Evaluating the Magnitude and the Stakes of Peer Effects analysing Science and Math Achievement across OECD

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Abstract

What follows is an exercise aimed at estimating peer effects' impact on science and math test scores of secondary school students surveyed in 1995 by the International Education Agency across OECD countries. It is also to discuss their importance for educational policy. particularly regarding the highly sensitive issue of ability-grouping. Using this unique international database. we assess the magnitude of the peer effect relative to more traditional inputs. Referring the education policy stakes, we control for the presence of increasing or decreasing return; We also check for cross effects in order to determine whether peer effects matter more to low or high SES pupils, and whether they final impact on achievement is affected by the underlying level of heterogeneity whithin the group. Using a methodology which a priori accounts for the clustering of the data within countries and schools/classrooms – i.e. fixed/random effect or hierarchichal model -- our analysis indicates that peer effects are strong determinants of both math and science achievement relative to individual SES and other school inputs. The presence of increasing of decreasing returns is not obvious. But we find systematic evidence that low-ability pupils are more sensitive to peer group characteristics. By contrast, we also find that -- for a given level of the peer effect -- higher heterogeneity comes a certain cost. In brief, our results provide no systematic evidence regarding grouping policies.

JEL classification: I28 (Education: Government Policy). H520 (National Government Expenditures and Education). D620 (Externalities).

Key words: educational economics, human capital, resource allocation, school choice, fixed-random effects models, hierarchical models

Introduction

It is clear that human capital accumulation requires a certain number of monetary resources. Yet. people like Hanushek (1986) have highlighted the fact that there is no mechanical relationship between the level of resources and pupils' results. Some incentive and organizational problems need apparently to be solved to ensure that more input results into better outcome. But another promising idea. when it comes to education policy design. is to consider that a child's ability to accumulate human capital is also influenced by the characteristics of his/her peers. Human capital production inevitably takes place in classrooms where pupils are together and interact. In turn. these classrooms are part of a school where pupils tend also to interact, generating what pedagogues call peer effects, sociologists contextual effects and economists social externalities. This idea was initially identified by Coleman et al. (1966) in the educational context, but this phenomenon has been extensively documented in several areas including urban security and crime, drug addiction and teenage pregnancy (Jencks & Meyer. 1987; Corcoran, Gordon, Laren & Solon, 1990).

Several empirical studies have attempted to *measure* the peer effect phenomenon. The issue has been addressed by sociologists (Coleman, 1966, 1988; Jencks & Meyer, 1987; Willms & Echos, 1992), pedagogues (Slavin, 1987 ; Grisay, 1993 ; Gamoran & Nystrand, 1994) and also some economists (Henderson, Mieskowski & Sauvageau, 1978 ; Hanushek, 1986 ; Brueckner & Lee, 1989 ; Bénabou, 1993, 1996 ; Glewwe, 1997).

Most researchers have concluded that peer effects exist for primary and early secondary education: The higher the proportion of high-achieving pupils in the classroom, the higher everybody's achievement. In other words, the higher the average ability of classmates, the higher will be the local social spillover to a pupil's benefit. Willms & Echols (1992) using Scottish data, estimate that peer effects (also called contextual effects) range from 0.15 to 0.35 of a standard deviation. A child whose ability is at the national average (NA) has an expected attainment about one-quarter of a standard deviation higher when moved from a school where the mean ability is one-half of a standard deviation below the NA to a school where it is one-half of a standard deviation above the NA. This is a substantial effect. This result was already present in previous studies: first in Coleman (1966), then Henderson, Mieskowski & Sauvageau (1978). It is also to be found in more recent studies in the United States (Duncan, 1994; Dynarski, Schwab & Zampelli, 1989; Willms & Echols,1992) and France (Leroy-Audouin, 1995 ; Durut-Bellat & Mingat, 1997).

If most observers agree that a pupil's achievement is influenced by the characteristics of his/her classmates, there is still no consensus about their *magnitude* relative to other educational inputs like socioeconomic status (SES) or per pupil expenditure. The other highly discussed issue is the adequate *grouping practices* in the presence of peer effects: should decision-makers, aiming at maximizing average achievement, promote "mixing" or "tracking" in order to fully exploit the benefits of this non-monetary input? This paper attempts to bring some new light to these two important issues.

