on the efficiency implications of tracking. Moreover, as remarked by Waldinger (2006), the inclusion of country × cohort dummies in our empirical specification does not preclude the possibility that the schooling indicator $T$ be correlated with unobserved country variables, and that these variables affect the relationship between $Y$ and $FB$. If this were the case, the estimate of $\gamma$, our parameter of interest, would be biased. Waldinger controls for these unobservables by using a difference-in-difference technique. We choose a different strategy, which exploits the variation across countries and over time in school tracking, and consists of adding to the set of explanatory variables the interaction of family background with potential confounding factors $C_{jk}$, as in Equation (2):

$$Y_{ijk} = \delta_{jk} + \alpha X_{ijk} + \beta_1 FB_{ijk} + \beta FB_{ijk} C_{jk} + \gamma FB_{ijk} T_{jk} + \varepsilon_{ijk} \tag{2}$$

and as done by Schuetz *et al.* (2005). Our confounding factors are enrolment in pre-primary schools, enrolment in private schools, the student–teacher ratio and public expenditure in education. All these factors have been found in the literature to be correlated with various measures of educational attainment.

Since the schooling indicator in Equation (2) is measured at the country by cohort rather than at the individual level, we allow the error term to be independent across countries and cohorts and interdependent within each combination of country and cohort. This means that we treat the standard errors as if there were only as many observations as there are combinations of countries and cohorts in the regression. Similarly, we abstract from survey specific weights (when available), and use weighed regressions, where weights are designed to give to each country in each wave the same weight.

We are aware that the estimated coefficients in (2) can be affected by the potential endogeneity of the regressors. In fact, let us decompose the error term in (2) as follows:

[25] A similar approach is discussed by Card and Krueger (1996a), in the literature of the impact of school quality, and more recently by Schuetz *et al.* (2005).

$$\varepsilon_{ijk} = u_i + u_{jk} + \eta_{ijk} \tag{3}$$

where the $u$ components are individual and country by cohort effects, and the residual $\eta$ is assumed to be orthogonal to the regressors in (2). Consider first the individual effect. As discussed by Card and Krueger (1996b), such effect could capture unobserved individual ability, which is correlated both with individual outcomes and with parental background, because ability can be genetically and/or culturally transmitted. In such a case, failure to control for this effect can bias our results. However, if this ability bias is invariant across countries and cohorts, then we can consider our estimates of $\gamma$ as informative of the relationship between the FBE and school tracking. We cannot think of factors that may systematically affect this potential bias, either across countries or over time, and therefore hold our estimates as informative of the impact of school tracking on the equality of opportunity, as measured by the relationship between family background and educational attainment.

Next let us consider the country by cohort component $u_{jk}$, which has the same level of aggregation as our indicators of school tracking, and assume for instance that our dependent variable $Y$ is individual educational attainment. This component can be interpreted as a country × cohort innovation in attainment, which can be correlated with $T$. In this case, our tracking indicators $T$ and educational attainment would be driven by a common factor, and our estimates would be distorted. Our remedy to this is to capture all country by cohort effects with country by cohort dummies. The price that we pay, as discussed above, is that we cannot identify the potential effects of school tracking on average school performance.

## 5. THE DATA

### 5.1. Description

As stressed in the introduction to this paper, we are interested in studying the impact of the design of schooling institutions on the relationship between family background and the education and labour market outcomes of young adults. For this purpose we need data that are representative of national populations, and contain at the same time a sufficient number of countries to allow for sufficient variation in schooling institutions. We identify four datasets with the required characteristics: (a) the European Community Household Panel (ECHP), a comparative panel covering 15 European countries and spanning 8 years, from 1994 to 2001. The ECHP is based on a fairly uniform questionnaire, and is explicitly designed to favour international comparisons. Individuals in this survey are interviewed once they reach age 16. We use the time span of the panel to extract from these data two cohorts of individuals, those aged 20 to 24 in 1995 and those aged 20 to 24 in 2000.[26] While the first cohort was born

[26] The age range of the cohorts is dictated by the need to avoid having the same individuals in both cohorts.

between 1971 and 1975, and went to upper secondary school between 1985 and 1994, the second cohort was born between 1976 and 1980 and went to high school between 1990 and 1999. The two schooling periods partly overlap, but not entirely so, and we assign to the former cohort the schooling institution indicators for the mid 1980s and to the latter cohort the institution indicators for the mid 1990s. Needless to say, this assignment is rather extreme, and perhaps exaggerates the variation occurring between the two cohorts. The advantage of using ECHP is that is allows us to construct two separate cohorts of individuals with the same age. One disadvantage is that the information on family background is not immediately available, and need to be constructed by linking households over time. This exercise generates important attrition in the data.[27]

The second dataset we use is the International Social Survey Programme (ISSP), a repeated cross-country survey of the adult population, in place since 1985, with a variable number of countries in each year. The survey contains information on maximum educational attainment (with country-specific coding), occupational status and earnings. In some surveys there is also information about parental education and job satisfaction. In order to extract from these data two sufficiently distanced cohorts, with the same age but who went to school in different years, we have selected the 1991 and the 1999 surveys.[28] By so doing we identify two age cohorts, both aged between 18 and 24 (included), who were born in the periods 1967–73 and 1975–81 respectively, and went to secondary school during 1981–92 and 1989–2000. Non-missing information on parental education and school stratification reduces the available sample to five countries (Australia, Germany [both East and West], Hungary, Poland and the United States). In order to increase the number of countries, we combine the data from ECHP and ISSP, and obtain a sample of 33 132 observations covering 16 countries.[29] The age restriction makes this sample more appropriate for the investigation of youth behaviour at labour market entry, but less appropriate for investigating educational attainment, since in some countries college completion occurs at a later age. Descriptive statistics for this sample are reported in Table 3.

We also generate data for two subsequent cohorts, using the International Adult Literacy Survey (IALS), which investigates the prose, document and quantitative

[27] D'Hombres and Brunello (2005) illustrate in detail the pros and cons of using family background in the ECHP, and present evidence that the endogenous selection problems originated by the construction of the data are not serious.

[28] The most recent wave reporting information on parental education is 1999, which includes 25 countries (Australia, Austria, Bulgaria, Canada, Chile, Cyprus, Czech Republic, France, Germany, Hungary, Israel, Japan, Latvia, New Zealand, Norway, Philippines, Poland, Portugal, Russian Federation, Slovakia, Slovenia, Spain, Sweden, United Kingdom and United States). A 10-year time lag between surveys would have been ideal, but the 1989 survey contains too few countries with valid information on parental education (Austria, Hungary and United States). Therefore we have selected the 1991 survey, which includes 16 countries (Australia, Austria, Germany, Hungary, Ireland, Israel, Italy, Netherlands, New Zealand, Norway, Philippines, Poland, Russian Federation, Slovenia, United Kingdom and United States).

[29] The countries are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Portugal, Spain, United Kingdom from ECHP and Australia, Hungary, Poland and United States from ISSP 1991–99. Sweden and the Netherlands are excluded from ECHP due to missing observations on parental background in one wave; Germany is excluded from ISSP in order to avoid overlapping with ECHP.

**Table 3. Descriptive statistics (unweighed)**

| Year of survey(s) | ECHP 1995–2000 | | ISSP 1991–1999 | | ISSP 1999 | | IALS 1994–1996–1998 | | PISA 2003 |
|---|---|---|---|---|---|---|---|---|---|
| Birth year of cohort 1 | 1971–75 | | 1967–73 | | 1965–1971 | | 1962–67 | | 1988 |
| Birth year of cohort 2 | 1976–80 | | 1975–81 | | 1975–1981 | | 1972–77 | | – |
| | Cohort 1 | Cohort 2 | Cohort 1 | Cohort 2 | Cohort 1 | Cohort 2 | Cohort 1 | Cohort 2 | |
| Observations | 16 163 | 15 911 | 447 | 611 | 3405 | 3251 | 7421 | 6029 | 275 369 |
| Age | 21.98 | 22.07 | 21.78 | 21.05 | 30.96 | 21.14 | 31.24 | 21.24 | 15.79 |
| Male | 50.21 | 46.86 | 46.53 | 43.04 | 47.47 | 47.57 | 44.09 | 47.40 | 49.59 |
| Dropout (without upper secondary degree) | 33.69 | 33.20 | 33.18 | 42.78 | 31.92 | 31.74 | 31.20 | 31.46 | |
| College enrol/completed | 27.64 | 28.75 | 47.98 | 32.82 | 23.53 | 31.51 | 27.71 | 15.36 | |
| Years of education (mean and SD) | | | 11.62 (2.27) | 12.01 (1.96) | 13.12 (3.94) | 12.27 (2.61) | 12.66 (3.31) | 12.30 (2.56) | |
| Log literacy skill (average across areas) (mean and SD) | | | | | | | 5.62 (0.22) | 5.62 (0.21) | 6.15 (0.21) |
| Employed | 45.50 | 45.29 | 62.75 | 60.67 | 77.62 | 48.53 | 74.52 | 46.41 | |
| On-the-job training | 17.32 | 16.95 | | | | | 44.55 | 53.09 | |
| Log wage (mean and SD) | 5.27 (1.95) | 5.37 (1.88) | 8.65 (1.07) | 9.15 (1.41) | 8.52 (2.32) | 8.07 (2.40) | | | |
| Both parents without secondary education | 35.43 | 29.28 | 21.36 | 9.48 | 29.99 | 18.03 | 54.71 | 39.26 | 30.38 |
| At least one parent with secondary education | 23.56 | 25.66 | 54.55 | 60.07 | 45.55 | 47.34 | 26.98 | 33.95 | 27.97 |
| At least one parent with college degree | 41.01 | 45.06 | 24.09 | 30.46 | 24.46 | 34.64 | 18.31 | 26.79 | 41.65 |
| Books at home | | | | | 125.18 | 145.10 | | | 158.43 |
| Number of countries | 12[a] | | 4[b] | | 21[c] | | 18[d] | | 41[e] |

[a] Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Portugal, Spain, United Kingdom.

[b] Australia, Hungary, Poland, and United States.

[c] Australia, Canada, Chile, Czech Republic, France, Germany, Hungary, Israel, Japan, Latvia, New Zealand, Norway, Philippines, Poland, Portugal, Russian Federation, Slovakia, Slovenia, Spain, Sweden, United States.

[d] Belgium, Chile, Czech Republic, Denmark, Finland, Germany, Hungary, Ireland, Italy, Netherlands, New Zealand, Norway, Poland, Slovenia, Sweden, Switzerland, United Kingdom and United States.

[e] Australia, Austria, Belgium, Brazil, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong (China), Hungary, Iceland, Indonesia, Ireland, Italy, Japan, Korea, Latvia, Liechtenstein, Luxembourg, Macao (China), Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Russian Federation, Slovakia, Spain, Sweden, Switzerland, Thailand, Tunisia, Turkey, United Kingdom, United States, Uruguay, Serbia and Montenegro.

literacy of adults in a sample of OECD countries, and ISSP. The countries included in IALS[30] have conducted their surveys at different points in time, some in 1994, some in 1996 and the rest in 1998. An advantage with respect to ECHP is that it provides data on parental education on a representative scale. Because of the different dates of the interviews, we select different age groups across countries: the age groups 17–22 and 27–32 for the countries which carried their surveys in 1994; the age groups 18–24 and 28–34 for the surveys undertaken in 1996; the age groups 20–25 and 30–35 for the surveys taken in 1998. In the first case, the younger cohort was

[30] The countries are Belgium, Chile, Czech Republic, Denmark, Finland, Germany, Hungary, Ireland, Italy, the Netherlands, New Zealand, Norway, Poland, Slovenia, Sweden, Switzerland, United Kingdom and United States.

born between 1972 and 1977, and went to high school during the period 1986–96. The older cohort was born and went to school 10 years earlier. In this case, there is no overlap between the two cohorts, and we attribute to the former cohort the schooling institutions of mid 1980s and to the latter cohort the institutions of mid 1990s.

We use a similar methodology for the 1999 ISSP survey, and identify two age cohorts, aged 18–24 and 28–34, which were born in 1975–81 and 1965–71 respectively, and went to upper secondary school during 1989–2000 and 1979–1990. We associate the former cohort to the schooling institutions of the mid 1990s, and the latter cohort to the institutions of the mid 1980s. Following this route, and excluding countries with missing information on parental education (Austria, Bulgaria and the United Kingdom),[31] or on school stratification (Cyprus), we end up with 21 countries (Australia, Canada, Chile, Czech Republic, France, Germany, Hungary, Israel, Japan, Latvia, New Zealand, Norway, Philippines, Poland, Portugal, Russian Federation, Slovakia, Slovenia, Spain, Sweden, United States). By combining IALS and ISSP, we obtain a second sample of 14 330 observations covering 24 countries (Australia, Belgium, Canada, Chile, Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Poland, Portugal, Russian Federation, Spain, Sweden, Switzerland, United Kingdom, United States). This sample includes adult individuals, and is more appropriate to study educational attainment, as well as the distribution of basic competences. Descriptive statistics are reported in Table 3.

To compare our results with the existing literature based on student test scores, we have also used a fourth dataset, drawn from PISA, an internationally standardized assessment promoted every three years by OECD and administered to 15-year-olds in schools. We use the 2003 survey, which includes 41 countries.[32] The survey measures competences in four areas (reading ability, numeracy, scientific knowledge and problem solving). The questionnaire contains detailed information on the family background of students, on their motivations and aspirations, as well as on the contents of their relationship with parents and teachers. Additional questionnaires report information on previous educational career, access and ability to use ICT (OECD, 2004). The main limit of this survey is that it is a cross-section of individuals with the same age, which prevents us from exploiting time variations to identify potential effects of institutional differences.[33] Thus, we use this dataset only to explore the role of parental background in secondary school choices.

[31] It is worth recalling that in addition to the question about father and mother educational attainment, the 1999 survey contains a question about 'how many books did you have at home when you were 15'. We have explored the significance of this alternative representation of family background, but in general it is less significant than maximum parental education.

[32] The countries participating in the 2003 survey are Australia, Austria, Belgium, Brazil, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong (China), Hungary, Iceland, Indonesia, Ireland, Italy, Japan, Korea, Latvia, Liechtenstein, Luxembourg, Macao (China), Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Russian Federation, Slovakia, Spain, Sweden, Switzerland, Thailand, Tunisia, Turkey, United Kingdom, United States, Uruguay, Serbia and Montenegro.

[33] For this reason many authors prefer the TIMMS surveys – see Schuetz *et al.* (2005) – or combine PISA survey with other surveys conducted on younger children – see Waldinger (2006).

### 5.2. The outcomes

We group education outcomes into three main groups: educational attainment, early labour market experience and skill development, and study their correlation with family background, with special focus on how tracking influences the FBE. We look at educational attainment from different perspectives:

(1) the attainment of the average individual, which we capture with the years of education (Table 4);
(2) the bottom tail of the distribution, by focusing on the probability of being a school dropout[34] (Table 5);
(3) the upper tail of the distribution, by considering the probability of being enrolled in college or having a college degree (Table 6);
(4) the dispersion of educational attainment in the population, which we capture with the coefficient of variation of attained years of schooling. We relate this measure to a measure of dispersion of parental background (Table 7).

We study the interaction of these outcomes with family background and schooling institutions by using the pooled IALS-ISSP dataset, which covers 24 countries.

Next, we look at the labour market outcomes of young adults by focusing on:

(5) employment, defined by the probability of being employed, unemployed or out of the labour force (Table 8);
(6) earnings, which we study by explicitly taking into account self-selection into paid employment with the usual Heckman procedure (Table 9);
(7) earnings inequality in the working population, which we analyse by looking at the correlation between a measure of dispersion (the coefficient of variation of wages) and the corresponding dispersion of family background (Table 10).

We look at labour market outcomes through the lenses of the ECHP-ISSP dataset.

Finally, we consider skill development by looking at:

(8) literacy, measured with the ability to read, process documents and carry out quantitative analysis (Table 11);
(9) literacy inequality, or the coefficient of variation of literacy, which we relate to the dispersion of family background (Table 12);
(10) access to job training, described by the probability of having participated to a training event since the year before the interview (Table 13).

We look at these outcomes by using either IALS or the ECHP dataset.

Before discussing our results, we briefly review our theoretical expectations, using a simple graph to illustrate. In Figure 1 we trace the relationship between the educational

[34] Following the OECD, we define school dropouts as individuals who are not in school and have at most ISCED 2 education.

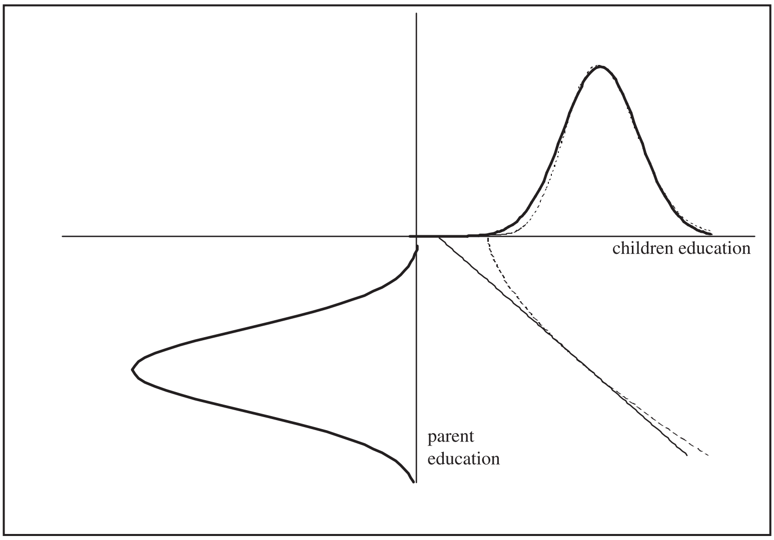


**Figure 1. Intergenerational persistence in education and tracking**

attainments of two subsequent generations. In the south-west quadrant we assume that parental education has a given normal distribution.

Next, we assume that the relationship between child and parent education is linear (the solid line in the south-east quadrant), and map the distribution of educational attainment of the children starting from the distribution of parental education. As argued in the model reported in Appendix 1, a change in schooling institutions may affect the relationship between the two distributions. Suppose that an increase in school tracking length raises the effect of parental education on the education of children in a non-linear way, as shown by the dashed line in the south-east quadrant.[35] If this is the case, the effect of parental background is attenuated for low-education families, but reinforced for better-educated parents. As a consequence, educational attainment varies at both tails, with an ensuing reduction in educational inequality. This is rather consistent with what we shall find in the empirical analysis.

Turning to the other outcomes, it is natural to expect that labour market outcomes be positively correlated with educational attainment. Thus, we expect to find an analogous relationship between parental education and either employment probability and/or earnings. On the contrary, we do not have strong *a priori* expectations with regard to skill development. We know that 'learning begets learning', and that this carries on from formal education to training opportunities (see Bassanini *et al.*, 2007).

[35] The solid line corresponds to the function $h_{t+1} = 1 + 0.8 \cdot h_t$, while the dashed line is obtained from $h_{t+1} = 2.54 + 0.2 \cdot h_t^{1.55}$. Given a normal distribution of $h_t$ with $\mu = 5$, $\sigma = 1$, these two functions generate two distributions with almost identical means, but the latter is characterized by lower variance than the former.

Actual skills, however, are also the product of work experience, which is not necessarily correlated with educational attainment. While we find it reasonable to expect a positive correlation between parental background and individual cognitive skills, we do not have strong expectations on how this relationship is modified by variations in school tracking.

### 5.3. Parental background and the role of confounding factors

In our framework it is essential to have good measures of parental background. While the ECHP includes measures of parental income (at least for the individuals still living with their families, which is more likely in southern countries), the other datasets have information on parental occupation, which is not cross-country comparable, except in the case of PISA, where occupation is associated with an index of social prestige. Thus we resort to parental education, which is available in all datasets as a 3-outcomes variable.[36] Two datasets (the ISSP survey in 1999 and PISA 2003) also report information on the (estimated) number of books when the interviewee was 15 years old, while another one (IALS) asks about the number of books currently at home, which cannot be taken as a proxy of parental background at the time of schooling. Using the number of books as an alternative proxy for family background yields similar results, which we do not report here to save space.

For each outcome variable, we estimate the following five specifications,[37] which include:

(a) parental background alone and interacted with tracking length;
(b) parental background alone and interacted with the share of students enrolled in vocational tracks;
(c) parental background alone and interacted both with the share of students enrolled in vocational tracks and with its square;
(d) parental background alone and interacted both with tracking length and with the share of students enrolled in vocational tracks (which enters both linearly and with a squared term);
(e) parental background alone and interacted with the product of tracking length by the share of students in vocational tracks.

While in specifications (b) and (c) the two measures of school tracking identified in the theoretical section are included separately, in the last specification we allow them to interact in their impact on the family background effect.[38]

[36] We have considered the highest educational attainment in the parents as a couple, coding 0 when no parent completed secondary education, 1 when at least one parent has a secondary education degree and 2 when at least one parent has a college degree.

