MAGYAR TUDOMÁNYOS AKADÉMIA
KÖZGAZDASÁGTUDOMÁNYI INTÉZET

INSTITUTE OF ECONOMICS
HUNGARIAN ACADEMY OF SCIENCES

MŰHELYTANULMÁNYOK **DISCUSSION PAPERS**

MT-**DP – 2011/24**

How inequality of opportunity and mean student performance are related?

A quantile regression approach using PISA data

ZOLTÁN HERMANN - DÁNIEL HORN

INSTITUTE OF ECONOMICS, HUNGARIAN ACADEMY OF SCIENCES
BUDAPEST, 2011

Discussion papers
MT-DP – 2011/24

Institute of Economics, Hungarian Academy of Sciences

How inequality of opportunity and mean student performance are related?
A quantile regression approach using PISA data

Authors:

Hermann, Zoltán
research fellow
Institute of Economics of the Hungarian Academy of Sciences
E-mail: hermann@econ.core.hu

Horn, Dániel
research fellow
Institute of Economics of the Hungarian Academy of Sciences
E-mail: horn@econ.core.hu

May 2011

ISBN 978-615-5024-61-0
ISSN 1785 377X

How inequality of opportunity and mean student performance are related?

A quantile regression approach using PISA data

Zoltán Hermann – Dániel Horn

Abstract

Previous research provided ambiguous results on the association between average student performance and inequality of opportunity, as measured by the effect of family background on student achievement. In this paper we explore this association distinguishing between inequality of opportunity at the bottom and the top of the score distribution using a two step method. In the first step, we use quantile regression models to estimate the family background effect at different points of the distribution within each country in PISA 2000-2009. In the second step, we analyse the association between these estimates and the mean achievement of countries. Both cross-section and country fixed-effect estimates indicate that while there is no clear pattern for the bottom of the distribution, lower inequality of opportunity at the top of the distribution goes strongly together with higher mean achievement. In other words, countries where family background has a weaker impact on achievement among the most able students tend to perform better. In short, there is indeed a positive association between equality of opportunity and mean student performance, at least for some groups of students.

Keywords: equality of opportunity, educational performance, quantile regression, PISA

JEL Classification: I21, J21, D63, C21

Acknowledgement:

The research was supported by the grant of the Hungarian Scientific Research Fund (OTKA-F68764).

Hogy függ össze az esélyegyenlőtlenség és az átlagos tanulói teljesítmény?

Kvantilis regressziós megközelítés a PISA-adatok felhasználásával

Hermann Zoltán – Horn Dániel

Összefoglaló

Az eddigi kutatások nem azonosítottak egyértelmű kapcsolatot az átlagos tanulói teljesítmény és az esélyegyenlőtlenség között, amelyekben az esélyegyenlőtlenséget a családi háttér tanulói teljesítményre gyakorolt hatásával mérték. Ebben a tanulmányban megkülönböztetjük az esélyegyenlőtlenséget a tanulói tesztpontszám-megoszlás különböző pontjain, és ennek kapcsolatát vizsgáljuk az átlagteljesítménnyel. Az első lépcsőben kvantilis regressziós modellekkel megbecsüljük a családi háttér hatását a tesztpontszám-megoszlás különböző pontjain a 2000 és 2009 közötti PISA résztvevő országok mindegyikére. A második lépcsőben az így becsült együtthatók és az országok átlag pontszámának együtt járását vizsgáljuk. Keresztmetszeti és fixhatás becslések is azt mutatják, hogy bár a megoszlás alján nincs egyértelmű összefüggés, a megoszlás tetején az esélyegyenlőtlenség negatívan függ össze az átlagos tesztpontszámmal. Vagyis azok az országok teljesítenek jobban a PISA-méréseken, amelyekben a legjobb tanulók között az esélyegyenlőtlenség a legkisebb. Tehát valóban van pozitív összefüggés az esélyegyenlőség és az átlagos tesztpontszámok között, legalábbis a diákok egy csoportjára nézve.

Tárgyszavak: esélyegyenlőtlenség, tanulói teljesítmény, kvantilis regresszió, PISA

JEL kód: I21, J21, D63, C21

Equality and economic growth has long been contrasted. In economics it has been argued that redistributing income from the rich to the poor necessarily comes at large transaction costs, so redistribution reduces overall welfare, hence there is a trade-off between these two policy goals (Okun 1975). On the same note inequality might be argued to increase incentives and thus create growth, assuming a textbook case economy with no transaction costs and perfect information. However, when capital markets are imperfect or principle-agent problems are present a virtuous trade-off between equality and efficiency can be shown in economic models as well (see Aghion, Caroli, and García-Peñalosa 1999; Benabou 1996). So the interaction between economic growth and equality is far from being obvious, especially if we consider the effects of institutions or modernization processes – such as technological change – which could have large effects on both of these policy goals at the same time.

Educational performance and educational equality have also been linked to economic growth. Hanushek and Woessmann (2008) have shown that the level and the dispersion of cognitive skills – rather than the level of educational attainment – is a very strong predictor of economic growth and income inequality, respectively. Countries with high levels of cognitive skills are likely to grow faster, while countries with low dispersion of skills are also likely to have lower earnings inequality. While the link between educational and economic performance and educational and economic equality seems clear, the interaction between overall equality and performance in education is just as unclear as in the economic dimension.

According to the standard human capital argument the level of investment into one's education should depend on the initial skill endowment: higher skilled have a higher returns to education thus investing more in their education will increase the mean return as well. In other words, unequal investments in human capital might increase overall performance. This line of thinking is complemented by a line of studies initiated by Heckman (Heckman 2000; 2006; Carneiro and Heckman 2003; Cunha et al. 2006; Woessmann 2008), which argues that returns to education declines over the life cycle and the returns for students with different family background and endowment also varies over the life cycle. Investing in education at the early stages not only increases the overall performance of the system but increases equalities as well. Heckman and his colleagues, thus, argue that there is a virtuous trade-off between equality and performance, but only at the early stages of the life cycle. However, investing in education at the later stages will either decrease performance or equality, i.e. investment in secondary and higher education has to face the vicious trade-off between equality and performance.

Most of the empirical results are either inconclusive or disagree with this latter negative conclusion. The cross country studies which are suitable to address such questions are mostly on the secondary school level. The early OECD PISA studies emphasize that social equality (as measured by the variation of student performance) and the mean level of reading or mathematical literacy are positively correlated (e.g. OECD 2001; 2004). The latest PISA study uses a different measure: the socio-economic gradient (OECD 2010). This measure shows the association between student performance and a composite index of family status; this can be understood as a general measure of inequality of opportunity. The OECD cannot show a direct link between this measure and the mean performance in the PISA 2009 study, but points out that there are countries in all four segments of the equality – performance distribution. Similarly, Woessmann and his colleagues are unable to find significant associations between the inequality of opportunity and the mean mathematical performance in the TIMSS studies (Woessmann 2004; Schuetz, Ursprung, and Woessmann 2008).

This paper contributes to this literature by exploring the relationship between inequality of opportunity and the mean performance of countries in more detail. In line with the previous findings we show that the equality of opportunity and performance for the average student are indeed not strongly associated. However, if we examine inequality of opportunity at different parts of the unobserved ability distribution we find a significant negative relationship between mean performance and inequality of opportunity at the top. We show that that this negative association dominates the positive or zero family background effect at the middle and at the bottom. It is likely that this relation drives the negative association between performance and inequality of opportunity at the mean, but not enough to generate a statistically significant result.

EQUALITY OF OPPORTUNITY, EQUALITY OF OUTCOME AND PERFORMANCE

Educational equality in general can be understood in two separate ways: equality of outcomes and equality of opportunity. Most studies use either of these two ways to reflect upon equality. Equality of outcomes is usually measured by the spread around the mean performance, while equality of opportunity is most often proxied by the association between family background and performance. Although the two measures are expected to correlate, they differ conceptually. Roemer (1998) understands equality of opportunity as differences in outcomes attributable only to individual efforts and not to factors outside the individual's control. The effect of family background on individual performance can be understood as an indicator of the effects of factors outside one's control, thus lowering this effect makes the system more equal. Hence many use the family background effect on student performance to proxy equality of opportunity (e.g. Schuetz et al. 2008).

Equality of outcomes is usually proxied by some spread measure around the mean performance. It can be either standard deviation or variance, the difference between the higher and the lower scorers, or some other spread measure (e.g. Hanushek and Woessmann 2006). Obviously these two measures associate positively. The larger the family background effect (FBE) the more likely better-off students will end up at the top of the test-score distribution, which will increase the spread as well (Figure 1 panel a).

Only a few studies test the association between equality of outcomes and equality of opportunity with mean performance directly. Freeman, Machin and Viarengo (2010), using the TIMSS studies,[1] show that equality of outcomes and performance associates positively. This they call a "virtuous equity-efficiency trade-off." They use a relative spread measure (the difference between the 95th-5th percentile score divided by the median) as a measure of equality of outcomes, and show that this measure associates negatively and strongly with the median mathematics score for both the 1999 and 2007 waves of TIMSS. Different OECD reports and policy notes (OECD 2004; 2001) have shown that there are numerous countries with high equality of outcomes and high performance, who should serve as "best practices", but there are also a number of cases with low equality and high performance. Note however, that OECD tends not to establish any direct relationship between equality and performance in their reports, but rather emphasize that equality and high performance can be achieved at the same time (OECD 2010 p.59.). We also tested the association of equality of outcomes (using the within country standard deviation of the test scores) with the mean performance score in the PISA studies and found no significant correlation between the two. However, this result is sensitive to the measurement of inequality of outcomes. When employing a relative spread measure PISA data provides results similar to that of Freeman et al. (2010) (Figure 1 panel c). At the other hand, if the inequality of outcomes is measured with the standard deviation of test scores, no clear pattern of correlation with mean performance can be discovered (Figure 1 panel b).

The results regarding the link between inequality of opportunity and mean performance are even more ambiguous. Using the family background effect as an indicator of inequality of opportunity Woessmann (2004) have found no association between equality of opportunity and performance in the TIMSS database. Using the PISA 2000 data Chiu and Khoo (2005) found a positive association between equality of opportunity and mean performance; however their measure of inequality differs considerably from that of the other cited studies. On the other hand, in their latest PISA 2009 report, the OECD shows no direct association between inequality of opportunity and mean performance (2010 , p.58.). Altogether, the direct evidence on the relationship of equality and mean performance is scarce and mixed.

