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School Segregation in Europe by Immigrant Status: Does the Distribution of Resources Exacerbate its Effects?*

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Abstract

In this paper, firstly, we offer a methodological framework to assess the between-school sorting of any target group of students (grouped by either family socioeconomic status, nativity, race, ethnicity, or any other characteristic) taking into account school resources adjusted for educational needs. We develop a family of indicators, which meet several basic criteria, with which we can analyze school segregation and school opportunities to learn in an integrated way. Secondly, we provide a comparative analysis in Europe of the between-school sorting of students by birthplace drawing on PISA 2022. Distinguishing among students from three family backgrounds (natives, first-generation immigrants, and second-generation immigrants), we document that, in many countries, segregation is accompanied by important differences about the human resources per pupil of schools, especially when school educational needs are taken into account, which accentuates the transmission of inequality. However, not all countries share this pattern or do not do it with the same intensity.

JEL Classification: D63; I24

Keywords: School segregation; school resources; school needs; immigrant children

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1. Introduction

Education is a key element for the development of individuals and the progress of society as a whole. Any schooling system should work as a social elevator, reducing the dependence of any generation's human capital, and therefore their earnings and well-being, on that of their parents. However, there is worldwide evidence of persistent between-school segregation by socioeconomic background, race, ethnicity, and nativity (Chmielewski and Savage, 2015; Brunello and De Paola, 2017; Gutiérrez et al., 2020; Owens, 2020; US Government Accountability Office (GAO), 2022).

Between-school segregation results in disparities in the educational achievements and opportunities of children from different social and economic backgrounds, whether due to school composition effects associated with school climate, teachers' expectations, teachers' experience and skills, support services, quantity/quality of school material resources, or curricula design (Chiu and Khoo, 2005; Dumay and Dupriez, 2008; Perry et al., 2022; Sciffer et al., 2022; Reardon et al., 2022; Rodríguez-Pose and Henry de Frahan, 2024). Moreover, the effects of segregation during childhood can extend to academic performance in college (Massey and Fischer, 2006). But beyond halting social mobility, separating students from different family backgrounds breaks the key role that any school system should play in building social cohesion.

To measure between-school segregation, most studies use indicators of unevenness that allow the comparison of only two distributions of students across schools, the socially disadvantaged and the privileged. This is the case, for example, of the well-known dissimilarity index and the square root index (Jahn et al.,1947; Duncan and Duncan, 1955; Hutchens, 2001) often used in studies. However, in empirical analyses it is often the case that a multigroup framework is advisable. To address this, scholars frequently set different thresholds to define the socially disadvantaged group and consider the advantaged group as the complementary one. Next, they calculate the corresponding binary segregation index for each of these thresholds. Likewise, they establish different thresholds for the advantaged group and calculate the segregation between each of these groups and their complementary group.

Yet, the literature provides various segregation measures, meeting basic criteria, with which the unevenness of more than two groups of students could be addressed (Reardon and Firebaugh, 2002; Frankel and Volij, 2011; Del Río and Alonso-Villar, 2022). These indices, called overall or aggregate multigroup segregation measures, allow us to move beyond pairwise comparisons, considering the simultaneous comparisons of all the students' groups into which the total population is partitioned (for example, those who belong to families with a low, intermediate, or high socioeconomic background). The literature also provides indicators, called local segregation measures to distinguish them from overall segregation measures, with which the unevenness of each group can be determined in a way that is consistent with how total unevenness is measured (Alonso-Villar and Del Río, 2010; Del Río and Alonso-Villar, 2022). In fact, the simultaneous unevenness of the different groups into which the total population is partitioned can be written as the weighted average of the unevenness of each group. In other words, the overall segregation of students by family background can be expressed as the weighted sum of the local segregation of students from each family origin.[1]

Segregation indices, whether binary or multigroup, overall or local, only allow to quantify the extent of the clustering of students from different family origins in different schools but not assess the between-school sorting. This paper seeks to extend the literature on school segregation by exploring whether the distribution of resources across schools accentuates the problem of "separation" by concentrating resources in schools that mainly serve students from the privileged group. If there were no segregation, differences in resources per pupil across schools would not impact some social groups more than others. However, to the extent that segregation by family background or race exists, an unequal distribution of resources may translate into different opportunities for children of different groups. On the other hand, schools' educational needs vary with their composition. For example, a school with low-income students or students from an immigrant background may require additional resources to provide its students the same chance of meeting academic standards as schools without additional needs. If all schools had a similar number of resources per pupil, after adjusting for those needs, the consequences of segregation in terms of education opportunities would

[1] As we discuss later on, with several unstandardized overall indices existing in the literature, the weight of each group in this decomposition is equal to its population share.

not be so important (beyond the other peer effects mentioned above). However, to the extent that the adjusted resources per pupil are not the same among schools, the consequences of school segregation in terms of educational gaps among groups widen.

The aim of this paper is twofold. The first goal is to offer a methodological framework to assess the distribution of any group of students (grouped by either family socioeconomic status, nativity, race, ethnicity, or any other characteristics) across schools that differ in terms of resources and educational needs. We seek to develop indicators, meeting some basic criteria, with which to analyze school segregation and school opportunities to learn in an integrated way. To build this framework, we draw on Del Río and Alonso-Villar (2015) and Alonso-Villar and Del Río (2017) and adapt their occupational segregation approach to our context. Within this setting, we incorporate the school resources per pupil, which are adjusted for educational needs associated with the schools' composition. The adjusted resources per pupil that we define are in line with the cost-adjusted resources used in Bifulco and Souders (2024).

The second aim is to provide a cross-country analysis in Europe of the between-school sorting of students by nativity in a multigroup context. We distinguish among natives, first-generation immigrants, and second-generation immigrants. Our analysis draws on PISA 2022 (Programme for International Student Assessment) data files for 15-year-old students provided by the OECD (Organization for Economic Cooperation and Development). Distinguishing among students from three family backgrounds, we seek to determine a) whether between-school segregation is accompanied by important differences in resources (adjusted by educational needs) across schools that could accentuate the transmission of inequality and b) whether this pattern differs across European countries.

The paper is structured as follows. In section 2, we discuss the related literature and explain how we depart from it. In Section 3, after presenting the segregation measures that we use in our empirical analysis, we develop the framework that allows us to assess the between-school sorting of students taking into account school resources and needs. In Section 4, we apply these measures to explore the situation of immigrant students in several European countries. Finally, Section 5 offers the main conclusions.

2. Background

Extensive literature for different countries documents that the socioeconomic status of families strongly shapes the educational outcomes and opportunities of their children (Sirin, 2005; Martins and Veiga, 2010; Duncan and Magnuson, 2011; Altonji and Mansfield, 2011; Duncan et al., 2012; Palardy, 2013). Children whose parents have higher educational attainments or income, or hold better occupations, tend to have better academic outcomes, although there is no agreement about the mechanisms behind this pattern, which include differences in social capital, material resources available at home, and time and resources invested in the children's cognitive development.

Drawing on the literature on economic inequality, part of this scholarship has focused on measuring inequality of opportunity in education, determining the inequality in achievements associated with students' circumstances, mainly parental background (Gamboa and Waltenberg, 2012; Ferreira and Gignoux, 2014; Lasso de la Vega et al., 2019; Palmisano et al., 2022). In other words, these studies quantify the fraction of inequality that remains after removing the effect of the student's effort, which is the only factor under their control and, therefore, the only source of acceptable variability from a fairness perspective (Roemer and Trannoy, 2015). Other studies explore the association between students' educational achievements and family background using various regression models (Schütz et al., 2008; Burger, 2019).

The literature has also explored the extent to which students from privileged and disadvantaged groups, whether defined based on income, race, or immigrant status, are unevenly distributed across schools. Most cross-country studies on school segregation from an unevenness perspective have focused on segregation by socioeconomic status (Jenkins et al., 2008; Murillo and Martínez-Garrido, 2017; Krüger, 2019; Gutiérrez et al., 2020, inter alia). On the contrary, comparative analyses on unevenness by immigrant status are scarce (Gorard and Smith, 2004; Park and Kyei, 2010; Murillo and Martínez-Garrido, 2017), with little recent evidence for Europe (Brunello and De Paola, 2017).[2]

[2] Holmlund and Björn (2021) explore segregation in Europe following a different approach, intraclass correlation, which measures the ratio of the between-school variation in predicted test scores and total variance.

The separation of students from different social groups fosters educational inequalities to the extent that students' outcomes are also influenced by their peers, many of whose effects are detected at the school level (Chiu and Khoo, 2005; Dumay and Dupriez, 2008; Perry et al., 2022; Sciffer et al., 2022; Reardon et al., 2022). The channels of these peer effects are multiple and often intertwined, including school environment in terms of discipline and behavior (Liu et al., 2015; Rodríguez-Pose and Henry de Frahan, 2024), teachers' expectations about students' performance (Brault et al., 2014), teachers' qualifications and experience and quantity of teachers (Chiu and Khoo, 2005; Reardon et al., 2022), and quality of the programs (Reardon et al., 2022). A few papers also document disparities in academic performance arising from disparities in financial/material resources (Chiu and Khoo, 2005).