[37] All regressions include age and gender.

[38] Since qualitative results are not affected, to save space we do not present a specification which includes all the explanatory variables relative to school tracking listed in (a) to (e).

These five specifications are replicated five times, first without any confounding factor and then by introducing one by one the interaction of parental background with schooling variables, which might influence the FBE independently of school tracking – the share of students in pre-primary schools, the share of private schools, public expenditure in education and the student–teacher ratio. We are forced to introduce these additional controls once at a time, to avoid collinearity problems. Our results are reported in Tables 4–13.

When we study the impact of schooling institutions on the distribution of outcomes, be it years of education, earnings or literacy, we regress our measure of outcome dispersion (the coefficient of variation, computed over cells defined by countries × cohorts × age × gender) on an analogous measure of dispersion of parental background, and interact the latter with schooling institutions. We expect to find a close correspondence in signs between the regressions in levels and those using the coefficients of variation.[39]

## 6. EMPIRICAL RESULTS

It is useful to organize the discussion of results in subsections, with each subsection devoted to a group of outcomes.

### 6.1. Education

We start with educational attainment, measured as the number of years of education attained by the average individual in the sample (Table 4), and use the IALS-ISSP sample.[40] As expected, we find that parental education and the educational attainment of the offspring are positively correlated. This effect is reinforced when tracking length is longer. However, the coefficient associated to the interaction between family background and tracking length is not always very precise – it is significant at the 10% level of confidence in some cases, at the 5% in some other cases – and becomes statistically not significant when we include the interaction of parental background with public expenditure in education as a share of GDP. The share of students enrolled in vocational schools, which in our model would affect FBE in the presence of non-linear peer or teacher quality or curricula effects, is never statistically significant.

---

[39] If we consider the relationship $Y = A \cdot FB^{\gamma(T)}$ where $Y$ is the outcome, $FB$ the measure of family background and $T$ a measure of school design, its corresponding log-version is $y = \alpha + \gamma(T)fb$. If $FB$ is lognormally distributed (which is reasonable especially when $FB$ represents family income), then $fb$ is normally distributed with moments $(\mu_{fb}, \sigma^2_{fb})$, and $y$ is also normally distributed with moments $(\alpha + \gamma\mu_{fb}, \gamma^2\sigma^2_{fb})$ Then the coefficient of variation of $fb$ is $CV_{fb} = \sigma_{fb}/\mu_{fb}$, and the corresponding measure of $y$ is $CV_y = \dfrac{\gamma(s)\sigma_{fb}}{\alpha + \gamma(s)\mu_{fb}} = \dfrac{1}{1 + \dfrac{\alpha}{\gamma(s)\mu_{fb}}} \cdot \dfrac{\sigma_{fb}}{\mu_{fb}} = \Gamma(s)CV_{fb}$. Therefore by construction $sign(\gamma') = sign(\Gamma')$.

[40] Estimates based on the other dataset can be found in a previous version of the present article, published as IZA Discussion Paper No. 2348/2006.

**Table 4. Determinants of educational attainment (OLS)**

| Dep.var.: years of education | **IALS + ISSP 1999** (18–24 and 28–34) | | | | |
|---|---|---|---|---|---|
| Family background | 1.0256 [7.82]*** | 1.3526 [4.70]*** | 1.3191 [3.42]*** | 1.2003 [3.27]*** | 0.9348 [6.90]*** |
| Fam.background × tracking length | 0.6781 [1.79]* | | | 1.3861 [2.19]** | 2.4254 [1.60] |
| Fam.background × vocational share in upp.secondary | | −0.2402 [0.49] | −0.0285 [0.02] | −0.3548 [0.23] | |
| Fam.background × vocational share in upp.secondary squared | | | −0.2437 [0.14] | −0.6918 [0.40] | |
| Fam.background × tracking length × vocational share | | | | | −2.4727 [1.25] |
| Observations | 14 038 | 14 038 | 14 038 | 14 038 | 14 038 |
| $R^2$ | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 |
| Log likelihood | −33 993.83 | −33 999.86 | −33 999.78 | −33 980.83 | −33 982.71 |
| Countries | 24[a] | 24[a] | 24[a] | 24[a] | 24[a] |
| *Controlling for enrolment in pre-primary schools* | | | | | |
| Family background | 1.0806 [5.65]*** | 1.3008 [3.99]*** | 1.2686 [3.05]*** | 1.2415 [3.14]*** | 0.9501 [5.78]*** |
| Fam.background × tracking length | 0.8054 [1.66] | | | 1.4969 [1.91]* | 2.4318 [1.58] |
| Fam.background × vocational share in upp.secondary | | −0.3055 [0.66] | −0.1 [0.06] | −0.3093 [0.20] | |
| Fam.background × vocational share in upp.secondary squared | | | −0.2363 [0.14] | −0.7351 [0.43] | |
| Fam.background × tracking length × vocational share | | | | | −2.4362 [1.29] |
| Family background × relative enrolment in pre-primary school | −0.2432 [0.51] | 0.2205 [0.64] | 0.2198 [0.63] | −0.2203 [0.48] | −0.0617 [0.15] |
| *Controlling for student/teacher ratio in secondary schools* | | | | | |
| Family background | 0.6913 [1.18] | 1.2995 [1.93]* | 1.2854 [1.61] | 1.0347 [1.30] | 0.6545 [1.15] |
| Fam.background × tracking length | 0.8418 [1.59] | | | 1.4156 [2.08]** | 2.4774 [1.52] |
| Fam.background × vocational share in upp.secondary | | −0.2125 [0.39] | −0.1057 [0.06] | −0.4022 [0.24] | |
| Fam.background × vocational share in upp.secondary squared | | | −0.1247 [0.07] | −0.5611 [0.33] | |
| Fam.background × tracking length × vocational share | | | | | −2.3518 [1.18] |
| Family background × pupil teacher ratio secnd.school | 0.02 [0.54] | 0.0023 [0.06] | 0.0022 [0.06] | 0.0098 [0.28] | 0.0173 [0.51] |

**Table 4.** *Continued*

| Dep.var.: years of education | IALS + ISSP 1999 (18–24 and 28–34) | | | | |
|---|---|---|---|---|---|
| *Controlling for public educational expenditure over GDP* | | | | | |
| Family background | 2.5068 | 2.7156 | 2.6833 | 2.4331 | 2.3479 |
| | [3.35]*** | [3.52]*** | [3.63]*** | [3.45]*** | [3.48]*** |
| Fam.background × tracking length | 0.5578 | | | 0.9367 | 1.7192 |
| | [1.30] | | | [1.66] | [1.40] |
| Fam.background × vocational share in upp.secondary | | 0.0252 | 0.2469 | −0.0084 | |
| | | [0.06] | [0.17] | [0.01] | |
| Fam.background × vocational share in upp.secondary squared | | | −0.2561 | −0.5568 | |
| | | | [0.17] | [0.36] | |
| Fam.background × tracking length × vocational share | | | | | −1.6362 |
| | | | | | [0.99] |
| Fam.background × school expenditure on GDP | −0.2572 | −0.2663 | −0.2666 | −0.2334 | −0.2395 |
| | [2.18]** | [2.32]** | [2.32]** | [2.11]** | [2.22]** |
| *Controlling for share of private school students in secondary schools* | | | | | |
| Family background | 1.0751 | 1.4133 | 1.339 | 1.2132 | 0.9867 |
| | [7.81]*** | [4.70]*** | [3.42]*** | [3.25]*** | [7.16]*** |
| Fam.background × tracking length | 0.7739 | | | 1.6537 | 3.1301 |
| | [2.02]** | | | [2.33]** | [1.65] |
| Fam.background × vocational share in upp.secondary | | −0.2438 | 0.2645 | 0.1112 | |
| | | [0.50] | [0.16] | [0.07] | |
| Fam.background × vocational share in upp.secondary squared | | | −0.5854 | −1.3954 | |
| | | | [0.33] | [0.79] | |
| Fam.background × tracking length × vocational share | | | | | −3.2495 |
| | | | | | [1.36] |
| Family background × share of private up.secnd.schools | −0.398 | −0.2991 | −0.3285 | −0.5931 | −0.6473 |
| | [0.97] | [0.74] | [0.81] | [1.68]* | [1.60] |

*Notes:* Weighed – Robust standard errors clustered by country × wave. *t* statistics in brackets.
[a] Excluded Chile 1985.
* significant at 10%; ** significant at 5%; *** significant at 1%. Country × year, gender, age controls included.

Turning to the analysis of the two tails of the distribution of educational attainment, we consider the probability that the individuals in the sample have not attained upper secondary education and dropped out of school.

Our results in Table 5 show rather clearly that earlier tracking reinforces the negative effects of a 'good' parental background on the probability of dropping out.[41] In Table 6 we focus on the probability of being enrolled at or having completed

[41] One may object that this measure fails to account for the education completed in the apprenticeship systems typical of countries with early tracking. Unfortunately this information is not available in our data set.

**Table 5. Failure to complete upper secondary education (probit marginal effect)**

| Dep.var.: 1 = no upper secondary education | **IALS + ISSP 1999** (18–24 and 28–34) | | | | |
|---|---|---|---|---|---|
| Family background | −0.1209 [6.22]*** | −0.1484 [4.10]*** | −0.1479 [2.38]** | −0.1279 [2.19]** | −0.1144 [5.13]*** |
| Fam.background × tracking length | −0.1342 [2.64]*** | | | −0.2017 [2.30]** | −0.2582 [1.36] |
| Fam.background × vocational share in upp.secondary | | −0.0249 [0.37] | −0.0277 [0.10] | −0.0155 [0.06] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0033 [0.01] | 0.1162 [0.43] | |
| Fam.background × tracking length × vocational share | | | | | 0.1738 [0.75] |
| Observations | 14 330 | 14 330 | 14 330 | 14 330 | 14 330 |
| Pseudo $R^2$ | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 |
| Log likelihood | −7035.44 | −7044.54 | −7044.54 | −7032.15 | −7033.74 |
| Countries | 24[a] | 24[a] | 24[a] | 24[a] | 24[a] |
| *Controlling for enrolment in pre-primary schools* | | | | | |
| Family background | −0.1362 [5.92]*** | −0.148 [3.96]*** | −0.1476 [2.33]** | −0.1397 [2.43]** | −0.1283 [5.08]*** |
| Fam.background × tracking length | −0.1645 [2.44]** | | | −0.2305 [2.18]** | −0.2622 [1.37] |
| Fam.background × vocational share in upp.secondary | | −0.0244 [0.34] | −0.0273 [0.10] | −0.0313 [0.13] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0034 [0.01] | 0.1315 [0.50] | |
| Fam.background × tracking length × vocational share | | | | | 0.1437 [0.62] |
| Family background × relative enrolment in pre-primary school | 0.0623 [0.91] | −0.0016 [0.03] | −0.0016 [0.03] | 0.0609 [0.89] | 0.052 [0.78] |
| *Controlling for student/teacher ratio in secondary schools* | | | | | |
| Family background | −0.0241 [0.35] | −0.079 [0.97] | −0.081 [0.86] | −0.0364 [0.40] | −0.019 [0.27] |
| Fam.background × tracking length | −0.1822 [2.72]*** | | | −0.2264 [2.45]** | −0.3049 [1.44] |
| Fam.background × vocational share in upp.secondary | | −0.0525 [0.70] | −0.0376 [0.14] | −0.0281 [0.11] | |
| Fam.background × vocational share in upp.secondary squared | | | −0.0175 [0.06] | 0.1031 [0.39] | |
| Fam.background × tracking length × vocational share | | | | | 0.173 [0.69] |
| Family background × pupil teacher ratio secnd.school | −0.006 [1.62] | −0.0041 [1.02] | −0.0041 [1.03] | −0.0054 [1.52] | −0.006 [1.68]* |

**Table 5.** *Continued*

| Dep.var.: 1 = no upper secondary education | **IALS + ISSP 1999** (18–24 and 28–34) | | | | |
|---|---|---|---|---|---|
| *Controlling for public educational expenditure over GDP* | | | | | |
| Family background | –0.2923 [3.37]*** | –0.3213 [3.58]*** | –0.3138 [3.19]*** | –0.2739 [2.80]*** | –0.2836 [3.24]*** |
| Fam.background × tracking length | –0.1242 [2.24]** | | | –0.155 [1.84]* | –0.1976 [1.11] |
| Fam.background × vocational share in upp.secondary | | –0.0562 [0.86] | –0.1166 [0.46] | –0.0989 [0.41] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0694 [0.27] | 0.152 [0.59] | |
| Fam.background × tracking length × vocational share | | | | | 0.1029 [0.47] |
| Fam.background × school expenditure on GDP | 0.0296 [1.95]* | 0.0332 [2.16]** | 0.0336 [2.18]** | 0.0287 [1.87]* | 0.0287 [1.90]* |
| *Controlling for share of private school students in secondary schools* | | | | | |
| Family background | –0.1217 [5.47]*** | –0.1469 [3.97]*** | –0.1475 [2.39]** | –0.1283 [2.21]** | –0.1162 [4.94]*** |
| Fam.background × tracking length | –0.1351 [2.70]*** | | | –0.2068 [2.30]** | –0.2733 [1.30] |
| Fam.background × vocational share in upp.secondary | | –0.0246 [0.37] | –0.0206 [0.07] | –0.0277 [0.10] | |
| Fam.background × vocational share in upp.secondary squared | | | –0.0046 [0.02] | 0.1328 [0.47] | |
| Fam.background × tracking length × vocational share | | | | | 0.1908 [0.74] |
| Family background × share of private up.secnd.schools | 0.0051 [0.11] | –0.0083 [0.16] | –0.0085 [0.16] | 0.0155 [0.34] | 0.017 [0.35] |

*Notes:* Weighed – Robust standard errors clustered by country × wave. *t* statistics in brackets.
[a] Excluded Chile 1985.
* significant at 10%; ** significant at 5%; *** significant at 1%. Country × year, gender, age controls included.

university. Here, the evidence is that individuals with a better family background are more likely to be enrolled at or to have completed college. This effect is reinforced when tracking length is longer or the share of students enrolled in vocational schools is lower. Based on the second model presented in Appendix 1, these results are consistent with the fact that tracking generates a specialization effect. They also suggest that average student ability matters more for individual human capital in academic than in vocational tracks.[42]

[42] One alternative explanation of these results could be the organization of tracking in most countries, which usually does not permit university enrolment to the graduates of vocational tracks.

**Table 6. Probability of college enrolment/attainment (probit marginal effect)**

| Dep.var.: 1 = college enrolment/college attained | **IALS + ISSP 1999** (18–24 and 28–34) | | | | |
|---|---|---|---|---|---|
| Family background | 0.138 [7.94]*** | 0.1887 [7.79]*** | 0.1992 [7.17]*** | 0.1872 [7.33]*** | 0.129 [7.39]*** |
| Fam.background × tracking length | 0.0513 [0.93] | | | 0.1444 [2.28]** | 0.2727 [2.26]** |
| Fam.background × vocational share in upp.secondary | | −0.0721 [1.61] | −0.1395 [1.05] | −0.1874 [1.44] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0784 [0.50] | 0.0564 [0.38] | |
| Fam.background × tracking length × vocational share | | | | | −0.3344 [2.01]** |
| Observations | 14 275 | 14 275 | 14 275 | 14 275 | 14 275 |
| Pseudo $R^2$ | 0.16 | 0.16 | 0.16 | 0.16 | 0.16 |
| Log likelihood | −6798.98 | −6795.98 | −6795.63 | −6786.78 | −6790.69 |
| Countries | 24[a] | 24[a] | 24[a] | 24[a] | 24[a] |
| *Controlling for enrolment in pre-primary schools* | | | | | |
| Family background | 0.1322 [5.98]*** | 0.1721 [6.02]*** | 0.1838 [6.01]*** | 0.1814 [6.26]*** | 0.1164 [5.39]*** |
| Fam.background × tracking length | 0.0381 [0.63] | | | 0.1283 [1.85]* | 0.2667 [2.16]** |
| Fam.background × vocational share in upp.secondary | | −0.0904 [2.06]** | −0.1676 [1.28] | −0.1956 [1.54] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0894 [0.58] | 0.0646 [0.44] | |
| Fam.background × tracking length × vocational share | | | | | −0.3664 [2.21]** |
| Family background × relative enrolment in pre-primary school | 0.0263 [0.48] | 0.0702 [1.47] | 0.0712 [1.52] | 0.0331 [0.62] | 0.0537 [1.06] |
| *Controlling for student/teacher ratio in secondary schools* | | | | | |
| Family background | 0.0901 [2.04]** | 0.1835 [3.51]*** | 0.1974 [3.59]*** | 0.1659 [3.24]*** | 0.0895 [2.08]** |
| Fam.background × tracking length | 0.0774 [1.39] | | | 0.1499 [2.54]** | 0.2736 [2.24]** |
| Fam.background × vocational share in upp.secondary | | −0.0685 [1.50] | −0.1742 [1.28] | −0.2202 [1.67]* | |
| Fam.background × vocational share in upp.secondary squared | | | 0.1247 [0.80] | 0.108 [0.74] | |
| Fam.background × tracking length × vocational share | | | | | −0.3027 [1.85]* |
| Family background × pupil teacher ratio secnd.school | 0.0027 [1.02] | 0.0001 [0.04] | 0.0002 [0.08] | 0.0013 [0.50] | 0.0023 [0.96] |

**Table 6.** *Continued*

| Dep.var.: 1 = college enrolment/college attained | **IALS + ISSP 1999** (18–24 and 28–34) | | | | |
|---|---|---|---|---|---|
| *Controlling for public educational expenditure over GDP* | | | | | |
| Family background | 0.2436 | 0.2737 | 0.2963 | 0.2637 | 0.2185 |
| | [4.20]*** | [4.83]*** | [4.60]*** | [4.42]*** | [3.84]*** |
| Fam.background × tracking length | 0.0444 | | | 0.1196 | 0.2158 |
| | [0.85] | | | [2.00]** | [1.90]* |
| Fam.background × vocational share in upp.secondary | | −0.0517 | −0.1801 | −0.2179 | |
| | | [1.18] | [1.53] | [1.83]* | |
| Fam.background × vocational share in upp.secondary squared | | | 0.1508 | 0.1252 | |
| | | | [1.05] | [0.89] | |
| Fam.background × tracking length × vocational share | | | | | −0.257 |
| | | | | | [1.63] |
| Fam.background × school expenditure on GDP | −0.019 | −0.0174 | −0.018 | −0.0137 | −0.0157 |
| | [1.95]* | [1.74]* | [1.73]* | [1.43] | [1.67]* |
| *Controlling for share of private school students in secondary schools* | | | | | |
| Family background | 0.1457 | 0.2018 | 0.2013 | 0.1859 | 0.1373 |
| | [8.07]*** | [7.13]*** | [6.85]*** | [6.74]*** | [8.10]*** |
| Fam.background × tracking length | 0.0783 | | | 0.2038 | 0.4145 |
| | [1.60] | | | [2.79]*** | [2.16]** |
| Fam.background × vocational share in upp.secondary | | −0.0731 | −0.0691 | −0.0863 | |
| | | [1.64] | [0.46] | [0.62] | |
| Fam.background × vocational share in upp.secondary squared | | | −0.0047 | −0.0952 | |
| | | | [0.03] | [0.58] | |
| Fam.background × tracking length × vocational share | | | | | −0.4861 |
| | | | | | [2.01]** |
| Family background × share of private up.secnd.schools | −0.0745 | −0.0605 | −0.0608 | −0.1061 | −0.1171 |
| | [1.69]* | [1.42] | [1.30] | [2.36]** | [2.38]** |

*Notes:* Weighed – Robust standard errors clustered by country × wave. *t* statistics in brackets.
[a] Excluded Chile 1985.
* significant at 10%; ** significant at 5%; *** significant at 1%. Country × year, gender, age controls included.

While these effects are robust to the introduction of confounding schooling variables, we are puzzled by the negative sign attracted by the interaction of parental background with the share of private schooling.

Finally, we consider the dispersion of educational attainment in Table 7. Here, we do not find statistically significant effects of school tracking, except when we control for the pupil–teacher ratio. If we consider this variable as a negative proxy of school resources, our results suggest that – other things constant – the inequality induced by parental background tends to be stronger in countries where the pupil–teacher ratio is higher.