Some studies have looked at the association of different educational institutions and the two measures of equality and performance indirectly. These papers usually look at the

[1] TIMSS – Trends in Mathematics and Science Study

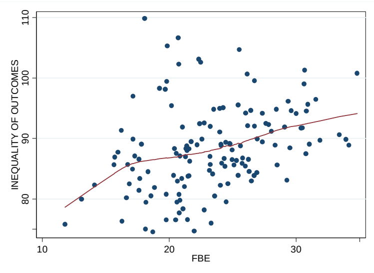
association between different educational institutions and equality or performance, and thus establish an indirect link between the two policy outcomes. The most robust finding is that early tracking associates with lower equality. Hanushek and Woessmann (2006) use TIMSS, PISA and PIRLS data to look at the effect of early tracking. In a difference-in-difference framework they observe that placing students into different tracks by the age of 10 associates strongly with higher dispersion of test scores. This association of tracking and inequality of outcomes is very robust. At he same time, the association of tracking with performance is not clear; it tends to be insignificant and change signs through datasets.

Tracking is also shown to associate with inequality of opportunity. Schuetz, Ursprung and Woessmann (2008) study the effect of several educational institutions – such as tracking, pre-school enrolment, and pre-school duration – and show that all of these have a significant effect on inequality of opportunity. Noteworthly, tracking has a negative effect; it enlarges differences in achievement related to family background. Schuetz, Ursprung and Woessmann (2008) finds that controlling for these institutions higher mean performance associates with stronger family background effect – so they see a vicious equality-performance trade-off – but only for the full sample of TIMSS countries; the same vicious trade-off does not hold for the OECD sample. Note that this weak association is conditional on the educational institutions they analyse. Other studies see a positive, albeit weak, association between performance and equality using the PISA studies. Horn (2009), for instance, looks at the association between the age of selection (among several other educational institutions) and the inequality of opportunity and performance. He shows that early tracking associates negatively with the family background effect and positively with mean performance. The relationship between tracking and performance, however, is very weak and sensitive to alternative specifications.

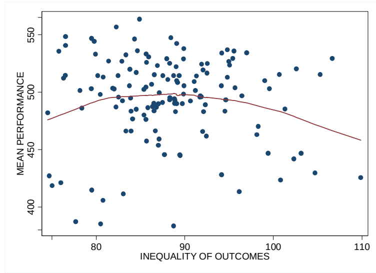
As opposed to the aforementioned papers analysing the impact of tracking, Ariga and Brunello (2007) find that tracking has a positive effect on performance. Their analysis differs from the other papers in three respects. First, data from an adult education survey (IALS) is used instead of student achievement data. Second, the effect of tracking in the entire lower- and upper-secondary education is measured, not only early tracking. Finally, the tracking effect is identified within countries, comparing individuals studying in tracked programmes for a different number of years, as opposed to identification based on country-specific institutions. Their conclusion is that de-tracking, while probably improving equity, may well incur an efficiency cost, thus a trade-off between equity end efficiency does exist in education. Though the papers are not directly comparable, the fact that the conclusion of Ariga and Brunello (2007) is at odds with the findings of Hanushek and Woessmann (2006) and Schuetz, Ursprung and Woessmann (2008) indicates that the relationship between equity and mean performance is far from unambiguous.

Figure 1

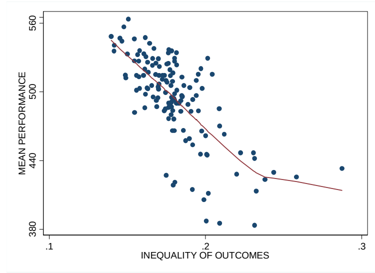
Association between mean performance, inequality of opportunity and inequality of outcomes, OECD+EU countries, 2000-2009



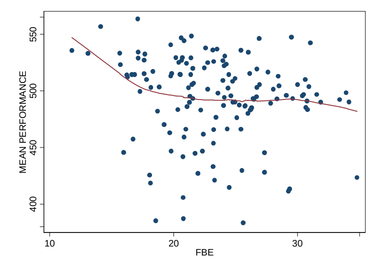
a Inequality of outcomes (s.d.) and inequality of opportunity*, math



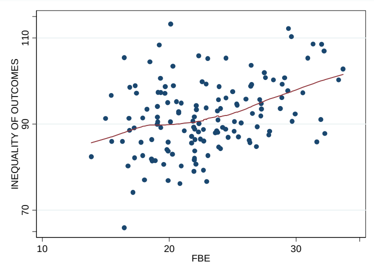
b Mean performance and inequality of outcomes (s.d.)*, math



c Mean performance and inequality of outcomes (relative s.d.), math



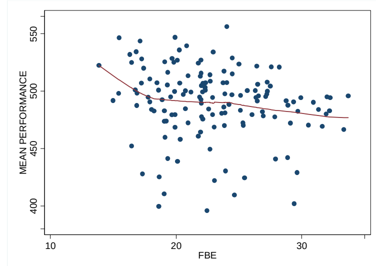
d Mean performance and inequality of opportunity, math



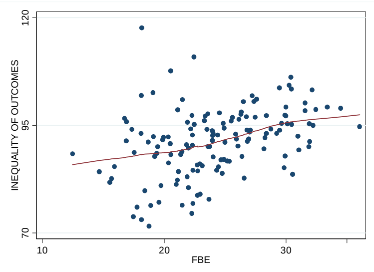
a Inequality of outcomes (s.d.) and inequality of opportunity, reading

b Mean performance and inequality of outcomes (s.d.), reading

c Mean performance and inequality of outcomes (relative s.d.), reading



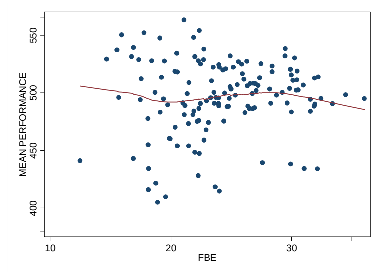
d Mean performance and inequality of opportunity, reading



a Inequality of outcomes (s.d.) and inequality of opportunity, science

b Mean performance and inequality of outcomes (s.d.), science

c Mean performance and inequality of outcomes (relative s.d.), science



d Mean performance and inequality of opportunity, science

–– : non-parametric (locally weighted) regression, inequality of opportunity: the estimated effect of the number of books and home on achievement, inequality of outcomes: the standard deviation of achievement (panel a, b), relative standard deviation of achievement (panel c)

*: Israel, 2000 is omitted because of an outlier value of inequality of outcomes

Alltogether, the existing literature on student achievement suggests that the association between inequality of opportunity and performance is either insignificant or weakly negative. The same conclusion can be drawn looking at the PISA data (Figure 1 panel d).

This paper intends to contribute to this line of research by looking at the association between inequality of opportunity and the mean performance of countries in more detail. We build on the concept of inequality of opportunity as defined by Roemer (1998), focus on inequality of opportunity related to socio-economic status and start from its standard measurement as the family background effect on student achievement (Woessmann 2004; Schuetz et al. 2008). In this approach inequality of opportunity is defined as a single measure to describe overall inequality, however, family background effect is not necessarily uniform within countries. Empirical evidence indicates considerable variation in the family background effect along the test score distribution, i.e. related to unobserved individual heterogeneity both regarding a pooled sample of countries (Fertig and Schmidt 2002; Freeman et al. 2010) and within a single country (Fertig 2003).

The unobserved heterogeneity in the family effect most likely represents ability (Woessmann 2004), the most important input in the production of student achievement that is not observed in international achievement data. Thus the heterogeneity in the family effect suggests that inequality of opportunity with respect to socio-economic status might interact with the impact of ability. Note that this is by no means obvious, since some dimensions of inequality of opportunity can be more or less independent, for instance gender- and family status related differences in student achievement seem not to be interrelated (Schnepf 2004). Thus the overall educational disadvantage of low-status, low-income students might conceal considerable variation in the situation of more and less able students. These groups may encounter different obstacles and may also receive different levels of support in education. Moreover, the heterogeneity in the family effect seems to vary across countries, as well (see Ammermueller 2004 for a German-Finland and Woessmann 2004 for a US-Europe comparison). This suggests that various educational policies and institutions may affect the family background-ability interaction in different ways.

In this paper we distinguish inequality of opportunity at different parts of the unobserved ability distribution. We measure these with the family background effect at the top, middle and bottom of the achievement distribution and explore their association with the mean performance of countries. In contrast to the existing literature providing ambiguous results, we find a significant negative relationship between inequality of opportunity at the top and mean performance, i.e. educational systems with smaller differences among the disadvantaged and high status students in the high-scorer range tend to perform better in general. At the same time, inequality of opportunity at the middle and at the bottom of the distribution is not unequivocally related to the mean achievement level. However, these latter associations are usually of the opposite sign, and although often statistically not significant, in part offset the former when overall inequality of opportunity is considered.

DATA

We use all four waves of the PISA data to explore the link between inequality of opportunity and mean performance. We constrain the group of countries in the estimation sample to those from the OECD and the EU in 2009, in order to minimize differences in economic development, and because we believe that out FBE indicator (see below) works the best in this relatively homogeneous group. With this limitation we have 141 country-year,[2] and 967,908 student level observations. PISA measures three different types of literacy: reading, mathematical and science. PISA test scores are standardized measures of literacy with a mean of 500 points and standard deviation of 100 points for the OECD countries. We use all of these outcome measures separately to make sure our results are not driven by the field of subject.

