School-level inequality and learning achievement:

Measurement, theory, and analysis based on the Programme for International Student Assessment (PISA)

Lucas Néstor Sempé

A thesis submitted for the degree of Doctor of Philosophy to the University of East Anglia, School of International Development

February 2022

This document is formatted for single printing and binding.

Abstract

Exogenous socioeconomic characteristics in schools, or school socioeconomic compositional effects (SCE), heavily influence students' cognitive and non-cognitive outcomes. The influence of SCE on learning achievements varies across individuals, schools, and wider contexts. SCE reflect structural individual and societal conditions that affect people's future lives and development. In this respect, understanding their complexity provides a greater opportunity to address disparities and enable people and societies to reach their potential.

The most common aspects studied in the academic literature are the student's socioeconomic status (SES) and the school socioeconomic status. This thesis focuses on a less studied SCE dimension, namely within-school economic inequality (hereafter *school inequality)*. This aggregated measure of inequality reflects the distribution of students' household wealth in each school and provides an understanding beyond the usual SCE aspects. The presence of *school inequality* matters to educational and development studies and practice because it sheds further light on the role of SCE inside schools. Studying *school inequality* across a range of contexts enables the development of appropriate policies to address its potential influence on students' learning outcomes.

I use data from the Programme for International Student Assessment (PISA), which measures *learning outcomes* as the Reading, Mathematics and Science skills of 15-year-old students across the world. I use waves 5, 6 and 7 corresponding to years 2012, 2015 and 2018.

I focus on four aspects related to the phenomenon of *school inequality*: i) its measurement based on categorical data using tools provided by Item Response

Theory models, which is axiomatised and validated with other inequality measurements; ii) a review of how socioeconomic inequalities affect schooling outcomes identifying four distinct academic bodies of literature, namely, difficulties in terms of access to education; the corrosive effect of inequality in the social fabric; relative deprivation and interpersonal comparisons; and, finally, social reproduction theory. Based on that, I develop a set of inferential analysis models to study the relationship between both *school inequality* and *learning scores*. I consistently find negative associations between them across the different PISA waves, model specifications and inequality measurements. I also find that school wealth interacts differently with *school inequality*, finding that students in wealthier schools tend to be more negatively influenced by inequality.

iii) I theorise potential channels of how *school inequality* affects schooling outcomes suggesting mechanisms such as social isolation, interpersonal comparisons and anomie. By understanding schools as socialising spaces and based on a social cohesion framework, I study how certain attitudes operate as mitigating resources – in terms of compensation, moderation and mitigation – of the negative consequences of inequality on *learning scores*. However, the negative effects remain in place after the inclusion of those explanatory variables.

iv) Finally, I develop an exploratory study addressing a theoretical and empirical trade-off between *school inequality* and country school segregation, showing how both factors coexist and negatively affect *learning scores*. Learning scores are used as a synthetic measurement of school achievement, and at the same time, are a relevant predictor of further academic advancement and economic development.

List of contents

List of figures

List of tables

List of abbreviations

1-PL	One parameter logistic regression
2-PL	Two parameters logistic regression
BELONG	Sense of belonging
CBA	Computer-based assessment
CNT	Country ISO Code
EM	Expectation-maximization
GLOBMIND	Sense of agency towards global issues
GPCM	Generalised partial credit model
HOMEPOS	Home Possessions Index
ICC	Item characteristics curve
ILSA	International Large-Scale Assessments
INUS	an insufficient, but necessary part of an unnecessary but sufficient condition
IRT	Item Response Theory
HISCED	Higher educational parent status
MCAR	Data missing completely at random
MNAR	Data missing not at random

OECD	Organisation for Economic Co-operation and Development
PERCOOP	Peers' cooperation
PERSPECT	Understanding of others' perspectives
PBA	Paper-based assessment
PISA	Programme for International Student Assessment
PLS	Penalised least-squares method
RESPECT	Respect for people from other cultures
RMSD	Root mean square deviance
SCE	School socioeconomic compositional effects
SEM	Structural equation models
VIF	Variance Inflation Factor
WLE	Posterior weighted maximum likelihood estimation
SIEP	Peruvian Society of Educational Research

The data used in this thesis can be found at: https://www.oecd.org/pisa/data/

The code for replication used in this thesis can be found at: https://osf.io/g8et9/

Acknowledgements

First, I would like to thank my supervisors Professor Laura Camfield and Doctor Lucio Esposito who have been extremely supportive throughout my research, my long and complicated sentences, COVID-19, and life disruptions, and with whom I have taken great satisfaction to work.

The School of International Development of the University of East Anglia has been both a friendly and challenging academic environment to be part of. My heterodox background and positionality made me choose the School of International Development of UEA as my nurturing and learning space. I find that its interdisciplinary nature, the range of topics, methodologies and theoretical approaches made it possible for me to develop my research skills according to my background and interests. I was extremely lucky to find supportive colleagues. Peter Lloyd-Sherlock has been a mentor, a colleague and a friend with enormous generosity and wisdom, for which I am deeply grateful. Jessica Budds, Teresa Armijos, Iokiñe Rodríguez, Bryan Maddox, Paul Clist, Rob Grant, and Catherine Butcher have been encouraging colleagues, sharing their knowledge and skills through my research process and academic life. I have enjoyed collaborating across projects, teaching, travelling and even discussing marking formative and summative work with them. Jessica has been also very helpful in proofreading my thesis, providing a better version of my work. Mistakes remain exclusively mine.

DEV also has a very diverse and vibrant postgraduate research community. Many colleagues made this journey very remarkable. I have made friends with colleagues and learned from their own backgrounds, interests, and research. From cricket and stolen games to Kashmir, from dams to mangroves, from the resource curse to facing scarcity in rural Uganda, from archaeological evaluation in Peru to food insecurity, from Amazonian children to urban informal settlements in Myanmar, and from land tenure in India to coastal management in Scottish islands. Many names cross my mind, and I am sure – apologising in advance – I might be forgetting a few others: Paul, Touseef, Francesca, Floris, Suvarna, Rajanya, Agathe, Thais, Ruth, Harsh, Katie, Rachel, Cindy, Heran, among many others.

This research would not have been possible without the initial help from people from Natura and allies: Karina, Davi, Jonas, Carolina, Sabina, Wendy, and Roberto. I am very grateful for their support, patience, and passion for improving Latin American education.

Many friends played also a very important role with their support and encouragement: Carlos, Ricardo, Kike, Francesca, Rosa, Liliana, Gabriella, Charlotte(†), Pepe y Jessica(†), Paty B., Pati, Pati, Pati, Lucho, Martin, Jorge, Jose Luis, Mariale, Carola, Sandra, Luciana, Fariba, George, Mamata, Diego, among many who I am very lucky to have. Two colleagues – also champions of better educational policies in Peru – were instrumental at the beginning of my academic process, for which I am very grateful: Santiago Cueto and César Guadalupe.

Lastly, the thesis only was possible because of the love of my family. Fabiola, eres el amor de mi vida. Mamá(†) y Tati(†), los extraño mucho, sé que están contento por nosotros. María Alicia y María Esther, las amo. Nico, Natalia, tia Susana, Pastor, tia Pelusa, Ignacio, Mili, Lupe, Tito, Fiama, Tito, gracias por todo el cariño y soporte.

Al Dios bueno que nos cuida y ama, A.M.G.D.

1. Introduction

1.1. Research motivation

Education is seen as crucial for the development of people and nations and also to close gaps in socioeconomic inequality (Green, 2009). For that reason, the international agenda towards reducing poverty and promoting development, such as the Sustainable Development Goals (SDGs), prioritises goals related to the access and quality of education for all. At the same time, education is also contended to be a negative contributor to economic disparity via the reproduction of socioeconomic inequality (Bourdieu and Passeron, 1990).

Socioeconomic inequality crosses boundaries in relation to geographies, cultures, ethnicities, religions, among others. As a global phenomenon, inequality has attracted attention in recent years among politicians, academics, multilateral organisations, and civil society in general. Best-selling books (Piketty, 2015), Sustainable Development Goals focusing on reducing inequalities within and between countries (United Nations, 2015), and international reports (United Nations Development Program, 2019) are high-profile examples of this trend.

Inequality also occurs in schools. For instance, according to the most recent results from the Programme for International Student Assessment (PISA) – with data collected in 2017 and 2018 across more than 80 countries and territories[1] – 90% of 15-year-old students attained a minimum level of proficiency in reading skills in countries and territories such as Chinese cities (Beijing, Shanghai, Jiangsu, and

[1] In this case, the OECD analyses results from the standard PISA and a special edition called Pisa for Development for low and middle income countries (Ward, 2018).

Zhejiang), Estonia, Macao, and Singapore, while less than 10% of students reached the same levels in countries like Cambodia, Senegal, and Zambia. An even harsher scenario was found in relation to the subject of mathematics, where the share of minimum proficiency ranges from 98% of students in the aforementioned Chinese cities to only 2% in Zambia (OECD, 2019a).

While this research is not about COVID-19, the topics examined are even more important after the pandemic hit. For example, Agostinelli *et al.* (2020) studied the case of the United States finding that school closures had an important effect on students in poorer areas measured at 0.4 standard deviations of learning scores, which is considered a very large effect, while no significant losses were found across students from richer areas.

In this sense, the emergence of the impacts of COVID-19 on education also requires a better understanding of the role of other socioeconomic processes in schools that did not receive sufficient attention in the past. To contribute to this effort, in this thesis I study the phenomenon of aggregated socioeconomic inequality in schools and its impact on *learning outcomes*. While educational research has been usually concerned with comparisons between schools, in this thesis, I centre my attention on socioeconomic differences that occur within-schools.

1.2. School composition effects and the role of *school inequality*

My research contribution falls into the academic field of socioeconomic composition effects (SCE) (Rumberger & Palardy, 2005). Since the publication of the influential "Equality of Educational Opportunity" Report by James Coleman (1966), the school socioeconomic composition has become prominent in explaining significant differences in students' achievement between schools across the world.

The SCE analyses the relationship between the socio-economic status of a school and individual schooling outcomes such as academic achievement, school dropout and completion. It is a separate construct – both theoretical and empirical – from each student's socioeconomic status (SES). In this sense, SCE is defined as a different influence made up of students' aggregated characteristics such as socio-economic status (SES), sociocultural capital, and prior achievements among others, after these attributes have been already considered at an individual level.

However, there is still academic controversy in terms of assessing both the causality and the magnitude of SCE, which have been debated for several years (Thrupp, Lauder and Robinson, 2002). Although SCE has been influential in educational research in predicting a range of outcomes and influencing public policy, there is still an ongoing academic discussion over the real relevance of SCE, as debated in recent issues of the *British Journal of Sociology of Education* (Sciffer, Perry and McConney, 2020, 2021; Malatinszky and Armor, 2021; Marks, 2021). For example, it has been suggested that SCE are merely statistical artefacts caused by omitted variables regarding within-school SES and also family resources (Nash, 2003).

Based on the SCE field of knowledge, I focus on the phenomenon of *school inequality* associated with *learning scores*. I measure *school inequality* as the distribution of students' wealth within a school. Higher values of *school inequality* indicate that the allocation of students' wealth is more uneven in the school. On the contrary, school equality occurs when all students within a school have the same amount of wealth.

In order to contextualise the study of *school inequality*, there is an important distinction to be made between horizontal and vertical inequalities (Stewart, 2014). On the one hand, vertical inequalities refer to variations among individuals in a society or group – in this case, inequalities within-schools. In this sense, Stewart (2002) makes an interesting contribution by arguing that inequalities between formed groups (horizontal inequalities) are still present and usually neglected as an important dimension of wellbeing. This will be the focus of this dissertation across chapters 2 to 5.

On the other hand, horizontal inequalities refer to variations among groups in a society – in this case, differences between schools or groups of schools. These have been the subject of ongoing vigorous debate and policy response that addresses the tension between different forms of schooling segregation driven, for instance, by social differences, religious affiliation, academic performance, or tuition-based access, among others (Rumberger and Palardy, 2005; Gutiérrez, Jerrim and Torres, 2019). This will be addressed in Chapter 5 where I analyse how both phenomena coexist and affect *learning scores*.

1.3. Why it is worth studying *school inequality*

Schools are usually understood as great social equalisers, although there is a latent risk that they may lose that status due to COVID-19 related persistent closures (Agostinelli *et al.*, 2020). Socioeconomic heterogeneity in schools has been seen as a means to achieve societal goals such as improving peace among communities, reducing anti-social behaviour, growing and consolidating social cohesion, decreasing economic inequality and promoting engaged citizens, among many other positive impacts at the individual and societal levels (Green, 2009; Hemming, 2011; Green and Janmaat, 2016; Janmaat, 2020). The opposite, a segregated educational system where schools are socioeconomically and ethnically very homogeneous, poses diverse social risks, such as in the cases of the historic racial division in the United States (Rumberger and Palardy, 2005) or the Apartheid regime in South Africa (Tabane and Human-Vogel, 2010). Beyond those extreme cases, there are many theoretical and empirical studies highlighting damaging impacts on learning outcomes across diverse settings, especially to more economically disadvantaged students (see, for example, Gorard and Fitz, 2000; Echenique, Fryer Jr and Kaufman, 2006; Ryabov and Van Hook, 2007; Billger, 2009; Walsemann and Bell, 2010; Benito, Alegre and Gonzàlez-Balletbò, 2014; Valenzuela, Bellei and Ríos, 2014).

The hypothesis underlying this thesis is that – *ceteris paribus* – schools that are relatively homogeneous in their socioeconomic status tend to have better learning outcomes – measures as standardised *learning scores* – than those that show higher degrees of socioeconomic heterogeneity. This hypothesis has been studied and tested within health research for outcomes such as mortality, although theoretical and empirical mechanisms to explain this are still discussed (Wilkinson and Pickett, 2006; Cockerham, 2021).

Willms (2006, p. 53) is one of the few authors to address this issue without finding any evidence to support this premise. He uses data from the first wave of PISA – held in 2000 – and from the Progress in International Reading Literacy Study (PIRLS), conducted in 2001. As he acknowledges, "these null findings are important, though, because they suggest that policies aimed at reducing school heterogeneity through policies such as streaming[2] or tracking are unlikely to increase literacy performance".

If the homogeneity hypothesis holds – as in the last two examples – this poses a conundrum, as a resulting policy could entail the promotion of strategies that could encourage the segregation of students according to their socioeconomic status or skills. Both as a social scientist and as an educational policy-maker and practitioner, I worry about the implications of these policy responses.

However, at the same time, neglecting the potential impact of *school inequality*, even in favour of promoting policies towards socioeconomic integration, may provoke negative consequences for individual students in terms of *learning scores* and other relevant outcomes. This is what I address both theoretically and empirically in terms of how to mitigate those effects – at least in part – in Chapter 4. In addition, I postulate the need to differentiate *school inequality* from an educational system *segregation* as two concurrent negative phenomena that burden students and schools, and that require specific policy measures. While the first is measured at the level of schools, the second is measured at a system level. This is addressed in Chapter 5.

1.4. Data and methodology

Across this thesis, I use data from PISA undertaken by the Organisation for Economic Co-operation and Development (OECD). PISA aims to measure, and has

[2] Streaming and tracking refer to educational policies where students are allocated into different subsystems according to skills shown at early ages.

been collecting data on, 15-year-old students' knowledge and skills across the globe triennially since 2000.

PISA is a large-scale international assessment launched in 2000 that occurs every three years and assesses students' knowledge and skills in reading, mathematics, and science. The population is made up of school students at the age of 15, who are enrolled at grade 7 or higher. In the 2018 wave, 79 countries and economies participated and in most of them, 4,000-8,000 students are assessed. In all countries except for the Russian Federation, PISA uses a two-stage stratified sample design ensuring statistical representativeness both at country and school levels. The first stage consists of a systematic sample selection of at least 150 schools per country to achieve national representativeness concerning school characteristics such as school location, size, type of education, geographical area, among others. The second stage consists of random sampling within each school, with a target of 42 students per school in the case of computer-based assessment, and 35 students per school in the case of paper-based assessment. Achieving representative samples of schools and students is key for PISA and data not meeting this requirement are dropped. This is in order "to ensure adequate accuracy in estimating variance components within and between schools – a major analytical objective of PISA" (OECD, 2017, p. 68). This feature enabled many studies focusing on variables at the school level (Marks, 2006; Hanushek, Link and Woessmann, 2013; Gutiérrez, Jerrim and Torres, 2019).

Specifically, I use data from waves 5, 6 and 7, corresponding to the years 2012, 2015 and 2018. Datasets contain information on the *learning scores* and the background questionnaires completed by students, teachers, parents, and school principals.

There has been an important growth in the number of countries and territories[3] participating in PISA cycles. While 65 countries and territories participated in PISA 2012, PISA 2015 reached 72, and the last data collection cycle in 2018 included 79 different countries and territories.

As with any robust International Large Scale Assessment (ILSA), PISA provides rich and important information to policymakers that enables them to have a robust snapshot of learning outcomes across their educational systems and to compare their own regions with others. It provides relevant background information to unpack the influence of different factors across students, schools, teachers, and parents. It allows learning gaps to be addressed and better policies to be produced in order to improve future learning outcomes.

At the same time, important limitations and risks have to be acknowledged in the use of data from PISA. First, I acknowledge the risk of reducing the relevant and technically complex concept of quality of education (Rose, 2015) only to quantitative learning score measurements provided by ILSAs (Grek, 2009; Sjøberg, 2015). Second, PISA data do not represent a comprehensive account of the benefits and advantages provided by schools. This has the potential consequence of reducing learning to only those measurable areas of knowledge and skills. Third, the quantitative data may be attractive to many who are naturally inclined to reduce reality to what can be measured. This seduction of quantification is seen

---

[3] Some territories are not recognised by other countries as independent nations, such as Chinese Taipei [Taiwan]. Hong Kong and Macao. Others are represented only by selected sub-national regions in the assessment, including for example: the city of Baku in Azerbaijan, and Beijing, Jiangsu, and Zhejiang in The Republic of China.

through the relevance given in the media to countries' positions in comparative rankings. Finally, there are methodological challenges in PISA. For example, there is a lack of transparency of certain methodological choices (for example, in the analysis of items' measurement invariance), data comparability across countries remains questionable and there is no access to the data analysis to guarantee reproducibility.

PISA presents a complex survey design, which requires specific methodological choices to be made during data analysis. Three methodological features will be discussed, namely: test design; sampling strategy; and sampling variance. These features have important implications for the further descriptive and inferential analysis performed through the thesis.

1.4.1.Cognitive scores and plausible values

The main goal of PISA is to capture students' academic achievement in domains such as literacy, mathematics, and science (hereafter, *learning scores* or *learning outcomes*). The assessment focuses on the students' ability to use their knowledge and skills to meet real-life challenges, rather than focus on a specific school curriculum. They provide a reliable – although partial – account of standardised academic progress made by 15-year-old students across the globe. For each cycle of PISA, one domain of knowledge is chosen as the major domain and receives greater emphasis than the remaining two. For example, science was the main domain in the last edition of PISA in 2015.

The test lasts a total of two hours in addition to the time given to answer the contextual questionnaire. Since 2015, each country decides the mode of application: computer-based or paper-based. During those two hours, students are randomly given one form of the test, which is composed of four clusters. The PISA survey uses a 'rotated design', where randomly selected sub-samples of children are asked different sets of questions. This allows more information to be collected on skills and knowledge but does not allow for individual comparisons between students (OECD, 2017b, 2020).

All students answer questions related to the core domain. In addition, they can be given questions on one or both additional domains. For example, in the paper-based mode of PISA 2015, the design included 30 different test forms (see Table 1). Each test form allocated to students comprised four 30-minute clusters of the test material. This test design included six clusters from each of the domains of science, reading and mathematics to measure trends over time. Of those, 24 forms combined two of the three domains. This provided strong pairwise covariance information between science and each of the two other domains. In that year, 44% of students were assigned to science and reading (forms 1 – 12), another 44% were assigned to science and mathematics (forms 13 – 24), while the remaining 12% were assigned to science, reading and mathematics (forms 25 – 30) (OECD, 2017b).

Table 1: PISA 2015 test design - Paper-based

Forms	Cluster 1	Cluster 2	Cluster 3	Cluster 4
1	PS01	PS02	PR01	PR02
2	PS03	PS04	PR02	PR03
3	PS05	PS06	PR03	PR04
4	PS02	PS03	PR04	PR05
5	PS04	PS05	PR05	PR06ab
6	PS06	PS01	PR06ab	PR01
7	PR01	PR03	PS01	PS02
8	PR02	PR04	PS03	PS04

9	PR03	PR05	PS05	PS06
10	PR04	PR06ab	PS02	PS03
11	PR05	PR01	PS04	PS05
12	PR06ab	PR02	PS06	PS01
13	PS01	PS03	PM01	PM02
14	PS02	PS04	PM02	PM03
15	PS03	PS05	PM03	PM04
16	PS04	PS06	PM04	PM05
17	PS05	PS01	PM05	PM06ab
18	PS06	PS02	PM06ab	PM01
19	PM01	PM03	PS01	PS03
20	PM02	PM04	PS02	PS04
21	PM03	PM05	PS03	PS05
22	PM04	PM06ab	PS04	PS06
23	PM05	PM01	PS05	PS01
24	PM06ab	PM02	PS06	PS02
25	PS01	PS02	PR01	PM01
26	PS03	PS04	PM02	PR02
27	PS05	PS06	PR03	PM03
28	PM04	PR04	PS02	PS03
29	PR05	PM05	PS04	PS05
30	PM06ab	PR06ab	PS06	PS01

Source: OECD (2017b)

Where PR01-PR06 represent reading items, PM01-PM06 correspond to mathematics items, PS01-PS06 represent science items; and finally, *a* and *b* represent two different degrees of difficulty, standard or easier, respectively.

Consequently, to deal with the uncertainty associated with the computation of students' proficiency, PISA uses multiple values to represent its distributional likelihood (Davier, Gonzalez and Mislevy, 1997), with mean and standard deviation equaling 500 and 100, respectively. Test scores are estimated as plausible values, where each student has 10 different marks. This is done using socio-economic information as auxiliary information to impute final *learning scores*, through a technique called plausible values, which are "drawn from a posteriori (data) distribution by combining the IRT scaling of the test items with a latent regression model using information from the student context questionnaire in a population model" (OECD, 2017b, p. 128).

In terms of analysis, PISA (OECD, 2017b) suggests considering student proficiency as a missing value and applying Rubin's rules for handling multiple imputations (Rubin, 1987). This can be divided into four steps.

I) The estimation of the models of interest has to be performed for each plausible value (10 dependent variables in the case of PISA 2018 and PISA 2015, and 5 in the case of PISA 2012). This generates separate sets of parameter estimates (β_{pv}) and standard errors (σ_{pv}).

II) To produce a final parameter (β_*) and standard error estimate (σ_*), For PISA 2018 and PISA 2015, the estimates are averaged as follows:

$$\beta_* = \frac{\sum_{pv=1}^{10} \beta_{pv}}{n_{pv}} \text{ and } \sigma_* = \frac{\sum_{pv=1}^{10} \sigma_{pv}}{n_{pv}} \qquad (2)$$

III)

Where n_{pv} refers to the number of plausible values.

III) I estimate the magnitude of the imputation error(δ_*), which is computed through the following formula:

$$\delta_* = \frac{\sum_{pv=1}^{10}(\beta_{pv} - \beta_*)^2}{n_{pv} - 1} \tag{3}$$

IV) Finally, I compute a final standard error estimation by combining the sampling error (σ_*) and δ_* via the following formula:

$$\text{s.e.} = \sqrt{\sigma_*^2 + \left(1 + \frac{1}{n_{pv}}\right) . \delta_*^2} \tag{4}$$

V)

The averaged parameter estimates (β_*) and their standard errors are used to conduct hypothesis tests and construct confidence intervals. The same method is applied in the computation of random effects and model fit parameters.

1.4.2.Stratified sampling design

PISA aims to represent the country population through a stratified sampling design. PISA uses a two-stage stratified sample design that allows statistical representativeness both at country and at school stages, except for the Russian Federation, where a three-stage design is used. Achieving representative samples of schools and students is key for PISA and data not meeting this requirement are dropped. This is in order "to ensure adequate accuracy in estimating variance components within and between schools – a major analytical objective of PISA" (OECD, 2017b, p. 68). In most countries, the sample falls into the range of 4,000 to 8,000 students assessed in each cycle.

Due to the sampling strategy to select schools and students, regression models require sampling weights to be used to account for differences in the probabilities of students, classes and schools being selected in the sample (Rutkowski *et al.*, 2010).

1.4.3. Sampling variance

Finally, due to the stratified multistage sampling design mentioned earlier, PISA deals with the uncertainty associated with the sampling using Fay's modification of the balanced repeated replication (BRR) method. This implies considering a method to take the sampling variance into account. I use two different strategies to estimate the uncertainty associated with the sampling under the PISA approach. In chapters 2 to 4, I include Fay's modification of the balanced repeated replication (BRR) method in the models, as is suggested by PISA. In chapter 5, due to computational limitations, I use robust clustered standard errors, as suggested in previous literature (Jerrim, Lopez-Agudo, Marcenaro-Gutierrez, *et al.*, 2017).

1.4.4. Latent variables

PISA uses Item Response Theory (IRT) to measure all its latent variables such as *learning scores* and HOMEPOS. IRT models are tools from modern psychometric theory extensively used to measure latent traits in the fields of education and psychology. The benefits of IRT models relate to the reduction of measurement error, meaningful scales of measurement, the extended sense of model reliability, a wide range of model calibration and equating (i.e., to allow comparisons of items and scores over time), and, finally, greater depth regarding the assessment of the fit of items, persons, and models to the data. More details are presented in Chapter 3.

PISA gathers rich data to reflect students' socioeconomic status. Among these, I focus on the home possessions index, HOMEPOS, which reflects household possessions. HOMEPOS is computed based on 25 questions that students are asked about their household belongings, such as electronics, books, and other educational resources. Each student is given a value for HOMEPOS.

1.5. Analytical methods used in this thesis

Across this thesis, I use two sets of dependent variables, Reading and Mathematics. As correlations between both are high across all cycles, which also occurs on other ILSAs and national examinations, I use them indistinguishably. I use *learning scores* as a proxy of the cognitive skills acquired during the schooling process. While capturing nuances of reading and mathematics skills is very important for the learning and teaching process, this direction falls outside the scope of this thesis.

Data in PISA has a hierarchical structure, where students are nested in schools, which are nested in countries. This construction allows two-level models to be used, such as mixed-effects linear models (used in *Chapter 2. Measurement of school-level inequality based on categorical data-; Chapter 3. School-level inequality and learning achievement: evidence from PISA; and Chapter 4. Inequality, social cohesion, and academic achievement: evidence from PISA 2018)* and two-level structural equation models (used in chapter 4). Multilevel models have the advantage of avoiding specification problems related to an underestimation of standard errors as well as to possible multicollinearity between school-level and country-level factors.

In chapter 2, I run separate models for each country, allowing for random intercepts at the school level.

In chapters 3 and 4, I run models aggregating all countries, allowing for random intercepts at the school level, and fixing country effects. Additionally, in chapter 3, I also model three-level models, allowing intercepts to vary both at the school and country level. I found results to be very similar between regressions with two and three random levels.

Finally, in *Chapter 5. Educational segregation and school inequality*, I run models aggregating all countries, allowing for random intercepts at the country-level. This allows a country-level variable, such as *segregation*, to be addressed.

1.5.1.Missing data

Across the thesis, I assume cognitive data are missing completely at random (MCAR). This relies on the fact that test booklets are randomly assigned to students. In this case, missing data from cognitive tests are usually considered to be MCAR (Jerrim, Lopez-Agudo, Marcenaro-Gutierreza, *et al.*, 2017; Pohl and Becker, 2020). However, in the case of background data, there is a possibility that data could be missing not at random (MNAR). While most of the discussion on ILSAs regards how missing background information affects the estimation of plausible values (Kaplan and Su, 2018; Grund, Lüdtke and Robitzsch, 2021), very little has been recommended in terms of inferential analysis. Based on Cheema (2014), I use listwise deletion methods because of the large size of the sample and the low percentage of missing data.

1.6. My epistemological and ontological position

"Inequality is a fact. Equality is a value." (Mason Cooley)

“It’s my impression that quantitative social science is generally taught with separation between measurement, descriptive analysis, causal inference, and theory building.” (Andrew Gelman)

“If only one man dies of hunger, that is a tragedy. If millions die, that’s only statistics.” (Attributed to Joseph Stalin in the Washington Post, *20 January 1947)*

The above-mentioned quotes have been my companion throughout the whole thesis. They remind me every day why I research inequality, what type of social scientist I aspire to be, and the importance of using statistics and data without forgetting that they represent real people.

As a quantitative social scientist – a label suggested by my supervisor to describe my skills and interests – I focus on studying complex social phenomena. To achieve that, I follow modern scientific methods based on evidence gathering, hypothesis formulation and deductive reasoning. While this could be seen as pure positivist-empiricist thinking, I find it enormously difficult to synthesize my stance under clear-cut labels, mostly because of their plurality regarding different meanings and interpretations. Although quantitative social science provides relevant information and interpretation of facts, I think developing a deeper reflection about these in terms of defending a thesis - in the original sense of the word, as expressing views that are held as valid given the evidence provided (Aristotle, Topica, 104b33-35) - could provide additional justification for my work.

Having a philosophy background, I prefer to follow a different approach and accept that the same vagueness will remain in my positionality. First, I need to discuss my metaphysical standpoint. Following Gilson, I accept that “Metaphysics is the knowledge gathered by a naturally transcendent reason in its search for the first principles, or first causes, of what is given in sensible experience” (1937[ed. 1982],

p. 308). Experience is the key aspect here. I consider reality exists and can be known. I also accept the possibility of finding the truth, which is not a tangible thing, but a relationship between the mind and the object (Aristotle, [ed.2011], sec. 16a3). At the same time, although I sustain that we can know the world around us, I recognise our contingency, which makes me aware of misinterpretations, wrongful perceptions, and bias in my process of interpreting and understanding.

This approach is closer to a school of thought known as critical realism (Downward, Finch and Ramsay, 2002). Succinctly, it postulates metaphysical realism - reality exists aside from the subject of inquiry – where the focus of the inquiry is "concerned with the nature of causation, agency, structure, and relations, and the implicit or explicit ontologies we are operating with" (Archer *et al.*, 2016, sec. Ontological realism). At the same time, it approaches reality with epistemic relativism given that our knowledge about that reality is always situated historically, socially, and culturally. This standing departs from a naïve realist perspective as I understand that all our representations of the world have limitations and are fallible, as well as coming from particular perspectives. In this sense, I understand that "scientific knowledge is always formulated in terms of conceptual frameworks which are themselves not unique ways of parsing the empirical world" (Archer *et al.*, 2016, sec. Epistemic Realism).

Although in this thesis I am limited to the analysis of secondary data using prevailing psychometric and econometric techniques, which are mainly used in positivist research paradigms, I emphasize one difference with the former approach. I understand that regularities are bound to time and place because of the "continual interplay between (intrinsic) reflexive human agency and structure

(…) where the cause of the events may only be revealed partially because of their complex codetermination and limited" (Downward, Finch and Ramsay, 2002, p. 483). This is well developed by the 'relational sociology' school, which falls into a critical realist realm (Archer, 2015). In applied terms, my current research focuses on the complexity of the macro-micro relationship between individuals (students) and structures (schools), where the agency is assumed as possible although constrained, and where structure plays a role. This is the focus of chapter 3, where I also deepen the theoretical grounds of relational sociology.

I follow the approach of the 'relational sociology' school (Donati, 2012; Archer, 2015; Donati and Archer, 2015), which understands the agency and structure tension as able to be solved by giving ontological value to social relations within the societal context. In this sense, I assume society (and schools as social institutions) are a product of "associative and dissociative relations that arise from societal structures and cultures and how human action continuously alters them" (Donati and Archer, 2015, p. 26), understanding that either positive and negative interactions drive the building of societies. Therefore, schools act as social institutions in at least three different ways (Wentzel and Looney, 2007). First, schools' social characteristics may influence or hinder children's social development. Second, social interactions among peers and others teach children how to integrate (positively or negatively) in the social world. Finally, the quality of children's relationships has a positive or negative impact on the likelihood of acceptance, adaptation and internalisation of expectations valued by others (Grusec and Goodnow, 1994).

1.7. Thesis outline and contribution

The thesis is organised into six chapters.

In this introductory chapter, Chapter 1, I provide an overview of the theoretical and empirical evidence of the phenomenon of *school inequality,* focusing on its measurement (see below). Here, I also account for my ontological and epistemological positionality, which influences how I comprehend the importance of inequality in our world.

This is followed by comprises four empirical chapters with discrete literature reviews and methodologies. Chapter 2 focuses on the relationship between *school inequality* and educational *segregation*. This chapter addresses a methodological limitation in measuring inequality based on survey data collected using Likert-scale or Yes/No style questions within a short questionnaire or in a limited amount of time. I suggest a novel approach to measure inequality relying both on the collected data and on the IRT models used by PISA. I use the equation parameter that defines the steepness of the logistic curve (called the discrimination parameter in IRT terminology and represented by the Greek letter α) as the key ingredient of the novel inequality measure, named *Alpha Inequality.* Lastly, I compare the behaviour of *Alpha Inequality* with another inequality index, namely, a Gini Coefficient based on the derived index HOMEPOS. The comparison is mainly based on assessing the significance of these variables in within-country mixed-effects regression models.

Chapter 3 addresses the relationship between aggregate inequality and educational outcomes, and the testing of the hypothesis of the association of *school inequality* with *learning scores.* This chapter concentrates on cross-sectional associations between *school inequality* and *learning outcomes*. First, it reviews the available body of literature that has studied the relationship between aggregate inequality and educational outcomes, which is divided into three categories: access to education, effects on the social fabric, and relative deprivation. Using data from 2012, 2015, and 2018, I consistently find negative correlations between *school inequality* and *learning scores*. These findings are robust across different model specifications, subsamples, and measures of inequality. Studying total relative deprivation – the interaction between Gini and wealth – also reveals an interesting phenomenon: across all waves of PISA, in wealthier schools, students' average scores deteriorate proportionally more than in less affluent institutions. Additionally, I find that *school inequality* significantly interacts with different levels of average school HOMEPOS. This suggests that the role of inequality differs depending on the economic context and I find that it is stronger for wealthier schools. Results are confirmed for three waves of PISA and are fairly robust in the use of different measures of inequality.

Chapter 4 examines moderating and mediating attitudes that can affect the relationship between *school inequality* and *learning scores*. In this chapter, I address the question regarding what individual or school-level factors may mitigate this pervasive association between *school inequality* and *learning scores*. The chapter offers a theoretical framework to explain how attitudes in the realm of social cohesion interplay with wealth inequality within-schools on *learning scores*. First, I theorise about which social psychology processes, such as social isolation, interpersonal comparisons and anomie, are postulated as mechanisms to explain these phenomena. Three theoretical pathways are hypothesised: a possible compensation, moderation, and mediation of certain individual features that reflect attitudes to social cohesion on inequality and *learning outcomes*. The variables chosen are the sense of school belonging, cooperation between peers, understanding others' perspectives, agency towards global issues, and respect for people from other cultures. I find strong associations between the social cohesion dimensions studied, *school inequality* and *learning scores*. Among them, the variables relating to the sense of belonging to schools and respect for others consistently show a positive effect across all hypotheses.

Finally, Chapter 5 was mainly developed in response to productive discussions with my colleagues during the VII National Educational Research Seminar of the Peruvian Society of Educational Research (SIEP, for its acronym in Spanish) in 2020. The seminar theme was 'Causes and challenges of educational segregation: implications for quality, equity and the construction of citizenship'. The main question raised regarding my presentation (of Chapters 2 and 3) was about a potential ethical and empirical conflict between *school inequality* and the inequality within an aggregated level of schools, namely, an educational system. The main theoretical conflict relies upon the fact that promoting school equality would potentially produce a socioeconomically stratified system. In this sense, I consider this chapter as a necessary digression towards differentiating and providing a better understanding of the issue of *school inequality* framed by the understanding of different theories of justice. While in a theoretical scenario both phenomena are contradictory, I use PISA 2018 data to provide an exploratory analysis showing how both phenomena are different in real life and concurrently occur with a negative independent effect on *learning scores*. In contrast to the previous chapters where I use country fixed effects that already capture the gradient of country *segregation*, in this final empirical chapter I explicitly model regressions adding country *segregation* as an independent variable.

The final chapter, Chapter 6, presents an intertwined discussion of the previous chapters and sets out my conclusions as well as suggestions for further research.

2. Measurement of school-level inequality based on categorical data[4]

2.1. Introduction

Categorical data collected by large-scale assessments pose diverse methodological challenges that hinder measuring inequality due to data truncation and asymmetric intervals between categories. This chapter introduces a new method to measure school-level inequality, named Alpha Inequality, based on Item Response Theory (IRT) models. I use the discrimination parameter of 2-parameter logistic regressions, which capture the degree of steepness of the sigmoid curve. This allows computing of the item degree of respondents' segmentation as adherence (or possession) of the item. I axiomatise the measurement in order to provide information regarding its properties. I apply Alpha Inequality to the items that capture household possessions data from PISA 2015. I exemplify the process of computing the measurement and develop a set of country-level mixed-effects linear regression models comparing the predictive performance of the novel inequality measure with school-level Gini coefficients. I find school-level inequality is negatively associated with learning outcomes across many non-European countries.

Although the relevance of socioeconomic factors as predictors of children's cognitive learning attainment is a highly disputed issue as regards causality (Mayer, 1997), there is extensive and long-standing research recognising its

[4] An abbreviated version of this chapter has been published as "Sempé, L. (2021). School-level inequality measurement based categorical data: a novel approach applied to PISA. Large-scale Assessments in Education, 9(1), 1-31".

important role in explaining educational disparities in access to schools and schooling outcomes (Coleman, 1966; Del Bello, Patacchini and Zenou, 2015). Furthermore, research from a range of disciplines has highlighted a negative association between socioeconomic disparity and individual outcomes, offering various explanations for the detrimental role of inequality on domains such as health and subjective well-being (Deaton, 2003; Wilkinson and Pickett, 2006; Schneider, 2016).

Socioeconomic variables also play an important role in Large-Scale Assessments to explain or control for differences among groups in relation to *learning outcomes* and other variables of interest (Hopfenbeck *et al.*, 2018). However, the possible interplay between school-level inequality and educational outcomes has been addressed less extensively. Although previous research has developed alternatives to address the measurement of inequality-based dichotomous or ordinal data, to my knowledge there has not been an alternative that computes inequality in the same statistical framework used in Large-Scale Assessments by using Item Response Theory (IRT). In this chapter, I develop a novel method to measure school-level assets inequality utilising IRT models based on the discrimination parameter α. The proposed inequality measure computes the dispersion of the data at a certain aggregated level, such as schools or countries. The measure allows both ranking of observations in terms of inequality, and the comparison of the average inequality across the schools. I exemplify this case by computing inequality based on HOMEPOS data from the PISA cycle in 2015.