This paper is organized in three sections. Section 1 briefly exposes our theoretical framework i.e. the human capital production function we attempt to estimate. Section 2 presents the international data set we use while Section 3 contains the results of empirical analysis.

1. Human Capital Production Function with Peer Effects: presentation and generic problems

To examine the peer effect in education we employ a standard education production function model. Following Summers & Wolfe (1977) and Toma & Zimmer (2000), we use test scores as a measure of output. These models estimate academic achievement, at any time period t, as a function of family and school resources, the peers of the student, and individual characteristics of the student, including ability. Conceptually, the model to be estimated at any time period t is:

$$A = f(SES, S, P, I) \qquad (1)$$

Where A = student/pupil's achievement, SES = vector of family/social background; S = vector of school inputs, P = some characterization of the group of peers (e.g. mean SES of the classroom) and I= a set of other individual characteristics. Many problems can occur with these models. We will focus here on those directly related to the peer variable as it is of primary importance in this research.

The recent literature on peer effects (Arnott & Rowse, 1987; Bruckner & Lee, 1989, Durlauf, 1994; Nechyba, 1996; Bénabou, 1993, 1996; Epple & Romano, 1998) highlights *the political stakes* they carry. Indeed, if peer effects matter, distribution of heterogeneous individuals between strictly delimited entities (schools, classrooms) becomes a critical issue as regards equity but also effectiveness. Average education outcomes might be directly affected by the way heterogeneous individuals are distributed. Similarly, the cost of an egalitarian objective aiming at equalizing educational achievement can be influenced by the way peer effects are distributed among schools.

Rising or diminishing returns to average peer quality

Regarding this issue, the first question worth assessing relates to the presence of *rising or diminishing returns* to **the level of** peers seen as a "non-monetary" input. Suppose that we measure the level of that non-monetary input as the average SES of the classroom (MEAN). Knowing that MEAN matter for individual achievement, we might want to know whether redistribution of this particular "input" among schools and classrooms amounts to a zero, negative or positive-sum game. In other words, does a marginal increment of MEAN in school 1 generates and improvement that is equal, inferior or superior to the negative consequences of the symmetric decrease of MEAN in School 2? This first question can be investigated by including a *quadratic* terms in the model:

$$A = f(\mathrm{SES}, S, \mathbf{MEAN(SES)}, \mathbf{MEAN^2(SES)}, I) \quad (2)$$

Individual profile and the level of peer effect: which interaction?

The second question has to do with the *interaction* between <u>the level</u> of peer "input" (i.e. MEAN) prevailing in a classroom or school and the socioeconomic profile of a pupil (SES). Are low SES pupils equally, less or more sensitive to peer effects than their more privileged comrades? Again, this can be easily estimated by the inclusion of interaction terms:

$$A = f(\mathrm{SES}, \mathrm{S}, \mathrm{MEAN}(\mathrm{SES}), \mathrm{MEAN}^2(\mathrm{SES}), \mathbf{SES^{*}\ MEAN(SES)}, \mathrm{I}) \qquad (3)$$

Peer effect level and intra-class heterogeneity

The third question relates to the delicate question of how the <u>level</u> of the peer input (P) is adequately "captured" by the mean of individual characteristics (SES). A certain value of MEAN can be obtained by aggregation of a relatively homogeneous group of pupils. But it can also correspond to relatively heterogeneous individuals. To which extend are these two situations equivalent in the sense that they generate the same level of the implicitly defined peer effect? In other words, for a given level of the MEAN, is achievement affected by the level of heterogeneity of the group of peers? Following Toma & Zimmer (2000), we treat this question by interacting *the average* (MEAN) with the *standard deviation* of the socio-economic profile (STD) of the pupil's classmates[2].

$$A = f(\mathrm{SES}, \mathrm{S}, \mathrm{MEAN}(\mathrm{SES}), \mathrm{MEAN}^2(\mathrm{SES}), \mathrm{SES^{*}\ MEAN(SES)}, \mathbf{STD(SES)^{*}\ MEAN(SES)}, \mathrm{I}) \qquad (3)$$

It is rather intuitive – but can also be shown analytically (Vandenberghe, 1996, 1998; Bénabou, 1996) – that a social planner who wants to maximize average achievement will prefer desegregation (i.e. mixing of abilities, SES profiles…) to segregation when, simultaneously:

- the marginal contribution of the level of the peer input (MEAN) is decreasing;
- low-SES pupils are more sensitive to the level of the input than their comrades;

[2] A positive coefficient for this term would mean that the "production function" of the peer input (by combination of individual SES) is concave. A negative coefficient would point to convexity.