The consequences of school segregation can be exacerbated if school resources do not take into account the extra services necessary so that students from disadvantaged families have the same opportunities to achieve educational standards as students from other families. Some US-based studies document the extra cost per pupil for students of poor families and those with limited English proficiency. In some cases, the cost per student can double the cost of students without that characteristic (Duncombe and Yinger, 2005; Bifulco and Souders, 2024). The literature also shows that, even if financial resources per pupil are greater in schools or districts in which the disadvantaged group tends to cluster (Bischoff and Owens, 2019; Bifulco and Souders, 2024), when accounting for school needs associated with their composition, the situation of disadvantaged social groups worsens making it impossible to secure equal educational opportunities. As Bifulco and Souders (2024) point out, in the US, the "per-pupil spending in the average Black and Hispanic students' schools are, respectively, 8.8% and 5.1% higher than the average white students schools" but when taking into account the cost-adjusted per-pupil spending, in typical Black student's school the spending is between zero and 14.1% less than that of typical White students' school. In the case of the typical Hispanic student's school, the spending is between 3.3% and 17.3% lower.

Although a few studies analyze financial resources per pupil at the school or district level in the US (Bischoff and Owens, 2019; Bifulco and Souders, 2024), little is known outside this country because financial resources per school are usually publicly unavailable information. In particular, we do not know much about whether the distribution of adjusted resources per pupil across schools in Europe accentuates the problem of school segregation (by concentrating resources in the schools where the advantaged group tends to cluster) and if this channel operates in all countries equally.

In this paper, we propose a general framework to assess the between-school sorting of students taking into account the resources per pupil of schools and the schools' educational needs, which depend on their composition. We apply this approach, using teaching staff resources and extra needs associated with students born abroad, for several European countries drawing on PISA 2022.[3] To build this framework, we draw on Del Río and Alonso-Villar (2015) and Alonso-Villar and Del Río (2017), who address segregation in the labor market, and adapt their approach to our context.

The first methodological novelty of our setting is that, to evaluate the between-school sorting of children from a certain family background, we build indices that simultaneously account for how unevenly distributed children are and whether they tend to cluster in schools with material, human, or financial resources per pupil that are above or below the average, given that this could affect students' performance. We establish some criteria for measuring this and put forward a family of indices that meet them. We parameterize this family using a parameter that accounts for the inequality that exists within the group for attending schools with different resources per pupil. This is done in a way similar to what is done in the literature of income inequality when accounting for inequality aversion.

The second methodological contribution is that our indicators take into account the adjusted resources of each school due to the fact that the needs of schools depend not only on their size but also on their composition. We parameterize the additional cost of students that require extra services with an α parameter that can take different values. The way we build the adjusted resources per pupil for each school is reminiscent of what is done in the literature on income distribution to determine family well-being by adjusting total family income by family composition using an equivalence scale. Our approach is also similar to that followed by Bifulco and Souders (2024), who put forward an indicator to calculate the average spending per pupil of a socially disadvantaged group relative to that of the advantaged group after accounting for the additional needs of schools. However, we depart from it by developing a general framework that involves comparing the situation of each group with the

[3] The method could also be implemented for countries with financial resource data per school.

national average rather than with another group. Our approach, which can be used in a multigroup context, offers a clear connection between segregation and the adjusted resources per pupil of schools.

3. A Framework to Assess Between-School Segregation

Let us assume that we have a country with *n* schools and that we have partitioned all the population of students into several mutually exclusive groups. Let $s^g \equiv (s_1^g, s_2^g, \dots, s_n^g)$ be the between-school sorting of target group *g* (e.g., students of a certain family background) whose size is denoted by S^g ($S^g = \sum_i s_i^g$). Let us denote by $t \equiv (t_1, t_2, \dots, t_n)$ the distribution of all students across schools ($t_i = \sum_g s_i^g$) and *T* is its size ($T = \sum_i t_i = \sum_g S^g$). In what follows, firstly, we offer the list of segregation indicators that we use in our empirical exercise and, secondly, we put forward a parameterized family of indices with which to assess the between-school sorting of the target group taking into account school resources and needs.

3.1 Overall Segregation and the Segregation of a Group in a Multigroup Context

Overall Segregation Indices

The literature provides a wide range of indicators to measure overall segregation in a multigroup context (i.e., to quantify the simultaneous disparities that exist among the distributions of three or more groups across schools). In our empirical analysis, we use three unstandardized segregation measures: the popular mutual information index *M* (proposed by Theil and Finizza, 1971, and explored by Frankel and Volij, 2011, in terms of basic properties), the generalized *Ip* index (developed by Silber, 1992, extending the Karmel and MacLachlan's (1988) index to a multigroup context), which we label here GI_p, and the unstandardized generalized Gini index (put forward by Alonso-Villar and Del Río, 2010, extending the Gini index proposed by Jahn et al, 1947, to a multigroup context), which we denote here by G_u. Namely,

$$M = \sum_g \frac{S^g}{T} \left(\sum_j \frac{s_j^g}{S^g} ln \frac{s_j^g / S^g}{t_j / T} \right),$$

$$GI_p = \frac{1}{2} \sum_g \frac{S^g}{T} \left(\sum_j \left| \frac{s_j^g}{S^g} - \frac{t_j}{T} \right| \right), \text{ and}$$

$$G_u = \frac{1}{2}\sum_g \sum_{i,j} \frac{t_i}{T}\frac{t_j}{T}\left|\frac{s_i^g}{t_i} - \frac{s_j^g}{t_j}\right|.$$

The GI_p index has a very intuitive interpretation since it provides the population share (including all the groups into which the population is partitioned) that would have to change schools to remove segregation. The other two indices, which also have good properties (Alonso-Villar and Del Río, 2010; Frankel and Volij, 2011) are used to check the robustness of our results.

There is no consensus in the literature about whether unstandardized or standardized segregation measures should be used. In our empirical analysis we also use the standardized versions of the above indices, i.e., the ones that result from dividing them by their maximum values.[4] These indices are, respectively, the information theory index (Theil and Finizza, 1971), the generalized dissimilarity index (Morgan, 1975; Sakoda, 1981; Reardon and Firebaugh, 2002), and the standardized generalized Gini index (Reardon and Firebaugh, 2002). We keep here the labels used in Reardon and Firebaugh (2002), *H*, *D*, and *G*, respectively, who explore them in terms of basic properties.[5]

Local Segregation Indices

Along with the simultaneous discrepancies among all the groups into which the whole population is partitioned, in a multigroup context, we may be interested in determining the degree of unevenness of each group. To do this, we use several local segregation measures, called that way to distinguish them from overall segregation measures. In particular, we use several unstandardized measures: a Theil-type index labeled Φ_1^g (put forward by Alonso-Villar and Del Río, 2010), the index proposed by Moir and Shelby Smith (1979) and explored by Alonso-Villar and Del Río (2010) in terms of basic properties, which we denote by D^g, and the local Gini index, G^g (Alonso-Villar and Del Río, 2010):

$$\Phi_1^g = \sum_i \frac{s_i^g}{S^g} ln\left(\frac{\frac{s_i^g}{S^g}}{\frac{t_i}{T}}\right),$$

[4] The maximum value in the case of both GI_p and G_u is $\sum_g \frac{S^g}{T}\left(1 - \frac{S^g}{T}\right)$. The maximum for M is $\sum_g \frac{S^g}{T} ln\left(\frac{T}{S^g}\right)$.

[5] Del Río and Alonso-Villar (2022) discus the relationship between these standardized measures and the unstandardized ones.

$$D^g = \frac{1}{2}\sum_i \left|\frac{s_i^g}{S^g} - \frac{t_i}{T}\right|, \text{ and}$$

$$G^g = \frac{\sum_{i,j}\frac{t_i}{T}\frac{t_j}{T}\left|\frac{s_i^g}{t_i} - \frac{s_j^g}{t_j}\right|}{2\frac{S^g}{T}}.$$

The D^g index, also called Gorard's index, has a very intuitive interpretation. It measures the proportion of individuals of group g that would have to change schools to be evenly distributed throughout them. An advantage of Φ_1^g is that it is decomposable in a way which is especially convenient in the case of school segregation, as we discuss below. In the empirical analysis, we use the three indices to check the robustness of our findings. We also use their standardized versions, i.e., $\tilde{\Phi}_1^g$, $\tilde{D}^g$, and $\tilde{G}^g$, respectively (Del Río and Alonso-Villar, 2022), whose expressions can be obtained from the above by dividing them by their maximum values.[6]

All these local segregation indices have been chosen based on their links to the above overall segregation measures (Del Río and Alonso-Villar, 2022). The local indices Φ_1^g, D^g, and G^g are related to the overall indices M, GI_p, and G_u, respectively, since overall segregation can be expressed as the weighted average of the local segregation of each group (with weights equal to the groups' population shares). The local indices $\tilde{\Phi}_1^g$, $\tilde{D}^g$, and $\tilde{G}^g$ are related to the overall measures H, D, and G (although in this case, the weights are not equal to the population shares).[7]

In order to interpret the unstandardized segregation indices, we have to keep in mind that, in this case, unevenness means departing from the egalitarian distribution. However, when we use standardized indices, we look at unevenness from a different angle since we measure how close we are to the worse possible scenario, i.e., full segregation, which depends on the groups' sizes (Reardon and Firebaugh, 2002; Alonso-Villar and Del Río, 2022). The two

[6] The maximum value for both D^g and G^g is $1 - \frac{S^g}{T}$. The maximum for Φ_1^g is $ln\left(\frac{T}{S^g}\right)$.