We use the number of books at home to proxy family background, as suggested by Schuetz et al. (2008). Using the number of books at home has the advantage of being simple as compared to the generated measures of family background, it is measured the same way in each country, unlike the level of education, and shown to be a stronger predictor of test scores than parental background (Fuchs and Woessmann 2006). The number of books at home is measured with a 6-category-variable[3] and its effect on test-scores is shown to be linear (Schuetz et al. 2008, p.289). Nevertheless, we ran robustness checks using the economic, social and cultural status index as well as an occupational prestige scale instead of the number of books to proxy family background.[4]

---

[2] We observe the following countries for
4 years: Australia, Austria, Belgium, Canada, Switzerland, Czech Republic, Germany, Denmark, Spain, Finland, France, Greece, Hungary, Ireland, Iceland, Italy, Japan, Korea, Lichtenstein, Luxembourg, Latvia, Mexico, the Netherlands, Norway, New Zealand, Poland, Portugal, Sweden
3 years: Bulgaria, Chile, Great Britain, Israel, Romania, Slovakia, USA
2 years: Estonia, Lithuania, Slovenia, Turkey

[3] The wording of the question was: How many books are there in your home? (There are usually about 40 books per metre of shelving. Do not include magazines, newspapers, or your schoolbooks.) 0-10 books ->1, 1-25 books ->2, 26-100 books ->3, 101-200 books ->4, 201-500 books ->5, more than books ->6,

[4] PISA data sets contains a so called economic, social and cultural background (escs) index, which comprises of several factors of occupational status, home possessions and parental education, as well as the index of highest occupational status of parents (hisei) (OECD 2005 , p.316)

ECONOMETRIC SPECIFICATION

In order to explore the association between the inequality of opportunity and the mean performance of countries we use a two step estimation method. In the first step we estimate our measure of inequality of opportunity, the family background effect for each country-years and for each test separately. The starting point is the form usually applied in the literature (e.g. Schuetz et al, 2008):

(1) $$A_i = \alpha + \beta B_i + \gamma Z_i + \varepsilon_i$$

where A denotes test score, B the number of books at home, Z the vector of control variables, α, β, and γ are the coefficients to be estimated and ε is the error term for student i. The family background effect is measured by the coefficient of the books at home; β. Besides this basic specification we estimate the same effect at different points of the conditional distribution using the quantile regression method:

(2) $$Q^q(A_i \mid X_i) = \alpha^q + \beta^q B_i + \gamma^q Z_i + \varepsilon_i$$

where q denotes the quantile at which the model is estimated. While OLS evaluates the estimated effect at the mean, the quantile regression method (see Koenker and Hallock 2001) aims at analysing the effect of the explanatory variables at different points in the conditional distribution of the dependent variable. That is in the median regression the effect of books is estimated on test scores at the median at given values of books and the control variables.

The set of control variables consists of gender and immigrant status of the student (variables parents born outside the country and the student born in another country). These controls are included in order to avoid mixing gender differences and the special situation of immigrants in school with family background effects. If these controls were not included, it would be possible, that the family background effect estimated at the bottom of the distribution were heavily affected by the performance of immigrant students in some countries. Also, gender differences could influence the differences in FBEs along the distribution if gender were not controlled for, even if gender and family background are not correlated. Moreover, since girls and boys perform differently in different fields of study, controlling for gender mitigates the expected differences between the tested fields

In the second step we estimate the association between the family background effect estimated in the first step and the mean performance of countries. First, we estimate this relationship on the pooled cross-section of countries in the form:

(3) $$A_{ct} = \kappa + \sum_q \lambda^q FBE_{ct}^q + \varphi R_{ct} + \sum_t \tau^t Y_t + \nu_{ct}$$

where Act denotes the country mean of student achievement for country c in year t, FBEq is the family background effect estimated at quantile q in the first step, the Y-s are year dummies, R is the vector of further control variables and υ is the error term. κ, the λ-s, τ-s and φ are the parameters to be estimated, with the main interest focused on the λ-s, the coefficients of the family background effects. Three specifications are used to estimate equation (3). In the basic specification no controls are included besides the year dummies. In the second variables representing the level and distribution of books at home are added as controls: the share of students with only few books at home and the share with lots of books. The reason for this is that the estimated family background effect may depend on the level of books, while the mean performance of countries can be expected to increase with the average number of books at home and decrease in the share of students with few books at home. In the third specification the log of GDP per capita at PPP is also included as a further control.

Besides the pooled cross-section estimates we also employ a panel model:

(4) $$A_{ct} = \kappa + \sum_q \lambda^q FBE_{ct}^q + \varphi R_{ct} + \sum_t \tau^t Y_t + \sum_c \theta^c C_c + \nu_{ct}$$

where C-s denotes country dummy variables and the θ-s are country fixed effects. In this model we rely solely on the variation within countries across time to identify the association between inequality of opportunity and mean performance. The fixed-effects model is also estimated in the three specifications discussed above.

Since the data in the four years for the same countries cannot be considered as independent observations, the standard errors are clustered on the country level, allowing for the error terms to be correlated within countries in both the pooled cross-section and panel models.

RESULTS

INEQUALITY OF OPPORTUNITY AT DIFFERENT POINTS OF THE DISTRIBUTION

In order to measure the family background effect (FBE) at different points of the conditional distribution, we estimate equation (1) for the three test scores, for each country in each year, for nine quantiles (from the 10th to the 90th) separately. The estimated family background effect was positive for each estimate and statistically significant in all, but a few cases.[5] The correlation between the FBEs estimated for different years is fairly strong (typically varies between 0.50 and 0.85), suggesting both that the level of equality of opportunity is relatively stable in time and that the random statistical errors in our estimates are not overwhelming.

Looking at the correlation structure between the FBEs estimated for the nine quantiles reveals that there is much more variation in inequality of opportunity between countries than within countries along the distribution of test scores. There is a strong positive correlation between the FBEs for the nine quantiles, however some differences exists within countries, as well. The principal component analysis of the effects indicates that most of the variation is captured by the general level of inequality of opportunity represented by the first component (table A1 in the appendix). However, besides this, countries also differ with respect to the difference in the inequality of opportunity between the top and the bottom of the test score distribution. In this second dimension, measured by the second component, the FBEs for the top quantiles bunch together on the one hand and those at the bottom at the other. The clear pattern confirms the assumption that the family background effect can be heterogeneous and the differences in the estimated effects at various quantiles do not exclusively originate from measurement error. This lends support to our concept of inequality of opportunity defined for different parts of the distribution.

In the second step of our analysis we use three FBEs to represent inequality of opportunity at the top, the middle and the bottom: those for the 20th, 50th and 80th quantiles. We prefer these to the FBEs outer on the tails of the distribution (to the 10th and 90th percentiles) since those might be more prone both to the contingencies in the performance of special subgroups of students and to statistical error. Descriptive statistics for our three indicators are shown in table A2 for the OECD-EU sample of countries.

The FBEs at the bottom seem to be marginally smaller than those at the middle and the top of the distribution. This might be related to the fact that the vast majority of countries tend to display three typical patterns in the FBEs (see Figure A1-A4 for the results by country and year). In some countries the FBEs are similar along the entire conditional distribution in test scores (e.g. Finland, Japan or Switzerland in 2009), in another group FBEs are increasing along the distribution (e.g. the Czech Republic or Sweden in 2009) while in the third group there is an inverse U-shaped pattern (e.g. the Netherlands, Austria or Slovenia in 2009) (Figure A4).

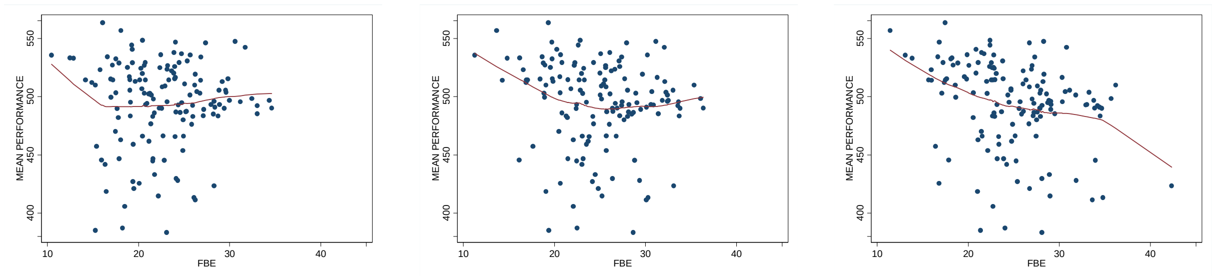
Altogether the descriptive analysis suggests, that some variation along the conditional distribution does exist between countries as inequality of opportunity can somewhat differ at the top and the bottom within a single country.

[5] Out of the 3807 FBE estimates 4 were not significant at the 10% level, while further 3 were significant only at 10%, all from Lichtenstein, typically at the 10th or 90th quantiles from year 2000.

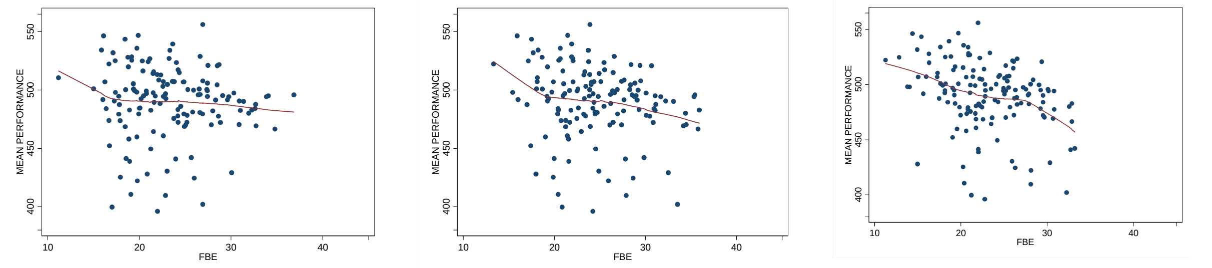
Before turning to estimation results it is worth to explore the bivariate relationship between the FBE measures and mean performance. Figure 2 represents these for the test scores. For the FBEs at the 20th and 50th percentiles no pronounced pattern can be detected, though FBEs at the 20th percentile for science seem to show a positive, while FBEs at the 50th percentile for reading a negative relationship with the mean score. In general, the lowest values of inequality of opportunity seem to incur somewhat higher mean performance, but for the majority of country-year observations there is no clear pattern in the data. At the same time, mean performance and the FBE at the top is negatively related over the entire range of values.

Figure 2

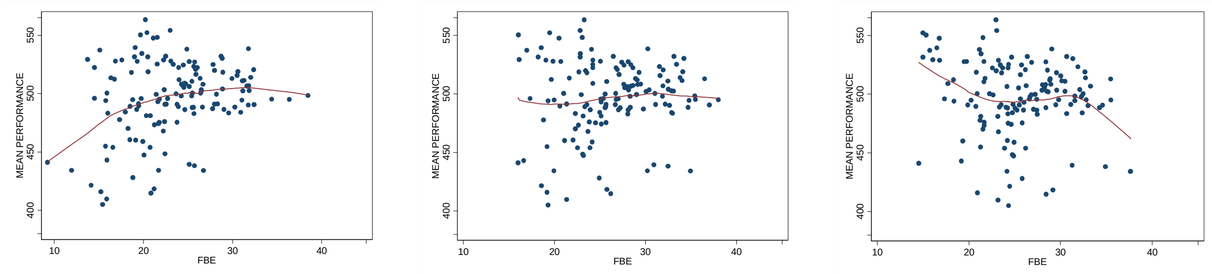
Mean performance and family background effect at the bottom, middle and top of the conditional test score distribution



math: FBE at 20th quantile   math: FBE at 50th quantile   math: FBE at 80th quantile



reading: FBE at 20th quantile   reading: FBE at 50th quantile   reading: FBE at 80th quantile



science: FBE at 20th quantile   science: FBE at 50th quantile   science: FBE at 80th quantile

—— : non-parametric (locally weighted) regression

Our main interest is focused on the estimation of equation (3) and equation (4). Family background effects at the 20th, 50th and 80th quantiles are included at the right hand side of the equations in order to represent inequality of opportunity at the bottom, the middle and the top of the distribution in each country. Estimation results are summarised in table 1. The FBE at the top clearly seems to be negatively related to mean performance. It has a negative coefficient in each estimate and for the pooled cross-section estimates is statistically significant in each case. Regarding the panel models the association is significant for the math and science scores, but proves to be less precisely estimated and not significant for reading. In general, the coefficients are somewhat smaller and the standards errors are larger for reading compared to math and science.