- for a certain level of the peer input, achievement is positively affected by a higher level of heterogeneity within the classroom (STD).

2. Data set and estimation strategy

Data and variable categories

The data we use to assess the impact of peer effects is relatively unique and fairly recent. It comes from the 1995 International Education Agency (IEA) survey (the so-called TIMSS project, Third Math and Science Study). This database contains the test scores of pupils attending grade 7 or 8 across OECD countries. These pupils are nested in (identified) classrooms within schools (2 classrooms were sampled in each school). To carry out our analysis, we pooled the information from 17 countries or regions (Australia, Austria, Flemish-Speaking Community of Belgium, French-Speaking Community of Belgium, Canada, France, Germany, Greece, South Korea, the Netherlands, New-Zealand, Norway, Singapore, Spain, Switzerland, Scotland and the USA). This leads to a total of 141,183 pupils nested in 3,225 classrooms distributed over 17 countries with very different educational arrangements and traditions.

Referring to equation (1) in section 1, we have a set of individual characteristics (I) like grade attended (UPGRADE=1 for grade 2 pupils), gender (GIRL). But we also know the age of students in years (AGE) and the time he or she spends on homework per week (HMW). The last two variables might tell us something about ability. Being older than the average might correspond to grade repetition due to learning difficulties. A similar argument can be put forth for time devoted to homework although this sounds a priori less convincing.

The data set is relatively rich in terms of family and socioeconomic background/statuts (SES) information. We opted for the use of a unique socioeconomic variable by aggregation of information available in TIMSS. This includes education of both parents, immigration status, correspondence between the test language and the language used at home, family structure, and a series of material possessions acting as proxies for disposable income (calculator, computer, study desk, dictionary, number of books). The aggregation procedure we used is fairly typical (Gamoran, 1996). It consists of building dummy variables (e.g.: possession of a computer means the computer dummy=1 and 0 otherwise) and then taking the mean of the non-missing components. This aggregation facilitates the investigation of the interaction between the peer effect and SES (see section 1). It may also be masking some potentially important relationships between background and achievement. Yet, simple correlation analysis shows that almost all components of our SES index affect achievement (be it Math or Science) in the same way.

[insert Table 1 about here]

We also have information about school inputs (S). Class size (PUPIL/TEACH) and teachers' experience (EXPT)[3]) are available. These two variables combined form a good proxy for per-pupil expenditure. School total enrollment (ENROLL) is also available and could also be interpreted as a proxy for per-pupil spending: the higher ENROLL the lower should per-pupil spending as economies of scale generally play a decisive role in secondary education cost functions.

Of central interest of course is the peer effect (P). We define it as *the average* of the pupil's classmates socioeconomic profile (MEAN) assuming that peer effect is better captured by the socioeconomic mix of the peer group. Following the discussion of section 1, in order to address a certain number of education policy stakes (e.g. should the central planner go for tracking or mixing...) we also introduce a quadratic term ($MEAN^2$) and interaction terms (MEAN*SES and MEAN*STD).

[3] Percentage of teachers with more than 5 years of experience in the teaching profession.

Estimation strategy

Our sample of 141,183 pupils is not composed or random units. In fact, these pupils are nested in a sample of 3,225 classrooms/schools[4] distributed over 17 countries. The student population (at its achievement) is likely to reflect teaching practices, institutional arrangements, which are country-specific.... This undermined the Ordinary Least Square (OLS) assumption that each of individual units is random. Similarly, each school/classroom will also have an effect on its pupils that also undermine the assumption that individuals are drawn randomly.