**Table 7. Inequality in educational attainment (OLS)**

| Dep.var.: coefficient of variation years of education | **IALS + ISSP 1999** (18–24 and 28–34) | | | | |
|---|---|---|---|---|---|
| CV family background | −0.0135 | 0.0088 | −0.0451 | −0.086 | −0.0297 |
| | [0.66] | [0.36] | [1.81]* | [2.16]** | [1.05] |
| CV fam.background × tracking length | 0.0743 | | | 0.1324 | 0.2331 |
| | [1.01] | | | [1.64] | [1.31] |
| CV fam.background × vocational share in upp.secondary | | −0.0009 | 0.2619 | 0.3038 | |
| | | [0.02] | [1.61] | [2.21]** | |
| CV fam.background × vocational share in upp.secondary squared | | | −0.3011 | −0.3773 | |
| | | | [1.41] | [2.00]** | |
| CV fam.background × tracking length × vocational share | | | | | −0.2267 |
| | | | | | [1.11] |
| Observations | 628 | 592 | 592 | 592 | 592 |
| $R^2$ | 0.63 | 0.59 | 0.6 | 0.61 | 0.6 |
| Log likelihood | 970.41 | 901.67 | 908.88 | 918.16 | 911.64 |
| Countries | 25 | 24[a] | 24[a] | 24[a] | 24[a] |
| *Controlling for enrolment in pre-primary schools* | | | | | |
| CV family background | −0.0295 | −0.0214 | −0.0819 | −0.0927 | −0.0437 |
| | [1.40] | [1.17] | [2.44]** | [2.31]** | [1.69]* |
| CV fam.background × tracking length | 0.0228 | | | 0.0682 | 0.1741 |
| | [0.22] | | | [0.67] | [0.98] |
| CV fam.background × vocational share in upp.secondary | | −0.0122 | 0.2728 | 0.2913 | |
| | | [0.32] | [2.03]** | [2.14]** | |
| CV fam.background × vocational share in upp.secondary squared | | | −0.3275 | −0.3593 | |
| | | | [1.84]* | [1.92]* | |
| CV fam.background × tracking length × vocational share | | | | | −0.265 |
| | | | | | [1.32] |
| CV family background × relative enrolment in pre-primary school | 0.1087 | 0.1237 | 0.1317 | 0.0949 | 0.127 |
| | [1.22] | [1.80]* | [1.97]* | [1.16] | [1.48] |
| *Controlling for student/teacher ratio in secondary schools* | | | | | |
| CV family background | −0.1117 | −0.1316 | −0.1364 | −0.1407 | −0.1095 |
| | [3.40]*** | [3.29]*** | [3.47]*** | [3.91]*** | [3.56]*** |
| CV fam.background × tracking length | 0.0603 | | | 0.0726 | 0.1075 |
| | [1.19] | | | [1.11] | [0.87] |
| CV fam.background × vocational share in upp.secondary | | 0.0407 | 0.1162 | 0.1682 | |
| | | [1.29] | [0.83] | [1.16] | |
| CV fam.background × vocational share in upp.secondary squared | | | −0.0903 | −0.1741 | |
| | | | [0.47] | [0.85] | |
| CV fam.background × tracking length × vocational share | | | | | −0.0731 |
| | | | | | [0.47] |
| CV family background × pupil teacher ratio secnd.school | 0.0066 | 0.0078 | 0.0072 | 0.0058 | 0.0063 |
| | [3.63]*** | [3.89]*** | [2.77]*** | [2.07]** | [3.00]*** |

**Table 7.** *Continued*

| Dep.var.: coefficient of variation years of education | **IALS + ISSP 1999** (18–24 and 28–34) | | | | |
|---|---|---|---|---|---|
| *Controlling for public educational expenditure over GDP* | | | | | |
| CV family background | 0.0361 [0.81] | 0.0635 [1.09] | 0.0045 [0.08] | −0.0545 [1.08] | 0.0143 [0.28] |
| CV fam.background × tracking length | 0.0888 [1.40] | | | 0.1222 [1.75]* | 0.1988 [1.36] |
| CV fam.background × vocational share in upp.secondary | | 0.0301 [0.79] | 0.2382 [1.66]* | 0.2882 [2.28]** | |
| CV fam.background × vocational share in upp.secondary squared | | | −0.2486 [1.32] | −0.3433 [1.94]* | |
| CV fam.background × tracking length × vocational share | | | | | −0.1763 [0.98] |
| CV fam.background × school expenditure on GDP | −0.0112 [1.13] | −0.0144 [1.13] | −0.0104 [0.86] | −0.0058 [0.65] | −0.0083 [0.86] |
| *Controlling for share of private school students in secondary schools* | | | | | |
| CV family background | −0.0201 [0.62] | 0.0074 [0.27] | −0.0444 [1.68]* | −0.0849 [2.00]** | −0.028 [0.81] |
| CV fam.background × tracking length | 0.0933 [1.18] | | | 0.133 [1.64] | 0.2362 [1.36] |
| CV fam.background × vocational share in upp.secondary | | −0.0012 [0.03] | 0.2641 [1.53] | 0.3082 [2.14]** | |
| CV fam.background × vocational share in upp.secondary squared | | | −0.3034 [1.35] | −0.382 [1.97]** | |
| CV fam.background × tracking length × vocational share | | | | | −0.2314 [1.15] |
| CV family background × share of private up.secnd.schools | 0.003 [0.08] | 0.0044 [0.10] | −0.0035 [0.07] | −0.0065 [0.17] | −0.0058 [0.16] |

*Notes:* CV = coefficient of variation. Weighed robust standard errors clustered by country × wave. *t* statistics in brackets.

[a] Excluded Slovenia.

* significant at 10%; ** significant at 5%; *** significant at 1%. Country × year, gender, age controls included.

Overall, these results are consistent with our theoretical model: the length of tracking tends to reinforce the family background effect, and its impact is reduced when the share of students in vocational schools increases.

## 6.2. Labour market outcomes

We now move to consider how school tracking and family background interact in the determination of employment and earnings, using the ECHP–ISSP dataset. In Table 8

**Table 8. Labour market conditions (employed/unemployed/out of labour force – multinomial logit – coefficients for employed)**

| Dep.var.: 2 = employment; 1 = unemployment; 0 = out of labour force condition | **ECHP + ISSP1991/99** (18–24) | | | | |
|---|---|---|---|---|---|
| Family background | −0.2044 [2.46]** | −0.2611 [3.92]*** | −0.3583 [4.11]*** | −0.2602 [3.21]*** | −0.2427 [3.47]*** |
| Fam.background × tracking length | −0.7383 [2.60]*** | | | −0.6148 [2.21]** | −0.3289 [1.20] |
| Fam.background × vocational share in upp.secondary | | −0.4191 [2.18]** | 0.301 [0.56] | 0.4205 [0.73] | |
| Fam.background × vocational share in upp.secondary squared | | | −0.8678 [1.16] | −0.6674 [0.93] | |
| Fam.background × tracking length × vocational share | | | | | −0.5534 [1.02] |
| Observations | 17 643 | 17 643 | 17 643 | 17 643 | 17 643 |
| Pseudo $R^2$ | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 |
| Log likelihood | −14 572.82 | −14 580.89 | −14 579.03 | −14 571.15 | −14 571.1 |
| Countries | 16 | 16 | 16 | 16 | 16 |
| *Controlling for enrolment in pre-primary schools* | | | | | |
| Family background | −0.1905 [1.62] | −0.2224 [2.31]** | −0.3124 [2.70]*** | −0.2574 [2.13]** | −0.2518 [1.92]* |
| Fam.background × tracking length | −0.6755 [2.83]*** | | | −0.6013 [2.55]** | −0.3149 [1.04] |
| Fam.background × vocational share in upp.secondary | | −0.3208 [1.41] | 0.2446 [0.47] | 0.3959 [0.70] | |
| Fam.background × vocational share in upp.secondary squared | | | −0.7123 [0.96] | −0.6431 [0.87] | |
| Fam.background × tracking length × vocational share | | | | | −0.5878 [0.90] |
| Family background × relative enrolment in pre-primary school | −0.1017 [0.35] | −0.237 [0.65] | −0.1753 [0.48] | −0.0095 [0.03] | 0.0281 [0.09] |
| *Controlling for student/teacher ratio in secondary schools* | | | | | |
| Family background | 0.0175 [0.08] | −0.0997 [0.49] | −0.1276 [0.65] | 0.0201 [0.10] | 0.0213 [0.10] |
| Fam.background × tracking length | −0.7942 [2.58]*** | | | −0.6599 [2.20]** | −0.2869 [1.02] |
| Fam.background × vocational share in upp.secondary | | −0.4445 [2.25]** | 0.5678 [0.85] | 0.7481 [1.03] | |
| Fam.background × vocational share in upp.secondary squared | | | −1.2436 [1.30] | −1.1024 [1.15] | |
| Fam.background × tracking length × vocational share | | | | | −0.7034 [1.16] |
| Family background × pupil teacher ratio secnd.school | −0.0147 [1.18] | −0.0109 [0.85] | −0.0183 [1.24] | −0.0216 [1.43] | −0.0182 [1.35] |

**Table 8.** *Continued*

| Dep.var.: 2 = employment; 1 = unemployment; 0 = out of labour force condition | | | **ECHP + ISSP1991/99** (18–24) | | |
|---|---|---|---|---|---|
| *Controlling for public educational expenditure over GDP* | | | | | |
| Family background | −0.0422 [0.18] | −0.1377 [0.57] | −0.2402 [0.96] | −0.1267 [0.53] | −0.1069 [0.50] |
| Fam.background × tracking length | −0.7088 [2.62]*** | | | −0.6315 [2.30]** | −0.3742 [1.45] |
| Fam.background × vocational share in upp.secondary | | −0.3801 [2.11]** | 0.3118 [0.57] | 0.4371 [0.78] | |
| Fam.background × vocational share in upp.secondary squared | | | −0.8373 [1.11] | −0.629 [0.87] | |
| Fam.background × tracking length × vocational share | | | | | −0.4623 [0.88] |
| Fam.background × school expenditure on GDP | −0.034 [0.78] | −0.028 [0.57] | −0.026 [0.52] | −0.0289 [0.64] | −0.0272 [0.63] |
| *Controlling for share of private school students in secondary schools* | | | | | |
| Family background | −0.2594 [3.13]*** | −0.3117 [4.47]*** | −0.3691 [4.24]*** | −0.2717 [3.28]*** | −0.2724 [3.53]*** |
| Fam.background × tracking length | −0.7447 [2.59]*** | | | −0.6686 [2.33]** | −0.4972 [1.81]* |
| Fam.background × vocational share in upp.secondary | | −0.3973 [2.20]** | 0.1581 [0.27] | 0.1756 [0.30] | |
| Fam.background × vocational share in upp.secondary squared | | | −0.6805 [0.85] | −0.3148 [0.44] | |
| Fam.background × tracking length × vocational share | | | | | −0.3326 [0.65] |
| Family background × share of private up.secnd.schools | 0.3059 [1.43] | 0.2179 [0.93] | 0.1404 [0.56] | 0.2537 [1.23] | 0.2475 [1.22] |

*Notes:* Weighed – Robust standard errors clustered by country × wave. *z* statistics in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%. Country × year, gender, age controls included. Baseline: out of labour force.

we report the estimated coefficients of the probability of being employed relative to the probability of being 'out of the labour market'. Since students are classified in the last group, it is not surprising that parental background is negatively associated to this probability. This effect is reinforced both by tracking length and by a higher share of students enrolled in vocational schools. Good parental background makes college attendance more likely and employment less likely. Moreover, a higher share of students in the vocational track should reduce parental background effects to be consistent with our results for college enrolment. However, this is not the case.

An explanation is that vocational tracks provide skills that can be spent rather easily in the labour market, thus favouring the employability of individuals with relatively poor family background, who have less access to favourable social networks.

Table 9 presents the results for earnings. Since assignment to employment is non-random, we estimate a simultaneous Heckman model and identify participation with variables, which capture the composition of households.

These variables – household size and the number of children younger than 12 – are only available in the ECHP dataset. Therefore, our earnings regressions are based on this dataset. We find that earnings are positively associated with parental education, and that this relationship is reinforced both by the extent of tracking and by the share of students enrolled in vocational schools. Table 10 looks at earnings inequality, using the combined ECHP–ISSP sample.

Here, only in a few specifications do we find that the dispersion of parental education is positively correlated with the dispersion of earnings (of the offspring). We also find that the interaction of the dispersion of parental background with tracking length is positive and statistically significant.

### 6.3. Life-long skills

Finally, we turn to skill formation. Table 11 looks at the correlation between parental background and literacy, using the IALS sample. It turns out that parental education is positively correlated with these skills. Interestingly, this effect is weaker when tracking length is higher or when the share of students enrolled in vocational schools is larger. Therefore, earlier tracking seems to reduce the impact of family background on the development of these skills.

This finding does not square well with previous findings in this literature. Schuetz *et al.* (2005), for instance, find that earlier tracking increases the impact of parental background on the standardized cognitive test scores taken by TIMMS at age 13. Waldinger (2006) on the other hand, finds no significant effect of schooling institutions on the FBE when examining the standardized tests taken at 15 by PISA.

While the tests taken by TIMMS, PISA and IALS are not strictly comparable, they all refer to cognitive skills. On the other hand, the IALS data used in this paper refer to individuals aged 17 or older, who may have completed high school or dropped out, and who are likely to have spent some time in the labour market. One way to reconcile our results with the rest of the literature is to argue that the time spent in the labour market undoes the negative impact of tracking on the family background effect. Another possible explanation is that our window of observation is more suitable to fully capture the effects of school tracking than earlier windows at 13 or 15, when the real effects on individual human capital have only started to unwind.

The positive contribution of tracking to reducing the impact of parental background on literacy extends also to the dispersion of literacy capabilities (Table 12). In addition,

**Table 9. Wages – OLS with Heckman selection equation**

| Dep.var.: log wage | | | **ECHP** (18–24) | | |
|---|---|---|---|---|---|
| Family background | 0.0197 | 0.039 | 0.0516 | −0.0152 | 0.0312 |
| | [0.81] | [1.88]* | [1.52] | [0.24] | [1.16] |
| Fam.background × tracking length | 0.1464 | | | 0.1504 | 0.0624 |
| | [2.29]** | | | [1.68]* | [0.57] |
| Fam.background × vocational share in upp.secondary | | 0.0702 | −0.0021 | 0.1594 | |
| | | [1.71]* | [0.01] | [0.59] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0824 | −0.1516 | |
| | | | [0.32] | [0.49] | |
| Fam.background × tracking length × vocational share | | | | | 0.1049 |
| | | | | | [0.98] |
| Observations | 14 300 | 14 300 | 14 300 | 14 300 | 14 300 |
| Log likelihood | −12 318.87 | −12 323.75 | −12 320.49 | −12 316.81 | −12 316.6 |
| Countries | 12 | 12 | 12 | 12 | 12 |
| *Controlling for enrolment in pre-primary schools* | | | | | |
| Family background | 0.0129 | 0.0346 | 0.0472 | −0.0158 | 0.0271 |
| | [0.55] | [1.55] | [1.24] | [0.25] | [0.83] |
| Fam.background × tracking length | 0.1268 | | | 0.1509 | 0.0694 |
| | [1.65]* | | | [1.60] | [0.60] |
| Fam.background × vocational share in upp.secondary | | 0.0333 | −0.0432 | 0.1411 | |
| | | [0.48] | [0.19] | [0.52] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0845 | −0.1453 | |
| | | | [0.32] | [0.47] | |
| Fam.background × tracking length × vocational share | | | | | 0.0883 |
| | | | | | [0.58] |
| Family background × relative enrolment in pre-primary school | 0.0378 | 0.0581 | 0.0619 | 0.0184 | 0.0124 |
| | [0.64] | [0.61] | [0.65] | [0.20] | [0.15] |
| *Controlling for student/teacher ratio in secondary schools* | | | | | |
| Family background | −0.0414 | −0.013 | 0.0067 | −0.0439 | −0.0335 |
| | [0.89] | [0.23] | [0.15] | [0.81] | [0.74] |
| Fam.background × tracking length | 0.165 | | | 0.1294 | 0.0542 |
| | [2.61]*** | | | [1.43] | [0.49] |
| Fam.background × vocational share in upp.secondary | | 0.0806 | −0.2282 | −0.0547 | |
| | | [1.66]* | [1.06] | [0.20] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.3561 | 0.1129 | |
| | | | [1.40] | [0.34] | |
| Fam.background × tracking length × vocational share | | | | | 0.1409 |
| | | | | | [1.21] |
| Family background × pupil teacher ratio secnd.school | 0.0039 | 0.0033 | 0.0055 | 0.0047 | 0.0043 |
| | [1.51] | [1.05] | [1.43] | [1.39] | [1.63] |

**Table 9.** *Continued*

| Dep.var.: log wage | | | ECHP (18–24) | | |
|---|---|---|---|---|---|
| *Controlling for public educational expenditure over GDP* | | | | | |
| Family background | 0.1263 | 0.1559 | 0.1646 | 0.0967 | 0.1474 |
| | [2.13]** | [2.69]*** | [2.68]*** | [1.51] | [2.59]*** |
| Fam.background × tracking length | 0.1622 | | | 0.1545 | 0.0555 |
| | [2.83]*** | | | [2.85]*** | [0.78] |
| Fam.background × vocational share in upp.secondary | | 0.1012 | 0.0592 | 0.2262 | |
| | | [2.99]*** | [0.40] | [1.42] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0489 | −0.1926 | |
| | | | [0.28] | [1.10] | |
| Fam.background × tracking length × vocational share | | | | | 0.1335 |
| | | | | | [2.24]** |
| Fam.background × school expenditure on GDP | −0.023 | −0.0268 | −0.0271 | −0.0273 | −0.0243 |
| | [1.76]* | [2.04]** | [2.03]** | [2.20]** | [1.90]* |
| *Controlling for share of private school students in secondary schools* | | | | | |
| Family background | 0.0199 | 0.0334 | 0.0491 | −0.0156 | 0.0286 |
| | [0.69] | [1.30] | [1.38] | [0.25] | [0.99] |
| Fam.background × tracking length | 0.1463 | | | 0.1528 | 0.0458 |
| | [2.27]** | | | [1.88]* | [0.42] |
| Fam.background × vocational share in upp.secondary | | 0.0736 | −0.0318 | 0.1669 | |
| | | [1.65]* | [0.15] | [0.62] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.1216 | −0.1629 | |
| | | | [0.50] | [0.53] | |
| Fam.background × tracking length × vocational share | | | | | 0.1258 |
| | | | | | [1.16] |
| Family background × share of private upp.secondary schools | −0.0005 | 0.0181 | 0.0281 | −0.0054 | 0.0213 |
| | [0.01] | [0.32] | [0.51] | [0.11] | [0.41] |

*Notes:* Weighed – Robust standard errors clustered by country × wave. $z$ statistics in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%. Country × year, gender, age controls included.

the parental background effect is also attenuated in countries with higher expenditure in education, while pre-primary enrolment works in the opposite direction.

Finally, we consider how tracking affects the relationship between parental background and training (Table 13), using either ECHP or IALS. If the 'learning begets learning' hypothesis holds, we should find results that are consistent with educational attainment. We find instead that parental background has a positive and statistically significant effect on training only in the IALS sample. Moreover, the interaction between parental background and tracking is negative, which suggests that the impact of family background on training is weaker in countries with earlier tracking.

