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ARE STRATIFICATION POLICIES RELATED TO THE IMMIGRANT EDUCATION GAP IN EUROPE? A COMPARATIVE ANALYSIS BASED ON PISA 2018 RESULTS

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ARE STRATIFICATION POLICIES RELATED TO THE IMMIGRANT EDUCATION GAP IN EUROPE? A COMPARATIVE ANALYSIS BASED ON PISA 2018 RESULTS

Abstract:

The aim of this paper is to analyse the role of stratification policies in the educational gap between immigrant and native students. This paper proposes a comparative study of the five most populated EU Member States based on the analysis of the PISA 2018 mathematics results. The empirical work studies the influence of three basic stratification policies (tracking, within-school ability grouping and grade repetition) on the immigrant education gap, together with the effect of school segregation. Among other results, it has been found that tracking explains a significant part of the effect associated with school segregation in Germany, France and Italy. In Spain, grade repetition particularly impacts immigrant students and explains a substantial part of the educational gap. On the other hand, once the study programme fixed effects are considered, the segregation of advantaged and disadvantaged students at school shows statistically significant effects that suggest the existence of peer effects.

Key words: Immigrant education gap; Stratification policies; Tracking; Grade repetition; Ability grouping; School segregation.

¿ESTÁN RELACIONADAS LAS POLÍTICAS DE ESTRATIFICACIÓN CON LA BRECHA EDUCATIVA DE LOS ESTUDIANTES INMIGRANTES EN EUROPA? UN ANÁLISIS COMPARATIVO BASADO EN PISA 2018

Resumen:

El objetivo de este trabajo es analizar el papel de las políticas de estratificación en la determinación del gap educativo de la población inmigrante. Se propone un análisis comparado a partir de la explotación de los datos de PISA 2018 en matemáticas. En el trabajo empírico se estudian tres políticas básicas de estratificación (tracking, agrupación por capacidad y repetición de curso) junto con el efecto de la segregación escolar. Entre otros resultados se ha encontrado que el tracking explica una parte importante del efecto de la segregación escolar en Alemania, Francia e Italia. Con relación a España, la repetición de curso afecta especialmente a los estudiantes inmigrantes y explica una parte sustancial de su brecha educativa. Además, una vez introducidos los efectos fijos de los programas de estudio, la segregación escolar de estudiantes aventajados y desaventajados muestra efectos estadísticamente significativos que sugieren la existencia de peer effects.

Palabras clave: Brecha educativa de los inmigrantes; Políticas de estratificación; *Tracking;* Repetición de curso; Agrupación por capacidad; Segregación escolar.

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1 INTRODUCTION

The objective of this work is to study the role that stratification policies play in the educational gap of students with an immigrant background. Stratification policies are understood as a broad set of practices aimed at sorting students by ability level, mainly into different classes, study programmes or schools. Some works have found that stratification tends to benefit higher-ability students and harm those with lower ability levels. To the extent that students with an immigrant background enter the educational system in an unfavourable position due to worse language skills, limitations in their previous training or because they belong to lower socioeconomic status families, stratification policies can negatively affect them.

The aging process in Europe will encourage a significant growth in immigration in the future, which is why problems regarding the integration of the immigrant population into the educational system must be addressed as soon as possible (Zinovyeva et al., 2014). In addition, the study of the school integration of students from an immigrant background is of particular interest in southern European countries, which in recent decades have become new destination regions for migration and where research on the subject is relatively scarce.

In the European context, different school models coexist when it comes to sorting students by ability level. Comprehensive or non-selective systems offer a common educational programme to all students. They do not stratify students by ability level and tend to apply automatic course promotion. Other models diverge from this one only in relation to grade repetition, which can be frequent among low-ability students. In other countries, there is a tendency to stratify students by ability, by sorting them into schools with different study programmes, or by creating, within the same school, groups of students who follow the same curriculum although with different pedagogical approaches or at different paces (Betts, 2011). This paper undertakes a comparative analysis of the five most populated European Union countries in 2018 (including the United Kingdom, which formally ceased to belong to the EU in January 2020) and which apply different stratification policies.

The database used for the empirical analysis is that of the 2018 PISA results, as compiled by the OECD. PISA is a test that measures the knowledge and skills of 15-year-old students in the fields of reading, mathematics and science. It provides a wealth of information about students and schools which is comparable by country. In this work, we are going to focus on analysing the results of the mathematics test, since, in principle, this subject should be less impacted by immigrant students' lower language skills.

Regarding the contribution of this work, first of all, there is an interest in carrying out a comparative analysis of the educational gap of the immigrant population in five EU countries. These countries apply different models with the aim of addressing skill heterogeneity, and they also have diverse migration histories. As for the methodological approach, the enormous difficulty of estimating peer effects from observational data should be noted. This paper aims to control for the selection bias affecting the estimation of educational production functions from the perspective of the omission of relevant variables. To do this, a broad set of variables related to students and schools is included in the models, together with study programme fixed effects, which are associated with the school selection process. Finally, this work bridges a gap in the literature, as the analysis of stratification policies' influence on the educational gap affecting students with an immigrant background has been scarcely researched.

The work is structured as follows: the following chapter (chapter 2) presents the literature review. Chapter 3 describes the PISA database and lists the variables used. In chapter 4, the methodology is shown. In chapter 5, the results of the empirical work are presented and, finally, in chapter 6, the main conclusions are collected.

2 LITERATURE REVIEW

The objective of this paper is to analyse the links between stratification policies and the educational gap affecting students with an immigrant background. Tracking or stratification policies are understood as the tendency, which is observed in many educational systems, to sort students by ability within the same class, or into different classes or schools (Betts, 2011). In contrast, comprehensive systems are those where a common educational programme is applied to students with diverse abilities and skills within the same class. In practice, tracking, stratification or streaming comprise a broad set of practices aimed at addressing skill heterogeneity. Following the terminology adopted by the OECD (2016a), we can classify them as follows:

- **Horizontal stratification: within-school ability grouping**. Students are sorted into classes, or into groups within the same class, based on their ability level. Students are classified based on academic results with the aim of creating a more homogeneous learning environment in each group by organizing classes by level of difficulty.

- **Horizontal stratification: tracking by educational programme**, which may have an academic or vocational orientation. Student selection can be carried out based on the results of an exam (Pischke and Manning, 2006) or on teacher recommendations derived from the student's academic performance during the previous educational stage (Jürges and Schneider, 2011).

- **Vertical stratification: grade repetition**. Grade retention policy is aimed at providing students who are lagging behind in the learning process with more time to master the curriculum (OECD, 2016a). However, in practice, it can end up leading to student segregation into academic or vocational programmes, or by grade levels.

The main motivation of stratification policies is efficiency. It is argued that, by reducing the heterogeneity of students' ability levels in the classroom, learning can be designed more in line with the needs of the group, which makes it easier to obtain better academic results (Hanushek and Wößmann, 2006; Rangvid-Schindler, 2007). For example, Duflo, Dupas and Kremer (2011) provide experimental evidence regarding the use of tracking in 121 primary schools in Kenya. The authors find that tracking leads to efficiency gains among both high- and low-performing students, by making it easier for learning to be adapted to each group's level. However, the authors caution that the context in which the experiment was conducted may have limited applicability in developed countries. For example, Vandenberge (2006) finds that tracking does not have a significant impact on educational performance in the OECD.

Betts (2011) points out that the most conservative societies can use tracking to favour the children of the wealthiest families. In other cases, tracking may be designed to segregate students with different family, racial, religious or immigrant backgrounds. The author suggests that native parents may react to an increase in immigration by demanding earlier tracking or a reinforcement of ability grouping.

Opponents of tracking argue that stratification policies are unfair, as they sort the most disadvantaged students into less demanding vocational programmes or learning environments

(OECD, 2016a). In addition, disadvantaged students do not benefit from the presence in the classroom of high-ability students who could stimulate their learning process. In this sense, Entorf and Lauk (2007) find that early tracking in the educational systems of Austria and Germany reinforces the negative effects of migrant student segregation by separating them from high-ability natives. The authors point out that stratification generates adverse peer effects that accentuate the differences between children from disadvantaged migrant families and those from more privileged native families. Along the same lines, Hanushek and Wößmann (2006) find that countries that apply tracking before the age of 15 show greater inequality in the 2003 PISA secondary education tests, once previously existing differences in inequality in primary education have been controlled for. Brunello and Checchi (2007) state that early tracking reinforces the effects of family background on years of schooling, and on the probability of dropping out of school and of studying at university. Lastly, Duflo, Dupas and Kremer (2011) warn that an indirect effect of tracking may be incentivising the best teachers to choose programmes or schools with higher-ability students, which harms lower-ability students.

In the literature, when evaluating the impact of tracking on equal opportunity, two dimensions are emphasised: the age at which sorting first occurs and the number of programmes offered. Migrant families may have more difficulty understanding the complexity of, and opportunities offered by, each educational path, or may simply have lower language skills, which hampers their negotiation with the school principal on behalf of their children. In addition, immigrant students may be harmed by early tracking if they have only been living in the destination country for a short time. The age of arrival of children of immigrant background is related to the educational gap due to, among other reasons, its impact on language skills (Basu, 2018). However, other authors find that language skills only play a minor role in explaining the educational gap of immigrant students (Schnepf, 2007). Along the same lines, Cebolla-Boado and Fernández-Reino (2021) find that the concentration of migrant students with poor language skills is negatively associated with the students' performance, although the effect is small.

Betts (2011) points out that tracking increases inequality, to the extent that it improves the academic results of medium- and high-ability students, and lowers those of students in low-ability tracks. On the other hand, Pischke and Manning (2006) reach a similar conclusion in a paper in which they analyse the educational reform that took place in England in the 1960s and 1970s, which meant a switch from an early tracking system to a model in which comprehensive schools predominate. The authors find that comprehensive schools benefit lower-ability students, while selective schools benefit higher-ability students. However, they are cautious about the obtained results due to the difficulty of controlling for selection bias with the instrumental variable strategy used.

Students from disadvantaged socioeconomic backgrounds or with an immigrant background benefit from greater diversity at school due to interaction with high-ability peers (Entorf and Lauk, 2007; Krüger, 2020). Peer effects are positive externalities resulting from the coexistence of students with different ability levels. This is based on the assumption that students learn not only from their teachers, but also from their schoolmates (Schneeweiss and Winter-Ebmer, 2007). Hoxby (2000) finds evidence in favour of the existence of peer effects in US schools: a 1-point increase in peer reading grades increases a student's grade by between 0.15 and 0.40 points, depending on the specification used. Sacerdote (2011) conducts a review of the literature and points out that linear models tend to find that peer effects are statistically significant, although small in size. When nonlinear models are used, high-ability students are observed to benefit the most from the presence of other high-ability students in the classroom.

Finally, Diemer (2022) finds significant and heterogeneous peer effects in Swedish schools: higher-ability native students do not receive any spillovers from their peers, unlike higher-ability immigrant students, who are negatively impacted by interacting with other migrant students.

School segregation accentuates the inequality in educational achievement to the extent that the interaction of vulnerable students with others who come from favoured socioeconomic backgrounds is limited. For this reason, Agasisti et al. (2021) recommend the desegregation of schools in order to promote the resilience of students from disadvantaged families. School segregation is determined by a complex set of factors, including the configuration of the educational system, the school admission policies and the families' own decisions about where they establish their residence and which school they want their children to attend (OECD, 2016). Besides, although the degree of school segregation varies geographically (Brunello and De Paola, 2017; Murillo, Martínez-Garrido and Belavi, 2017), in some European countries, such as Spain, the observed trend is towards an increase in the size of the problem, as the proportion of native students in public schools decreases and the proportion of immigrants increases (Choi and Calero, 2012; Salinas and Santín, 2012; Murillo and Martínez-Garrido, 2018). A similar trend is observed in metropolitan areas in the US, where a higher proportion of migrants within the student population is associated with a higher enrolment of native students in private schools (Betts, 2011).