The most efficient method for estimation in such a case is to use a methodology which a priori accounts for the clustering of the data within countries and schools/classrooms. In the economics literature, these models are called fixed/random effects models[5]. In the education literature they are multilevel/hierarchical models (Bryk & Rodenbush, 1992). Following the economics terminology, we opted for a country fixed-effect & classroom random-effect model that we estimated with the SAS MIXED proceedure (Littell, Milliken, Stroup, Wolfinger, 2000):

$$A= \alpha_i + \beta X + \mu_{ij} + \varepsilon_{ijk} \qquad (4)$$

- where X is our vector of explanatory variables (i.e. SES, S, MEAN(SES), $MEAN^2$(SES), SES* MEAN(SES), STD(SES)* MEAN(SES), I) from equation 3;
- ε_{ijk} is the usual disturbance (random) term characterising pupil k in classroom j, country i;
- α_i represents the country *fixed* effect. i=1 to 17;
- μ_{ij} represents the classroom *random* effect. j=1 to N_i; N_i being the number of school/classrooms sampled in country i.

The country-specific term α_i is called *fixed* as it captures some country specific *constant* potentially affecting all pupils sampled in country i. The classroom term μ_{ij} applies to all pupils of a particular

[4] School and classroom levels tend to confound here as only 2 classrooms (one per grade) were selected in each school.
[5] "Mixed models" in the SAS world (Little, Milliken, Stroup, Wolfinger, 2000).

classroom. Contrary to the country effect, we find more appropriate to treat it as a disturbance term as the N_i classrooms we have for country i were sampled from a large population of classrooms.

Table 2 reports the full list of variables we used, their definition, mean and standard deviation. Note that both math and science have a cross-country mean of 500 and a standard deviation of 100. We also standardized the SES variable and all variables describing the peer effect in order to facilitate the interpretation of estimated coefficients (mean=100, standard deviation = 10). Note that all non-dummy variables, including peer variables, were centered on the cross-country mean before estimation.

[Insert Table 2 about here]

3. Results and analysis

Tables 3 and 4 report estimated coefficients for the fixed-random effects model described by equation 4.

About peer effects

Of great interest for our purpose are the coefficients of the peer effect proxies. Let us begin with the the level of peer group of classmates characterized by the MEAN of individual SES across the classroom. A very robust result that appears in all cases envisaged here is that the higher the mean SES of the classmates, *ceteris paribus*, the higher the achievement level of the student, be it science or math. This supports the findings of previous research (Henderson, Mieskowski & Sauvageau, 1978; Toma & Zimmer, 2000). On average across countries and school types, increasing the class mean SES by 10 points (i.e. a standard-deviation increment) generates an improvement of science achievement of about 18.5 points. The effect on math achievement of a similar shift is slightly higher (21.4 points). Given that the average achievement is 500 (standard deviation=100), these gains are economically significant[6]. The average socioeconomic profile of classmates appears to play an important role in the production of learning.

It is also interesting to look at the marginal effect of the MEAN variable. Remember that when peer effects matter, it is particularly important from a social point of view to know whether redistribution of this particular "input" among schools and classrooms amounts to a zero, negative or positive-sum game. Part of the answer to this can be found by looking at the coefficient of the squared variable (MEAN*MEAN). A negative coefficient would imply that the effect of increasing the mean SES of classmates improves achievement at a decreasing rate, and this would plead in favor of 'mixing'. The results show the opposite for math achievement. The positive coefficient we observe points to increasing returns supporting the 'tracking' option. In the case of science achievement the coefficient appears not significantly different that zero.

Of equal interest, given education policy stakes, is the coefficient of the variable MEAN*SES interacting the peer effect and individual socioeconomic profile. A negative coefficient would indicate that low-SES pupils are *equally, less or more sensitive* to peer effects than their more privileged comrades and such a result would support the case for desegregation policies. Tables 3 & 4 bring some evidence here. Depending on the proxy we use to capture the peer effect, the sign of the coefficient varies. It is negative in all cases suggesting that pupils who enjoy a higher SES are less sensitive to the level of their group of peers. This results peads in favour of "mixing" along the SES line.