[7] The weights in the case of D and G are $\frac{\frac{S^g}{T}\left(1-\frac{S^g}{T}\right)}{\sum_g \frac{S^g}{T}\left(1-\frac{S^g}{T}\right)}$. The weight for H is $\frac{\frac{S^g}{T} ln\left(\frac{T}{S^g}\right)}{\sum_g \frac{S^g}{T} ln\left(\frac{T}{S^g}\right)}$.

views are complementary since each of them uses an extreme distribution (the egalitarian distribution or the distribution of maximum segregation) as the benchmark. The egalitarian distribution does not depend on the size of the groups and, therefore, is the same for all of them. However, the distribution of maximum segregation of a group varies with its size. The larger the group, the more difficult it is to accommodate those students in a few schools.

Decomposing Index Φ_1^g

Index Φ_1^g is a member of a family of indices that are decomposable by subgroups of schools (Del Río and Alonso-Villar, 2010). This decomposition is quite useful in empirical analyses because it allows us to determine what part of the unevenness that we observe in a country arises from our target group (e.g., students born abroad) being unequally distributed across regions and what part arises from the segregation that the group experiences within regions.

Let us consider that we group schools by region or any other spatial criterion. At this point, it is convenient to express Φ_1^g as a function of distributions s^g and t. Index Φ_1^g can be decomposed in a within-region term and a between-region term as follows:

$$\Phi_1(s^g;t) = \sum_k \left({S^{gk}}/{S^g}\right)\Phi_1(s^{gk};t^k) + \Phi_1(S^{g1},\ldots,S^{gK};T^1,\ldots,T^K)\ ,$$

where S^{gk} is the number of students of group g who are in region k ($k = 1,\ldots,K$), T^k is the students' population in k. Vectors s^{gk} and t^k are, respectively, the distribution of group g and the distribution of all students across schools in region k. The first addend is a weighted average of the unevenness of target group g within each region k (taking the distribution of students across schools in that region as the benchmark) and the second addend represents the unequal distribution of group g across regions (neglecting the between-school segregation that exits within each region).

3.2 Assessing the Between-School Sorting of a Group: A Proposal

Let us denote by $r \equiv (r_1, r_2, \ldots, r_n)$ the distribution of resources of schools, adjusted for their needs, per pupil. To assess the between-school sorting of a target group g, we build an indicator I that is equal to zero when the group is evenly distributed across schools (i.e., when the share of children of group g in each school i equals the population share of the school,

$\frac{s_i^g}{S^g} = \frac{t_i}{T}$) and/or when all schools have the same adjusted resources per pupil (i.e., $r_i = r_j$ for any i and j) because in these two scenarios the distribution of the group across schools would not bring the group advantages or disadvantages. Ceteris paribus, the index should increase (decrease) when some students of the group move to another school with higher (lower) adjusted resources per pupil. Additionally, we want the index to be unaffected by the total size of the group, so that, ceteris paribus, if the group doubles in each school, the index does not change.[8]

To build an index that meet the above criteria, we adapt to our context the index proposed by Del Río and Alonso-Villar (2015) to assess occupational segregation:

$$I_0(s;t;r) = \sum_i \left(\frac{s_i^g}{S^g} - \frac{t_i}{T}\right)\frac{r_i}{\bar{r}},$$

where in our case $\bar{r}$ represents the average adjusted resources of schools per pupil (rather than the average salary of the economy). This index is negative (positive) so long as the group tends to be enrolled in schools with adjusted resources per pupil below (above) average. In other words, if the value of the index is, for example, -0.1, this means that, on average, group g attends schools with a ratio of adjusted resources per pupil which is 10% lower than the country's average ratio.

We propose to measure the adjusted resources per pupil of each school i by

$$r_i = \frac{h_i}{t_i(1+\alpha x_i)},$$

where h_i are the resources of school i (e.g., human resources or financial resources), t_i is the numbers of students enrolled in i, x_i represents the extra needs of the school given its educational circumstances, and α is a parameter that represents the additional resources that any child in those circumstances would need to achieve academic standards compared to a child not in those circumstances.[9] Variable x_i could involve several educational needs. Such

[8] For formal expressions of these properties in the case of occupational segregation, see Alonso-Villar and Del Río (2017), who labels them as *normalization*, *monotonicity regarding increasing-wage movements*, and *scale invariance*, respectively.

[9] In our empirical application, our population of students is that of 15-year-olds, but the information about resources is determined at the school level. In other words, we proxy the adjusted resources per pupil of 15-

as special learning needs, needs based on cultural or ethnic background (particularly when a different language is spoken), needs arising from socioeconomically disadvantaged homes, or a combination of the aforementioned characteristics.

To better understand this index, consider for example that we focus on human resources, which we can proxy by the total number of teachers, and that x_i is the proportion of immigrant students in the school. Given that α embeds the extra resources that an immigrant student needs to achieve the educational standards, the school needs could be expressed as the total number of students (t_i) plus the number of immigrant students (i.e., $t_i x_i$) multiplied by α, given that each immigrant student involves additional needs.

If $\alpha = 0$, then $r_i = \frac{h_i}{t_i}$ and, therefore, having students from an immigrant background would not require extra resources compared to a scenario with only native-born students. Each student from an immigrant background would count the same as a native student.

If $\alpha = 1$, and a half of the students are immigrants ($x_i = 0.5$), to have the same adjusted resources as a school with only native-born students, the school would need to increase the number of teachers by 50%. If x_i is instead 0.1, we would need to increase teaching staff by 10%. In other words, when $\alpha = 1$, to determine r_i, we consider that each native-born student counts as one, but each immigrant student counts as two. Namely, if we denote by t_i^{immig} and t_i^{native} the immigrant and native population, respectively, in school *i*:

$$r_i = \frac{h_i}{t_i(1+x_i)} = \frac{h_i}{t_i + t_i\left(\frac{t_i^{immig}}{t_i}\right)} = \frac{h_i}{t_i^{native} + t_i^{immig} + t_i^{immig}} = \frac{h_i}{t_i^{native} + 2t_i^{immig}}.$$

If α takes instead a value between zero and one, we would be in a situation between the two extremes just mentioned.[10] One student from an immigration background would count

year-old students in a school using the total number of the students in that school and the number of teachers and pedagogues there. Therefore, in our case, $r_i = \frac{h_i}{p_i(1+\alpha x_i)}$, where p_i is the size of the school *i*.

[10] For a discussion on the cost of disadvantaged students, see Duncombe and Yinger (2005). These authors estimate pupil weights for the US that reflect the extra cost that, on average, students belonging to disadvantaged groups would need to achieve the same academic standards as other students. This pupil weighting scheme is consistent with our approach and also with public founding schemes employed by governments.

between one and two native-born students in terms of teaching needs.[11] Given that we parameterize the extra cost per pupil to serve students with additional needs, we can assess the between-school sorting of the target group in different scenarios, which permits a general setting in which to compare different countries.

It is straightforward to see that I_0 meets the criteria we mentioned earlier. In particular, the index is positive as long as the group tends to be clustered in schools with adjusted resources per pupil above the national average and it is negative if the group tends to cluster in schools with adjusted resources per pupil below average. Additionally, it accounts for the fact that a given number of resources translates into higher or lower "education per pupil" depending on the needs of that school, which depends on its composition.

However, the above index does not take into consideration the inequality that exists within the target group arising from the fact that some children of the group attend schools with adjusted resources per pupil above the average while others do not. In other words, schools contributing positively to the index offset negative values of the same magnitude arising from other schools. To account for inequality aversion, i.e., if we want that an improvement for a student who is in a "better" school than another student in the group cannot compensate a worsening of the same magnitude for the latter, we require two additional properties.[12] Firstly, we want our index to increase when students in the target group move to another school with higher adjusted resources per pupil, and we want this increase to be greater, the lower the adjusted resources per pupil of their former school are. In other words, we want our index to increase more when students moving to better schools are those from schools with fewer resources. Secondly, when many students from the target group make small improvements (arising from switching to schools with a bit more resources), we want our index to increase more than it would when just a few students of the group move to much better schools.

[11] This is a conservative view, although in some circumstances, values of α above one could be appropriate (Bifulco and Souders, 2024). Different countries could have different α values.

[12] For formal definitions of these properties in the case of occupational segregation, and of additional properties of a more technical nature, see Alonso-Villar and Del Río (2017). The first property mentioned here corresponds to *sensitivity against increasing-wage movements*. The second property refers to *preference for egalitarian improvements*.