At the same time, no consistent results emerge regarding the FBE at the middle and the bottom. The coefficients of the FBE at the median tend to be positive but non-significant (with the exception of the pooled cross-section estimates for science). The FBE at the bottom is also positive for the pooled estimates and marginally significant for math and science, but its sign is overturned and significance is lost in the panel models. This lack of significance is in part due to multicollinearity among the FBEs expanding the standard errors. In the pooled cross-section estimates the joint F-tests of the FBE for the 50th and 20th quantiles are statistically significant in most cases (except specification (3) for reading scores). However, in the panel models this joint significance is absent in each estimates, while the sign of the coefficients also shifts in many cases. Overall, we regard the results inconclusive for the FBE at the middle and at the bottom, while at the top we find a consistent negative association with the mean performance of students.

In Table 1 we also present estimates including the mean family background effect instead of those for the three quantiles analysed above. These are in accordance with the ambiguous findings of the literature. The sign of the FBE is consistently negative (with one exception), but in most cases insignificant. This implies that the negative association with the FBE at the top dominates the positive/zero FBE at the middle and the bottom, but not strong enough to generate a statistically significant correlation at the mean.

The negative sign of the FBE at the top means that countries, where the test score gap between the best-performing low- and high-status students is smaller, tend to have higher mean test scores. The panel estimates indicate that the association also holds within countries, for the differences between the four waves of PISA. In other words, a decreasing the gap along the family background dimension among the best-performing students within a country from year to year goes together with increasing mean performance.

How large is this effect? The standard deviation of the FBEs at the top is about 5 points (see Table A2), while the estimated coefficients are concentrated around 5 in the cross section and 1.4 in the panel estimates (Table 1). This implies that a one standard deviation weaker FBE at the top implies a 25-point difference in the mean performance between countries and about 7 points within countries. Nevertheless, the difference derived from the cross-section estimates should be considered rather as an upper-bound due to the correlation between the FBEs at the top, middle and bottom. Large differences in the FBE at the top hardly occur without a similar difference in the FBEs in the other parts of the distribution in our sample. Since in the cross-section of countries the latter tend to have an association with the mean performance of the opposite sign, this mitigates the observable difference between countries related to the FBE at the top.

Table 1

Regression estimates of the mean country performance, coefficients of the family background

	Pooled cross-section (1)	(2)	(3)	Panel (fixed effects) (4)	(5)	(6)
math						
fbe_q80	-6.645***	-5.679***	-4.589***	-1.447**	-1.486**	-1.791***
	(1.15)	(1.36)	(1.36)	(0.63)	(0.61)	(0.60)
fbe_q50	2.357	2.146	2.820*	0.930	0.810	1.096
	(1.50)	(1.55)	(1.48)	(0.83)	(0.79)	(0.78)
fbe_q20	3.181*	2.306**	0.982	-0.695	-0.629	-0.616
	(1.59)	(0.94)	(1.08)	(0.73)	(0.79)	(0.78)
reading						
fbe_q80	-5.452***	-3.744***	-2.673*	-0.962	-1.104	-1.234
	(1.38)	(1.37)	(1.49)	(0.95)	(0.93)	(0.88)
fbe_q50	2.154	1.392	0.951	-0.484	-0.211	-0.036
	(1.86)	(1.85)	(1.95)	(1.45)	(1.38)	(1.33)
fbe_q20	1.693	0.935	0.648	0.422	0.291	0.198
	(1.44)	(1.14)	(0.92)	(1.04)	(1.07)	(1.10)
science						
fbe_q80	-6.969***	-4.979***	-4.049***	-1.485**	-1.330**	-1.287**
	(1.33)	(1.03)	(1.13)	(0.60)	(0.63)	(0.62)
fbe_q50	4.020**	2.697**	2.046	0.714	0.719	0.672
	(1.52)	(1.33)	(1.40)	(0.95)	(0.96)	(0.97)
fbe_q20	2.701**	1.734*	1.537*	-0.137	-0.284	-0.288
	(1.14)	(0.98)	(0.86)	(0.63)	(0.66)	(0.65)
math						
fbe	-1.483	-1.587**	-0.723	-1.088	-1.182*	-1.150*
	(1.10)	(0.67)	(0.57)	(0.67)	(0.62)	(0.61)
reading						
fbe	-1.161	-1.130	-0.777	-0.719	-0.701	-0.690
	(0.85)	(0.71)	(0.58)	(0.56)	(0.52)	(0.49)
science						
fbe	0.279	-0.287	-0.288	-0.921	-0.856	-0.867
	(1.15)	(0.81)	(0.70)	(0.60)	(0.57)	(0.59)
Control variables:						
year dummies	yes	yes	yes	yes	yes	yes
share of students with few and many books	no	yes	yes	no	yes	yes
GDP per capita	no	no	yes	no	no	yes
country fixed-effects	no	no	no	yes	yes	yes
N obs	141	141	141	141	141	141
N countries	39	39	39	39	39	39

Standard errors clustered at the country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

As a robustness check, we analyse how sensitive our results are to the sample of countries and the measurement of family background. First, we check whether our results are driven by including few exceptional countries in the sample. Analysis of the influence statistics suggests that no single country has an overwhelming influence on the results. Also, excluding the group of the five countries with the lowest GDP and average number of books from the sample leaves the results unchanged (Table A3). Second, we re-estimated equation (3) and (4) for the full sample of countries participating in PISA (Table A4). Again, the results proved to be similar, the only difference found is that the coefficients in the fixed-effects models for science are non-significant. Third, we replaced the number of books as the measure of family background with two other indicators provided by PISA: the socio-economic status index on the one hand and the highest occupational status index of parents on the other (Table A5 and A6). Using these measures produced the same results for the cross-section models, however, in the fixed-effects estimates the FBEs were non-significant. Since the panel estimates are especially strong tests for the association between of inequality of opportunity and mean performance due to the limited variation within countries over time, we conclude that these results are in line with our main findings. Finally, in order to eliminate any possible bias coming from the differences between countries in the quality of the number of books as an indicator of family background, we included in equation (3) and (4) the correlation between the number of books on the one hand and the socio-economic and occupational status indices on the other. If the number of books is a weaker indicator of family background, the conditional variance of test scores at given values of books is expected to be larger, which may affect the estimated FBE at different points of the distribution. We assume, that the higher the correlation is between the number of books and other indicators of family background, the better indicator is the former. Hence, controlling for this correlation mitigates the possible bias related to the quality of the indicator. The results are again qualitatively unchanged (Table A7). Altogether, the association between inequality of opportunity at the top and country mean performance seems to be robust to the sample of countries and the measurement of family background.

INTERPRETING THE ASSOCIATION OF INEQUALITY OF OPPORTUNITY AND MEAN PERFORMANCE

Obviously, the association between the FBE at the top and mean performance cannot be interpreted as a causal relationship. Neither direction of causation is inconceivable; while the most plausible source of the association is that some institutional features or educational policies affect both at the same time. We do not pursue identifying these causal effects here, but it's worth to distinguish between two possible forms of this association. First, it is possible that the association is driven simply by the performance of poor students with the highest test scores. If a weaker FBE at the top usually means higher scores for them, while the scores of everybody else remain unchanged, this moves the mean performance up. Assuming the heterogeneity in the FBEs reflects the unobserved ability of students, this mechanism means, that improving the education of smart, but poor students advances equality of opportunity at the top and raises the overall mean performance at the same time. Second, it is possible, that the association is not confined to this specific group of students. If, for example, certain institutions or education policies improve the performance of students in general, but the best-performing poor students profit the most from these (or alternatively, the best-performing high-status students benefit less than others), then again, equality of opportunity at the top and the overall mean performance can increase simultaneously.

In order to get some clues regarding these two possible sources of the positive association we re-estimate equation (3) and (4) for subgroups of students. Table 2 presents results for three subgroups with respect to family background.

Table 2

Regression estimates of the mean country performance for subgroups of students, coefficients of the family background effect

	number of books: few		number of books: medium		number of books: many	
	pooled	fe	pooled	fe	pooled	fe
math						
fbe_q80	-5.752***	-1.732***	-5.757***	-1.791***	-4.904***	-0.347
	(1.47)	(0.63)	(1.37)	(0.62)	(1.64)	(0.81)
fbe_q50	0.999	-0.050	2.575*	1.010	2.244	1.165
	(1.62)	(0.87)	(1.52)	(0.61)	(1.83)	(1.36)
fbe_q20	1.548	-1.205	2.112**	-0.635	3.225***	-0.251
	(0.96)	(0.81)	(0.91)	(0.74)	(0.99)	(0.92)
reading						
fbe_q80	-4.665***	-2.015*	-3.422**	-0.840	-3.289**	-0.225
	(1.46)	(1.09)	(1.35)	(0.91)	(1.49)	(1.00)
fbe_q50	1.374	-0.130	1.151	-0.386	2.293	0.497
	(1.98)	(1.52)	(1.72)	(1.27)	(2.03)	(1.53)
fbe_q20	-0.242	-0.595	1.117	0.213	1.299	0.409
	(1.15)	(0.94)	(1.06)	(1.05)	(1.30)	(1.09)
science						
fbe_q80	-5.134***	-1.534**	-5.123***	-1.619***	-4.471***	0.036
	(1.06)	(0.59)	(0.95)	(0.60)	(1.23)	(0.88)
fbe_q50	1.456	-0.284	2.981**	0.802	3.707**	1.330
	(1.37)	(0.78)	(1.21)	(0.83)	(1.57)	(1.11)
fbe_q20	1.230	-0.658	1.786*	-0.289	2.084*	-0.275
	(0.99)	(0.54)	(0.88)	(0.66)	(1.12)	(0.78)

Standard errors clustered at the country level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
pooled: specification (2) in Table 1
fe: specification (5) in Table 1

The magnitude of the coefficients clearly decreases in the status of the family, i.e. more equality of opportunity at the top is associated with higher gains in test scores for poor students compared to the rich. The association has the same negative sign in all but one of the estimates.[6] For the cross-section estimates it is statistically significant for each group of students, while in the panel models, for students with the most books at home the association is statistically not significant. Overall, this pattern suggest, that higher performance is not confined to the best-performing poor students, when equality of opportunity at the top improves. Instead, students in various subgroups are all seem to perform better, though the gains for poor students (and especially the top of the distribution among the poor) exceed those of the others. Repeating these estimations for other grouping of students, according to their position in the performance distribution or the combination of this with family background also support this conclusion.[7]

Figure 3 displays the most likely scenario that is consistent with our estimation results in a stylised manner. Let us consider four student types with respect to family background and unobserved ability. Improving education quality affects achievement in each of the groups positively, however, to a different degree (an upward shift from full circles to hollow circles on Figure 3). The mean performance is naturally increasing. The family background effect also changes, but with a different sign at the top and the bottom along the test score distribution. Since the achievement of low-status high-ability students has increased the most, they catch up with high-status high-ability students, implying a considerable decrease in the FBE at the top. At the same time, the family background effect may slightly increase at the bottom, even if the achievement of low-status low-ability students do not deteriorates in absolute terms. Their relative performance slipping back compared to the high-status low-ability group is enough to produce this result. Altogether, in this case the overall increase in mean performance is accompanied by an improvement in equality of opportunity at the top, while the change of this at the bottom is less robust. The shift in the overall equality of opportunity is also not clear-cut. The improvement at the top is in part offset by the decline at the bottom, thus the association of the sum of the two with mean performance is again, not robust.