**Table 10. Earnings inequality (OLS)**

| Dep.var.: coefficient of variation of earnings | **ECHP + ISSP1991/99** (18–24) | | | | |
|---|---|---|---|---|---|
| CV family background | −0.321 [2.09]** | −0.0751 [0.33] | 0.3265 [1.18] | 0.0852 [0.31] | −0.3305 [2.04]** |
| CV fam.background × tracking length | 0.9547 [3.67]*** | | | 1.1494 [4.37]*** | 1.0793 [1.28] |
| CV fam.background × vocational share in upp.secondary | | 0.2903 [0.79] | −2.4961 [1.80]* | −1.9179 [1.56] | |
| CV fam.background × vocational share in upp.secondary squared | | | 3.0742 [1.92]* | 1.6356 [1.28] | |
| CV fam.background × tracking length × vocational share | | | | | −0.1485 [0.15] |
| Observations | 331 | 331 | 331 | 331 | 331 |
| $R^2$ | 0.62 | 0.61 | 0.61 | 0.62 | 0.62 |
| Log likelihood | 13 | 9.79 | 11.1 | 13.96 | 13 |
| Countries | 16 | 16 | 16 | 16 | 16 |
| *Controlling for enrolment in pre-primary schools* | | | | | |
| CV family background | −0.3265 [1.98]* | −0.1369 [0.65] | 0.1825 [0.67] | 0.0904 [0.29] | −0.3335 [1.95]* |
| CV fam.background × tracking length | 1.07 [1.87]* | | | 1.4928 [2.45]** | 1.1597 [1.13] |
| CV fam.background × vocational share in upp.secondary | | −0.0164 [0.06] | −2.1281 [1.55] | −1.9426 [1.51] | |
| CV fam.background × vocational share in upp.secondary squared | | | 2.3778 [1.53] | 1.5793 [1.22] | |
| CV fam.background × tracking length × vocational share | | | | | −0.1131 [0.12] |
| CV family background × relative enrolment in pre-primary school | −0.1017 [0.29] | 0.5637 [3.14]*** | 0.4836 [3.32]*** | −0.2596 [0.75] | −0.0971 [0.28] |
| *Controlling for student/teacher ratio in secondary schools* | | | | | |
| Family background | −0.3094 [0.77] | −0.0453 [0.07] | 0.2944 [0.49] | 0.1557 [0.32] | −0.3123 [0.78] |
| CV fam.background × tracking length | 0.9541 [3.77]*** | | | 1.1558 [4.27]*** | 1.0855 [1.24] |
| CV fam.background × vocational share in upp.secondary | | 0.2862 [0.75] | −2.5003 [1.82]* | −1.905 [1.54] | |
| CV fam.background × vocational share in upp.secondary squared | | | 3.084 [1.96]* | 1.6055 [1.25] | |
| CV fam.background × tracking length × vocational share | | | | | −0.1571 [0.16] |
| CV family background × pupil teacher ratio secnd.school | −0.0009 [0.03] | −0.0021 [0.05] | 0.0023 [0.06] | −0.0052 [0.18] | −0.0014 [0.04] |

**Table 10.** *Continued*

| Dep.var.: coefficient of variation of earnings | **ECHP + ISSP1991/99** (18–24) | | | | |
|---|---|---|---|---|---|
| *Controlling for public educational expenditure over GDP* | | | | | |
| CV family background | −0.1288 [0.26] | −0.6671 [1.19] | −0.2261 [0.41] | 0.1137 [0.21] | −0.1242 [0.28] |
| CV fam.background × tracking length | 1.0864 [2.77]*** | | | 1.1673 [2.63]** | 1.0668 [1.27] |
| CV fam.background × vocational share in upp.secondary | | −0.0656 [0.24] | −2.5576 [1.84]* | −1.9052 [1.52] | |
| CV fam.background × vocational share in upp.secondary squared | | | 2.7993 [1.81]* | 1.6291 [1.25] | |
| CV fam.background × tracking length × vocational share | | | | | 0.0257 [0.03] |
| CV fam.background × school expenditure on GDP | −0.0434 [0.43] | 0.1414 [1.42] | 0.1234 [1.37] | −0.0072 [0.07] | −0.044 [0.48] |
| *Controlling for share of private school students in secondary schools* | | | | | |
| CV family background | −0.2073 [1.37] | 0.1595 [0.71] | 0.386 [1.47] | 0.1412 [0.51] | −0.2526 [1.61] |
| CV fam.background × tracking length | 0.815 [3.37]*** | | | 1.1909 [4.82]*** | 1.6134 [1.77]* |
| CV fam.background × vocational share in upp.secondary | | 0.0322 [0.10] | −1.7958 [1.32] | −1.1358 [0.87] | |
| CV fam.background × vocational share in upp.secondary squared | | | | 0.4922 [0.34] | |
| CV fam.background × tracking length × vocational share | | | | | −0.9772 [0.90] |
| CV family background × share of private upp.secondary schools | −0.772 [2.35]** | | 2.0701 [1.29] | −0.9231 [2.66]** | −0.8891 [2.65]** |

*Notes:* CV = coefficient of variation. Weighed robust standard errors clustered by country × wave. *t* statistics in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%. Country × year, gender, age controls included.

### 6.4. Summing up

Table 14 summarizes our findings, by focusing on the estimated coefficients of parental background and the interactions of this variable with tracking length and the share of students in vocational schools. Inspection of the second column in the table suggests that school tracking interacts in a complex way with parental background in the determination of educational and labour market outcomes. Whenever tracking reinforces the FBE, it contributes to reducing intergenerational mobility in educational attainment and to foster inequality. While reinforcement is the common pattern for

**Table 11. Competences – IALS sample (OLS)**

| Dep.var.: log competences (average across areas) | **IALS** (18–24 and 28–34) | | | | |
|---|---|---|---|---|---|
| Family background | 0.1122<br>[5.81]*** | 0.1213<br>[5.11]*** | 0.1227<br>[4.82]*** | 0.123<br>[4.82]*** | 0.1129<br>[5.48]*** |
| Fam.background × tracking length | −0.0991<br>[2.50]** | | | −0.0414<br>[0.96] | −0.1357<br>[0.94] |
| Fam.background × vocational share in upp.secondary | | −0.0825<br>[2.24]** | −0.1293<br>[1.31] | −0.1334<br>[1.33] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0641<br>[0.65] | 0.1069<br>[0.91] | |
| Fam.background × tracking length × vocational share | | | | | 0.0488<br>[0.32] |
| Observations | 12 195 | 12 195 | 12 195 | 12 195 | 12 195 |
| $R^2$ | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 |
| Log likelihood | 2771.78 | 2781.48 | 2782.43 | 2784.16 | 2772.05 |
| Countries | 17[a] | 17[a] | 17[a] | 17[a] | 17[a] |
| *Controlling for enrolment in pre-primary schools* | | | | | |
| Family background | 0.1029<br>[6.13]*** | 0.126<br>[5.69]*** | 0.1357<br>[4.59]*** | 0.1325<br>[4.42]*** | 0.1027<br>[5.16]*** |
| Fam.background × tracking length | −0.1168<br>[1.78]* | | | −0.0192<br>[0.38] | −0.1146<br>[0.89] |
| Fam.background × vocational share in upp.secondary | | −0.0788<br>[1.88]* | −0.1669<br>[1.57] | −0.1591<br>[1.54] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.1279<br>[1.08] | 0.1313<br>[1.08] | |
| Fam.background × tracking length × vocational share | | | | | −0.0033<br>[0.02] |
| Family background × relative enrolment in pre-primary school | 0.0375<br>[0.53] | −0.0168<br>[0.42] | −0.0411<br>[0.88] | −0.0305<br>[0.52] | 0.0379<br>[0.51] |
| *Controlling for student/teacher ratio in secondary schools* | | | | | |
| Family background | 0.0831<br>[2.81]*** | 0.1034<br>[2.28]** | 0.1028<br>[2.28]** | 0.0995<br>[2.31]** | 0.084<br>[2.74]*** |
| Fam.background × tracking length | −0.0961<br>[2.50]** | | | −0.0453<br>[1.00] | −0.1317<br>[0.94] |
| Fam.background × vocational share in upp.secondary | | −0.0806<br>[2.16]** | −0.1313<br>[1.34] | −0.1362<br>[1.37] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0698<br>[0.69] | 0.1177<br>[0.98] | |
| Fam.background × tracking length × vocational share | | | | | 0.0475<br>[0.31] |
| Family background × pupil teacher ratio secnd.school | 0.0021<br>[0.98] | 0.0013<br>[0.47] | 0.0014<br>[0.53] | 0.0017<br>[0.67] | 0.0021<br>[0.98] |

**Table 11.** *Continued*

| Dep.var.: log competences (average across areas) | | | **IALS** (18–24 and 28–34) | | |
|---|---|---|---|---|---|
| *Controlling for public educational expenditure over GDP* | | | | | |
| Family background | 0.1384 [3.13]*** | 0.1154 [2.51]** | 0.1126 [2.37]** | 0.1193 [2.39]** | 0.1378 [3.04]*** |
| Fam.background × tracking length | –0.0976 [2.37]** | | | –0.0405 [0.93] | –0.1267 [0.88] |
| Fam.background × vocational share in upp.secondary | | –0.0832 [2.23]** | –0.1336 [1.31] | –0.1349 [1.28] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0684 [0.67] | 0.1076 [0.89] | |
| Fam.background × tracking length × vocational share | | | | | 0.0386 [0.26] |
| Fam.background × school expenditure on GDP | –0.0052 [0.66] | 0.0012 [0.14] | 0.0021 [0.23] | 0.0008 [0.08] | –0.005 [0.59] |
| *Controlling for share of private school students in secondary schools* | | | | | |
| Family background | 0.1197 [5.69]*** | 0.1256 [5.10]*** | 0.1257 [4.98]*** | 0.126 [4.98]*** | 0.1195 [5.60]*** |
| Fam.background × tracking length | –0.0999 [2.54]** | | | –0.0414 [0.99] | –0.0471 [0.34] |
| Fam.background × vocational share in upp.secondary | | –0.0806 [2.20]** | –0.0873 [0.85] | –0.0914 [0.88] | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0091 [0.09] | 0.0519 [0.44] | |
| Fam.background × tracking length × vocational share | | | | | –0.0705 [0.47] |
| Family background × share of private upp.secondary schools | –0.0449 [2.30]** | –0.0318 [1.81]* | –0.0308 [1.92]* | –0.0308 [2.09]** | –0.0499 [3.02]*** |

*Notes:* Weighed – Robust standard errors clustered by country × wave. *t* statistics in brackets.
[a] Excluded Chile 1985.
* significant at 10%; ** significant at 5%; *** significant at 1%. Country × year, gender, age controls included.

educational attainment and early labour market outcomes, the opposite holds for literacy and training.

Our findings on literacy apparently contradict those obtained by Schuetz *et al.* (2005), who argue that early tracking reinforces the effect of parental background on standardized reading and maths skills, thereby exacerbating inequality of opportunities. To further investigate, we have replicated the estimates of the determinants of literacy in the PISA 2003 sample to check whether our contrasting results can be attributed either to a different sample or to different tracking indicators or finally to other

**Table 12. Inequality in the distribution of competences (OLS)**

| Dep. var.: coefficient of variation of competences | **IALS** (18–24 and 28–34) | | | | |
|---|---|---|---|---|---|
| CV family background | 0.0438 [3.59]*** | 0.0802 [4.04]*** | 0.0869 [2.58]** | 0.1548 [8.69]*** | 0.0629 [7.30]*** |
| CV fam.background × tracking length | −0.0757 [2.75]*** | | | −0.1503 [5.11]*** | −0.142 [4.21]*** |
| CV fam.background × vocational share in upp.secondary | | −0.1062 [3.73]*** | −0.1357 [1.37] | −0.3048 [4.96]*** | |
| CV fam.background × vocational share in upp.secondary squared | | | 0.0327 [0.40] | 0.2704 [4.18]*** | |
| CV fam.background × tracking length × vocational share | | | | | 0.0076 [0.15] |
| Observations | 444 | 408 | 408 | 408 | 408 |
| $R^2$ | 0.58 | 0.59 | 0.59 | 0.63 | 0.59 |
| Log likelihood | 887.18 | 850.03 | 850.18 | 868.49 | 848.14 |
| Countries | 18 | 17[a] | 17[a] | 17[a] | 17[a] |
| *Controlling for enrolment in pre-primary schools* | | | | | |
| CV family background | 0.052 [7.74]*** | 0.0831 [4.72]*** | 0.1011 [3.22]*** | 0.1323 [7.17]*** | 0.0493 [6.90]*** |
| CV fam.background × tracking length | −0.2587 [7.65]*** | | | −0.2399 [9.64]*** | −0.2315 [6.30]*** |
| CV fam.background × vocational share in upp.secondary | | −0.1043 [3.42]*** | −0.1694 [1.86]* | −0.2566 [4.08]*** | |
| CV fam.background × vocational share in upp.secondary squared | | | 0.0742 [0.95] | 0.2286 [3.42]*** | |
| CV fam.background × tracking length × vocational share | | | | | −0.043 [0.80] |
| CV family background × relative enrolment in pre-primary school | 0.171 [4.99]*** | −0.015 [0.51] | −0.0289 [1.02] | 0.1276 [4.48]*** | 0.1754 [4.90]*** |
| *Controlling for student/teacher ratio in secondary schools* | | | | | |
| CV family background | 0.0152 [0.53] | 0.0457 [0.86] | 0.0507 [0.87] | 0.1559 [5.30]*** | 0.0114 [0.37] |
| CV fam.background × tracking length | −0.1212 [4.05]*** | | | −0.1505 [5.06]*** | −0.1348 [3.79]*** |
| CV fam.background × vocational share in upp.secondary | | −0.0967 [2.72]*** | −0.1375 [1.42] | −0.305 [4.98]*** | |
| CV fam.background × vocational share in upp.secondary squared | | | 0.0466 [0.60] | 0.2703 [4.15]*** | |
| CV fam.background × tracking length × vocational share | | | | | 0.0218 [0.46] |
| CV family background × pupil teacher ratio secnd.school | 0.0029 [1.85]* | 0.002 [0.91] | 0.0023 [1.12] | −0.0001 [0.04] | 0.0033 [1.84]* |

**Table 12.** *Continued*

| Dep. var.: coefficient of variation of competences | **IALS** (18–24 and 28–34) | | | | |
|---|---|---|---|---|---|
| *Controlling for public educational expenditure over GDP* | | | | | |
| CV family background | 0.1197<br>[6.85]*** | 0.1384<br>[5.63]*** | 0.1517<br>[6.48]*** | 0.1882<br>[8.17]*** | 0.1216<br>[6.64]*** |
| CV fam.background × tracking length | −0.1078<br>[3.33]*** | | | −0.1326<br>[5.16]*** | −0.0888<br>[1.87]* |
| CV fam.background × vocational share in upp.secondary | | −0.0856<br>[2.72]*** | −0.1368<br>[1.67]* | −0.2856<br>[4.26]*** | |
| CV fam.background × vocational share in upp.secondary squared | | | 0.0574<br>[0.87] | 0.2581<br>[3.78]*** | |
| CV fam.background × tracking length × vocational share | | | | | −0.0246<br>[0.52] |
| CV fam.background × school expenditure on GDP | −0.013<br>[2.95]*** | −0.0137<br>[2.11]** | −0.014<br>[2.18]** | −0.0089<br>[2.28]** | −0.0137<br>[2.93]*** |
| *Controlling for share of private school students in secondary schools* | | | | | |
| CV family background | 0.0552<br>[6.06]*** | 0.07<br>[3.44]*** | 0.0757<br>[2.15]** | 0.1446<br>[6.90]*** | 0.0559<br>[6.09]*** |
| CV fam.background × tracking length | −0.1322<br>[4.83]*** | | | −0.1409<br>[4.14]*** | −0.1435<br>[4.64]*** |
| CV fam.background × vocational share in upp.secondary | | −0.1078<br>[3.59]*** | −0.1323<br>[1.31] | −0.2925<br>[4.37]*** | |
| CV fam.background × vocational share in upp.secondary squared | | | 0.0272<br>[0.31] | 0.2526<br>[3.36]*** | |
| CV fam.background × tracking length × vocational share | | | | | 0.0162<br>[0.32] |
| CV family background × share of private upp.secondary schools | 0.0155<br>[2.30]** | 0.0284<br>[1.40] | 0.0282<br>[1.35] | 0.0151<br>[1.27] | 0.0158<br>[2.46]** |

*Notes:* CV = coefficient of variation. Weighed robust standard errors clustered by country × wave. *t* statistics in brackets.
[a] Excluded Slovenia and Chile 1985.
* significant at 10%; ** significant at 5%; *** significant at 1%. Country × year, gender, age controls included.

factors (see Table 15).[43] Using our indicators, we confirm that tracking length reinforces the impact of parental education on the literacy of 15-year-old students, and that this effect survives even when we include additional indicators of school tracking.

We conclude from this that the relationship between school tracking and parental background is not independent of the window of observation when standardized test scores are the outcome of interest. Tracking possibly exacerbates the FBE early on,

[43] In order to increase comparability, our dependent variable is the (log of the) average test score on mathematical literacy, reading literacy, scientific literacy, problem solving. Parental background is defined so as to maintain comparability with IALS.

**Table 13. Probability of receiving on-the-job training (probit marginal effect)**

| Dep.var.: 1=use of training | **IALS** (18–24 and 28–34) | | | | | **ECHP** (18–24) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Family background | 0.188 | 0.1945 | 0.1963 | 0.197 | 0.1888 | 0.0073 | 0.0005 | –0.0604 | –0.0533 | 0.0015 |
| | [8.28]*** | [8.36]*** | [8.25]*** | [8.31]*** | [8.30]*** | [0.57] | [0.03] | [3.78]*** | [2.07]** | [0.11] |
| Fam.background × | –0.1295 | | | –0.1072 | –0.1729 | –0.0635 | | | –0.0122 | –0.0168 |
| tracking length | [1.39] | | | [0.60] | [0.60] | [1.97]** | | | [0.32] | [0.32] |
| Fam.background × | | –0.0967 | –0.1591 | –0.1632 | | | –0.032 | 0.274 | 0.2536 | |
| vocational share in upp.secondary | | [1.63] | [0.88] | [0.86] | | | [1.01] | [2.93]*** | [2.40]** | |
| Fam.background × | | | 0.0857 | 0.1881 | | | | –0.3239 | –0.2977 | |
| vocational share in upp.secondary squared | | | [0.31] | [0.66] | | | | [3.17]*** | [2.46]** | |
| Fam.background × | | | | | 0.0583 | | | | | –0.0588 |
| tracking length × vocational share | | | | | [0.14] | | | | | [1.09] |
| Observations | 11 146 | 11 146 | 11 146 | 11 146 | 11 146 | 14 892 | 14 892 | 14 892 | 14 892 | 14 892 |
| Pseudo $R^2$ | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 |
| Log likelihood | –6791.6 | –6791.77 | –6791.56 | –6790.16 | –6791.55 | –5845 | –5847.5 | –5841.44 | –5841.35 | –5844.3 |
| Countries | 17[a] | 17[a] | 17[a] | 17[a] | 17[a] | 12 | 12 | 12 | 12 | 12 |
| *Controlling for enrolment in pre-primary schools* | | | | | | | | | | |
| Family background | 0.156 | 0.1892 | 0.1953 | 0.1644 | 0.149 | 0.0093 | 0.0017 | –0.0593 | –0.0532 | –0.0012 |
| | [4.68]*** | [4.84]*** | [5.25]*** | [2.93]*** | [4.61]*** | [0.56] | [0.10] | [3.77]*** | [2.04]** | [0.05] |
| Fam.background × | –0.1879 | | | –0.1834 | –0.0919 | –0.0594 | | | –0.0111 | –0.0129 |
| tracking length | [1.87]* | | | [0.70] | [0.31] | [2.02]** | | | [0.29] | [0.21] |
| Fam.background × | | –0.1008 | –0.1563 | –0.0723 | | | –0.0223 | 0.2766 | 0.2574 | |
| vocational share in upp.secondary | | [2.08]** | [0.96] | [0.32] | | | [0.61] | [2.80]*** | [2.26]** | |
| Fam.background × | | | 0.0808 | 0.1003 | | | | –0.3217 | –0.2985 | |
| vocational share in upp.secondary squared | | | [0.36] | [0.39] | | | | [3.25]*** | [2.43]** | |
| Fam.background × | | | | | –0.1409 | | | | | –0.0685 |
| tracking length × vocational share | | | | | [0.33] | | | | | [0.95] |

**Table 13.** *Continued*

| Dep.var.: 1=use of training | IALS (18–24 and 28–34) | | | | | ECHP (18–24) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Family background × relative enrolment in pre-primary school | 0.126 | 0.0187 | 0.0032 | 0.1051 | 0.1459 | −0.009 | −0.0156 | −0.0075 | −0.0057 | 0.0081 |
| | [1.09] | [0.18] | [0.04] | [0.65] | [1.29] | [0.28] | [0.33] | [0.17] | [0.13] | [0.20] |
| *Controlling for student/teacher ratio in secondary schools* | | | | | | | | | | |
| Family background | 0.3233 | 0.3472 | 0.3467 | 0.3404 | 0.3243 | −0.0028 | −0.0146 | −0.0503 | −0.0474 | −0.0045 |
| | [3.11]*** | [3.21]*** | [3.20]*** | [3.41]*** | [3.16]*** | [0.12] | [0.48] | [3.71]*** | [2.70]*** | [0.19] |
| Fam.background × tracking length | −0.1432 | | | −0.0822 | −0.1896 | −0.0599 | | | −0.0055 | −0.0177 |
| | [1.50] | | | [0.49] | [0.64] | [1.79]* | | | [0.14] | [0.33] |
| Fam.background × vocational share in upp.secondary | | −0.1128 | −0.1436 | −0.1475 | | | −0.0274 | 0.3271 | 0.316 | |
| | | [1.98]** | [0.76] | [0.76] | | | [0.84] | [2.54]** | [2.08]** | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0425 | 0.1231 | | | | −0.3873 | −0.3732 | |
| | | | [0.15] | [0.43] | | | | [2.73]*** | [2.13]** | |
| Fam.background × tracking length × vocational share | | | | | 0.0622 | | | | | −0.0548 |
| | | | | | [0.14] | | | | | [0.92] |
| Family background × pupil teacher ratio secnd.school | −0.0098 | −0.0108 | −0.0107 | −0.0102 | −0.0098 | 0.0006 | 0.0009 | −0.0012 | −0.0012 | 0.0004 |
| | [1.41] | [1.46] | [1.41] | [1.47] | [1.42] | [0.57] | [0.71] | [0.86] | [0.77] | [0.32] |
| *Controlling for public educational expenditure over GDP* | | | | | | | | | | |
| Family background | 0.3554 | 0.3306 | 0.3294 | 0.3545 | 0.3557 | 0.0392 | 0.0237 | −0.0376 | −0.0249 | 0.0321 |
| | [4.38]*** | [3.76]*** | [3.95]*** | [4.33]*** | [4.43]*** | [1.39] | [0.87] | [1.07] | [0.58] | [1.16] |
| Fam.background × tracking length | −0.1191 | | | −0.148 | −0.1093 | −0.0627 | | | −0.0192 | −0.0268 |
| | [1.30] | | | [0.88] | [0.53] | [1.81]* | | | [0.45] | [0.48] |
| Fam.background × vocational share in upp.secondary | | −0.0812 | −0.101 | −0.0963 | | | −0.0241 | 0.2783 | 0.2467 | |
| | | [1.31] | [0.68] | [0.56] | | | [0.71] | [2.69]*** | [1.91]* | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0269 | 0.1581 | | | | −0.3207 | −0.2794 | |
| | | | [0.11] | [0.69] | | | | [2.79]*** | [1.87]* | |