3. DESCRIPTION OF THE DATA

PISA is the OECD Program for International Student Assessment. It has been carried out every three years since the year 2000. In the 2018 edition, around 600,000 students from 79 countries (including 37 OECD members) participated. PISA measures how 15-year-olds use their knowledge and skills to function in real life, by testing their skills in reading, mathematics and science. In this work, we focus on the mathematics test, aimed at assessing how students formulate, apply and interpret mathematics in different contexts (INEE, 2020). The five most-populated countries in the European Union have been selected for analysis: Germany, Italy, France, the United Kingdom and Spain.

The survey provides information on cognitive tests, as well as a whole set of variables on the personal characteristics of the students and their families (socioeconomic and cultural status, attitudes towards learning, perceptions of teachers, among others) and on their schools (material and human resources, teaching practices, academic policies) (OECD, 2020). The data are representative of the school population aged 15-16 in each country, with a sample size of 5,000 to 10,000 students. However, in some countries, such as Spain, the sample has been extended in order to obtain internationally-comparable regional results, which is why the final sample is of around 35,000 students. Regarding the sampling method, it is a two-stage sampling design, first, of schools, and second, of students.

The results of the cognitive tests are scaled to achieve a normal distribution, with a mean of 500 points and a standard deviation of 100 points. In practice, PISA provides test data using ten plausible values obtained from Item Response Theory models. Plausible values are obtained through multiple imputations based on students' responses to the randomly assigned subset of test questions. On the other hand, given the complex sample design of PISA, standard error estimates provided by the usual statistical packages may be biased. For this reason, sample variance estimation is based on Bootstrap replication methods with the Fay modification, which requires 80 weights (OECD, 2009). The OECD developed the "repest" package to analyse PISA data with STATA using replicate weights and multiple imputation variables (plausible values).

The package calculates the average estimator of the plausible values and provides the imputation error of the variance estimator.

The variables used in the analysis are described below and grouped into three blocks: variables regarding the students and their family background; school-related variables; and variables representative of the stratification policies applied in each country or school.

A) STUDENT-RELATED VARIABLES

- Immigrant students are those whose father and mother were born in a country other than the one where the test was taken (OECD, 2016b). Second-generation immigrant students (mig. 2nd gener.) are those who were born in the country where the test was sat but whose parents were born abroad, while, first-generation migrants are those who were born abroad, like their parents. In the empirical analysis, a difference has been made between first-generation students who arrived in the destination country between the ages of 0 and 6 (mig 1st age arr.(0-6)) from those who arrived between the ages of 7 and 16 (mig 1st age arr.(7-16)). The three variables characterizing the student's immigrant profile are dichotomous variables that take the value 1 if the student belongs to the defined category and 0 if they do not.

- The student's gender (female) is measured with a dummy variable that takes the value 1 if the student is female and 0 if they are male.

- Socioeconomic and cultural status (ESCS) is an index with a mean of 0 for the OECD average and a standard deviation of 1. It is comprised of the parents' occupational category and educational level and the resources available at home (number of books and digital devices, among others). Based on the information from this index, PISA classifies students below the first quartile of ESCS in their country as socioeconomically disadvantaged and students above the third quartile of ESCS in their country as socioeconomically advantaged. For more details about the construction of the indices in PISA, see OECD (2019a).

- To estimate immigrant students' proficiency in the language of the destination country, the question "Which language do you usually speak with: My best friend?" has been used, from which a dummy variable (other language) has been constructed. This dummy variable takes a value of 1 when the student states that "most of the time I speak in my heritage language", and of 0 when they state that "most of the time I speak in the language in which I answer the test", "I speak in my heritage language or the language of the test with the same frequency" or when their answer is "not applicable", a category that includes, among other situations, the heritage language matching the test language. This question was chosen instead of the alternative "What language do you speak at home most of the time?", also used in the literature, because the choice of the language used at home may be conditioned by the limited language skills of the parents, and not those of the children, who, depending on how long they have been living in the destination country, may speak the local language fluently (Schnepf, 2007).

- From the question about the student's birth month, two dummy variables were created for the first (January-March) and last (October-December) quarters of the year.

- To assess school absenteeism, PISA 2018 constructs a dichotomous variable (student truancy) from two questions, which reports on whether the student has missed classes or full days in the two weeks prior to the test. The variable takes the value 1 if the student has missed at least one class or full day in the previous two weeks and 0 if the student has not missed any class or full day in the same reference period.

- In order to control for emotional support from parents, we worked with the variable "My parents support my educational efforts and achievements" relating to the academic year in which the student took the PISA test. Based on this question, a dichotomous variable (parents support) was constructed. It takes the value 1 when the student answers that they totally agree and 0 if they answer that they strongly disagree, disagree or agree.

- PISA 2018 asks parents about the most important criteria when choosing a school for their children. One of the criteria studied is "The school has a good reputation". Based on this question, a dummy variable (good reputation school) was constructed, which takes the value 1 when parents answer that said criterion is “important” or “very important” for their choice and 0 if they answer that the criterion is “not important” or “somewhat important”. The inclusion of this question in the models is highly relevant insofar as it makes it possible to reduce the sorting bias (Entorf and Lauk, 2007). The main limitation is that this information is only available for two of the five countries analyzed: Germany and Italy.

- PISA 2018 asks students several questions about their assessment of education: “Doing my best in school will help me get a good job”; “Trying hard in school will help me get into a good university”; and “It is important to try hard in school”. From these, the "index of the value of school" (trying hard) is constructed, where positive values indicate that the student values education more than the OECD average.

- Finally, PISA 2018 builds a teacher enthusiasm index by asking students various questions about their last two language classes prior to taking the test: "It was clear to me that the teacher enjoyed teaching us"; "I was inspired by the teacher's enthusiasm"; “It was clear that the teacher liked the topic of the lesson”; and "The teacher showed enjoyment in teaching". Positive values of the variable indicate that language teachers are more enthusiastic than the OECD average.

B) SCHOOL-RELATED VARIABLES

- In order to assess the eventual existence of peer effects, three variables have been constructed to measure the peer characteristics of the school by combining information on socioeconomic status and immigrant background. Empirical evidence shows that it is the concentration of disadvantaged immigrants, and not the concentration of immigrants per se, that has a negative impact on learning (OECD, 2016b). For this reason, two dummy variables are defined to measure the concentration of disadvantaged migrants at the school (mig. disadv. (> 20%)) and disadvantaged natives (nat. disadv. (> 30%)), that is, those who are located in the first quartile of the socioeconomic and cultural status index. To compare the peer effects of attending schools with high proportions of students from the fourth quartile of the ESCS index, a dichotomous variable was constructed to measure the school concentration of advantaged students (>40%); both native and immigrant students were considered, given the reduced presence of the latter in the upper part of the distribution of the ESCS index. As in other papers, we worked with the hypothesis that peer effects appear when the concentration of students of a specific profile exceeds a certain threshold (Cebolla-

Boado and Garrido-Medina, 2011; Brunello and De Paula, 2017). The established thresholds are the same for all five countries and have been set at 20%, 30% and 40%, taking into account the distribution of the three categories of students in the sample.

- The size of the town where the school is located was obtained from the question "Which of the following definitions best describes the community in which your school is located?" The response options were transformed into the following dichotomous variables: "A village, hamlet or rural area (fewer than 3,000 people)" (village), "A small town (3,000 to about 15,000 people)" (smalltown), "A city (100,000 to about 1,000,000 people)" (city) "A large city (with over 1,000,000 people)" (largecity), taking the excluded category "A town (15,000 to about 100,000 people)" (town) as the reference.

- The survey provides information about school ownership, from which two corresponding dichotomous variables were constructed with the categories of "Private Independent" (private) and "Private Government-dependent" (priv. gov .funded). The reference category, excluded from the analysis, is that of publicly-owned schools.

- In relation to school admission policies, two dichotomous variables were created to measure admission, based on academic performance (stu. admis. record) or on residence in a particular area (stu. admis. resid). In both cases, the variables take the value 1 if the school principal answers "always" to the implementation of one of the aforementioned admission policies, and they take the value 0 when they respond "never" or "sometimes".

- Regarding the size of the class, a dummy variable (class size ≤20) was created. It takes the value 1 if the class has up to 20 students and 0 if the size is greater. (class size >40) takes the value 1 if the class has more than 40 students and 0 if the size is less. The reference category, excluded from the model, is a class size of between 21 and 40 students.

- PISA 2018 poses a series of questions to principals about the factors that can hinder the training process: lack of teaching staff; inadequate or underqualified teaching staff; lack of auxiliary personnel; inadequate or underqualified support staff. Based on these questions, they construct "the staff short index", where positive values indicate that the quantity and/or quality of human resources available in their schools are an obstacle in their teaching work to a greater extent than the OECD average.

C) STRATIFICACTION POLICIES

- Within-school ability grouping: in relation to the school policy of grouping students by ability, two dummy variables were constructed: "students are grouped by ability into different classes" (gr. by abil. (betw. class)), and "students are grouped by ability within their classes" (gr. by abil. (with. class)), which take the value 1 if the student answers "in all subjects" or "in some subjects" and value 0 if you answer "in no subject".

- Grade repetition: PISA provides a dichotomous variable (repeat) that takes the value 1 if the student has repeated a grade and 0 in the case of not having done so.

- Tracking by study programme: PISA 2018 provides information on the study programmes offered in each country. In the estimation of the models, a dichotomous variable is included for each educational programme, keeping the programme with an academic profile as a reference. The offer of educational programmes varies from 1 in the UK to 5 in Germany. However, the level of disaggregation of the variable is broader. For example, in the United Kingdom, it differentiates between students studying to obtain GCSEs or A levels by region. This brings the number of dummy variables in the UK estimate to 8 (plus the reference category). In the case of Germany, the level of detail is even broader, so that 17 dummy variables are included in the models (plus the reference category). The OECD classified study programmes according to the International Standard Classification of Education (ISCED 1997). For more information on the educational programmes available in PISA, see OECD (2020).

Table 1 shows the descriptive statistics in the five analysed countries. The number of observations ranges from 5,451 students in Germany to 35,943 in Spain. However, in order to estimate the composition of schools more adequately, those with a sample of 10 or fewer students have been excluded, which implies a loss of barely 1% of the sample of the 5 researched countries (782/73,305=0.011). Among other results, we see that the proportion of second-generation migrant students is higher in Germany, France and the United Kingdom than in Italy and Spain. Regarding the first generation, the differences are less pronounced, and the United Kingdom and Spain stand out. With regard to the concentration of disadvantaged immigrant students in schools, Germany stands out, partly because it has, like the United Kingdom, a higher proportion of students from immigrant families, and partly as a result of early tracking. Something similar happens with the concentration of students from advantaged families, where Germany once again stands out. In contrast, the differences between countries when it comes to the concentration of disadvantaged native students are notably smaller. On the other hand, the share of classrooms with more than 40 students is noteworthy in the Spanish case (13%), as it is significantly above the rest of the countries, with rates below 2%.

TABLE 1.- Descriptive statistics (around here)

The lower panel of Table 1 has been supplemented with information from the OECD on horizontal tracking in the five target countries and on the average resources that each country allocated to secondary education in the 2012-2018 period. It shows that Germany, Italy and France sort students into educational programmes prior to taking the PISA test, while Spain and the United Kingdom only do so after the PISA test is taken. On the other hand, the percentage of GDP devoted to education is similar in Germany, France and the United Kingdom, in the 2.2-2.5% range. In contrast, in southern European countries, the resources allocated to secondary education, in a period of serious economic crisis, were lower, especially in the case of Spain, which devoted 1.7% on average. Based on available data, average expenditure per student is unequal and ranges from $9,294 in Spain to $12,149 in Germany.

Table 2 shows some data about the evolution of the stock of immigrants by area of origin in the 1995-2015 period. As can be seen, the volume of immigrants increased extraordinarily in Spain and Italy, where the stock of migrants quintupled and tripled, respectively, in just two decades. In the OECD's (2016b) classification, both countries are considered new destination countries with large populations of low-educated immigrants. The next country in terms of immigration growth is the United Kingdom, which doubled its stock of immigrants during the target period. In OECD terminology, the United Kingdom is a traditional destination for migrants which in recent years has received a significant flow of highly-qualified immigrants. Lastly, the volume of immigrants is growing at a slower rate in Germany (37%) and France (29%), which have been common destinations for low-skilled immigration. Regarding the origin of migrants, developing countries tend to predominate, except in Germany's case; by areas of origin, the influence of geographical proximity and colonial history on migratory flows is observed (Latin America and the Caribbean, in Spain's case; Asia in the United Kingdom's; and North Africa in France's). Regarding the changes in the composition of the migrant population by origin, it is striking that

Italy is the only country where immigration from developing countries decreased in relative terms, as the stock of migrants from Europe and North America increased by 9 percentage points.