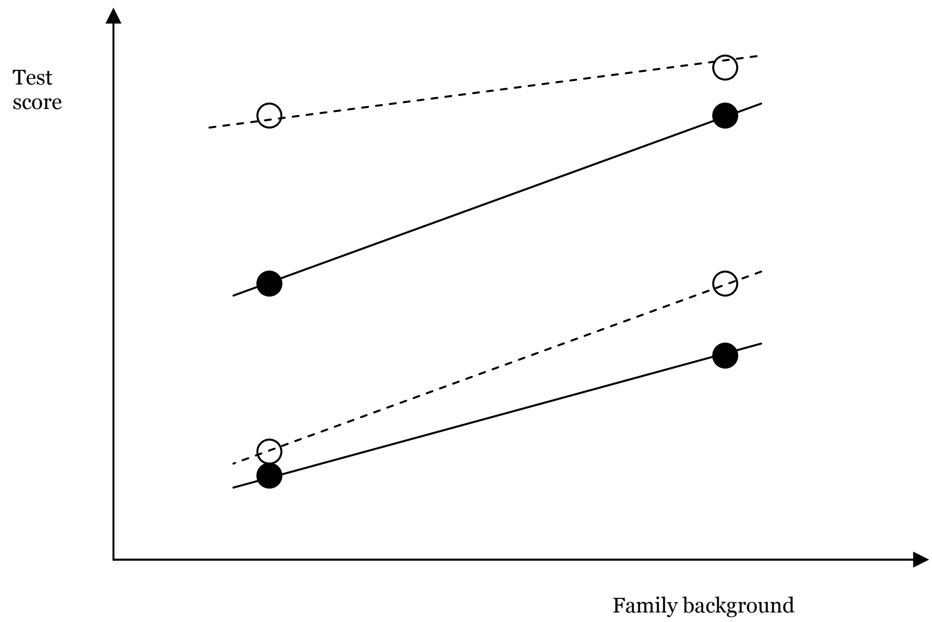
How can this scenario emerge? One can assume that certain educational institutions and policies tend to have this kind of impact, while others not. There is empirical evidence that students with higher ability and/or more disadvantaged family background may benefit more from certain education policies than other students. For example, Meghir-Palme (1995) analysing the impact of an educational reform in Sweden find that low status high ability

[6] The exception is the fixed-effects model for science for students with the most books at home.
[7] Results not shown, available from the authors on request.

students gained the most from the reform and poor students altogether profited more than their high status fellows. Another example is that higher teacher quality seems to exert a stronger impact on the achievement of poor and/or low performing students (see e.g. Aaronson, Barrow, and Sander 2007; Nye, Konstantopoulos, and Hedges 2004). Hence, if either general teacher quality is rising or teacher-student matching changes in favour of low status students, one can expect an effect similar to that of Figure 3.

Figure 3

A hypothetical change in inequality of opportunity and mean performance



CONCLUSION

Previous research has shown that the association between educational inequality and performance is either weakly negative or insignificant. We contribute to this line of research by looking at the association between inequality of opportunity, measured as family background effect on test scores, and performance in more detail. Instead of looking at the link between the average inequality of opportunity and performance we examine this association at the top, middle and bottom of the unobserved ability distribution. To explore this association we use a two step method. In the first step, we use quantile regression models to estimate the family background effect, the indicator of inequality of opportunity at different points of the distribution within each country in PISA 2000-2009. In the second step, we analyse the association between these estimates and the mean achievement of countries using pooled cross-section and country fixed-effect panel models.

In contrast to the existing literature we find a significant negative relationship between inequality of opportunity at the top and mean performance. Educational systems with smaller differences among the disadvantaged and high status students in the high-scorer range tend to perform better in general. At the same time, inequality of opportunity at the middle and at the bottom of the distribution is not unequivocally related to mean achievement. However, these latter associations are usually of the opposite sign, and although often statistically not significant, in part offset the former when overall inequality of opportunity is considered. The negative association of mean performance and family background effect at the top dominates the positive or zero family background effect at the middle and at the bottom, resulting in a weak, though insignificant negative association overall.

These results suggest that in many cases educational institutions and policies that are effective in raising educational quality in general naturally improve equality of opportunity for the best-performing poor students. However, if equality of opportunity is to be advanced further, policy should focus on the groups of relatively less able students from disadvantaged families.

REFERENCES

Aaronson, Daniel, Lisa Barrow, and William Sander. 2007. "Teachers and Student Achievement in the Chicago Public High Schools." Journal of Labor Economics 25(1):95-135. Retrieved March 31, 2011.

Aghion, Philippe, Eve Caroli, and Cecilia García-Peñalosa. 1999. "Inequality and Economic Growth: The Perspective of the New Growth Theories." Journal of Economic Literature 37(4):1615-1660.

Ariga, Kenn, and Giorgo Brunello. 2007. "Does Secondary School Tracking Affect Performance? Evidence from IALS." IZA Discussion Papers No. 2643

Ammermueller, Andreas. 2004. "PISA: What Makes the Difference? Explaining the Gap in PISA Test Scores Between Finland and Germany." ZEW Discussion Papers (04-04).

Benabou, Roland. 1996. "Inequality and Growth." NBER Macroeconomics Annual 11:11-74.

Carneiro, Pedro Manuel, and James J. Heckman. 2003. "Human Capital Policy." NBER working paper No. w9495.

Chiu, Ming Ming, and Lawrence Khoo. 2005. "Effects of Resources, Inequality, and Privilege Bias on Achievement: Country, School, and Student Level Analyses." American Educational Research Journal 42(4):575 -603.

Cunha, Flavio, James J. Heckman, Lance Lochner, and Dimitriy V. Masterov. 2006. "Chapter 12 Interpreting the Evidence on Life Cycle Skill Formation."Pp. 697-812 in Handbook of the Economics of Education, vol. Volume 2. Elsevier.

Fertig, Michael. 2003. "Who's to Blame? The Determinants of German Students' Achievement in the PISA 2000 Study." IZA DP No. 739.

Fertig, Michael, and Christoph M. Schmidt. 2002. "The Role of Background Factors for Reading Literacy: Straight National Scores in the PISA 2000 Study." IZA DP No. 545.

Freeman, Richard B., Stephen Machin, and Martina Viarengo. 2010. "Variation in Educational Outcomes and Policies across Countries and of Schools within Countries." National Bureau of Economic Research Working Paper Series No. 16293.

Fuchs, Thomas, and Ludger Woessmann. 2006. "What accounts for international differences in student performance? A re-examination using PISA data." Empirical Economics 32(2-3):433-464.

Hanushek, Eric A., and Ludger Woessmann. 2006. "Does Educational Tracking Affect Performance and Inequality? Differences- in-Differences Evidence Across Countries*." The Economic Journal 116(510):C63-C76.

Hanushek, Eric A., and Ludger Woessmann. 2008. "The Role of Cognitive Skills in Economic Development." Journal of Economic Literature 46(3):607-668.

Heckman, James J. 2000. "Policies to foster human capital." Research in Economics 54(1):3-56.

Heckman, James J. 2006. "Skill Formation and the Economics of Investing in Disadvantaged Children." Science 312(5782):1900 -1902.

Horn, Daniel. 2009. "Age of selection counts: a cross-country analysis of educational institutions." Educational Research and Evaluation: An International Journal on Theory and Practice 15(4):343.

Koenker, Roger, and Kevin F. Hallock. 2001. “Quantile Regression.” The Journal of Economic Perspectives 15(4):143-156.

Meghir, Costas and Marten Palme. 2005. "Educational Reform, Ability, and Family

Background." American Economic Review 95(1): 414–424.

Nye, Barbara, Spyros Konstantopoulos, and Larry V. Hedges. 2004. “How Large Are Teacher Effects?” Educational Evaluation and Policy Analysis 26(3):237 -257.

OECD. 2004. “Education and Equity - Policy Brief.”

OECD. 2001. “Knowledge and Skills for life - first results from PISA 2000.”

OECD. 2005. “PISA 2003 technical report.”

OECD. 2010. “PISA 2009 Results: Overcoming Social Background - equity in learning opportunities and outcomes Vol. II.”

Okun, Arthur M. 1975. Equality and efficiency, the big tradeoff. Brookings Institution Press.

Roemer, John E. 1998. Equality of opportunity. Harvard University Press.

Schnepf, Sylke V. 2004. “Gender Equality in Educational Achievement: An East-West Comparison.” IZA DP No. 1317.

Schuetz, Gabriela, Heinrich W. Ursprung, and Ludger Woessmann. 2008. “Education Policy and Equality of Opportunity.” Kyklos 61(2):279-308.

Woessmann, Ludger. 2008. “Efficiency and equity of European education and training policies.” International Tax and Public Finance 15(2):199-230.

Woessmann, Ludger. 2004. “How Equal Are Educational Opportunities? Family Background and Student Achievement in Europe and the US.” IZA DP No. 1284.