Drawing on Alonso-Villar and Del Río (2017), to assess the between-school sorting of group g, we can define the following family of indices:

$$I_{\varepsilon}(s;t;r) = \begin{cases} \sum_i \left(\frac{s_i^g}{S^g} - \frac{t_i}{T}\right) \frac{\left(\frac{r_i}{\bar{r}}\right)^{1-\varepsilon} - 1}{1-\varepsilon} & if \;\; \varepsilon \neq 1 \\ \sum_i \left(\frac{s_i^g}{S^g} - \frac{t_i}{T}\right) ln\left(\frac{r_i}{\bar{r}}\right) & if \; \varepsilon = 1 \end{cases},$$

which depends on a parameter ε>0 that shows inequality aversion, i.e., the larger the value of this parameter, the more the index cares for the inequality that exists within the group for attending schools with different ratios of adjusted resources per pupil. It is easy to see that these indices satisfy all the properties mentioned above.[13] Note that we can obtain the above index I_0 as a limit case of this family when the parameter tends to zero. In our empirical analysis, we use index I_0 (which has an intuitive interpretation) and I_1 (given that ε=1 is an inequality aversion value commonly used in the inequality literature).

4. An Illustration: School Segregation of Immigrants in Europe and School Resources

In this section, after presenting the data, we estimate the levels of school segregation by immigrant background in 12 European countries and assess in each of them the disadvantage (or advantage) that immigrant students face in terms of educational human resources. We distinguish between first-generation immigrant students (children born abroad) and second-generation immigrant students (children born in the country to parents born abroad). Following an evenness perspective, we use both multigroup overall segregation measures with which to simultaneously compare the distributions across schools of first-generation immigrants, second-generation immigrants, and natives, and local segregation indices that allow us to measure the degree of unevenness for each group. Next, we assess the distributions of first- and second-generation immigrants throughout schools taking into account the human resources that schools have (including teachers and pedagogical support) and their needs, which in this illustration depend on the proportion of first-generation immigrants in the school.

[13] The proofs in the case of occupational segregation can be seen in Alonso-Villar and Del Río (2017).

4.1 Data

To address this study, we use the information provided by PISA 2022 for 15-year-old students from 12 European countries: Austria, Belgium, Finland, France, Germany, Italy, Norway, Portugal, Spain, Sweden, Switzerland, and the UK. This selection of countries has been made taking into account the size of 1st and 2nd generation immigrant students in the PISA samples of the countries, since our aim is to be able to identify possible differences between students born abroad and those born in the country to parents born abroad.

Two public-use data files contain information from all countries that are part of the PISA sample: the student and the school file. The variables included in these files were constructed using standardized procedures that ensure that the results are comparable across countries. The Student Questionnaire collects information from students on various aspects of their home, family, and school background (as well as sampling weights and cognitive assessments). We use the variables involving students' weights ("W_FSTUWT"), the school they attend ("cntschid"), and the index on immigrant background ("immig"): native, second-generation immigrant, and first-generation immigrant.

The School Questionnaire collects information on various aspects of organization and educational provision in schools. To construct the adjusted resources per pupil of each school (which we then assign to each student in that school), we use the school educational human resources and its needs. School human resources are obtained adding up the total number of full-time teachers working at the school ("SC018Q01TA01"), the total number of part-time teachers ("SC018Q01TA02") divided by two (to adjust their working hours), and the total number of pedagogues ("SC168Q01JA"). We then divide the amount of human resources by a variable that reflects both the size of the school ("schsize") and the greater needs that schools with higher percentages of first-generation immigrant students have. Since PISA does not provide this latter information, we approximate it by the percentage of 15-year-old students who are first-generation immigrants ("SC211Q04JA").

In the case of Spain, the UK, and Belgium, given that the sample allows us to identify the region to which each school belongs ("region"), we can use the decomposability of index Φ_1^g (Del Río and Alonso-Villar, 2010), to estimate what part of the school segregation faced by group g (for example, first-generation immigrants) arises from the group's unequal distribution across regions and what part arises from the unevenness that the group experiences within each region.

Table A1 in the Appendix provides the size of the sample of 15-year-old students and schools in PISA 2022 by country, together with the sample loss (in percentage terms) due to lack of information about the immigrant background of 15-year-old students, school size (i.e., the total number of students in the school), or the number of teaching staff in the school. The last two variables do not affect the segregation analysis, but it might bias the assessment of the distributions of our target subgroups across schools if the lack of information does not involve native and immigrant students alike. As we can see, in Norway we lose the whole sample of schools. For this country, we cannot calculate the human resources per pupil because Norway does not provide information about the school size or number of teaching staff. This is why Norway is included in the segregation analysis but not in the assessment of the between-school sorting. The sample loss of schools is also important in France, Germany, Switzerland, Belgium, and the UK. In the case of the UK and Germany, we also lose an important share of 15-year-old students (22% and 12%, respectively) because there is no information about their immigrant background.[14]

To lose the smallest number of students in the sample, those schools that report the number of full-time teachers but not part-time teachers and pedagogues are kept in the sample assuming that the number of part-time teachers and pedagogues are zero. [15] Given that PISA does not provide information about the percentage of total students born abroad, we proxy it with the percentage within the 15-year-olds in those circumstances, an information provided by schools. When that information is missing, we take it from the sample.

[14] These percentages reach 42% and 32% of 15-year-olds when we jointly consider the lack of information about immigrant origin and school resources. This implies that the results for Germany and especially the UK should be taken with caution. In Belgium, Switzerland, and France the loss of students in the sample due to one reason or another also exceeds 20%.

[15] In Spain, we drop one school from the sample because its odd values (the school size is 100, teaching staff is 90, and it reports no special needs).

4.2 Measuring the Extent of Segregation

Measuring the Unevenness of Each Group Using Local Segregation Indices

Figure 1 shows how unevenly distributed across schools first- and second-generation immigrants are when we use the D^g index, which has an easy interpretation: it provides the proportion of children from group g that would have to change schools to be evenly distributed across them. Tables A2 and A3 in the Appendix provide the values using other indices for these two groups of immigrants and also for natives. All values are expressed multiplied by 100.

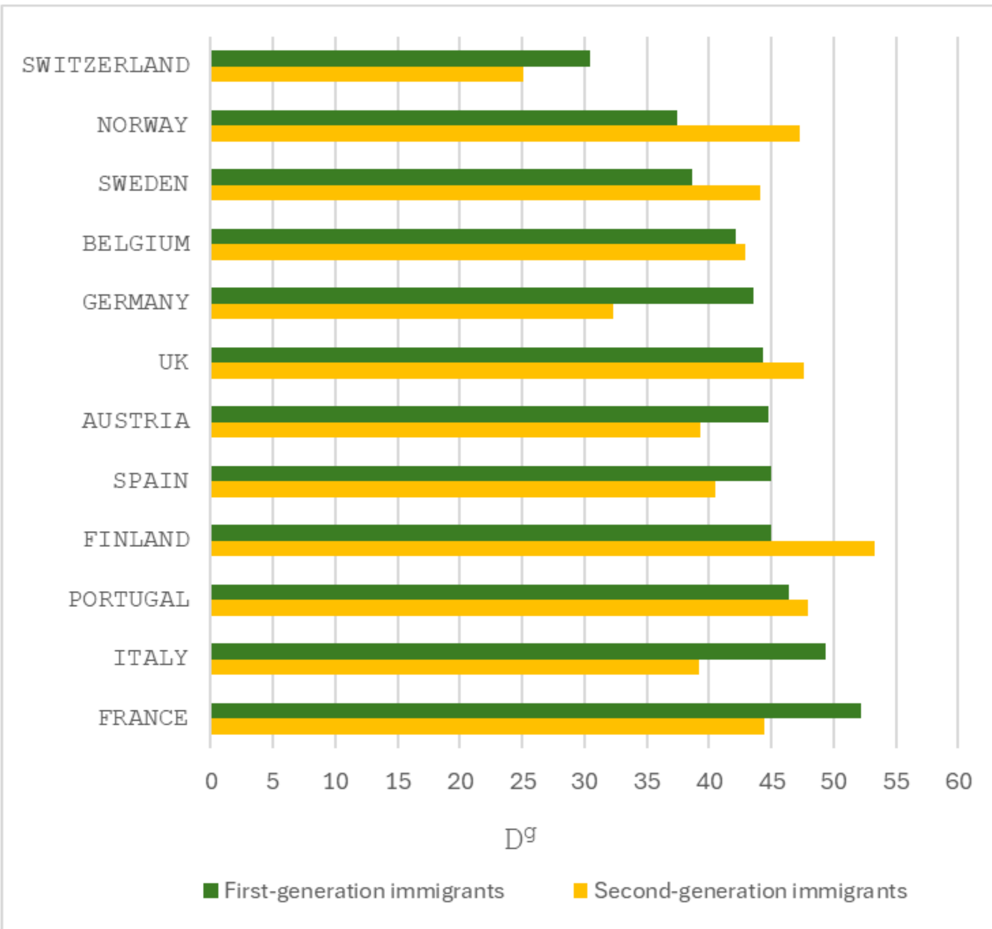

Figure 1. The unevenness of first- and second-generation immigrants using index D^g, PISA 2022

We see that in Switzerland, 30% of students born abroad would have to switch schools to be evenly distributed across schools (D^g=30.5), while in France the percentage rises to 52% (D^g=52.2). When using other indices (whether standardized or unstandardized), Switzerland also has the lowest value while France has the highest value.