TABLE 2: International migrant stock by area of origin and development group (1995-2015) (around here)

4. **METHODS**

One of the main econometric problems pointed out in the peer effects literature is the sorting bias. As is well known, the assignment of students to schools is not random and, often, students self-select. If the students with the highest ability tend to attend the best schools, the peer effects estimate will be biased, to the extent that it will not be possible to differentiate between the selection effect and the actual peer effect. Hoxby (2000) points out that the selection bias is generated in both the family and the school environment. Regarding the former, families self-select schools based on household income, job location and residential preferences. As for the latter, there is also a selection of teachers based on their training and experience, and also of students, who are sorted into groups based on their ability.

Various authors have approached the problem of endogeneity in peer effect estimation from the perspective of the omission of relevant variables (among others, Rangvid-Schindler, 2003; Schneeweiss and Winter-Ebmer, 2007; and Entorf and Lauk, 2007). If students (or, rather, their parents) select into ability groups as a consequence of unobservable variables such as motivation or school quality, and these variables are correlated with academic performance, the estimate of peer effects will be biased. In addition, the parents who are most concerned about their children's education will try to choose schools with better teachers and good peer groups. The student will thus obtain good academic results due to the combined impact of parent support, teacher quality and their peer group. The most basic models, which do not incorporate these explanatory variables, will tend to overestimate the size of the peer effects (Rangvid-Schindler, 2007).

Let us suppose that the true model is

$$A_{ij} \; = \; \alpha \; + \; \beta \, M_{ij} + \; \delta_1 \, P_j + \delta_2 \, TQ_j + \; X_{ki} \, \gamma_k + Z_{mj} \, \gamma_m + SP_{nij} \, \gamma_n + \varepsilon_{ij} \qquad (1)$$

where A_{ij} represents the achievement of student *i* in school *j*, M_{ij} is the variable that identifies the student's migrant background, P_j represents peer characteristics, TQ_j measures the quality of teachers, X_{ki} is a vector of the student’s individual and family characteristics, Z_{mj} is a vector representing the school’s characteristics, SP_{nij} is a vector of stratification policies which can be applied to student *i* (for example, grade repetition) or in school *j* (for example, ability grouping).

The estimated model is usually

$$A_{ij} \; = \; \alpha \; + \beta^{*} M_{ij} + \; \delta^{*} \, P_j + X_{ki} \, \gamma_k^{*} + Z_{mj} \, \gamma_m^{*} + SP_{nij} \, \gamma_n^{*} + u_{ij} \qquad (2)$$

where the error term u_{ij} includes a typically unobservable characteristic of schools (teacher quality, TQ_j) together with the random component ($u_{ij} = \delta_2 \, TQ_j + \varepsilon_{ij}$). If the TQ_j variable is omitted from the model and the correlation between peer characteristics and quality of the teaching staff is positive ($cov(P_j, TQ_j) > O$), the peer group effect on academic achievement will be overestimated.

The identification strategy used by Schneeweiss and Winter-Ebmer (2007) consists of incorporating comprehensive information about the students' families' socioeconomic status into their models in order to reduce the omitted variable bias, and also including school type fixed effects, insofar as the selection of students in the target country (Austria) is mainly based on school type.

Using a similar approach, this paper will try to control for sorting bias by including a set of variables associated with the school selection process (and, in turn, with classmates), such as family background, the importance that parents assign -in choosing the school- to it having a good reputation, parent support, the value of school for the student (trying hard), student truancy, teaching staff quality, (approximated through the "teacher enthusiasm" variable) school type (public, private or publicly-funded private school), school admission policies (based on academic performance or residence), shortage of educational staff, and finally, the study programmes followed by each student.

The introduction of study programme fixed effects helps to control for sorting bias, especially in countries that apply horizontal stratification policies. To the extent that self-selection is driven by the segregation of students into different study programmes, controlling for this variable reduces the omitted variables bias, since students and families following the same study programme may share unobservable characteristics (Schneeweiss and Winter-Ebmer, 2007). Betts (2011) emphasizes the need to control for the specific track to which a student is assigned, since, with tracking, school administrators are able to modify school characteristics and parents may reduce spending on private tutoring.

5. RESULTS

Table 3 shows the results of the OLS estimation of the gross educational gap of immigrant students in the 2018 mathematics tests. The top panel includes only the variables that define the profile of the immigrant student together with language skills. The middle panel includes the socioeconomic and cultural status. Finally, the variables related to school segregation are also added in the bottom panel. In all estimations, version 15.0 of STATA/MP has been used with the "repest" module that enables working with the replicated weights and the plausible values of the cognitive tests.

TABLE 3.- Migrant educational gap in the PISA 2018 mathematics test
(around here)

Regarding the results, it should first be noted that first-generation migrants who arrived in the destination country between the ages of 7 and 16 are the ones showing the highest educational gap, except in the United Kingdom, where this group does not show a statistically significant difference compared to native students. The gap in the other countries ranges from 45 points in Italy to 96 in Germany. On the other hand, in Italy and Spain, the educational gap of immigrant students diminishes as the time they have been in the educational system of the country of destination increases, so that second-generation migrants show a gap that is 40.5% and 57.1% lower, respectively, than that of first-generation migrants who arrived in the country aged 7 or older. This difference goes down to 14.7% and 44.0% for second-generation migrants who arrived aged 6 or younger. On the other hand, the language skills variable shows a penalty ranging between 9 points in Germany and 34 in the United Kingdom. Lastly, the United Kingdom shows the smallest educational gap in all three categories of migrant students, a matter on which we will focus later on.

The middle panel allows us to analyse the effect of incorporating the index regarding economic, social and cultural status into the models. The ESCS variable is statistically significant in all countries. As regards its influence, assuming that the standard deviation of the variable is around 1 (see Table 1), an increase of one standard deviation of the ESCS variable increases the achievement in mathematics by between 28 points, in Spain, and 45 points, in France. When the economic, social and cultural status is included in the equation, the models' coefficient of determination increases substantially, by between 10.0 percentage points, in Italy, and 18.5, in France. In addition, when ESCS is controlled for, the educational gap for immigrant students falls across the board, especially among second-generation migrants, where it decreases by between 47% (UK) and 62% (Italy). Among members of the first generation who arrived aged 7 to 16, the reduction is less remarkable, at 21% (Spain) to 35% (France). These first results suggest that educational policy should be aimed at correcting the negative effects associated with belonging to disadvantaged backgrounds. In turn, immigrant students, especially those who have been in the educational systems of destination countries for a short time, require special attention to strengthen their language skills and make up for the shortcomings of their previous education. Otherwise, the results are in line with what is found in the literature (see, for example, Marks, 2005; and Zinovyeva et al., 2014).

The bottom panel also includes the three variables related to school segregation. This allows to significantly increase the explanatory power of the models, especially in countries with tracking: the coefficient of determination increases by 10.5 percentage points in Germany, 15.0 points in Italy and 13.9 points in France. In contrast, in the two countries with comprehensive education systems, the United Kingdom and Spain, R^2 barely grows by 4.6 and 1.1 points, respectively. The three new variables show statistically significant coefficients in all samples. However, their inclusion in the models has a lower impact on reducing the educational gap for immigrant students, with the exception of first-generation students who arrived aged 7 to 16 in Germany and France, where the gap decreases by 21% and 33%, respectively.

The penalty associated with attending a school with a high proportion of disadvantaged migrants is notably higher in the three countries with tracking (Germany (46 points), Italy (49 points) and France (45 points)) than in the two that do not apply it (United Kingdom (18 points) and Spain (12 points)). The size of the coefficients increases when the effect of attending a school with a high concentration of disadvantaged natives is studied; here, the penalty rises to 74 points in Italy and 76 points in France, once again well above the coefficients recorded in the United Kingdom (19 points) and Spain (15 points). At the same time, attending a school with a significant proportion of students from advantaged families is associated with an increase in achievement in mathematics ranging between 15 points in Spain and 45 points in the United Kingdom or 47 in Germany. These results are, in principle, predictable if we take into account the importance of economic, social and cultural status in determining academic achievement, as well as the effect of horizontal stratification policies that sort students into different educational programmes (and schools). In any case, these coefficients cannot be interpreted as an estimate of peer effects because the influence of no other student or school characteristic has been controlled for in these basic models.

As stated above, the small size of the educational gap of migrant students in the United Kingdom is striking. When controlling for ESCS, it amounts to around 10-11 points, with the exception of first-generation immigrants who arrived aged 7 to 16, where the coefficient is not statistically different from 0. As pointed out in section 4, in recent years, the United Kingdom has received a significant volume of highly qualified immigrants. This fact is reflected in that, unlike the other European countries, the distribution of the economic, social and cultural status of immigrants from the United Kingdom hardly differs from that of the native population, as can be seen in the kernel density estimates presented in the Annex.

Table 4 shows the results of the OLS estimations of the model including all student and school variables, with the exception of those informing stratification policies, which will be analysed in later tables. Starting at the end, the improvement in the explanatory power of the model including 27 independent variables compared to the previous model's 8 variables is relatively small. The two countries in which the coefficient of determination increases the most are the United Kingdom and Italy, where R^2 increases by 5.5 and 4.3 percentage points, respectively. However, some changes are observed in the coefficients of the variables of interest. For example, in the case of the United Kingdom, none of the individual effects for immigrant student status is statistically different from zero. Along the same lines, in Germany, the educational gap of first-generation migrants who arrive in the country aged 7 or over decreases from 55 points to 32. Regarding the variables related to school segregation, the pattern of results does not change substantially, with the exception of the 17-point drop in the penalty associated with schools with high proportions of disadvantaged migrants in Italy, or the 15-point drop for those with high concentrations of disadvantaged natives in Germany. On the other hand, in the United Kingdom, the positive effect associated with attending a school with a high proportion of advantaged students falls by 22 points. This result is largely explained by the inclusion of variables measuring attendance at private schools (+32 points) or schools whose admissions policies focus on students' academic performance (+25 points), such as the selective and academically oriented grammar schools that are still in operation today (Pischke and Manning, 2006).

TABLE 4.- OLS estimates of the full model without controls for stratification policies
(around here)

Regarding the remaining student variables, it should be noted that women tend to obtain lower scores on the mathematics test. Birth months have a relatively large effect in Germany and Spain, where students born in the first quarter of the year score 19 and 16 points higher, respectively, than those born in the last quarter. Truancy is associated with lower scores in all countries except Germany, where the effect is not statistically significant. Parental support has a positive and statistically significant effect in Italy and Spain, and so does, in the United Kingdom and Spain, the student's appreciation of making an effort at school. Teacher quality, estimated through the "teacher enthusiasm" variable, has a positive and significant effect in all countries. Finally, parents considering a school's good reputation important for their choice raises the mathematics test results by 17 points in the two countries for which such information is available (Germany and Italy).

Regarding school variables, it should be noted that school admission systems based on academic records are associated with score increases in Germany, Italy and the United Kingdom, while admission according to area of residence only has a positive and significant effect in France. Attending a school with classes comprised of fewer than 20 students is associated with a reduction of at least 20 points in all countries except Spain. The same happens in Germany, in relation to classes with more than 40 students, where the penalty reaches 60 points. Finally, staff shortages are associated with a statistically significant reduction in scores in Germany and Spain (in line with what was found in Tourón et al., 2018).

Table 5 shows the estimation results for the full model, once the stratification practice of grouping students by ability within schools has been controlled for. As described in Table 1, these practices are common in all countries, especially in the UK, where most schools sort their students into different classes (78%) or into groups within the same class (53%). However, ability grouping within schools does not have a statistically significant effect on mathematics test results, except in Germany, where sorting into different classes shows a negative effect (-18 points). In addition, the models' explanatory power hardly improves once these new variables are included; the largest increase in the coefficient of determination is recorded in Germany, where it increases by 0.9 percentage points. For the rest, there were no changes in the variables of interest worth highlighting.