APPENDIX

Table A1

Principal component analysis of the estimated family background effects for the 10th-90th quantiles

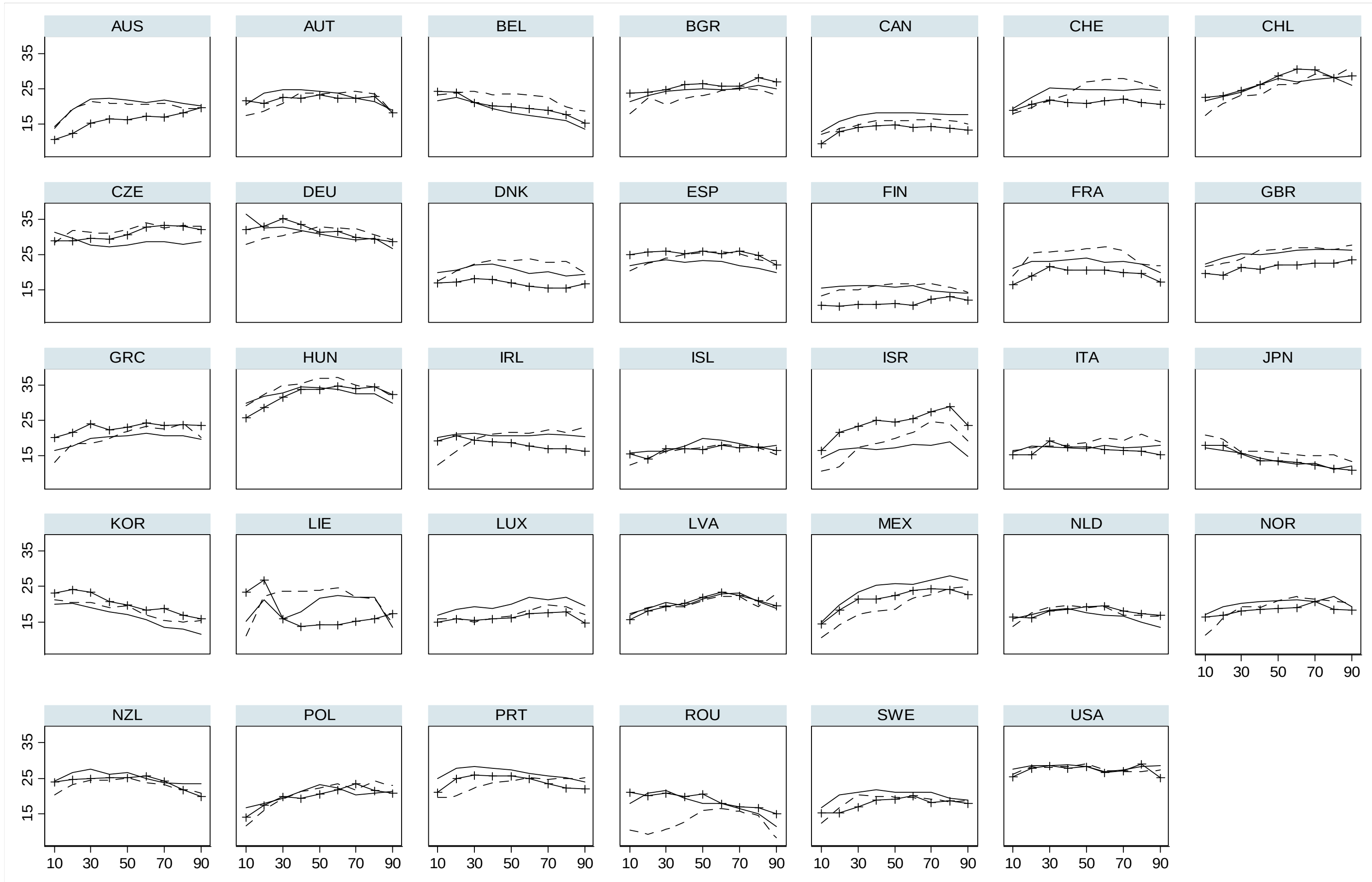
	math		reading		science	
	1. component	2. component	1. component	2. component	1. component	2. component
fbe_q90	0,31	-0,46	0,30	-0,51	0,30	-0,50
fbe_q80	0,33	-0,37	0,33	-0,36	0,33	-0,40
fbe_q70	0,34	-0,28	0,34	-0,26	0,34	-0,25
fbe_q60	0,35	-0,16	0,35	-0,14	0,35	-0,16
fbe_q50	0,35	-0,02	0,35	-0,01	0,35	0,00
fbe_q40	0,35	0,12	0,35	0,11	0,35	0,15
fbe_q30	0,34	0,26	0,34	0,27	0,34	0,26
fbe_q20	0,32	0,43	0,33	0,38	0,33	0,41
fbe_q10	0,29	0,53	0,30	0,54	0,30	0,49
share of explained variance	0,8709	0,096	0,8725	0,0855	0,8681	0,094

Countries with equal sum of weights (countries not participating in all PISA rounds has higher weights).

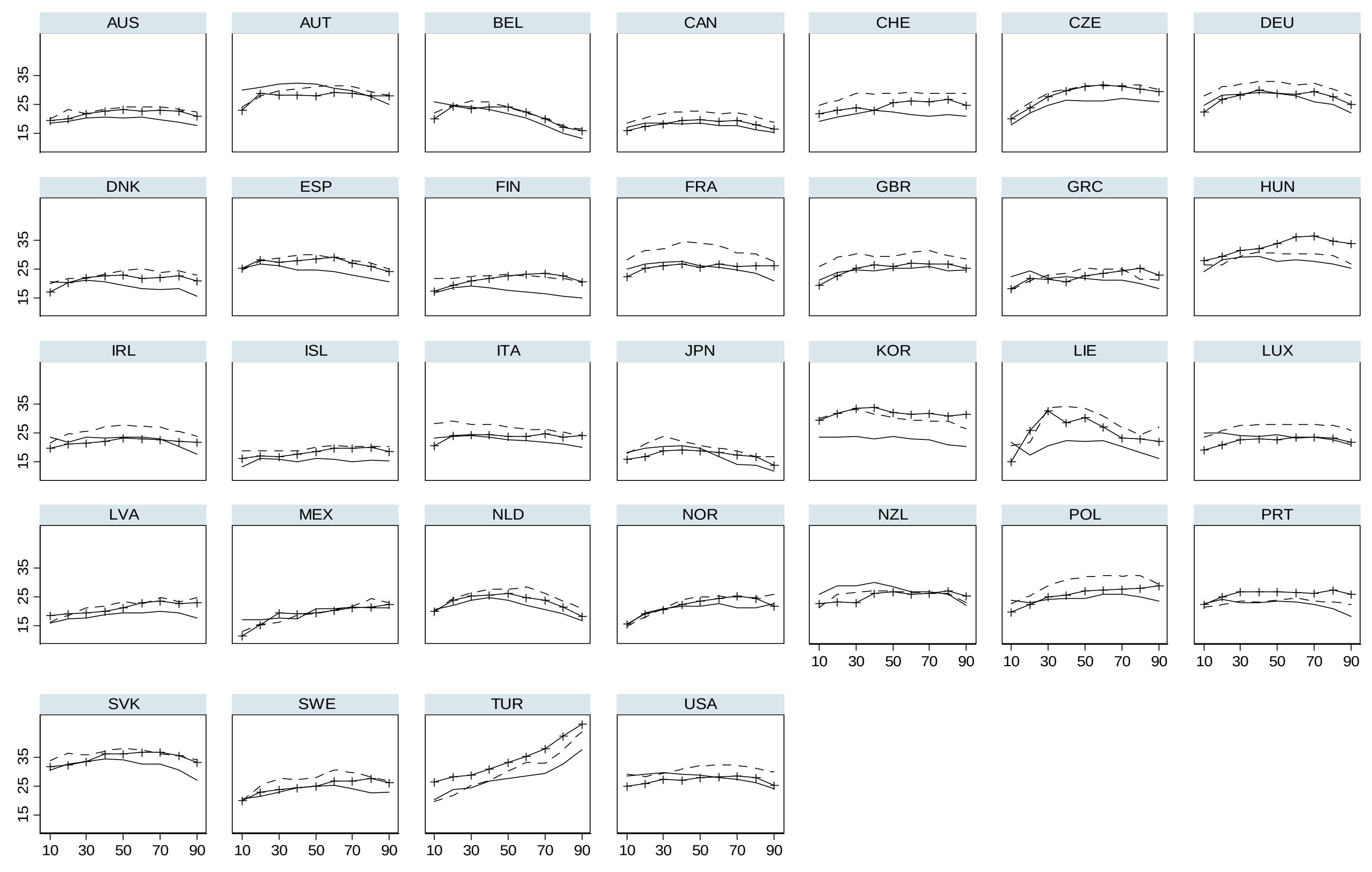
Table A2

Descriptive statistics of the estimated family background effects at the 20th, 50th and 80th quantiles

		fbe_q20				fbe_q50				fbe_q80			
	N	mean	s.d.	p25	p75	mean	s.d.	p25	p75	mean	s.d.	p25	p75
math													
2000	34	20,5	5,3	17,0	24,1	21,5	5,3	17,7	25,1	21,2	5,7	17,1	24,0
2003	32	23,3	4,3	20,2	25,8	25,8	4,5	22,7	28,3	25,6	5,4	22,5	27,9
2006	36	23,1	4,4	19,5	26,1	26,0	4,6	22,8	30,1	26,4	4,8	22,9	29,7
2009	39	23,6	4,6	20,4	26,8	26,2	4,5	22,2	29,4	26,0	4,4	22,4	28,7
reading													
2000	34	21,6	4,5	17,9	23,0	22,4	4,6	18,2	25,5	21,5	5,1	17,6	25,2
2003	32	23,1	4,3	19,6	25,7	23,8	4,1	21,3	26,2	21,8	4,5	19,0	25,0
2006	36	24,3	5,2	20,0	26,9	25,3	5,1	21,5	29,5	23,8	4,6	20,5	26,2
2009	39	24,2	5,0	20,5	27,4	26,3	4,7	21,9	30,1	24,6	4,3	21,7	29,1
science													
2000	34	19,9	5,3	16,0	22,5	22,7	5,0	19,1	25,7	22,4	5,0	19,2	24,7
2003	32	24,8	4,6	21,6	27,9	27,7	4,4	24,2	30,8	26,4	4,8	23,4	29,6
2006	36	24,2	4,7	20,8	27,3	27,7	4,6	24,1	32,0	27,1	4,8	24,5	30,2
2009	39	24,5	5,4	20,7	28,0	26,7	4,8	22,9	30,9	26,1	4,3	23,0	28,8