**Table 13.** *Continued*

| Dep.var.: 1=use of training | **IALS** (18–24 and 28–34) | | | | | **ECHP** (18–24) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Fam.background × tracking length × vocational share | | | | | −0.0131<br>[0.04] | | | | | −0.0453<br>[0.78] |
| Fam.background × school expenditure on GDP | −0.0332<br>[2.04]** | −0.0278<br>[1.55] | −0.0275<br>[1.65]* | −0.0325<br>[1.97]** | −0.0333<br>[2.09]** | −0.0066<br>[1.28] | −0.0055<br>[1.11] | −0.0053<br>[0.81] | −0.0056<br>[0.90] | −0.0061<br>[1.20] |
| *Controlling for share of private school students in secondary schools* | | | | | | | | | | |
| Family background | 0.2<br>[8.71]*** | 0.2031<br>[8.52]*** | 0.2029<br>[8.31]*** | 0.2034<br>[8.35]*** | 0.1996<br>[8.54]*** | −0.0067<br>[0.39] | −0.0181<br>[0.82] | −0.0642<br>[3.96]*** | −0.0476<br>[1.86]* | −0.0065<br>[0.40] |
| Fam.background × tracking length | −0.1285<br>[1.38] | | | −0.1035<br>[0.58] | −0.0162<br>[0.05] | −0.0603<br>[2.09]** | | | −0.0299<br>[0.95] | −0.0627<br>[1.35] |
| Fam.background × vocational share in upp.secondary | | −0.0926<br>[1.53] | −0.0714<br>[0.40] | −0.0777<br>[0.41] | | | −0.0186<br>[0.59] | 0.2393<br>[2.31]** | 0.1834<br>[1.51] | |
| Fam.background × vocational share in upp.secondary squared | | | −0.0288<br>[0.11] | 0.0732<br>[0.26] | | | | −0.2776<br>[2.32]** | −0.2053<br>[1.45] | |
| Fam.background × tracking length × vocational share | | | | | −0.1502<br>[0.34] | | | | | 0.0031<br>[0.05] |
| Family background × share of private upp.secondary schools | −0.0772<br>[1.41] | −0.065<br>[1.18] | −0.068<br>[1.48] | −0.0664<br>[1.33] | −0.0885<br>[1.87]* | 0.056<br>[2.05]** | 0.0536<br>[1.55] | 0.036<br>[1.09] | 0.0423<br>[1.34] | 0.0565<br>[1.81]* |

*Notes:* Weighed – Robust standard errors clustered by country × wave. *z* statistics in brackets.

[a] Excluded Chile 1985.

* significant at 10%; ** significant at 5%; *** significant at 1%. Country × year, gender, age controls included.

**Table 14. Summary of empirical results**

| | Parental background | Parental background × tracking length | Parental background × share in vocational |
|---|---|---|---|
| Years of education | + | + | − |
| Probability of dropping out of school | − | − | − |
| Probability of college enrolment/attainment | + | + | − |
| Schooling inequality | − | + | |
| Probability of employment | − | − | + |
| Earnings | + | + | + |
| Earnings inequality | − | + | |
| Literacy | + | − | − |
| Literacy inequality | + | − | − |
| Training | + | − | − |

at the age of selection into tracks or immediately after. When we take a longer perspective, however, and ask whether these reinforcing effects persist in tests taken later on, we find that they do not survive.

## 7. POLICY IMPLICATIONS

In this paper, we have investigated whether the potential role of tracking in reducing equality of opportunity by reinforcing family background effects persists beyond the early tests taken at 13 and 15 and affects the educational attainment, skill development and early labour market history of young adults. Suppose that it does, perhaps because learning is persistent over time, or because the negative effects of tracking do not concentrate at the time of track selection, but unravel during secondary school and at the critical time of college choice. Then the damaging effects of early tracking on inequality are even more relevant for policy, because they spread from the classrooms of early secondary school to early working life.

Suppose instead that the reinforcing effects of tracking weaken or even disappear at age 18 or later, during college or in the early stage of labour market experience. Then policy concern on the inequality implications of early tracking is likely to be over-emphasized, and policy measures such as de-tracking are less justified on equity grounds. On balance, our results are mixed. Consider for instance the literacy scores in the standardized tests taken by young adults, aged between 17 and 35. Presumably these scores reflect not only formal schooling until the mid twenties, but also training and early labour market experience. For this sample of individuals we find that early school tracking reduces the impact of family background on the level and the coefficient of variation of literacy. This could depend on training, as we find that early tracking also reduces the impact of family background on the provision of training. One plausible story is that the type of skills provided by vocational schools increases the

**Table 15. Competences – PISA sample (OLS)**

| Dep.var.: log competences (average across areas) | **PISA 2003** (full sample 32 countries) | | | | | **PISA 2003** (sample comparable to IALS 14 countries) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Family background | 0.0612 | 0.0672 | 0.0683 | 0.0646 | 0.0624 | 0.066 | 0.0699 | 0.0699 | 0.0701 | 0.0665 |
| | [9.67]*** | [20.31]*** | [24.63]*** | [10.69]*** | [10.81]*** | [13.97]*** | [29.24]*** | [51.54]*** | [70.40]*** | [15.19]*** |
| Fam.background × tracking length | 0.0326 | | | 0.0387 | 0.0075 | 0.0354 | | | 0.0763 | 0.0015 |
| | [1.76]* | | | [1.89]* | [0.41] | [2.39]** | | | [4.65]*** | [0.03] |
| Fam.background × vocational share in upp.secondary | | 0.0114 | −0.0009 | −0.0446 | | | 0.0158 | 0.0165 | −0.1463 | |
| | | [0.82] | [0.03] | [0.85] | | | [0.96] | [0.25] | [2.07]* | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0182 | 0.0588 | | | | −0.001 | 0.1656 | |
| | | | [0.31] | [0.88] | | | | [0.01] | [1.84]* | |
| Fam.background × tracking length × vocational share | | | | | 0.0559 | | | | | 0.0581 |
| | | | | | [2.08]** | | | | | [0.72] |
| Observations | 216 974 | 212 615 | 212 615 | 212 615 | 212 615 | 75 388 | 75 388 | 75 388 | 75 388 | 75 388 |
| $R^2$ | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.09 | 0.09 | 0.09 | 0.1 | 0.09 |
| Log likelihood | 65 633.76 | 64 230.27 | 64 231.42 | 64 293.66 | 64 308.15 | 21 990.14 | 21 961.79 | 21 961.79 | 22 012.19 | 21 994.74 |
| Countries | 32 | 32 | 32 | 32 | 32 | 14 | 14 | 14 | 14 | 14 |
| *Controlling for enrolment in pre-primary schools* | | | | | | | | | | |
| Family background | 0.0552 | 0.062 | 0.0635 | 0.0583 | 0.0581 | 0.0657 | 0.0545 | 0.0489 | 0.0804 | 0.0597 |
| | [6.45]*** | [8.58]*** | [11.86]*** | [8.98]*** | [6.70]*** | [2.92]** | [4.71]*** | [3.26]*** | [2.13]* | [2.38]** |
| Fam.background × tracking length | 0.0311 | | | 0.042 | 0.0112 | 0.0347 | | | 0.1008 | −0.0218 |
| | [1.69] | | | [2.59]** | [0.56] | [0.77] | | | [1.14] | [0.24] |
| Fam.background × vocational share in upp.secondary | | 0.0067 | −0.0146 | −0.0652 | | | 0.0065 | −0.0894 | −0.147 | |
| | | [0.49] | [0.31] | [1.45] | | | [0.39] | [0.80] | [2.18]** | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0308 | 0.078 | | | | 0.1346 | 0.153 | |
| | | | [0.49] | [1.40] | | | | [0.95] | [1.53] | |
| Fam.background × tracking length × vocational share | | | | | 0.0455 | | | | | 0.0764 |
| | | | | | [1.40] | | | | | [0.86] |

**Table 15.** *Continued*

| Dep.var.: log competences (average across areas) | **PISA 2003** (full sample 32 countries) | | | | | **PISA 2003** (sample comparable to IALS 14 countries) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Family background × relative enrolment in pre-primary school | 0.0168 | 0.0172 | 0.0185 | 0.0229 | 0.0112 | 0.0014 | 0.0441 | 0.0686 | −0.0335 | 0.0245 |
| | [1.09] | [0.88] | [0.84] | [1.25] | [0.65] | [0.02] | [1.22] | [1.36] | [0.27] | [0.29] |
| *Controlling for student/teacher ratio in secondary schools* | | | | | | | | | | |
| Family background | 0.0711 | 0.0706 | 0.072 | 0.0972 | 0.067 | 0.0229 | 0.0504 | 0.0197 | 0.0611 | 0.0182 |
| | [9.53]*** | [8.21]*** | [10.26]*** | [8.99]*** | [7.16]*** | [0.77] | [1.49] | [0.36] | [2.17]** | [0.41] |
| Fam.background × tracking length | 0.0372 | | | 0.077 | 0.014 | 0.0428 | | | 0.0749 | 0.051 |
| | [1.90]* | | | [4.11]*** | [0.41] | [3.67]*** | | | [4.72]*** | [0.82] |
| Fam.background × vocational share in upp.secondary | | 0.0092 | −0.0027 | −0.1213 | | | 0.0178 | 0.0869 | −0.1307 | |
| | | [0.59] | [0.08] | [3.50]*** | | | [0.97] | [0.84] | [2.19]** | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0173 | 0.1203 | | | | −0.0983 | 0.1451 | |
| | | | [0.31] | [2.63]** | | | | [0.69] | [2.17]** | |
| Fam.background × tracking length × vocational share | | | | | 0.043 | | | | | −0.0127 |
| | | | | | [0.86] | | | | | [0.13] |
| Family background × pupil teacher ratio secnd.school | −0.0007 | −0.0001 | −0.0001 | −0.0018 | −0.0003 | 0.0029 | 0.0013 | | 0.0006 | 0.0032 |
| | [1.74]* | [0.34] | [0.41] | [2.93]*** | [0.42] | [1.48] | [0.60] | | [0.32] | [1.12] |
| *Controlling for public educational expenditure over GDP* | | | | | | | | | | |
| Family background | 0.0222 | 0.0596 | 0.0716 | 0.0312 | 0.0412 | 0.0279 | −0.0005 | −0.0021 | 0.0605 | 0.0152 |
| | [1.00] | [5.14]*** | [5.90]*** | [1.68] | [1.72]* | [0.91] | [0.01] | [0.03] | [1.52] | [0.63] |
| Fam.background × tracking length | 0.04 | | | 0.053 | 0.0125 | 0.043 | | | 0.0752 | −0.0005 |
| | [2.06]** | | | [3.98]*** | [0.54] | [3.19]*** | | | [3.79]*** | [0.01] |
| Fam.background × vocational share in upp.secondary | | 0.0083 | −0.0551 | −0.1018 | | | 0.0348 | 0.0266 | −0.1426 | |
| | | [0.56] | [1.74]* | [3.04]*** | | | [1.39] | [0.39] | [1.82]* | |
| Fam.background × vocational share in upp.secondary squared | | | 0.091 | 0.1344 | | | | 0.0129 | 0.165 | |
| | | | [1.75]* | [2.76]** | | | | [0.14] | [1.82]* | |

**Table 15.** *Continued*

| Dep.var.: log competences (average across areas) | **PISA 2003** (full sample 32 countries) | | | | | **PISA 2003** (sample comparable to IALS 14 countries) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Fam.background × tracking length × vocational share | | | | | 0.0477 | | | | | 0.079 |
| | | | | | [1.38] | | | | | [1.00] |
| Fam.background × school expenditure on GDP | 0.0013 | 0.0002 | 0 | 0.0012 | 0.0007 | 0.0013 | 0.0023 | 0.0023 | 0.0003 | 0.0017 |
| | [1.71]* | [0.55] | [0.03] | [2.02]* | [0.83] | [1.22] | [1.03] | [1.08] | [0.24] | [2.17]** |
| *Controlling for share of private school students in secondary schools* | | | | | | | | | | |
| Family background | 0.0681 | 0.0719 | 0.0754 | 0.0717 | 0.0695 | 0.0707 | 0.0723 | 0.077 | 0.0755 | 0.073 |
| | [14.11]*** | [26.34]*** | [37.88]*** | [20.62]*** | [16.35]*** | [17.24]*** | [17.82]*** | [86.03]*** | [37.88]*** | [24.79]*** |
| Fam.background × tracking length | 0.034 | | | 0.034 | 0.0063 | 0.0368 | | | 0.0437 | −0.0271 |
| | [2.59]** | | | [2.64]** | [0.50] | [3.52]*** | | | [1.50] | [0.54] |
| Fam.background × vocational share in upp.secondary | | 0.025 | −0.01 | −0.0477 | | | 0.0378 | −0.0708 | −0.1435 | |
| | | [2.12]** | [0.40] | [1.42] | | | [3.11]*** | [1.58] | [2.57]** | |
| Fam.background × vocational share in upp.secondary squared | | | 0.0526 | 0.086 | | | | 0.174 | 0.2281 | |
| | | | [1.31] | [1.93]* | | | | [2.46]** | [3.74]*** | |
| Fam.background × tracking length × vocational share | | | | | 0.0618 | | | | | 0.1102 |
| | | | | | [3.38]*** | | | | | [1.41] |
| Family background × share of private upp.secondary schools | −0.0372 | −0.0459 | −0.0486 | −0.0454 | −0.0386 | −0.0273 | −0.0496 | −0.0695 | −0.0531 | −0.0353 |
| | [3.06]*** | [4.39]*** | [4.53]*** | [4.13]*** | [3.61]*** | [2.31]** | [4.02]*** | [6.29]*** | [2.28]** | [2.97]** |

*Notes:* Weighed – Robust standard errors clustered by country. *t* statistics in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%. Country, gender, age controls included.

trainability of workers, thereby reducing the scope for alternative selection mechanisms, such as those based on parental background and the associated informal networks.

Can we then conclude that early tracking is beneficial in reducing inequality of opportunity? Not if we look also at educational attainment and early labour market history. Here, we find that early tracking reinforces the family background effects on the years of completed education, on the probability of dropping out and on the probability of enrolling or graduating from college. Therefore, in countries with less pronounced tracking, the difference between the children of poorly and better educated parents in the dropout rate and college enrolment or completion is smaller than in countries with longer tracking. Perhaps more importantly, we also find that early tracking reinforces the impact of parental background on earnings.

How do we reconcile these findings with the findings on literacy and training? In our empirical estimates, we have associated (log) earnings to individual controls, country × cohort dummies, parental background and the interaction of parental background with school tracking and other confounding factors. We can think of this specification as a reduced form. More precisely, suppose that log earnings depend on educational attainment, training and accumulated skills, measured by the literacy test scores. In our empirical model, these variables depend on parental background and its interactions with tracking and other confounding factors. If we replace the explanatory variables in the earnings regressions with their empirical determinants, we obtain an empirical specification where (log) earnings depend – among other things – on parental background and its interactions with tracking and other confounding effects. Thus, the overall impact of tracking on the FBE for earnings that we find in our data is the combination of the positive impact on the FBE for educational attainment and the negative impact on the FBE for literacy and training, with the former effect prevailing on the latter.

If we take labour market earnings as the key indicator of inequality of opportunity, the natural conclusion we draw from our analysis is that we should concentrate our attention on the effect of tracking on the relationship between parental background and educational attainment. This is far from surprising, since we know that the impact of education on wages is particularly important in the early stages of individual careers, and that the signalling effect of schooling loses importance in favour of labour market experience as individuals age.

Our empirical results have also interesting implications for intergenerational mobility. To see why, assume that the government cares about intertemporal inequality in educational attainment, and therefore tries to maximize intergenerational mobility. Our regressions can be framed in terms of intergenerational mobility as follows:

$$H_{it+1} = \alpha + \beta_0 H_{it} + \beta_1 H_{it}\tau + \beta_2 H_{it}\Phi + \beta_3 H_{it}\Phi^2 + \varepsilon_{it} \qquad (4)$$

where $H_{it+1}$ is the educational attainment of individual $i$, and $H_{it}$ is the educational attainment of her parent. We define the family background effect (*FBE*) in this set-up as:

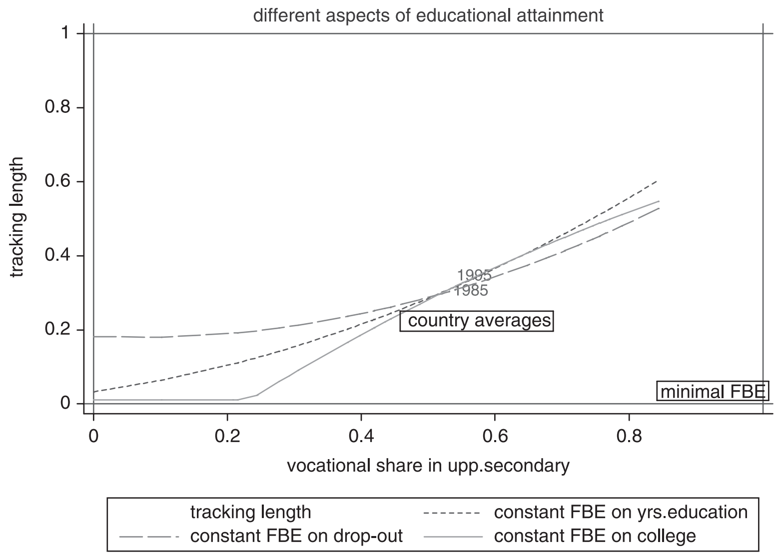


**Figure 2. Normative analysis: educational attainments**

$$FBE = \frac{dH_{it+1}}{dH_{it}} = \beta_0 + \beta_1\tau + \beta_2\Phi + \beta_3\Phi^2 \tag{5}$$

Equation (5) can be used to obtain a map of 'iso-FBE' loci, given by:

$$\tau = \frac{\overline{FBE} - \beta_0 - \beta_2\Phi - \beta_3\Phi^2}{\beta_1} \tag{6}$$

where $\overline{FBE}$ is evaluated at the sample average values of $\tau$ and $\Phi$.

Suppose that the government chooses tracking length and the share of students in vocational education to minimize the FBE, which measures the persistence of educational attainment across generations. Using our alternative measures of educational attainment for $H$ (years of education, dropout probability and probability of college enrolment/graduation – see Tables 4, 5 and 6), the minimum is attained at $\tau^* = 0$, $\Phi^* = 1$: therefore, countries characterized by no tracking ($\tau^* = 0$) and/or by homogenous secondary schools ($\Phi^* = 1$ or $\Phi^* = 0$ are equivalent in this respect) have the lowest *FBE*, or the highest intergenerational mobility in education. We draw these loci in Figure 2, and also pinpoint the combination $\tau^* = 0$, $\Phi^* = 1$ which maximizes intergenerational mobility. Qualitatively similar results are obtained when we consider the impact of family background on either employment or earnings: in these cases intergenerational mobility is maximized at $\tau^* = 0.18$, $\Phi^* = 0.20$ and $\tau^* = 0.20$, $\Phi^* = 0.72$ respectively.