The chapter research questions are formulated as follows:

1 - To what extent *school inequality* can be measured using categorical data? (Measurement)

2 - To what extent a novel method of measurement of *school inequality* relates to typical measurements of association with learning scores? (External validity)

The remainder of the chapter is structured as follows. Section 2 discusses the role and limitations of socioeconomic variables in PISA and International Large-Scale Assessments (ILSAs), while section 3 reviews the relevant literature regarding the measurement of inequality using categorical data, discussing the main methods developed in recent literature. Section 4 briefly introduces IRT and summarises the methodological construction process of the inequality measure, *Alpha Inequality*. Section 5 introduces the criteria used to analyse *Alpha Inequality* and the data used in the empirical section. Section 6 presents the findings of the construction process of *Alpha Inequality* and a comparative analysis of descriptive and inferential results with models using the Gini coefficient, while Section 7 concludes the study.

2.2. Socioeconomic measurement in PISA

The relevance of socioeconomic background questions in PISA as well as in ILSAs is twofold. First, socioeconomic variables are constantly used as control regressors as well as in the analysis of equality of opportunities of educational systems. For instance, PISA reports differences among scores within quintiles of wealth and gaps explained by less privileged socioeconomic backgrounds (OECD, 2016). Second, due to the nature of PISA and other ILSAs, where there is limited time to cover diverse aspects of knowledge, students are exposed only to a portion of cognitive tests. Subsequently, socio-economic information is used as auxiliary information to impute final *learning scores*, through a technique called plausible values, which are "drawn from a posteriori (data) distribution by combining the IRT scaling of the test items with a latent regression model using information from the student context questionnaire in a population model" (OECD, 2017b, p. 128).

Extensive research has been done analysing background questionnaires in PISA, showing diverse limitations on socioeconomic indicators. For instance, there is evidence of cross-country comparability deficiencies within and between PISA cycles (Sandoval-Hernandez *et al.*, 2019; Lee and Von Davier, 2020) and poor model fit (Rutkowski and Rutkowski, 2013). One of the main consequences is the distortion of achievement estimates – see, for example, Rutkowski (2011, 2014) and also Rutkowski and Zhou (2015). Additionally, prior research also reports deficiencies regarding the cultural validity of some questions. For instance, there is a particular bias towards better describing the contexts of developed countries, such as the number of questions that reflect a certain type of cultural possession (e.g., the possession of certain classic musical instruments or having books of art at home) (Rutkowski and Rutkowski, 2010, 2013). The greater access to electronic goods or internet provision at the present time does not necessarily differentiate among more and less privileged social groups as could have been the case in the recent past (Avvisati, 2020).

Turning specifically to HOMEPOS in PISA 2015, I observe the wording of questions that raises concerns regarding their weight in the computation of the index. For instance, six of the common 22 questions (27%) refer to the possession of different books, while four questions (18%) refer to electronic possessions. In that regard, two questions present similarities: 'Computers [desktop computer, portable laptop, or notebook]' and 'A computer you can use for school work', which presents a strong polychoric correlation, $r(492{,}640) = .739$, $p < .001$. Finally, the question asking about the possession of 'works of art' at home is open to diverse interpretations, which may confuse respondents. This last question parameter is not included in official reports, although it was also not formally excluded from the index (OECD, 2016, 2017b).

Another relevant topic relates to the national items that are identified in three questions chosen by each country or territory, which has been praised as a step forward in the better contextualisation of socioeconomic status (Rutkowski and Rutkowski, 2013). However, diverse points can be raised about those questions: first, they do not necessarily reflect socioeconomic status but household choices (e.g., espresso machine in France or paid cultural television programs in Albania). Second, they may refer to outdated technology ('Blu-ray player' in Mexico) or are biased towards specific sensitivities ('Violin / Cello' in Hong Kong, 'Piano or violin' in Chinese Taipei and Macao, or a 'piano' in the Netherlands). Third, in a few cases, they relate to the possession of luxury goods ('summer residence' and 'swimming pool' in Malta), which produce extreme parameters. It is also possible to detect redundancy of those national questions with the common questions. For instance, many questions regarding electronics are repeated (e.g. 'laptop' in Moldova and Finland or 'tablet' in Norway, Spain, Switzerland and the UK; 'musical instruments' in the United States; an 'encyclopedia' in Colombia), while local dependencies and inconsistencies among answers are not explicitly assessed by PISA (Avvisati, 2020). Finally, it is possible to find important differences in factor loadings among countries (OECD, 2017b), which suggests room for improvement as regards capturing wealth in families. Additionally, one of the trade-offs of extending national items in HOMEPOS is the difficulty of addressing cross-country comparability issues using fewer common items across countries. While many criticisms can be made of HOMEPOS that highlight limitations and challenges, these still are relevant sources to be used with caution to shed light on the role of socioeconomic differences in schools.

2.3. The complexity of measuring inequality based on categorical data

Measuring inequality based on ordinal or binomial data, or a mixture of both, creates a set of methodological challenges. First, certain distributional statistics, such as the mean or variance or standard deviation, cannot be properly drawn (Zheng, 2008; Cowell and Flachaire, 2012a). Proportions and modes will be appropriate tools to analyse this type of data. Second, in many cases, ordinal data depict an arbitrary scale or asymmetric intervals in their response choices, which may also bias the analysis. For instance, a 5-point Likert scale question does not necessarily represent the same difference between pairs of options. I could either choose the category 'agree' or 'strongly agree' – both options are closer in my mind in this case – for an opinion regarding certain policies addressing inequality within-schools, although I would never choose the middle-point category – 'neither agree nor disagree' – because I consider it as much further removed from the 'agree' I might have chosen.

One of the consequences of dealing with categorical data is that traditional inequality measures, such as the Gini coefficient and generalised entropy indexes (for example, Theil or Atkinson indexes), which refer to inequality as a deviation from the mean or are mean-normalised, cannot be suitably employed to measure inequality using categorical raw data (Zheng, 2011; Cowell and Flachaire, 2012a). In the next Chapter, I will also use and compare those measures of inequality using HOMEPOS as the basis of the computation.

Recent research has been developing alternatives to develop inequality measurements based on categorical data. Allison and Foster (2004) suggest comparing one-variable cumulative distributions of Likert-type questions by ordering the data and identifying the distance from the median as an inequality measure. As they note, their method only applies when the median coincides across variables. Additionally, this method does not meet a desirable characteristic of any inequality index -the normalization axiom-, where a distribution of identical observations in the presence of total equality, desirably portrays a zero value. Based on that seminal idea, Abul Naga and Yalcin (2008) introduce a family of inequality indices based on the analysis of one variable that normalises the scales of different questions. Within their method, different Likert-scale questions – portraying 3, 5 or 7 alternatives – can be compared in terms of inequality. Zheng (2011) extends the approach to measuring inequality based on two variables. However, if the median does not provide an adequate reference for inequality (for example, when there is skewness of data), all previous measures may not capture the extent of the inequality.

A second approach developed to address this limitation is proposed by Cowell and Flachaire (2012a, 2012b). Instead of using the median as a reference, they compute inequality relative to a reference status. They suggest counting ranking positions of all observations and expressing them as proportions of the population. The measure could be either 'downwards' or 'upwards' as a relative position on a scale. Although very suggestive, this method does not seem adequate for measuring household's assets inequality due to the multivariate nature of a continuous wealth trait. However, the idea of maintaining the ordinality of the scales and ranking them rather than measuring inequality remains in my proposed approach.

A third approach that addresses multiple variables consists of computing inequality based on latent variable methods. For instance, McKenzie (2005) suggests a relative inequality measure towards identifying the disparity between subpopulations based on a polychoric Principal Component Analysis index data. His method computes each subpopulation's standard deviations divided by the variance explained by the first principal component, which additionally allows the comparison of subgroups with the overall population inequality. The idea of ratios and comparing with the overall inequality average are kept in my proposal. In this instance, IRT is chosen over polychoric PCA as a specific approach to model categorical data.

Finally, at least three caveats can be drawn when assessing school-level inequality based on HOMEPOS. First, HOMEPOS is derived through a posterior weighted maximum likelihood estimation (WLE), which assumes a normal distribution (Warm, 1989). In the case of PISA 2015, significant differences between countries occur in the mean of HOMEPOS, while there are fewer variations in the distribution across countries (see ***Figure*** 17 in Annexes). Second, simulations show that WLE tends to overestimate within-school variance (OECD, 2009). This is relevant for my case as school-level inequality is relative to the variance of School HOMEPOS. Third, WLE is sensitive to ceiling and floor effects if items are too easy or difficult, respectively. This contradicts another desired property of any inequality measure – scale invariance, where proportion changes to answers should not modify inequality. For example, if we add 10% of wealth to everyone, inequality remains the same as before. Finally, as WLE is only a single possible realization of the estimation, it does not address the uncertainty of the model, which could be adapted by using plausible values as independent variables (Pokropek, 2015). However, to address current limitations in measuring inequality based on WLE, I compute inequality based on the raw answers of family possessions rather than using the derived-index HOMEPOS.

2.4. *Alpha Inequality*: inequality based on an IRT paradigm

2.4.1. Item Response Theory models

The proposed inequality measure *Alpha Inequality* builds upon the discrimination parameter from IRT models. IRT is a statistical family of latent construct analysis that focuses on categorical data and is mainly used in educational and psychological fields. IRT assumes that each person has a certain level – called individual trait – of an unobservable continuous construct (e.g., knowledge, competencies, attitudes) that predict the probability of answering correctly or endorsing an observable item (e.g., cognitive questions or household possesions). In this case, the higher the possession of the construct family wealth, the higher the probability of confirming the possession of the item electronic goods.

This is based on the notion that the probability of a correct response or endorsement to an item is a function of both the person's trait and certain item parameters such as difficulty, discrimination or pseudo guessing (Embretson and Yang, 2006). The item parameters determine the information offered by each item to any person's trait level.

The simplest IRT model is often called the *Rasch* model (Rasch, 1960). According to the *Rasch* model, an individual's response to a binary item (i.e., right/wrong, agree/disagree) is determined by the individual's trait level (θ_j) and one item parameter – the difficulty of the item, β_i–. Because this model uses the logistic density function and a single item parameter, it is called the One-parameter logistic model (1-PL) (Fischer, 1995), although there are some conceptual differences between *Rasch* and 1-PL. The distribution of θ_j is estimated through a maximum likelihood function that weights each item by all the IRT function parameters and considers the endorsement of the question.

Other IRT models have been developed covering ordinal and nominal data, adding parameters to the logistic function such as the discrimination or guessing parameters (Embretson and Yang, 2006), and also using distinct methods towards dichotomising data for the analytical modelling process. For instance, in 2015, PISA uses two IRT models: the generalised partial credit model (GPCM) (Muraki, 1992) for multi-item questions, and the two-parameter logistic model for dichotomous items. In both cases, it adds the item discrimination parameter α_i to the function, which will be explained later. The GPCM presents the following notation:

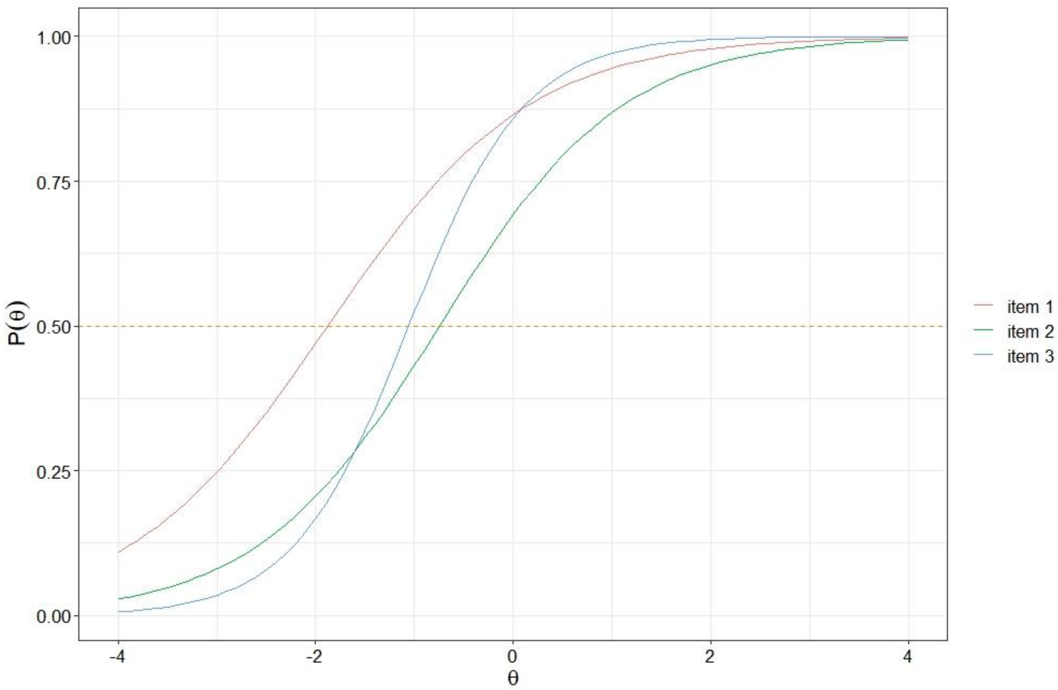
$$P\left(X_{ij} = k \middle| \theta_j, \beta_k, \alpha_i\right) = \frac{e^{\left[ak_{k-1}\left(\alpha_{2i}\theta_{2j}+\alpha_{2i}\theta_{2j}+\ldots+\alpha_{ni}\theta_{nj}\right)+\beta_{k-1}\right)]}}{\sum_{k=1}^{K} e^{\left[ak_{k-1}\left(\alpha_{2i}\theta_{2j}+\alpha_{2i}\theta_{2j}+\ldots+\alpha_{ni}\theta_{nj}\right)+\beta_{k-1}\right)]}} \quad \textbf{(1)}$$

Which expresses the probability of an individual $i$correct response (or endorsement)X_i to an item$j$ for the total number of categories K of each question. θ_j represents the individual's trait level, while β_k refers to the item difficulty or location. The parameter ak_k indicates the ordering of the categories from 0 to $k - 1$ (Chalmers, 2012).

The discrimination parameter $\boldsymbol{\alpha_i}$ represents the degree to which respondents are differentiated in regions of the measured latent trait $\boldsymbol{\theta_j}$ (in this case, household possessions). The parameter defines the steepness of the slope when $\boldsymbol{P(\theta) = .5}$, where higher values suggest a better separation between individuals with higher and lower latent traits. Therefore, if $\boldsymbol{\alpha_i} \to \infty$, the item represents a perfect separation between those who respond correctly, (i.e., in this situation, have a specific possession), and those who do not.

Figure 1 is a simulated example of an item characteristics curve (ICC) for three items, where item 3 has a higher discrimination parameter than the other two items because it shows a steeper curve than item 1 or 2. The item discrimination parameter α_i reflects the sensitivity of the response probability to trait levels changes (Embretson and Yang, 2006) and gives information on the importance of the item to the individual trait – in this case, how possessing a certain good reflects family wealth.

Figure 1: Example of 3-item Characteristic Curves



Source: own elaboration. Original in colour.

Now I depart from the usual IRT parameter interpretation to turn to the consideration of inequalities. First, it is important to remember that inequality is an aggregated measure and not an individual condition. Therefore, we can think about the latent trait as a continuum of equality (or inequality) of wealth for all respondents. In the hypothetical case that all respondents fall into the same value of θ, then the item represents an egalitarian condition – irrespective of the location on the x-axis – of $P(\theta) = .5$, where values on the left of the axis would represent poverty while those on the right would represent wealth). If the same occurred for all items, then there would be a status of full egalitarianism. Additionally, as the parameter defines the steepness of the ICC, larger item discrimination also means that the gap between those that are below the 50% probability of endorsing the item and those over that threshold has greater weight in terms of splitting individuals in the trait. The *Alpha Inequality* is based on this interpretation of the discrimination parameter.

2.4.2. Developing *Alpha Inequality*

The building process of *Alpha Inequality*, I_j, of any economic variable of interest – in this case, household assets possession – implies the following steps. The method involves modelling any IRT or latent variable model that considers the binary or ordinary nature of the responses – such as the graded response model, continuation ratio model, among many others – and assumes the existence of a discrimination parameter that differs between items, which is not the case of a 1-PL model. In this example, I use GPMC for polytomous questions and 2-PL for binary items to coincide with the PISA 2015 modelling strategy.

Turning to the building process of *Alpha Inequality* more formally, let $x = \{x_1, x_2, \dots\} \subseteq \mathbb{R}$ represent a vector describing the distribution of any economic variable of interest, in this case, household assets possession as home wealth. The computation of *Alpha Inequality*, $\mathrm{I}_{\varphi}(x)$, implies the following steps.

The first step involves computing the IRT models for each item used in building the index and extracting the α_i parameters. The second step consists of normalising all alternative answers, ς_j, into the same range of values, in this case, from 0 to 1. This is done to give the same importance to polytomous and binomial questions and to produce an equal contribution to the inequality measure. The third step involves the sum of the product of each parameter α_i and the observation score ς_j for each observation (person), j, of the dataset. This is noted as follows:

$$\xi_j = \sum_{j=1}^{n} \alpha_i \varsigma_j \tag{2}$$

where α_i is constant across students and schools and only varies for different items and the variable ς_j varies for each student and school.

In the case of missing data, I weight each observation j according to the number of questions answered, q_j to differentiate questions not answered from the absence of possession of an item, such as in:

$$\omega\xi_j = \frac{\xi_j}{q_j} \tag{3}$$

$where \omega\xi_j$ is a standardised form of ξ_j.

The final step implies computing the inequality measure for each school. Following McKenzie (2005), the inequality measure for each school φ is computed as the ratio between the standard deviation of $\omega\xi_j$ and the standard deviation of the entire population c, in this case, each country, ξ_c, which can be expressed as:

$$\mathrm{I}_\varphi = \frac{\sigma(\omega\xi_j)}{\sigma(\xi_c)} \tag{4}$$

I_φ provides at least three different pieces of relevant information. First, it allows for the comparison of inequality levels between schools; second, when $I_\varphi = 0$, it represents a within-school egalitarian status; finally, when I_φ is greater than one, the school displays more inequality than the average inequality for that country.

Every inequality measure has some properties to fulfil in order to provide reliable information regarding the distribution of any variable, in this case, wealth: scale and anonymity invariance, population independence, and binding the Pigeou-Dalton transfer principle (Cowell, 2016). Axiomatisations are also important because they characterise a measurement of basic inequality properties, which facilitates the comparison with other different measures.

Henceforth, I present how I_{φ} fulfils all main inequality axioms.

$Lemma 1. I_{\varphi}$ satisfies the main properties of an inequality measure.

- I_{φ} is continuous on the domain of distributions I.
- I_{φ} is invariant to permutations of the measure among students in the same population (anonymity invariance).
- I_{φ} is invariant to any multiplication of each student score observation by any positive integer constant. The inequality measure is, therefore, independent of the aggregate level of income (scale invariance).
- I_{φ} remains invariant to the size of the population, and therefore, to the replication of observation of the original population (population independence).
- Redistributing benefits from richer to poorer individuals (without individual re-ranking) reduces I_{φ}, as the standard deviation at the numerator decreases while the denominator remains unchanged (Pigou-Dalton transfer).
- I_{φ} takes a value of zero when all individuals rank their health status identically (normalisation).

Proof of Lemma 1

(Continuity) $I_{\varphi_1}$and I_{φ_2} represent two inequality measures. If $I_{\varphi_1} \approx I_{\varphi_2}$, then they will have very similar inequality values.

(Anonymity) Let x denote any distribution of assets with elements $\{x_{1,}x_2, \ldots\}$. As $I_\varphi(x)$ depends only on the set $\{x_{1,}x_2, \ldots\}$, any permutation of elements of x does not produce changes in I_φ,so $I_\varphi\big(P(x)\big) = I_\varphi(x)$.

(Scale invariance) For any $I_\varphi(x)$, multiplying a constant $\gamma > 0$to all elements of the set $\{x_{1,}x_2, \ldots\}$ produces $I'_\varphi(x\gamma) = I_\varphi(x)$.

(Population invariance) For any x, replicating the population would produce$\xi'_l = \alpha_{l1}\varsigma_{l1} + \alpha'_{l1}\varsigma_{l1} + \alpha_{l2}\varsigma_{l2} + \alpha'_{l2}\varsigma_{l2} + \cdots + \alpha_{ln}\varsigma_{ln} + \alpha'_{ln}\varsigma_{ln}$. Then

$I'_\varphi = \frac{\xi'_l}{\xi'_p} = I_\varphi(x \cup x) = I_\varphi$.

(Pigou-Dalton transfer property) Let ξ denote a wealth score of individuals l and m, where $\xi_l > \xi_\mathrm{m}$. Let $\hat{\xi_l} = \xi_l - \delta$and$\hat{\xi_m} = \xi_m + \delta$, when δ > o transferred from l to m. Let I_φ and $\hat{I_\varphi}$ represent the initial and transformed inequality measure. As $\sigma_j > \hat{\sigma_j}$, then $I_\varphi > \hat{I_\varphi}$.

(Normalisation) For any x where $\{x_1 = x_2, \ldots\}$, $\sigma(\xi)$=o, then $I_\varphi = 0$.

This section suggests the inequality measure fulfils the main properties customarily deemed desirable for an inequality measure, and therefore, can be accepted as a desirable measurement of inequality.

2.5. Methods

2.5.1. Data

I use the wealth index, HOMEPOS from PISA 2015 to exemplify and evaluate the performance of *Alpha Inequality*. PISA 2015 collects data from dichotomous and ordinal questions on 25 household indicators across 73 countries and economies. The target population and sampling strategy aimed to represent the universe of 15-year-old students enrolled in each educational system. Students are sampled following a stratified design, where a minimum of 150 schools with proportional probabilities to the student population is initially selected. The minimum sample expected by a school is 20 students to ensure adequate accuracy in estimating variance between and within-schools (OECD, 2017b).

HOMEPOS is computed based on data collected from three student's questions (ST011, ST012, ST013), with 25 questions covering different household assets and characteristics. Question ST011 displays two sets of dichotomic questions (possible answers: 'yes', 'no'): 13 that are common to all countries and three questions that differ by country (called national items). Question ST012 displays eight 4-response option questions (possible answers are: 'none', 'one', 'two' and 'three or more'), common to all countries, while Question ST013 presents one question with six scales (with the following possible answers: '0–10 books', '11–25 books', '26–100 books', '101–200 books', '201–500 books', and 'More than 500 books').

Following PISA's criteria (OECD, 2017b), I remove those observations with at least three answers on the HOMEPOS scale and no missing values for the computed HOMEPOS scale. I exclude observations from schools with less than 20 observations. Additionally, data from two USA states and Puerto Rico, which did not provide identification of schools, are also excluded. The sample was reduced from 519,334 to 454,734 observations pertaining to 69 countries, administrative regions, and economies and 13,387 schools. Descriptive statistics of variables used in this chapter are in Table 2. Table 23 in Annexes shows the frequency of observations per country.

Table 2: Descriptive statistics HOMEPOS items

Item	n	M	SD	Min	Median	Max	Description
ST011Q01TA	448,112	0.886	0.318	0	1	1	A desk to study at
ST011Q02TA	443,628	0.818	0.386	0	1	1	A room of your own
ST011Q03TA	447,922	0.878	0.328	0	1	1	A quiet place to study
ST011Q04TA	448,642	0.858	0.349	0	1	1	A computer you can use for school work
ST011Q05TA	439,751	0.522	0.500	0	1	1	Educational software
ST011Q06TA	448,498	0.897	0.304	0	1	1	A link to the Internet
ST011Q07TA	442,540	0.522	0.500	0	1	1	Classic literature
ST011Q08TA	442,974	0.483	0.500	0	0	1	Books of poetry
ST011Q09TA	443,413	0.599	0.490	0	1	1	Works of art
ST011Q10TA	446,376	0.824	0.381	0	1	1	Books to help you with your schoolwork
ST011Q11TA	440,147	0.588	0.492	0	1	1	Technical reference books
ST011Q12TA	447,453	0.926	0.262	0	1	1	A dictionary
ST011Q16NA	441,943	0.561	0.496	0	1	1	Books on art, music or design

ST011D17TA	444,699	0.631	0.482	0	1	1	*Country-specific item 1*
ST011D18TA	429,510	0.612	0.487	0	1	1	*Country-specific item 2*
ST011D19TA	408,365	0.534	0.499	0	1	1	*Country-specific item 3*
ST012Q01TA	450,081	3.156	0.829	1	3	4	Televisions
ST012Q02TA	442,555	2.419	0.967	1	2	4	Cars
ST012Q03TA	439,415	2.506	0.839	1	2	4	Rooms with a bath or shower
ST012Q05NA	448,358	3.499	0.870	1	4	4	Cell phones with internet access
ST012Q06NA	448,500	2.847	1.003	1	3	4	Computers (desktop computer, portable laptop)
ST012Q07NA	443,428	2.116	1.040	1	2	4	Tablet computers
ST012Q08NA	442,489	1.326	0.685	1	1	4	E-books
ST012Q09NA	448,337	2.063	1.108	1	2	4	Musical instruments
ST013Q01TA	450,608	2.978	1.460	1	3	6	Number of books in your house
HOMEPOS	454,734	-0.338	1.199	-9.481	-0.248	5.994	Home possessions index

Source: OECD (2017)

PISA's modelling strategy for HOMEPOS is a two-step process. First, a multiple group IRT two-parameter model is estimated (GPCM for ordinal questions and 2-PL for dichotomous questions). Subsequently, HOMEPOS is computed based on the posterior weighted maximum likelihood estimation (WLE) (OECD, 2017b). As the parameters for HOMEPOS published by PISA are estimated from a sample and do not reflect the observations used in this study (OECD, 2017b), I replicate the first step of PISA's modelling strategy to extract the α discrimination parameters for each item, and in the case of country items, for each country. Following PISA, I estimate 22 common questions with equal parameters while 3 questions had parameters freely estimated per country. Correlations between PISA's HOMEPOS and the replicated index are over .939 for each country (see Table 24 in Annexes).

The discrimination parameter shows great variability across items (Table 3), where, for instance, the answers for the items 'book of poetry' and 'classic literature' present lower values, and at the other end of the scale, 'internet access' and 'computers' present the highest values among the common parameters.

Table 3: Item Alpha parameter – common items

Item	Alpha		Item	Alpha
ST011Q01TA	1.116		ST011D17TA	1.288
ST011Q02TA	0.803		ST011D18TA	1.215
ST011Q03TA	0.931		ST011D19TA	1.247
ST011Q04TA	2.18		ST012Q01TA	0.632
ST011Q05TA	0.914		ST012Q02TA	0.923
ST011Q06TA	2.536		ST012Q03TA	0.918
ST011Q07TA	0.643		ST012Q05NA	0.901
ST011Q08TA	0.509		ST012Q06NA	1.612
ST011Q09TA	0.906		ST012Q07NA	0.796
ST011Q10TA	0.623		ST012Q08NA	0.671
ST011Q11TA	0.903		ST012Q09NA	0.594
ST011Q12TA	0.788		ST013Q01TA	0.475
ST011Q16NA	0.827			

Source: own calculations based on OECD (2017)

There is also large variability in the parameters of the country-specific items, shown in Table 4. For instance, some countries present higher values in all three items, such as the case of Thailand, while the opposite also occurs in others, such as in the case of the United Kingdom. Germany is the only case that presents a negative discrimination parameter for the question 'A TV in your own room'. A negative discrimination parameter suggests the latent trait diminishes with the ownership of the good.

Table 4: Item Alpha parameter – country-specific items

CNT	ST011D17 TA	ST011D18 TA	ST011D19 TA		CNT	ST011D 17TA	ST011D18 TA	ST011D19TA
ARE	1.288	1.215	1.247		LBN	1.456	1.365	0.749
AUS	0.655	0.610	1.015		LTU	1.781	0.929	1.511
AUT	1.132	0.539	1.106		LUX	0.614	1.218	0.353
BEL	0.522	0.749	1.365		LVA	1.340	1.193	0.679
BGR	1.575	1.734	1.110		MAC	1.587	1.860	1.482
BRA	1.331	1.149	1.448		MDA	1.712	0.851	0.851
CAN	1.090	0.745	0.704		MEX	1.155	1.381	1.374
CHE	1.644	0.499	1.107		MKD	0.969	0.757	0.851
CHL	0.764	1.599	1.058		MLT	0.969	0.683	0.991
COL	1.819	0.851	0.907		MNE	1.557	1.761	1.900
CRI	1.189	1.552	1.177		NLD	0.631	1.724	0.767
CZE	0.851	0.851	0.851		NOR	1.747	0.811	0.851
DEU	0.212	-0.197	1.484		NZL	0.784	0.739	1.098
DNK	1.883	0.270	0.851		PER	1.510	1.922	2.132
DOM	1.318	1.694	1.158		POL	1.474	1.853	1.789
DZA	0.851	0.851	0.851		PRT	0.448	1.063	1.071
ESP	1.311	0.648	0.763		QAR	0.383	1.495	1.115
EST	1.228	1.435	1.314		QAT	0.837	1.348	1.094
FIN	1.727	0.655	0.851		QCH	1.899	2.501	1.315
FRA	0.785	1.109	1.171		QES	1.271	0.623	0.771
GBR	0.347	0.835	0.570		ROU	1.018	0.720	1.725
GEO	1.013	1.119	1.195		RUS	1.694	1.286	1.246
GRC	1.441	0.993	1.227		SGP	1.615	1.283	0.851
HKG	1.036	1.569	0.653		SVK	1.177	1.994	0.851

HRV	0.806	0.921	1.157		SVN	0.709	1.186	1.176
HUN	0.750	1.114	1.858		SWE	1.092	0.725	0.785
IDN	1.631	1.036	2.162		TAP	1.724	1.148	1.465
IRL	0.956	0.741	0.746		THA	2.377	1.155	1.932
ISL	1.038	0.976	0.622		TTO	1.156	0.810	0.566
ISR	0.800	1.207	0.914		TUN	1.572	1.824	1.098
ITA	0.881	0.952	0.742		TUR	1.075	1.659	1.502
JOR	0.953	1.238	1.589		URY	0.499	1.251	2.294
JPN	1.360	0.619	0.738		USA	0.863	1.375	1.142
KOR	1.077	1.128	1.291		VNM	2.577	0.794	2.052
KSV	1.221	1.199	1.536					

Source: own calculations based on OECD (2017)

As the objective of the study is to exemplify the construction of the inequality measure, I do not address or evaluate model fit and invariance analysis. I rely on PISA's item invariance analysis, named root mean square deviance (RMSD), which states that invariance of HOMEPOS items across countries was analysed and "unique parameters were assigned if necessary" (OECD, 2017b, p. 342). However, as previously mentioned, prior research reports dispute the reliability and validity of socioeconomic scales in PISA. I acknowledge those limitations and in the present study focus only on the methodological contribution of building an inequality measure.

2.5.2.Criteria to assess *Alpha Inequality* validity

A strategy was chosen to examine *Alpha Inequality* in order to assess its validity in comparison with prior evidence and to compare results with a well-known inequality index based on HOMEPOS such as the Gini Coefficient. The Gini Coefficient is computed based on HOMEPOS, applying a correction for finite populations (Nygärd and Sandström, 1985). HOMEPOS was transformed into a range of positive values [0,15.457] to address a requirement of the computation of the Gini coefficient.

First, I compare cross-country rankings from both measures and exemplify the relevance of inequality on *learning scores* in the case of the USA by comparing schools at both extremes of the inequality continuum.

Second, I model a set of textbook regressions to examine how *Alpha Inequality* and the Gini coefficient are associated with Mathematics scores. For each country, I fit two sets of two-level mixed-effects linear models, allowing random intercepts to vary at the school level. This addresses the hierarchical structure of PISA, where students are nested in schools. Formally, the equation of two-level random intercept model reads as:

$$\mathrm{Y_{ij}} = \beta_{0j} + \beta_1 homepos_{1ij} + \beta_2 \mathrm{x}_{1ij} + \mathrm{u_j} + \epsilon_{ij} \tag{5}$$

Where Y_{ij} denotes the outcome variable for the i-th observation (student) of group j (School), β_{0j} the school intercepts (which are random variables enabling the quantification of the differences between groups). $\beta's$ are regression parameters invariant across groups. The different inequality measures are denoted by x_{1ij}, while u_j is the group-dependent deviation from the intercept mean and ϵ_{ij}represents the error term. HOMEPOS was included in the model due to the influence of the difficulty parameter on the posterior estimation of HOMEPOS, which may allow a better understanding of the role of an inequality measure independent from the possession of wealth.

Three key methodological considerations should be considered when modelling data from PISA. PISA uses a two-level stratified sampling strategy to select schools and students. To account for that in the analysis, I follow the PISA's current procedure (OECD, 2017b) using sampling weights at the student level. Weights are computed following Rabe-Hesketh and Skrondal (2006), which adjusts students' weights by the ratio of the school size and the sum of students' weights. Secondly, as all students in PISA receive 10 different plausible values to represent a range of their cognitive skills; I apply Rubin's rules for handling multiple imputations (1987). The procedure implies computing adjusted sets of regression coefficients and standard error estimates, and joining them in a final estimate. Lastly, I estimate the uncertainty associated with sampling using PISA's approach – Fay's modification of the balanced repeated replication (BRR) method –.

Item parameters were estimated through an iterative marginal maximum likelihood approach (Bock and Aitkin, 1981), using the expectation-maximization (EM) algorithm provided by *mirt* package (Chalmers, 2012) in statistical software R (R Core Team, 2020), inequality indexes were computed using *ineq* (Zeileis, 2014) and *OasisR* (Tivadar, 2019), and statistical analysis was performed using package *BIFIEsurvey* (Robitzsch and Oberwimmer, 2015).

2.6. Results and discussion

2.6.1. Comparison between two school-level inequality measurements

Comparisons between countries are only feasible if we assume the existence of measurement invariance across countries, which allows further inferential analysis in the same metric. Conditionally to the assumption of measurement invariance claimed by PISA (OECD, 2017b, p. 342), Table 5 presents the average *Alpha*

Inequality/*Gini* per country. Looking at the *Alpha Inequality* values, countries from Latin America and South Asia such as Peru, China (4 cities), Indonesia, Thailand and Colombia present the lowest values of *Alpha Inequality*. The opposite occurs with countries such as Iceland, Finland, Estonia, Poland, and Norway, which present *Alpha Inequality* close to 1. This suggests important differences between the two groups of countries. The first group of countries are characterised by educational systems with socioeconomically more homogeneous schools and larger degrees of segregation between schools, dividing poor and rich into different schools. The second group presents relatively smaller socioeconomic differences between schools while having larger economic diversity within-schools. Additionally, *Alpha Inequality* allows comparisons between countries. For instance, Iceland, Kosovo, Moldova, Montenegro, New Zealand, and Qatar are characterised by having more than 35% of schools with *school inequality* above their national average, while Indonesia, Israel, Peru, China (4 cities) and Thailand only have less than 5% of schools above the national average of inequality (see Table 25 in Annexes).

Table 5: Country Alpha Inequality and Gini Coefficient

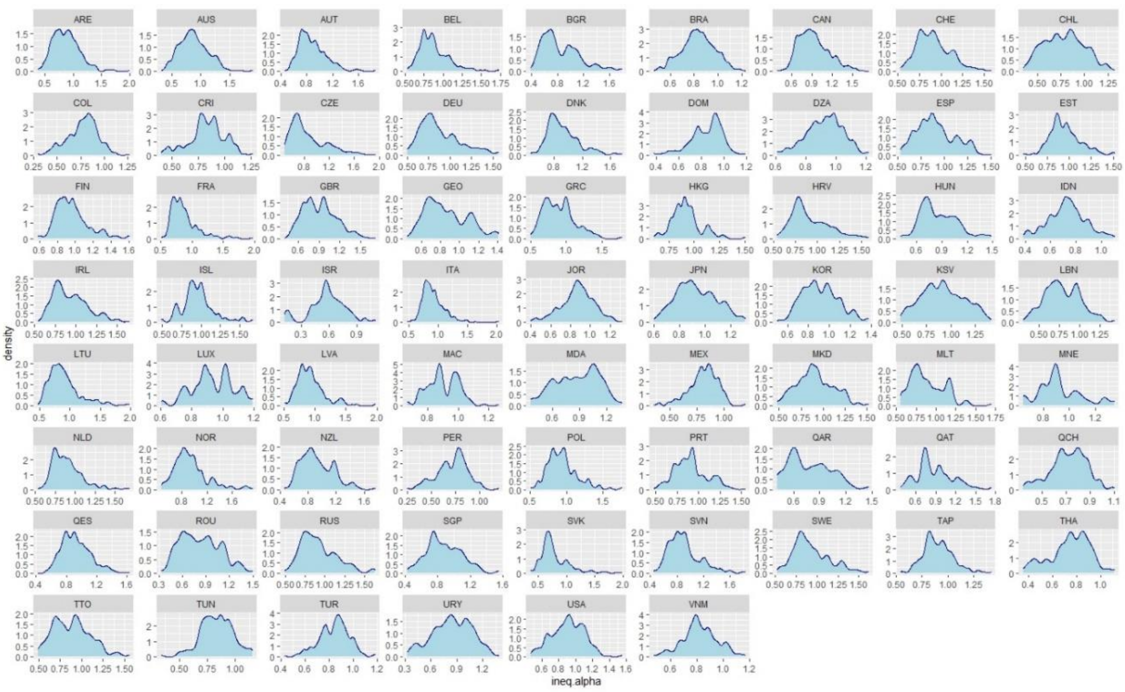
Country	*Alpha Inequality*	Gini		Country	*Alpha Inequality*	Gini
ARE	0.875	0.005		KSV	0.918	0.004
AUS	0.881	0.005		LBN	0.792	0.005
AUT	0.888	0.004		LTU	0.911	0.003
BEL	0.884	0.004		LUX	0.933	0.005
BGR	0.856	0.004		LVA	0.935	0.003
BRA	0.832	0.005		MAC	0.9	0.004
CAN	0.922	0.005		MDA	0.873	0.004
CHE	0.915	0.003		MEX	0.808	0.005

CHL	0.785	0.004		MKD	0.908	0.004
COL	0.77	0.005		MLT	0.894	0.004
CRI	0.827	0.005		MNE	0.93	0.004
CZE	0.861	0.003		NLD	0.897	0.003
DEU	0.882	0.003		NOR	0.942	0.004
DNK	0.92	0.003		NZL	0.925	0.004
DOM	0.845	0.005		PER	0.714	0.005
DZA	0.924	0.006		POL	0.943	0.004
ESP	0.904	0.004		PRT	0.906	0.004
EST	0.951	0.004		QAR	0.782	0.004
FIN	0.961	0.003		QAT	0.883	0.005
FRA	0.873	0.003		QCH	0.719	0.004
GBR	0.906	0.005		QES	0.926	0.004
GEO	0.862	0.004		ROU	0.828	0.004
GRC	0.902	0.004		RUS	0.92	0.004
HKG	0.921	0.004		SGP	0.877	0.004
HRV	0.911	0.003		SVK	0.788	0.004
HUN	0.861	0.004		SVN	0.908	0.003
IDN	0.729	0.005		SWE	0.933	0.004
IRL	0.933	0.004		TAP	0.906	0.004
ISL	0.963	0.003		THA	0.744	0.005
ISR	0.581	0.005		TTO	0.884	0.006
ITA	0.919	0.003		TUN	0.834	0.005
JOR	0.87	0.006		TUR	0.84	0.005
JPN	0.931	0.004		URY	0.846	0.004
KOR	0.912	0.003		USA	0.911	0.005
				VNM	0.825	0.004

Source: own calculations based on OECD (2017)

Figure 2 shows the distribution of *Alpha Inequality* for each school by country. *Alpha Inequality* presents different distributions across countries, as could be expected based on prior cross-country analysis (Thomas, Wang and Fan, 2001). In some cases, distributions approximate Gaussian functions, such as the cases of Brazil, Indonesia, and Australia, while in other cases there are bimodal distributions, such as in Malta, Macedonia, and Trinidad and Tobago. In many cases, kurtosis and skewness are observed on the distributions and inferential analysis.