Yet, a third set of results regarding peer effects goes into the opposite direction, leading to the general conclusion that nothing very conclusive can be said regarding the 'mixing' vs. 'tracking' option. The results on STD*MEAN in Tables 3 & 4 suggest that – for a given level of the average SES in the classroom -- a student's achievement level in both Math and Science is *lower, ceteris paribus*, the greater the underlying heterogeneity.

[6] Willms & Echols (1992) estimated peer effects in Scotland to represent 0.15 to 0.35 of a standard deviation, which is about the figure that we get here.

[Insert Table 3 about here]

[Insert Table 4 about here]

Other results

It should be noted that other important patterns appear in the results from the whole production function estimation. First, the variable representing family or socioeconomic input (SES) is systematically significant and somehow confirms the well established results that a pupil's background is a good predictor of his/her academic success. Relatively speaking however, *the magnitude* of the SES coefficient is not so important here. In all cases it seems to have a *lower* impact on achievement than the group of peers. A 10 points increment (equivalent to a standard deviation shift) of the SES variable generates a less than 10 point improvement on the achievement scale. The impact of the peer effect variable is about twice as large. Part of the explanation could be that, somehow, our model controls relatively well for innate ability throug the AGE variable. It displays a large negative coefficients. Any additional year of age reduces science achievement by about 10 points and math achievement by almost 14 points. Finally, it is worth noting that there continues to be a gender gap, especially in science where the cross-country gap is of about 15 points.

Second, the peer effect seems to be particularly more important that the level of traditional school (monetary) inputs. Both pupils to teacher ratio (PUPIL/TEACH) and percentage of experienced teachers in the school (EXPT) show positive but non-significant coefficients. There is also no evidence that smaller schools – often synonymous with higher per-pupil costs – generate better academic achievement. Estimated coefficients even support the opposite, althougth their magnitude is very small (adding 100 pupils to a school raises achievement by 9 to 18 points).

Third, country of residence (the fixed-effect in equation 4) is extremely important for both subjects. Using for example Canada as a reference, we see that average math achievement, *ceteris paribus*, is about 88 points higher in Singapore (SGP), 59 points higher in Austria (AUT), 41 points higher in the

Flemish-Speaking Community of Belgium (BFL). At the other extreme, the average math achievement of pupils in the French-Speaking Community of Belgium (BFR) is about 31 points below that of Canadian pupils. A similar inter-country ranking emerges for math achievement, although there is no perfect correspondence. Compared to Canada, the performance of Singapore looks astonishingly better (+ 135 points). Then come South Korea (KOR), the Flemish-Speaking Community of Belgium (BFL), Switzerland(CHE). The worst performers are Greece (GRC) and Scotland (SCO).

Conclusion

Our analysis confirms the importance of non-monetary inputs like peer effects in learning. This idea was initially highlighted by Coleman et al. (1966) and regularly confirmed since (Henderson, Mieskowski & Sauvageau, 1978 ; Robertson & Symons, 1996 ; Toma & Zimmer, 2000). Our own confirmation is derived from the econometric examination of the determinants of achievement of the largest, most diverse student study to date. Students aged 13 to 14 years from 17 OCDE countries or regions are in the sample. These entities differ radically in many respects ranging from financing policies, importance of school choice, share of private schools, wage and recruitment policies. Despite these differences, we can say that peer effects systematically affect math and science achievement, even when allowing for clustering (i.e. fixed/random) effects. In other words, the higher the average ability of classmates, the higher will be the local social spillover to a pupil’s benefit.

Compared to similar studies, our research also shows that peer effects might matter *more* than some of the other inputs traditionally analyzed in the 'production function' literature (Hanushek, 1986). Our results suggest that the impact of the peer group could be more important that that of the socioeconomic and family background. The same is true when we compare the impact of peer group inputs to that of traditional monetary inputs like pupils/teachers ratio, teachers' experience or school size. In this study, the latter have no significant impact on academic achievement.