TABLE 5.- OLS estimates of the full model with controls for within-school ability grouping (around here)

The next stratification policy to be analysed is grade repetition. Table 6 shows the results of the estimation of the previous model, to which the grade repetition dummy variable is added. First, it should be noted that grade retention is associated with a very large reduction in the results of the mathematics test; namely between 42 and 44 points in Germany, Italy and the United Kingdom, and 74 and 86 points in France and Spain, respectively. The inclusion of grade repetition increases the explanatory power of the model by 16.0 percentage points in Spain, where grade repetition is a very common practice. The increase in the coefficient of determination is also notable in France (+5.2 percentage points) and marginal in the United Kingdom (+0.5 percentage points), a country where grade repetition is very infrequent.

The inclusion of grade retention in the models reduces the educational gap of migrant students, which means that this practice especially affects this group. Just to mention one example, the educational gap of first-generation immigrants who arrived in Europe between the ages of 7 and 16 is reduced by 5 points in Germany, 3 in Italy, 6 in France and 16 in Spain. In the Spanish case, the drop in individual effects spreads to the other two categories related to immigration, reaching the point of not being statistically different from zero in the case of second-generation immigrants. On the other hand, there is also a small but general drop in the coefficients that measure school segregation; this is remarkable in the case of France, since the penalty associated with attending a school with a high concentration of disadvantaged migrants drops by 49.6%, while the penalty associated with a high concentration of disadvantaged natives does so by 40.6%.

TABLE 6.- OLS estimates of the full model with controls for grade repetition (around here)

The use of grade repetition is very uneven among the target countries, ranging from a minimum value of 2% in the United Kingdom to a maximum of 28% in Spain. In addition, the probability of repeating a grade is higher among immigrant students than among native students (see Table 7). For example, the likelihood of a second-generation immigrant student repeating a grade is 8 percentage points higher in Germany, 10 points higher in France, 17 points in Italy, and 15 points higher in Spain, compared to the native population. Regarding first-generation immigrants, the probability of repeating a grade of those who arrived in the destination country between the ages of 0 and 6 is similar to that of second-generation immigrants. In contrast, migrant students who arrived between the ages of 7 and 16 tend to show a probability of repeating a grade that is 9 percentage points higher, on average, than those who did so between the ages of 0 and 6.

This means that, for first-generation migrant students who arrived in Europe between the ages of 7 and 16, the probability of repeating a grade is around 33% in Germany, Italy and France, and 53% in Spain.

TABLE 7.- Probability of repeating a grade and immigration (around here)

Before analysing the last stratification policy, we are going to focus on the role played by grade repetition in the segregation of students by study levels and their general or vocational orientation. This is observed in France and, to a lesser extent, Italy, and has been previously analysed in OECD (2016a). PISA 2018 provides information on the variable "ISCED level" which, for the purposes of the analysed countries, is distributed into two categories: "Lower Secondary Education" (ISCED 2) and "Upper Secondary Education" (ISCED 3). On the other hand, the variable “ISCED orientation” includes the categories “General”, “Pre-Vocational” and “Vocational”. In the case of France, 96.4% of students who repeat a grade study lower secondary education, while 98.0% of those who do not repeat a grade study upper secondary education. In addition, classification by levels is relevant, since 17.5% of students remain in the lower level of studies. Something similar, although to a lesser degree, happens in Italy, where 89.0% of lower secondary education students have repeated a grade, even though this level of studies is relatively marginal, since 99.0% of Italian students reach upper secondary education. Among the latter, it is much more common for a student who repeats a grade to follow a vocational training programme (78.1%), an option chosen by a significantly lower proportion of students who do not repeat a grade (45.9%).

Table 8 shows the results of the estimation of the previous model, including controls for ISCED level and orientation. The inclusion of these new variables notably improves the explanatory power of the model in the case of France, where R^2 increases by 5.1 percentage points, reaching 49.0%. One of the most remarkable impacts of controlling for orientation and educational level is that the penalty associated with repeating a grade in France drops from 74 to 32 points. In parallel, the individual effect of first-generation migrant students who arrived aged 7 to 16 decreases from –28 to –21 points. This reduction is also observed in the school segregation coefficients; for disadvantaged natives, the coefficient drops from –42 to –17 points. In the Italian case, the penalty associated with repeating a grade hardly changes, although the coefficients for school segregation do; for disadvantaged migrant students, the coefficient decreases from –27 to –18 points.

TABLE 8.- OLS estimates of the full model with controls for ISCED level and orientation (around here)

Finally, Table 9 shows the results of the OLS estimations, including the study programmes fixed effects, through which the impact of tracking on the educational gap of students of immigrant background is analysed. Given the overlap between study programmes and ISCED levels of study and orientation in some countries, we have decided not to include these variables in the models. Therefore, Table 9 includes controls for the three stratification policies that were analysed: within-school ability grouping, grade repetition and tracking. Compared to the results in Table 6, the inclusion of the new variables has no impact on the United Kingdom and Spain, two countries with comprehensive education systems. On the other hand, it does impact the three countries that do apply horizontal stratification policies. In terms of improving the explanatory power of the models, the new controls increase R^2 by 7.1 percentage points in Germany, by 5.2 points in France, and by 2.2 points in Italy. The penalty associated with repeating a grade decreases in all three cases, to –35 points in Germany, –38 in Italy and –32 in France. The individual effects of first-generation migrants arriving in Europe aged 7 or over tend to decrease in the three countries, to around –21 points on average. However, the impact is more substantial on the variables that measure school segregation; especially in Germany and France, the values recorded in Table 6 tend to halve. For example, once study programme is controlled for in Germany, the penalty associated with attending a school with a high proportion of disadvantaged migrants is –17 points, and that of attending a school with a high concentration of disadvantaged natives is –11 points, while the positive effect of studying with a significant proportion of socioeconomically advantaged peers stands at +11 points.

TABLE 9.- OLS estimates of the full model with controls for study programmes
(around here)

The results suggest the existence of peer effects associated with attending schools with a high proportion of disadvantaged migrant students, with the exception of the Italian case, where the sign of the coefficient changes and is not statistically different from zero. The same pattern is observed in relation to disadvantaged native students, as results point at the existence of adverse peer effects in all countries. At the opposite end of the spectrum, once a broad set of variables associated with school selection is controlled for, the evidence found suggests the existence of peer effects in schools with a high concentration of advantaged students. Other than that, these results are in line with those found by Entorf and Lauk (2007) and Schneeweis and Winter-Ebmer (2007).

As seen throughout this section, the two stratification policies with the greatest influence on educational performance are tracking and grade repetition. Furthermore, these two policies play a key role in explaining the educational gap affecting immigrant students. To close this chapter, an analysis of variance has been carried out on the mathematics test results with the following explanatory variables: the three stratification policies, the schools and, finally, the economic, social and cultural status (see Table 10). As can be seen, within-school ability grouping plays a minor role in defining academic performance. On the other hand, the practice of grade retention shows a notable explanatory power, especially in Spain and France, where the model explains 26.0% and 22.6%, respectively, of the variability of the results in mathematics. Differences between study programmes explain around 40.0% of result variance in Germany, France and, to a lesser extent, Italy, where the explanatory power of the model stands at 22.1%. In contrast, in the two countries that do not apply horizontal stratification, the explanatory power of the model is marginal. The classification of students into programmes means that results differences between schools are significant and in the range of 47.5%-49.5% in Germany, France and Italy. In contrast, the differences in mean achievement between schools explain less than 25.0% of the variance of PISA scores in the United Kingdom and Spain, where most of the variability is within-school. For this reason, the first three countries fit into the OECD (2016a) characterization of exclusive education systems, while the latter can be defined as inclusive. In addition, it is observed that family background, estimated through the ESCS variable, plays a lesser role in determining academic results in comprehensive education systems, compared to stratified ones, with the exception of Italy's.

TABLE 10.- Analysis of variance of the mathematics test
(around here)

6. CONCLUSIONS

The objective of this work was to analyse the role that stratification policies play in the educational gap of students with an immigrant background. From a methodological point of view, an attempt has been made to deal with the problem of self-selection, which affects the estimation of educational production functions, by controlling for a broad set of variables that underlie school selection. Among them, we should highlight study programme fixed effects, which are especially relevant in countries where horizontal stratification policies are applied.

Based on the fact that students with an immigrant background are a heterogeneous group, it has been shown that language skills and the time spent in the educational system of the destination country are two decisive factors when it comes to the gap in PISA results. It has also been found that economic, social and cultural status explains a substantial part of immigrant students' lower academic performance, more so in second-generation students than in newcomers, who may show specific difficulties during the integration process. In addition, according to ANOVA results, around half of the variance in educational achievement is explained by differences between schools in the countries that apply tracking, while in comprehensive systems, more than 75% of grade variability is due to differences within schools. Horizontal stratification policies strengthen the influence of ESCS on academic achievement, which is especially detrimental to immigrant students, who tend to be overrepresented among lower socioeconomic and cultural status families.

Taking the previous results into account, in terms of educational policy, support programmes for students from disadvantaged families, both native and immigrant, have to be developed. At the same time, policies aimed at meeting the specific needs of migrant students should be implemented. Special attention should be paid to first-generation migrants who arrive in destination countries at a later age and to those with language difficulties.

Regarding vertical stratification, the literature has found that grade repetition is an expensive policy that does not lead to better learning than automatic promotion (Hong and Raudenbush, 2005) and that increases absenteeism (Martin, 2011) and the probability of dropping out from school (Manacorda, 2012). In this work, it has been found that grade retention affects immigrant students, in relative terms, more severely, especially those who arrive in destination countries at an older age. Grade repetition explains a substantial part of the educational gap of students with an immigrant background in Spain, while in other countries, such as France, it conditions the programme they pursue and the level of studies they achieve and largely determines the penalty associated with the school segregation of disadvantaged students, both immigrant and native.

The sequential estimation of the models has made it possible to detect that stratification policies lead to an upward bias of the effect of school segregation. However, once the influence of vertical and horizontal stratification has been controlled for, results point at the existence of peer effects derived from the concentration of advantaged students at the school, as well as of adverse peer effects caused by high concentrations of disadvantaged students. What follows is that immigrant students can benefit from changing the peer group with whom they interact. A reduction of school segregation is not expected to produce substantial net efficiency gains, although it can generate significant equity benefits, help combat immigration-related prejudice and stereotyping, as well as improve integration and social cohesion (Brunello and De Paola, 2017).

The obtained results must be interpreted with care, given the complexity of the studied phenomenon, where different educational models, heterogeneous migratory trajectories and unequal resources allocated to secondary education in each country are compared. In any case, with all due precautions, the results of the empirical analysis suggest that stratification policies pose an obstacle to the school integration of immigrant students. For this reason, we propose to delay the sorting of students into educational programmes and reduce the practice of grade repetition in order to improve equal opportunity.

The educational integration of students with an immigrant background is a challenge due to the fact that they are migrants and also have a lower economic, social and cultural status. To the extent that academic performance in secondary education conditions future educational investments, expectations and careers in adulthood, this problem must be addressed early, so that school can mitigate the disadvantages faced by immigrant and native-born students of lower socioeconomic status. The goal should be for students to reach their full potential, regardless of their families' income and country of origin.