In Norway and Sweden, the segregation of first-generation immigrant children tends to be lower than it is in other countries (except Switzerland). On the other side, we have Portugal and especially Italy, whose segregation levels tend to be higher than they are in the remaining countries (excluding France) when we use unstandardized indices, although when we use standardized measures, Germany, Austria, UK, and Spain also join the group of high unevenness. In France, the number of students born abroad who must change schools to be evenly distributed represents 55% of all students born abroad who would have to change in case of maximum unevenness ($\tilde{D}^g$ =55.1%). In Portugal, Italy, and Austria the percentage is around 50%, while in the UK, Germany, and Spain, the percentage is around 48%.

When comparing first- and second-generation immigrant children, we find that in some countries the segregation is lower for the latter. This is the case of Switzerland, Germany, Italy, Austria, Spain, and France. However, in Sweden and especially in Norway and Finland, the segregation of the second generation is significantly higher than that of the first generation. These patterns are robust to the different indices, standardized and unstandardized.

When looking at the second generation, Switzerland has again lower values than other countries with all the indices. Around 25% of children born in Switzerland whose parents were born abroad would have to change schools to be evenly distributed across schools. Germany comes next in the ranking (in this case, 32% of them would have to switch schools). On the other extreme, we have Finland and, to a lower extent, Norway, Sweden, France, UK, and Portugal, whose values tend to be higher than those of other countries with the various indices. The relative position of Italy in terms of second-generation immigrant children seems to be better than it is in terms of first-generation students, with lower segregation levels than other countries have. Austria has segregation levels like those of Italy when using the unstandardized indices, but with the standardized measures their values are higher than those of Italy.

How Does the Distribution of Immigrants Across Regions Affect Overall Segregation?

The level of unevenness of a group could be affected by the distribution of the immigrant population across regions. An even distribution of immigrant students across schools may be impossible to achieve if the immigrant population is concentrated in a given territory (city or region). In other words, not all schools are available to immigrant students given their geographical distribution. We deal with this problem by exploring whether the distribution of immigrant students (first and second generation) across regions help explain their level of unevenness. The analysis is undertaken for Spain, Belgium, and the UK, which are the countries for which PISA provides information at a regional level.[16] To do this, we use the within-between decomposition of the Φ_1^g (Del Río and Alonso-Villar, 2010) shown above, which allows us to determine whether the unevenness of the group arises mainly from differences in the distribution of group *g* across regions (this is the between term) or from the between-school unevenness that the group experiences within each region (the within term). Table 1 provides this decomposition in percentage terms.

Table 1. Unevenness of native and immigrant students with Φ_1^g and the within-between decomposition

	ϕ_1^g	Within term (%)	Between term (%)
SPAIN			
Natives	0.0199	87.3	12.7
Second-generation immigrants	0.5617	80.9	19.1
First-generation immigrants	0.7076	90.1	9.9
BELGIUM			
Natives	0.0378	98.1	1.9
Second-generation immigrants	0.5864	96.9	3.1
First-generation immigrants	0.5877	98.9	1.1
UK			
Natives	0.0438	97.4	2.6
Second-generation immigrants	0.7053	94.3	5.7
First-generation immigrants	0.6446	98.4	1.6

As we can see, in Spain the between component explains 10% and 19%, respectively, of the unevenness of first- and second-generation immigrant students. This means that in Spain, part of the segregation by nativity that we observe is due to an unequal distribution of immigrant children across regions, especially in the case of those born in Spain to parents

[16] The numbers for the UK should be taken with caution given the sample loss in this country.

born abroad. [The fact that the between component is much larger for second-generation immigrant children could arise from previous immigrant inflows being less spatially spread across the country than the recent ones.] However, in Belgium and the UK, the between component is much lower, which suggests that the regional distribution of immigrants does not play an important role in explaining school segregation.

Measuring Overall Segregation Using Multigroup Segregation Indices

What happens when we summarize the unevenness of the three groups (first-generation immigrants, second-generation immigrants, and natives) for each country? In other words, what is the extent of overall segregation when we use multigroup measures? Figure 2 shows the overall segregation using the generalized I_p index (GI_p), which is the one consistent with the D^g index discussed above and has an intuitive interpretation, as already mentioned. It measures the proportion of students (first-generation, second-generation, and natives) that would have to change schools in that country in order to remove segregation by nativity. Figure 2 also provides the values of the standardized version of GI_p, which is the generalized dissimilarity index D. D shows the number of students that would have to change schools to remove segregation by nativity in that country with respect to the total number of students that would have to change schools in case of maximum segregation in that country. The values of the remaining overall indices are provided in the Appendix (Tables A2 and A3).

When we use unstandardized measures like the generalized I_p index (GI_p), the mutual information index (M), or the unstandardized Gini index (G_u), the lowest overall segregation is found in Finland, followed by Italy and Portugal. In these countries, the proportion of students that would have to change schools to remove segregation by nativity ranges between 6% and 10% (see the values of GI_p). However, the shares of immigrant students in these three countries are also low, which could explain their good positions compared with other countries since, as we mentioned earlier, when using unstandardized overall indices, the contribution of a group to overall segregation depends on the group's size. In fact, things change significantly when we use the standardized versions of the above indices: the generalized dissimilarity index (D), the information theory index (H), and the generalized Gini index (G). In Switzerland, the number of students that would have to change schools, to remove segregation by nativity, represents 34% of all students that would have to change schools in case of maximum segregation (*D*=33.8), which is the lowest value, followed by Germany (41%) and Italy (43%) at a certain distance. With *H* and *G*, the lowest overall segregation is also found in Switzerland, followed by Germany and Italy.

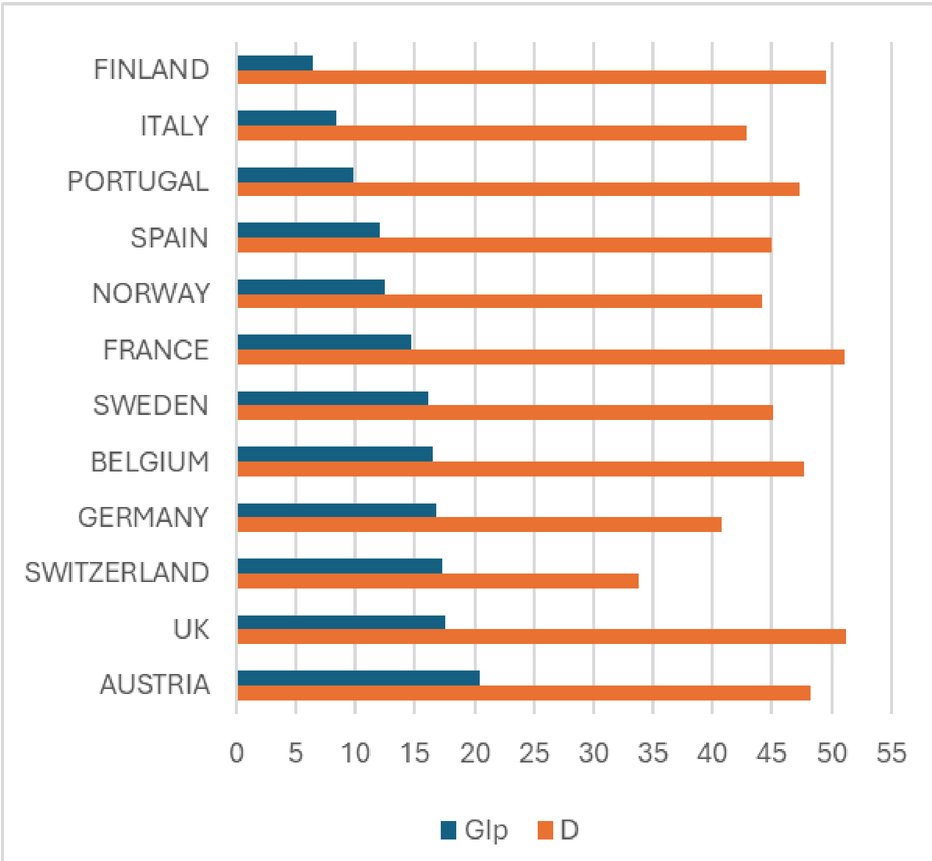

Figure 2. Overall multigroup segregation by nativity using indices GI_p and *D*, PISA 2022

Hence, the good positions of Finland and Portugal identified above disappear when accounting for the sizes of the groups. In fact, with the standardized indices, Finland and Portugal have higher segregation than most countries. Of the three countries with the lowest segregation when using unstandardized measures, only Italy has a low overall segregation when using standardized measures. The low overall segregation detected in Italy seems to arise from the low clustering of second-generation immigrants, shown above, and not from its low shares of immigrants.