Thus a benevolent social planner, who aims at maximizing intertemporal mobility in educational attainment, should select a comprehensive educational system at the secondary level. Slightly different prescriptions emerge if we consider the intergenerational

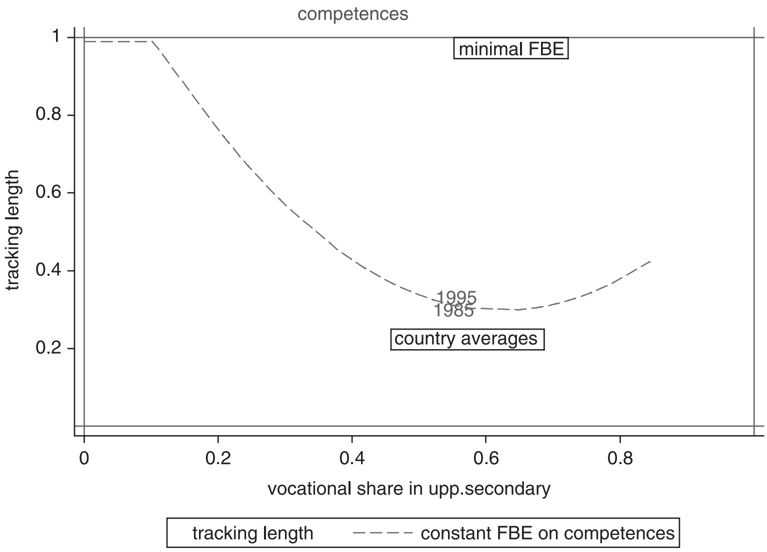


**Figure 3. Normative analysis: adult competences (IALS)**

mobility of earnings because in such case some tracking (approximately two years) would be beneficial, even without any concern for efficiency. This implication is reinforced when we consider adult competences. Consistently with previous estimates (see Tables 11 and 13), the institutional design in the ($\tau$, $\Phi$) space that increases equality of opportunity in the distribution of competences (see Figure 3) or in the access to training (see Figure 4) is a fully tracked secondary educational system, with a share of students in the vocational track $\Phi$* ranging between 0.43 and 0.62.

This reinforces our claim that in our sample of countries school tracking has an ambiguous effect. On the one hand, and consistently with the previous literature, tracking has a detrimental impact on educational attainment, because it prevents some individuals from further progressing to the tertiary level of education (the *diversion effect*). On the other hand, the curricula offered in vocational schools are more effective in promoting further training and adult competences (the *specialization effect*), thereby reducing the impact of parental background on these two outcomes.

Due to data limitations – we ignore the type of track attended by the adult individuals in our sample – our empirical evidence does not cover all the relevant aspects of tracking from an equity perspective. For instance, an evaluation of tracking in terms of equity would also require that we investigate the assignment rule used in a tracked system. For the sake of simplicity, our theoretical discussion was carried out on the assumption that individual talents were perfectly observable, and that assignment was based on pure ability. This may be overly simple, and other important factors could be at play.

We can provide some evidence on this by looking at the allocation of students to tracks as they can be inferred from the PISA 2003 survey. In most countries where

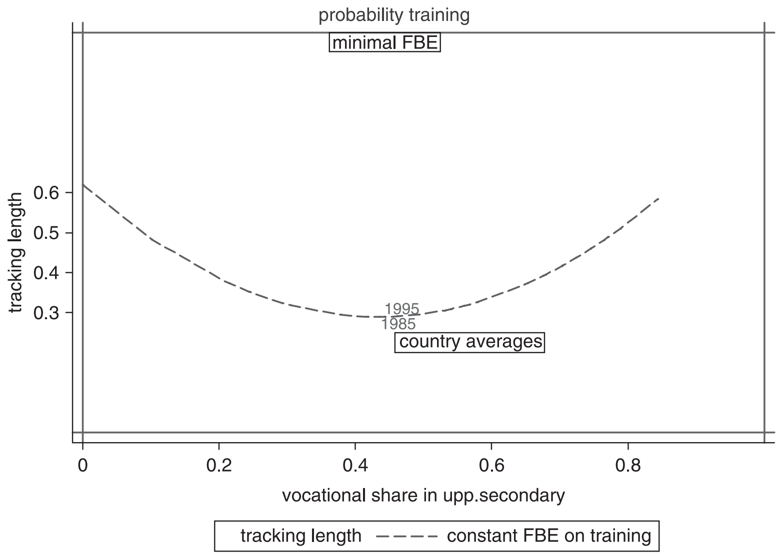


**Figure 4. Normative analysis: training probability**

vocational schools are available, students are sorted into qualitatively different tracks, and the vocational track provides lower quality education. Table 16 reports the median differences in test scores between students in general and vocational tracks, at the same age and in the same grade. On average, 40% of the students in these countries are enrolled in vocational tracks, and have a lower level of literacy than the students in academic tracks (the difference being highest in reading and lowest in problem solving).

We cannot tell whether the observed differences are the reflection of individual characteristics and peer effects, the outcome of the different educational curricula provided in vocational schools, the result of teacher self-sorting, or a combination of all these factors. *Ceteris paribus*, whether a tracked educational system is more or less equitable depends on the criteria, which regulate student sorting. We explore the sorting process taking place in countries with tracking in Table 17, which reports the estimates of a probit model, where the dependent variable is attending a vocational school (Columns 1 to 4). To provide a benchmark for comparison, especially in the case of non-tracked countries, we have also investigated the probability of attending a private school (Columns 5 to 8). We are interested in understanding whether student sorting is based on ability, parental education and/or parental income, and whether this is affected by institutional differences in the extent of tracking. Since we cannot use test scores as measures of ability – they could be endogenous when different types of schools provide different types of education – we resort to information on whether during the previous year a student has obtained scores that are equal to

**Table 16. Competences, by school type. PISA 2003. Countries with secondary vocational programmes**

| | Median score of students in general schools/median score of students in vocational schools | | | | Share of 15-year-old in vocational schools |
|---|---|---|---|---|---|
| | Mathematics | Reading | Scientific knowledge | Problem solving | |
| Austria | 1.152 | 1.196 | 1.182 | 1.156 | 77.55 |
| Belgium | 1.185 | 1.166 | 1.186 | 1.171 | 36.45 |
| Czech Republic | 1.220 | 1.212 | 1.218 | 1.197 | 66.45 |
| Germany | 1.197 | 1.204 | 1.199 | 1.181 | 55.21 |
| Greece | 1.254 | 1.259 | 1.248 | 1.286 | 20.99 |
| Hungary | 1.204 | 1.203 | 1.185 | 1.209 | 61.39 |
| Indonesia | 1.084 | 1.082 | 1.061 | 1.097 | 0.00 |
| Ireland | 1.052 | 1.051 | 1.051 | 1.066 | 0.00 |
| Italy | 1.094 | 1.134 | 1.115 | 1.109 | 58.14 |
| Japan | 1.095 | 1.088 | 1.096 | 1.089 | 25.54 |
| Korea | 1.207 | 1.171 | 1.226 | 1.177 | 28.85 |
| Luxembourg | 1.119 | 1.125 | 1.140 | 1.129 | 0.00 |
| Mexico | 1.014 | 1.004 | 0.980 | 0.979 | 37.97 |
| Netherlands | 1.249 | 1.231 | 1.295 | 1.238 | 69.11 |
| Portugal | 1.082 | 1.064 | 1.095 | 1.047 | 12.63 |
| Russian Federation | 1.107 | 1.100 | 1.102 | 1.103 | 24.24 |
| Slovakia | 1.207 | 1.216 | 1.221 | 1.200 | 71.41 |
| Turkey | 1.035 | 1.005 | 1.021 | 1.014 | 33.27 |
| Uruguay | 1.074 | 1.121 | 1.105 | 1.095 | 14.98 |
| Yugoslavia | 1.190 | 1.186 | 1.180 | 1.174 | 79.44 |
| *Mean* | *1.035* | *1.050* | *1.039* | *1.026* | *39.14* |

*Note:* Students are restricted to belong to the modal grade in the country (except for Indonesia, Ireland and Luxemburg, where students in vocational schools are typically one or two years ahead of the modal class).

or above/below the pass mark in mathematics.[44] To capture the role played by cultural resources, we also include a variable measuring the number of books available at home. For parental income, we use two alternative measures: an index of occupational prestige,[45] and an index of possession of durables and cultural resources (both variables are positively correlated with unreported family income).

[44] We have also considered alternative proxies of ability, based on the number of repetitions during the previous schooling career (see Goux and Maurin, 2006), but not all the countries resort to grade repetition to cope with low ability students, and therefore this measure is not available for all countries. The current information on ability based on marks is available only for a subgroup of countries. In Table 17 we report the following countries (in columns 1–4: Austria, Czech Republic, Germany, Greece, Hungary, Ireland, Italy, Mexico, the Netherlands, Portugal, Slovakia, whereas in columns 5–8: Austria, Czech Republic, Germany, Greece, Hungary, Ireland, Italy, Mexico, the Netherlands, Portugal, Slovakia, United States).

[45] 'The PISA *international socio-economic index of occupational status* (ISEI) is derived from students' responses to questions about parental occupation. The index captures the attributes of occupations that convert parental education into income. It is derived by optimal scaling occupation groups so as to maximize the indirect effect of education on income via occupation and to minimize the direct effect of education on income, net of occupation (both effects are net of age). For more information on the methodology, see Ganzeboom *et al.* (1992). The *highest international socio-economic index of occupational status* (HISEI) corresponds to the highest ISEI of either the father or the mother' (OECD, 2004, p. 307).

**Table 17. Choice of vocational or private schools (probit marginal effect) – PISA 2003**

| | 1<br>vocational | 2<br>vocational | 3<br>vocational | 4<br>vocational | 5<br>private | 6<br>private | 7<br>private | 8<br>private |
|---|---|---|---|---|---|---|---|---|
| Male | 0.0789 | 0.0744 | 0.0808 | 0.0803 | –0.0232 | –0.0229 | –0.0211 | –0.0209 |
| | [2.29]** | [2.10]** | [2.24]** | [2.29]** | [2.42]** | [2.42]** | [2.07]** | [2.08]** |
| Age | 0.1189 | 0.1215 | 0.1248 | 0.1263 | 0.0128 | 0.0125 | 0.0124 | 0.0121 |
| | [1.73]* | [1.82]* | [1.83]* | [1.84]* | [2.86]*** | [2.82]*** | [2.79]*** | [2.76]*** |
| Low marks in | 0.047 | 0.0765 | 0.0438 | 0.0744 | –0.0089 | –0.0142 | –0.0053 | –0.0099 |
| mathematics | [1.85]* | [2.15]** | [1.89]* | [2.54]** | [3.16]*** | [7.97]*** | [2.16]** | [4.29]*** |
| Family background | –0.0957 | –0.0498 | –0.037 | 0.0156 | 0.041 | 0.0464 | 0.0216 | 0.0258 |
| | [2.83]*** | [1.65]* | [2.04]** | [0.71] | [3.20]*** | [2.61]*** | [2.85]*** | [2.11]** |
| Books at home | –0.0005 | –0.0005 | –0.0004 | –0.0003 | 0.0001 | 0.0001 | 0 | 0 |
| | [17.32]*** | [5.44]*** | [9.10]*** | [3.39]*** | [4.18]*** | [4.49]*** | [1.24] | [1.71]* |
| Intact family | –0.0045 | –0.0066 | 0.0019 | 0.0027 | 0.0185 | 0.0186 | 0.0132 | 0.0134 |
| | [0.27] | [0.40] | [0.13] | [0.18] | [2.05]** | [2.05]** | [1.53] | [1.54] |
| Speaking dialect | 0.0709 | 0.0823 | 0.0339 | 0.044 | 0.0052 | 0.0059 | 0.0187 | 0.0192 |
| at home | [1.47] | [1.83]* | [0.69] | [1.00] | [0.16] | [0.18] | [0.67] | [0.69] |
| Foreign born | 0.0212 | 0.0146 | 0.0006 | –0.0136 | –0.0348 | –0.035 | –0.0311 | –0.0314 |
| | [0.91] | [0.59] | [0.02] | [0.71] | [8.65]*** | [9.90]*** | [6.01]*** | [6.95]*** |
| Low marks in | | –0.2145 | | –0.2098 | | 0.0537 | | 0.0446 |
| mathematics × | | [2.17]** | | [2.26]** | | [2.75]*** | | [2.80]*** |
| length × voc.share | | | | | | | | |
| Fam.background × | | –0.2591 | | –0.3 | | –0.0471 | | –0.0354 |
| length × voc.share | | [3.79]*** | | [4.65]*** | | [0.93] | | [0.79] |
| Books at home × | | –0.0001 | | –0.0002 | | 0.0001 | | 0 |
| length × voc.share | | [0.51] | | [0.65] | | [0.62] | | [0.58] |
| Highest parental | | | –0.0047 | –0.0048 | | | 0.001 | 0.001 |
| occupational status | | | [2.98]*** | [2.98]*** | | | [7.74]*** | [7.92]*** |
| Index of home | | | –0.0428 | –0.0457 | | | 0.0194 | 0.0191 |
| possessions (wle) | | | [2.27]** | [2.57]** | | | [2.18]** | [2.25]** |
| Observations | 72 860 | 72 860 | 72 860 | 72 860 | 77 532 | 77 532 | 77 532 | 77 532 |
| Countries | 11 | 11 | 11 | 11 | 12 | 12 | 12 | 12 |
| Pseudo $R^2$ | 0.12 | 0.12 | 0.14 | 0.14 | 0.19 | 0.19 | 0.21 | 0.21 |
| Log likelihood | –44 326.75 | –45 447.93 | –43 503.46 | –43 295.97 | –20 791.21 | –20 775.38 | –20 487.35 | –20 477.44 |

*Notes:* Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%. Country dummies included.

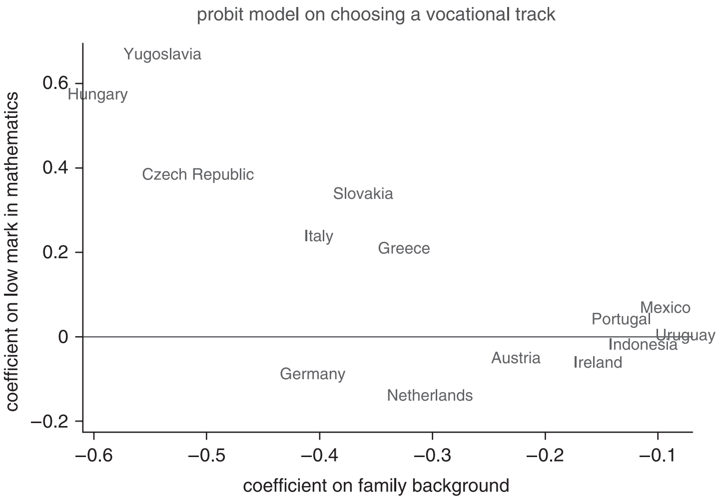


**Figure 5. Determinants of the probability of choosing a vocational track – 15-year-old students – PISA 2003**

The results in Table 17 show that students enrolled in vocational schools are more likely to be older boys, with low performance at school, coming from less educated parents (either in terms of educational attainment or in terms of books available at home), who are typically also poorer (Columns 3 and 4). We conclude that sorting into vocational schools is based on both ability and family background.

When we interact these variables with institutional design, we notice that more tracked systems attenuate the impact of ability, while reinforcing the role of the cultural resources in the family of origin (Columns 2 and 4). For comparison, let us consider the sorting process between public and private schools: students enrolled in private schools are also sorted by ability, by parental educational attainment and, more effectively, by parental income – because abler students with more educated and richer parents are more likely to be enrolled in private schools. In this case, however, tracking plays a less significant role. Are there country differences in the impact of ability and parental background on student sorting? Estimated country specific effects are shown in Figure 5. While there is significant cross-country variation in the impact of ability on sorting, we are unable to find a clear trade-off between sorting on ability and sorting on family background. If anything, the two factors appear to reinforce each other.

A final element that needs to be taken into account when discussing the costs and benefits of tracking is the imperfect observability of individual talent. We have already mentioned that early tracking is exposed to the risk of misallocation, since either student ability is hard to measure or their willingness to proceed in the educational ladder is not well formed. On the contrary, later tracking may represent a waste of resources, since it retains into general education individuals who have already made their mind in a work-based career.

In the past decades, many countries have opted to postpone tracking. From the viewpoint of equality of opportunity, we are sympathetic to this choice. Our research confirms that parental background matters, and that excessive tracking could be detrimental to equality of opportunity in educational attainment and early labour market earnings. However, it is still an open question whether such move makes sense from the viewpoint of efficiency. What are the efficiency costs of de-tracking schools? Suppose that these costs are very high. Then perhaps equality of opportunity could be attained at a lower cost by facilitating sorting by ability rather than by delaying tracking, or by policy interventions in the early stages of life that compensate initial differences in parental background. Suppose instead that these costs are low. Then de-tracking is a sensible policy option to reduce inequality of opportunity. Unfortunately, our paper – like most of the relevant literature – is silent on this relevant question, which must be left to future research and to better data.

# Discussion


## Christian Gollier

### Toulouse School of Economics


This nice paper raises important questions about whether one should segregate pupils in our secondary schools according to their intellectual achievements. Two aspects of the question must be considered here. Brunello and Checchi claim that they mostly focused on the effect of the stratification on the equality of opportunity, but their discussion is often contaminated by the discussion of the other important aspect of the problem, which is the efficiency of the educational system.

The authors show that stratification in secondary schools has globally an effect of reducing equality of opportunity. The degree of stratification is measured by the number of years (tracking length) during which pupils are separated in different tracks according to their observable talents. The degree of inequality in opportunity is measured by the sensitivity of the individual accumulation of human capital to the individual family background. As shown by the authors, more stratified systems yield more inequalities, for most proxies measuring human capital. The intuition, as suggested in the literature and by the authors themselves in their modelling of the educational system, relies on a peer effect. Pupils benefit from the presence of the talents of other pupils in their class. In a highly stratified system, high-skilled pupils, who often have a good family background, stay longer with other high-skilled pupils, thereby reinforcing their initial advantage. However, the available data are not rich enough to estimate this peer effect, which casts some doubt on whether this is actually what explains the results. Indeed, an alternative explanation is that good teachers have a preference for teaching in high-skilled classes. If good teachers have a priority in determining in which classes they teach, a highly stratified system will allocate the best teachers for the most skilled pupils, yielding the same conclusion.

Even if equality of opportunity is an important goal of schooling, it should not be pursued at any cost. Our economies also need to face global competition with the help of a high human capital per capita. This is the efficiency goal of schooling to maximize talents. The standard argument in favour of stratification is that it is more efficient to teach in homogeneous classes. There is another efficiency argument in favour of stratification based on the peer effect. The transfer of a high-skilled student from a low-skilled class to a high-skilled class has a positive peer effect on the high-skilled class and a negative effect on the low-skilled class. The global effect on the per capita accumulation of human capital is ambiguous and depends upon quite a complex property of the peer effect: Is the presence of a high-skilled pupil more useful for a high-skilled pupil or for a low-skilled pupil? Testing a structural model would be required to answer this important question, but I don't think that we have rich enough data to do this.

Suppose now that stratification is useful for efficiency but bad for equality of opportunity. Then solving the dilemma for the public decision-maker would require measuring the aversion to inequality of opportunities in our society. However, this difficulty can be overcome by implementing a policy combining stratification and investing more effort in the vocational tracks, for example by the transfer of better teachers there. This policy is currently implemented in France for example, where the number of pupils per teacher has been reduced in some high schools that have been selected for their low performance. The cost-benefit analysis of this policy remains to be done.

The paper does not answer another important question. If some stratification is desirable on the basis of an efficiency/equality objective, what is the optimal age at which differentiated tracks should be proposed? The optimal timing is critical, because too early a selection can lead to many mistakes in the allocation of pupils according to their observable talents, which are noisy at a young age. This would have the additional adverse effect of reducing incentives for young pupils to perform well because of the sense of arbitrariness in the selection process.

The authors also consider another measure of the strength of the stratification which takes into account the proportion $\Phi$ of pupils that are in the vocational track. I agree that the allocation of heterogeneous pupils across different tracks is an important element to determine the impact of the tracking system on equality. But it is too simplistic to believe that a unidimensional number like $\Phi$ can summarize everything that we need to know to answer the question. Let me illustrate this point on an example. There are three types of pupils, respectively High, Medium and Low skills. Their proportions are (1/3, 1/3, 1/3) in the two countries. In both countries, quality L goes to vocational, whereas quality H goes to the academic track. In country A, quality M goes to the academic track, whereas it goes to the vocational track in country B. It implies that the tracking index equals $S_A = 1/3$ in country A, whereas it equals $S_B = 2/3$ in country B. Here are the educational achievements in the two countries, for the three types:

| | L | M | H |
|---|---|---|---|
| Country A | 1 | 2.3 | 2.7 |
| Country B | 1.3 | 1.7 | 3 |

Pupils of type M take advantage of the presence of pupils H in their tracks (peer effect) in country A. In country B, pupils of type L take advantage of the presence of pupils M in their tracks. Notice that I assume a zero-sum game in the externalities generated by the peer effect: the school tracking system has no efficiency effect. The question is: can the larger track index observed in country B explain the international differences in the relationship between educational attainments and family backgrounds (given here by types H, M, L)? The answer is clearly no. The larger index of stratification in country B has a positive impact on the achievement of qualities L and H, but it has a large negative impact on the attainment of quality M! This means that we can anticipate a non-linear, U-shaped, effect of this stratification index.

## Omer Moav

Hebrew University, University of London, Shalem Center, and CEPR

Brunello and Checchi examine cross-country differences in educational outcomes. In particular, they study the effect of family background, such as parental education and income, and the interaction between family background and school tracking, on various individual outcomes. Their contribution over existing research stems from the richness of these outcomes in the data set. Rather than focusing on test scores at young age, as previously done, variables such as dropping out of school, graduating college, and even employment and earnings, are examined.