7. APPENDIX

Note: vertical lines represent the 25th and 75th percentiles of ESCS in each country

Figure 1. Kernel density estimates of ESCS by immigration status: GERMANY

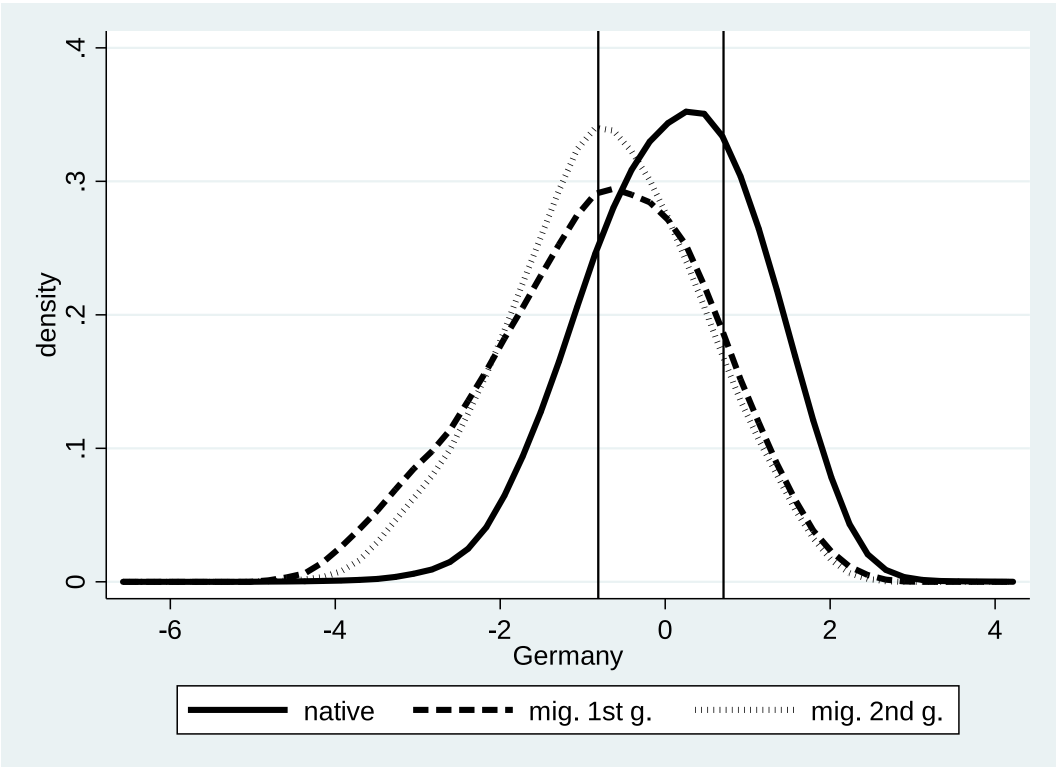


Figure 2. Kernel density estimates of ESCS by immigration status: ITALY

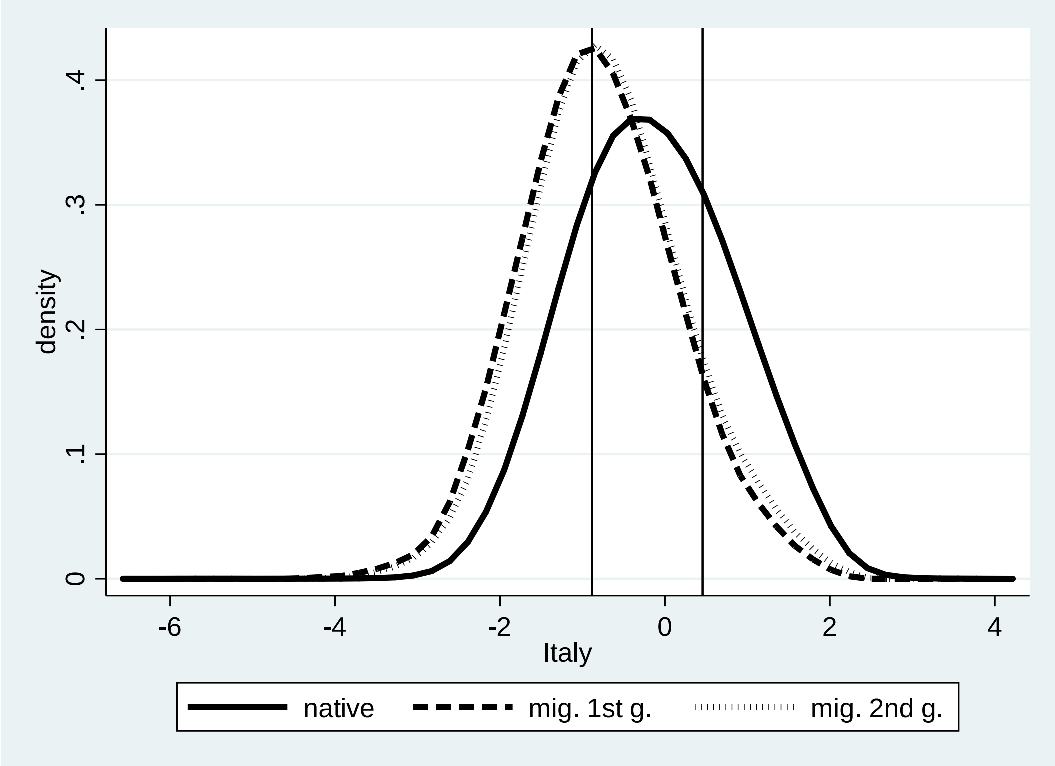


Figure 3. Kernel density estimates of ESCS by immigration status: FRANCE

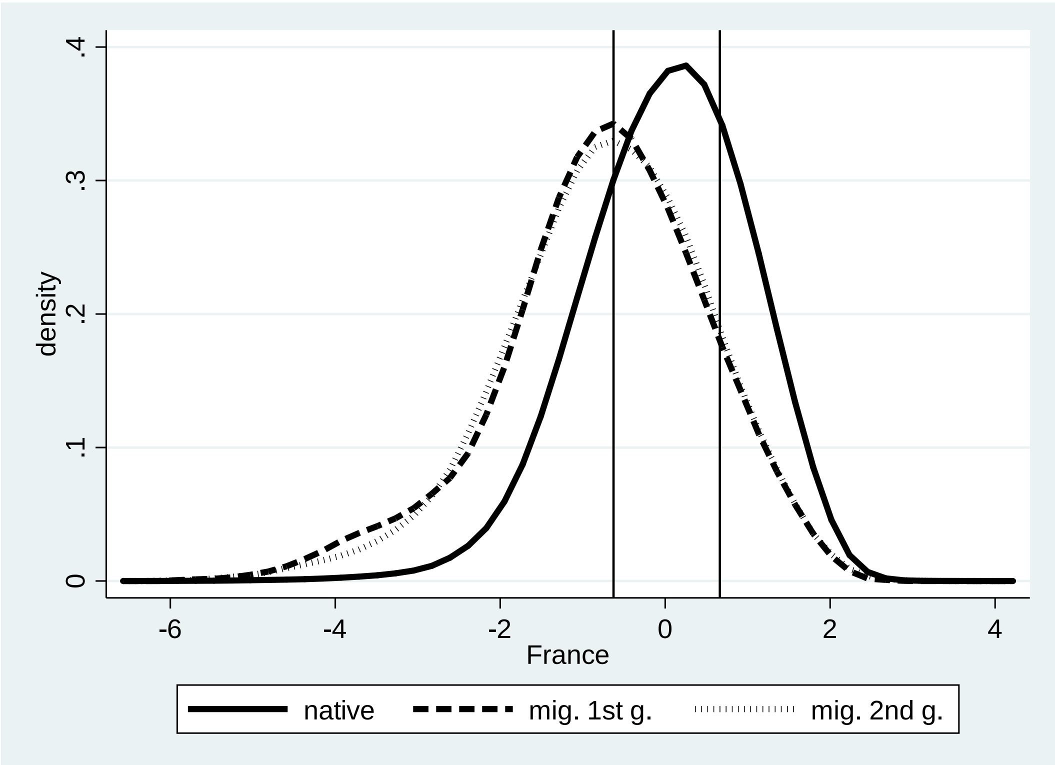


Figure 4. Kernel density estimates of ESCS by immigration status: UNITED KINGDOM

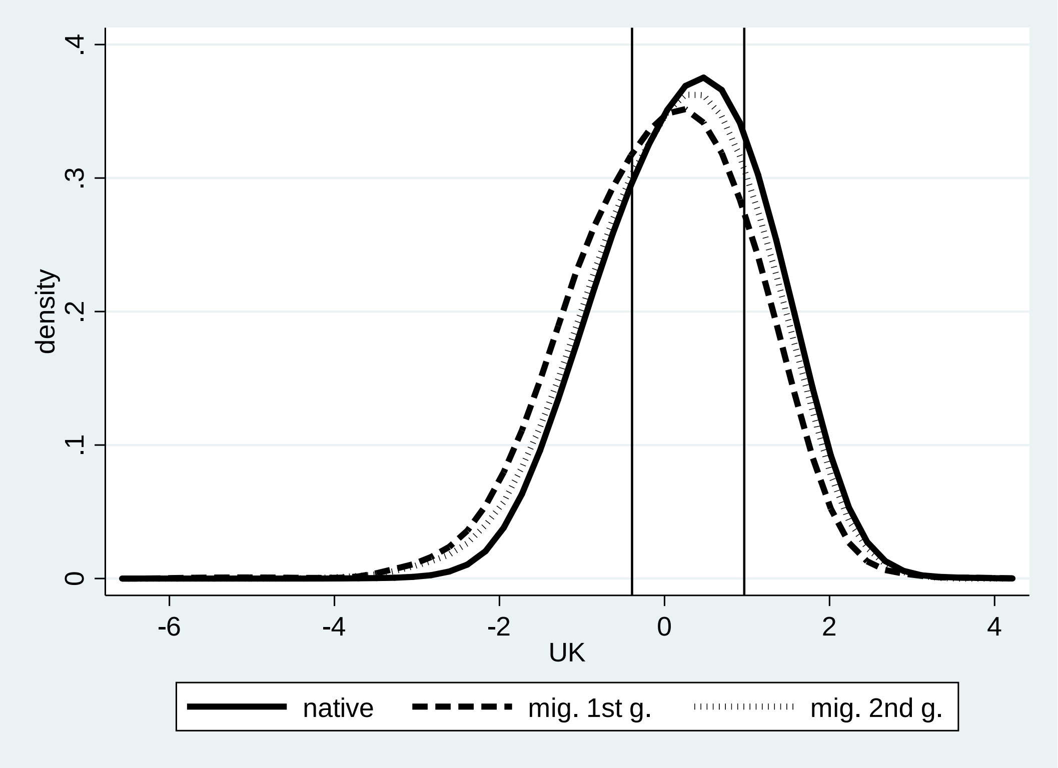
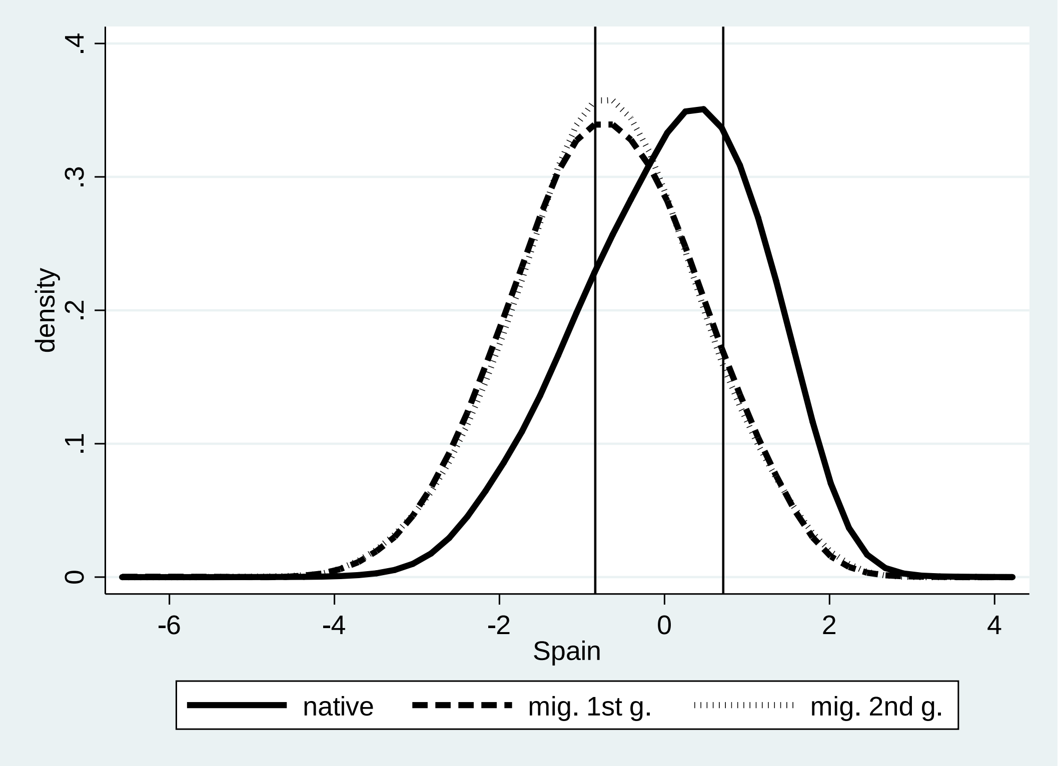


Figure 5. Kernel density estimates of ESCS by immigration status: SPAIN



8. REFERENCES

- Agasisti, T., F. Avvisati, F. Borgonovi et al. (2021) What School Factors are Associated with the Success of Socio-Economically Disadvantaged Students? An Empirical Investigation Using PISA Data. *Soc Indic Res* 157, 749–781. https://doi.org/10.1007/s11205-021-02668-w

- Basu, S. (2018) Age-of-Arrival Effects on the Education of Immigrant Children: A Sibling Study. *Journal of Family and Economic Issues*, 39, 474–493. https://doi.org/10.1007/s10834-018-9569-4

- Betts, J.R., (2011), "The Economics of Tracking in Education", in Hanushek, E.A., S. Machin and L. Woessmann (Eds.), *Handbook of the Economics Of Education*, Volume 3, Amsterdam: North Holland, pp. 341-381.