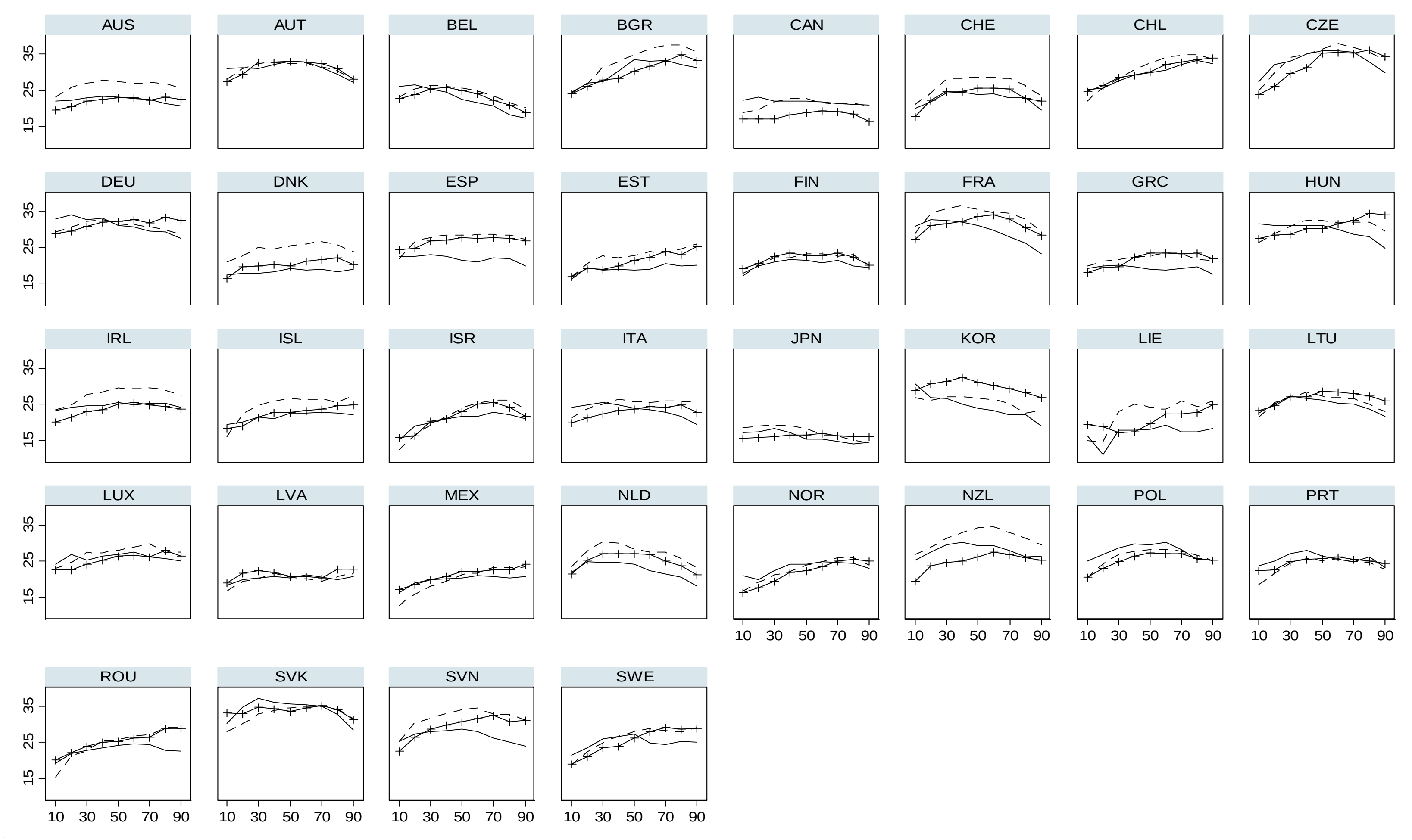


Patterns of the family background effect along the conditional distribution of test scores, 2000
+++: math, –––: reading, - - -: science



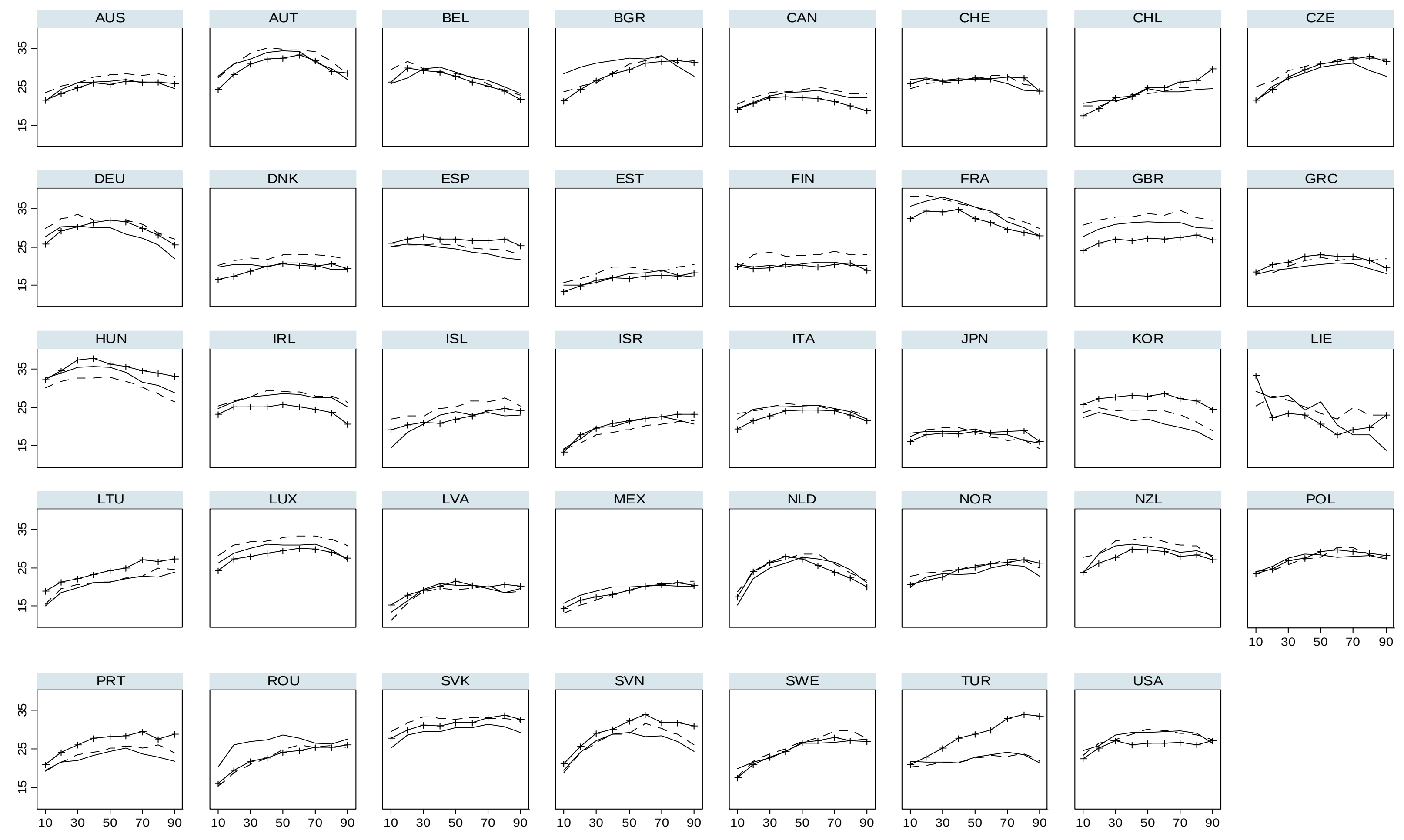
Patterns of the family background effect along the conditional distribution of test scores, 2003
+++: math, –––: reading, - - -: science

Figure A3



Patterns of the family background effect along the conditional distribution of test scores, 2006
+++: math, –––: reading, - - -: science

Figure A4



Patterns of the family background effect along the conditional distribution of test scores, 2009
+++: math, –––: reading, - - -: science

Table A3

Regression estimates of the mean country performance, coefficients of the family background, excluding 5 countries with the lowest level of GDP and average number of books

		Pooled cross-section			Panel (fixed effects)		
		(1)	(2)	(3)	(4)	(5)	(6)
math	fbe_q80	-4.662***	-6.218***	-5.961***	-1.235*	-1.282*	-1.469**
		(1.15)	(1.20)	(1.30)	(0.71)	(0.69)	(0.65)
	fbe_q50	2.239*	3.195**	3.996***	1.226	1.199*	1.563**
		(1.25)	(1.34)	(1.32)	(0.73)	(0.66)	(0.62)
	fbe_q20	1.119	1.694	0.936	-0.842	-0.821	-0.986
		(1.12)	(1.06)	(1.07)	(0.75)	(0.73)	(0.68)
reading	fbe_q80	-3.941***	-4.346***	-4.084***	-1.251	-1.324	-1.468
		(1.26)	(1.36)	(1.48)	(1.03)	(1.04)	(0.96)
	fbe_q50	2.530	2.686	2.585	0.268	0.358	0.734
		(1.82)	(1.78)	(1.84)	(1.43)	(1.40)	(1.34)
	fbe_q20	-0.086	0.192	0.196	-0.063	-0.099	-0.297
		(1.14)	(1.10)	(0.99)	(1.01)	(1.01)	(1.03)
science	fbe_q80	-6.969***	-4.991***	-4.736***	-1.367**	-1.351*	-1.328*
		(1.33)	(1.14)	(1.25)	(0.61)	(0.68)	(0.67)
	fbe_q50	4.020**	3.061**	2.847*	0.825	0.759	0.724
		(1.52)	(1.28)	(1.41)	(0.93)	(1.00)	(1.05)
	fbe_q20	2.701**	1.205	1.225	-0.240	-0.239	-0.240
		(1.14)	(0.94)	(0.92)	(0.63)	(0.67)	(0.67)
	N obs	126	126	126	126	126	126
	N countries	34	34	34	34	34	34

Standard errors clustered at the country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1
The countries excluded: MEX, CHL, TUR, BGR, ROU

Table A4

Regression estimates of the mean country performance, coefficients of the family background, full sample of PISA countries