The importance of peer effects might explain why teachers and schools pay so much attention to grouping decisions. Similarly, the role played by the group of classmates could possibly help us understand why expansion of free school choice generally leads to more inter-schools ability segregation (Willms & Echos, 1992; Vandenberghe, 1998). From a social point of view now, because peer effects matter, allocation of heterogeneous individuals between strictly delimited entities becomes a critical issue as regards equity but also efficiency. An objective consisting of maximizing the *average* level of human capital can be compromised if individuals are inappropriately allocated among schools and classrooms. Desegregation will be preferable to segregation when i) the presence of an additional high-ability pupil in classroom 1 generates peer-effect (teaching climate) improvement that does not offset the negative consequences of the presence of an additional low-ability pupil in classroom 2, when ii) low-ability pupils are more sensitive to peer-effects than their more able comrades, and when iii) for a certain level of the peer input, achievement is positively affected by a higher level of heterogeneity within the classroom

These three conditions are systematically verified here. Contrary to Henderson, Mieskowski & Sauvageau (1978) or Toma & Zimmer (2000) we do not find strong evidence of decreasing return to peer effect increments. We even detect slightly increasing return to scale for Math achievement favourable to the "tracking" option. By contrast, like Leroy-Audouin (1995) and Toma & Zimmer (2000) we find systematic evidence that low-ability pupils are more sensitive to peer group characteristics and this is pro "mixing". But like Toma & Zimmer (2000), we also find that -- for a given average SES -- increasing heterogeneity comes a certain cost. In brief, our results provide no systematic evidence regarding grouping policies. If the aim of education policy is to maximise average achievment, the choice between tracking or mixing is still unclear.

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Table 1 – SES aggregate index. SES components and achievement. Pearson correlation

	Math	Science
SES index	**0.12**	**0.15**
Education father	0.17	0.18
Education mother	0.13	0.15
Speak language of test at home	-0.02	0.07
Pupil lives with mother and father	0.11	0.07
Mother born in country	0.04	0.07
Father born in county	0.04	0.07
Home possesses a calculator	0.11	0.11
Home possesses a computer	0.12	0.14
Home possesses a study desk	0.11	0.10
Home possesses a dictionary	0.09	0.08
25 books or more in student's home	0.17	0.20

All correlation coefficients are significantly different from 0 at .05 level

Table 2 – Descriptive Statements

Variable	Description	Mean	Std Dev.
Achievement			
MATHSCR	Math achievement	500.00	100.00
SCISCR	Science achievement	500.00	100.00
Individual/background characteristiscs			
SES*	Socioeconomic index	3.69	1.06
AGE	Age of pupils in years	13.76	0.81
UPGRADE	Binary variable=1 if upper grade attended (grade 8)	0.55	0.50
GIRL	Binary variable=1 if pupil=girl	0.49	0.50
HWKm	Binary var.=1 if pupil reports at least 1 h/w homework in math	0.33	0.47
HWKs	Binary var.=1 if pupil reports at least 1 h/w homework in science	0.25	0.43
Peer group characteristics			
MEANses*	means SES of the classroom	3.69	0.45
STDses*	standard deviation of SES in classroom	0.94	0.28
School characteristics			
PUPIL/TEACH	Pupils to full-time equivalent teachers ratio	12.90	3.25
ENROLL	Total enrollment = school size	653.30	428.19
EXPT	Percentage of teachers with more that 5 years exp.	62.93	25.15
Countries			
AUS	Binary variable=1 if school is located in Australia	0.09	0.29
AUT	Binary variable=1 if school is located in Austria	0.04	0.20
BFL	Binary variable=1 if school is located in Flemish-speaking Belgium	0.04	0.20
CFR	Binary variable=1 if school is located in French-speaking Belgium	0.03	0.18
CAN	Binary variable=1 if school is located in Canada	0.12	0.32
CHE	Binary variable=1 if school is located in Switzerland	0.08	0.28
DEU	Binary variable=1 if school is located in Germany	0.04	0.20
ESP	Binary variable=1 if school is located in Spain	0.05	0.23
FRA	Binary variable=1 if school is located in France	0.04	0.20
GRC	Binary variable=1 if school is located in Greece	0.06	0.23
KOR	Binary variable=1 if school is located in South Korea	0.04	0.20
NLD	Binary variable=1 if school is located in the Netherlands	0.03	0.17
NOR	Binary variable=1 if school is located in Norway	0.04	0.20
NZL	Binary variable=1 if school is located in New-Zealand	0.05	0.22
SCO	Binary variable=1 if school is located in Scotland	0.04	0.20
SGP	Binary variable=1 if school is located in Singapore	0.06	0.24
SWE	Binary variable=1 if school is located in Sweden	0.06	0.24
USA	Binary variable=1 if school is located in the USA	0.08	0.27

* variables that were standardized (mean=100. std=10) before regression analysis.