- Brunello, G., and D. Checchi (2007) Does School Tracking Affect Equality of Opportunity? New International Evidence. *Economic Policy*, 22(52), 781–861. http://www.jstor.org/stable/4502215.

- Brunello, G. and M. De Paola (2017) *School segregation of immigrants and its effects on educational outcomes in Europe,* European Commission, Directorate-General for Education, Youth, Sport and Culture. https://data.europa.eu/doi/10.2766/045520

- Cebolla-Boado, H. and L. Garrido-Medina (2011) The Impact of Immigrant Concentration in Spanish Schools: School, Class, and Composition Effects, *European Sociological Review*, Volume 27, Issue 5, October, Pages 606–623, https://doi.org/10.1093/esr/jcq024.

- Cebolla-Boado, H., and M. Fernández-Reino (2021) Migrant Concentration in Schools and Students' Performance: Does It Matter When Migrants Speak the Same Language as Nonmigrant Students? *American Behavioral Scientist*, 65(9), 1206–1221. https://doi.org/10.1177/0002764221996776

- Choi, A. y J. Calero (2012) Rendimiento académico y titularidad del centro en España, *Profesorado, Revista de curriculum y formación de profesorado*, Vol. 16, Nº 3, (sep.-dic.).

- Diemer, A. (2022) Endogenous peer effects in diverse friendship networks: Evidence from Swedish classrooms, *Economics of Education Review*, Volume 89, 102269. https://doi.org/10.1016/j.econedurev.2022.102269.

- Duflo, E., P. Dupas, and M. Kremer (2011) "Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya", *American Economic Review* 101.5: 1739–1774. http://dx.doi.org/10.1257/aer.101.5.1739

- Entorf, H. and M. Lauk (2008) Peer Effects, Social Multipliers and Migrants at School: An International Comparison, *Journal of Ethnic and Migration Studies,* 34:4, 633-654, DOI: 10.1080/13691830801961639

- Hanushek, E.A. and L. Wößmann (2006) Does Educational Tracking Affect Performance And Inequality? Differencesin-Differences Evidence Across Countries, *The Economic Journal*, 116 (March), pp. 63–76.

- Hong, G. and S.W. Raudenbush (2005) Effects of Kindergarten Retention Policy on Children's Cognitive Growth in Reading and Mathematics. *Educational Evaluation and Policy Analysis*, 27(3), 205–224. https://doi.org/10.3102/01623737027003205

- Hoxby, C. (2000) *Peer Effects in the Classroom: Learning from Gender and Race Variation*, NBER Working Papers 7867, National Bureau of Economic Research, Inc.

- INEE (2020): *PISA 2018. La organización escolar.* Ministerio De Educación y Formación Profesional.

- Jürges, H. and K. Schneider (2011) "Why Young Boys Stumble: Early Tracking, Age and Gender Bias in the German School System" *German Economic Review*, vol. 12, no. 4, pp. 371-394. https://doi.org/10.1111/j.1468-0475.2011.00533.x

- Krüger, N. (2020) Efectos Compañero en Contextos Escolares Altamente Segregados, en *REICE. Revista Iberoamericana sobre Calidad, Eficacia y Cambio en Educación*, 2020, 18(4), 171-196. https://doi.org/10.15366/reice2020.18.4.007

- Marks, G.N. (2005) Accounting for immigrant nonimmigrant differences in reading and mathematics in twenty countries, *Ethnic and Racial Studies* Vol. 28 No. 5 September 2005 pp. 925/946

- Martin, A.J. (2011), Holding back and holding behind: Grade retention and students' non-academic and academic outcomes. *British Educational Research Journal*, 37: 739-763. https://doi.org/10.1080/01411926.2010.490874

- Micklewrighta, J., S.V. Schnepfb and P.N. Silva (2012) Peer effects and measurement error: The impact of sampling variation in school survey data (evidence from PISA), *Economics of Education Review* 31, 1136– 1142.

- Murillo, F. J., C. Martínez-Garrido y G. Belavi (2017). "Segregación escolar por origen nacional en España". *OBETS. Revista de Ciencias Sociales*, 12(2): pp-pp. 395-423. doi:10.14198/OBETS2017.12.2.04

- Murillo, F. J. y C. Martínez-Garrido (2018) Incidencia de la crisis económica en la segregación escolar en España, *Revista de Educación,* 381, Julio-Septiembre, pp. 67-93.

- OECD (2009), *PISA Data Analysis Manual: SAS, Second Edition*, PISA, OECD Publishing, Paris, https://doi.org/10.1787/9789264056251-en

- OECD (2016a), "Selecting and grouping students", in *PISA 2015 Results (Volume II): Policies and Practices for Successful Schools*, OECD Publishing, Paris. DOI: https://doi.org/10.1787/9789264267510-9-en

- OECD (2016b) "Immigrant background, student performance and students' attitudes towards science", in *PISA 2015 Results (Volume I): Excellence and Equity in Education*, OECD Publishing, Paris. https://doi.org/10.1787/9789264266490-11-en

- OECD (2019a) *PISA 2018 Results (Volume III): What School Life Means for Students' Lives. Annex A1. Construction of indices*. OECD Publishing, Paris. https://doi.org/10.1787/acd78851-en

- OECD (2020), *PISA 2018 Results (Volume V): Effective Policies, Successful Schools*, OECD Publishing, Paris. https://doi.org/10.1787/ca768d40-en

- OECD (2022) *Education spending (indicator)*. https://doi.org/10.1787/ca274bac-en

- Pischke, J.S. and Al. Manning (2006) *Comprehensive Versus Selective Schooling in England in Wales: What Do We Know?* NBER Working Paper No. w12176, Available at SSRN: https://ssrn.com/abstract=897030

- Rangvid-Schindler, B. (2007) School composition effects in Denmark: quantile regression evidence from PISA 2000, *Empirical Economic*s, 32, 359–86.

- Sacerdote, B. (2011) Chapter 4 - Peer Effects in Education: How Might They Work, How Big Are They and How Much Do We Know Thus Far?, Editor(s): E. A. Hanushek, S. Machin, L. Woessmann, *Handbook of the Economics of Education*, Elsevier, Vol. 3, pp. 249-277, https://doi.org/10.1016/B978-0-444-53429-3.00004-1.

- Salinas, J. y D. Santín (2012) Selección escolar y efectos de la inmigración sobre los resultados académicos españoles en PISA 2006, *Revista de Educación,* 358. Mayo-agosto, pp. 382-405. *DOI: 10-4438/1988-592X-RE-2010-358-083*

- Schneeweis, N. & R. Winter-Ebmer (2007) Peer Effects in Austrian Schools, *Empirical Economics* 32:387–409. DOI 10.1007/s00181-006-0091-4

- Schnepf, S.V. (2007) Immigrants' educational disadvantage: an examination across ten countries and three surveys. *Journal of Population Economics*, 20, 527–545. https://doi.org/10.1007/s00148-006-0102-y

- Tourón, J., E. López, L. Lizasoain, M. J. García y E. Navarro (2018) Alumnado español de alto y bajo rendimiento en ciencias en PISA 2015: análisis del impacto de algunas variables de contexto, *Revista de Educación*, 380. Abril-Junio 2018, pp. 156-184

- United Nations (2020) *International Migrant Stock*. Department of Economic and Social Affairs, Population Division.

- Vandenberge, V. (2006) Achievement effectiveness and equity: the role of tracking, grade repetition and inter-school segregation, *Applied Economics Letters*, 13:11, 685-693. DOI: https://doi.org/10.1080/13504850500404944

- Zinovyeva, N., F. Felgueroso and P. Vazquez (2014) Immigration and student achievement in Spain: evidence from PISA. *SERIEs* 5, 25–60. https://doi.org/10.1007/s13209-013-0101-7

TABLE 1. Descriptive statistics

		GERMANY		ITALY		FRANCE		UNITED KINGDOM		SPAIN	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Student Variables	Female	**0.46**	0.50	**0.49**	0.50	**0.50**	0.50	**0.51**	0.50	**0.50**	0.50
	ESCS	**-0.09**	1.04	**-0.21**	0.91	**-0.03**	0.90	**0.27**	0.91	**-0.12**	1.04
	Mig. 2nd gener.	**0.14**	0.34	**0.05**	0.22	**0.10**	0.29	**0.11**	0.31	**0.05**	0.21
	Mig 1st age arr.(0-6)	**0.03**	0.17	**0.04**	0.18	**0.04**	0.19	**0.06**	0.24	**0.06**	0.25
	Mig 1st age arr.(7-16)	**0.04**	0.20	**0.02**	0.15	**0.03**	0.17	**0.05**	0.22	**0.04**	0.18
	Other language	**0.20**	0.40	**0.20**	0.40	**0.11**	0.31	**0.13**	0.34	**0.27**	0.45
	January-March	**0.25**	0.43	**0.22**	0.42	**0.24**	0.43	**0.27**	0.44	**0.23**	0.42
	October-December	**0.25**	0.43	**0.26**	0.44	**0.25**	0.44	**0.25**	0.43	**0.26**	0.44
	Student truancy	**0.04**	0.19	**0.06**	0.24	**0.11**	0.32	**0.02**	0.13	**0.05**	0.23
	Parents support	**0.25**	0.44	**0.32**	0.47	**0.48**	0.50	**0.49**	0.50	**0.37**	0.48
	Good Reput. School	**0.41**	0.49	**0.68**	0.47	**-**	-	**-**	-	**-**	-
	Trying hard	**0.02**	0.95	**0.00**	0.94	**-0.02**	0.98	**0.21**	0.97	**0.16**	0.99
	Teacher enthusiasm	**-0.12**	0.97	**-0.07**	0.95	**0.03**	1.02	**0.23**	0.98	**0.04**	1.04
	Repeat	**0.17**	0.37	**0.12**	0.33	**0.14**	0.35	**0.02**	0.15	**0.28**	0.45
School Variables	Disadv. mig. (> 20%)	**0.34**	0.47	**0.06**	0.24	**0.11**	0.31	**0.18**	0.38	**0.05**	0.22
	Disadv. nat. (> 30%)	**0.29**	0.46	**0.28**	0.45	**0.20**	0.40	**0.27**	0.44	**0.26**	0.44
	Advantaged (> 40%)	**0.35**	0.48	**0.23**	0.42	**0.23**	0.42	**0.26**	0.44	**0.19**	0.39
	Gr. by abil. (betw. class)	**0.22**	0.41	**0.12**	0.32	**0.14**	0.35	**0.78**	0.42	**0.36**	0.48
	Gr. by abil. (with. class)	**0.34**	0.48	**0.46**	0.50	**0.39**	0.49	**0.53**	0.50	**0.40**	0.49
	Village	**0.01**	0.11	**0.01**	0.11	**0.02**	0.12	**0.04**	0.19	**0.03**	0.16
	Small town	**0.24**	0.43	**0.16**	0.37	**0.22**	0.41	**0.18**	0.38	**0.24**	0.43
	City	**0.15**	0.36	**0.19**	0.39	**0.15**	0.36	**0.20**	0.40	**0.23**	0.42
	Large city	**0.09**	0.29	**0.08**	0.27	**0.06**	0.24	**0.11**	0.31	**0.10**	0.30
	Private	**0.01**	0.07	**0.02**	0.12	**0.07**	0.26	**0.07**	0.26	**0.06**	0.24
	Priv. Gov. Funded	**0.03**	0.17	**0.01**	0.11	**0.08**	0.27	**0.45**	0.50	**0.24**	0.43
	Stu. Admis. Record	**0.34**	0.48	**0.42**	0.49	**0.23**	0.42	**0.14**	0.35	**0.03**	0.16
	Stu. Admis. Resid	**0.44**	0.50	**0.29**	0.45	**0.60**	0.49	**0.41**	0.49	**0.61**	0.49
	Class size ≤20	**0.11**	0.31	**0.23**	0.42	**0.05**	0.22	**0.10**	0.29	**0.10**	0.29
	Class size >40	**0.00**	0.06	**0.02**	0.13	**0.00**	0.00	**0.00**	0.07	**0.13**	0.34
	Staff short	**0.38**	0.79	**0.46**	0.92	**0.03**	0.84	**-0.19**	0.92	**0.33**	0.92
Observations (students)		5,451		11,785		6,308		13,818		35,943	