The paper asks an important policy question: does tracking amplify the effect of family background on schooling outcomes? The basic premise of the paper is that differences across tracks, such as peer effects, allocation of resources and curricula, are important factors for schooling outcomes. Therefore, the result of tracking, where the allocation to tracks is highly correlated with family background, might amplify income inequality and reduce intergenerational mobility.

The authors suggest that extensive tracking reduces achievements of pupils in vocational schools, typically coming from weaker background, while improving the achievements of pupils in academic schools, coming from stronger backgrounds. Tracking is, therefore, harmful for the former and beneficial for the latter. According to this approach, tracking increases inequality, but perhaps generates efficiency gains, stemming from more effective teaching in homogenous classes. The empirical specifications, due to data limitations, do not include the direct effect of tracking on schooling and labour market outcomes, only the interaction of tracking and family background, and cannot estimate the trade-off that might exist between inequality and efficiency.

The findings, based on the sign of the interaction coefficient, suggest that tracking, by and large, reinforces family background. It increases inequality and reduces intergenerational mobility for most measures of educational attainment and early labour market outcomes; however, the opposite is true for literacy and training.

In this discussion we will (1) question the premise that a trade-off between inequality and efficiency, associated with tracking, necessarily exists, (2) discuss the endogenous nature of the schooling system, suggesting that the estimation could be biased, and (3) discuss the role of changing rewards for general skills, as a consequence of changes in technological progress, and suggest that the welfare impact of tracking is not universal.

Efficiency gains stem from more effective teaching in homogenous classes, but this comes with a potential cost of increased inequality. However, perhaps the more relevant question from a policy point of view is the impact of tracking on pupils from weaker background. Inequality could increase with tracking because of a negative effect it might have on pupils from weaker backgrounds allocated to vocational schools, while having a positive effect on pupils from stronger backgrounds, who are allocated to academic schools, or because the gains to the pupils from the stronger backgrounds exceed the gains for the weaker pupils. After all, if teaching is more effective in homogenous classes, gains from tracking to weaker students are not unreasonable. The former option suggests that tracking is associated with a trade-off between the welfare of different families in society. The latter suggest that everyone gains from tracking (in absolute terms), but this gain is associated with a rise in inequality. Clearly, the two options might have different policy implications, where in the latter it is easier to justify tracking. The empirical exercise, due to the data limitation, cannot distinguish between the two; a positive interaction coefficient implies that tracking amplifies the impact of family backgrounds, which is true in both cases.

Moreover, the data cannot distinguish between different potential mechanisms underlying the effect of the interaction between tracking and family background on individual outcomes. In particular, if tracking deprives weaker pupils from their potential achievements, the underlying mechanism is important for policy. If the main force is the peer effect, it has to be the case that efficiency gains from tracking come with a cost to the achievements of pupils from weaker backgrounds and there is not much that could be done to reduce this cost. If, however, it is differences in curricula or resources, then gains from tracking could be maintained, while improving outcomes in the vocational track; the focus of policy should be on improved curricula or reallocation of resources.

Our second comment regards the endogenous nature of the schooling system. The authors take the school system, in particular the degree of tracking, as given, and estimate its impact on the distribution of income. However, the school system itself is an endogenous outcome of the political process, which could be affected by the industrial organization of the economy and the distribution of wealth in society. Differences across countries in the distribution of wealth or the industrial structure, could affect school design as well as individual outcomes, and thereby introduce a bias to the estimated coefficient. For instance, Engerman and Sokolof (2000) suggest that inequality brought about oppressive institutions, in particular restricted access to education, designed to maintain the political power of the elite and to preserve the existing inequality.

In contrast, focusing on the direct economic incentives rather than political power, Benabou (2000) studies wealth redistribution which could be associated with efficiency gains, such as investment in public schooling, identifying two channels by which a rise in the inequality of the wealth distribution affects redistribution and possibly schooling. A rise in inequality increases the fraction of the poor in the population, thereby increasing pressure for redistribution. At the same time, the rich become richer, implying the burden of taxation they have to carry increases, and thereby lobbying against redistribution could increase. Similarly, Galor *et al.* (2005) suggest that landowners could raise a hurdle for public schooling, if land is abundant and its ownership highly unequal. Clearly, according to these theories, the structure of the economy could have a direct effect on the distribution of income, as well as an indirect effect via school design.

Alternatively, Galor and Moav (2006) argue that a significant force in the construction of a universal schooling system is a productive cooperation between capitalists and workers. Due to capital-skill complementarity, human capital has a role in sustaining the rate of return to physical capital. Thus capitalists have an interest that the state would provide public education for the masses. This approach implies that differences in the needs of the industry would be reflected in school design. For instance, a larger traditional industry requires more vocational training in comparison to an economy with a larger modern sector that demands more workers with general skills. Clearly, the industrial structure could also have a direct impact on the distribution of wages and the returns to schooling, as well as the impact of family background and its interaction with tracking.

Finally, the welfare consequences of tracking are most likely not universal and they depend on the technological environment. In a rapidly changing technological environment that has characterized the past three decades, investment in general human capital has been highly rewarded and the tracking system has probably contributed to inequality, whereas in the slower era of technological progress in earlier decades, the reward to specific human capital and thus vocational schooling was relatively higher and the tracking system was less likely to contribute to inequality.

## APPENDIX 1: SCHOOL TRACKING AND PARENTAL BACKGROUND: TWO ILLUSTRATIVE MODELS

### Tracking in the presence of pure peer effects

We start by illustrating a simple relationship between tracking and peer effects. Let us consider the following simple model, based on the original work of Benabou (1996) on geographical segregation. Start with $n$ students, indexed by $i = 1, 2, \ldots, n$, and $m$ schools, indexed by $j = 1, 2, \ldots, m < n$, with $\gamma = n/m$ being the school size, assumed identical for all schools. Without loss of generality, we rescale the number of students to be equal to the number of schools, so that the school size becomes unitary ($\gamma = 1$). The formation of individual human capital is assumed to depend on parental background $F$, individual ability $A$ and the school peer effect $P$, which is based on the ability composition of the class.[46]

For simplicity we assume that these inputs are imperfect substitutes in the human capital production function:

$$H_{ij} = f(F_{ij}, A_{ij}, P_j) = F_{ij}^{\delta} A_{ij}^{\eta} P_j^{\theta} \tag{7}$$

where $H_{ij}$ is the human capital of student $i$ enrolled in school $j$, $F_{ij}$ is her family background (be it parental education, parental income, family wealth or any combination of them), $A_{ij}$ is her individual ability and $P_i$ is the peer effect in school $j$. In order to allow for different forms of interaction and cooperation among students, we follow Benabou (1996) in assuming that the peer effect can be measured by a CES (constant elasticity of substitution) index:

$$P_j = \left[\sum_{i=1}^{\gamma} A_{ij}^{\sigma}\right]^{\frac{1}{\sigma}} \tag{8}$$

We assume that students belong to one of two ability types, $A_H > A_L > 0$, with $n_1$ being the number of 'high' types and $(n - n_1)$ the number of 'low' types. We also define $\alpha = n_1/n$ as the corresponding fraction of high types in the population. We know from Benabou (1996) that when $\sigma < 1$ ability types are complements, $P$ is convex in $\alpha$, the number of talented students in the class, and heterogeneity is a source of efficiency loss, since

$$P_j = [\alpha A_{H,j}^{\sigma} + (1 - \alpha) A_{L,j}^{\sigma}]^{\frac{1}{\sigma}} \leq \bar{A}_j = \alpha A_{H,j} + (1 - \alpha) A_{L,j} \tag{9}$$

On the contrary, when $\sigma > 1$, $P$ is concave in $\alpha$, heterogeneity is a source of gain, and the integration of students reinforces the peer effect.

Applying these concepts to school design, they imply that pooling students of different ability into a comprehensive educational system is more efficient (in terms of the production of human capital) when ability types are substitutes, whereas tracking systems, which gather students of similar abilities in the same schools, are more

[46] Benabou (1996) calls this term the 'local interaction' effect, which more generally could include the social composition of the class, and capture role models, social capital, family networking and related phenomena. We restrict our analysis to the pure 'peer effect' based on student ability. Since student ability in this model is assumed to be perfectly observable, sorting does not entail the misallocation of students.

efficient when abilities are complements. More formally, if students are sorted into classes with homogeneous ability, this is considered as equivalent to a *tracked system*, where high ability students are selected into the academic track H and low ability students go to the vocational track L. With tracking, individual human capital formation is given by:[47]

$$H_i = F_i^{\delta} A_i^{\eta+\theta}, \quad i = L, H \tag{10}$$

The total human capital accumulated in the society will therefore be:

$$H_{track} = \sum_{i=1}^{n} H_i = \sum_{i=1}^{n} F_i^{\delta} A_i^{\eta+\theta} = A_H^{\eta+\theta}\left(\sum_{i=1}^{n_1} F_i^{\delta}\right) + A_L^{\eta+\theta}\left(\sum_{i=n_1+1}^{n} F_i^{\delta}\right) \tag{11}$$

If instead the system is fully integrated, each school exhibits the same ability composition, and individual human capital formation is given by:

$$H_i = F_i^{\delta} A_i^{\eta}[\alpha A_H^{\sigma} + (1-\alpha)A_L^{\sigma}]^{\frac{\theta}{\sigma}}, \quad i = L, H \tag{12}$$

while total human capital in the society is:

$$\begin{aligned} H_{comprehensive} = \sum_{i=1}^{n} H_i &= A_H^{\eta}[\alpha A_H^{\sigma} + (1-\alpha)A_L^{\sigma}]^{\frac{\theta}{\sigma}}\left(\sum_{i=1}^{n_1} F_i^{\delta}\right) \\ &+ A_L^{\eta}[\alpha A_H^{\sigma} + (1-\alpha)A_L^{\sigma}]^{\frac{\theta}{\sigma}}\left(\sum_{i=n_1+1}^{n} F_i^{\delta}\right) \end{aligned} \tag{13}$$

The comparison of Equations (11) and (13) does not lead to clear-cut conclusions, since the peer effect interacts with individual ability and family background, and the aggregate effect depends on the joint distribution of these two variables. If we abstract from these effects – and set $\delta = \eta = 0$, $\theta = 1$ – it is easy to show that $H_{comprehensive} > H_{track}$ if and only if $\sigma > 1$, and vice versa. Therefore de-tracking schools is efficiency-enhancing if student abilities are substitutes in the generation of the peer effect.

One problem with the current simplified set-up is that in most countries both comprehensive and tracked schools coexist, often in sequence, with an initial period of comprehensive (primary and in most cases lower secondary) school, followed by tracked (upper) secondary schools. Defining $\tau$ as the length of tracked education in a country, each student accumulates human capital as follows:

$$\begin{aligned} H_i &= (1-\tau)F_i^{\delta} A_i^{\eta}[\alpha A_H^{\sigma} + (1-\alpha)A_L^{\sigma}]^{\frac{\theta}{\sigma}} + \tau F_i^{\delta} A_i^{\eta+\theta} \\ &= F_i^{\delta} A_i^{\eta}\left\{(1-\tau)[\alpha A_H^{\sigma} + (1-\alpha)A_L^{\sigma}]^{\frac{\theta}{\sigma}} + \tau A_i^{\theta}\right\}, \quad i = L, H \end{aligned} \tag{14}$$

[47] Notice that we are implicitly assuming that the distribution of school types matches the distribution of ability types in the society.

Since we want to assess how education reforms which de-track schools affect human capital inequality, we define the family background effect (FBE) as the contribution of family background to individual educational attainment (namely $FBE = \partial H_i / \partial F$) and compute:

$$\frac{\partial FBE}{\partial \tau} = \frac{\partial^2 H_i}{\partial F_i \partial \tau} = \delta F_i^{\delta-1} A_i^{\eta} \left\{ A_i^{\theta} - [\alpha A_H^{\sigma} + (1-\alpha) A_L^{\sigma}]^{\frac{\theta}{\sigma}} \right\}, \qquad i = L, H \tag{15}$$

which shows that the second order mixed derivative is positive for 'high talent' students and negative for 'low talent' students. This implies that an increase in the length of school tracking reduces the impact of family background for low ability students but increases it for the high ability group. The effect of longer tracking on the *FBE* for the average student depends on the relative share of each ability type in the population of students. By extension, given the distribution of family background, this differential effect should produce a reduction in inequality in the lower tail of the human capital distribution and an increase in dispersion in the upper tail. The overall effect will therefore be indeterminate. Symmetrically, a reform which de-tracks school is likely to reinforce the *FBE* for low talent students and to reduce it for the high talent group.

## Parental background and the allocation to tracks

The model in the previous subsection illustrates the efficiency gains and losses of tracking students in different classes and emphasizes the technical relationship between ability types. In that model, however, parental background has no effect on the allocation of students to tracks. In policy discussions, this is an important aspect, which lies at the very root of equity concerns. The main issue here is whether individuals are allocated to the lower ability track not because of actions they control, such as low effort, but because of circumstances outside their own control, such as being born in an affluent household.

In this second model, we assume that the allocation of students to tracks depends on ability. Ability has two components: the first component depends on parental background, either because ability is partly in the genes or because of the household environment where the individual spends her pre-school years. The second component is purely idiosyncratic ability, which is orthogonal to parental background. By affecting the development of individual talent, parental background can affect the allocation to tracks. Needless to say, there are other channels which link parental background to type of school, such as household resources and social networks. Since these channels have also the implication that family privilege increases the likelihood of allocation to the best track, as does the channel we emphasize, we ignore them here for the sake of simplicity.

Consider a secondary schooling system, which consists of a comprehensive school (C) of duration $(1 - \tau)$, and of a stratified school, of duration $\tau$. The stratified school is composed of a vocational (V) and an academic (G) track.[48] Households consist of a mother and a daughter. Individual ability $\Theta$ has a component $B$ common to the mother and the daughter, which we broadly identify with family background, and an additional idiosyncratic component $D$, which is independent of family background. The underlying idea is that individual talent depends on the genes and develops during the initial stages of life. This development is favoured by good family characteristics, such as parental education and the presence of books at home.[49] Family background, however, cannot explain entirely individual differences in talents, which depend also on idiosyncratic factors.

We model the production of talent $\Theta$ as follows:

$$\Theta = B^{\lambda}D^{1-\lambda} \tag{16}$$

where $\lambda \in (0, 1)$; good family background can compensate low endowment of idiosyncratic ability, and a large endowment of the latter can compensate, albeit at a different rate, poor family background. If $\lambda$ is close to 1, then the allocation to tracks depends almost exclusively on family background. Both components in the production of talent are log-normally distributed. Let $b$ be the log of $B$ and $d$ be the log of $D$. Then

$$b \sim \mathcal{N}(f, \sigma_f^2) \tag{17}$$

$$d \sim \mathcal{N}(0, \sigma_a^2) \tag{18}$$

$$\theta = \lambda b + (1 - \lambda)d \sim \Phi(\lambda f, \sigma_\theta^2) \tag{19}$$

where $\sigma_\theta^2 = \lambda^2\sigma_f^2 + (1 - \lambda)^2\sigma_a^2$. Enrolment in school depends on $\theta$: individuals with observed log ability $\theta$ higher than a predefined threshold $\theta^*$ enrol in the G track, and individuals with a lower log ability enrol in the V track. The threshold $\theta^*$ is determined by the local or central authority, and defines the number of slots available in each type of school. The probability of enrolling in a V school is:

$$\Phi\left(\frac{\theta^*}{\sigma_\theta^2}\right) = \mathrm{Prob}(\theta < \theta^*) \tag{20}$$

which corresponds also to the share of pupils enrolled in that type of school.

Let $H$ be the outcome of schooling. This outcome includes the accumulation of skills and the completion of a curriculum, but extends also to the labour market: a good education is measured not only by the portfolio of competencies learned at school, but also by employability and the quality of work it gives access to.[50] Briefly, we call this outcome human capital. Human capital is produced at school and depends both on individual talent $\Theta$ and on additional factors, such as teachers,

[48] This model follows rather closely Brunello *et al.* (2007).

[49] Carneiro and Heckman (2003) show that important differences in ability across family types appear at early ages and persist.

[50] Card and Krueger (1992) emphasize labour market outcomes as the natural measure of the returns to schooling.

resources, the selected curriculum and the average ability of students in the class.[51] These factors are likely to be closely related. For instance, teachers typically prefer to teach in classes where the average ability of students is higher and less dispersed. If teachers can self-select into classes, and better quality teachers have a priority in class allocation, average teacher ability and average student ability are positively correlated in a cross-section of classes and schools. Similarly, the contents and the relative difficulty of the selected curriculum vary with average student ability in the class, and students in classes with relatively high average ability are typically taught more advanced material.[52] While comprehensive classes might force teachers to 'teach to the middle', this is less of a problem when students are streamed into different classes according to their ability. Finally, higher average ability can attract more resources, for instance in terms of the number of pupils per teacher.

The positive relationship between teacher quality, choice of curriculum and average student ability in the class allows us to reduce the factors affecting individual human capital to the following two: individual and average ability. When schools are fully comprehensive, individual human capital is:

$$H_C = \Theta[\exp \beta E(\theta)] \tag{21}$$

where $E(\theta)$ is unconditional average student ability in the track and $\beta > 0$ is the contribution of this factor to human capital. In logs, this is also

$$h_C = \theta + \beta E(\theta) \tag{22}$$

where we use small letters for logs. With tracking, human capital produced in the G track is:

$$H_G = \Theta[\exp \beta_H E(\theta | \theta \geq \theta^*)] \tag{23}$$

and in the V school is:

$$H_V = \Theta[\exp \beta_L E(\theta | \theta < \theta^*)] \tag{24}$$

where $E(\theta | \theta \geq \theta^*)$ is the conditional expectation of ability, given that all students in the G school have ability above or equal to the threshold $\theta^*$, and the parameters $\beta_i$ measure the impact of average student ability in the class on individual human capital. If $\beta_L > \beta$ and $\beta_H > \beta$, the contribution of average student ability to output is higher in schools with tracking than in comprehensive schools. Why should this be the case? Since the dispersion of ability in tracked classes is lower with respect to comprehensive classes, we posit that this lower dispersion improves the effectiveness of teaching, which increases the accumulation of individual human capital associated

[51] The literature on peer effects is too large to review here. See Nechyba (2005), for a theoretical review and Minter-Hoxby and Weingarth (2005), for an overview of the empirical research.

[52] In the US students are assigned to advanced, regular or basic courses depending on their past performance, and students in the advanced tracks are taught a more advanced curriculum. See Hallinan (2004).

to better peers, higher teacher quality, or more advanced curricula. We call this 'the specialization effect'.

The selected specification of the production of individual human capital at school is amenable to different interpretations. One interpretation of the terms within brackets in (23) and (24) stresses peer effects. When students are allocated to different types of schools and tracks based on their ability, the average talent of the class is either higher or lower than the unconditional mean, depending on the track. When peer effects matter, individual school performance increases with the average ability of the track. Importantly, peer effects can be non-linear. In this case the benefit attained by talented students from being allocated to a good track differs from the loss borne by talented students who are allocated to a not so good track. If peer effects are non-linear, then $\beta_H \neq \beta_L$. If instead peer effects are linear, then $\beta_H = \beta_L$.

An alternative interpretation is average teacher quality. Self-selection of better teachers into G tracks implies that the conditional average ability of teachers is positively correlated with the conditional average ability of students. In this case, individual school performance in G schools is higher not because of the peer effect, but because the quality of teachers is higher.[53] Other alternative explanations are the curriculum being taught and the distribution of resources between tracks.

Suppose that individuals spend time $(1 - \tau)$ in the comprehensive school, and the rest of time $\tau$ in a stratified school. The expected log human capital at the end of school is:

$$Eh_G = (1 - \tau)\beta\lambda f + [1 + \tau\beta_H]E(\theta | \theta \geq \theta^*)] \tag{25}$$

for the individuals who go to the G track and

$$Eh_V = (1 - \tau)\beta\lambda f + [1 + \tau\beta_L]E(\theta | \theta < \theta^*)] \tag{26}$$

for the individuals allocated to the V track. Using the algebra of truncated normal standard distributions, we obtain:

$$E(\theta \mid \theta \geq \theta^*) = \lambda f + \sigma_\theta \frac{\phi\left(\frac{\theta^*}{\sigma_\theta}\right)}{1 - \Phi\left(\frac{\theta^*}{\sigma_\theta}\right)} \tag{27}$$

$$E(\theta \mid \theta < \theta^*) = \lambda f - \sigma_\theta \frac{\phi\left(\frac{\theta^*}{\sigma_\theta}\right)}{\Phi\left(\frac{\theta^*}{\sigma_\theta}\right)} \tag{28}$$

[53] More in detail, write (23) as $H_G = \Theta[\exp \gamma_H E(T \mid T \geq T^*)]$, where $T$ is teacher quality. If better teachers self-sort in better classes, we can assume that $[E(T \mid T \geq T^*) = \delta E(\theta \mid \theta \geq \theta^*)]$ which implies that $H_G = \Theta[\exp \beta_H E(\theta \mid \theta \geq \theta^*)]$, where $[\beta_H = \delta\gamma_H]$.