On the other hand, the fact that Switzerland and Germany appear as countries with high overall segregation when we use unstandardized measures but not with standardized measures seems to be due to their large proportions of immigrant students and not because immigrant students are more unevenly distributed across schools in those countries than in other countries (as we showed in our previous analysis based on local segregation measures). On the contrary, the UK and Austria (and to a lower extent, Belgium) have higher overall segregation than other countries using both standardized and unstandardized measures. When using standardized measures, segregation also tends to be high in France (and to a lower extent, Finland and Portugal).

4.3 Assessing the Sorting of the Groups Across Schools Based on School Resources and Needs

So far, we have dealt with the unevenness of the distribution of immigrant students across schools documenting its extent using several indicators. In what follows, we take a step further by assessing whether the clustering of immigrant students happens in schools with human resources per pupil (after adjusting by school needs) above or below average. To do this, we use the indices I_0 and I_1 proposed earlier. As already mentioned, in this empirical illustration, x_i is the proportion of first-generation student immigrants in school i and h_i is the number of teachers and pedagogues in the school. Each full-time teacher counts as 1 and each part-time teacher counts as 0.5.

Figure 3 provides the indices (vertical axis) for different values of the α parameter (horizontal axis) in the case of first-generation immigrant students (I_0 is shown in the top panel and I_1 in the bottom, see also Table A4 in the Appendix). Figure 4 reports the corresponding values in the case of second-generation immigrant students. In what follows, we focus on index I_0 and we provide additional comments using I_1.

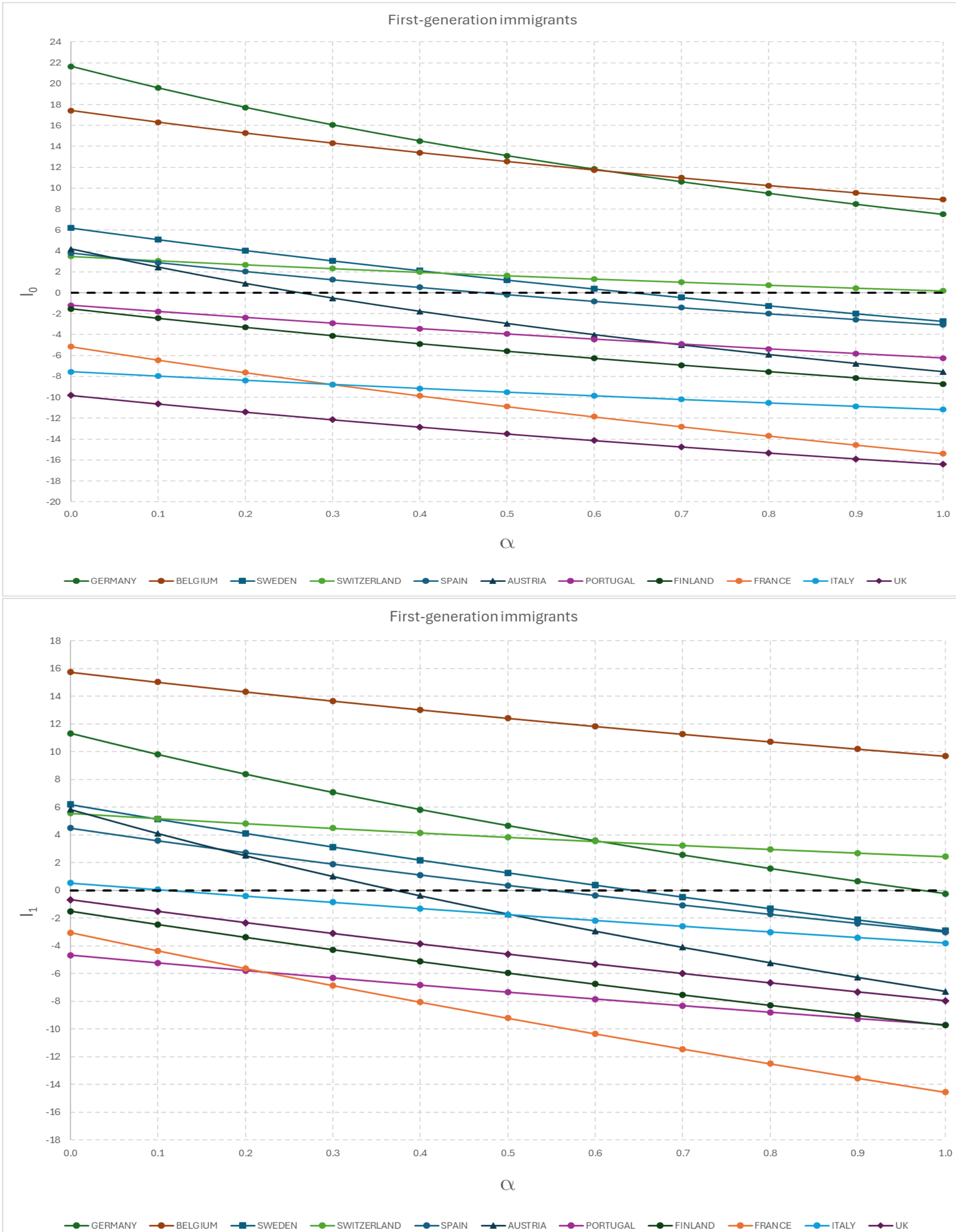

Figure 3. Assessing the school sorting of first-generation immigrant students in several European countries using indices I_0 (top panel) and I_1 (bottom) for different values of the extra needs α, PISA 2022.

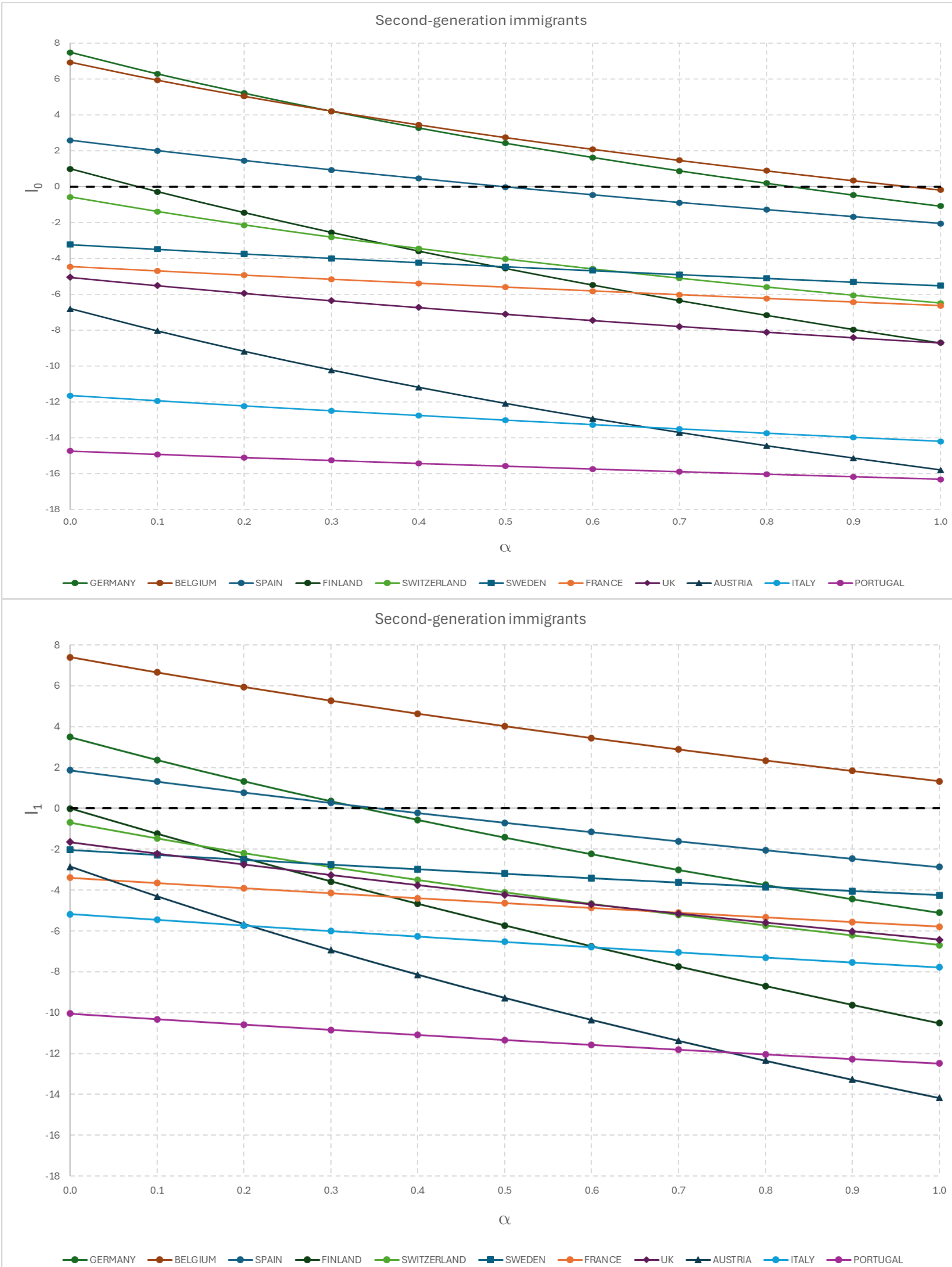

Figure 4. Assessing the school sorting of second-generation immigrant students in several European countries using indices I_0 (top panel) and I_1 (bottom) for different values of the extra needs α, PISA 2022.