		GERMANY	ITALY	FRANCE	UNITED KINGDOM	SPAIN
Country data	Age 1st track	10	14	15	16	16
	Number study programs	5	4	3	1	2
	Edu. sp. (2012-18) % GDP	2.18	1.91	2.54	2.51	1.73
	Edu. sp. (2012-18) $/stu.	12,149	9,634	12,052	11,499	9,294

Source: Source: Author's calculations using the PISA 2018 database and OECD (2022).

Note: Spending on secondary education includes instruction and ancillary services for students and families provided through educational institutions, public and private. For more details, see OECD (2022).

TABLE 2: International migrant stock by area of origin and development group (1995-2015)

	Germany		Italy		France		United Kingdom		Spain	
	1995	**2015**	**1995**	**2015**	**1995**	**2015**	**1995**	**2015**	**1995**	**2015**
Total immigrants (thousands)	7,464	10,220	1,775	5,805	6,088	7,878	4,155	8,407	1,020	5,891
Immigrant/population ratio	0.09	0.12	0.03	0.10	0.11	0.12	0.07	0.13	0.03	0.13
distribution according to area of origin										
WORLD	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Sub-Saharan Africa	0.02	0.02	0.09	0.07	0.09	0.13	0.14	0.15	0.03	0.04
Northern Africa and W. Asia	0.25	0.19	0.22	0.13	0.36	0.42	0.06	0.05	0.19	0.14
Central and Southern Asia	0.07	0.13	0.06	0.08	0.02	0.02	0.22	0.22	0.01	0.02
Eastern and South-E. Asia	0.03	0.04	0.08	0.06	0.06	0.06	0.09	0.09	0.02	0.04
Latin America and the Carib.	0.01	0.02	0.09	0.10	0.02	0.04	0.07	0.05	0.26	0.38
Oceania (excl. Australia & N.Z.)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Australia and New Zealand	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.02	0.00	0.00
Europe and Northern America	0.62	0.60	0.46	0.55	0.46	0.33	0.40	0.41	0.49	0.39
distribution according to development group										
Developed regions	0.62	0.61	0.47	0.56	0.46	0.34	0.44	0.44	0.49	0.39
Less developed regions	0.38	0.39	0.53	0.44	0.54	0.66	0.56	0.56	0.51	0.61

Source: United Nations (2020).

TABLE 3.- Migrant educational gap in the PISA 2018 mathematics test

	GERMANY		ITALY		FRANCE		UNITED KINGDOM		SPAIN	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
A.- BASIC MODEL										
Mig. 2nd gener.	**-38.49*** **	6.53	**-26.66*** **	6.97	**-46.41*** **	6.13	**-18.51*** **	5.34	**-27.96*** **	4.55
Mig 1st age arr.(0-6)	**-24.27***	12.73	**-38.22*** **	8.23	**-38.54*** **	8.75	**-16.72*** **	5.92	**-36.44*** **	3.91
Mig 1st age arr.(7-16)	**-95.51*** **	10.25	**-44.81*** **	10.56	**-70.07*** **	12.54	**-6.52**	10.55	**-65.12*** **	6.73
Other language	**-9.20** **	3.92	**-15.52*** **	3.82	**-20.45*** **	4.57	**-33.87*** **	3.97	**-18.06*** **	2.60
Constant	**513.35*** **	3.06	**495.47*** **	3.06	**507.26*** **	2.69	**509.52*** **	2.87	**492.56*** **	1.59
R^2	0.05		0.02		0.04		0.02		0.04	
N	5,376		11,426		6,166		13,770		35,785	
B.- BASIC MODEL + ESCS										
ESCS	**35.38*** **	1.91	**32.65*** **	2.16	**45.12*** **	2.265	**33.64*** **	1.850	**28.16*** **	0.81
Mig. 2nd gener.	**-18.44*** **	6.30	**-10.16**	6.84	**-18.72*** **	6.010	**-9.73***	5.431	**-10.93*** **	4.15
Mig 1st age arr.(0-6)	**-22.42***	13.00	**-28.25*** **	8.06	**-25.22*** **	8.313	**-10.76***	6.121	**-26.41*** **	3.75
Mig 1st age arr.(7-16)	**-69.83*** **	9.95	**-29.71*** **	10.22	**-45.72*** **	11.111	**0.67**	8.564	**-51.58*** **	6.68
Other language	**-18.34*** **	3.63	**-16.37*** **	3.69	**-19.12*** **	3.783	**-30.55*** **	3.738	**-17.72*** **	2.33
Constant	**522.53*** **	2.58	**501.49*** **	2.89	**505.53*** **	2.233	**500.88*** **	2.577	**494.90*** **	1.37
R^2	0.21		0.12		0.23		0.13		0.15	
N	4,588		11,141		6,038		12,845		35,138	
C.- BASIC MODEL + ESCS + SEGREGATION										
ESCS	**20.79*** **	2.07	**13.95*** **	2.038	**25.70*** **	1.78	**23.13*** **	1.72	**23.69*** **	0.81
Mig. 2nd gener.	**-14.68*** **	5.07	**-15.57*** **	5.923	**-21.75*** **	5.03	**-7.74**	5.50	**-12.42*** **	4.07
Mig 1st age arr.(0-6)	**-15.62**	10.73	**-26.01*** **	7.327	**-22.98*** **	7.77	**-10.85***	6.00	**-27.16*** **	3.70
Mig 1st age arr.(7-16)	**-54.93*** **	9.63	**-32.56*** **	10.609	**-30.76*** **	8.92	**1.78**	7.83	**-52.39*** **	6.57
Other language	**-14.51*** **	3.56	**-12.23*** **	3.287	**-13.18*** **	3.32	**-28.91*** **	3.52	**-18.03*** **	2.25
Disadv. mig. (> 20%)	**-45.82*** **	7.25	**-49.36*** **	9.747	**-45.05*** **	9.06	**-18.08*** **	6.65	**-11.61** **	4.88
Disadv. nat. (> 30%)	**-49.87*** **	8.46	**-74.50*** **	6.892	**-76.08*** **	7.27	**-19.08*** **	4.27	**-15.34*** **	2.52
Advantaged (> 40%)	**46.72*** **	6.19	**36.41*** **	7.559	**34.24*** **	4.96	**44.94*** **	6.14	**15.42*** **	3.03
Constant	**523.31*** **	4.77	**510.58*** **	4.060	**515.49*** **	3.08	**500.22*** **	2.88	**495.94*** **	1.60
R^2	0.32		0.27		0.37		0.18		0.16	
N	4,588		11,141		6,038		12,845		35,138	

Source: Author's calculations using the PISA 2018 database.

Note: Significance levels: *** 1%, ** 5%, * 10%.

TABLE 4.- OLS estimates of the full model without controls for stratification policies

		GERMANY		ITALY		FRANCE		UNITED KINGDOM		SPAIN	
		Coef.	**St. Err.**	**Coef.**	**St. Err.**	**Coef.**	**St. Err.**	**Coef.**	**St. Err.**	**Coef.**	**St. Err.**
Student Variables	Female	**-20.75*** **	3.28	**-24.55*** **	3.22	**-18.05*** **	2.19	**-19.42*** **	3.05	**-12.19*** **	2.13
	ESCS	**18.85*** **	1.70	**10.82*** **	1.89	**23.81*** **	1.70	**18.16*** **	1.80	**22.09*** **	0.87
	Mig. 2nd gener.	**-13.12** **	5.42	**-16.62*** **	5.93	**-23.10*** **	4.76	**-4.96**	6.01	**-10.63*** **	4.08
	Mig 1st age arr.(0-6)	**-18.55** **	9.05	**-23.25*** **	7.09	**-21.97*** **	8.06	**-6.90**	5.98	**-26.60*** **	3.91
	Mig 1st age arr.(7-16)	**-32.28*** **	9.41	**-28.02*** **	8.99	**-33.67*** **	9.55	**-3.18**	9.02	**-49.89*** **	6.87
	Other language	**-15.39*** **	3.71	**-10.55*** **	3.26	**-13.42*** **	3.42	**-31.83*** **	3.92	**-20.16*** **	2.41
	January-March	**8.71** **	3.37	**6.38** **	3.20	**5.46***	2.96	**-3.03**	3.55	**4.42***	2.42
	October-December	**-9.96*** **	3.62	**-4.35**	3.13	**-1.04**	2.66	**2.35**	3.75	**-11.29*** **	1.86
	Student truancy	**-12.11**	12.74	**-19.30***	10.93	**-13.49***	7.80	**-33.12*** **	11.97	**-7.45***	4.23
	Parents support	**-2.40**	3.44	**7.38** **	2.99	**3.27**	2.66	**3.88**	2.66	**5.22** **	2.29
	Trying hard	**2.36**	1.55	**-0.71**	1.55	**2.37**	1.44	**7.55*** **	1.42	**4.29*** **	0.81
	Teacher enthusiasm	**3.70** **	1.53	**3.10** **	1.51	**6.24*** **	1.37	**4.65*** **	1.58	**4.85*** **	1.11
	Good Reput. School	**17.25*** **	3.65	**17.33*** **	3.33	-	-	-	-	-	-
School Variables	Disadv. mig. (> 20%)	**-42.70*** **	9.52	**-32.68*** **	11.80	**-39.79*** **	9.51	**-22.65** **	9.05	**-9.97***	5.18
	Disadv. nat. (> 30%)	**-34.67*** **	8.89	**-63.77*** **	6.59	**-71.25*** **	7.94	**-18.50*** **	4.62	**-8.00*** **	2.94
	Advantaged (> 40%)	**44.53*** **	6.67	**37.16*** **	7.01	**30.60*** **	5.40	**23.24*** **	8.36	**11.35*** **	3.17
	Village	**-26.22***	15.09	**-4.41**	28.08	**-25.80**	21.49	**-8.46**	7.87	**-8.41***	4.54
	Small town	**1.42**	7.20	**18.38** **	8.07	**3.63**	5.80	**-7.11**	5.63	**-6.24** **	2.79
	City	**-12.86***	6.95	**14.56** **	6.92	**-9.58**	6.13	**-7.31**	4.56	**0.21**	2.68
	Large city	**8.94**	12.66	**-5.24**	8.37	**-0.14**	9.74	**-8.91**	7.36	**2.73**	5.45
	Private	**-35.49** **	17.59	**-11.73**	19.32	**9.54**	9.52	**32.38** **	15.95	**4.58**	6.15
	Priv. Gov. Funded	**-32.75** **	15.22	**-9.32**	12.77	**24.60** **	11.08	**3.46**	5.12	**-3.11**	2.87
	Stu. Admis. Record	**12.58** **	5.67	**9.58***	5.62	**6.34**	5.59	**25.40*** **	9.30	**-3.21**	5.68
	Stu. Admis. Resid	**-5.38**	5.30	**-2.19**	6.02	**14.00** **	6.73	**-0.95**	4.11	**-0.24**	2.36
	Class size ≤20	**-22.21** **	8.83	**-24.55*** **	6.24	**-26.96** **	11.61	**-20.39*** **	5.78	**-0.13**	3.88
	Class size >40	**-60.26*** **	13.69	**-25.71**	21.22	-	-	**2.39**	11.63	**2.36**	3.48
	Staff short	**-9.83** **	3.92	**4.04**	3.08	**-2.39**	2.84	**-1.29**	2.36	**-2.82** **	1.23
	Constant	**535.17*** **	8.03	**502.50*** **	6.92	**514.63*** **	9.51	**514.39*** **	6.75	**497.81*** **	4.78
	R^2	0.34		0.31		0.39		0.23		0.18	
	N	3,606		10,244		5,000		9,994		32,249	
	Region FE	No		Yes		No		Yes		Yes	
	Program FE	No		No		No		No		No	

Source: Author's calculations using the PISA 2018 database.