		Pooled cross-section			Panel (fixed effects)		
		(1)	(2)	(3)	(4)	(5)	(6)
math	fbe_q80	-11.431***	-8.137***	-5.903***	-1.621**	-1.642**	-1.795**
		(1.32)	(1.62)	(1.33)	(0.66)	(0.65)	(0.69)
	fbe_q50	7.134***	4.591**	3.167*	0.636	0.496	0.633
		(2.09)	(1.83)	(1.67)	(1.11)	(1.13)	(1.18)
	fbe_q20	4.801***	2.798***	2.407***	-0.105	-0.002	0.059
		(1.29)	(1.00)	(0.84)	(0.76)	(0.80)	(0.81)
reading	fbe_q80	-10.288***	-6.042***	-3.509**	0.239	0.109	-0.084
		(1.36)	(1.54)	(1.32)	(0.92)	(0.89)	(0.82)
	fbe_q50	5.876**	3.454*	1.677	-2.089	-1.791	-1.328
		(2.23)	(2.00)	(1.90)	(1.37)	(1.32)	(1.27)
	fbe_q20	3.920**	1.652	1.184	1.141	0.969	0.634
		(1.48)	(1.25)	(1.11)	(1.04)	(1.04)	(1.01)
science	fbe_q80	-9.747***	-5.648***	-3.905***	-1.033*	-0.959	-0.959
		(1.33)	(1.28)	(1.06)	(0.58)	(0.62)	(0.60)
	fbe_q50	7.104***	2.903*	2.928**	0.519	0.489	0.489
		(1.77)	(1.71)	(1.38)	(0.80)	(0.83)	(0.83)
	fbe_q20	3.437***	2.601*	1.112	-0.033	-0.053	-0.053
		(1.25)	(1.39)	(1.06)	(0.64)	(0.65)	(0.66)
	N obs	200	200	200	193	193	193
	N countries	66	66	66	59	59	59

Standard errors clustered at the country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A5

Regression estimates of the mean country performance, coefficients of the family background, family background measured with the ESCS index of socio-economic position

		Pooled cross-section			Panel (fixed effects)		
		(1)	(2)	(3)	(4)	(5)	(6)
math	fbe_q80	-3.828***	-2.519***	-2.275***	-0.458	-0.372	-0.467
		(1.22)	(0.90)	(0.83)	(0.60)	(0.56)	(0.51)
	fbe_q50	1.707	0.450	0.883	0.273	0.327	0.502
		(1.36)	(1.08)	(1.01)	(0.75)	(0.70)	(0.64)
	fbe_q20	2.376**	1.508*	0.878	-0.674	-0.623	-0.725*
		(1.00)	(0.75)	(0.75)	(0.47)	(0.40)	(0.40)
reading	fbe_q80	-2.288*	-0.856	-0.839	-0.013	0.127	0.157
		(1.14)	(0.78)	(0.72)	(0.84)	(0.83)	(0.84)
	fbe_q50	0.280	-2.174**	-1.768*	-0.380	-0.372	-0.337
		(1.24)	(1.05)	(0.99)	(0.80)	(0.78)	(0.78)
	fbe_q20	1.653*	2.132**	1.744**	-0.053	-0.032	-0.115
		(0.87)	(0.82)	(0.71)	(0.65)	(0.65)	(0.66)
science	fbe_q80	-2.703***	-1.984***	-1.660*	0.097	0.168	0.169
		(0.95)	(0.73)	(0.86)	(0.69)	(0.76)	(0.74)
	fbe_q50	0.272	-0.540	-0.855	-0.113	-0.104	-0.139
		(0.91)	(0.64)	(0.88)	(0.57)	(0.52)	(0.51)
	fbe_q20	2.857**	2.069***	2.063***	-0.585	-0.491	-0.453
		(1.08)	(0.73)	(0.63)	(0.62)	(0.64)	(0.62)
	N obs	141	141	141	141	141	141
	N countries	39	39	39	39	39	39

Standard errors clustered at the country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A6

Regression estimates of the mean country performance, coefficients of the family background, family background measured with the occupational prestige index (highest of parents)

		Pooled cross-section			Panel (fixed effects)		
		(1)	(2)	(3)	(4)	(5)	(6)
math	fbe_q80	-74.867***	-61.147***	-51.607***	-5.039	-8.167	-10.340
		(16.24)	(13.44)	(12.91)	(7.77)	(8.50)	(8.32)
	fbe_q50	57.967***	21.030*	19.158*	6.427	7.146	10.600
		(20.71)	(10.51)	(10.74)	(8.74)	(8.87)	(8.16)
	fbe_q20	-10.360	12.255	7.784	-8.068	-6.809	-8.539
		(13.57)	(10.49)	(9.79)	(6.60)	(6.80)	(5.78)
reading	fbe_q80	-58.656***	-38.287***	-33.432***	-5.578	-12.445	-11.055
		(19.21)	(14.07)	(11.57)	(10.51)	(10.56)	(10.68)
	fbe_q50	36.057	-11.121	-9.325	-1.035	3.438	2.574
		(23.56)	(17.76)	(16.56)	(11.85)	(12.51)	(12.96)
	fbe_q20	-6.585	25.088**	20.317**	3.891	2.538	1.964
		(12.01)	(10.66)	(9.14)	(8.52)	(8.80)	(8.73)
science	fbe_q80	-64.862***	-47.232***	-44.528***	-9.339	-12.704	-12.219
		(15.97)	(10.14)	(9.64)	(10.75)	(10.76)	(10.85)
	fbe_q50	28.640	1.639	0.364	3.663	3.252	2.697
		(19.64)	(12.24)	(12.59)	(9.60)	(10.56)	(10.46)
	fbe_q20	18.891	27.954**	26.325***	-2.677	-0.150	0.205
		(15.65)	(11.53)	(9.61)	(8.53)	(7.24)	(7.24)
	N obs	141	141	141	141	141	141
	N countries	39	39	39	39	39	39

Standard errors clustered at the country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A7

Regression estimates of the mean country performance, coefficients of the family background, controlling for the correlation between books at the one hand and the ESCS and occupational prestige indices at the other

		Pooled cross-section			Panel (fixed effects)		
		(1)	(2)	(3)	(4)	(5)	(6)
math	fbe_q80	-6.555***	-5.683***	-4.546***	-1.546**	-1.572**	-1.862***
		(1.14)	(1.37)	(1.30)	(0.63)	(0.61)	(0.61)
	fbe_q50	3.629*	2.182	3.117*	1.220	1.069	1.334
		(1.86)	(1.95)	(1.81)	(0.81)	(0.81)	(0.80)
	fbe_q20	3.332**	2.534**	1.153	-0.806	-0.749	-0.737
		(1.30)	(1.00)	(1.02)	(0.81)	(0.86)	(0.87)
reading	fbe_q80	-4.645***	-3.709***	-2.576*	-0.882	-0.999	-1.119
		(1.27)	(1.36)	(1.48)	(0.87)	(0.87)	(0.82)
	fbe_q50	1.299	0.967	0.465	-0.792	-0.558	-0.398
		(1.55)	(1.67)	(1.86)	(1.29)	(1.23)	(1.17)
	fbe_q20	2.632**	1.248	0.983	0.712	0.573	0.474
		(1.28)	(0.96)	(0.84)	(0.88)	(0.85)	(0.87)
science	fbe_q80	-5.942***	-4.821***	-3.773***	-1.394**	-1.177*	-1.150*
		(1.05)	(1.02)	(1.10)	(0.56)	(0.59)	(0.60)
	fbe_q50	4.334***	2.881**	2.094	0.488	0.403	0.375
		(1.08)	(1.09)	(1.37)	(0.85)	(0.89)	(0.94)
	fbe_q20	2.299***	1.718**	1.495**	-0.025	-0.175	-0.179
		(0.65)	(0.73)	(0.62)	(0.54)	(0.54)	(0.54)
	N obs	141	141	141	141	141	141
	N countries	39	39	39	39	39	39

Standard errors clustered at the country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Discussion Papers published in 2011

Mihályi Péter: Utolérési kísérletek Magyarországon, 1870-2030. MT-DP 2011/1

Zsolt Darvas - Jean Pisani-Ferry: The Threat of 'Currency Wars': A European Perspective. MT-DP 2011/2

Zsolt Darvas: Beyond the Crisis: Prospects for Emerging Europe. MT-DP 2011/3

Barnabás M. Garay - András Simonovits - János Tóth: Local Interaction in Tax Evasion.
MT-DP 2011/4

Maria Csanadi: Varieties of System Transformations and Their Structural Background Based on the IPS Model. MT-DP 2011/5

Mária Lackó: The Poor Health Status of the Hungarians; Comparative Macro-Analysis of the Likely Explanatory Factors on Hungarian and Austrian Data, 1960-2004. MT-DP 2011/6

Fazekas Károly: Közgazdasági kutatások szerepe az oktatási rendszerek fejlesztésében. MT-DP 2011/7

Gábor Kézdi - Gergely Csorba: Estimating the Lock-in Effects of Switching Costs from Firm-Level Data. MT-DP 2011/8

Antal-Pomázi Krisztina: A kis- és középvállalkozások növekedését meghatározó tényezők - A különböző finanszírozási formák hatása a vállalati növekedésre. MT-DP 2011/9

Zsolt Darvas - Jean Pisani-Ferry - André Sapir: A Comprehensive Approach to the Euro-Area Debt Crisis. MT-DP 2011/10

András Simonovits: International Economic Crisis and the Hungarian Pension Reform. MT-DP 2011/11

András Simonovits: The Mandatory Private Pension Pillar in Hungary: An Obituary. MT-DP 2011/12

Horn Dániel: Az oktatási elszámoltathatósági rendszerek elmélete. MT-DP 2011/13

Miklós Koren - Márton Csillag: Machines and machinists: Capital-skill complementarity from an international trade perspective. MT-DP 2011/14

Áron Kiss: Divisive Politics and Accountability. MT-DP 2011/15

Áron Kiss: Minimum Taxes and Repeated Tax Competition. MT-DP 2011/16

Péter Csóka - Miklós Pintér: On the Impossibility of Fair Risk Allocation. MT-DP 2011/17

Gergely Csorba - Gábor Koltay - Dávid Farkas: Separating the ex post effects of mergers: an analysis of structural changes on the Hungarian retail gasoline market. MT-DP 2011/18

Helga Habis and P. Jean-Jacques Herings: Core Concepts for Incomplete Market Economies. MT-DP 2011/19

Helga Habis and P. Jean-Jacques Herings: Transferable Utility Games with Uncertainty. MT-DP 2011/20

Valentiny Pál: Árukapcsolás és csomagban történő értékesítés: jogesetek és közgazdasági elmélet. MT-DP 2011/21

Seres Antal – Felföldi János – Kozak Anita – Szabó Márton: Termelői szervezetek zöldség-gyümölcs kisárutermelőket integráló szerepe a nagy kereskedelmi láncoknak történő értékesítésben. MT-DP 2011/22

Tamás Fleiner - Balázs Sziklai: Notes on the Bankruptcy Problem: an Application of Hydraulic Rationing. MT-DP 2011/23