Figure 2: Density plots per country: Alpha Inequality

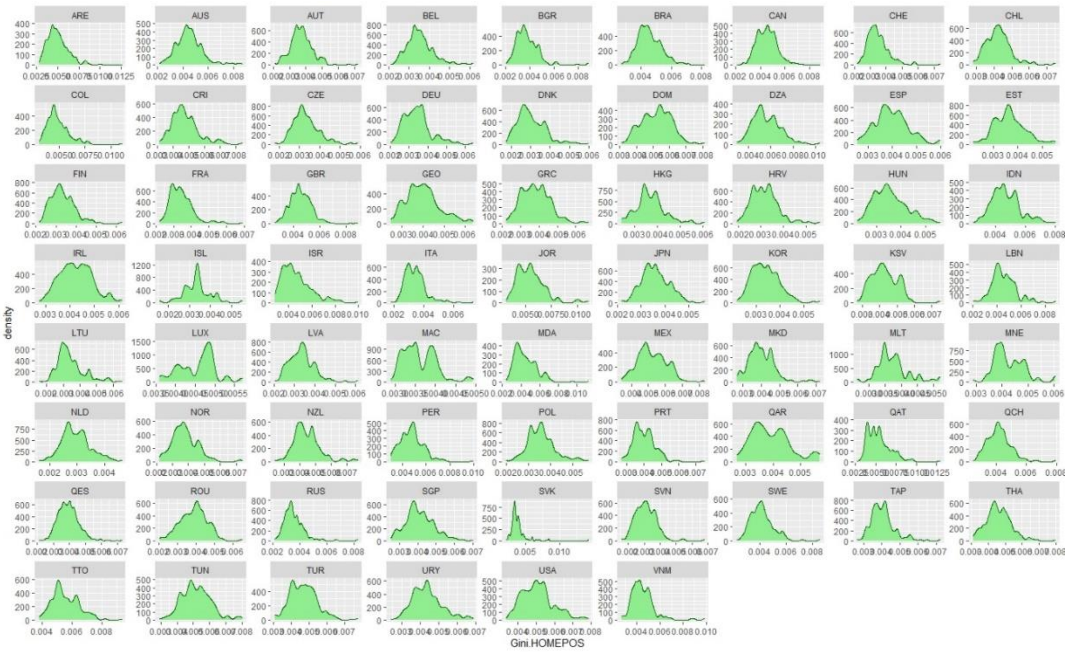


Source: own calculations based on OECD (2017). Original in colour.

On the other hand, the Gini coefficient presents, in general, very low coefficients across countries and schools. National averages are within a range between .003 and .006, and countries such as The Netherlands, Denmark, and Slovakia appear with the smallest values while countries such as Trinidad and Tobago, Qatar and Algeria display the largest values.

Figure 3 shows school Gini density functions for each country, where in general, they present heavy-tailed distributions. Exceptions of bimodal distributions are Macedonia and Montenegro.

Figure 3: Density plots per country: school Gini coefficient

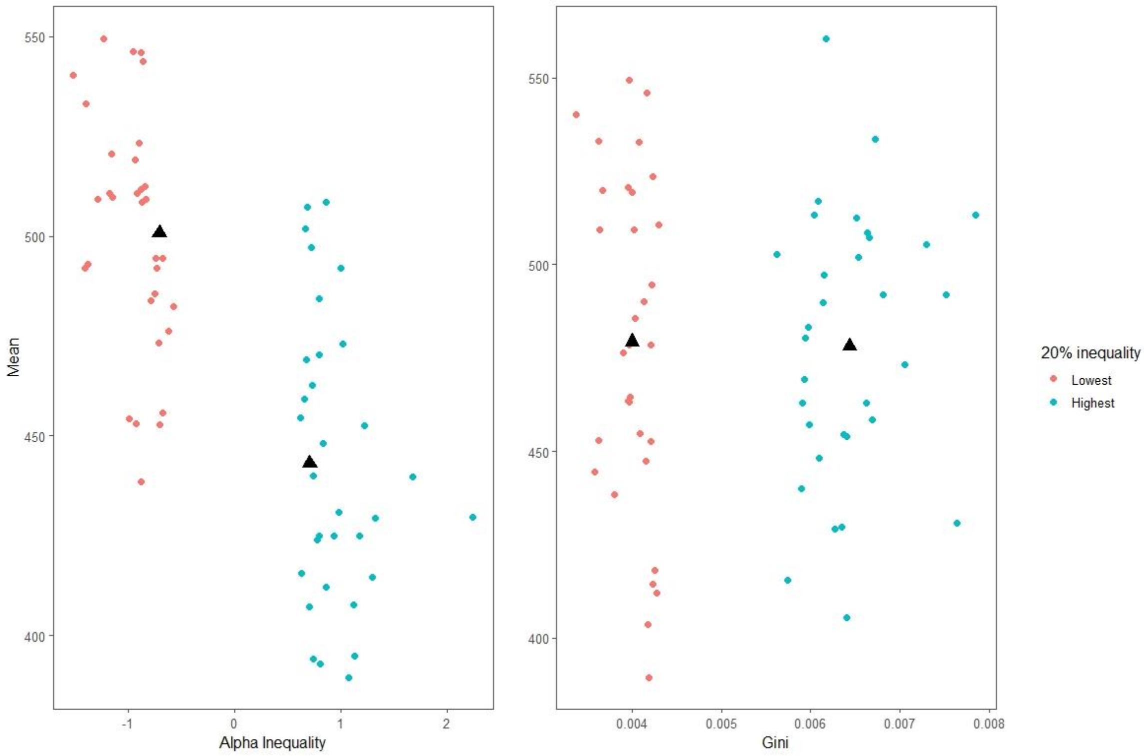


Source: own calculations based on OECD (2017). Original in colour.

Country-level correlations of both inequality measurements present an overall mean of $.612(SD.131)$ ranging from $.105$ (Israel) to $.846$(Qatar) (Table 26 in Annexes).

To examine the impact of differences between both measurements, I turn to the case of the USA, which has more prior empirical analysis on segregation and inequality. The Gini coefficient does not provide a trace of difference between schools in the top 20% and the bottom 20% of the Gini index on Mathematics *learning scores* per school. This contradicts prior estimations (Rutkowski *et al.*, 2018) as well as cross-country studies that focus on the segregation levels of USA schools and educational scores (Benito, Alegre and Gonzàlez-Balletbò, 2014; OECD, 2018). In contrast, Figure 4 shows that schools with lower *Alpha Inequality* outperform schools with the largest share of inequality by 0.57 standard deviations, with statistically significant differences between groups, $t(60.36) = -7.01$, $p < .001$. This represents about two more years of schooling according to PISA (2009).

Figure 4: 20% of schools with higher and lower inequality – the USA



Source: own calculations based on OECD (2017)

2.6.2. Models' coefficients

Results from country-level mixed-effects regressions models can be seen in Table 6 with *Alpha Inequality* as a predictor of the mathematics score. I find that 67 out of 69 countries show statistically significant negative parameters, while in the cases of Indonesia and Vietnam the null hypothesis of a parameter different from 0 cannot be rejected under a standard cut-off of $p < .05$.

Table 6: Regression coefficients per country – Alpha Inequality

CNT	HOMEPOS			*Alpha Inequality*		
	Est	SE	p-value	Est	SE	p-value
ARE	2.97	0.854	0.006	-39.9	1.5	0
AUS	22.5	1.29	0	-19.3	1.61	0
AUT	27.4	1.37	0	-25	1.37	0
BEL	28.7	1.1	0	-33.9	0.94	0
BGR	13	1.55	0	-41.1	1.76	0
BRA	24.2	0.976	0	-23.2	1.14	0
CAN	14.6	1.19	0	-16.5	0.589	0
CHE	25.4	1.33	0	-31.2	1.29	0
CHL	17.5	1.12	0	-35.8	1.34	0
COL	16.8	0.998	0	-16.3	1.09	0
CRI	16.8	0.571	0	-14.7	1.16	0
CZE	25.6	1.2	0	-39	2.32	0
DEU	30.4	1.36	0	-29.6	1.07	0
DNK	34.1	1.59	0	-13	0.87	0
DOM	14.1	1.29	0	-15.7	1.23	0
DZA	4.65	0.906	0	-14.5	2.18	0
ESP	29.2	0.861	0	-11.6	0.785	0
EST	17.5	1.52	0	-13.4	1.36	0
FIN	24.3	1.47	0	-8.51	1.04	0
FRA	31.6	1	0	-33.8	0.989	0
GBR	20.9	0.836	0	-20.6	1.06	0
GEO	22.4	1.68	0	-27.2	2.02	0
GRC	14.4	1.56	0	-23.7	1.41	0
HKG	19.7	1.46	0	-20.4	1.54	0
HRV	24.1	1.91	0	-34	1.15	0
HUN	23	1.28	0	-36.9	1.85	0
IDN	26.6	0.884	0	-2.31	1.23	0.062

IRL	22.6	1.09	0	-14.7	0.968	0
ISL	22.1	1.51	0	-4.25	1.4	0.008
ISR	12	1.33	0	-32.4	1.37	0
ITA	22.4	1.62	0	-20.2	1.3	0
JOR	13.8	1.3	0	-18.1	1.4	0
JPN	23.4	1.65	0	-24.8	2.04	0
KOR	35	2	0	-23.6	1.18	0
KSV	14.1	1.24	0	-21.3	1.08	0
LBN	23.9	1.65	0	-32	1.41	0
LTU	18.9	1.67	0	-22.1	1.2	0
LUX	25.4	0.846	0	-27.2	0.648	0
LVA	20.1	1.69	0	-8.92	0.992	0
MAC	7.58	1.29	0	-22.1	0.802	0
MDA	22.4	1.2	0	-21.2	1.34	0
MEX	13.8	0.753	0	-6.59	1.31	0
MKD	20.4	1.17	0	-29.6	1.24	0
MLT	30.7	1.41	0	-41.1	0.915	0
MNE	7.03	0.981	0	-30.8	0.972	0
NLD	26.3	2.51	0	-35.2	1.82	0
NOR	26.1	1.39	0	-7.08	1.3	0
NZL	21.3	1.23	0	-16.7	1.51	0
PER	23.6	1.02	0	-13.4	1.25	0
POL	30.6	1.25	0	-10.9	1.04	0
PRT	30.3	1.77	0	-22.5	1.08	0
QAR	21.4	1.95	0	-32.4	3.01	0
QAT	0.094	0.569	0.868	-52.5	1.03	0
QCH	31.8	1.4	0	-18.6	1.56	0
QES	27.2	1.15	0	-11.3	0.475	0
ROU	22.4	1.1	0	-29.3	1.09	0
RUS	9.82	1.74	0	-16.2	1.7	0

SGP	28.4	1.03	0	-26.8	0.87	0
SVK	19	1.72	0	-35.2	1.69	0
SVN	17.6	1.54	0	-26.3	0.981	0
SWE	23.8	1.09	0	-16.7	0.958	0
TAP	26.4	0.875	0	-34.2	1.17	0
THA	19.2	1.12	0	-27.2	1.5	0
TTO	12.8	1.37	0	-43.1	0.801	0
TUN	19.6	1.15	0	-10.9	1.99	0
TUR	20.8	1.24	0	-12.9	1.77	0
URY	18.5	1.52	0	-33.2	0.968	0
USA	21.2	0.639	0	-14.5	1.19	0
VNM	22.2	1.62	0	-2.39	1.74	0.17

Source: own calculations based on OECD (2017)

On the other hand, Table 7 presents the estimations of regression parameters using the Gini Coefficient for each county. In this case, the number of cases not showing a statistically significant association raises to five: Estonia, Iceland, Latvia, the United Kingdom, and the United States of America. The case of the United States, as previously discussed, raises concerns regarding the reliability of estimation of the Gini parameter due to the inability to find statistical significance given the previous empirical evidence in the literature. Additionally, Luxembourg is the only case portraying a positive coefficient for the slope of *Alpha Inequality* and mathematics scores.

Table 7: Regression coefficients per country – Gini coefficient

CNT	**HOMEPOS**				**Gini**		
	Est	**SE**	**p-value**		**Est**	**SE**	**p-value**
ARE	7.806	0.919	0		-38.54	1.448	0

AUS	25.86	1.354	0		-11.87	1.41	0
AUT	33.9	1.251	0		-5.152	1.361	0
BEL	32.9	1.15	0		-23.09	1.293	0
BGR	22.15	1.587	0		-23.78	1.219	0
BRA	26.57	1.078	0		-13.07	1.233	0
CAN	16.89	1.143	0		-10.24	0.739	0
CHE	32.2	1.323	0		-16.6	1.422	0
CHL	33.64	1.122	0		-13.12	0.988	0
COL	19.76	1.012	0		-9.5	0.913	0
CRI	20.28	0.638	0		-6.613	1.258	0
CZE	41.04	1.345	0		-12.21	1.402	0
DEU	38.26	1.365	0		-8.616	1.218	0
DNK	35.5	1.612	0		-10.1	0.946	0
DOM	14.71	1.356	0		-11.44	1.439	0
DZA	3.332	0.856	0.001		-15.3	1.829	0
ESP	32.59	0.768	0		-4.624	0.766	0
EST	20.16	1.545	0		-2.324	1.583	0.143
FIN	25.32	1.486	0		-4.941	0.981	0
FRA	40.24	1.123	0		-19.72	1.152	0
GBR	24.79	0.913	0		-0.239	0.969	0.803
GEO	28.2	1.692	0		-17.42	1.966	0
GRC	19.09	1.568	0		-8.292	1.674	0
HKG	23.35	1.408	0		-7.728	1.31	0
HRV	32.71	1.849	0		-16.78	1.018	0
HUN	36.97	0.957	0		-11.31	1.713	0
IDN	24.22	0.966	0		-11.79	1.25	0
IRL	25.34	1.019	0		-4.903	0.785	0
ISL	22.17	1.531	0		1.03	0.967	0.3
ISR	16.04	1.404	0		-33.42	1.565	0
ITA	26.79	1.641	0		-7.458	1.496	0

JOR	14.89	1.304	0		-14.56	1.204	0
JPN	27.44	1.419	0		-14.31	2.228	0
KOR	40.99	2.105	0		-14.57	1.299	0
KSV	18.48	1.128	0		-8.201	1.338	0
LBN	32.87	1.511	0		-11.9	1.917	0
LTU	22.81	1.606	0		-13.67	1.231	0
LUX	31.25	0.971	0		4.094	0.77	0
LVA	22.19	1.642	0		-1.699	0.959	0.083
MAC	16.36	1.258	0		-12.88	0.793	0
MDA	25.61	1.482	0		-11.58	1.665	0
MEX	13.7	0.715	0		-7.866	1.205	0
MKD	25.14	1.187	0		-17.75	1.249	0
MLT	41.74	1.322	0		-16.23	0.793	0
MNE	13.91	1.007	0		-10.79	1.128	0
NLD	32.84	2.349	0		-18.22	2.519	0
NOR	27.06	1.386	0		-4.043	1.131	0.001
NZL	23.49	1.259	0		-9.83	1.592	0
PER	21.76	1.065	0		-14.65	1.379	0
POL	32.85	1.16	0		-3.204	1.126	0.005
PRT	36.02	1.731	0		-12.37	1.713	0
QAR	33.41	1.796	0		-18.13	2.734	0
QAT	3.285	0.593	0		-47.95	0.966	0
QCH	37.11	1.386	0		-11.16	1.317	0
QES	30.08	1.122	0		-5.165	0.498	0
ROU	32	1.415	0		-14.79	1.759	0
RUS	11.37	1.655	0		-4.531	1.666	0.015
SGP	34.19	1.021	0		-18.75	0.758	0
SVK	27.7	1.911	0		-16.98	2.016	0
SVN	25.59	1.516	0		-12.04	0.86	0
SWE	25.39	1.104	0		-11.42	1.229	0

TAP	35.24	1.083	0		-18.9	1.043	0
THA	28.82	1.315	0		-3.797	1.003	0
TTO	22.19	1.387	0		-12.99	0.826	0
TUN	20.44	1.115	0		-3.963	1.675	0.022
TUR	20.98	1.286	0		-9.549	1.432	0
URY	27.59	1.5	0		-16.99	1.232	0
USA	24.46	0.61	0		-0.655	1.57	0.675
VNM	19.47	1.344	0		-10.62	1.804	0

Source: own calculations based on OECD (2017)

2.7. Discussion

This chapter has found that a set of multivariate household possessions collected as categorical data can be used to provide a novel measure of inequality. The proposed inequality measure is independent of the scale of wealth and fulfils the main properties of inequality measures. Additionally, *Alpha Inequality* also allows for comparisons between and within countries.

While *Alpha Inequality* does not replace the use of any other standard inequality index in PISA, which can be computed based on the derived socioeconomic index such as HOMEPOS (see Chapter 3), it addresses the complexity of measuring inequality based on categorical data, making a novel use of 2-PL IRT models. The ease of visualising and evaluating each item facilitates, for example, the understanding of the influence of certain goods on the total account of inequality.

Computing school-level inequality using data from PISA 2015, I find a consistent and significant negative association of school-level inequality and mathematics scores across countries – the great exception being the majority of European countries. Although this occurs across countries, the weight of school socioeconomic compositional effects differs in terms of how much they influence students' skills acquisition. In the next chapter I will address these associations in further detail, both theoretically and empirically.

It is also suggested that the inequality measure outperforms the Gini coefficient in relation to assessing the association of school-level inequality and *learning outcomes*. This is consistent with previous research on the topic that identifies different levels of inequality within and across countries. In the case of known negative effects of inequality, *Alpha Inequality* is shown to better grasp the relevance of socioeconomic disparities between schools that affect *learning scores*.

There are important limitations to be acknowledged. Comparability of items between countries in terms of reflecting a similar wealth status is still a matter of concern among researchers. Additionally, the need to renew the pool of items between waves – as electronic goods become rapidly obsolete – also poses difficulties in terms of longitudinal comparisons. Additionally, psychometric measurement issues are still not robust enough or do not show adequate measurement invariance (for instance, adequate model fit parameters across all countries).

Further research could point to different directions such as the assessment of inequality on cognitive and non-cognitive educational outcomes across different waves of PISA as well the interplay between inequality, segregation and educational outcomes.

Second, there is a methodological debate regarding the inclusion of survey weights design into IRT scoring procedures to take account of the complex sampling designs and nested structure of item response data of PISA and other ILSAs. This uses multilevel item response methods and different weighting strategies (Zheng and Yang, 2016).

Third, alternative methods for scaling sampling weights at both levels were explored (Mang *et al.*, 2021), addressing the complexity of using within and between weights in multilevel clustered analysis. Although the number of statistically significant models varied, similar negative coefficients were found in all cases, and, in all those cases, models with *Alpha Inequality* predictors were more sensitive than Gini. However, in some weighting configurations, large standard errors were found, suggesting model identification or convergence issues.

This is relevant as sample design in PISA is informed by school socioeconomic attributes and the estimation of parameters – among them discrimination – that could be affected by the lack of weights. Further research could point to the relevance of weighting IRT models to address socioeconomic sampling variances. In this case, I mimic IRT by modelling a single-level strategy and address the stratified complex sampling design using multilevel regression model analysis including replicate and scale weights.

3. School-level inequality and learning achievement: evidence from PISA[5]

3.1. Introduction

A large body of literature has documented a strong economic gradient of educational outcomes, with pupils from richer households obtaining on average better outcomes than pupils from poorer households. However, there is surprisingly very little evidence on the role of aggregate economic inequality on individual educational attainment. Using the 2012, 2015 and 2018 waves of multi-country data from the OECD Programme for International Student Assessment (PISA), I study the relationship between school-level wealth inequality and test scores controlling for individual economic status. I find a negative and significant relationship, and I observe that school-level inequality interacts with school-level mean wealth. This suggests that the role of inequality may differ depending on the economic milieu – being stronger for schools attended by pupils from richer families. I go beyond the standard econometric interpretation of this interaction term and provide a reading of it in terms of school-level absolute inequality and relative deprivation. Results hold for the pooled data as well as for each of the three waves alone and are confirmed by alternative robustness checks.

In the previous chapter I developed a novel way of measuring aggregated inequality based on categorical data and assessed, at country-level, its relationship with *learning scores* in text-book multilevel regressions. The main purpose of the chapter was to develop an inequality measurement. The use of other inequality measures served as an

[5] This chapter has been jointly developed with Dr. Lucio Esposito (LE). I developed the original research design, literature review, analysis, and discussion.

external validity exercise. Based on the validity of the measure, in this chapter I focus on the substantial relationship between *school inequality* and *learning scores.* I examine both theoretically and empirically, controlling for relevant confounders and across different datasets, and I study how the relationship between wealth and *school inequality* affect differently *learning scores.*

Differences in academic achievement across countries, schools and students have been associated with an array of individual, household, school, and educational system characteristics. The range of factors that have been argued to determine academic outcomes is vast and includes students' cognitive skills, levels of public funding, classroom sizes and climate, teacher quality, and parental engagement (Hoover-Dempsey, Bassler and Brissie, 1987; Marks, 2006). Among the key explanatory dimensions for the existence and persistence of educational inequalities are socioeconomic factors. Their relevance as predictors of learning attainment has been established by a large body of cross-disciplinary research, with an overwhelming consensus around a positive gradient where economic status fosters educational outcomes (Coleman, 1966; Willms and Somer, 2001; Sirin, 2005).

While the existence of an economic gradient in educational outcome is well documented in the literature, the specific role of aggregate level inequality (rather than individual-level economic status) is however far less studied and understood. This chapter aims to further our understanding of the role played by economic aggregate factors as a determinant of *learning scores*. I contribute to the literature on the economic determinants of education in three ways: i) controlling for measures of individual economic status, I study the possible role played by aggregate economic inequality; ii) I take the school as the level of aggregation for the computation and the analysis of economic inequality, rather than customary higher-level administrative boundaries; and iii) I investigate the interplay between aggregate school-level economic determinants (inequality and average wealth) and interpret the interaction term between these two factors in light of not only econometric theory but also of the meanings this term has in sociological and economic theory (Runciman, 1966; Yitzhaki, 1979; Hey and Lambert, 1980). The link between school-level inequality and educational outcome involves a complex interplay between 'social facts' and individual attitudes and behaviours, which can be traced back to the seminal work of sociological theorists like Durkheim (1897 [2008]). This approach understands individual educational outcomes as dependent not only on individual or household factors but also on the social context, in line with a body of sociological and economic research on education (e.g. Crane, 1991; Lalive and Cattaneo, 2009; Strulik, 2013).

I use three waves (2012, 2015 and 2018) of the OECD Programme for International Student Assessment (PISA). The analysis is carried out through multilevel econometric models, which incorporate socioeconomic variables as different aggregation levels (e.g., household assets and school-level inequality) by explicitly accounting for how these are entwined. The study of the relationship between socioeconomic factors and educational outcomes benefited from the spread of international large-scale educational assessments. Among these, PISA has stimulated a valuable body of cross- and within-country research that was able to shed light on common as well as country-specific patterns (Hopfenbeck *et al.*, 2018). The economic gradient in education is evident in PISA data. For example, the 2018 wave confirms a pattern of differences in learning performance along the economic spectrum, with an average learning gap between the richest and the poorest 10% equivalent to more than three years of schooling (Schleicher, 2019).

The chapter research questions are formulated as follows:

1 - To what extent *school inequality* can be associated to learning achievements?

2 - To what extent the role of *school inequality* differs according to different levels of wealth in explaining learning scores?

My results confirm the hypothesis that school-level inequality is negatively associated with learning achievements. This was developed in my theoretical framework based on a cross-disciplinary examination of the existing literature. Importantly, I find that the role played by economic inequality as a predictor of test scores differs at different levels of school affluence. Models including an interaction term between school-level inequality and mean school wealth suggest indeed that the role of inequality varies at different levels of wealth, being more severe for wealthier schools. This finding can be interpreted not only as a significant interaction term indicating heterogeneity in the potential role of (relative) inequality at different wealth levels, but also as a measurement of the role played by school absolute inequality and relative deprivation (Runciman, 1966; Yitzhaki, 1979; Hey and Lambert, 1980). My results are robust across all PISA cycles studied, *learning outcomes*, different inequality indexes, and analyses in which I use different samples of the data (i.e., schools larger than the median school size - to exclude schools where inequality figures may be inaccurate due to the low numbers of students).

The remainder of this article is structured as follows. Section 2 reviews the literature regarding school-level inequality and learning achievement, which informs the development of my theoretical framework and hypotheses to be tested. Section 3 presents the data and my empirical strategy, including the computation of assets-based inequality. Section 4 contains results and section 5 concludes.

3.2. Literature review

A large part of the SCE academic literature has focused on specific economic variables and their roles as determinants of educational outcomes. Most of this work employed individual/household-level income, wealth, or economic status, and identified several pathways linking greater family economic resources to higher child educational outcomes. Among these pathways is the ability to purchase educational resources and adequate nutrition, and the need for the pupil to engage in child work, (see McLoyd (1990); Connell (1994), Basu and Van (1998), Glewwe, Jacoby and King (2001), Bradley and Corwyn (2002), Sirin (2005), Walker *et al.* (2011)). Fewer papers investigated the potential role of aggregate measures of economic inequality (e.g., the Gini coefficient), which is the objective of this work. Aggregate inequality measures enable the quantification of the *disparity* of individual economic circumstances (e.g., family income or wealth) within a certain group or society, rather than pupils' own economic circumstances. The body of literature that studied the relationship between aggregate inequality and educational outcomes can be roughly divided into the following four major categories.

i) Access. Some contributions examined the role of aggregate inequality by focusing on access and affordability of education, e.g. Galor and Zeira (1993), Perotti (1993), García-

Peñalosa (1995), Chiu (1998) and Checchi (2003). In this strand of the literature, inequality matters for education because for a given amount of total economic resources in society and in the presence of credit constraints, the way these resources are distributed determines how many individuals lie in the left tail of the distribution and cannot afford education. A negative relationship would typically exist between inequality and educational outcomes as the more unequally economic resources are distributed, the greater the left tail of the distribution that is below the minimum amount of resources necessary to afford education (Galor and Zeira, 1993). An exception would be extremely poor societies where inequality would enable at least some to afford education (García-Peñalosa, 1995). In addition, aggregate inequality may be detrimental to educational outcomes because it jeopardises poverty reduction, for example by weakening the pro-poor character of economic growth (Kalwij and Verschoor, 2007; Iniguez-Montiel, 2014).

ii) Social fabric. Other work saw economic inequality as a determinant of educational outcomes via fostering a series of phenomena, attitudes and behaviours, which are corrosive to the social fabric (Pickett and Wilkinson, 2015; Esposito and Villaseñor, 2018). Economic inequality has been found to erode trust, social cohesion, civic engagement, agreeableness, and increase different sorts of antisocial or unethical behaviour and crime (Thorbecke and Charumilind, 2002; Gustavsson and Jordahl, 2008; Barone and Mocetti, 2016; Kyriacou and Trivin, 2020; De Courson and Nettle, 2021). These include school-level phenomena such as victimisation, crime by adolescents, and bullying (Due *et al.*, 2009; Elgar *et al.*, 2009; Azeredo *et al.*, 2015). These phenomena can be seen as detrimental for educational outcomes by reducing the value attached to education and through a deterioration of the social conditions enabling educational attainment. Dincer (2011) for example show a positive relationship between trust and schooling. In addition, by reducing belief in economic opportunity and upward mobility, inequality may decrease the willingness to invest in education or avoid teenage pregnancies (Browman *et al.*, 2019). Along these lines, a negative impact on educational effort can also be hypothesised considering that inequality was found to undermine beliefs in a meritocracy (Kuhn, 2019) as well as increase short-sighted behaviour (Bak and Yi, 2020).

iii) Relative deprivation. A second reason relates to the consequences of relative standing on the economic ladder and interpersonal comparisons, which have been indicated as being one of the mechanisms through which economic inequality affects societies. People tend to compare themselves with better-off individuals, and the relative deprivation experienced based on such upward comparisons has prejudicial consequences on a range of social outcomes including subjective wellbeing, health and education (Wilkinson and Pickett, 2007; Clark and D'Ambrosio, 2015; Gerber, Wheeler and Suls, 2018). Since unfavourable comparisons and their intensities would be greater in more unequal societies, social outcomes would be hindered by aggregate inequality. In the case of educational outcomes, the negative effects of relative deprivation would manifest through a number of pathways which include curbing pupils' and parents' aspirations (Mayer, 1997), carving social identities with lower motivation to invest in human capital (Oyserman, 2013), and triggering adverse effects of psychosocial stress on cognitive development (Hackman, Farah and Meaney, 2010). Esposito and Villaseñor (2019) discuss these and other mechanisms through which relative deprivation may lead to lower educational outcomes and provide evidence of a negative relationship between relative deprivation and school enrolment in Mexico even after controlling for absolute standards of living.

iv) *Social Reproduction Theory.* The harmful effects of the schooling process have been related to Pierre Bourdieu's social reproduction theory (Bourdieu and Passeron, 1990). This refers mainly to an intergenerational schema where schools appear to work as relevant mechanisms of "perpetuation of socioeconomic inequality, as it serves to legitimate the existing social hierarchy" (Edgerton and Roberts, 2014, p. 193). While there is ambiguity relating to how empirical findings support or deny that thesis (Kingston, 2008; van de Werfhorst, 2010; Tzanakis, 2011), there has been extensive research operationalising different Bourdieusian concepts such as social and cultural capital, habitus and field, towards analysing diverse aspects such as relations between peers, school culture or parent involvement (Nash, 1990; Sullivan, 2002; Smith, 2003; Lee and Bowen, 2006; Edgerton and Roberts, 2014). For instance, this theory explains the repetition of antisocial attitudes and behavioural patterns due to both individual and ecological reasons (Hong and Espelage, 2012). Those also portray negative consequences for *learning outcomes*, students' socioemotional disengagement, discrimination in diverse forms, and violence (at different levels) (Merrell *et al.*, 2008).

The above considerations support the hypothesis of a negative relationship between aggregate inequality and educational outcomes. An important issue to be taken into account is the decision around the level of aggregation at which inequality is considered. The sparse literature that has studied the relationship between aggregate economic inequality and educational outcomes has considered levels of aggregation based on administrative/political criteria, finding for example a negative relationship in the case of country-level inequality (Chiu and Khoo, 2005; Siddiqi *et al.*, 2012) and municipal-level inequality (Esposito and Villaseñor, 2018). However, evidence with regards to lower levels of aggregation such as within-*school inequality* is lacking. Adding this evidence is a worthwhile endeavour because the processes described above are likely to be relevant for social milieus like schools, in particular, as well as the *social fabric,* the *relative deprivation* and *the social reproduction* mechanisms.

In this regard, it is useful to consider findings from the health literature, which report a positive association between within-school aggregate inequality and adolescents' depressive symptoms (Goodman *et al.*, 2003). In addition, studying the potential role of school-level economic inequality would shed more light on what Oppedisano and Turati (2015) term the "black box of schools" (p. 22); i.e. it would enhance our understanding of school-level mechanisms and school characteristics, which may play an important role in student outcomes. Finally, the analysis of school-level inequality examines the role of contextual lower-scale aggregate variables based on criteria other than administrative boundaries such as states or municipalities (Merlo, Viciana-Fernández and Ramiro-Fariñas, 2012).

School socioeconomic composition, intended as the average economic status of pupils' households, has been found to be associated with student *learning scores* beyond the effects of students' own economic backgrounds, as was initially described by Coleman: "The social composition of the student body is more highly related to achievement, independent of the student's own social background, than is any school factor" (1966, p. 325). More recent studies support the independent and positive associations between mean school socioeconomic status and student outcomes (Rumberger and Palardy, 2005; Perry and McConney, 2010), suggesting that schools that gather students with a certain socioeconomic status appear to reinforce the effect of students' own socioeconomic backgrounds. This has been negatively characterised as a twofold disadvantage, whereby students in socially disadvantaged schools are more likely to perform worse than those in better-off settings (Caro and Lenkeit, 2012). We, therefore, expect a positive relationship between within-school average student wealth and PISA scores.

Moreover, the literature that has discussed the possible interplay between school-level inequality and average economic status on educational outcomes has been less extensively addressed in the literature. One set of theories postulates that institutions or social externalities may constrain an individual's behaviour and, thus, affect individual outcomes. This route suggests that the allocation of school resources mediates the link between wealth, inequality and schooling, benefiting richer schools (Chiu and Khoo, 2005). In a different direction, social cognition theory posits that internal channels affect the relationship between inequality, wealth, and individual outcomes. In that sense, Lindenberg (1977) argues that individuals from lower social classes have a lower ability to detect economic status differences and nuances compared with individuals from higher classes. This suggests that awareness of socioeconomic hierarchy is greater in wealthier contexts, and therefore pupils in such contexts would feel the negative effects of interpersonal comparisons more strongly. Using data from Germany, Schneider (2012) finds that perceptions of social inequality affect the life satisfaction of upper-income groups but not of lower-income groups. Based on the above considerations, I hypothesise that the relationship between economic inequality and PISA scores is stronger in a wealthier context; i.e., a negative interaction term between school-level inequality and school-level average wealth.

3.3. Empirical operationalisation

3.3.1. Data description

In this study, I use data from rounds 5, 6 and 7 from PISA, corresponding to years 2012, 2015 and 2018, which have sample sizes of 464,783, 431,223 and 600,316, respectively (see Table 27 for frequencies per country). I use the original datasets containing information on the test and the background questionnaires completed by students and school principals. The outcome variables are test scores on mathematics and reading and the explanatory variables of interest are within-school wealth inequality and average wealth, i.e. school-level wealth inequality and mean school wealth, calculated based on household wealth. School-level controls are school management type (public or private) and the location (urban or rural) where the school is located. Control variables at the student/household level include individual characteristics such as students' sex, age and previous repetition of grade, and household characteristics such as household assets, highest schooling level of parents, immigrant status and language spoken at home. Although not impossible, it is unlikely that more than one student from the same household participates in the PISA.

3.3.2. Empirical modelling

Considering the hierarchical structure of the dataset, where students are nested in schools, I estimate two-level mixed-effects linear models with a full maximum likelihood estimation method conducted by an EM algorithm (Robitzsch and Oberwimmer, 2015). Multilevel models enable the researcher to avoid the problems related to an underestimation of standard errors as well as to possible multicollinearity between school-level and country-level factors, allowing random intercepts to vary at school levels. Formally, the equation of the two-level random intercept model reads as:

$$Y_{ij} = \beta_{0j} + \beta_1 x_{1ij} + \beta_2 x_{2ij} + \beta_3 x_{1ij} x_{2ij} + u_j + \epsilon_{ij} \qquad \textit{(1)}$$

Where Y_{ij} denotes the outcome variable for the i-th observation (student, Level 1) of group j (School, Level 2), β_{0j} the school intercepts enabling the quantification of the differences between schools, while other $\beta's$ are regression parameters are invariant across groups. The different explanatory variables are denoted by x_{ij}, while u_j is the group-dependent deviation from the intercept mean and ϵ_{ij}represents the error term. Additionally, some models allow for cross-level interaction of inequality and other variables – as in the case of coefficient β_3. In the cases of *H2* and *H3*, the interaction is between *school inequality* and mean school-level HOMEPOS. Additionally, I add country dummy variables as fixed effects to address potential bias due to omitted variables at the country level. Data fit was judged using R^2 parameters. Fixed effects parameters are tested through Wald Chi-Squared Tests. Empirical analyses are run using the statistical program *R* version 4.0.2 (R Core Team, 2020), *RStudio* version 1.4.1099 (RStudio Team, 2020); in particular, models are estimated through the packages *BIFIE.survey* (Robitzsch and Oberwimmer, 2015) and *lme4* (Bates, 2010).

Modelling PISA data requires careful consideration of sampling weights. PISA uses survey weights "to ensure that each sampled student appropriately represents the correct number of students in the full PISA population" (OECD, 2017b, p. 116). The use of weights in the analysis adjusts for factors such as non-participation of similar schools and students in the test as well as under and oversampling of schools. Weights are based upon a complex stratified sampling strategy that oversamples schools or students to both represent the country target population – in this case, 15-year-old students – and to prevent sample loss due to non-responsiveness, especially for certain populations such as minorities, rural areas, or certain geographical spaces. Additionally, to address the uncertainty and variability due to sampling, PISA uses replicate weights to associate uncertainty with the computation of its population statistics. Specifically, PISA uses an appropriate method for two-stage samples known as Fay's version of balanced replicate weights (OECD, 2017b). Therefore, it is important to take those sampling weights into account in the analysis, because ignoring them "essentially gives more importance to some students, based solely on decisions linked to the choice of the sampling design" (Rutkowski *et al.*, 2010, p. 143). In this case, I recompute total students' weights following method B from Rabe-Hesketh and Skrondal (2006) to address level 2 (school) differences. I use them in the level 1 (student) of the hierarchical regression as this already represents the inverse of the joint probability of selection of a student, class and school (Rutkowski *et al.*, 2010).