First-generation immigrants

When we use I_0 and α=0 (i.e., if we do not take into account especial needs of schools arising from their composition), we find that the best school sorting of first-generation immigrants occurs in Germany, followed by Belgium. Therefore, although the degree of unevenness of first-generation immigrants in Germany and Belgium is not negligible, as shown above, when taking into consideration the ratio of human resources (teachers plus pedagogues) per pupil (including all students in the school), we see in these countries the situation is not that severe: children born abroad tend to enroll in schools with human resources per pupil above the national average (21% and 17% above, respectively). This pattern clearly departs from what happens in other countries.

With I_0, the next countries in the ranking are Sweden, Austria, Switzerland, and Spain, countries in which children born abroad tend to attend schools with resources per pupil ranging between 4% and 6% above the corresponding national average. Next, we have Portugal and Finland, who have negative values, although close to zero. As mentioned earlier, these two countries also tend to have higher segregation than others.

The worst results are found in the UK, Italy, and France, in which the value of the index is well below zero. In other words, in these countries, children born abroad tend to attend schools with ratios of human resources per pupil below the national average (between 5% and 10% below average). Therefore, in Italy and France, first-generation immigrant children are not only more segregated than in other countries, as shown earlier, but they tend to cluster in schools with fewer teaching staff per pupil.

When α increases, I_0 decreases in all countries, showing that when accounting for the additional needs that schools have due to their composition, the situation of children born abroad worsens.[17] Notwithstanding, with α=1, I_0 is still positive in Germany and Belgium, which implies that if the teaching needs of a student born abroad were twice that of a native student, the average resources per pupil of children born abroad would still be above the

[17] The values of parameter α that we are considering here are in line with the extra cost of students belonging to disadvantaged groups estimated in the literature (Bifulco and Souders, 2024). If the disadvantage arises from speaking a different language, the extra cost considered in studies for the US ranges between 10% and 92%, whereas for disadvantages arising from family income, the extra cost ranges between 33% and 125%.

national average. In Switzerland, the average resources per pupil of these children would be about the national average.

In Sweden, Spain, and Austria, the parameter at which the index becomes negative is, respectively, around 0.7, 0.5, and 0.3. This implies that if children born abroad required, respectively, up to 70%, 50%, and 30% of what native children in these countries need to achieve academic standards, the average adjusted resources per pupil of schools in which the first-generation immigrants enroll would still be around or above the national average.

When we use I_1, and therefore we account for the inequality that exists within the group, first-generation immigrants in Belgium still have a better school sorting than they do in other countries, and the index keeps being positive for all α. However, in Germany, in relative terms, the situation of the group is not as advantageous as before, which suggests that in this country foreign-born students are a fairly heterogenous group in terms of the per-pupil resources of the schools they attend. Moreover, for α=1 the index becomes zero, and for large values of α, the index is higher in Switzerland than it is in Germany. In any case, the situation of the group in Germany is better than in most countries.

Accounting for the inequality of the group does not seem to change much the situation of the group in Switzerland, Sweden, Spain, and Austria, which still have positive values for some α values, nor that in Finland and France, which still have negative values for all α values.

Unlike other countries, in the UK and Italy, the group is much better when we account for inequality aversion, which suggests that the situation of some members of the group is good enough to compensate for part of the disadvantages of other members of the group. This makes these two countries have higher index values than Finland, France, and Portugal, the latter being a country that worsens significantly after accounting for inequality.

Second-generation immigrants

When we use I_0 and α=0, the position of second-generation immigrant students in terms of human resources in Germany and Belgium is not as good as that of the first generation, becoming closer to the national average. In these countries, second-generation immigrant students tend to attend schools in which the teaching staff per pupil is around 7% above the national average. In Spain, the situation does not change much compared to the first generation (second-generation immigrant children tend to concentrate in schools whose human resources per pupil are 2.6% above average). Unlike the aforementioned, Switzerland, Sweden, and Austria have now negative values (whereas for the first generation these countries had positive values). Therefore, in these countries, children born domestically to foreign-born parents tend to cluster in schools with resources (between 0.6% and 6.8%) below the national average. This implies that, although the unevenness across schools of second-generation immigrant students in Switzerland is lower than in Germany, as shown earlier, when taking into account the school human resources per pupil, the situation in Germany is better. In France and the UK, the values are again negative (the resources of these children are around 5% below average). The situation is much worse in Italy and Portugal, where the resources of second-generation immigrant students are 12% and 15% below the national average. Therefore, even though the segregation of children born domestically to foreign parents is not particularly high in Italy compared to other countries, when accounting for resources, Italy worsens.

The relationship between index I_0 and α is strongly negative in the case of Austria. Germany, Belgium, and Finland also have large slopes, although they start with positive values. This means that when taking into account the needs of the first-generation students attending their schools, the situation of second-generation immigrant students worsens considerably. This suggests that second-generation immigrant students in these countries tend to be concentrated in schools where first-generation immigrant students are also clustered. The situation of second-generation immigrant students in Portugal is much worse than that of the first generation. Also note that with α=1 (i.e., if a first-generation immigrant student requires twice the teaching staff of a native student), we do not find any country with positive values.

When we use I_1, we see again that the situation in Belgium is much better than it is in other countries and that the index is positive for all α values, whereas in Germany, I_1 turns negative much earlier than I_0. In Spain, which comes next in the ranking and has a positive value for low α values, the situation of the group with I_1 does not change much with respect to I_0. In Switzerland, which has negative values for all α values, the situation also remains like before. Countries like Sweden, Austria, France, and Finland do not change much either when we compare I_1 and I_0, although all of them but the latter experience small increases. As in the case of first-generation immigrants, Italy improves significantly when we account for inequality. Although Portugal is still among the countries with the worst school sorting, the situation of second-generation immigrants seems to improve slightly when accounting for inequality.

5. Final Comments

Drawing on PISA 2022 data, this paper shows that when we use unstandardized overall measures, school segregation by nativity in some countries (like Switzerland and Germany) may be higher than it is in others not because the degree of unevenness for immigrant children is especially high there but because these children represent an important share of total students. On the contrary, some other countries (like Finland and Portugal) do not have larger segregation than others when using unstandardized overall segregation indices, but they do with standardized indices that take into account the (small) shares of immigrant children in these countries. In any case, the analysis suggests that segregation tends to be higher in France, UK, and Austria than it is in other countries according to most overall multigroup indices standardized or not.

This research also documents that school segregation by immigrant status is a widespread and intense phenomenon in Europe. When we look at the segregation of 15-year-old students born abroad (i.e., first-generation immigrants), we find that in Switzerland, the country of our list in which this group has the lowest segregation, 30% of these children would have to change schools to be evenly distributed across them. The percentage rises to 52% in France, and in many countries (Belgium, Germany, UK, Austria, Finland, Spain, and especially Portugal and Italy) it is above 40%. These ratios represent around half of the maximum unevenness that this group of children could face given its size in each country. In the case of Spain, we find that a significant share of the segregation of the group arises from its unequal distribution across regions, a pattern that countries like the UK and Belgium (which also provide information at the regional level) do not share.

For 15-year-old children born in the country to foreign-born parents, we find that in some countries the level of segregation is significantly lower than that of the first generation, which suggests that school segregation by immigration status could decrease over time. This is the case, using several indicators, of France, Germany, Italy, Spain, Austria, and Switzerland.

However, in Scandinavian countries and the UK, second-generation immigrant students have significantly higher segregation levels than the first generation using several indices.

Does the distribution of human resources across schools exacerbate the problem of segregation by immigrant status in Europe? The answer is that generally speaking it does, especially when we consider the additional needs of schools associated with their composition, although there are important differences among countries.

PISA data suggest that in about half of the European countries we studied, students are not only separated by nationality. The human resources per pupil from schools in which first-generation immigrants tend to enroll are also below the national average. This is the case of Portugal, Finland, and especially France, Italy, and the UK (in these three countries the gap ranges between 5% and 10%). This means that in these countries the opportunities to learn are lower in the schools in which immigrant students tend to cluster. However, in other countries, this ratio is above the national average (as happens in Sweden, Spain, Switzerland, and Austria) or well above it (21% in the case of Germany and 17% in Belgium). This suggests that large levels of segregation do not necessarily translate into a disadvantaged position for immigrant students in terms of resources.