Notice that conditional average ability in the G track is higher than the unconditional average ability $\lambda f$. Therefore, the student enrolled in the G track stands to gain, either because of the positive peer effect, or because of better teacher quality, or because of a more advanced curriculum, with respect to the student in the V track, where conditional average ability is lower than $\lambda f$.

Average log human capital is the weighted average of expected human capital in the two tracks. Therefore:

$$Eh = (1 - \Phi)Eh_G + \Phi Eh_V \tag{29}$$

and

$$Eh = (1 - \tau)\beta\lambda f + \lambda f[1 + \tau\beta_H - \tau\Phi(\beta_H - \beta_L)] + \tau(\beta_H - \beta_L)\sigma_\theta\phi \tag{30}$$

The above equation suggests that average log human capital depends on the tracking length $\tau$, on the percentage $\Phi$ of workers enrolled in the V track, and on average family background $\lambda f$.

While our focus in this paper is on the equity implications of tracking, Equation (30) allows us to draw some implications on the efficiency of tracking. Assume that accumulated human capital at school translates into higher labour productivity in the labour market, and assume also that the labour market is perfectly competitive (i.e. without frictions). Then average human capital $Eh$ is a good proxy of average net output. The differentiation of Equation (30) with respect to $\tau$ yields:

$$\frac{\partial Eh}{\partial \tau} = E(\theta)(\beta_H - \beta) - (\beta_H - \beta_L)\Phi E(\theta \mid \theta < \theta^*) > 0 \tag{31}$$

showing that an increase in tracking length increases $Eh$ if tracking generates a specialization effect.

Define $FBE$ as the effect of an increase in average family background on average human capital. This is given by:

$$\frac{\partial Eh}{\partial f} = FBE = \lambda\{1 + (1 - \tau)\beta + \beta_H\tau - \tau[(\beta_H - \beta_L)\Phi]\} \tag{32}$$

By contributing to the development of individual talent, a shift in the mean of the distribution of log family background affects average log human capital. The direction of the effect is certainly positive if tracking generates a specialization effect. The size of the effect declines with the share $\Phi$ of students enrolled in the vocational track if $\beta_H > \beta_L$.

Notice that a shift in average family background is different from a shift in individual family background: an individual who is assigned to a better background is more likely to be allocated to the G track, and to end up with higher human capital. An increase in average parental background shifts instead the entire distribution of talent. Notice also that we are keeping the threshold $\theta^*$ as given. Suppose instead that a shift in the mean of the distribution of parental background, due for instance to an increase in average income per head, leads to political pressure for more school slots in G schools.[54] In this case $(\partial\theta^*/\partial f) < 0$ and

$$\frac{\partial Eh}{\partial f} = FBE$$
$$= \lambda\left\{1 + (1-\tau)\beta + \beta_H\tau - \tau[(\beta_H - \beta_L)\Phi] - \tau f(\beta_H - \beta_L)\frac{\phi}{\sigma_\theta}\frac{\partial\theta^*}{\partial f} - \tau(\beta_H - \beta_L)\phi\frac{\theta^*}{\sigma_\theta}\frac{\partial\theta^*}{\partial f}\right\} \quad (33)$$

which is positive if $\beta_H > \beta_L$.

The question we ask in the paper is whether the relationship between family background and human capital varies with school design. First consider an increase in the length of tracking time, and keep the threshold $\theta^*$ as given. Then the differentiation of (32) with respect to $\tau$ yields:

$$\frac{\partial FBE}{\partial\tau} = \lambda[\beta_H - \beta - (\beta_H - \beta_L)\Phi] \quad (34)$$

A longer tracking time increases the effect of family background on human capital if tracking generates a specialization effect. When $\beta_H > \beta_L$, which we interpret as indicating that peer or teacher quality or curricula effects are non-linear, the increase in *FBE* associated to longer tracking is reduced by a higher share of vocational schools, because these schools are less effective than academic schools in the production of human capital.

Next, we investigate the effect of an increase in the threshold $\theta^*$, which corresponds to an increase in the share of vocational schools $\Phi$. We have:

$$\frac{\partial FBE}{\partial\Phi} = \frac{\partial FBE}{\partial\theta^*}\frac{\partial\theta^*}{\partial\Phi} = -\lambda\tau(\beta_H - \beta_L) \quad (35)$$

which is negative if $\beta_H > \beta_L$. In this case, a higher share of vocational schools reduces the impact of family background on human capital. This is because, when the percentage of students ending up in the vocational track is relatively high, there are relatively fewer slots in the more prestigious academic track, and family background is less effective in guaranteeing a place in such track. Put differently, a higher share of slots in vocational tracks implies that even children with a good family background end up studying where the impact of average student ability is lower ($\beta_L < \beta_H$).

Relation (35) is built on the assumption that both $\beta_H$ and $\beta_L$ are constant. We have argued that the size of these coefficients is higher when the dispersion of ability in the class is lower, which generates a specialization effect of tracking with respect to no tracking. Let us now formalize this by explicitly positing that individual human capital depends not only on the average ability of students in the track, but also on the dispersion of ability. This would happen if learning and teaching are more efficient when the students in the class or track are more homogeneous. Now, the

[54] See the discussion in Ariga, Brunello, Iwahashi and Rocco, 2006.

dispersion of ability in the track V increases with the share of students in vocational schools $\Phi$. Similarly, the dispersion of ability in the track G raises with the share of students in general schools $(1 - \Phi)$. We can use this argument to write:

$$\beta_H = v_H - \xi_H(1 - \Phi) \tag{36}$$

$$\beta_L = v_L - \xi_L\Phi \tag{37}$$

which yields:

$$\beta_H - \beta_L = [v_H - v_L - \xi_H] + (\xi_H + \xi_L)\Phi \tag{38}$$

While the expression in brackets can take either sign, the expression in parentheses is positive. Using (38) into (32) and differentiating with respect to $\Phi$ yields:

$$\frac{\partial FBE}{\partial \Phi} = \frac{\partial FBE}{\partial \theta^*}\frac{\partial \theta^*}{\partial \Phi} = -\{[v_H - v_L - \xi_H] - 2(\xi_H + \xi_L)\Phi\}\lambda\tau \tag{39}$$

which suggests that the relationship between the share of vocational schools and the family background effect can be non-linear.

The non-linearity in this relationship can also be seen from a different perspective. So far, we have considered the impact of a change in school design on average human capital. It is instructive, however, to ask how changes in school design affect the human capital of different groups of students. To do so, consider a situation where both $\tau$ and $\theta^*$ are given. In this case, individuals would distribute in the V and G tracks according to the mechanism outlined above. We ask: what happens if the government decides to increase the slots available to vocational tracks, relative to G tracks? In our set-up, this is obtained by increasing $\theta^*$. There are three groups of individuals: first consider the group who would have enrolled in G before the change in the threshold, and who still enrol there. For these individuals, the expected human capital is affected by the change in $\theta^*$ as follows:

$$\frac{\partial Eh_G}{\partial \theta^*} = [1 + \tau\beta_H]\frac{\phi\left[\dfrac{\phi}{1-\Phi} - \dfrac{\theta}{\sigma}\right]}{(1-\Phi)} > 0 \tag{40}$$

The second group is the one which would have enrolled in V before the change, and still does. For this group:

$$\frac{\partial Eh_V}{\partial \theta^*} = [1 + \tau\beta_L]\frac{\phi\left[\dfrac{\phi}{\Phi} + \dfrac{\theta}{\sigma}\right]}{\Phi} > 0 \tag{41}$$

For both groups, the increase in the threshold increases expected human capital. Consider finally the group of individuals who would have gone to G before the change and ends up in V after the change. Let $\theta^*$ be the standard before the change and $\theta^{**}$ the standard after the change. The variation in expected human capital is:

$$Eh_V - Eh_G = \tau(\beta_L - \beta_H)\lambda f - [1 + \tau\beta_H]\sigma_\theta \frac{\phi\left(\frac{\theta^*}{\sigma_\theta}\right)}{1 - \Phi\left(\frac{\theta^*}{\sigma_\theta}\right)} - [1 + \tau\beta_L]\sigma_\theta \frac{\phi\left(\frac{\theta^{**}}{\sigma_\theta}\right)}{1 - \Phi\left(\frac{\theta^{**}}{\sigma_\theta}\right)} \quad (42)$$

A sufficient condition for (42) to be negative is $\beta_H > \beta_L$. In this case, the intermediate group stands to lose from an increase in the threshold. This is the classical 'ends against the middle' result (see De Fraja and Martinez Mora, 2006 for a similar model). One implication of this asymmetry is that an increase in $\theta^*$ reduces the *FBE* for the less privileged below the average *FBE* effect.

We also ask how an increase in tracking time affects students. A longer tracking time affects the expected human capital of students in the G and V tracks as follows:

$$\frac{\partial Eh_G}{\partial \tau} = (\beta_H - \beta)\lambda f + \beta_H \frac{\sigma_\theta \phi}{(1 - \Phi)} > 0 \quad (43)$$

$$\frac{\partial Eh_V}{\partial \tau} = (\beta_L - \beta)\lambda f + \beta_L \frac{\sigma_\theta \phi}{\Phi} \quad (44)$$

While the former effect is positive, the latter effect can be negative, as individuals in the V track need to spend more time with peers having lower ability. It is also true that:

$$\frac{\partial Eh_G}{\partial \tau} - \frac{\partial Eh_V}{\partial \tau} > 0 \quad (45)$$

when $\beta_H \geq \beta_L$. Since individuals in the G track have better family background, an increase in the tracking time also raises the positive impact of family background on expected human capital, consistently with (34).

## APPENDIX 2: DATA SOURCES

Our empirical measure of school stratification is based on the analysis of the educational systems of the countries included in our datasets. Our main sources are the following:

- OECD (1993), *Education in OECD Countries – A Compendium of Statistical Information 1988/89–1989/90*.
- OECD (1996), *Education at a Glance*.
- Eurydice (2002), *Key Data on Education in Europe*.
- Eurydice (2005), *Key Data on Education in Europe*.

In addition, several international (for example, the UNESCO World Higher Education Database (WHED) http://www.unesco.org/iau/onlinedatabases/index.html) and national websites have been consulted.

Data on school attendance by education level (pre-primary, primary, secondary and tertiary) and type of institution (public or private, vocational and general) are from the OECD Education Database 2000 (CDROM – online at http://www1.oecd.org/scripts/cde/viewsubj.asp? SUBJNAME=education&SUBJNAME_E=Education)

The definition of variables is as follows:

| | |
|---|---|
| ENROLPRE | Enrolment in pre-primary education (ISCED0) relative to enrolment in primary education (ISCED1)[55] |
| VOCUPPSEC | ISCED3: vocational education on all programmes – upper secondary schools only – see Table 1 |
| PRIVUPPSEC | Enrolment in private institutions – upper secondary schools only |

School resources are measured by the following variables:

| | |
|---|---|
| STUTEASEC | ISCED3 all programmes: students to teaching staff (from J.W. Lee and R. Barro (2001). 'Schooling quality in a cross-section of countries', *Economica*, 68(272), 465–88) |
| EDEXPGDP | Public expenditure in education over GDP (from OECD, *Education at a Glance*, 1996) |

We want data that refer to the years 1985, 1995 and 2002. When this information is not available for the exact year, we use neighbouring years.

## REFERENCES


Ammermüller, A. (2005). 'Educational opportunities and the role of institutions', ZEW Discussion Paper, No. 05–44.

Ammermüller, A. and J.S. Pischke (2006). 'Peer effects in European primary schools: Evidence from PIRLS', NBER Working Paper No. 12180.

Ariga, K., G. Brunello, M. Giannini and R. Iwahashi (2005). 'Why is the timing of school tracking so heterogeneous?' IZA Discussion Paper No. 1854.

Ariga, K., G. Brunello, R. Iwahashi and L. Rocco (2006). 'School tracking in imperfectly competitive labour markets', mimeo, University of Padova.

Arum, R., A. Gamoran and Y. Shavit (2004). 'Inclusion and diversion in higher education: Expansion, differentiation, and market structure in fifteen countries', mimeo.

Bassanini, A., A. Booth, G. Brunello, M. De Paola and E. Leuven (2007). 'Workplace training in Europe', forthcoming in G. Brunello, P. Garibaldi and E. Wasmer (eds.), *Education and Training in Europe*, Oxford: Oxford University Press (also IZA Discussion Paper No. 1640).

Bauer, P. and R. Riphahn (2006). 'Timing of school tracking as a determinant of intergenerational transmission of education', *Economics Letters*, 91(1), 90–97.

Benabou, R. (1996). 'Equity and efficiency in human capital investment: The local connection', *Review of Economic Studies*, 63, 237–64.

Betts, J. and J. Shkolnik (2000). 'The effects of ability grouping on student math achievement and resource allocation in secondary schools', *Economics of Education Review*, 19(1), 1–15.

Black, S., P. Devereux and K. Silvanes (2005). 'Why the apple doesn't fall far: Understanding intergenerational transmission of human capital', *American Economic Review*, 95(1), 437–49.

Brown, G., J. Micklewright, S. Schnepf and R. Waldmann (2005). 'Cross-national surveys of learning achievement: How robust are the findings?' IZA Discussion Paper No. 1652.

Breen, R., R. Luijkx, W. Müller and R. Pollak (2005). 'Non persistent inequality in educational attainment: Evidence from eight European countries', mimeo.


[55] In the absence of reliable information on the relevant population, this variable proxies the attendance rate for pre-primary education.

Brunello, G., K. Ariga and M. Giannini (2007). 'The optimal timing of school tracking', in P. Peterson and L. Wößmann (eds.), *Schools and the Equal Opportunity Problem*, Cambridge MA: MIT Press (also IZA Discussion Paper 955).

Card, D. and A. Krueger (1992). 'Does school quality matter? Returns to education and the characteristics of public schools in the United States', *Journal of Political Economy*, 1–39.

— (1996a). 'School resources and student outcomes: An overview of the literature and new evidence from North and South Carolina', *Journal of Economic Perspectives* 10(4), 31–50.

— (1996b). 'Labor market effects of school quality: Theory and evidence', in G. Burtless (ed.), *Does Money Matter? The Link between Schools, Student Achievement and Adult Success*. Washington, DC: The Brookings Institution.

Carneiro, P. and J. Heckman (2003). 'Human capital policy', NBER Working Paper No. 9495.

Checchi, D. and L. Flabbi (2005). 'Intergenerational mobility and schooling decisions in Italy and Germany', IZA Discussion Paper 2876.

D'Hombres, B. and G. Brunello (2005). 'Does obesity hurt your wages more in Dublin than in Madrid? Evidence from ECHP', IZA Discussion Paper No. 1704.

Dee, T. and B. Jacob (2006). 'Do high school exit exams influence educational attainment or labor market performance?' NBER Working Paper No. 12199.

DeFraja, G. and F. Martinez Mora (2006). 'Ability tracking, the peer group effect and location choices', mimeo.

Ding, W. and S. Lehrer (2006). 'Do peers affect student achievement in China's secondary school?' NBER Working Paper No. 12305.

Dustmann, C. (2004). 'Parental background, secondary school track choice, and wages', *Oxford Economic Papers*, 56, 209–30.

Engerman, S. and K.L. Sokoloff (2000). 'Factor endowment, inequality, and paths of development among New World economies', UCLA.

Entorf, H. and M. Lauk. (2006). 'Peer effects, social multipliers and migrants at school: An international comparison', IZA Discussion Paper No. 2182.

Fertig, M. (2004). 'What can we learn from international student performance studies?' RWI Discussion Paper No. 23.

Figlio, D. and M. Page (2002). 'School choice and the distributional effects of ability tracking: Does separation increase inequality?' *Journal of Urban Economics*, 51(3), 497–514.

Galindo-Rueda, F. and A. Vignoles (2004). 'The heterogeneous effect of selection in secondary schools: Understanding the changing role of ability', CESIfo conference on Schooling and Human Capital Formation in the Global Economy, Munich, September.

Galor, O., O. Moav and D. Vollrath (2005). 'Inequality in land ownership, the emergence of human capital promoting institutions, and the great divergence', Brown University.

Gangl, M., W. Müller and D. Raffe (2003). 'Conclusions: Explaining cross national differences in school to work transitions', in W. Müller and M. Gangl (eds.), *Transition from Education to Work in Europe: The Integration of the Youth into the EU Labour Market*. Oxford: Oxford University Press.

Ganzeboom, H.B.G., P.M. De Graaf and D.J. Treiman (1992). 'A standard international socio-economic index of occupational status', *Social Science Research*, 21(1), 1–56.

Gorard, S. and E. Smith (2004). 'An international comparison of equity in educational systems'. *Comparative Education*, 40(1), 15–28.

Goux, D. and E. Maurin (2006). 'Neighbourhood effects on performance at school', IZA Discussion Paper No. 2095.

Hallinan, M. (2004). 'The detracking movement', *Education Next*, 4, 12–17.

Hanushek, E. (1986). 'The economics of schooling: production and efficiency in public schools', *The Journal of Economic Literature*, 24, 1141–77.

Hanushek, E. and L. Wößmann (2006). 'Does educational tracking affect performance and inequality? Differences-in-differences evidence across countries', *Economic Journal*, 116, C63–C76.

Jenkins, S., J. Micklewright and S. Schnepf (2006). 'Social segregation in secondary schools: How does England compare with other countries?' IZA Discussion Paper No. 1959.

Manning, A. and J.S. Pischke (2006). 'Comprehensive versus selective schooling in England in Wales: What do we know?' IZA Discussion Paper No. 2072.

Mare, R.D. (1981). 'Change and stability in educational stratification', *American Sociological Review*, 46, 72–87.

Maurin, E. and S. MacNally (2006). 'Selective schooling', mimeo.
Meghir, C. and M. Palme (2004). 'Educational reform, ability and family background', IFS Working Paper 04/10.
Minter Hoxby, C. (2000). 'Peer effect in the classroom: Learning from gender and race variation', NBER Working Paper 7867.
Minter Hoxby, C. and G. Weingarth (2005). 'Taking race out of the equation: School reassignment and the structure of peers effects', MIT mimeo.
Nechyba, T. (2005). 'Tiebout choice and education', in E. Hanushek and Finis Welch (eds.), *Handbook of the Economics of Education*, Amsterdam: North Holland.
Noden, P. (2000). 'Rediscovering the impact of marketisation: Dimensions of social segregation in England's secondary schools, 1994–99', *British Journal of Sociology of Education*, 21(3), 371–90.
Oakes, J. (1992). 'Can tracking research inform practice? Technical, normative, and political considerations'. *Educational Researcher*, 21(4), 12–21.
OECD (2004). *Learning for Tomorrow's World*. Paris: OECD.
Oosterbeek, H. and D. Webbink (2004). 'Wage effects of an extra year of lower vocational education: Evidence from a simultaneous change of compulsory school leaving age and program length', Scholar Discussion Paper No. 44–04.
Palme, M. and C. Meghir (2005). 'Assessing the effects of schooling on wages using a social experiment', *American Economic Review*, 95(1), 414–24.
Pekkarinen, T. (2005). 'Gender differences in educational attainment: Evidence on the role of the tracking age from a Finnish quasi-experiment', IZA Discussion Paper No. 1897.
Pekkarinen, T., R. Uusitalo and S. Pekkala (2006). 'Education policy and intergenerational income mobility: Evidence from the Finnish Comprehensive School Reform', IZA Discussion Paper No. 2204.
Sacerdote, B. (2001). 'Peer effects with random assignment: Results for Dartmouth roommates', *Quarterly Journal of Economics*, 116(2), 681–704.
Schnepf, S.V. (2002). 'A sorting hat that fails? The transition from primary to secondary school in Germany', Innocenti Working Paper No. 92, Florence: UNICEF Innocenti Research Center.
Schuetz, G., H. Ursprung and L. Wößmann (2005). 'Education policy and equality of opportunity', CESIFO Working Paper 1518.
Schneeweis, N. and R. Winter-Ebmer (2005). 'Peer effects in Austrian schools', University of Linz Working Paper No. 0502.
Stiglitz, J. (1974). 'The demand for education in public and private school system', *Journal of Public Economics*, 3(4), 349–85.
Taylor, C., J. Fitz and S. Gorard (2005). 'Diversity, specialisation and equity in education', *Oxford Review of Education*, 31(1), 47–69.
Vandenberghe, V. (2006). 'Achievement effectiveness and equity: The role of tracking, grade repetition and inter-school segregation', *Applied Economics Letters*, 13, 685–93.
Vandenberghe, V. and S. Robin (2004). 'Evaluating the effectiveness of private education across countries: A comparison of methods', *Labour Economics*, 11(4), 487–506.
Waldinger, F. (2006). 'Does tracking affect the importance of family background on students' test scores?', mimeo.