3.3.3. Details on the explanatory variables of interest

The main explanatory variables of interest, within-school household wealth inequality and average wealth are computed as aggregates of individual wealth indexes. PISA derives such indexes from information on household assets via Item Response Theory logistic regressions (IRT). While PISA employed 1-parameter logistic regression models until the 2012 wave (OECD, 2014), from 2015 onwards it added a second parameter to the IRT (OECD, 2017b). Therefore, for the sake of consistency across all waves, I have derived the 2012 wealth index by employing PISA's post-2015 2-parameter IRT methodology. Based on these wealth indices, I derive the school-level Gini index of economic inequality to be used in the specifications presented in this chapter, as well the *Alpha Inequality,* and the Atkinson and Theil Generalised Entropy indices to be used to test the robustness of my results. Definitions of all variables employed in my estimations are shown in Table 8, and their summary statistics in Table 9.

Table 8: Definitions of variables

Variable	Definition
Sex	0=female; 1=male
Language spoken at home	0=same as PISA; 1=different from PISA
Age	Age in years
Higher educational parental status[a]	0=None; 1=ISCED 1 (Primary education); 2=ISCED 2(Lower secondary education); 3=ISCED 3B-3C (upper secondary education providing access to labour market or non-university tertiary education); 4=ISCED 3A-4 (upper secondary education providing access to university); 5=ISCED 5B (non-university tertiary education); 6=ISCED 5A-6 (university level tertiary education and advanced research programmes).
Immigrant	0=Native; 1=2nd generation of immigration; 2=1st generation of immigration.
Repeat	0=no; 1=yes
Population in living area[a]	1=A village, hamlet or rural area (fewer than 3 000 people); 2=A small town (3 000 to about 15 000 people); 3=A town (15 000 to about 100 000 people); 4=A city (100 000 to about 1 000 000 people); 5=A large city (with over 1 000 000 people).

Type of school	0=public; 1=private.
HOMEPOS	Home possessions (original from PISA)
School HOMEPOS	mean HOMEPOS per school
Gini	Gini coefficient of HOMEPOS (non-negative numbers)
Atkinson	Atkinson (parameter .5) coefficient of HOMEPOS (non-negative numbers)
Theil	Theil (parameter 0) coefficient of HOMEPOS (non-negative numbers)
PV1READ-PV10READ	10 variables of plausible values for READING results (5 variables in 2012)
PV1MATH-PV10MATH	10 variables of plausible values for MATH results (5 variables in 2012)
a: for ease of presentation of results, these two ordinal variables are entered in the regressions as continuous and presented accordingly in the regression table. Results are quantitatively unchanged if they are entered as categorical.	

Source: PISA 2012, 2015, 2018 and own calculation

Table 9: Descriptive statistics of variables

Statistic	N	Mean	St. Dev.	Min	Max	N	Mean	St. Dev.	Min	Max	N	Mean	St. Dev.	Min	Max
Sex	600,316	0.501	0.500	0.000	1.000	431,223	0.499	0.500	0.000	1.000	464,783	0.495	0.500	0.000	1.000
Language spoken at home	596,186	0.173	0.378	0.000	1.000	423,197	0.129	0.335	0.000	1.000	450,261	0.124	0.329	0.000	1.000
Age	600,316	15.790	0.291	15.080	16.330	431,223	15.793	0.292	15.170	16.420	464,668	15.785	0.290	15.170	16.330
Higher educational parental status	593,292	4.657	1.505	0.000	6.000	419,303	4.461	1.593	0.000	6.000	457,056	4.304	1.639	0.000	6.000
Immigrant	578,648	0.185	0.523	0.000	2.000	415,310	0.193	0.536	0.000	2.000	456,095	0.169	0.501	0.000	2.000
Repeat	574,606	0.118	0.323	0.000	1.000	419,175	0.153	0.360	0.000	1.000	449,667	0.147	0.354	0.000	1.000
Population on living area	567,884	2.208	1.204	0.000	4.000	397,864	0.159	1.176	0.000	4.000	464,783	2.246	1.289	0.000	4.000
Type of school	542,256	0.196	0.397	0.000	1.000	389,474	0.227	0.419	0.000	1.000	464,783	0.300	0.861	0.000	1.000
HOMEPOS	600,316	9.767	1.177	0.000	16.127	429,606	9.163	1.203	0.000	15.475	464,545	-0.344	1.161	-6.880	4.150
School HOMEPOS	600,316	-0.437	0.819	-5.886	3.643	431,223	-0.320	0.853	-6.763	2.367	464,783	-0.021	0.782	-6.118	2.394
Gini	600,316	0.046	0.014	0.000	0.317	431,223	0.049	0.015	0.000	0.338	464,783	0.057	0.015	0.000	0.654
Atkinson	600,316	0.009	0.015	0.000	1.000	431,223	0.011	0.029	0.000	1.000	464,783	0.014	0.039	0.000	1.000
Theil	600,316	0.004	0.004	0.000	0.194	431,223	0.005	0.004	0.000	0.180	464,718	0.006	0.005	0.000	0.963
Alpha Inequality	600,316	0.804	0.211	0.002	2.451	431,223	0.868	0.255	0.002	3.428	464,783	0.854	0.264	0.000	4.184
PV1READ	559,466	454.967	108.764	0.000	887.692	431,223	468.713	104.190	0.000	882.120	464,783	472.151	101.790	0.083	904.803
PV2READ	559,466	455.026	108.738	28.726	898.478	431,223	468.705	104.179	0.000	881.433	464,783	472.189	101.915	0.704	881.239
PV3READ	559,466	454.949	108.783	0.341	888.223	431,223	468.763	104.195	0.000	874.013	464,783	472.156	101.910	0.704	884.447
PV4READ	559,466	454.966	108.717	0.000	885.259	431,223	468.434	104.239	0.000	854.437	464,783	472.048	101.854	4.134	881.159

PV5READ	559,466	455.035	108.614	16.891	885.244	431,223	468.801	104.131	0.000	865.085	464,783	472.147	101.936	2.307	901.609
PV6READ	559,466	455.099	108.672	31.955	873.895	431,223	468.774	104.261	0.000	857.400					
PV7READ	559,466	454.994	108.737	14.165	890.932	431,223	468.776	104.191	0.000	898.018					
PV8READ	559,466	454.946	108.604	0.000	928.687	431,223	468.686	104.249	0.000	849.645					
PV9READ	559,466	454.931	108.714	0.000	862.252	431,223	468.895	104.357	0.000	864.958					
PV10READ	559,466	454.939	108.722	0.000	884.019	431,223	468.798	104.427	0.000	841.277					
PV1MATH	594,940	461.695	104.495	24.743	888.064	431,223	465.272	102.542	0.000	870.509	464,783	470.043	103.205	19.793	962.229
PV2MATH	594,940	461.563	104.625	25.561	916.276	431,223	465.259	102.592	0.000	860.657	464,783	470.063	103.300	43.784	957.010
PV3MATH	594,940	461.586	104.478	0.000	910.443	431,223	465.428	102.365	0.000	889.648	464,783	470.082	103.338	43.940	935.745
PV4MATH	594,940	461.645	104.628	29.973	878.031	431,223	465.498	102.348	38.481	884.822	464,783	470.062	103.331	24.622	943.457
PV5MATH	594,940	461.398	104.687	8.269	915.101	431,223	465.236	102.764	0.000	901.830	464,783	470.124	103.330	37.085	907.626
PV6MATH	594,940	461.617	104.513	5.215	870.202	431,223	465.549	102.627	3.305	893.694					
PV7MATH	594,940	461.818	104.682	3.210	890.587	431,223	465.527	102.607	0.000	852.506					
PV8MATH	594,940	461.583	104.529	0.000	889.800	431,223	465.445	102.632	24.846	871.610					
PV9MATH	594,940	461.369	104.548	26.576	899.891	431,223	465.536	102.847	0.000	889.142					
PV10MATH	594,940	461.497	104.613	24.916	894.590	431,223	465.357	102.594	0.000	869.230					

Source: PISA 2012, 2015, 2018 and own calculation

3.4. Results

Results from the two-level model estimations for each of the three waves of PISA are presented in Table 10. Specifications (1) - (2), (3) - (4) and (5) - (6) use, the 2018, 2015 and 2012 waves, respectively. Specifications (2), (4) and (6) differ from (1), (3) and (5) in the inclusion of the interaction between mean school wealth and *school inequality* in line with the arguments expressed in the theoretical framework. Households' assets (HOMEPOS) and the mean school wealth (School HOMEPOS) and *school inequality* are strong positive predictors of *learning scores* across all specifications ($p < 0.001$), which is in line with the literature on the topic discussed earlier. *Learning scores* are predicted to increase in a range from .06 to .08 standard deviations for 1 additional unit of students' household assets (HOMEPOS) and between .30 and .44 standard deviations for additional units of school households' assets (School HOMEPOS).

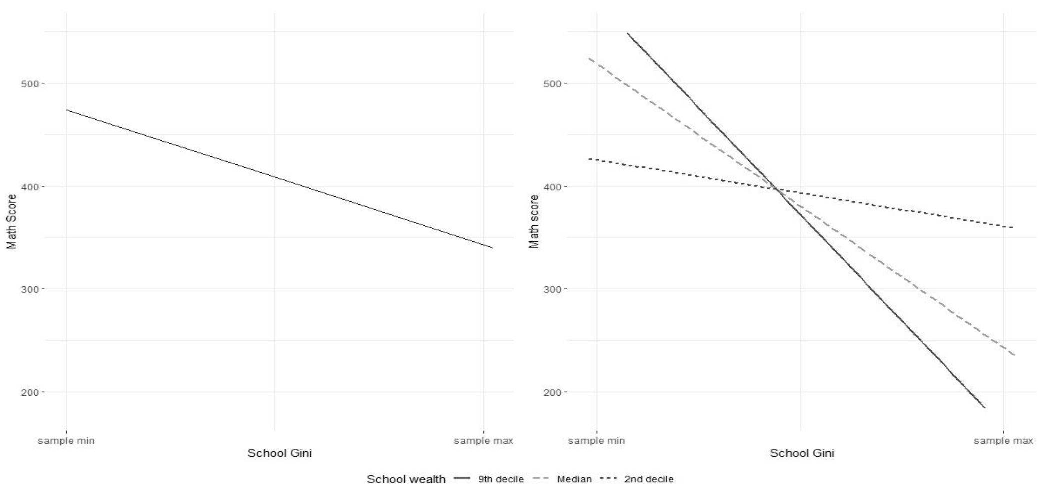
An increase of .1 unit of *school inequality* is found to be negatively associated with individual mathematics *learning scores* across all waves in a range between .007 and .022 standard deviations, equivalent to .2 to 1 fewer months of schooling. The PISA 2018 model (2) shows the highest variance explanation (33%), with 7% for students' level and 60% for school level. The intraclass correlation (ICC) across unconditional models (intercept only models) reveals that 49% of the total model variance occurs between schools while 51% occurs within-schools in 2018. Results are very similar in PISA 2015 (48% and 52%) and slightly lower in PISA 2012 (36% and 64%). When predictors are included, ICC is within a range of 29% in 2018 to 39% in 2012. In this last case, ICC increases with the addition of parameters, while it decreases in 2018 and 2015.

Interacted terms are statistically significant (p < 0.001) and specifications (2), (4), and (6) outperform specifications (1), (3), (5) according to R^2 as the proportion of outcome variance explained by the model. The nuances of how school-level inequality predicts test scores at different levels of school assets are graphically described by plotting predicted scores from specification (2) in Figure 5 for ease of representation. Following Jerrim *et al.*'s (2017) approach for large samples, I plot this graph by employing only the first plausible value. In line with the negative sign of the interacted term, the negative slope of inequality is visibly steeper for schools with higher average wealth. These findings suggest that social cognition mechanisms could be in operation, with wealthier groups being more susceptible to the negative effects of inequality (Schneider, 2012), rather than processes related to the government allocation of resources to schools, which would instead predict stronger impacts of inequality for poorer contexts.

As I mentioned above, the interaction term can be interpreted as a standalone measure quantifying the total amount of relative deprivation experienced in the school, as shown by Yitzhaki's (1979) and Hey and Lambert's (1980) seminal work on the quantification of Runciman's (1966) sociological notion of relative deprivation. In addition, the interaction term is also equivalent to school absolute inequality: while measures of relative inequality (like the customary Gini coefficient, which I use in this chapter) reflect imbalances in the ownership of shares of total economic resources, absolute inequality reflects the actual gaps (as opposed to proportional gaps) and socioeconomic divide among individuals. For an example of how absolute and relative inequality figures may differ, see Ravallion and Chen (2007). The two interpretations of the interaction term as a standalone variable suggest that controlling for the proportional distribution of total resources and for the amount of total resources, *learning scores* are lower the greater the amount of total relative deprivation in school and the greater the socioeconomic divide in school.

Finally, I carry out several robustness checks for each of the three waves: i) using reading scores as the dependent variable (Table 28 in Annexes); ii) carrying out the analysis on a subsample of the data where only schools that are larger than the overall median were considered in the analysis; and, iii) employing different inequality measures (Theil and Atkinson indexes) for mathematics and reading scores. For each of these robustness checks, results are qualitatively unchanged; regression output can be found in the Annexes. Robustness checks discussed above also confirm interaction results (Table 29 and Table 30 in Annexes). The only exception occurs when modelling the variable *Alpha Inequality* across all waves, which yields a significant positive interaction parameter. However, when the same models are estimated using a penalised least squares method (PLS) (Bates and Debroy, 2004), the estimations show similar negative parameters for the interaction between both variables (Table 31 in Annexes).

Figure 5: Predicted values of MATHS for different school wealth values over the school inequality domain



Source: own elaboration

Table 10: Multilevel models of Mathematics attainment – Gini: PISA 2018, 2015 and 2012

	2018		2015		2012	
	(1) MATH	(2) MATH	(3) MATH	(4) MATH	(5) MATH	(6) MATH
Fixed effects						
Gini	-7.04 *** (0.25)	-13.02 *** (0.4)	-13.12 *** (0.34)	-21.71 *** (0.56)	-8.14 *** (0.43)	-12.58 *** (0.45)
School HOMEPOS	36.17 *** (0.36)	37.69 *** (0.38)	29.58 *** (0.43)	32.5 *** (0.44)	42.35 *** (0.5)	43.84 *** (0.49)
Gini*School HOMEPOS		-6.52 *** (0.19)		-7.24 *** (0.25)		-4.89 *** (0.44)
Sex (Male = 1)	12.17 *** (0.35)	12.19 *** (0.35)	14.6 *** (0.42)	14.62 *** (0.42)	17.34 *** (0.13)	17.34 *** (0.13)
Parental higher educational level (HISCED)	1.97 *** (0.13)	1.96 *** (0.13)	3.07 *** (0.12)	3.05 *** (0.12)	3.82 *** (0.1)	3.82 *** (0.1)
Immigration (Native = 1)	0.75 (0.39)	0.78 (0.39)	-0.09 (0.5)	-0.03 (0.49)	-2.82 *** (0.43)	-2.79 *** (0.43)
Language spoken at home (different from test = 1)	-11.78 *** (0.6)	-11.86 *** (0.6)	-13.26 *** (0.62)	-13.43 *** (0.62)	-9.43 *** (0.35)	-9.48 *** (0.35)
Age	3.36 *** (0.13)	3.36 *** (0.13)	3.08 *** (0.16)	3.07 *** (0.16)	3.13 *** (0.1)	3.14 *** (0.1)

Repeated course (Yes = 1)	-55.4 *** (0.58)	-55.48 *** (0.58)	-55.46 *** (0.54)	-55.38 *** (0.53)	-54.24 *** (0.4)	-54.25 *** (0.4)
School type (Private = 1)	2.3 ** (0.88)	1.1 (0.89)	8.73 *** (0.84)	6.18 *** (0.84)	5.8 *** (0.82)	4.83 *** (0.81)
School Area (Urban = 1)	3.87 *** (0.22)	4.11 *** (0.21)	3.73 *** (0.4)	4.15 *** (0.36)	4.17 *** (0.41)	4.47 *** (0.39)
HOMEPOS	8.41 *** (0.16)	8.41 *** (0.16)	8.18 *** (0.19)	8.19 *** (0.19)	6.35 *** (0.12)	6.36 *** (0.12)
Intercept	396.2 *** (2.31)	393.44 *** (2.32)	400.54 *** (2.73)	399.11 *** (2.67)	420.18 *** (1.61)	418.58 *** (1.61)
Random effects						
Variance Intercept	2164.14 (18.94)	2046.49 (17.66)	2460.86 (27.7)	2321.06 (24.94)	2764.64 (14.54)	2683.02 (11.57)
Residual variance	4961.54 (10.9)	4962.12 (10.9)	4798.26 (13.82)	4798.35 (13.81)	4400.42 (5.92)	4400.38 (5.91)
R2 Level 2	0.58 (0)	0.6 (0)	0.49 (0)	0.52 (0)	0 (0)	0 (0)
R2 Level 1	0.07 (0)	0.07 (0)	0.08 (0.01)	0.08 (0.01)	0.09 (0.01)	0.09 (0.01)
R2 Total	0.32 (0)	0.33 (0)	0.28 (0)	0.29 (0)	0.05 (0.01)	0.05 (0.01)
ICC Unconditional	0.49 (0)	0.49 (0)	0.48 (0)	0.48 (0)	0.36 (0)	0.36 (0)

ICC Unconditional Within and Between effects	0.53 (0)	0.53 (0)	0.5 (0)	0.5 (0)	0 (0)	0 (0)
ICC Conditional	0.3 (0)	0.29 (0)	0.34 (0)	0.33 (0)	0.39 (0)	0.38 (0)
Observations	496689	496689	358338	358338	413832	413832
Fixed effects	Countries	Countries	Countries	Countries	Countries	Countries

Note: *** <.001, ** <.01, *<.05

3.5. Discussion

This chapter contributes to furthering the understanding of economic determinants of education in three ways. First, I go beyond measures of individual economic status and examine how the distribution of economic resources relates to educational attainment by employing measures of aggregate economic inequality, for which the available evidence is surprisingly scant. In this sense, I confirm the findings developed in Chapter 2. Second, I focus on schools as the level of aggregation for the computation and the analysis of economic inequality, showing how lower levels of aggregation which differ from commonly used administrative boundaries can shed useful light on educational achievement. Third, I find an interplay between aggregate school-level economic determinants (inequality and average wealth) and I provide two interpretations of this result: one based on the customary econometric reading of an interaction term and one based on an alternative interpretation of the interaction term as a standalone economic variable discussed in the literature.

My empirical analysis based on the 2012, 2015 and 2018 waves of PISA data shows a significant negative relationship between school-level inequality and *learning scores*, which holds after many robustness checks. This finding suggests that beyond well-known economic determinants of educational outcomes such as household standard of living and purchasing power, the scale of socioeconomic disparities may jeopardise learning. This result is in line with potential pathways between the aggregate economic inequality and educational outcomes that I discussed in the literature review, and which depict unequal social milieus as detrimental to a series of socioeconomic outcomes via the negative effects of upward interpersonal comparisons and a deterioration of the social fabric. It is likely that such dynamics are indeed crucial in secondary schools, where pupils' close everyday contact with one another during adolescence is a key factor shaping their social identities, affecting their aspirations, and laying the foundations for their self-esteem.

The interaction between school-level inequality and mean school wealth sheds light on how school-level inequality may behave differently in wealthier or poorer environments. The interaction indicates that the negative association between economic inequality and educational outcomes is stronger for schools with higher average wealth. This result is in keeping with social cognitive theory, according to which the negative consequences of inequality could be perceived more strongly at higher socioeconomic status, supporting the idea that wealthier groups may be more susceptible to the negative influences of inequality. Alternative interpretations of the interaction term indicate a negative relationship between *learning scores* and school-level relative deprivation or absolute inequality. These alternative perspectives towards my result shed light on the importance of the actual economic gap among individuals, too often neglected by the almost exclusive focus of the existing inequality literature on a relative understanding of inequality.

One of the main limitations of this study relies on the empirical strategy used. I did not intend to isolate and address the direction and magnitude of a causal relationship between *school inequality* and learning scores, which is even more complex due to the risk of falling into an ecological fallacy. This calls for caution concerning the causal interpretation of the results presented, which can be suggested based on conceptual arguments but not from a formal empirical identification strategy.

My empirical limitation in terms of identifying causality does not prevent the formulate of postulates based on previous academic literature and knowledge. In this sense, I understand *school inequality* as a contributing factor of negative schooling outcomes. This affirmation, however, requires some additional explanation. I categorise *school inequality* as a contributing factor of negative learning achievement. By doing so, I support it in terms of what in logical causality is referred as a INUS condition, which stands for 'an insufficient, but necessary part of an unnecessary but sufficient condition' (Mackie, 1974, p. 245). While the wording may appear to be abstruse, the intention is to clarify the important distinction between sufficiency and necessity. *School inequality* does not necessarily need to be a necessary condition towards explaining lower *learning scores,* although it could be understood as a sufficient condition to shed light over the phenomenon.

Another limitation, similar to previous studies, relates to the use of cross-sectional survey data, which does not allow to study and test empirical causality. The increasing availability of panel data will offer exciting opportunities to empirically test the causal nature of the associations highlighted in this work. However, ILSAs do not provide many possibilities to develop longitudinal analysis as they do not follow-up students' cohorts (with some exceptions in countries such as Germany and the United States of America).

Finally, the findings of this chapter, and also the previous one, raise a question regarding what individual and societal aspects can be fostered towards reversing the negative association between *school inequality* and *learning scores.* This is the main research question I address in the following chapter, where I suggest a theoretical framework based on social cohesion, encompassing several individual related attitudes that I will study to see how they may serve as a counterbalance to *school inequality*.

4. Inequality, social cohesion, and academic achievement: evidence from PISA 2018

4.1. Introduction

This chapter revisits the notion of social cohesion applying it to schools. It aims to highlight the socialising aspect of the schooling process. It understands that social cohesion mitigates the adverse effects of inequality. In this sense, I build a theoretical framework to capture some potential pathways through which inequality affects schools, and how certain individual attitudes interplay with school inequality and learning scores. Social cohesion is conceptualised with three main dimensions: a sense of belonging to the school, meaningful social relations among peers and teachers, and attitudes towards building a common good. The variables chosen to operationalise social cohesion are the sense of school belonging, cooperation among peers, understanding others' perspectives, agency towards global issues and respect for people from other cultures.

Three different mechanisms on how these attitudes affect learning scores through inequality are hypothesised, namely compensation, moderation, and mediation effects. I use multilevel structural equation models using data from countries that participated in PISA 2018. Results suggest that the sense of belonging, respect for others' perspectives. and agency toward global issues consistently show a positive relationship across all hypotheses.

Chapters 2 and 3 show robust evidence of the negative interplay between *school inequality* and learning achievement in the Programme for International Students Assessment (PISA) by the Organisation for Economic Co-operation and

Development (OECD). I theorise – based on previous psychological and sociological literature – potential explanatory channels such as social isolation, anomie, and interpersonal comparisons to explain why *school inequality* negatively affects *learning outcomes*.

This chapter aims to test a set of hypotheses to understand how certain attitudes in the realm of social cohesion may mitigate or moderate these adverse consequences of inequality in schools. Based on the premise that *school inequality* has a causal connection to *learning scores,* I address test three sets of hypotheses addressing the possible *compensation*, *moderation,* and *mediation* of certain individual attitudes on *learning scores.* I use multilevel structural equation models and focus on the following attitudes: i) sense of belonging; ii) cooperation among peers; iii) understanding others' perspectives; iv) agency towards global issues; and v) respect for people from other cultures.

One of the original purposes of a universal school system was to foster peaceful coexistence among people with different backgrounds and cultures. Nurturing social cohesion was a key driver of the first compulsory primary school system, which traces back to Prussia in 1763, under Frederick the Great. Education came as a solution to disseminate tolerance so that Catholics and Protestants could peacefully live together (Heyneman, 2003). A century later, Émile Durkheim used the term 'social cohesion' to characterise a society that shows strong social bonds between its members without latent or manifest social conflicts (Durkheim, 1897). In Durkheim's functionalist view, one of the roles of the state is to promote social cohesion through its institutions, whereby education plays an important role in fostering a common national identity and a set of shared values (Durkheim, 1925; Walford and Pickering, 1998).

In this chapter, I argue for a new understanding of schools as agents of socialisation, specifically fostering societal cohesion. I emphasise that the development of socio-emotional skills and attitudes beyond desired individual features is not just about developing future abilities in life, which is the mainstream emphasis of educational policies. Nor is it just as a means to an end in terms of the schooling process (such as in the case of improving school climate or mitigating bullying). I understand schools to operate as primary socialisation agents (Brint, 2017) that affect the acquisition of knowledge and values, and to also exert influence through their ability to limit and oversee children's exposure to different social issues (van Deth, Abendschön and Vollmar, 2011).

The emphasis I make addresses two challenges that educational systems face at the present time. First, the international discourse has switched to the promotion of skills such as socio-emotional abilities by individuals without emphasis on the role of schools to foster them. This could be seen as highlighting education as an individualistic rather than a social process. For example, all SDG 4 targets – which focus on education – are stated at an individual level (United Nations, 2015). Target 4.7[6] promotes a set of individual knowledge and skills such as global citizenship,

[6] Target 4.7 is expressed as: "By 2030, ensure that all learners acquire the knowledge and skills needed to promote sustainable development, including, among others, through education for sustainable development and sustainable lifestyles, human rights, gender equality, promotion of a culture of peace and non- violence, global

human rights, the promotion of non-violence, and the appreciation of cultural diversity (Mochizuki, 2016; UNESCO, 2016; Schulz *et al.*, 2017). Certainly, those attitudes are socially desirable and focus on building a better world. However, I dispute the omission of the role of schools as communities and agents of change in this international discourse. Another example can be found in the Incheon Declaration and Framework for Action for the implementation of Sustainable Development Goal 4 (UNESCO, 2015), where there are no references to the relationship between education and community or society.

Recent academic research is another example of this individualistic paradigm. While there is extensive growth of theoretical and empirical research focusing on the individual socio-emotional skills development of students (Durlak *et al.*, 2011), research on the role of schools focuses mainly on them as a means to an end, such as in the case of the relationship between school climate and bullying and *learning outcomes* (MacNeil, Prater and Busch, 2009). Another important improvement is the emphasis given to education as a crucial engine of the economic development of people and nations. Again, schools are solely understood instrumentally, as a channel to achieve an extrinsic end. This is supported, for example, by widespread empirical research that finds strong causal connections between cognitive achievement, usually measured as *learning scores* in academic areas such as literacy, mathematics, science and economic-related outcomes (Hedges, Laine and Greenwald, 1994; Krueger and Lindahl, 2001; Hanushek, 2005).

---

citizenship and appreciation of cultural diversity and of culture's contribution to sustainable development" (United Nations, 2015).

Redirecting attention towards schools as a positive social force – with both individual and social effects – also raises the question of how other social dimensions affect school dynamics. I understand the role of social cohesion in schools based on theoretical underpinnings from relational sociology, which proposes that the dichotomy between agency and structure is resolved by giving ontological value to social relations (Archer, 2015). This is further developed in section 4.2.2, where I address the socialisation process in schools. Understanding schools as relational places offers the opportunity to nurture diverse attitudes such as tolerance, respect for diverse others, promoting common identity and shared values, and democratic participation. It is widely accepted that social cohesion is a desired attribute of any society or community. This desirability could be both based on principles, such as the need for solidarity among people, or because of some tangible effects, such as peace and stability.

However, I find two limitations in the literature relating to social cohesion and schools, which will be further addressed. First, the conceptualisation of social cohesion at a school level usually highlights certain aspects of the phenomenon, such as a sense of community or prevention of bullying, but does not capture its full depth. Secondly, as social cohesion is usually defined at a higher societal level, for example, at a country-level, the concept needs adaptation to school settings. This implies a lack of a school-specific understanding of social cohesion.

Definitions of social cohesion found in the academic literature portray different attributes and characteristics. In this research, I adopt Green and Janmaat's (2011, p. 18) definition of social cohesion as "the property by which whole societies, and the individuals within them, are bound together through the action of specific attitudes, behaviours, rules and institutions which rely on consensus rather than pure coercion". I understand the school as a unit of social cohesion, which is equivalent to their macro-perspective understood as the 'whole society'.

Previous research has found links between socioeconomic inequality and social cohesion. Putnam (2007) theorises that there is an inverse relationship between ethnic and socioeconomic differences and dimensions of social cohesion in a community, such as solidarity and trust. This has been tested at a cross-country level, suggesting that more equal countries show higher levels of trust among populations (Bjørnskov, 2008; Layte, 2012). However, a more recent study focusing on state-level inequality in the United States presents differing results. The cross-sectional analysis does not support the association of inequality with less trust. On the contrary, there is some evidence that the growth in income inequality over time is associated with a decrease in trust (Hastings, 2018). In light of this, I conceive fostering social relations and individual attitudes linked to them – such as trust or perception of community – as potential mechanisms for overcoming the adverse effects of inequality on academic outcomes.

This chapter presents theoretical pathways linking three dimensions within-schools: *contexts* such as the degree of wealth inequality; *potential mechanisms*, namely, attitudes linked to fostering social cohesion developed by the psychological and sociological literature; and *learning scores*, measured as standardised test reading scores in PISA cycle 2018. Using PISA 2018 allows for a cross-country comparable measurement of acquired skills. My study focuses on attitudes expressing a sense of belonging, valuing personal relations, and the orientation towards a common good. Based on that, I test different hypotheses regarding whether those mechanisms compensate, moderate and/or mediate the association between the influence of wealth inequality on *learning outcomes*.

The research questions can be formulated as follows:

1 - To what extent do attitudes explain within- and between-school variations in reading scores above and beyond *school inequality*?

2 - To what extent does a social cohesion variable explain between-school variation in the relation between *school inequality* and reading scores?

3 - To what extent does a social cohesion variable mediate the relation between *school inequality* and reading scores?

I apply this analysis to data collected from countries and territories that participated in PISA 2018.

To the best of my knowledge, there are no studies in educational settings focusing on social cohesion and how related attitudes can work as potential channels between inequality and educational attainment. In this sense, this chapter addresses gaps in the literature on at least two different fronts. First, I provide a theoretical framework that interconnects economic inequality, social cohesion in schools, and cognitive outcomes, highlighting the role of schools as agents of socialisation. Second, I offer empirical findings supporting the thesis that individual attitudes linked to social cohesion mitigate the harmful effects of wealth inequality within-schools.

The remainder of this chapter is organised as follows: Section 2 reviews relevant literature on wealth inequality and social cohesion in schools, addressing theoretical and measurement features; section 3 presents the data and sets the empirical strategy based on multilevel mediation and moderation models; finally, sections 4 and 5 present the results and discusses them in relation to the previous literature.

4.2. Literature review

The literature review presented in the previous chapter addresses mostly the economic literature regarding SEC effects. I categorise the literature into four different topics, namely, how SEC affects access to education, the social fabric, how it provokes relative deprivation, and finally, Bourdieu's social reproduction theory.

In this chapter, I present a theoretical understanding of social cohesion as a key aspect of schools. This understanding is underpinned by my preference for a relational sociology (Donati, 2012; Archer, 2015; Donati and Archer, 2015), where I understand schools as social institutions and places for nurturing human relations. Based on that, I chose to deepen my exploration into the topic of interpersonal comparisons and schools' social fabric.

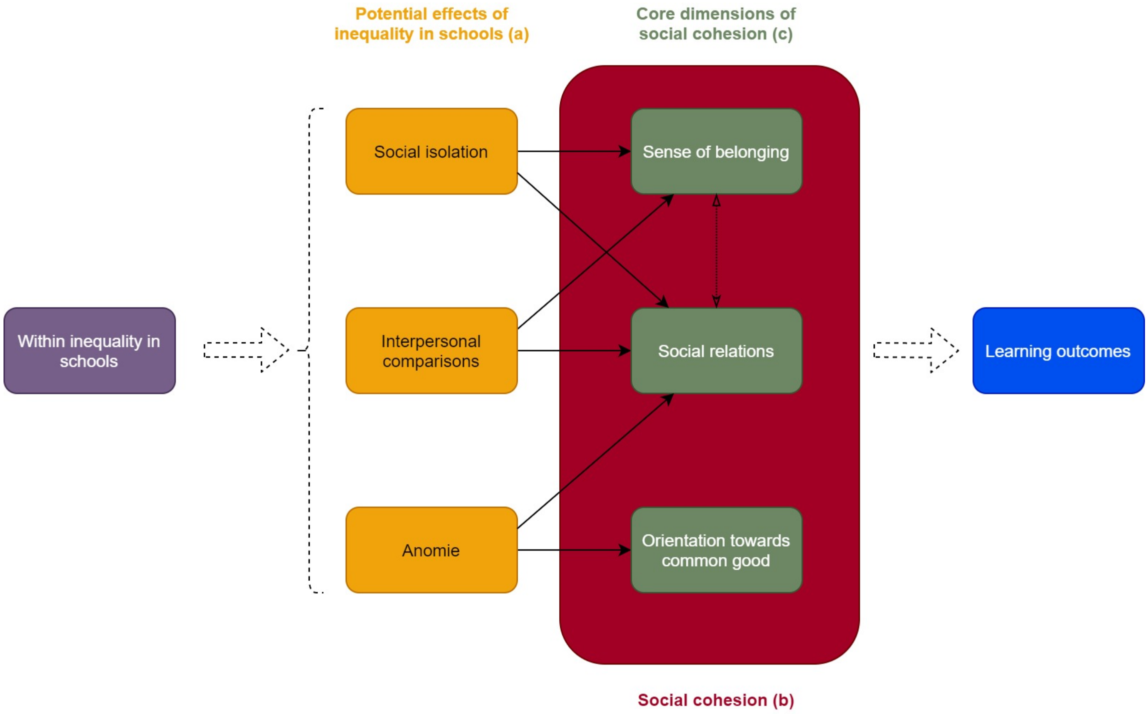
This literature review is organised into three sections, which follows the conceptual framework summarised in Figure 6. The first step to create the theoretical framework was developing an understanding of the core social cohesion dimensions which were relevant at school-level (column c). I found that Schiefer and van der Noll's (2017) approach to the core dimensions of social cohesion were an adequate account of my own experience in visiting and working in schools – it is worth mentioning that my original Ph.D. research was an evaluation of an intervention in schools in six Latin American countries, where I visited 130 schools during 4 years –.

Based on that, I performed an academic review across different fields such as education, sociology, psychology, economics, health, and development studies. The main search topic was the consequences of aggregated inequalities at a micro-level. Among many potential consequences, I chose to focus on those that emphasized the relationships between people – as I mentioned before, expanding on interpersonal comparisons and schools' social constitution.

Hereafter, I explain the conceptual framework for this chapter. First, I address the contextual influence of wealth inequality in schools by identifying potential channels through which economic inequality affects individual and social behaviour, namely: interpersonal comparisons (Esposito and Villaseñor, 2019); social isolation (Barry, 1998); and, social anomie. I draw on Durkheim and Merton's insights into the mismatch between individual actions and the system of social norms (Durkheim, 1897; Merton, 1957) (column *a*).

Second, I theorise the socialising role of schools and how social cohesion has a relevant role in influencing students´ socialising skills (box *b*). Finally, within a social cohesion framework, I review the core characteristics of social cohesion based on Schiefer and van der Noll's (2017) study and how they relate to the schooling context (column *c*).

Figure 6: Conceptual framework



Source: own construction. Original in colour.

4.2.1. Potential mechanisms of wealth inequality in schools

Educational systems and policies cannot be detached from contextual factors delineated by countries, schools, families, as well as students' particular characteristics. It is well established, for instance, that socioeconomic features play a relevant role in explaining cognitive success (Sirin, 2005), non-academic performance in dimensions such as school climate (Thapa *et al.*, 2013; Wang and Degol, 2016), bullying (Jiménez-Barbero *et al.*, 2016), and socio-emotional skills (Durlak *et al.*, 2011).

In this chapter, I focus on the role of a less-studied contextual phenomenon, namely, within-school wealth inequality. Wealth inequality has been associated – both theoretically and empirically – with individual negative effects on human development aspects such as education and health. For instance, *school inequality* has been negatively associated with learning achievements across the vast majority of countries participating in the latest cycle of PISA (Sempé, 2021).

Mechanisms of how inequality may affect the schooling process, however, have not yet been studied in any depth. Based on a literature review from different fields of social science, I summarise three features of inequality that I consider to be observed across the schooling process, namely, (i) social isolation of certain individuals; (ii) interpersonal comparisons; and (iii) a condition of anomie in schools.

i. *Social isolation.* Barry (1998) defines social isolation as the phenomenon of voluntary or non-voluntary non-participation – either of an individual or a group – in a society's typical institutions and activities.

The relation between social isolation and inequality has been studied mostly within human geography. For example, Krivo et al. (2013) find social isolation is experienced by residents of neighbourhoods in both extremes of wealth in the city of Los Angeles. In this instance, urban segregation is a driver of isolation as people do not cross the city. According to this logic, material inequality within-schools can be seen as a driver of social isolation, whereby the more unequal any distribution in a school, the larger the difficulties of those at both extremes to engage with others.

ii. *Interpersonal comparisons* are a usual dimension of human life. Interpersonal comparisons refer to people's proclivity to compare themselves with other individuals. People usually use a group as a point of comparison to form their own attitudes, values, beliefs, and behaviour, known as a reference group (Lindemann and Saar, 2014). Several studies show that income and wealth comparisons act as one source of people´s dissatisfaction (Clark and Senik, 2010). People generally choose to compare upwards – as in looking to someone else who is seen as superior in some way – especially with those that are closer to them. This occurs even in the presence of a threat to self-esteem and tends to result in worsened mood and lower self-appraisal (Suls, Martin and Wheeler, 2002; Gerber, Wheeler and Suls, 2018). Lindemann and Sarr (2014) find cross-country evidence of an interpersonal comparison mechanism whereby the poorest people feel more stigmatised in an unequal society than an equal one due to the greater social distance from others.

Comparisons have been also linked to negative educational consequences, for example, to lower educational enrolment in schools in Mexico (Esposito and Villaseñor, 2019). Finally, research has also found a link between social isolation and interpersonal comparisons, whereby the more isolated people are also more likely to be concerned about whether they earn more or less than others (Bartolini *et al.*, 2019). This also suggests a possible concurrence of both phenomena, although there are no empirical pathways yet to explain how they interact.

iii. *Anomie:* the concept of anomie refers to people's lack of commitment to prevailing social standards such as shared values and rules, which occurs through deviant behaviours and attitudes (Merton, 1957). This phenomenon also occurs within-schools where the replication of antisocial attitudes and behavioural patterns are usually explained due to the different individual and home characteristics - such as age, sex, quality of relationships, among many others-, and ecological reasons – such as school culture and norms and neighbourhood environment (Hong and Espelage, 2012). Anomie is associated with negative consequences to *learning outcomes*, students' socioemotional disengagement, and diverse forms of discrimination and violence between students (Merrell *et al.*, 2008).