However, the situation of first-generation immigrants worsens dramatically in all countries when we consider the additional resources needed to provide first-generation immigrant children with the same academic standards as native-born students. Our findings suggest that if the extra resources required by first-generation immigrants were 50% above those of their native peers, only first-generation immigrant students in Sweden, Switzerland, and especially Germany and Belgium would be clustered in schools with adjusted resources per pupil above the national average (in Spain they would be around the national average). If instead the extra educational resources required twice those of a native student, only in Germany and Belgium would first-generation immigrants tend to cluster in "good" schools.

Our analysis also suggests that second-generation immigrant students in Austria, Germany, Belgium, and Finland tend to cluster in schools in which first-generation immigrants are also clustered, which explains why in these countries the assessment of the between-school sorting of the second generation worsens faster when we account for the extra needs of the first-generation immigrant children attending the same schools.

The reasons that explain the differences among countries documented here go beyond the scope of this paper but could be related to both differences in their educational systems and in characteristics of first- and second-generation immigrants. Regarding the former, it would be interesting to analyze the mechanisms for assigning students to schools, explore if there are differences between public and private schools, as well as differences in the curricular itineraries that students face and the age at which they have to choose them. Differences in school funding schemes also appear as a key element. On the other hand, having information about the country of origin and language of first-generation immigrant students (as well as their age at arrival in the country) would allow the identification of different subgroups, which could play a role in explaining inner differences in the group and also differences among countries.

The framework offered here is a useful tool to delve deeper into the reality of each country if national databases with richer information are available. Our approach opens the possibility of going beyond the quantification of segregation by assessing its consequences in terms of equality of opportunity.

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Appendix

Table A1. Size of the samples of 15-year-old students and schools in each country and loss of sample due to lack of information (about immigrant background, total number of students, or teachers in the school), PISA 2022.

	Size of the original sample		**Sample loss due to lack of information (in %)**			
	Schools	Students	Schools without information about resources	Students without information about immigrant background	Students in schools without information about resources	Sample loss due to lack of information (immigrant background and resources)
			(unweighted sample)	(weighted sample)	(weighted sample)	(weighted sample)
AUSTRIA	302	6,151	6.3	**2.5**	6.1	**8.3**
BELGIUM	285	8,286	20.4	**4.9**	20.4	**23.9**
FINLAND	241	10,239	6.6	**2.7**	6.0	**8.6**
FRANCE	282	6,770	20.6	**4.2**	19.0	**22.7**
GERMANY	257	6,116	24.5	**11.9**	23.8	**31.6**
ITALY	344	10,552	7.6	**2.7**	5.3	**7.8**
NORWAY	265	6,611	100.0	**8.0**	100.0	**100.0**
PORTUGAL	224	6,793	0.5	**2.8**	0.5	**3.3**
SPAIN	966	30,800	12.4	**6.5**	14.0	**19.4**
SWEDEN	262	6,072	14.1	**5.4**	14.0	**18.2**
SWITZERLAND	260	6,829	19.2	**2.6**	21.4	**23.2**
UK	451	12,972	26.8	**21.9**	25.4	**42.3**
				Segregation analysis		**Analysis of School opportunities**

Table A2. Unstandardized overall and local segregation indices, PISA 2022

	Local segregation indices									Overall segregation indices		
	D^g			G^g			ϕ_1^g			GIp	G_u	M
	Natives	Second-generation immigrants	First-generation immigrants	Natives	Second-generation immigrants	First-generation immigrants	Natives	Second-generation immigrants	First-generation immigrants			
AUSTRIA	12.9	39.3	44.7	17.3	51.9	61.0	6.7	46.8	69.9	20.4	27.4	19.6
BELGIUM	9.8	42.9	42.1	13.0	57.4	56.9	3.8	58.6	58.8	16.5	22.0	15.0
FINLAND	3.3	53.3	45.0	4.4	70.7	60.6	0.5	98.5	67.2	6.4	8.5	6.0
FRANCE	8.3	44.5	52.2	11.0	59.0	69.2	2.7	63.0	95.8	14.7	19.5	14.4
GERMANY	10.1	32.3	43.6	13.8	44.2	59.5	3.7	33.5	66.7	16.8	23.0	14.4
ITALY	4.3	39.2	49.4	5.9	52.7	66.0	0.7	50.5	89.1	8.4	11.3	7.2
NORWAY	6.6	47.2	37.5	9.4	64.3	51.2	2.8	79.0	48.7	12.4	17.2	12.7
PORTUGAL	5.0	48.0	46.4	7.0	62.5	63.1	1.1	73.3	74.7	9.8	13.3	9.4
SPAIN	6.7	40.5	45.0	9.1	55.6	61.3	2.0	56.2	70.8	12.0	16.5	11.1
SWEDEN	9.3	44.1	38.7	12.8	59.7	52.8	3.7	64.6	50.6	16.2	22.1	15.3
SWITZERLAND	12.1	25.1	30.5	17.1	35.0	42.0	5.3	20.9	31.0	17.3	24.3	12.0
UK	10.3	47.6	44.3	13.7	62.0	59.2	4.4	70.5	64.5	17.5	23.2	17.1

Table A3. Standardized overall and local segregation indices, PISA 2022

	Standardized local segregation indices									Standardized overall segregation indices		
	$\tilde{D}^g$			$\tilde{G}^g$			$\tilde{\phi}_1^g$			D	G	H
	Natives	Second-generation immigrants	First-generation immigrants	Natives	Second-generation immigrants	First-generation immigrants	Natives	Second-generation immigrants	First-generation immigrants			
AUSTRIA	48.3	47.3	49.5	65.2	62.6	67.5	21.8	26.5	29.8	48.2	64.8	26.0
BELGIUM	47.9	48.5	46.2	63.4	64.9	62.5	16.5	27.2	24.3	47.7	63.6	23.2
FINLAND	48.8	54.9	46.8	65.2	72.8	63.1	7.7	27.8	20.7	49.5	66.2	20.3
FRANCE	50.5	50.1	55.1	66.9	66.5	73.1	15.0	28.9	32.5	51.2	67.8	26.1
GERMANY	39.0	38.7	48.0	53.4	53.0	65.5	12.5	18.7	27.9	40.7	55.7	19.6
ITALY	40.6	42.4	50.9	55.6	57.0	68.1	6.4	19.6	25.6	42.8	58.0	17.9
NORWAY	41.6	51.7	40.4	59.1	70.4	55.2	16.2	32.3	18.6	44.2	61.3	23.2
PORTUGAL	44.5	50.3	49.8	61.9	65.5	67.6	9.3	23.8	27.7	47.3	64.4	21.8
SPAIN	44.1	44.4	48.0	60.3	60.9	65.5	12.1	23.1	25.6	44.9	61.5	21.0
SWEDEN	43.7	49.5	43.3	60.1	66.8	59.1	15.6	29.0	22.6	45.1	61.6	22.9
SWITZERLAND	34.5	32.3	34.9	49.0	45.0	48.1	12.3	13.9	15.0	33.8	47.5	13.7
UK	51.2	53.6	48.7	68.3	69.8	65.0	19.5	32.1	26.7	51.3	67.9	26.8

Table A4. Values of the indices I_0 and I_1 for different α values, PISA 2022

	First-generation immigrants							Second-generation immigrants					
	I_0			**I_1**				**I_0**			**I_1**		
	α = 0	α = 0.5	α = 1	α = 0	α = 0.5	α = 1		α = 0	α = 0.5	α = 1	α = 0	α = 0.5	α = 1
AUSTRIA	3.8	-0.2	-3.1	5.8	-1.7	-7.3		2.6	0.0	-2.1	-2.9	-9.3	-14.2
BELGIUM	17.4	12.6	8.9	15.7	12.4	9.7		6.9	2.7	-0.2	7.4	4.0	1.3
FINLAND	-1.5	-5.6	-8.7	-1.5	-6.0	-9.7		1.0	-4.6	-8.7	0.0	-5.7	-10.5
FRANCE	-5.2	-10.9	-15.4	-3.0	-9.2	-14.6		-4.5	-5.6	-6.7	-3.4	-4.6	-5.8
GERMANY	21.6	13.1	7.5	11.3	4.7	-0.2		7.5	2.4	-1.1	3.5	-1.4	-5.1
ITALY	-7.6	-9.5	-11.2	0.5	-1.7	-3.8		-11.7	-13.0	-14.2	-5.2	-6.5	-7.8
PORTUGAL	-1.2	-4.0	-6.2	-4.7	-7.4	-9.7		-14.8	-15.6	-16.3	-10.1	-11.3	-12.5
SPAIN	3.8	-0.2	-3.1	4.5	0.4	-3.0		2.6	0.0	-2.1	1.9	-0.7	-2.9
SWEDEN	6.2	1.2	-2.7	6.2	1.3	-2.9		-3.2	-4.5	-5.5	-2.0	-3.2	-4.2
SWITZERLAND	3.5	1.6	0.2	5.6	3.8	2.4		-0.6	-4.1	-6.5	-0.7	-4.1	-6.7
UK	-9.8	-13.5	-16.4	-0.7	-4.6	-8.0		-5.1	-7.1	-8.7	-1.7	-4.2	-6.4