Note: Significance levels: *** 1%, ** 5%, * 10%.

TABLE 5.- OLS estimates of the full model with controls for within school ability grouping

		GERMANY		ITALY		FRANCE		UNITED KINGDOM		SPAIN	
		Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Stu. Variables	ESCS	18.325***	1.716	10.861***	1.893	23.686***	1.655	18.203***	1.795	22.087***	0.874
	Mig. 2nd gener.	-13.404**	5.418	-16.740***	5.953	-23.116***	4.759	-5.134	5.976	-10.596***	4.085
	Mig 1st age arr.(0-6)	-18.866**	9.119	-23.324***	7.124	-21.931***	8.038	-7.029	5.989	-26.609***	3.898
	Mig 1st age arr.(7-16)	-31.975***	9.371	-27.954***	8.944	-33.836***	9.453	-3.809	8.992	-49.860***	6.875
	other language	-15.179***	3.613	-10.470***	3.269	-13.469***	3.422	-31.925***	3.891	-20.141***	2.419
School Variables	Disadv. mig. (> 20%)	-45.359***	9.310	-32.156***	11.161	-39.826***	9.400	-24.044***	8.829	-9.899*	5.177
	Disadv. nat. (> 30%)	-28.717***	8.636	-63.284***	6.686	-71.207***	7.930	-18.977***	4.594	-7.984***	2.933
	Advantaged (> 40%)	39.743***	7.392	36.636***	6.874	31.160***	5.539	22.869***	8.257	11.367***	3.099
	Group by abil. (betwe. class)	-18.264***	6.955	2.757	8.834	-1.862	5.658	-9.665	7.620	0.635	2.266
	Group by abil. (within class)	-9.626	6.018	-4.846	5.849	-3.087	5.309	3.220	4.298	-0.694	2.330
	constant	544.378***	7.960	504.455***	7.743	515.739***	7.739	522.355***	10.066	497.769***	4.683
	R^2	0.353		0.310		0.387		0.230		0.178	
	N	3,606		10,244		5,000		9,994		32,249	
	Region FE	No		Yes		No		Yes		Yes	
	Program FE	No		No		No		No		No	

Source: Author's calculations using the PISA 2018 database.

Note: Significance levels: *** 1%, ** 5%, * 10%. All student and school explanatory variables used in Table 4 are included in the model.

TABLE 6.- OLS estimates of the full model with controls for grade repetition

		GERMANY		ITALY		FRANCE		UNITED KINGDOM		SPAIN	
		Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Stu. Variables	ESCS	16.612***	1.708	9.415***	1.925	21.932***	1.548	17.718***	1.811	12.137***	0.882
	Mig. 2nd gener.	-13.331**	5.227	-12.361**	5.998	-20.759***	4.830	-5.548	5.946	-5.705	4.033
	Mig 1st age arr.(0-6)	-16.127*	9.094	-20.548***	7.103	-19.941***	7.523	-5.963	5.983	-16.170***	3.784
	Mig 1st age arr.(7-16)	-27.263***	9.452	-24.717***	9.162	-27.751***	9.266	-0.305	8.705	-34.023***	6.749
	other language	-15.154***	3.464	-9.863***	3.215	-12.068***	3.176	-31.768***	3.894	-16.659***	2.335
	Repeat	-44.176***	4.708	-42.144***	4.754	-74.302***	6.663	-43.919***	10.714	-85.537***	2.742
School Variables	Disadv. mig. (> 20%)	-39.039***	8.629	-27.493**	11.768	-20.068***	6.876	-23.930***	8.713	-8.202*	4.749
	Disadv. nat. (> 30%)	-26.541***	8.279	-60.604***	6.872	-42.347***	6.198	-18.448***	4.511	-7.030**	2.766
	Advantaged (> 40%)	37.402***	6.941	34.598***	6.894	29.559***	5.374	23.227***	8.203	9.188***	2.921
	Group by abil. (betwe. class)	-16.546**	6.820	3.279	8.887	-3.324	4.537	-10.941	7.409	1.522	2.345
	Group by abil. (within class)	-10.996*	5.723	-5.877	5.818	-5.736	4.162	2.861	4.246	-1.586	2.308
	constant	555.051***	7.701	510.590***	7.621	519.983***	6.966	524.372***	9.950	528.436***	4.852
	R^2	0.385		0.330		0.439		0.235		0.338	
	N	3,606		10,244		5,000		9,994		32,249	
	Region FE	No		Yes		No		Yes		Yes	
	Program FE	No		No		No		No		No	

Source: Author's calculations using the PISA 2018 database.

Note: Significance levels: *** 1%, ** 5%, * 10%. All student and school explanatory variables used in Table 4 are included in the model.

TABLE 7.- Probability of repeating a course and immigration

	Native	2nd generation migrants	1st generation migrants			Total
			Age arrival 0-6	Age arrival 7-16	Total	
GERMANY	0.17	0.25	0.26	0.32	0.30	0.17
ITALY	0.11	0.28	0.22	0.31	0.30	0.13
FRANCE	0.14	0.24	0.25	0.37	0.35	0.16
UNITED KINGDOM	0.02	0.02	0.04	0.12	0.08	0.02
SPAIN	0.26	0.41	0.43	0.53	0.50	0.28

Source: Author’s calculations using the PISA 2018 database.

TABLE 8.- OLS estimates of the full model with controls for ISCED level and orientation

		GERMANY		ITALY		FRANCE		UNITED KINGDOM		SPAIN	
		Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Stu. Variables	ESCS	16.134***	1.667	8.342***	1.931	17.529***	1.557	17.720***	1.816	12.093***	0.880
	Mig. 2nd gener.	-13.595***	5.208	-10.974*	6.197	-23.155***	4.656	-5.592	5.953	-5.981	4.065
	Mig 1st age arr.(0-6)	-16.243*	9.325	-18.610***	7.138	-16.826**	7.511	-5.891	5.987	-16.209***	3.784
	Mig 1st age arr.(7-16)	-27.198***	9.396	-22.842**	8.815	-20.862**	8.570	-0.314	8.712	-34.358***	6.760
	other language	-14.763***	3.492	-9.454***	3.177	-12.054***	2.874	-31.728***	3.901	-16.675***	2.340
	Repeat	-45.023***	4.513	-40.310***	4.710	-31.651***	9.410	-43.964***	10.722	-84.724***	2.731
School Variables	Disadv. mig. (> 20%)	-38.707***	8.565	-17.572	12.418	-13.248*	6.771	-23.860***	8.709	-8.055*	4.687
	Disadv. nat. (> 30%)	-23.136***	8.043	-52.631***	7.463	-17.328***	5.516	-18.458***	4.501	-6.874**	2.764
	Advantaged (> 40%)	36.378***	7.140	26.213***	7.694	22.310***	5.240	23.218***	8.204	9.082***	2.905
	Group by abil. (betwe. class)	-15.805**	6.611	6.877	9.330	-3.458	4.010	-10.884	7.429	1.466	2.339
	Group by abil. (within class)	-11.362**	5.565	-7.423	5.757	-4.704	3.423	2.801	4.245	-1.582	2.298
	ISCED pre-vocational	-25.484	29.788	-	-	-66.070***	11.374	-20.011	51.691	-26.011***	9.648
	ISCED vocational	-66.147**	25.701	-21.194***	7.002	-64.568***	6.097	-18.578	35.100	-	-
	ISCED level 3	36.953**	18.383	-	-	61.359***	10.397	21.661	62.699	49.462	33.588
	constant	555.732***	7.438	523.262***	7.278	475.901***	11.955	502.698***	65.064	528.700***	4.829
	R^2	0.390		0.338		0.490		0.235		0.339	
	N	3,606		10,244		5,000		9,994		32,249	
	Region FE	No		Yes		No		Yes		Yes	
	Program FE	No		No		No		No		No	

Source: Author's calculations using the PISA 2018 database.

Note: Significance levels: *** 1%, ** 5%, * 10%. All student and school explanatory variables used in Table 4 are included in the model.

TABLE 9.- OLS estimates of the full model with controls for study programmes

		GERMANY		ITALY		FRANCE		UNITED KINGDOM		SPAIN	
		Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Stu. Variables	ESCS	11.698***	1.575	7.702***	1.848	17.436***	1.564	17.276***	1.813	12.093***	0.880
	Mig. 2nd gener.	-14.425***	4.768	-11.642*	6.301	-23.303***	4.685	-5.203	5.877	-5.981	4.065
	Mig 1st age arr.(0-6)	-12.490	8.942	-15.793**	7.213	-16.606**	7.559	-5.746	5.982	-16.209***	3.784
	Mig 1st age arr.(7-16)	-20.956**	8.669	-19.547**	8.720	-21.067**	8.577	-0.186	8.692	-34.358***	6.760
	other language	-11.086***	3.129	-9.154***	3.176	-11.819***	2.889	-31.436***	3.902	-16.675***	2.340
	Repeat	-35.369***	4.332	-38.085***	4.592	-31.601***	9.379	-45.697***	10.844	-84.724***	2.731
School Variables	Disadv. mig. (> 20%)	-16.729**	8.318	5.606	12.058	-13.406**	6.776	-23.956***	8.682	-8.055*	4.687
	Disadv. nat. (> 30%)	-11.352*	6.367	-42.655***	8.558	-16.992***	5.492	-18.557***	4.484	-6.874**	2.764
	Advantaged (> 40%)	10.630*	5.475	27.709***	7.540	22.647***	5.262	22.557***	8.153	9.082***	2.905
	Group by abil. (betwe. class)	-3.125	5.278	7.248	9.077	-3.475	3.985	-12.835*	7.458	1.466	2.339
	Group by abil. (within class)	2.991	4.570	-7.831	5.626	-4.756	3.450	2.614	4.257	-1.582	2.298
	constant	578.139***	5.758	520.416***	6.982	536.919***	5.499	525.754***	9.990	528.700***	4.829
	R^2	0.456		0.352		0.491		0.242		0.339	
	N	3,606		10,244		5,000		9,994		32,249	
	Region FE	No		Yes		No		Yes		Yes	
	Program FE	Yes		Yes		Yes		Yes		Yes	

Source: Author's calculations using the PISA 2018 database.

Note: Significance levels: *** 1%, ** 5%, * 10%. All student and school explanatory variables used in Table 4 are included in the model.

TABLE 10.- Analysis of variance on the mathematics test results

	GERMANY	ITALY	FRANCE	UNITED KINGDOM	SPAIN
Within-school ability grouping	0.058	0.002	0.000	0.008	0.001
Grade repetition	0.060	0.082	0.226	0.011	0.260
Study programmes	0.392	0.221	0.411	0.022	0.012
Schools	0.475	0.492	0.495	0.235	0.160
ESCS	0.180	0.109	0.211	0.116	0.123

Source: Author's calculations using the PISA 2018 database.