Several scholars have assumed that socioeconomic inequality, understood through the lens of relative deprivation theory (introduced in Chapter 4), leads to higher rates of deviance (Passas, 1997; Napoletano *et al.*, 2016). One hypothesis to causally explain this phenomenon suggests that rising income inequality results in increased levels of frustration, which may have damaging behavioural consequences in a community (Kelly, 2000). An alternative hypothesis is derived from social disorganization theory. Social disorganisation theory suggests that poverty and inequality are structural problems that intrinsically tend to produce higher incidences of negative behaviours, such as criminality (Sampson and Groves, 1989).

Finally, in this section I am assuming there is a relationship between wealth inequality, these potential consequences and *learning scores.* While there is space to develop an extended analysis, I provide in the Annex 8.3, a mediation analysis between school inequality, variables that could be understood as proxies of social isolation, anomie and interpersonal relationships and *learning scores.* The exploratory analysis suggests the existence of partial mediation in all cases. This supports the theoretical elaboration and allows further analysis on the current question of interest.

4.2.2.Socialisation and social cohesion in schools

Social relations have a pragmatic role in society. We inherit and build our social relations based on cultural and family ties, affinity, and values, or we are just motivated by self-interest, among other reasons. The phenomenon occurs in all dimensions of our lives, especially in spaces where we spend more time, such as schools. Besides that instrumental dimension, I argue that social relations are partly constitutive of the personhood, through an understanding of humans as a 'subject-in-relation' (Donati and Archer, 2015, p. 15).

Through that lens, Wentzel & Looney's (2007) three mechanisms through which schools influence students´ social skills are useful. First, the school's structure, context, and characteristics – for example, school and classroom sizes, location, or educational system – may boost or hinder students' social development. Classroom size, for instance, has been linked to better student behaviour due to higher visibility of individuals and a greater sense of belonging and responsibility in classrooms (Finn, Pannozzo and Achilles, 2003). Second, social interactions among peers and teachers provide students with resources, information and examples showing how to integrate into and behave positively in the social world (Wang and Degol, 2016). Third, the quality of social relationships is likely to have a motivational effect on influencing the internalisation of expectations and goals that are appreciated by others (Grusec and Goodnow, 1994).

The connection between the socialisation process that occurs within-schools and social cohesion includes both values and identity formation. This affects how people interact with other individuals and groups. For example, how they decide whom they trust, with whom they cooperate, and to which group they belong (Green and Janmaat, 2016). I posit that the notion of social cohesion requires an important set of attitudes and skills that are conveyed by schools in their role as socialising agents.

I focus on three dimensions that are consistently theorised as the essential features of cohesion: a sense of belonging, social relations, and orientation towards the common good (Schiefer and van der Noll, 2017).

The relationship between social cohesion and education has been mainly analysed from two different perspectives. First, education is understood as an input to social cohesion as a wider societal output (Mickelson and Nkomo, 2012). Previous cross-country research, for instance, has found positive associations between educational outcomes – such as the degree of literacy at the secondary school level or the tertiary education ratio in a given population – and social cohesion, measured as increased trust in others and institutions, civic cooperation, and, absence of violent crime (Green, Preston and Janmaat, 2006).

The second body of literature applies the concept of cohesion to school settings in their role as social institutions and socialization agents, highlighting students' attitudes. Schools influence children's acquisition and development of social norms and values (Wentzel and Looney, 2007). Schools are recognised as key institutions affecting social cohesion due to their ability to foster attitudes such as tolerance and respect for diverse others. They also promote common identity and shared values, and encourage social and democratic participation (Oder, 2005; Pabayo *et al.*, 2014). Mooij *et al.* (2011), for example, identify a set of characteristics to express the notion of school social cohesion, although they restrict their interpretation of social cohesion to the idea of the sense of belonging to a community.

A different approach was followed by Salahuddin *et al.* (2016), who operationalise social cohesion by asking parents about their perceptions of trust and reciprocity in the community and the school. Along similar lines, there are also studies focusing on the relationships among peers and the school climate (Springer *et al.*, 2016). However, the largest share of research has been related to the links between school cohesion and bullying and violence (Springer *et al.*, 2016; Diclemente *et al.*, 2018; van den Bos *et al.*, 2018; O'Neill and Vogel, 2020), and, to a lesser degree, the relationship between social cohesion and teachers' experiences and beliefs (Fuller and Izu, 1986; Fuller, Waite and Torres Irribarra, 2016). In both cases, these studies firmly show a positive association between cohesion and those educational features.

However, there is almost no research addressing the relationship between social cohesion and academic achievement. For instance, Deng and Gopinathan's (2016) history of education in Singapore suggests social cohesion is one of the elements that contributed to configuring institutional arrangements in educational policies that produced exemplary learning outputs in standardised assessments such as PISA. Nevertheless, the authors do not provide quantitative evidence to support these claims.

4.2.3. Operationalising social cohesion within-schools

An important body of literature suggests that certain individual and societal characteristics linked to social cohesion may mitigate the negative impacts of inequality (Kawachi *et al.*, 1996). While the positive broad effects of cohesion are known, there is little information about how these mechanisms work in schools, except for the study of the influence of classmates on students' educational achievement, known in the literature as 'peer group effects', which have been found as positive predictors of higher students' motivation levels (van Ewijk and Sleegers, 2010; OECD, 2019b).

Schiefer & van der Noll (2017) studied previous definitions of social cohesion in the academic and policy literature, identifying three interconnected dimensions they consider essential to explain the phenomenon: a sense of belonging; social relations; and the orientation towards the common good. I describe these in further detail below. These dimensions share at least two characteristics. First, they are more appropriately measured at a societal level than at an individual level; second, they are interconnected to a greater or lesser degree. For example, trust is a necessary condition to build a social network, while solidarity actions express a member's sense of community. Trust and solidarity enhance compliance with school norms due to a higher value placed on individual relationships.

Sense of belonging, understood as the perception of being part of the school community, is a feature that refers to the existence of shared values and a sense of collective or community identity, which is opposite to the feeling of loneliness and the experience of isolation (Jenson, 1998). Students with a high sense of belonging feel they belong to a community, considering themselves accepted, liked, and related to their peers, teachers, and families. At the same time, the quality of interpersonal relationships also predicts the sense of belonging within social groups, especially between those who perceive themselves as having similarities to others (Easterbrook and Vignoles, 2013).

Diverse predictors are found to be linked to improvements in students' sense of belonging in the literature, such as a positive disciplinary climate at school (OECD, 2017a), greater support and communication between students and their families (Chiu *et al.*, 2016), and teacher support (Greenwood and Kelly, 2018). At the same time, research suggests that a sense of community can be increased through pedagogical interventions promoting academic and social collaboration and participation in school decisions (Battistich *et al.*, 1995, 1997). This has been associated with positive academic attitudes and achievement (Goodenow and Grady, 2010; Osterman, 2016), psychosocial features such as higher self-esteem and efficacy (Slaten *et al.*, 2016; Morrison, Morrison and McCutcheon, 2017), and also behavioural aspects such as greater engagement with the school and good behaviour (Battistich and Hom, 1997; Korpershoek *et al.*, 2019).

The relationship between the sense of community in schools and *school inequality* has been less examined in the literature. For instance, research in developed countries has documented that inequality unfavourably affects students from disadvantaged groups such as immigrants (Denicolo *et al.*, 2017), those who are socioeconomically deprived (Chiu *et al.*, 2016), and ethnic minorities (Morris *et al.*, 2020). This occurs due to language and cultural differences and previous learning deficits. Although a sense of belonging to school is associated with positive outcomes across the socioeconomic gradient, the strongest positive effects are found among schools with the most disadvantaged student populations (Battistich *et al.*, 1995, 1997).

Social relations between individuals and groups are the most prominent facet of social cohesion (Schiefer and van der Noll, 2017). Schiefer and van der Noll identify two foundational dimensions of social relations, namely, trust and social networks (van den Bos *et al.*, 2018). Trust has been linked to increased school solidarity (Lenzi *et al.*, 2012) and to positive relationships between parents and teachers, which produces better academic outcomes (Adams and Christenson, 2000). This suggests that schools could be privileged places to foster personal relationships that may boost social cohesion in unequal societies (Mikulyuk and Braddock, 2018).

There is also research studying the relationship between students' networks and schooling outcomes. For instance, in Colombia, better interpersonal relationships are inversely associated with bullying, even after controlling for students' sense of belonging to their schools (Springer *et al.*, 2016). Social relations – mapped using social network analysis at the classroom level – are also associated with reduced levels of antisocial behaviour towards peers and a general increase in trust (van den Bos *et al.*, 2018).

There are also links between social relations and interpersonal comparisons, specifically understood as relative deprivation – the belief that one is worse off than comparable others (Runciman, 1966). Research has shown that people experiencing higher relative deprivation are less inclined to help others, which differs from findings associated with higher levels of generosity among materially poor people. This occurs through mechanisms such as feelings of resentment and unfairness (Callan *et al.*, 2017). In that sense, inequality has been suggested to have a deteriorating effect on societal cohesion because mistrust is deemed to increase (Bjørnskov, 2008).

A cohesive society needs members that feel responsible and are willing to commit to their communities. For this purpose, **orientation towards the common good** can be divided into two components: compliance to social order (culture) and norms; and attitudes of solidarity (Schiefer and van der Noll, 2017). Both elements can be applied to school settings.

Culture is defined as “the set of shared meanings, shared beliefs, and shared assumptions of the members of the organization" (Van Houtte, 2005, p. 77). Agreement with certain social rules among students as a part of a socialisation process is considered relevant to increase school bonding in children (Maddox and Prinz, 2003). Behaviours such as reciprocity, mutual assistance and solidarity in school are also related to enhancing school performance regarding students’ attention and involvement in class (Hernandez, Oubrayrie-Roussel and Prêteur, 2016).

To summarise, I understand as critical the socialisation that occurs within-schools. Under this umbrella, social cohesion attitudes such as sense of belonging, social relations, and orientation towards the common good appear as relevant dimensions to build community and also are linked to better educational outcomes, such as the acquisition of learning skills. In the following sections, I will operationalise and test this theory.

4.3. Methods

4.3.1. Data

In this chapter, I use data collected in the seventh cycle of the OECD Programme for International Student Assessment (PISA), which attempts to measure the knowledge and use of reading, mathematics and science of 15-year-old students across 79 educational systems in the world (Schleicher, 2019). I use data from all available countries in the dataset.

I operationalise the aforementioned social cohesion attitudes through different indexes built by PISA: the sense of belonging (BELONG, using the PISA acronym) for the homonymous dimension. For the dimension related to social relations, I choose two variables that reflect positive attitudes and behaviour toward others: cooperation among peers (PEERCOP) and students' understanding of others' perspectives (PERSPECT). Both variables are reliable proxies of trust and social networks, which are relevant characteristics of this dimension. Finally, I use the sense of agency towards global issues (GLOBMIND) and students' respect for people from other cultures (RESPECT) as a proxy of the dimension orientation towards the common good. These reflect the sense of responsibility and commitment to others and the world.

Table 11 presents the sentences, the scale of answers and the interpretation of these variables. Each variable is built from Likert-type questions using IRT models and scores are computed depicting a mean of 0 and a standard deviation of 1 across

OECD countries. Methodological details on the construction of each index can be found in PISA's 2018 Technical Note (OECD, 2020).

Additionally, I use the *Alpha Inequality* measurement built in Chapter 1 to represent school-level wealth inequality. Contextual variables are included in the regression models such as sex; age; grade repetition; students' household wealth (HOMEPOS); mean school wealth (SCHOOL HOMEPOS); the size of the population in the location of the school; and the school type (private or public).

Due to the PISA design, where students do not answer the same set of questions to maximise gathering population-level information, the use of only one score for each student could yield uncertainty, especially in smaller samples. To address this, PISA imputes 10 plausible values representing a distribution of random *learning scores* associated with the probability for each of these values to be estimated (Davier, Gonzalez and Mislevy, 1997). In this chapter, I use each plausible value as a dependent variable in a separate set of regression models, and then, estimations are combined using multiple imputation guidelines (Rubin, 1987).

Table 12 shows summary statistics of unweighted data used in the analysis. Socio-demographic data provides a general picture of the population. For instance, while the students' sex is nearly split across the sample (as can be expected as it represents populations), the percentage of students that repeated reaches 12% of the sample. Public schools account for 80% of the sample and the survey shows the majority of students living in cities between 15,000 and 100,000 inhabitants. PV1READ-PV10READ represent the plausible values for reading scores, while the indexes BELONG, PERCOOP, PERSPECT, GLOBMIND and RESPECT show means close to 0, as expected due to the PISA's scaling method.

Table 11: PISA 2018 indexes used in this research

INDEX	BELONG	PERSPECT	PERCOOP	RESPECT	GLOBMIND
Sentence 1	"I feel like an outsider (or left out of things) at school"	"I try to look at everybody's side of a disagreement before I make a decision"	"Students seem to value co-operation"	I respect people from other cultures as equal human beings"	"I think of myself as a citizen of the world"
Sentence 2	"I make friends easily at school"	"I believe that there are two sides to every question and try to look at them both"	"It seems that students are co-operating with each other"	"I treat all people with respect regardless of their cultural background"	"When I see the poor conditions that some people live under, I feel a responsibility to do something about it"

Sentence 3	"I feel like I belong at school"	"I sometimes try to understand my friends better by imagining how things look from their perspective"	"Students seem to share the feeling that co-operating with each other is important"	"I give space to people from other cultures to express themselves"	"I think my behaviour can impact people in other countries"
Sentence 4	"I feel awkward and out of place in my school"	"Before criticising somebody, I try to imagine how I would feel if I were in their place"		"I respect the values of people from different cultures"	"It is right to boycott companies that are known to provide poor workplace conditions for their employees"
Sentence 5	"Other students seem to like me"	"When I'm upset at someone, I try to take the perspective of that person for a while"		"I value the opinions of people from different cultures"	"I can do something about the problems of the world"

Sentence 6	"I feel lonely at school"				"Looking after the global environment is important to me"
Scale	Four-point-scale Likert scale: "strongly disagree", "disagree", "agree", "strongly agree"	Five-point scale: "very much like me", "mostly like me", "somewhat like me", "not much like me" and "not at all like me"	Four-point-scale Likert scale: "not at all true", "slightly true", "very true", "extremely true"	Five-point scale: "very much like me", "mostly like me", "somewhat like me", "not much like me" and "not at all like me"	Four-point-scale Likert scale: "strongly disagree", "disagree", "agree", "strongly agree"

Interpretation	Positive values in this index indicate a greater sense of belonging to a school than the average student across OECD countries	Positive values in this index indicate a greater ability to understand and take different perspectives than the average student across OECD countries.	Positive values in this index mean that students perceived their peers to co-operate to a greater extent than did the average student across OECD countries.	Positive values in this index indicate that students reported greater respect for people from other cultures than the average student across OECD countries	Positive values in this index indicate that students have a greater sense of global-mindedness than the average student across OECD countries.

Source: PISA 2018 (OECD, 2020)

Table 12: Summary statistics

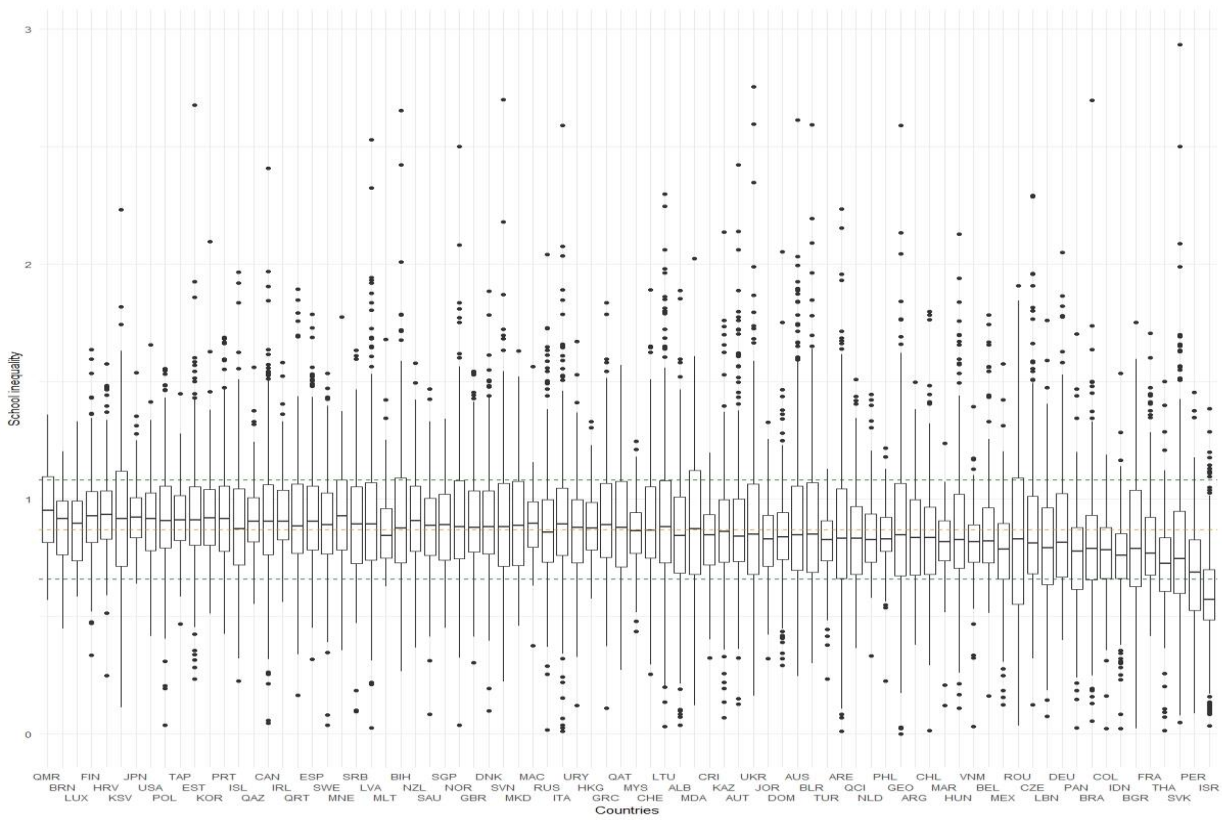
Characteristic	N = 600,316[1]
SEX	
Female	299,761 (50%)
Male	300,555 (50%)
AGE	15.75 (15.58, 16.00)
REPEAT	
No	506,705 (88%)
Yes	67,901 (12%)
HOMEPOS	9.83 (9.08, 10.51)
SCHOOL HOMEPOS	-0.32 (-0.89, 0.14)
BELONG	-0.32 (-0.67, 0.34)
PERCOOP	0.60 (-0.94, 0.60)
PERSPECT	0.06 (-0.64, 0.67)
GLOBMIND	0.01 (-0.50, 0.44)
RESPECT	0.17 (-0.69, 0.93)
PV1READ-PV10READ	456 (379, 534)
SCHOOL AREA (INHABITANTS)	
< 3,000	53,276 (9.4%)
3,000 > 15,000	111,422 (20%)
15,000 > 100,000	160,551 (28%)
100,000 < 1millon	149,267 (26%)
> 1millon	93,368 (16%)
SCHOOL TYPE	
Public	435,910 (80%)
Private	106,346 (20%)
ALPHA INEQUALITY	0.85 (0.73, 0.99)

Characteristic	N = 600,316[1]
Gini	0.044 (0.037, 0.052)
[1]n (%); Median (IQR)	

Source: PISA 2018 (OECD, 2020) and own calculation

Figure 7 portrays boxplots of the school *Alpha Inequality* measure across countries. Broken lines represent the cross-country mean and one standard deviation. Moscow, followed by Brunei, depicts the highest average of inequality among all territories while Israel shows the lowest. Outlier schools appear across all countries with Slovakia showing a significant number of these.

Figure 7: School Alpha Inequality across countries in PISA 2018

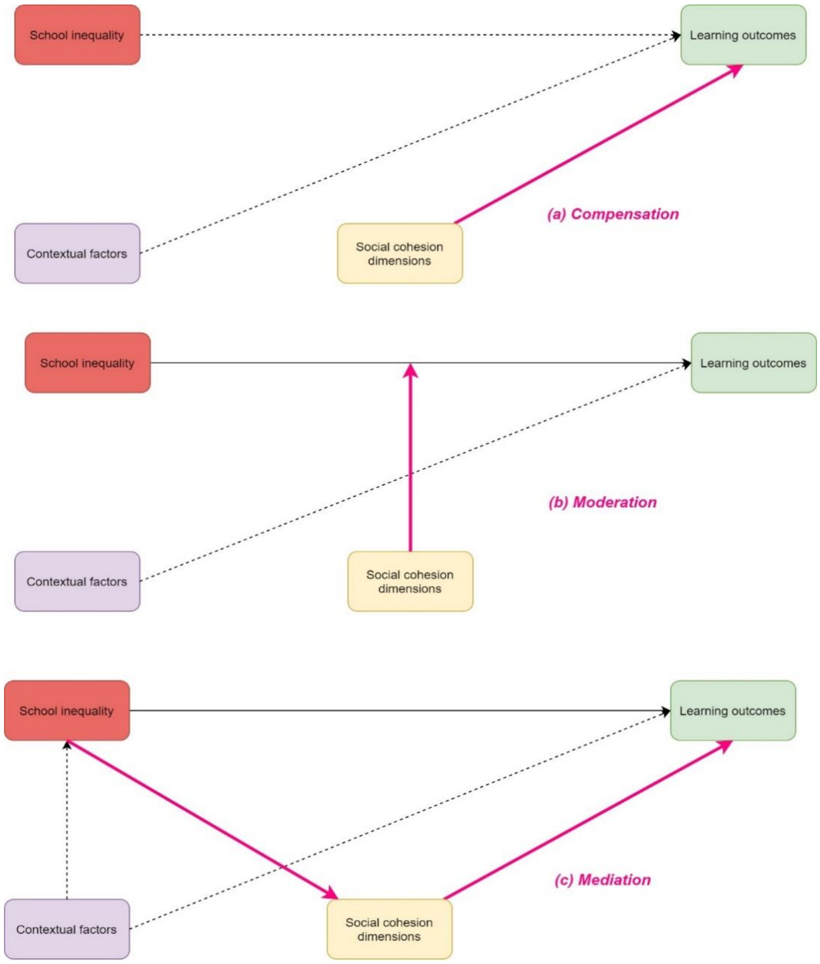


Source: own calculations based on PISA 2018 (OECD, 2020)

4.3.2. Empirical strategy

The empirical strategy used in this research addresses different potential mechanisms of how social cohesion interacts with inequality and may affect *learning scores*. For each cohesion-related variable (BELONG, PERCOOP, PERSPECT, RESPECT, GLOBMIND), first, I examine whether they compensate for the negative consequences of inequality on *learning scores* (compensation); second, whether different degrees of the variable affects the effects of inequality in *learning scores* (moderation); and finally, whether social cohesion totally or partially mediates the effect of inequality on *learning outcomes* (mediation) (Scherer, 2020). These hypotheses are graphically represented in Figure 8. The upper panel (a) shows a compensation mechanism, where I hypothesize that social cohesion variables have a role in terms of reducing the influence of *school inequality* in learning outcomes. This compensation model represents the basic concurrence of diverse factors – positive and negative ones – on schools. The hypothesis does not isolate (and measure) the magnitude of the compensation, but reveals if the existence of certain positive attitudes linked to social cohesion may play a positive role on learning outcomes. Panel (b) represents a different hypothesis where I suggest the existence of moderating role of social cohesion attitudes between *school inequality* and *learning scores.* If the hypothesis holds, the interaction between both *school inequality* and social cohesion variables will show different behaviours at different levels of *social inequality.* Finally, panel (c) represents a mediation hypothesis, where social cohesion attitudes are posed as intermediaries between *school inequality* and *learning scores.* In this model, if the hypothesis fully holds, the promotion of social cohesion attitudes may drive the disappearance of the negative effects of *school inequality* on *learning scores.*

Figure 8: Representation of hypotheses



Source: own elaboration

In this chapter, I use structural equation models (SEM). SEM has been supported by many scholars as a relevant tool for theory-driven research (Cordray, 1986; Chen, 1989; Smith, 1994; Coryn *et al.*, 2011).

For each variable representing an attitude linked to social cohesion, I model two-level path analysis with random intercepts. I decompose the total score (y_{ij}) of the outcome variable (*learning scores*) into two parts: a within part that corresponds to the student, and a between part that corresponds to the school. The formal notation of the decomposition is given by:

$$y_{ij} = \left(y_{ij} - \bar{y}_i\right) + \bar{y}_i \tag{1}$$

Where $i = \{1, \dots, I\}$ is an index for the clusters (in this case, schools) and $j = \{1, \dots, n_i\}$ is an index for the students within-schools; and $\bar{y}_i$ is the school mean of school i. As mentioned, the outcome variable y_{ij} is decomposed into $\left(y_{ij} - \bar{y}_i\right)$, which corresponds to the within-school *learning scores*, y_W; and the term $\bar{y}_i$ corresponds to the between-school *learning scores*, y_B. Both components are treated as additive and orthogonal latent variables composing the total score, as follows:

$$y_{ij} = y_W + y_B \tag{2}$$

As the observed $\bar{y}_i$ for each cluster is not necessarily the 'true' mean of each school i due to sampling and measurement errors, the SEM framework treats $\bar{y}_i$ as unobserved scores. Therefore, both y_W and y_B in equation (2) are also treated as latent variables.

The *compensation hypothesis* (Figure 8, panel a) assumes that social cohesion explains some variation in academic achievement both at the within and between school level beyond the effects captured by inequality. In this sense, this hypothesis can be interpreted as evidence for a compensating effect – assuming parameters shall be positive – of social cohesion on *learning scores*. I emphasise that this hypothesis does not make any assumptions of causality on the link between inequality and social cohesion and consider them as potential concurrent explanatory variables of academic achievement. To test this, I use multi-level random intercept models to gauge the effects of social cohesion proxies on *learning outcomes*, which is represented as follows:

$$y_{ij} = \beta_{0j} + \beta_1 \left(x_{1ij} - \bar{x}_{1i}\right) + \beta_2 \bar{x}_{1i} + \beta_3 x_{2i} + \cdots + \beta_n x_{nij} + \beta_m z_{mi} + b_{0i} + \epsilon_{ij} \qquad (3)$$

Where β_1 represents the predicted change in y for a change of one unit of the social cohesion dimension x_1 and β_2 represents the predicted change in y for one unit of the social cohesion dimension for the between level only. β_3 denotes the predicted change in y for one unit of *school inequality*, x_{2i}. β_n represents the coefficient for a set of n covariates at the within-level (i.e.: sex, age) and β_m represents the coefficient for a set of m covariates at the between level (i.e.: school type, school location); b_{0i}represents the deviation of the cluster mean of y in cluster i from the general mean; finally, ϵ_{ij} denotes the residuals of *j*'s scores in cluster i. I make use of group-mean centring of continuous and dichotomous variables, which allows for the identification of within effects on the regression models (Enders and Tofighi, 2007) as expressed in $\left(x_{1ij} - \bar{x}_{1i}\right)$. A model with the parameter corresponding to social cohesion variables$\left(x_{1ij} - \bar{x}_{1i}\right) = 0$ serves as a baseline to compare the additional explained variance by the models.

The *moderation hypothesis* (Figure 8, panel b) assumes that schools with students portraying different degrees of social cohesion variables may show different inequality–achievement relations. This will be tested by adding a cross-level interaction between inequality – a school-level variable – and the social cohesion proxy variables – measured at the student level – to the multilevel models. The moderation model adds the parameterβ_4 into the equation (3) to capture the predicted change in y of the interaction among one unit of each social cohesion at the between-level variable $\bar{x}_{1i}$ and *school inequality* x_{2i}as follows:

$$y_{ij} = \beta_{0j} + \beta_1\left(\mathrm{x}_{1ij} - \bar{x}_{1i}\right) + \beta_2\bar{x}_{1i} + \beta_3 x_{2i} + \beta_4\bar{x}_{1i} * x_{2i} + \ldots + \beta_n x_{nij} + \beta_m \mathrm{z}_{mi} \quad (4)$$

$$+ \mathrm{b}_{0i} + \epsilon_{ij}$$

Finally, the *mediation hypothesis* (Figure 8, panel c) assumes a causal mechanism underlying the relation between inequality and academic achievement via school cohesion. In light of this premise, schools with higher inequality may benefit or strive towards the higher presence of certain individual/school characteristics, which will affect academic achievement. For this purpose, I conduct a multilevel mediation analysis known as 2-1-1, referring to the level where variables are found in the sequence: cause, mediator and outcome (Preacher, Zyphur and Zhang, 2010). In this case, inequality is measured at the school level (#2), and both the social cohesion and outcome variables are measured at the individual level (#1). I also use fixed effects per country at level 2. They are noted as a set of regressions at both levels, such as in:

Level 1: $\mathrm{x}_{1ij} = \beta_{\mathrm{x}0j} + \cdots + \beta_n x_{nij} + \epsilon_{ij}$, and (5a)

Level 2: $\beta_{\mathrm{x}0j} = r_{00} + \beta_{0j} + a x_{2i} + \beta_{\mathrm{m}} x_{\mathrm{m}ij} + \mu_{0j}$ (5b)

Which represents the effect of one unit of *school inequality* x_{2i} on the mediator - each social cohesion variable x_{1ij}-. The parameter r_{00} is the intercept for x_{1ij}; a is the effect of x_{2i} on x_{1ij}; finally, ϵ_{ij} and $\mu_{0j}$are within- and between- residuals, respectively. The remainder of the mediation model related to the outcome variable y_{ij} is represented by the following equations:

$$\text{Level 1: } y_{ij} = \beta_{0j} + \beta_1 \left(x_{1ij} - \bar{x}_{1i}\right) + \cdots + \beta_n x_{nij} + \epsilon_{ij}, \text{ and} \tag{6a}$$

$$\text{Level 2: } \beta_{y_{0j}} = r_{10} + c'\beta_{0j} + b\bar{x}_{1i} + \cdots + \beta_m b_{mi} + b_{0i} + \mu_{0j} \tag{6b}$$

Where the parameter b is the effect of the mediator on y_{ij} at the between level only, and r_{10} is the effect of the mediator on y_{ij} at the within level only. The mediation effect is indicated by the product of a from equation (5b) and b from equation (6b). The total effect is given by adding *c'* from equation (6b) to *ab*.

In all cases, I adjust the regression using variables at different levels: *sex, age, repeat*. *HOMEPOS* are used in level 1, while *School HOMEPOS*, *School Type* and *School Area* are used in level 2.

Considering that usual SEM goodness-of-fit parameters such as CFI, TLI and RMSEA are not sensitive to between level misspecifications (Hsu *et al.*, 2015), I use standardised root mean square residuals (SRMS) for each level considering values lower than .05 as indicators of a good fit of the model to the data (Hu and Bentler, 1999). Finally, due to the nature of PISA data, three further methodological points were considered during the modelling process. First, PISA 2018 built its sample through a stratified two-stage process (schools and students). To address the intended population representativeness, I use student-level weights following Rabe-Hesketh and Skrondal's (2006) scaling method to take account of this. Secondly, as already mentioned, I model 10 regression variables per outcome to account for each plausible value. To address this uncertainty, I apply Rubin's (1987) rules for handling multiple imputations. Finally, I estimate the uncertainty associated with the stratified sampling process using the Hubber-White correction to the standard deviations, which grounds similar results to PISA's approach to replicate weights (Jerrim, Lopez-Agudo, Marcenaro-Gutierrez, *et al.*, 2017). I use the statistical software *R* (R Core Team, 2020) and statistical analysis was performed using the package *lavaan* (Rosseel, 2012).

4.4. Results

Results from the multilevel structural equation model estimations are presented in Table 13, Table 15, and Table 16. Goodness-of-fit statistics (square root mean residuals at within and between levels under <.05) across all models suggest that models show an adequate fit to the data. The lower adjusted Bayesian Information Criteria (BIC) favours the full model specifications in all cases.

Specification (1) in Table 13 serves as a baseline model for the compensation hypothesis showing a negative association between *school inequality* and *learning outcomes*. Other factors are also negatively associated with reading scores such as being male, having repeated at least one school year, and belonging to a public school as opposed to a private school. On the contrary, household wealth (HOMEPOS) and mean school wealth (school HOMEPOS) are strong predictors of higher test scores ($p < 0.001$), as has been well documented in the literature.

Specifications (2)-(6) display estimations referring to the compensation hypothesis for each social cohesion variable, while specification (7) represents a full model including all previous variables. *School inequality* remains negatively associated with *learning scores* across all models, although with smaller effects than in specification (1). This supports the compensation hypothesis at the student level in all cases but PERCOOP and for all cases at the between-school level.

The coefficients differ significantly at both levels considering that 100 points in PISA scores represent 1 standard deviation. For instance, for the within-level, one standard deviation (s.d.) of the social cohesion variables implies changes in PISA scores ranging from 3.82 to 16.14 (3.8% to 16.1% s.d.). At the between-school level, the size of the effects is greater, varying from 15.68 to 42.86. For both levels, RESPECT appears to be the dimension with the higher compensation effects on *learning scores*.

Specification (7) shows that both at within- and between- school levels, BELONG, RESPECT and GLOBMIND are positively associated with *learning scores*, presenting moderate to large effect sizes. PERSPECT and PERCOOP are also positively associated at the within-level, but their sign becomes negative at the between-level. This differs from specifications (3) and (4) where the association to *learning outcomes* is positive.

In the full model, at the between-level (schools), the variable GLOBMIND shows the largest coefficients in comparison with the other social cohesion variables. The fact that between-level coefficients are significantly greater than within-level ones suggests that the school ethos plays an additional relevant role besides individual traits, which agrees with the theoretical framework provided. The risk of falling into an ecological fallacy, in this case, is low, as the methodology used allows partitioning the variable into two factors, which permits a separate assessment of the influence of both on the variable of interest.

Table 13: Coefficients for compensation models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Within							
BELONG		4.48 (0.14) ***					1.79 (0.16) ***
PERCOOP			3.82 (0.15) ***				0.41 (0.16) *
PERSPECT				8.38 (0.15) ***			2.83 (0.17) ***
RESPECT					16.14 (0.18) ***		13.54 (0.2) ***
GLOBMIND						6.86 (0.17) ***	3.62 (0.18) ***
Sex (1 = Male)	-19.41 (0.27) ***	-18.75 (0.28) ***	-19.59 (0.31) ***	-16.54 (0.3) ***	-12.47 (0.3) ***	-17.74 (0.31) ***	-11.73 (0.34) ***
Repeat (1 = Yes)	-56.53 (0.51) ***	-55.68 (0.55) ***	-55.7 (0.57) ***	-56.24 (0.56) ***	-54.52 (0.56) ***	-56.48 (0.62) ***	-52.91 (0.63) ***
HOMEPOS	8.29 (0.43) ***	8.07 (0.5) ***	8.05 (0.54) ***	7.53 (0.55) ***	6.88 (0.57) ***	7.93 (0.61) ***	6.5 (0.74) ***
Age	11.42 (6.27)	11.11 (7.03)	10.93 (7.64)	10.97 (7.67)	10.64 (8)	10.94 (8.45)	9.63 (9.79)
Between							

INEQ ALPHA	-50.53 (1.7) ***	-31.79 (1.65) ***	-37.21 (1.81) ***	-32.35 (1.78) ***	-20.53 (1.7) ***	-33.01 (5.17) ***	-30.41 (1.73) ***
BELONG		30.44 (1.06) ***					8.33 (1.19) ***
PERCOOP			15.68 (0.99) ***				-8.09 (1.01) ***
PERSPECT				22.98 (1.2) ***			-7.02 (1.46) ***
RESPECT					42.86 (0.96) ***		39.77 (1.23) ***
GLOBMIND						24.66 (2.87) ***	4.45 (1.31) ***
School HOMEPOS	47.84 (0.6) ***	44.11 (0.66) ***	47.96 (0.69) ***	45.76 (0.7) ***	41.73 (0.72) ***	46.72 (0.79) ***	43.62 (0.81) ***
School type (1 = Public)	-7.34 (1.08) ***	-2.8 (1.03) **	-7.37 (1.1) ***	-2.64 (1.13) *	-1.33 (1.07)	-3.97 (2.47)	-0.72 (1.11)
School area population	6.66 (0.32) ***	6.74 (0.31) ***	7.36 (0.34) ***	6.28 (0.33) ***	5.06 (0.32) ***	6.27 (0.34) ***	4.6 (0.33) ***
Intercept	246.74 (112.90) *	240.74 (115.95) *	249.21 (126.06) *	249.83 (126.65) *	247.97 (132.06)	254.18 (140.16)	285.8 (161.97)
Goodness-of-fit							

BIC	5962398.654	5393485	4588086	4564700	4431410	4219767	3437303
BIC adjusted	5962360.517	5393440	4588042	4564655	4431365	4219722	3437233
SRMR between	0.002337676	0.010669	0.009787	0.010083	0.010983	0.007635	0.004423
SRMR within	0.00004	0.000253	0.000146	0.0001	0.000158	0.000584	0.000247
Observations	516575	467612	397835	396666	385877	366703	300446
Fixed country effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: p <.001 ***, p <.01 **, p <.05 *

Table 14 shows the variance explained by each model for specifications (2)-(7) compared with the explained variance from specification (1). Almost all models show higher values for additional explained variance than the baseline. The model with the variable RESPECT and GLOBMIND shows higher values for additional explained variance, which suggests the confirmation of the compensation hypothesis, especially in these cases.