Table 3 – Determinants of MATH achievement. Country fixed-effect. classroom-random effect model.

Effect	Estimate	StdErr	tValue	Probt
AUS	467.63	3.108	150.46	<.0001
AUT	505.79	3.7608	134.49	<.0001
BFL	519.28	3.487	148.92	<.0001
BFR	488.41	3.9715	122.98	<.0001
CAN	453.45	2.1854	207.49	<.0001
CHE	515.58	2.3105	223.15	<.0001
DEU	470.06	3.9675	118.48	<.0001
ESP	440.57	3.1428	140.18	<.0001
FRA	514.84	3.9137	131.55	<.0001
GRC	417.71	3.1676	131.87	<.0001
KOR	538.53	3.7358	144.15	<.0001
NLD	480.77	4.3658	110.12	<.0001
NOR	429.27	3.0906	138.9	<.0001
NZL	445.03	2.5172	176.79	<.0001
SCO	430.17	3.647	117.95	<.0001
SGP	588.76	3.7239	158.11	<.0001
SWE	466.78	2.6106	178.81	<.0001
USA	425.19	3.054	139.22	<.0001
UPGRADE	51.5344	0.6638	77.64	<.0001
FILLE	-7.3792	0.4763	-15.49	<.0001
AGEY	-13.9536	0.4286	-32.56	<.0001
SES	0.8109	0.02524	32.13	<.0001
MEAN	**2.137**	0.08171	26.15	<.0001
MEAN*MEAN	0.01707	0.005494	3.11	0.0019
MEAN*SES	-0.01256	0.002305	-5.45	<.0001
MEAN*STD	-0.06625	0.006906	-9.59	<.0001
ELCL	0.1734	0.292	0.59	0.5527
ENROL	0.01788	0.002104	8.5	<.0001
EXPT	0.0176	0.03104	0.57	0.5706

Table 4 – Determinants of SCIENCE achievement. Country fixed-effect. classroom-random effect model.

Effect	**Estimate**	**StdErr**	**tValue**	**Probt**
AUS	489.6	2.9343	166.86	<.0001
AUT	520.73	3.564	146.11	<.0001
BFL	502.6	3.315	151.61	<.0001
BFR	431.1	3.7726	114.27	<.0001
CAN	461.66	2.0846	221.46	<.0001
CHE	490.91	2.2098	222.15	<.0001
DEU	490.17	3.7672	130.11	<.0001
ESP	473.49	2.9818	158.79	<.0001
FRA	478.73	3.7129	128.94	<.0001
GRC	434.22	3.0073	144.39	<.0001
KOR	507.35	3.5538	142.76	<.0001
NLD	499.81	4.1407	120.71	<.0001
NOR	458.69	2.9708	154.4	<.0001
NZL	465.63	2.4281	191.77	<.0001
SCO	451.84	3.4627	130.49	<.0001
SGP	549.64	3.524	155.97	<.0001
SWE	485.73	2.5023	194.11	<.0001
USA	467.77	2.8894	161.89	<.0001
UPGRADE	51.6342	0.7159	72.12	<.0001
FILLE	-16.1615	0.5141	-31.44	<.0001
AGEY	-10.2321	0.4626	-22.12	<.0001
SES	0.9371	0.02732	34.31	<.0001
MEAN	**1.8489**	0.07782	23.76	<.0001
MEAN*MEAN	0.005703	0.005238	1.09	0.2763
MEAN*SES	-0.01868	0.002494	-7.49	<.0001
MEAN*STD	-0.06072	0.00657	-9.24	<.0001
ELCL	0.2571	0.2777	0.93	0.3546
ENROL	0.008917	0.001997	4.46	<.0001
EXPT	0.007695	0.02949	0.26	0.7942