Table 14: R^2 of compensation models

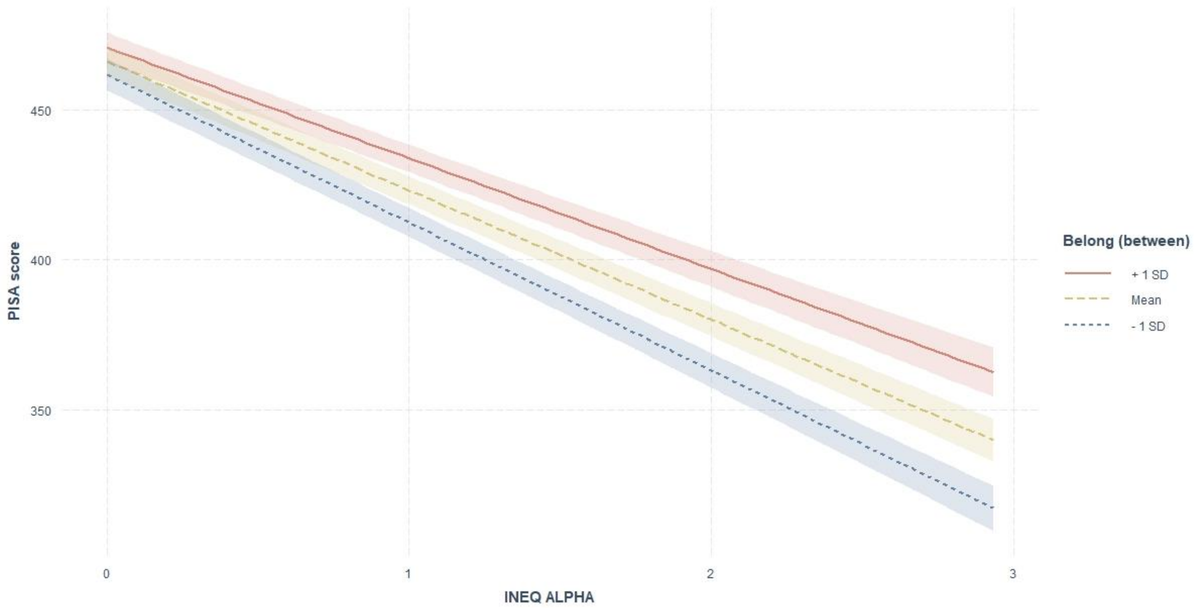
Model	R2 Within	Difference within (baseline) (%)	R2 Between	Difference Between (baseline) (%)
Baseline	0.10		0.49	
BELONG	0.09	-0.01	0.51	0.02
PERCOOP	0.09	-0.01	0.48	-0.01
PERSPECT	0.10	0.00	0.51	0.02
RESPECT	0.12	0.02	0.57	0.08
GLOBMIND	0.10	0.00	0.55	0.06
Full model	0.10	0.00	0.50	0.00

Source: own calculations based on PISA 2018 (OECD, 2020)

Table 15 presents coefficient models to test the moderation hypothesis, where interactions are added at the between-school level among each social cohesion variable and the school-level inequality measure. Specifications corresponding to models testing the moderating role of BELONG, PERSPECT, RESPECT and GLOBMIND support this hypothesis. However, in the full model portrayed in the specification (13), the only main effect and interaction that supports the negative impact of *school inequality* on *learning scores* is RESPECT.

Turning back to specification (8), Figure 9 shows the moderation effects at the between-school level on how the sense of belonging to the school attenuates the negative association between inequality and *learning scores*. This corresponds to the hypothesis stated in Figure 8 Panel (b). In this model the moderation occurs where at lower levels of *school inequality*, the sense of belonging does not predict relevant differences in *learning scores*. However, when *school inequality* is higher, a higher sense of belonging than average (red line) predicts an attenuated loss of *learning scores* than in the cases of schools with a lower sense of belonging.

Figure 9: Moderation hypothesis – BELONG



Source: own calculations based on PISA 2018 (OECD, 2020). Original in colour.

Table 15: Coefficients for moderation models

	(8)	(9)	(10)	(11)	(12)	(13)
Within						
BELONG	4.48 (0.14) ***					1.79 (0.17) ***
PERCOOP		3.82 (0.15) ***				0.41 (0.16) *
PERSPECT			8.38 (0.15) ***			2.82 (0.17) ***
RESPECT				16.14 (0.18) ***		13.54 (0.2) ***
GLOBMIND					6.86 (0.17) ***	3.61 (0.18) ***
Sex (1 = Male)	-18.75 (0.28) ***	-19.6 (0.31) ***	-16.57 (0.3) ***	-12.5 (0.3) ***	-17.75 (0.31) ***	-11.72 (0.34) ***
Repeat (1 = Yes)	-55.41 (0.55) ***	-55.75 (0.57) ***	-56.3 (0.57) ***	-54.53 (0.56) ***	-56.51 (0.59) ***	-52.52 (0.85) ***
HOMEPOS	8.07 (0.5) ***	8.04 (0.55) ***	7.52 (0.55) ***	6.85 (0.57) ***	7.92 (0.61) ***	6.56 (0.74) ***
Age	12.39 (7.06)	10.87 (7.65)	10.61 (7.69)	9.99 (8.03)	10.57 (8.42)	9.96 (9.8)
Between						

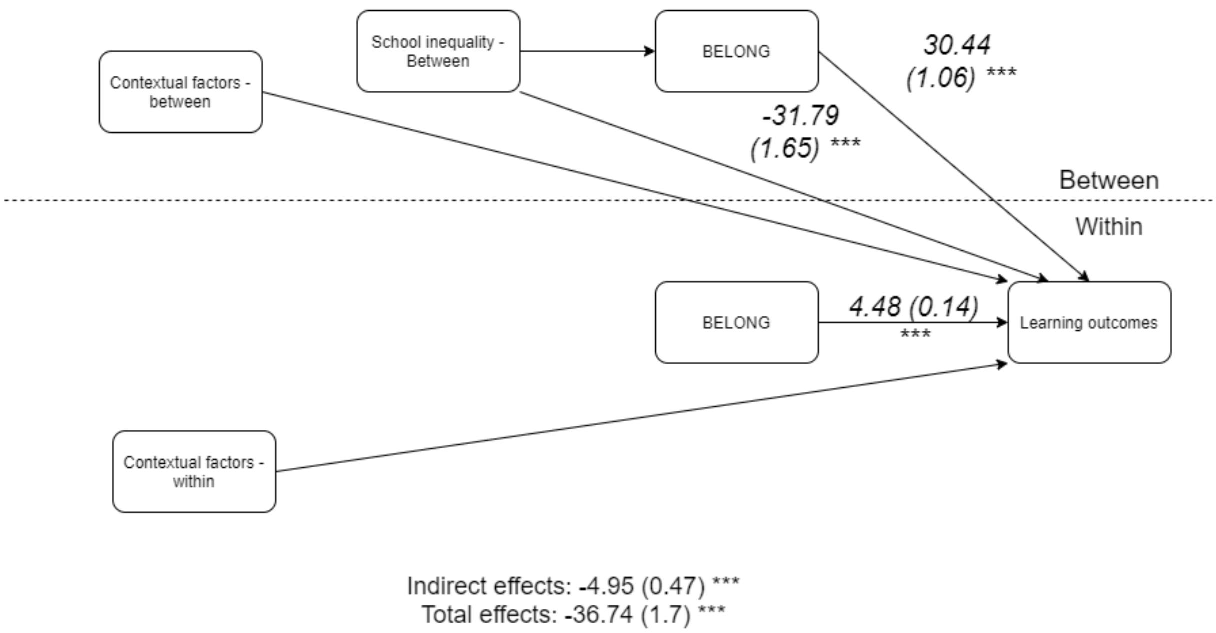
INEQ ALPHA	-41.12 (1.68) ***	-41.9 (1.82) ***	-42.37 (1.77) ***	-32.57 (1.75) ***	-39.49 (1.77) ***	-25.16 (3.19) ***
BELONG	9.98 (3.46) **					3.44 (4.22)
INEQ ALPHA * BELONG	16.01 (3.67) ***					5.73 (4.58)
PERCOOP		6.38 (3.23) *				-2.12 (3.82)
INEQ ALPHA * PERCOOP		5.46 (3.56)				-2.45 (4.17)
PERSPECT			7.79 (3.78) *			-5.9 (5.01)
INEQ ALPHA * PERSPECT			9.61 (4.11) *			-4.58 (5.46)
RESPECT				21.03 (3.39) ***		23.25 (4.49) ***
INEQ ALPHA * RESPECT				19.02 (3.61) ***		21.07 (4.93) ***
GLOBMIND					10.73 (3.74) **	3.01 (4.33)
INEQ ALPHA * GLOBMIND					11.28 (3.97) **	3.17 (4.68)
School HOMEPOS	45.05 (0.66) ***	48.46 (0.69) ***	46.12 (0.7) ***	43.08 (0.72) ***	47.13 (0.74) ***	43.08 (0.85) ***

School type (1 = Public)	-5.92 (1.03) ***	-9.73 (1.1) ***	-4.72 (1.12) ***	-5.44 (1.09) ***	-6.77 (1.11) ***	0.51 (1.13)
School area population	6.61 (0.31) ***	7.3 (0.34) ***	6.32 (0.33) ***	5.26 (0.32) ***	6.41 (0.33) ***	4.69 (0.33) ***
Intercept	230.67 (116.53) *	255.41 (126.26) *	265.68 (127.04) *	271.11 (132.63) *	266.72 (139.15)	275.02 (162.24)
Goodness-of-fit						
BIC	5393360	4588051	4564613	4431311	4219714	3437370
BIC adjusted	5393312	4588003	4564566	4431263	4219666	3437284
SRMR between	0.001966	0.00562	0.001075	0.001897	0.002104	0.00317
SRMR within	0.000835	0.000178	0.000236	0.00044	0.000637	0.000298
Observations	467612	397834.6	396665.7	385876.7	366702.6	300446
	Yes	Yes	Yes	Yes	Yes	Yes

Note: p <.001 ***, p <.01 **, p <.05 *

Table 16 presents model results for the mediation hypothesis. The coefficients suggest evidence for partial mitigation of the negative impacts of inequality on *learning outcomes* made by each social cohesion variable. In all cases, the increase in *school inequality* is associated with less social cohesion, which is depicted as a negative slope at the mediator variable regressions. At the same time, *learning outcomes* are positively associated with social cohesion attitudes, which is expressed as a positive slope at the outcome regressions. Finally, the full model presented in the specification (19) shows that all variables remain significant and support the hypothesis of partially mediating the impacts of inequality on *learning scores*. Figure 10 shows a graphical representation of the mediation model for the specification (14), which allows the concurrence of regression coefficients to be observed. This is an example of the hypothesis presented on Figure 8 Panel (c).

Figure 10: Mediation analysis – BELONG



Source: own elaboration based on PISA 2018 (OECD, 2020)

Although models predict a significant and positive indirect effect of social cohesion attitudes on *learning outcomes*, the direct effect of inequality variables remains negative and significant. These findings indicate that social cohesion does not fully mediate the adverse effects of inequality on *learning scores*, which is seen in the negative sign of the indirect effects on the cases of BELONG, RESPECT and GLOBMIND. In the cases of PERCOOP and PERSPECT, positive indirect effects occur due to the multiplication of negative signs of both effects, such as in PERCOOP -> *Alpha Inequality* and *Alpha Inequality* -> *Learning scores*.

Table 16: Coefficients for mediation models

	(14)	(15)	(16)	(17)	(18)	(19)				
	Mediator variable									
	BELONG	PERCOOP	PERSPECT	RESPECT	GLOBMIND	BELONG	PERCOOP	PERSPECT	RESPECT	GLOBMIND
INEQ ALPHA	-0.16 (0.01) ***	-0.22 (0.02) ***	-0.15 (0.02) ***	-0.26 (0.02) ***	-0.13 (0.02) ***	-0.14 (0.02) ***	-0.21 (0.02) ***	-0.14 (0.02) ***	-0.25 (0.02) ***	-0.12 (0.02) ***
School HOMEPOS	0.09 (0) ***	0.04 (0) ***	0.02 (0) ***	0.13 (0) ***	0.02 (0) ***	0.11 (0) ***	0.04 (0.01) ***	0.02 (0) ***	0.12 (0) ***	0 (0)
School type (1 = Public)	0.05 (0.01) ***	0.06 (0.01) ***	0.01 (0.01)	0.01 (0.01)	0.11 (0.01) ***	0.06 (0.01) ***	0.07 (0.01) ***	0 (0.01)	0.01 (0.01)	0.12 (0.01) ***
School area population	-0.01 (0) ***	-0.03 (0) ***	0.02 (0) ***	0.04 (0) ***	0.02 (0) ***	-0.01 (0) **	-0.03 (0) ***	0.02 (0) ***	0.04 (0) ***	0.02 (0) ***
	Dependent variable (PV1READ – PV10READ)									
Within										
BELONG	4.48 (0.14) ***					1.79 (0.16) ***				
PERCOOP		3.82 (0.15) ***				0.41 (0.16) *				
PERSPECT			8.38 (0.15) ***			2.83 (0.17) ***				
RESPECT				16.14 (0.18) ***		13.54 (0.2) ***				

GLOBMIND					6.86 (0.17) ***		3.62 (0.18) ***
Sex	-18.75 (0.28) ***	-19.59 (0.31) ***	-16.54 (0.3) ***	-12.47 (0.3) ***	-17.74 (0.31) ***		-11.73 (0.34) ***
Repeat	-55.68 (0.55) ***	-55.7 (0.57) ***	-56.24 (0.56) ***	-54.52 (0.56) ***	-56.4 (0.59) ***		-52.91 (0.63) ***
HOMEPOS	8.07 (0.5) ***	8.05 (0.54) ***	7.53 (0.55) ***	6.88 (0.57) ***	7.94 (0.61) ***		6.5 (0.74) ***
Age	11.11 (7.03)	10.94 (7.64)	10.97 (7.67)	10.64 (8)	11.58 (8.4)		9.63 (9.79)
Between							
INEQ ALPHA	-31.79 (1.65) ***	-37.22 (1.81) ***	-32.35 (1.78) ***	-20.54 (1.7) ***	-29.45 (1.77) ***		-30.44 (1.73) ***
BELONG	30.44 (1.06) ***						8.33 (1.19) ***
PERCOOP		15.67 (0.99) ***					-8.08 (1.01) ***
PERSPECT			22.98 (1.2) ***				-7.04 (1.46) ***
RESPECT				42.86 (0.96) ***			39.77 (1.23) ***
GLOBMIND					26.62 (1.15) ***		4.45 (1.31) ***

School HOMEPOS	44.11 (0.66) ***	47.96 (0.69) ***	45.76 (0.7) ***	41.73 (0.72) ***	46.53 (0.74) ***		43.62 (0.81) ***
School type (1 = Public)	-2.81 (1.03) **	-7.37 (1.1) ***	-2.64 (1.13) *	-1.33 (1.07)	-2.43 (1.11) *		-0.72 (1.11)
School area population	6.74 (0.31) ***	7.36 (0.34) ***	6.28 (0.33) ***	5.06 (0.32) ***	6.2 (0.33) ***		4.6 (0.33) ***
Intercept	240.68 (115.96) *	249.18 (126.06) *	249.83 (126.65) *	247.98 (132.06)	240.36 (138.71)		285.7 (161.97)
Indirect effects	-4.95 (0.47) ***	-3.49 (0.35) ***	-3.38 (0.41) ***	-11.06 (0.83) ***	-3.37 (0.47) ***		
BELONG							-1.13 (0.21) ***
PERCOOP							1.71 (0.26) ***
PERSPECT							0.97 (0.24) ***
RESPECT							-9.9 (0.82) ***
GLOBMIND							-0.55 (0.18) **
Total effects	-36.74 (1.7) ***	-40.71 (1.81) ***	-35.73 (1.79) ***	-31.6 (1.83) ***	-32.81 (1.8) ***		
BELONG							-31.57 (1.75) ***
PERCOOP							-28.72 (1.72) ***
PERSPECT							-29.46 (1.73) ***
RESPECT							-40.33 (1.89) ***

GLOBMIND							-30.98 (1.74) ***
Goodness-of-fit							
BIC	5409394	4609852	4579387	4450398	4234656		3507625
BIC adjusted	5409328	4609785	4579320	4450331	4234589		3507444
SRMR between	0.010668	0.009782	0.010079	0.01098	0.010739		0.121387
SRMR within	0.00025	0.000145	8.74E-05	0.000158	0.000216		0.000243
Observations	467612	397835	396666	385877	3667023		300446
Fixed country effects	Yes	Yes	Yes	Yes	Yes		Yes

Note: p <.001 ***, p <.01 **, p <.05 *

4.5. Discussion

Understanding schools as socialising spaces provides the opportunity to understand how student features such as attitudes and skills, contextual factors like socioeconomic status, and school-level factors such as wealth inequality, are entangled within-schools.

This chapter offers a theoretical framework linking three dimensions within-schools: a contextual dimension such as the degree of wealth inequality; potential mechanisms linked to fostering social cohesion; and, finally, reading and maths scores. I also test if social cohesion attitudes act as mechanisms that may compensate, moderate, and mediate the negative influence of wealth inequality on *learning outcomes*. All social cohesion attitudes studied are found to be associated with *school inequality* and *learning scores*. Among them, the variables BELONG, RESPECT and GLOBMIND consistently show a positive effect across all hypotheses.

These findings are important because they indicate diverse lines of future research that could open the black box of the schooling process to understand how wealth inequality adversely affects *learning scores*. This includes the shift from remedial policies towards strategies that acknowledge within-school socio-economic differences and prioritise the integration of students and families to the school, improving their sense of belonging and nurturing attitudes and skills linked to enhancing social relations and the orientation towards building the common good.

Additionally, this study indirectly contributes to an academic discussion on the use of concepts of social capital and social cohesion in schools. I argue that the notion of social cohesion is appropriate to be used as an explanatory variable at the school level. It has been suggested that social capital should be considered as a micro concept whereas social cohesion, being a broader concept than social capital, is more appropriate for macro and meso analysis (Klein, 2013). One important aspect that appears across almost all definitions of social capital is framing the development of individuals in terms of generation of some future returns, similar to what occurs with other types of capitals. Although the main characteristics of social cohesion are not fundamentally different from those of social capital, the major difference between them seems to be that social capital is developed at the individual level with the perspective of a future return whereas social cohesion exists at the community or society level and will be more than the simple sum of individuals' social capital due to the existence of externalities in its production. In this sense, it is reasonable to argue that social capital is one of the key elements of social cohesion.

The fact that across all regression models the between-level coefficients are greater than within-level ones suggests that the school ethos plays an additional relevant role besides individual traits, which agrees with the theoretical framework provided under the umbrella of social cohesion understood as a social feature.

This study also has limitations that need to be acknowledged. Firstly, like previous studies, I only use cross-sectional survey data. Even causality is set at a theoretical level, which calls for caution about causal interpretations of the results presented. Causality can be suggested based on conceptual arguments but not a formal econometric identification strategy. This is particularly important, as I cannot reject arguments on reversed causality between students' attitudes and school-level inequality, even if my theoretical framework suggests this is unlikely to be the case. Additionally, I focus on remedies to mitigate the adverse consequences of socioeconomic inequality in schools. However, this should not eclipse the need to address what causes inequality and remedy it through diverse general mechanisms such as progressive taxation and stronger social protection policies, and also to develop educational policies such as substantially increasing financing of schools for vulnerable groups. Finally, variables were chosen on a theoretical basis from a limited pool of variables made available by PISA. Developing, validating, and using an ad hoc instrument may provide important insights towards widening the role of inequality and social cohesion in schools.

5. Educational *segregation* and *school inequality*

5.1. Introduction

If schools within a school system only put together students from the same socioeconomic status, the educational system will be considered as segregated. In this sense, the perfect segregation of an educational system implies the non-existence of any within-school inequality. While this holds in theory, real-world educational systems present concurrently different gradients of segregation and within-school inequality.

In this chapter, I provide a simple method to measure country segregation based on a previously developed Alpha Inequality measure. Based on data from PISA 2018, I compare the segregation measure with the gold standard index used in the segregation literature, namely the Duncan Dissimilarity index. Duncan's index is computed by dividing the population into different groups. I model a set of linear mixed-effect models to assess the association between school inequality and country segregation with learning scores using both measurements. Results across models suggest that the two variables capture different phenomena and contribute to a better understanding of the negative influence of inequality and segregation on learning scores.

This chapter addresses a concern that has been discussed with many colleagues across these years. Basically, it answers to the challenge of understanding *school inequality* as a negative factor in a schooling system. As choices carry consequences, the natural conclusion of highlighting the negative effects of within-schools inequality could produce another poor solution: segregating schools by socioeconomic factors. I explore here how segregation and inequality are present in schooling systems in different degrees, which allows me to address them as concurrent phenomena.

Are we facing a Scylla and Charybdis dilemma between choosing *school inequality* or *segregation* in an educational system? Although they are measured at two different levels, can we find a theoretical and, later on, an operational solution to it? To prevent segregation, educational policies will make a trade-off with inequality, although this does not come necessarily in a conscious form. Can we address both *segregation* and within-school *inequality* at the same time? Those are the questions that guide this exploratory study, in which I address the conjunction of both phenomena.

5.2. *School inequality* and country *segregation*: two sides of the same coin?

Basic educational systems across the world present multifaceted diversity. Diversity occurs inside and outside schools. This is expressed as students' skills, religious affiliations, among many other socioeconomic and cultural characteristics. Schools are also different in terms of ownership, size or location, environment, and cognitive demand.

Between-school differences based on exogenous factors – mostly socioeconomic – are usually understood among educationalists as an expression of some type of stratification or segregation practice (Gorard and Fitz, 2000). When these disparities either cause, influence or reflect the separation of students within a schooling system, then an educational system can be referred to as (partially or totally) segregated. In this sense, segregation between schools refers to the extent to which two or more defined groups are separated from each other in different schools. The definition considers the degree of unevenness as a differential distribution – of any variable, for example, wealth – between groups (Massey and Denton, 1988) in any educational system.

There are many examples of segregation across educational systems during the world's recent history. For example, several states in the United States had single-race schooling systems until the mid-20th century (Rumberger and Palardy, 2005); Germany separates students based on their academic skills measured in their early academic years – a contested policy known as tracking – (Hoskins, Janmaat and Melis, 2017). Additionally, there are still single-sex schools or religious-affiliated schools – not necessarily excluding students from other ethnic groups - across the world. This type of segregation has been studied in terms of causality and as an association in topics such as disruptive behaviours and *learning scores*, raising important discussions in terms of school effectiveness, societal goals and school choice (Billger, 2009; Gordillo, Calcina and Gamero, 2014; Gordillo, 2017).

There is another type of segregation, which is the concern of this chapter. It is a non-institutional segregation between schools based on socioeconomic status (Gorard and Fitz, 2000). This occurs via different pathways: in developed countries, usually through school systems capturing students based on neighbourhoods, whereby cities with higher segregation across neighbourhoods will produce at least several segregated schools. In developing countries, the most common mechanism is through the pricing of schools, which may produce a twotier system – public and private schools – or the rise of a three-tiered arrangement: public, low-fee private and high-fee private schools (Balarin, 2015).

In some cases, schools and educational systems are considerably dissimilar in terms of social and economic composition, resources, and also regarding schooling outcomes. The issue also unveils a greater social stratification phenomenon (Gorard and Fitz, 2000). The argument is that the concentration of children from disadvantaged backgrounds in a school gives rise to certain peer effects and school responses that negatively affect achievement. In this way, an uneven distribution of children of different social backgrounds will exacerbate pre-existing social disparities (Janmaat, 2020). Differences in school composition across educational systems usually reflect wider societal differences. For that reason, educationalists and policymakers tend to characterise schools as leveraging institutions. Schools represent an opportunity to overcome the unfair inequalities students carry with them.

Considerable academic research has documented the damaging effects of socioeconomic segregation across countries. Societal effects include lower social mobility as well as widening social, cultural, and economic gaps; while individual effects are linked to deteriorating academic scores (Dumay and Dupriez, 2008; Willms, 2010). Additionally, the existence of an educational system with signs of high degrees of segregation is regarded as unjust or inequitable, especially towards those less favoured. This occurs because schools serving students from lower-income areas tend to have fewer resources, lower quality teachers, greater school climate issues and lower educational expectations from all relevant stakeholders (Chiu, 2015). In this sense, Allen and Vignoles (2007) argue that, although the phenomenon of segregation has diverse facets, there is one characteristic – its unevenness – that should be the centre of attention of any educational policy, as it is the only dimension that can be influenced in terms of modifying the distribution of a given minority group between schools.

However, there is some controversy surrounding the topic as societal goals may compete or clash with certain individual freedoms. For example, family law across multiple countries acknowledges parental responsibility for their children's education. This derives from the understanding of schools as a subsidiary institution and the legal right of school choice. It becomes even more complex when in the balance of parental school choice and the right of conscientious objection, societal equality collides with the idea of for-profit institutions in education.

However, extensive research done on between-school socioeconomic differences is in sharp contrast to the almost non-existent theoretical and empirical approach to within-school disparities. To my knowledge, very little research has been done in this area. For instance, Willms (2010) tests the hypothesis that homogenous schools are linked to better academic outcomes, without finding much empirical evidence to support it. Additionally, few studies on court-mandated desegregation policies in the United States present contradictory results. Hanushek et al. (2009) studied the case of Texas, finding that ethnic segregation negatively affects learning outcomes of schools with a larger share of minorities, but the same does not hold for socioeconomic disparities. Moreover, Billings et al. (2012) and Gamoran and An (2016) studied the case of Charlotte, North Carolina, and Nashville, Tennessee, finding evidence that the reallocation of students to schools with a higher proportion of minority students decreased their learning achievement and increased crime for males from ethnic minority groups.

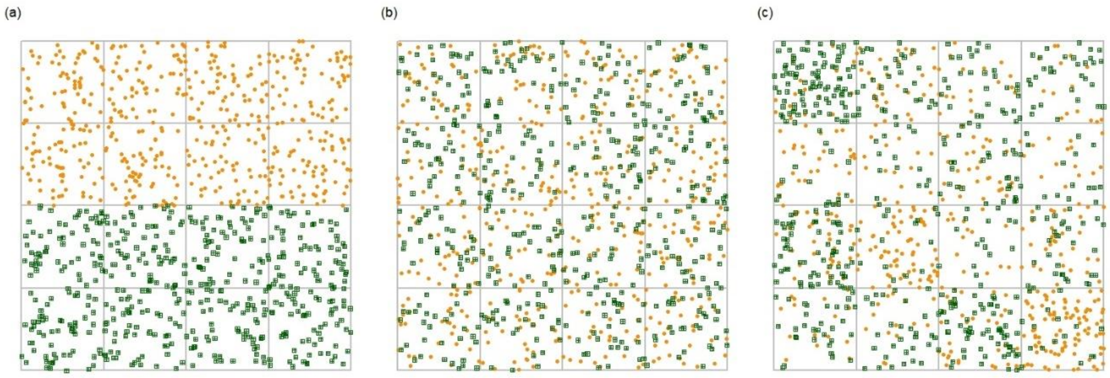
I argue that the little interest academic research has given to within-school differences arises from the notion that *school inequality* and *segregation* of educational systems appear to be diametrically opposed phenomena.

Indeed, in an archetypical scenario, school equality in schools will imply a situation of full *segregation* of an educational system. To exemplify this,

Figure 11 shows a theoretical example of three educational systems, each constituted by 16 schools composed only of two types of students, which are represented by green and orange. All systems have the same number of students.

The educational system in panel (a) represents a scenario of full *segregation*, and at the same time, it shows homogeneous schools, without any trace of *school inequality*. At the other extreme, panel (b) represents a system without any trace of school *segregation*, while *school inequality* is constant across schools. Finally, panel (c) shows a hypothetical mixture of both phenomena, where the system shows important signs of *segregation* and many schools display a certain level of *school inequality*. In this study, I focus on educational systems and schools that resemble this last panel. In this sense, I argue that *school inequality* and school *segregation* are different phenomena in the real world – although linked in many ways – and they represent different challenges (and policy solutions) that affect how students' educational efforts are addressed.

Figure 11: Example of educational segregation and school inequality



Source: Adapted from https://sejdemyr.github.io/r-tutorials/statistics/measuring-segregation.html. Original in colour.

The intricacy of these colliding perspectives is explained by different theoretical foundations on how to balance fundamental notions such as common good, freedom and justice. In the next section, I examine three main schools of thought regarding how they understand distributive justice as a way to unpack the notion of inequality. Later, in the discussion section, I link these to the interpretation of the empirical findings.

5.3. Revisiting the notion of inequality within theories of justice

Theoretical reflections on inequality have been evolving throughout history. The body of knowledge, which is both a source of consensus and disagreement, spans from ancient Greece (Aristotle, 2014b) to contemporary academic fields such as economics (e.g., Sen and Foster, 1997), sociology (e.g., Coleman, 1974; Diprete, 2007; Kenworthy, 2007) and social psychology (e.g., Baron and Pfeffer, 1994).

Inequality as a societal phenomenon can be defined by two concurrent characteristics: the existence of aggregated economic differences, and its unfair nature (Almås *et al.*, 2011). While Chapter 2 focuses on the measurement of inequality, which addresses the distribution of one economic variable in a population, namely household wealth, hereafter I focus on the notion of unfairness related to inequality, as it poses important ethical considerations. This reflection also serves as the background framework for the analysis regarding the tension between *school inequality* and country *segregation*.

Even opposing sociological schools understand unfairness as a key element to define inequality. For example, Wright and Rodgers (2011, ch. 10) emphasise the unfair dimension: “what we mean is that there is an inequality which is unfair and which could be remedied if our social institutions were different”. In a very opposite strand, Morandé (1996, p. 71) states that “inequality as such cannot be identified with injustice; only ‘certain’ inequalities are unjust in virtue of an ethical judgement and not in virtue of an act of mere cognition”.

In this chapter, I argue that academic and policy decisions regarding school *segregation* are based on implicit views of inequality and fairness. In my opinion, the trade-off between country *segregation* and *school inequality* should be understood as a theoretical and ethical issue.

In order to elucidate and discuss these views, I revisit a widespread categorisation of relevant schools of thought regarding their understanding of justice. Given the wide range of ethical premises that someone can adopt, it is inevitable that there will also be many theories of justice that understand actions and social organization in a widely divergent way. The notion of theory of justice refers to a set of normative postulates about social organization derived from a specific logical structure that combines ethical and factual premises (Bandrés, 1994).

Theories of justice usually are categorised into those that focus their approach on what is good as an individual and societal end – for instance, how they choose certain social welfare functions based on a certain conception of what is good – and those that focus on the method to adopt these individual and societal ends. A third group of theories focus on the ways of achieving a societal consensus.

In the first group of theories, important distinctions can be made. One type of theory justifies the choice of what is good based on its consequences; these are classified as teleological theories. The best known is a range of utilitarianisms proposed, for example, by Mill and Bentham (Mill *et al.*, 2003). Many economic theories rely on this approach, such as a welfarist approach such as Bergson–Samuelson (Burk, 1938) and Arrow's social welfare function (Arrow, 2012).

A second approach also based on the choice of an evaluation criterion to define the social welfare function assumes the existence of an intrinsic moral value based on a certain conception of what is good; these are collectively known as deontological theories. This is a wide umbrella that covers perspectives from Kant (1836) to more recent thinkers under the label of communitarianism (Taylor, 1992; Etzioni, 1995, 2000, 2002; MacIntyre, 2020).

Finally, a contractual approach focuses its attention on the method by which one arrives at an agreed set of norms of social evaluation. A recent example is Rawls's theory of justice, which presents two harmonising principles addressing justice as fairness. The first principle states that every individual has an equal right to basic liberties. The second principle states that a society cannot arrange inequalities to maximise the share of the least advantaged whilst not allowing access to certain offices or positions. This principle regulates inequalities: it only permits inequalities that work to the advantage of the worst-off. Another extreme example within this group is based on libertarian approaches that privilege self-ownership and the maximisation of individual utility, claiming that the subject of economic distributions shall not be a matter of public interest (Nozick, 1974).

5.4. Empirical strategy

5.4.1. *Segregation* measure

In order to understand how *school inequality* and *segregation* occur concurrently and affect students' *learning outcomes*, first I address the computation of a *segregation* measure based on the *Alpha Inequality* measure, I_{φ} (Sempé, 2021). This facilitates further analysis as both measures are computed from the same source of information: PISA 2018.

The difference between the suggested *segregation* measure – developed in this section – and a traditional *segregation* measure for socioeconomic status – such as Duncan's index – is the fact that the latter requires dichotomising the population into groups, for example, defining a cut-off in a certain quantile. The *segregation* measure I suggest does not require any prior categorisation of continuous data.

In the following paragraphs, I explain the construction of the *segregation* measure based on I_{φ}, which requires a summary of its process of being built.

The discrimination parameter $\alpha_i$in any IRT model reflects how well an item is differentiated between two groups: those who answer correctly (or adhere to) a question, and those who do not. In a hypothetical situation – in this case, the possession of any good – where $\alpha_i \rightarrow \infty$, the parameter characterises a perfect separation between those who possess and those who do not possess the good. In this sense, α_i can also be interpreted as a *segregation* measurement between (two) groups for that specific item.

The inequality measure, I_φ, proposed in Chapter 2, is calculated as the ratio between two distributions: the school standard deviation, $\omega\xi_j$ and the country standard deviationξ_c, with the following notation:

$$\mathrm{I}_\varphi = \frac{\sigma(\omega\xi_\mathrm{j})}{\sigma(\xi_\mathrm{c})} \tag{1}$$

Based on the nature α_i, Eq. (1) captures how well a sum of items divides respondents into two groups as the statistic $\sigma(\xi_\mathrm{c})$ reflects how dispersed the *segregation* of students is in any given country. Lower levels of $\sigma(\xi_\mathrm{c})$ suggest there is lower *segregation* between students than in countries with a higher $\sigma(\xi_\mathrm{c})$.

In case the numerator $\sigma(\omega\xi_\mathrm{j})$ remains constant, which refers to inequality in schools, and allow for changes in the denominator $\sigma(\xi_\mathrm{c})$, which refers to the country inequality, it is possible to observe an inverse relationship between *Alpha Inequality,* I_φ, and $\sigma(\xi_\mathrm{c})$. This is seen when $\sigma(\xi_\mathrm{c})_1 > \sigma(\xi_\mathrm{c})_2$, which leads to $\frac{\sigma(\omega\xi_\mathrm{j})}{\sigma(\xi_\mathrm{c})_1} <$

$\frac{\sigma(\omega\xi_j)}{\sigma(\xi_c)_2}$, and therefore, $I_{\varphi 1} < I_{\varphi 2}$. This leads to $I_\varphi \cong \sigma(\xi_c)^{-1}$, considering $\sigma(\xi_c) > 0$. Based on empirical data, I also find that in the case of $\sigma(\xi_c) \to 0$, then $I_\varphi \cong e^{\sigma(\xi_c)\lambda}$, where λ is a rate parameter of change. Therefore, I compute a country-level measure $S_c$as the inverse average of I_φ, as follows:

$$S_c = -1 * \left(\frac{1}{n}\sum_{i=1}^{n} I_\varphi\right) \tag{2}$$

Where n represents the number of schools in a country c. To facilitate further analysis, S_c is transformed into positive numbers so higher values of $S_c$represent higher levels of *segregation* in an educational system.

Every segregation measure also has some desirable properties to provide reliable information regarding how it is being measured. Hereafter, I present how S_c fulfils all desirable segregation index properties (Hutchens, 2004).

$Lemma 1. S_c$ satisfies the main properties of a segregation measure.

- S_c is invariant to any multiplication of each student score observation by any positive integer constant. Then the segregation measure does not change (weak scale invariance).

  S_c is invariant to any reordering of the groups in the same population (symmetry).

- Any movement of the population that increases the proportion of the dominant type (those who adhere to the set of items) in a school results in a more segregated system. This is due to the new allocation, whereby within-school conditions become more homogeneous and differences between schools become higher (Transfer principle).

- S_c is continuous on the domain of distributions $S(Continuity)$.

- S_c is insensitive to proportional divisions ($Proportional\ division$).

Proof of Lemma 1

(Scale invariance) Multiplying by a constant $\gamma > 0$, all elements of any set of scores $(x) = \{x_{1,}x_2, \dots\}, produces\ S'_c(x\gamma) = S_c(x)$.

(Symmetry) Let x denote any distribution of assets with elements $\{x_{1,}x_2, \dots\}$. As $S_c(x)$ depends only on the set $\{x_{1,}x_2, \dots\}$, any permutation of elements of x does not produce changes in S_c, so $S_c\big(P(x)\big) = S_c(x)$.

(Transfer principle) Let S and $\hat{S}$ represent the initial and transformed segregation measure of an educational system of two schools, a and b. I_φ and $\hat{I_\varphi}$ represent their respective inequality measures. Let ϱ denote the sum of wealth scores of schools e_1 and $e_2, where \varrho_{e1} > \varrho_{e2}$. Let $\hat{\varrho}_{e1} = \varrho_{e1} - \delta and \hat{\varrho}_{e2} = \varrho_{e2} + \delta$, when δ > 0 is transferred from e_1 to e_2.From eq. (4), $\sigma_e > \hat{\sigma}_e$, then $I_\varphi > \hat{I_\varphi}$ producing $S > \hat{S}$.

(Continuity) $S_1$and S_2 represent two inequality measures. If $S_1 \approx S_2$, then they will have very similar segregation values.

(Proportional division) Dividing by a constant $\gamma > 0$, all elements of any set of scores $(x) = \{x_{1,}x_2, \dots\}$, $produces\ S'_c(x/\gamma) = S_c(x)$.

5.4.2. Criteria to assess S_c

As an exercise to validate the measurement, I compare S_c with a gold standard of segregation measures, namely, the Duncan Dissimilarity indexes (Allen and Vignoles, 2007).

The Duncan Dissimilarity index segregates the population into two groups based on schools' wealth, HOMEPOS. Following previous research (Gutiérrez, Jerrim and Torres, 2019), I chose three cut-offs to define groups: HOMEPOS median (P50 cut-off point); the bottom HOMEPOS quintile from the remaining 80% (P20 cut-off point); and the top HOMEPOS quintile from the bottom 80% (P80 cut-off point).

In this circumstance, the index measures whether there is a larger than expected presence of one group over another in any given school in the country. The formal notation is the following:

$$D_c = \frac{1}{2}\sum_{i=1}^{s}\left|\frac{a_i}{A} - \frac{b_i}{B}\right| \qquad (3)$$

Where A and B represent the total number of students belonging to each group in a country c. Finally, a and b account for the number of students i in groups A and B for each school s.

Then, I compare both $Segregation_c$ and Duncan's coefficients measured at country level through Pearson's correlations.

Later, I test the hypothesis that country *segregation*, *school inequality* and School HOMEPOS affect students' Mathematics scores differently. For that purpose, I fit a set of two-level mixed-effects linear models, allowing random intercepts to vary at the country level. The formal notation for the model is the following:

$$\begin{aligned}\mathrm{Y_{ic}} = \beta_{0c} + \beta_1 Z_\mathrm{i} + \beta_2 I_\varphi + \beta_3 S_c + \beta_4 SchoolHOMPEPOS_\mathrm{i} + \beta_5 I_\varphi * S_c + \beta_6 I_\varphi \\ * SchoolHOMPEPOS_\mathrm{i} + \beta_7 S_c * SchoolHOMPEPOS_\mathrm{i} + \beta_8 I_\varphi \\ * S_c * SchoolHOMPEPOS_\mathrm{j} + \mathrm{u_c} + \epsilon_\mathrm{ic}\end{aligned} \tag{4}$$

Where Y_{ij} indicates the *learning scores* variable for students i of country c and β_{0c} the country intercepts as random variables that allow the quantification of differences between countries. $\beta' s$ are regression parameters invariant across groups, while u_j represents the group difference from the intercept mean and ϵ_{ic}represents the error term. Finally, Z_i represents a set of covariates measured at the student level to adjust the regression estimates.

I use all possible combinations of two explanatory variables. For country *segregation*, I use the parameter S_c and Duncan's index. For *school inequality,* I use *Alpha Inequality* and school Gini. In all cases, I control the models using contextual variables such as sex, age, repetition of grade, HOMEPOS, School Type and School Area. Furthermore, I test whether the inclusion of macroeconomic data (World Bank, 2018), such as GDP per capita or the country Gini in 2018, modify the regression coefficients.

Due to computation challenges, and relying on the large sample used (Jerrim, Lopez-Agudo, Marcenaro-Gutierrez, *et al.*, 2017), I modelled only the first plausible value for Mathematics as an outcome variable. I use students' weights computed according to Rabe-Hesketh and Skrondal (2006) to address PISA's population inference based on the two-staged sampling strategy.

5.5. Data

I use data from PISA 2018 as it is the most recent and extended database available, covering 79 countries and territories. I use all plausible values, students' weights at level-1 and an extended list of contextual variables and one learning score variable described in Table 17. I use student-level characteristics such as sex, age, previous grade repetition, household wealth, language spoken at home, immigration background, and parental higher educational attainment. At the school level, I use average household wealth, school type (private or public) and population area of the settlement where the school is. The variables of interest are the plausible values for reading scores, *school inequality*, and country *segregation* S_c.

Table 17: Variables used in regression models

Characteristic	N = 395,508[1]
Sex	
Female	198,930 (50%)
Male	196,578 (50%)
AGE	-0.14 (-1.00, 0.72)
REPEAT	40,765 (10%)
HOMEPOS	9.75 (9.02, 10.41)
School HOMEPOS	0.02 (-0.65, 0.57)
PV1READ	452 (376, 529)
PV2READ	452 (376, 529)
PV3READ	452 (377, 529)
PV4READ	452 (377, 529)
PV5READ	452 (377, 529)
PV6READ	452 (377, 529)
PV7READ	452 (377, 529)
PV8READ	452 (377, 529)
PV9READ	452 (377, 529)
PV10READ	452 (377, 529)
Area	
<3k	36,130 (9.1%)
3k>15k	76,731 (19%)

Characteristic	N = 395,508[1]
15k>100k	113,416 (29%)
100k>1m	104,100 (26%)
>1m	65,131 (16%)
School Type	
Public	317,915 (80%)
Private	77,593 (20%)
Alpha Inequality	0.83 (0.70, 0.98)
S_c	0.12 (0.09, 0.17)
Duncan *segregation* (median)	0.34 (0.30, 0.40)
School Gini	-0.18 (-0.69, 0.49)
IMMIG	
Native	351,076 (89%)
Second generation	22,705 (5.7%)
First generation	21,727 (5.5%)
Language	
Language of test	331,482 (84%)
Other language	64,026 (16%)
HISCED	
None	4,003 (1.0%)
ISCED 1	12,400 (3.1%)

Characteristic	N = 395,508[1]
ISCED 2	32,384 (8.2%)
ISCED 3B-C	23,913 (6.0%)
ISCED 3A-4	97,446 (25%)
ISCED 5B	58,194 (15%)
ISCED 5A-6	167,168 (42%)
[1]n (%); Median (IQR)	

Source: PISA 2018 and own elaboration

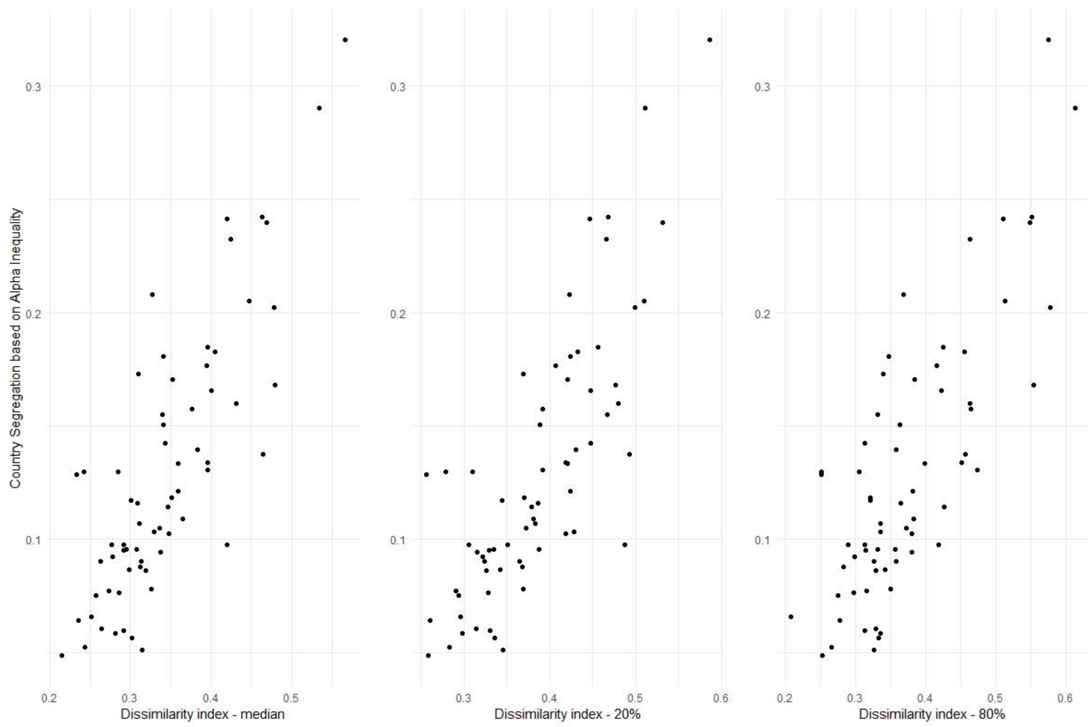
5.6. Results

5.6.1. S_c and the Duncan Dissimilarity

I compute S_c and three versions of the Duncan Dissimilarity index across the different predefined cut-offs (median, 20% and 80%).

Figure 12 shows robust significant country correlations found between S_c and the Duncan Dissimilarity index across all cut-offs. Unweighted correlation coefficients range from .79 to .81, $r(64)$, $p < .001$. This suggests that S_c, although based on a continuous variable, performs as an adequate measurement of *segregation* between two groups. The same countries and territories show the highest values across all indexes, including Peru, Colombia, Mexico, Panama, Chile, Indonesia, and Thailand. The opposite also occurs, whereby Moscow (city), Croatia, Estonia, Finland, Bosnia and Herzegovina and Montenegro consistently show the lowest values across all indexes.

Figure 12: Country segregation Sc and HOMEPOS Duncan Dissimilarity indexes

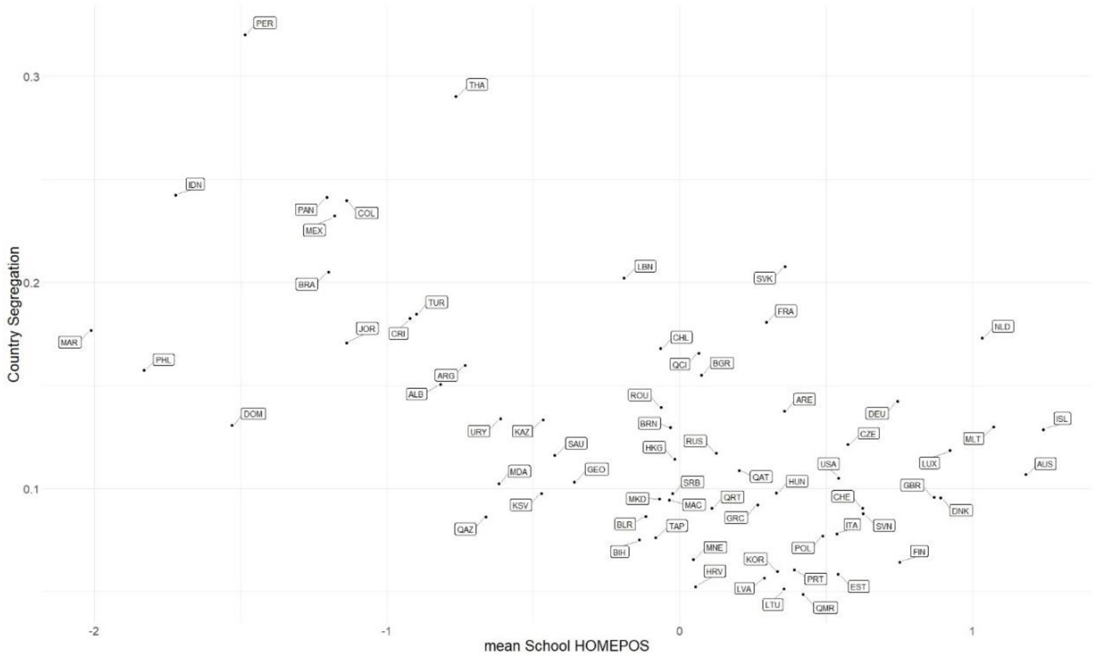


Source: own calculations based on PISA 2018 (OECD, 2020)

Figure 13 shows the relationship between the country average of school HOMEPOS and S_c, in which the former value captures the average wealth of schools. As expected, an important group of the most developed countries appears on the right of the x-axis, as in the case of the Netherlands, Iceland, and Australia. In contrast, it is possible to observe less developed countries like Morocco, Indonesia, Peru, and the Dominican Republic. The graph shows a moderate negative significant relationship between both, $r(64) = -.58$, $p < .001$, whereby countries with higher degrees of *segregation* between schools are consistently found below the average of school wealth. This confirms previous findings related to the existence of dual systems in those countries, where rich and poor students attend a different school, and where the proportion of private schooling is higher

(Kaztman and Retamoso, 2007; Roberts, 2011; Benito, Alegre and Gonzàlez-Balletbò, 2014; Glebbeek and Koonings, 2016; Logan and Burdick-Will, 2017).

Figure 13: Mean School HOMEPOS per country and Country segregation S_c



Source: own calculations based on PISA 2018 (OECD, 2020)

5.6.2.Regression coefficients

Based on the previous findings, in which I confirm a robust similarity between segregation measures, I progress to develop regression models assessing the association between School HOMEPOS, *school inequality*, Country *segregation* S_c and *learning scores*. ***Ta***ble 18 shows coefficients for the regression models across different specifications using S_c and Alpha Inequality. In specifications (1)-(3), the above-mentioned variables are individually associated with *learning scores*. I find that, after adjusting for diverse contextual variables, *Alpha Inequality* remains statistically significant with a similar negative sign found in models reported in

Chapters 2 and 3. Specifications (2) and (3) suggest country *segregation* S_c is not significantly related to *learning scores* after controlling for contextual variables and *school inequality*.

Table 18: Coefficients for regression models - Country segregation Sc and Alpha Inequality

Parameter	(1)	(2)	(3)	(4)	(5)
School HOMEPOS	34.060***	43.270***	34.054***	34.418***	45.024***
	(0.271)	(0.261)	(0.271)	(0.274)	(1.398)
Alpha Inequality	-63.115***		-63.123***	-75.466***	-45.539***
	(0.597)		(0.597)	(1.381)	(1.646)
Country segregation S_c		61.865	-65.152	-146.028*	2.898
		(77.163)	(79.265)	(79.666)	(78.594)
Country segregation S_c**Alpha Inequality*				105.185***	-12.564
				(10.61)	(7.662)
School HOMEPOS**Alpha Inequality*					11.788***
					(1.635)
School HOMEPOS*Country segregation S_c					-137.268***

					(13.271)
School HOMEPOS*Country segregation S_c**Alpha Inequality*					-142.152***
					(10.313
Sex Male	9.434***	8.111***	9.433***	9.443***	9.593***
	(0.248)	(0.251)	(0.248)	(0.248)	(0.247)
HISCED 1	0.231	-0.063	0.231	0.218	0.059
	(1.421)	(1.441)	(1.421)	(1.42)	(1.418)
HISCED 2	-5.630***	-8.021***	-5.630***	-5.589***	-4.033***
	(1.318)	(1.336)	(1.318)	(1.317)	(1.316)
HISCED 3B-C	-1.827	-4.528***	-1.828	-1.733	0.418
	(1.36)	(1.379)	(1.36)	(1.36)	(1.359)
HISCED 3A-4	1.138	-1.214	1.138	1.203	3.303***
	(1.282)	(1.3)	(1.282)	(1.282)	(1.281)
HISCED 5B	0.803	-1.386	0.802	0.896	2.954**
	(1.305)	(1.324)	(1.305)	(1.305)	(1.305)

HISCED 5A-6	10.199***	8.723***	10.199***	10.263***	11.609***
	(1.287)	(1.305)	(1.287)	(1.287)	(1.286)
IMMIG Second generation	4.279***	4.938***	4.277***	4.327***	4.970***
	(0.577)	(0.585)	(0.577)	(0.577)	(0.576)
IMMIG First generation	21.943***	23.953***	21.941***	21.998***	22.352***
	(0.622)	(0.63)	(0.622)	(0.622)	(0.621)
Language Other language	-11.331***	-12.082***	-11.330***	-11.367***	-11.855***
	(0.434)	(0.44)	(0.434)	(0.434)	(0.434)
Age	3.512***	3.674***	3.512***	3.521***	3.538***
	(0.125)	(0.127)	(0.125)	(0.125)	(0.125)
Repeat Yes	-55.391***	-57.506***	-55.390***	-55.489***	-55.464***
	(0.434)	(0.44)	(0.434)	(0.434)	(0.433)
School Type Private	-3.207***	-0.602	-3.204***	-2.919***	-3.566***

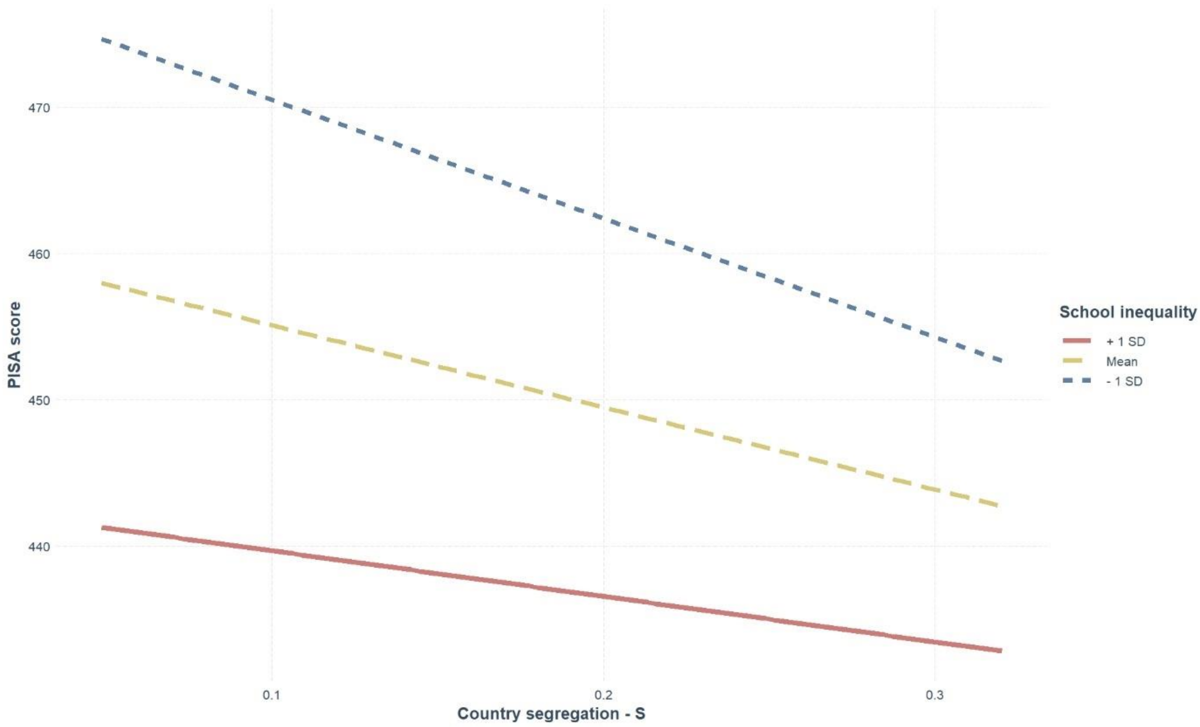
	(0.391)	(0.396)	(0.391)	(0.392)	(0.394)
School Area 3k> 15k	0.41	-1.171**	0.41	0.148	0.677
	(0.512)	(0.519)	(0.512)	(0.513)	(0.513)
School Area 15k> 100k	2.446***	1.691***	2.447***	2.138***	2.834***
	(0.497)	(0.504)	(0.497)	(0.498)	(0.498)
School Area 100k> 1m	7.196***	7.041***	7.197***	6.893***	7.625***
	(0.506)	(0.513)	(0.506)	(0.507)	(0.507)
School Area > 1m	6.321***	6.282***	6.323***	6.120***	6.187***
	(0.571)	(0.579)	(0.571)	(0.572)	(0.571)
HOMEPOS	7.419***	7.320***	7.419***	7.417***	7.438***
	(0.154)	(0.156)	(0.154)	(0.153)	(0.153)
Intercept	438.538***	381.069***	446.995***	456.902***	432.574***
	(5.039)	(11.155)	(11.461)	(11.502)	(11.352)

Observations	395,508	395,508	395,508	395,508	395,508
Log Likelihood	-2,281,346.00	-2,286,845.00	-2,281,341.00	-2,281,288.00	-2,280,642.00
Akaike Inf. Crit.	4,562,739.00	4,573,737.00	4,562,730.00	4,562,627.00	4,561,341.00
Bayesian Inf. Crit.	4,562,989.00	4,573,987.00	4,562,991.00	4,562,899.00	4,561,646.00

Note: *p<0.1; **p<0.05; ***p<0.01

Conversely, the interaction between *Alpha Inequality* and Country *segregation* S_c yields significant coefficients as reported in the specification (4). This suggests that both higher levels of country *segregation* S_c and *school inequality* are negatively associated with PISA scores, which constitutes a two-fold burden on students' schooling performance. This also considers the fact that countries with higher segregation are usually those with lower socioeconomic status among their students, which usually perform worse in PISA. Additionally, schools with lower levels of inequality (i.e., mean -1 s.d.), represented as a continuous (red) line in f, show a less abrupt decrease in *learning outcomes* on different country *segregation* $S_c$levels than other schools experiencing higher levels.

Figure 14: Adjusted predictions for model (4)



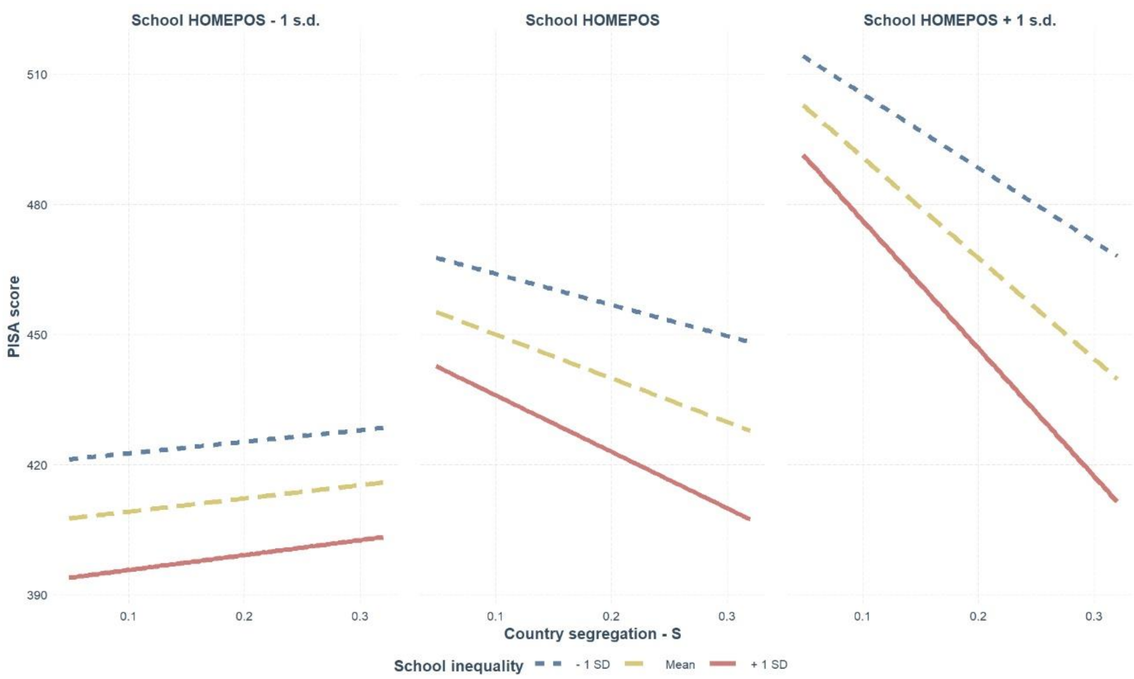
Source: own calculations based on PISA 2018 (OECD, 2020). Original in colour.

Finally, specification (5) shows additional interactions of both variables with School HOMEPOS. The addition of this variable elucidates how school wealth exerts a separate influence on *learning scores*, besides the dispersion of wealth captured by the *Alpha Inequality* parameter. I find a significant positive coefficient for the triple interaction. To facilitate understanding of this, Figure 16 represents the adjusted predictions showing three panels with different levels of School HOMEPOS (the mean minus 1 s.d, mean, the mean, and the mean plus 1 s.d., respectively). In a similar way to the previous specification, lower *school inequality* (blue line) consistently predicts higher PISA scores in comparison with schools with higher inequality (yellow and red lines).

However, the predicted behaviour of *school inequality* and country *segregation* $S_c$on *learning scores* varies across the different levels of School HOMEPOS. When school wealth is lower (left panel), the parallel lines of *Alpha Inequality* suggest no interaction between *school inequality* and country *segregation* S_c. However, the other two panels show that country *segregation* $S_c$is negatively associated with *learning scores*, especially when schools portray higher levels of inequality (red line). The opposite behaviour of the interacted variables on *learning scores* depending on the school HOMEPOS level also suggests different mechanisms could be in place.

Finally, a different interpretation can be given to the complex interplay between country *segregation* $S_c$and *school inequality* across different school HOMEPOS scenarios. It highlights the need to address both the harmful effects of educational *segregation* and *school inequality* separately. These should be understood as different burdens on students' performance and may require different remedies. Figure 15 suggests that country *segregation* S_c plays a structural negative role on *learning outcomes* in those countries, while the opposite occurs in richer countries, where school socioeconomic inequality shows a negative relationship with *learning outcomes* and the country *segregation* acts as an important buffer of those adverse effects. Although these interpretations call for caution due to possible ecological bias, omitted variables and reverse causality, they are grounded in extensive previous literature research highlighting the negative effects of segregation in educational systems (Dumay and Dupriez, 2008; Benito, Alegre and Gonzàlez-Balletbò, 2014).

Figure 15: Adjusted predictions for model (6)



Source: own calculations based on PISA 2018 (OECD, 2020)

Multicollinearity was examined through a Variance Inflation Factor analysis (VIF) without traces of moderate or high correlation between variables (see Table 19). Only the case of triple interaction in the specification (5) shows a high correlation, as expected due to the nature of the added term to the regression model.

Table 19: VIF for regression models - Country segregation S_c and Alpha Inequality

Parameter	(1)	(2)	(3)	(4)	(5)
Sex	1.0	1.0	1.0	1.0	1.0
HISCED	1.2	1.2	1.2	1.2	1.3
IMMIG	1.1	1.1	1.1	1.1	1.1
Language	1.1	1.1	1.1	1.1	1.1
AGE	1.0	1.0	1.0	1.0	1.0
REPEAT	1.0	1.0	1.0	1.0	1.0
School Type	1.2	1.2	1.2	1.2	1.2
School Area	1.2	1.2	1.2	1.2	1.2
School HOMEPOS	1.9	1.7	1.9	2.0	51.2
HOMEPOS	1.5	1.5	1.5	1.5	1.5
Alpha Inequality	1.3		1.3	6.7	9.5
Country segregation S_c		1.0	1.0	1.0	1.0
Country segregation S_c * *Alpha Inequality*				7.0	10.9
School HOMEPOS*Country segregation S_c					51.4
School HOMEPOS**Alpha Inequality*					49.6
School HOMEPOS*Country segregation S_c**Alpha Inequality*					58.1

Source: own calculations based on PISA 2018 (OECD, 2020)

Coefficients found when I use Duncan's Dissimilarity Index as the Country *segregation* and school Gini for *school inequality* (see Table 20) show a similar sign to the previous set of models. The only difference in terms of sign appears in one parameter of the specification (9), posing a positive sign for the triple interaction between school HOMEPOS, Duncan's index and School Gini. Figure 15 represents the adjusted predictions showing three panels with different levels of School HOMEPOS (the mean minus 1 s.d, mean, the mean, and the mean plus 1 s.d., respectively). In a similar way to the previous specification, lower *school inequality* (blue line) consistently predicts higher PISA scores in comparison with schools with higher inequality (yellow and red lines). However, segregation appears to play a positive role in schools with low and medium levels of HOMEPOS, while the effect of country segregation appears to be irrelevant for the wealthier schools.

Table 20: Coefficients for regression models – Country Duncan a School Gini

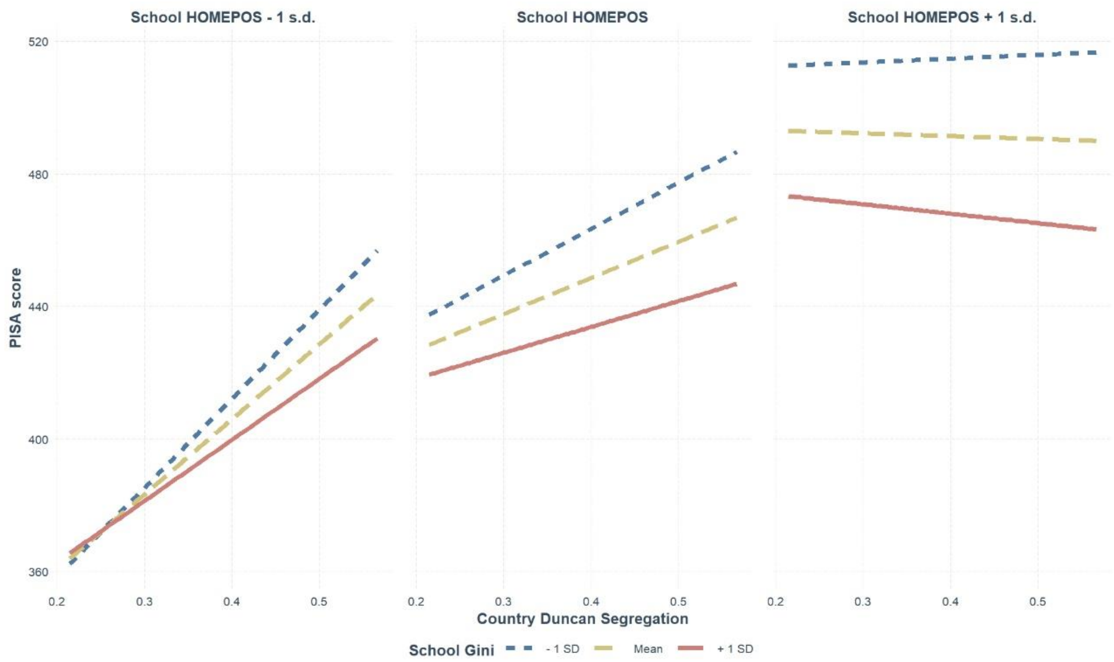
Coefficients	**(6)**	**(7)**	**(8)**	**(9)**
School HOMEPOS	43.271***	39.962***	40.946***	91.331***
	(0.261)	(0.271)	(0.272)	(1.09)
Country segregation Duncan	59.524	73.453	79.542	96.422
	(60.71)	(59.895)	(59.607)	(59.475)
Gini		-7.429***	-31.970***	-3.677***
		(0.171)	(0.806)	(0.935)
School HOMEPOS * Country segregation Duncan				-119.524***
				(2.666)
School HOMEPOS * Gini				-13.193***
				(0.602)

Country segregation Duncan * Gini			65.399***	-29.640***
			(2.1)	(2.581)
School HOMEPOS * Country segregation Duncan * Gini				11.258***
				(1.515)
Sex Male	8.111***	8.522***	8.618***	9.360***
	(0.251)	(0.25)	(0.25)	(0.248)
HISCED ISCED 1	-0.063	-1.555	-1.263	1.483
	(1.441)	(1.438)	(1.436)	(1.422)
HISCED ISCED 2	-8.021***	-9.744***	-8.885***	-3.053**
	(1.336)	(1.333)	(1.332)	(1.32)
HISCED ISCED 3B-C	-4.528***	-6.553***	-5.678***	1.283
	(1.379)	(1.377)	(1.375)	(1.363)
HISCED ISCED 3A-4	-1.214	-3.136**	-2.372*	4.112***
	(1.3)	(1.298)	(1.296)	(1.285)
HISCED ISCED 5B	-1.386	-3.303**	-2.552*	3.729***
	(1.324)	(1.321)	(1.32)	(1.308)
HISCED ISCED 5A-6	8.723***	7.130***	7.721***	11.736***
	(1.305)	(1.303)	(1.301)	(1.289)
IMMIG Second generation	4.938***	4.398***	4.830***	5.349***
	(0.585)	(0.583)	(0.583)	(0.577)
IMMIG First generation	23.953***	22.996***	23.895***	21.932***
	(0.63)	(0.629)	(0.629)	(0.624)
Language Other language	-12.081***	-12.130***	-11.811***	-11.797***
	(0.44)	(0.439)	(0.439)	(0.435)
AGE	3.674***	3.655***	3.649***	3.568***
	(0.127)	(0.126)	(0.126)	(0.125)
REPEAT Yes	-57.506***	-56.828***	-56.806***	-56.456***

	(0.44)	(0.439)	(0.438)	(0.434)
School Type Private	-0.604	-1.850***	-1.319***	-5.380***
	(0.396)	(0.396)	(0.396)	(0.395)
School Area 3k> 15k	-1.171**	-1.101**	-0.854*	0.655
	(0.519)	(0.518)	(0.518)	(0.513)
School Area 15k> 100k	1.691***	1.466***	1.452***	2.654***
	(0.504)	(0.503)	(0.502)	(0.497)
Area 100k> 1m	7.040***	6.578***	6.631***	7.144***
	(0.513)	(0.512)	(0.512)	(0.507)
School Area > 1m	6.280***	5.893***	6.075***	5.447***
	(0.579)	(0.578)	(0.577)	(0.571)
HOMEPOS	7.320***	7.316***	7.351***	7.473***
	(0.156)	(0.155)	(0.155)	(0.153)
Constant	368.621***	365.521***	360.503***	341.967***
	(21.452)	(21.166)	(21.065)	(21.018)
Observations	395,508	395,508	395,508	395,508
Log Likelihood	-2,286,845	-2,285,900	-2,285,414	-2,281,280
Akaike Inf. Crit.	4,573,737	4,571,848	4,570,878	4,562,615
Bayesian Inf. Crit.	4,573,987	4,572,109	4,571,150	4,562,920

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 16: Adjusted predictions for model (9)



Source: own calculations based on PISA 2018 (OECD, 2020)

Similarly to the previous case, multicollinearity was examined through a Variance Inflation Factor analysis (VIF) without traces of moderate or high correlation between variables (Table 21). Only the case of triple interaction in the specification (9) shows a high correlation, as expected due to the nature of the term added to the regression model.

Table 21: VIF for regression models - Country Duncan segregation & Gini

Parameters	**(6)**	**(7)**	**(8)**	**(9)**
Sex	1.01	1.01	1.01	1.01
HISCED	1.23	1.24	1.24	1.26
IMMIG	1.08	1.09	1.09	1.09
Language	1.06	1.06	1.06	1.07
AGE	1.00	1.00	1.00	1.00
REPEAT	1.05	1.05	1.05	1.05

School Type	1.17	1.17	1.18	1.20
School Area	1.17	1.17	1.17	1.18
HOMEPOS	1.48	1.48	1.48	1.48
School HOMEPOS	1.72	1.87	1.90	31.01
Country segregation Duncan	1.00	1.00	1.00	1.00
Gini		1.20	26.79	36.77
Country segregation Duncan * Gini			27.39	42.26
School HOMEPOS * Country segregation Duncan				31.04
School HOMEPOS * Gini				50.57
School HOMEPOS * Country segregation Duncan * Gini				55.88

Source: own calculations based on PISA 2018 (OECD, 2020)

In all other models, coefficients found are similar in terms of signs to models utilising Country *segregation* S_c and Alpha Inequality. Models' coefficients and VIF values can be found in the Annexes (see Table 35 to Table 39).

5.7. Discussion

In this chapter, I provide a simple method to measure country *segregation* S_c based on a previously developed *school inequality* measure. I validate against a gold standard such as the Duncan Dissimilarity Index (Allen and Vignoles, 2007). The results found suggest the derived segregation measure shows strong correlations with Duncan's index.

Based on that, I develop different linear mixed-effect models to assess the association between *school inequality* and country *segregation* with *learning scores*. Coefficients, interactions, and low variance inflation factors suggest that both variables capture different phenomena and contribute to a better understanding of the negative influence of inequalities on *learning scores*.

While the *segregation* of an educational system and *school inequality* are inversely related – both theoretically and based on the most recent available data when analysed from PISA at a country level – they constitute a concurrent phenomenon that affects students' ability to address standardised tests.

The empirical findings also shed light on the ethical case for assessing between-school and within-school inequality. Coefficients from models using interactions between school HOMEPOS, country *segregation* S_c and *Alpha inequality* suggests that the best possible scenario for *learning scores* across all models is formed by lower levels of country *segregation* and *school inequality.* In all cases, school HOMEPOS as a proxy of school wealth plays a significant role as leverage on how segregation and *school inequality are* associated with *learning scores*. However, in the case of Duncan and school Gini, segregation appears to be a positive force for *learning scores* – on average – for schools with lower degrees of wealth.

A consequentialist approach could emphasise – as has been done through educational policies – the fact that segregation and *school inequality* both show negative associations with *learning scores*. In this case, if discrepancy between both factors may arise (for instance, one being positively and the other negatively associated to learning outcomes), a numerical welfarist approaches based on cost-benefit analysis, could be suggested as a solution to the problem. Similar conclusions could be sustained based on Rawls's downwards inequality. As country segregation can be driven down through mixing policies, one could argue that this will be valuable for those who are less advantaged. However, considering the concurrence of influences, I prefer to stand with a deontologist approach whereby both features shall be understood as evil. Instead of suggesting a trade-off between *school inequality* and country segregation, I emphasise the need to separate policies that mitigate both negative influences on students' lives.

This theoretical and empirical exploratory study presents many limitations. One is its cross-sectional nature, which prevents causality and changes over time being addressed. Another constraint refers to the complex nature of both phenomena, *school inequality* and country segregation, which can be distinguished yet may overlap in many senses on their effects on *learning outcomes*. Finally, while subsampling geographical regions (for example, Latin America or Europe) does not produce considerably different coefficients, the levels of inequality and segregation vary significantly across countries, which requires very distinctive educational policies.

Further research is needed towards disentangling how both facts jointly affect students' development. Additionally, it poses a complex dilemma as to how to balance policies to address both negative forces.

6. Conclusions

There is well-established research that reveals that socioeconomic characteristics (Coleman, 1966) and exogenous conditions to schools (Nieuwenhuis *et al.*, 2013; Del Bello, Patacchini and Zenou, 2015) are associated with differences in cognitive and non-cognitive educational outcomes. Students coming from wealthier households or attending wealthier schools, on average, tend to have better schooling performance in comparison to those that come from less privileged backgrounds and schools.

Those previous (to schooling) and external factors, grouped under the label of school composition effects – which are not related to effort or individual attitudes – reflect the relevance that different factors have for pupils' education. This is one of the reasons why the distribution of students from different socioeconomic backgrounds across schools has been of significant interest to policymakers across the world. The relationship between contextual societal factors and schools is addressed under the umbrella of schools being key agents of social equity (Allen, 2016; Agostinelli *et al.*, 2020).

Among those factors, a less studied dimension is the role of the aggregated distribution of wealth in school on learning outcomes. In this thesis, I contribute to this dimension by providing a theoretical and empirical basis for studying how the distribution of economic resources relates to educational achievement, and by employing measures of aggregate wealth inequality measured at a school level.

The existence of *school inequality* – and educational segregation, as explored in Chapter 5 – raises diverse problems to be addressed through different school and national educational policies. Furthermore, it signals how human and social development are intertwined in persons, places and circumstances. This evokes the need of addressing social complexity without losing sight of individuals. Again, I found in the relational sociology theory an enriching approach that provides theoretical tools to find solutions to complex social problems. While mainstream development theories may also shed light on how to unwrap and address the effects of inequality, in this thesis I explored new theoretical avenues less known to our field of knowledge.

In the following section, I synthesise each chapter and highlight my main findings and arguments. This also provides a recapitulation that allows me to summarise my main contributions to the academic literature.

6.1. Synthesis of chapters 2 to 5

Chapter 2 starts by addressing the complexity and limitations of measuring socioeconomic status using categorical data in surveys such as PISA. While typical inequality measures as the Gini, Atkinson or Theil indexes depend on continuous data (in this case they are based on HOMEPOS), the proposed measurement, *Alpha Inequality* is based on the discrimination parameter α of 2-PL IRT models. The chapter provides an axiomatisation of the measurement and a validation exercise comparing regression model coefficients across countries where the outcome variable is Mathematics scores. I use data from the 6th cycle of PISA, collected in 2015, and I find a consistent significant negative association of school-level inequality and scores across the majority of countries – the positive exception being several European countries.

Based on that initial finding, Chapter 3 contributes to the body of knowledge on the economic factors affecting education in two ways. First, I focus on schools as the level of aggregation for the computation and the analysis of economic inequality. I show how lower levels of aggregation, such as schools – which differ from commonly used administrative boundaries – can usefully shed light on educational achievement. Second, I find an interplay between aggregate school-level economic determinants (inequality and average wealth), and I provide two interpretations of these results. One is based on the usual econometric reading of an interaction term and the other is based on the interpretation of the interaction term as a standalone economic variable, namely total relative deprivation. The interaction between school-level inequality and mean school wealth sheds light on how school-level inequality behaves differently in wealthier or poorer environments. The interaction indicates that the negative association between economic inequality and educational outcomes is stronger for schools with higher average wealth. This result agrees with social cognitive theory, according to which the effects of inequality could be perceived more strongly by people who are higher up on the socioeconomic ladder. This supports the idea that wealthier groups are more susceptible to the negative consequences of inequality than less wealthy ones, who usually have a lesser understanding of the gradient of wealth. The other interpretation suggests a negative relationship between *learning scores* and school-level relative deprivation or absolute inequality. These alternative perspectives on the result shed light on the importance of the actual economic gap among individuals, too often neglected by the existing inequality literature that focuses only on a relative understanding of inequality.

Chapter 4 builds on the previous analyses and provides a theoretical framework and empirical analysis on potential mitigators of the negative impacts of inequality in schools. I start by understanding schools as socialising places – emphasising the importance of socioemotional skills not only as a means to an end – and suggesting the concept of social cohesion as an umbrella to address the effects of *school inequality*. I test whether social cohesion attitudes act as mechanisms that may compensate, moderate, and mediate the negative influence of wealth inequality on *learning outcomes*. Although I find positive associations that suggest different mitigating effects, the strength of social inequality remains a negative predictor of *learning scores*.

Finally, chapter 5 addresses the dilemma of assessing the problem of country segregation and *school inequality.* I start by computing a segregation measure, which I validate against the Duncan Dissimilarity Index. Additionally, I develop linear mixed-effect models to assess the association between *school inequality* and/or country segregation with *learning scores*, in order to test the underlying hypothesis that both variables capture complementarity but constitute different phenomena that negatively influence students' *learning scores*. The empirical findings are interpreted in the light of how different theories of justice –

utilitarianism, contractualism and deontologism – understand inequalities, their remedies, and choices that could be made based on them.

6.2. Synthesis of main contributions, limitations and further research

This discussion on inequality gives way to reflection on the specific topic of interest of the dissertation, which is the study of wealth inequalities in schools. I make different contributions to the academic literature on SCE throughout this thesis, which I summarise as follows.

First, I engaged with previous relevant academic literature to address the relationship between aggregated economic inequality and education, theorising about potential mechanisms through which *school inequality* plausibly impacts *learning outcomes*. Chapters 2 and 3 organise and discuss previous theoretical contributions from diverse fields such as economics, sociology, social psychology, and education.

While Chapter 2 focuses on the macro associations and impacts between socioeconomic inequality and schooling outcomes, Chapter 3 concentrates on the micromechanisms by which school inequality affects learning attainment. In chapter 3, I review the previous body of literature that studied the relationship between aggregate inequality and educational outcomes, classifying it into the following four major categories: how inequality affects access to education; how it affects the social fabric; the negative consequences of relative deprivation and interpersonal comparisons of educational outcomes; and, finally, how intergenerational societal differences reproduce some patterns of inequality within and across schools. This broad delineation serves as a background to understand how specific mechanisms – developed in Chapter 4 – occur in schools as a consequence of the existence of inequality: the process of social isolation of certain individuals; the existence of interpersonal upwards and downwards comparisons; and the potential growth of a condition of anomie in schools.

Based on these previous academic contributions, I hypothesise that *school inequality* is associated with reduced learning scores. As expected, my empirical findings consistently show that *school inequality* is negatively associated with *learning scores* in PISA. These findings are robust to different PISA datasets – I utilised data collected during cycles 5, 6 and 7 corresponding to years 2012, 2015 and 2018 to test several measurements of inequality – *Alpha Inequality* and *Gini, Theil, Atkinson* indexes, and various model specifications, using different control variables and fixed effects.

Furthermore, I examined whether the effects of *learning scores* on *school inequality* vary according to the mean wealth of the school. By interacting the variable *school Gini* and the average wealth of the school, measured by school HOMEPOS, I provide two different insights to the literature. On the one hand, my analysis enables an understanding of the impact of absolute inequality on students (Yitzhaki, 1979). On the other hand, it shows how wealthier schools tend to show more damaging effects – which is mostly explained through social cognitive theories (Schneider, 2019). These findings offer useful and novel insights on the pathways through which socioeconomic disparities may affect educational outcomes, and how schools may be prime environments for such pathways to operate. I hope my work encourages future research to investigate further the school-level dynamics I discussed in the chapter, in particular through the use of different datasets and by including countries that do not participate in PISA. In terms of the policy, the invisible assumption made by many schooling systems of the existence of school-level economic homogeneity should be re-examined. This includes the desirability of shifts from remedial policies such as grade repetition towards more inclusive strategies that consider within-school socioeconomic differences, such as prioritising the development and integration of students' and families' social and non-cognitive skills.

Addressing this adverse scenario, chapter 4 revisits the concept of schools as social spaces by providing a theoretical background to the use of social cohesion as a powerful idea to address *school inequalities*. A third theoretical contribution made in this thesis refers to the development of a framework linking *school inequality* and social cohesion. Furthermore, I test different hypotheses regarding the compensation, moderation, and mediation effects of social cohesion dimensions – operationalised via variables that capture different students' attitudes – on *learning scores.* In general, I find that those variables mitigate the harmful effects of *school inequality* on *learning scores.* These findings hold across different model specifications, although they do not entirely suppress the negative effects on *learning scores.*

Another contribution of this thesis is the discussion and empirical analysis of the complexity of a two-fold phenomenon: *school inequality* – measured at the school-level - and educational segregation – measured, in this case, at a country level. I find that both negatively relate to *learning scores*. This raises a theoretical debate with strong ethical consequences regarding the conflicts that arise between policies made to reduce the negative influence of both factors. Making sense of the broader picture should allow the issue of educational inequality to be addressed, especially when wealth inequality could be just an undesired side effect of promoting social heterogeneity in schools, to prevent another undesirable feature, namely segregation. However, promoting lesser horizontal inequality, and therefore more socio-economic diversity within-schools, also has the effect of being understood within-schools, which relates to the above-mentioned vertical inequality. This poses a dilemma for educational policies. While diminishing segregation across an educational system requires a certain course of action (for example, by widening the number of vacancies for students with different backgrounds in every school), the experience of *school inequality* is an issue that requires a different set of answers and I emphasise that it cannot be overlooked. As shown in chapter 5, both phenomena coexist and are negatively linked to cognitive *learning outcomes*. Future research should disentangle both mechanisms to understand how they operate in schools. All these cases highlight challenges in educational systems as well as reflect some policy options. Deciding the priority of the desired outcomes – for instance, social cohesion or academic achievement – could make important differences in how schools are organised within systems.

Additionally, this thesis makes two methodological contributions. It develops a novel school-inequality measurement, *Alpha Inequality,* based on categorical data. In conjunction, it also develops a simple segregation measure derived from *Alpha Inequality.* Both measures rely on 2-PL IRT models, whose easiness in terms of use and visualisation provides useful insights regarding item analysis and a better understanding of what assets influence inequalities. Additionally, the method avoids measuring inequality based on HOMEPOS, which can be biased as it is always based on a normal distribution.

I acknowledge that this research presents diverse limitations. First, it focuses on cross-sectional analysis rather than a longitudinal examination of the issues over time. This prevents understanding empirical associations – even when models fit with previous theory – as causal connections. This shortcoming responds to the nature of the data used. Although PISA has collected data across 7 cycles since 2000, the complex sampling design and the rotated-blocks design prevent robust pseudo-panel analysis.

The second limitation is related to falling into an ecological fallacy, as *school inequality* is measured as an aggregate-level indicator. Using individual measures of inequality such as relative deprivation could shed light on the complexity at the individual level (Esposito, Villaseñor and Jacobs, 2021).

A third limitation relates to the use of cognitive educational outcomes rather than non-cognitive ones. While there is a clearer relationship between the gradient of SCE and *learning outcomes,* I assert that educational outcomes cannot be reduced to gaining and developing cognitive skills. Furthermore, measuring important cognitive skills solely through learning tests reduces, even more, the scope of education and schools. As I further developed in the fourth chapter, I value the intrinsic social value of schools as social spaces for nurturing humanity. Consequently, I realise that separating students according to predetermined parameters drastically limits their possibilities of human exchange, restricts their horizons, reduces social mobility, and confines them to their own world.

These findings open up different new lines of research. Testing similar hypotheses across other datasets such as PIRLS would provide external validity to the empirical findings. Developing quasi-experimental analysis based on longitudinal data – for example, based on rich datasets as Young Lives (Boyden *et al.*, 2021) – would provide a better understanding of the potential causal effects of *school inequality* on diverse outcomes. In this sense, there is also a pending task in terms of studying the association of *school inequality* and non-cognitive outcomes, defiant behaviours, and other relevant social outcomes. Unpacking how processes occur inside schools also may provide relevant insights into which mechanisms are more relevant in terms of negative consequences on students' outcomes. This will allow the theoretical contributions made in this study to be refined. Finally, further studies that disentangle the concurrent influence of segregation and *school inequality* will increase the understanding of both influences to allow for the development of specific policies – compensatory, promoting and aimed at reducing disparities – to address them.

7. Bibliography

Abul Naga, R. H. and Yalcin, T. (2008) 'Inequality measurement for ordered response health data', *Journal of Health Economics*, 27(6), pp. 1614–1625. doi: 10.1016/j.jhealeco.2008.07.015.

Adams, K. S. and Christenson, S. L. (2000) 'Trust and the family-school relationship examination of parent-teacher differences in elementary and secondary grades', *Journal of School Psychology*, 38(5), pp. 477–497. doi: 10.1016/S0022-4405(00)00048-0.

Agostinelli, F. *et al.* (2020) 'When the Great Equalizer Shuts Down: Schools, Peers, and Parents in Pandemic Times', *SSRN*. doi: 10.3386/w28264.

Allen, D. (2016) *Education and Equality*. University of Chicago Press. doi: 10.1080/00204866400020303.

Allen, R. and Vignoles, A. (2007) 'What should an index of school segregation measure?', *Oxford Review of Education*, 33(5), pp. 643–668. doi: 10.1080/03054980701366306.

Allison, R. A. and Foster, J. E. (2004) 'Measuring health inequality using qualitative data', *Journal of Health Economics*, 23(3), pp. 505–524. doi: 10.1016/j.jhealeco.2003.10.006.

Almås, I. *et al.* (2011) 'Measuring unfair (in)equality', *Journal of Public Economics*, 95(7–8), pp. 488–499. doi: 10.1016/j.jpubeco.2010.11.002.

Archer, M. *et al.* (2016) 'What is Critical Realism?', *ASA Theory*. Available at: http://www.asatheory.org/current-newsletter-online/what-is-critical-realism (Accessed: 13 May 2021).

Archer, M. S. (2015) 'The relational subject and the person: Self, agent, and actor', in *The relational subject*. Cambridge University Press, pp. 85–122. doi: 10.1017/CBO9781316226780.004.

Aristotle (2014a) *De interpretatione*. De Gruyter.

Aristotle (2014b) *The Nicomachean ethics*. 6th edn. Edited by W. D. Ross. Oxford: Princeton University Press.

Arrow, K. (2012) *Social choice and individual values*. Yale university press.

Avvisati, F. (2020) 'The measure of socio-economic status in PISA: a review and some suggested improvements', *Large-scale Assessments in Education*, 8. doi: 10.1186/s40536-020-00086-x.

Azeredo, C. M. *et al.* (2015) 'School bullying: A systematic review of contextual-level risk factors in observational studies', *Aggression and Violent Behavior*. Pergamon, pp. 65–76. doi: 10.1016/j.avb.2015.04.006.

Bak, H. and Yi, Y. (2020) 'When the American dream fails: The effect of perceived economic inequality on present-oriented behavior', *Psychology and Marketing*, 37(10), pp. 1321–1341. doi: 10.1002/mar.21369.

Balarin, M. (2015) *The default privatization of Peruvian education and the rise of low-fee private schools: Better or worse opportunities for the poor?* 65.

Bandrés, E. (1994) 'Amartya Sen, Inequality Reexamined', *Revista de Economía Aplicada*, 2(6), pp. 231–240.

Baron, J. N. and Pfeffer, J. (1994) 'The Social Psychology of Organizations and Inequality', *Social Psychology Quarterly*, 57(3), p. 190. doi: 10.2307/2786876.

Barone, G. and Mocetti, S. (2016) 'Inequality and trust: New evidence from panel data', *Economic Inquiry*, 54(2), pp. 794–809. doi: 10.1111/ecin.12309.

Barry, B. (1998) *Social Exclusion, Social Isolation and the Distribution of Income*. 12. London. Available at: http://sticerd.lse.ac.uk/case.htm (Accessed: 19 June 2021).

Bartolini, S. *et al.* (2019) *A Social Cure for Social Comparisons*. 797. Siena.

Basu, K. and Van, P. H. (1998) 'The Economics of Child Labor', *The American Economic Review*, 88(3), pp. 412–27. doi: 10.1038/scientificamerican1003-84.

Bates, D. (2010) 'Mixed models in R using the lme4 package Part 8: Nonlinear mixed models', pp. 1–9.

Bates, D. M. and Debroy, S. (2004) 'Linear mixed models and penalized least squares', *Journal of Multivariate Analysis*, 91, pp. 1–17. doi: 10.1016/j.jmva.2004.04.013.

Battistich, V. *et al.* (1995) 'Schools as Communities, Poverty Levels of Student Populations, and Students' Attitudes, Motives, and Performance: A Multilevel

Analysis', *American Educational Research Journal*, 32(3), pp. 627–658. doi: 10.3102/00028312032003627.

Battistich, V. *et al.* (1997) 'Caring school communities', *Educational Psychologist*, 32(3), pp. 137–151. doi: 10.1207/s15326985ep3203.

Battistich, V. and Hom, A. (1997) 'The relationship between students' sense of their school as a community and their involvement in problem behaviors.', *American journal of public health*, 87(12), pp. 1997–2001. doi: 10.2105/AJPH.87.12.1997.

Del Bello, C. L., Patacchini, E. and Zenou, Y. (2015) *Neighborhood Effects in Education*. 8956.

Benito, R., Alegre, M. À. and Gonzàlez-Balletbò, I. (2014) 'School Segregation and Its Effects on Educational Equality and Efficiency in 16 OECD Comprehensive School Systems', *Comparative Education Review*, 58(1), pp. 104–134. doi: 10.1086/672011.

Billger, S. M. (2009) 'On reconstructing school segregation: The efficacy and equity of single-sex schooling', *Economics of Education Review*, 28(3), pp. 393–402. doi: 10.1016/J.ECONEDUREV.2007.08.005.

Billings, S. B., Deming, D. J. and Rockoff, J. E. (2012) 'School segregation, educational attainment and crime: Evidence from the end of busing in Charlotte-Mecklenburg (No. w18487)', *The Quarterly Journal of Economics*, 129(1), pp. 435–472.

Bjørnskov, C. (2008) 'Social trust and fractionalization: A possible reinterpretation', *European Sociological Review*, 24(3), pp. 271–283. doi: 10.1093/esr/jcn004.

Bock, R. D. and Aitkin, M. (1981) 'Marginal maximum likelihood estimation of item parameters: Application of an EM algorithm', *Psychometrika*, 46(4), pp. 443–459.

van den Bos, W. *et al.* (2018) 'Social network cohesion in school classes promotes prosocial behavior', *PLoS ONE*, 13(4), p. e0194656. doi: 10.1371/journal.pone.0194656.

Bourdieu, P. and Passeron, J.-C. (1990) *Reproduction in Education, Society and Culture*, *Sage Publications*. London: Sage Publications.

Boyden, J. *et al.* (2021) *Designing Comparative, Longitudinal Mixed-Methods Research: Learning from Young Lives*.

Bradley, R. H. and Corwyn, R. F. (2002) 'Socioeconomic status and child development', *Annual Review of Psychology*, 53, pp. 371–399. doi: 10.1146/annurev.psych.53.100901.135233.

Brint, S. (2017) 'Schools and Socialization', in *Schools and Societies*. Stanford University Press, pp. 150–185. doi: doi:10.1515/9781503601031-007.

Browman, A. S. *et al.* (2019) 'How economic inequality shapes mobility expectations and behaviour in disadvantaged youth', *Nature Human Behaviour*. Nature Publishing Group, pp. 214–220. doi: 10.1038/s41562-018-0523-0.

Burk, A. (1938) 'A Reformulation of Certain Aspects of Welfare Economics', *The Quarterly Journal of Economics*, 52(2), pp. 310–334. doi: 10.2307/1881737.

Callan, M. J. *et al.* (2017) 'The Interrelations Between Social Class, Personal Relative Deprivation, and Prosociality', *Social Psychological and Personality Science*, 8(6), pp. 660–669. doi: 10.1177/1948550616673877.

Caro, D. H. and Lenkeit, J. (2012) 'An analytical approach to study educational inequalities: 10 hypothesis tests in PIRLS 2006', *International Journal of Research and Method in Education*, 35(1), pp. 3–30. doi: 10.1080/1743727X.2012.666718.

Chalmers, R. P. (2012) 'mirt: A multidimensional item response theory package for the R environment', *Journal of Statistical Software*, 48(6), pp. 1–29.

Checchi, D. (2003) 'Inequality in Incomes and Access to Education: A Cross-Country Analysis (1960-95)', *Labour*, 17(2), pp. 153–201. doi: 10.1111/1467-9914.00226.

Cheema, J. R. (2014) 'Some general guidelines for choosing missing data handling methods in educational research', *Journal of Modern Applied Statistical Methods*, 13(2), p. 3.

Chen, H. T. (1989) 'The conceptual framework of the theory-driven perspective', *Evaluation and Program Planning*, 12(4), pp. 391–396. doi: 10.1016/0149-7189(89)90057-8.

Chiu, M. M. (2015) 'Family inequality, school inequalities, and mathematics achievement in 65 countries: Microeconomic mechanisms of rent seeking and diminishing marginal returns', *Teachers College Record*, 117(1).

Chiu, M. M. *et al.* (2016) 'Students' Sense of Belonging at School in 41 Countries: Cross-Cultural Variability', *Journal of Cross-Cultural Psychology*, 47(2), pp. 175–

196. doi: 10.1177/0022022115617031.

Chiu, M. M. and Khoo, L. (2005) 'Effects of resources, inequality, and privilege bias on achievement: Country, school, and student level analyses', *American Educational Research Journal*, 42(4), pp. 575–603. doi: 10.3102/00028312042004575.

Chiu, W. H. (1998) 'Income Inequality, Human Capital Accumulation and Economic Performance', *The Economic Journal*, 108(446), pp. 44–59. doi: 10.1111/1468-0297.00272.

Clark, A. E. and D'Ambrosio, C. (2015) 'Attitudes to income inequality: Experimental and survey evidence', in *Handbook of Income Distribution*. Elsevier, pp. 1147–1208. doi: 10.1016/B978-0-444-59428-0.00014-X.

Clark, A. E. and Senik, C. (2010) 'Who Compares to Whom? The Anatomy of Income Comparisons in Europe', *The Economic Journal*, 120(544), pp. 573–594. doi: 10.1111/J.1468-0297.2010.02359.X.

Cockerham, W. C. (2021) *The social causes of health and disease*. John Wiley & Sons.

Coleman, J. (1966) 'Equality of Educational Opportunity'. Ann Arbor.

Coleman, J. S. (1974) 'Inequality, Sociology, and Moral Philosophy', *Source: American Journal of Sociology*, 80(3), pp. 739–764. Available at: https://about.jstor.org/terms (Accessed: 25 November 2021).

Connell, R. (1994) 'Poverty and Education', *Harvard Educational Review*, 64(2), pp. 125–150. doi: 10.17763/haer.64.2.m14947g30k1x5781.

Cordray, D. S. (1986) 'Quasi-experimental analysis: A mixture of methods and judgment', *New Directions for Evaluation*, 1986(31), pp. 9–27.

Coryn, C. L. S. *et al.* (2011) 'A Systematic Review of Theory-Driven Evaluation Practice From 1990 to 2009', *American Journal of Evaluation*, 32(2), pp. 199–226. doi: 10.1177/1098214010389321.

De Courson, B. and Nettle, D. (2021) 'Why do inequality and deprivation produce high crime and low trust?', *Scientific Reports*, 11(1), pp. 1–11. doi: 10.1038/s41598-020-80897-8.

Cowell, F. (2016) 'Inequality and poverty measures', in Adler, M. and Fleurbaey, M. (eds) *The Oxford Handbook of Well-Being and Public Policy*. Oxford, UK: Oxford University Press.

Cowell, F. A. and Flachaire, E. (2012a) 'Inequality with Ordinal Data', *Economica*, 84(334), pp. 290–321. doi: 10.1111/ecca.12232.

Cowell, F. A. and Flachaire, E. (2012b) 'Inequality with Ordinal Data', *Economica*, 84(334), pp. 290–321. doi: 10.1111/ecca.12232.

Crane, J. (1991) 'The Epidemic Theory of Ghettos and Neighborhood Effects on Dropping Out and Teenage Childbearing', *American Journal of Sociology*, 96(5), pp. 1226–1259. doi: 10.1086/229654.

Davier, M. Von, Gonzalez, E. and Mislevy, R. J. (1997) *What are plausible values and why are they useful ?*

Deaton, A. (2003) 'Health, Inequality, and Economic Development', *Journal of*

Economic Literature, 41(1), pp. 113–158.

Decerf, B. *et al.* (2021) 'Lives and livelihoods: Estimates of the global mortality and poverty effects of the Covid-19 pandemic', *World Development*, 146, p. 105561. doi: 10.1016/J.WORLDDEV.2021.105561.

Deng, Z. and Gopinathan, S. (2016) 'PISA and high-performing education systems: explaining Singapore's education success', *Comparative Education*, 52(4), pp. 449–472. doi: 10.1080/03050068.2016.1219535.

Denicolo, C. P. *et al.* (2017) 'Reimagining Critical Care and Problematizing Sense of School Belonging as a Response to Inequality for Immigrants and Children of Immigrants', *Source: Review of Research in Education*, 41, pp. 500–530. doi: 10.3102/0091732X17690498.

van Deth, J. W., Abendschön, S. and Vollmar, M. (2011) 'Children and Politics: An Empirical Reassessment of Early Political Socialization', *Political Psychology*, 32(1), pp. 147–174. doi: 10.1111/J.1467-9221.2010.00798.X.

Diclemente, C. M. *et al.* (2018) 'Resilience in Urban African American Adolescents: The Protective Enhancing Effects of Neighborhood, Family, and School Cohesion Following Violence Exposure', *Journal of Early Adolescence*, 38(9), pp. 1286–1321. doi: 10.1177/0272431616675974.

Dincer, O. C. (2011) 'Trust and schooling in the United States', *Economics of Education Review*, 30(5), pp. 1097–1102. doi: 10.1016/j.econedurev.2011.05.014.

Diprete, T. A. (2007) 'What Has Sociology to Contribute to the Study of Inequality

Trends? A Historical and Comparative Perspective', *American Behavioral Scientist*, 50, pp. 603–618. doi: 10.1177/0002764206295009.

Donati, P. (2012) *Relational Sociology: A New Paradigm for the Social Sciences*. Routledge. doi: 10.1016/j.amepre.2013.09.008.Relational.

Donati, P. and Archer, M. S. (2015) 'Introduction relational sociology: Reflexive and realist', in *The Relational Subject*. Cambridge University Press, pp. 3–32. doi: 10.1017/CBO9781316226780.001.

Downward, P., Finch, J. H. and Ramsay, J. (2002) 'Critical Realism, Empirical Methods and Inference: A Critical Discussion', *Cambridge Journal of Economics*, 26(4). Available at: https://web.b.ebscohost.com/ehost/pdfviewer/pdfviewer?vid=2&sid=01924b66-675a-4bc1-b14f-0dbeab94cc48%40sessionmgr101 (Accessed: 12 May 2021).

Due, P. *et al.* (2009) 'Socioeconomic inequality in exposure to bullying during adolescence: A comparative, cross-sectional, multilevel study in 35 countries', *American Journal of Public Health*, 99(5), pp. 907–914. doi: 10.2105/AJPH.2008.139303.

Dumay, X. and Dupriez, V. (2008) 'Does the school composition effect matter? evidence from belgian data', *British Journal of Educational Studies*, 56(4), pp. 440–477. doi: 10.1111/j.1467-8527.2008.00418.x.

Durkheim (1897) *Le suicide: étude de sociologie*. Alcan.

Durkheim, É. (1925) *Moral education*. Mineola, N.Y. : Dover; Newton Abbot : David

& Charles, 2002. Available at: http://search.ebscohost.com/login.aspx?direct=true&db=cat01883a&AN=uea.003658253&authtype=sso&custid=s8993828&site=eds-live&scope=site.

Durlak, J. A. *et al.* (2011) 'The impact of enhancing students' social and emotional learning: A meta-analysis of school-based universal interventions', *Child Development*, 82(1), pp. 405–432. doi: 10.1111/j.1467-8624.2010.01564.x.

Easterbrook, M. and Vignoles, V. L. (2013) 'What does it mean to belong? Interpersonal bonds and intragroup similarities as predictors of felt belonging in different types of groups', *European Journal of Social Psychology*, 43(6), pp. 455–462. doi: 10.1002/EJSP.1972.

Echenique, F., Fryer Jr, R. G. and Kaufman, A. (2006) 'Is school segregation good or bad?', *American Economic Review*, 96(2), pp. 265–269.

Edgerton, J. D. and Roberts, L. W. (2014) 'Cultural capital or habitus? Bourdieu and beyond in the explanation of enduring educational inequality', *Theory and Research in Education*, 12(2), pp. 193–220. doi: 10.1177/1477878514530231.

Elgar, F. J. *et al.* (2009) 'Income Inequality and School Bullying: Multilevel Study of Adolescents in 37 Countries', *Journal of Adolescent Health*, 45(4), pp. 351–359. doi: 10.1016/j.jadohealth.2009.04.004.

Embretson, S. E. and Yang, X. (2006) 'Item Response Theory', in Green, J. et al. (eds) *Handbook of Complementary Methods in Education Research*. Routledge, pp. 385–409. doi: 10.4324/9780203874769.ch23.

Enders, C. K. and Tofighi, D. (2007) 'Centering Predictor Variables in Cross-Sectional Multilevel Models: A New Look at an Old Issue', *Psychological Methods*, 12(2), pp. 121–138. doi: 10.1037/1082-989X.12.2.121.

Esposito, L. and Villaseñor, A. (2018) 'Wealth Inequality, Educational Environment and School Enrolment: Evidence from Mexico', *Journal of Development Studies*, 54(11), pp. 2095–2118. doi: 10.1080/00220388.2017.1385768.

Esposito, L. and Villaseñor, A. (2019) 'Relative Deprivation and School Enrolment. Evidence from Mexico', *Review of Income and Wealth*, 65(1), pp. 166–186. doi: 10.1111/roiw.12344.

Esposito, L., Villaseñor, A. and Jacobs, R. (2021) 'Economic inequality and depressive symptoms: An individual versus aggregate-level analysis using Mexican survey data', *Journal of Epidemiology and Community Health*. doi: 10.1136/JECH-2020-214682.

Etzioni, A. (1995) *The spirit of community: rights, responsibilities and the communitarian agenda*. London : Fontana, 1995. Available at: http://search.ebscohost.com/login.aspx?direct=true&db=cat01883a&AN=uea.000959975&authtype=sso&custid=s8993828&site=eds-live&scope=site.

Etzioni, A. (2000) 'Creating good communities and good societies', *Contemporary Sociology*, 29(1), pp. 188–195.

Etzioni, A. (2002) 'The good society', *Seattle J. Soc. Just.*, 1, p. 83.

van Ewijk, R. and Sleegers, P. (2010) 'The effect of peer socioeconomic status on student achievement: A meta-analysis', *Educational Research Review*, 5(2), pp. 134–150. doi: 10.1016/j.edurev.2010.02.001.

Finn, J. D., Pannozzo, G. M. and Achilles, C. M. (2003) 'The "Why's" of Class Size: Student Behavior in Small Classes', *Review of Educational Research*, 73(3), pp. 321–368.

Fischer, G. H. (1995) 'The linear logistic test model', in *Rasch models*. Springer, pp. 131–155.

Fuller, B. and Izu, J. A. (1986) 'Explaining School Cohesion: What Shapes the Organizational Beliefs of Teachers?', *American Journal of Education*, 94(4), pp. 501–535.

Fuller, B., Waite, A. and Torres Irribarra, D. (2016) 'Explaining Teacher Turnover: School Cohesion and Intrinsic Motivation in Los Angeles', *American Journal of Education*, 122(4), pp. 537–567. doi: 10.1086/687272.

Galor, O. and Zeira, J. (1993) 'Income Distribution and Macroeconomics', *The Review of Economic Studies*, 60(1), pp. 35–52.

Gamoran, A. and An, B. P. (2016) 'Effects of school segregation and school resources in a changing policy context', *Educational Evaluation and Policy Analysis*, 38(1), pp. 43–64.

García-Peñalosa, C. (1995) 'The Paradox of Education or the Good Side of Inequality', *Oxford Economic Papers*, 47(2), pp. 265–285.

Gerber, J. P., Wheeler, L. and Suls, J. (2018) 'A social comparison theory meta-analysis 60+ years on', *Psychological Bulletin*, 144(2), pp. 177–197. doi: 10.1037/bul0000127.

Gilson, E. (1937) *The unity of philosophical experience.* Westminster, Md. : Christian Classics ; Dublin : Four Courts, 1982, c1965. Available at: http://search.ebscohost.com/login.aspx?direct=true&db=cat01883a&AN=uea.000748194&authtype=sso&custid=s8993828&site=eds-live&scope=site.

Glebbeek, M. L. and Koonings, K. (2016) 'Between Morro and Asfalto. Violence, insecurity and socio-spatial segregation in Latin American cities', *Habitat International*, 54, pp. 3–9. doi: 10.1016/j.habitatint.2015.08.012.

Glewwe, P., Jacoby, H. G. and King, E. M. (2001) 'Early childhood nutrition and academic achievement: A longitudinal analysis', *Journal of Public Economics*, 81(3), pp. 345–368. doi: 10.1016/S0047-2727(00)00118-3.

Goodenow, C. and Grady, K. E. (2010) 'The Relationship of School Belonging and Friends' Values to Academic Motivation Among Urban Adolescent Students', *http://dx.doi.org/10.1080/00220973.1993.9943831*, 62(1), pp. 60–71. doi: 10.1080/00220973.1993.9943831.

Goodman, E. *et al.* (2003) 'A multilevel analysis of the relation of socioeconomic status to adolescent depressive symptoms: Does school context matter?', *Journal of Pediatrics*, 143(4), pp. 451–456. doi: 10.1067/S0022-3476(03)00456-6.

Gorard, S. and Fitz, J. (2000) 'Investigating the determinants of segregation between schools', *Research Papers in Education*, 15(2), pp. 115–132. doi:

10.1080/026715200402452.

Gordillo, E. (2017) ‘Single-sex schooling and coeducation: the continuation of the debate and the defence of science’, *Revista Española de Pedagogía*, 75(267), pp. 255–271. doi: 10.22550/REP75-2-2017-05.

Gordillo, E., Calcina, R. R. and Gamero, G. J. (2014) ‘Conductas disruptivas en estudiantes de escuelas diferenciadas, coeducativas e intereducativas’, *Educación y Educadores*, 17(3).

Green, A. (2009) ‘Education, Inequality and Erosion of Social Cohesion’, *Forum*, 51(1), pp. 5–8. doi: 10.2304/forum.2009.51.1.5.

Green, A. and Janmaat, J. G. (2011) *Regimes of Social Cohesion: Societies and the Crisis of Globalisation*. London: Palgrave Macmillan UK.

Green, A. and Janmaat, J. G. (2016) ‘Education and Social Cohesion: A Panglossian Global Discourse’, *The Handbook of Global Education Policy*, (Oecd 2007), pp. 169–188.

Green, A., Preston, J. and Janmaat, J. G. (2006) *Educational, Inequality and Social Cohesion: A Comparative Analysis*. Edited by A. Green, J. Preston, and J. G. Janmaat. London: Palgrave Macmillan UK. doi: 10.1007/978-0-230-20745-5_3.

Greenwood, L. and Kelly, C. (2018) ‘A systematic literature review to explore how staff in schools describe how a sense of belonging is created for their pupils’, *https://doi.org/10.1080/13632752.2018.1511113*, 24(1), pp. 3–19. doi: 10.1080/13632752.2018.1511113.

Grek, S. (2009) ‘Governing by numbers: the PISA “effect” in Europe’, *Journal of Education Policy*, 24(1), pp. 22–37. doi: 10.1080/02680930802412669.

Grund, S., Lüdtke, O. and Robitzsch, A. (2021) ‘On the treatment of missing data in background questionnaires in educational large-scale assessments: An evaluation of different procedures’, *Journal of Educational and Behavioral Statistics*, 46(4), pp. 430–465.

Grusec, J. E. and Goodnow, J. J. (1994) ‘Impact of Parental Discipline Methods on the Child’s Internalization of Values: A Reconceptualization of Current Points of View’, *Developmental Psychology*, 30(1), pp. 4–19.

Gustavsson, M. and Jordahl, H. (2008) ‘Inequality and trust in Sweden: Some inequalities are more harmful than others’, *Journal of Public Economics*, 92(1–2), pp. 348–365. doi: 10.1016/j.jpubeco.2007.06.010.

Gutiérrez, G., Jerrim, J. and Torres, R. (2019) ‘School Segregation Across the World: Has Any Progress Been Made in Reducing the Separation of the Rich from the Poor?’, *Journal of Economic Inequality*. doi: 10.1007/s10888-019-09437-3.

Hackman, D. A., Farah, M. J. and Meaney, M. J. (2010) ‘Socioeconomic status and the brain: Mechanistic insights from human and animal research’, *Nature Reviews Neuroscience*. Nature Publishing Group, pp. 651–659. doi: 10.1038/nrn2897.

Hanushek, E. A. (2005) *Economic outcomes and school quality*. International Institute for Educational Planning.

Hanushek, E. A., Kain, J. F. and Rivkin, S. G. (2009) ‘New evidence about Brown v.

Board of Education: The complex effects of school racial composition on achievement', *Journal of labor economics*, 27(3), pp. 349–383.

Hanushek, E. A., Link, S. and Woessmann, L. (2013) 'Does school autonomy make sense everywhere? Panel estimates from PISA', *Journal of Development Economics*, 104, pp. 212–232. doi: 10.1016/j.jdeveco.2012.08.002.

Hastings, O. P. (2018) 'Less equal, less trusting? Longitudinal and cross-sectional effects of income inequality on trust in U.S. States, 1973–2012', *Social Science Research*, 74, pp. 77–95. doi: 10.1016/j.ssresearch.2018.04.005.

Hedges, L. V, Laine, R. D. and Greenwald, R. (1994) 'An exchange: Part I*: Does money matter? A meta-analysis of studies of the effects of differential school inputs on student outcomes', *Educational researcher*, 23(3), pp. 5–14.

Hemming, P. J. (2011) 'Meaningful encounters? Religion and social cohesion in the English primary school', *Social & Cultural Geography*, 12(1), pp. 63–81. doi: 10.1080/14649360903514384.

Hernandez, L., Oubrayrie-Roussel, N. and Prêteur, Y. (2016) 'Educational goals and motives as possible mediators in the relationship between social support and academic achievement', *European Journal of Psychology of Education*, 31, pp. 193–207. doi: 10.1007/s10212-015-0252-y.

Hey, J. D. and Lambert, P. J. (1980) 'Relative Deprivation and the Gini Coefficient: Comment', *The Quarterly Journal of Economics*, 95(3), p. 567. doi: 10.2307/1885094.

Heyneman, S. P. (2003) 'Education, Social Cohesion, and the Future Role of

International Organizations', *Peabody Journal of Education*, 78(3), pp. 25–38.

Hong, J. S. and Espelage, D. L. (2012) 'A review of research on bullying and peer victimization in school: An ecological system analysis', *Aggression and Violent Behavior*, 17(4), pp. 311–322. doi: 10.1016/j.avb.2012.03.003.

Hoover-Dempsey, K. V., Bassler, O. C. and Brissie, J. S. (1987) 'Parent Involvement: Contributions of Teacher Efficacy, School Socioeconomic Status, and Other School Characteristics', *American Educational Research Journal*, 24(3), pp. 417–435. doi: 10.3102/00028312024003417.

Hopfenbeck, T. N. *et al.* (2018) 'Lessons Learned from PISA: A Systematic Review of Peer-Reviewed Articles on the Programme for International Student Assessment', *Scandinavian Journal of Educational Research*, 62(3), pp. 333–353. doi: 10.1080/00313831.2016.1258726.

Hoskins, B., Janmaat, J. G. and Melis, G. (2017) 'Tackling inequalities in political socialisation: A systematic analysis of access to and mitigation effects of learning citizenship at school', *Social Science Research*, 68(September), pp. 88–101. doi: 10.1016/j.ssresearch.2017.09.001.

Van Houtte, M. (2005) 'Climate or culture? A plea for conceptual clarity in school effectiveness research', *School Effectiveness and School Improvement*, 16(1), pp. 71–89. doi: 10.1080/09243450500113977.

Hsu, H. Y. *et al.* (2015) 'Detecting Misspecified Multilevel Structural Equation Models with Common Fit Indices: A Monte Carlo Study', *Multivariate Behavioral*

Research, 50(2), pp. 197–215. doi: 10.1080/00273171.2014.977429.

Hu, L. T. and Bentler, P. M. (1999) 'Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives', *Structural Equation Modeling*, 6(1), pp. 1–55. doi: 10.1080/10705519909540118.

Hutchens, R. (2004) 'One Measure of Segregation', *International Economic Review*, 45(2), pp. 555–578.

Iniguez-Montiel, A. J. (2014) 'Growth with equity for the development of Mexico: Poverty, inequality, and economic growth (1992-2008)', *World Development*, 59, pp. 313–326. doi: 10.1016/j.worlddev.2014.01.011.

Janmaat, J. G. (2020) 'School social segregation and social inequalities in political engagement among 16 to 20 year olds in fourteen countries'. doi: 10.1080/02671522.2020.1789716.

Jenson, J. (1998) *Mapping Social Cohesion: The State of Canadian Research*, *Canadian Policy Research Networks Inc*. doi: 10.1007/s13398-014-0173-7.2.

Jerrim, J., Lopez-Agudo, L. A., Marcenaro-Gutierrez, O. D., *et al.* (2017) 'To weight or not to weight?: the case of PISA data', in *Proceedings of the XXVI Meeting of the Economics of Education Association, Murcia, Spain*, pp. 29–30.

Jerrim, J., Lopez-Agudo, L. A., Marcenaro-Gutierreza, O., *et al.* (2017) 'What happens when econometrics and psychometrics collide? An example using the PISA data', *Economics of Education Review*, 61, pp. 51–58.

Jiménez-Barbero, J. A. *et al.* (2016) 'Effectiveness of anti-bullying school programs:

A meta-analysis', *Children and Youth Services Review*, 61, pp. 165–175. doi: 10.1016/j.childyouth.2015.12.015.

Kalwij, A. and Verschoor, A. (2007) 'Not by growth alone: The role of the distribution of income in regional diversity in poverty reduction', *European Economic Review*, 51(4), pp. 805–829. doi: 10.1016/j.euroecorev.2006.06.003.

Kant, I. (1836) *The Metaphysic of ethics*. Edited by T. Clark.

Kaplan, D. and Su, D. (2018) 'On imputation for planned missing data in context questionnaires using plausible values: a comparison of three designs', *Large-Scale Assessments in Education*, 6(1), pp. 1–31.

Kawachi, I. *et al.* (1996) 'Social Capital, Income Inequality, and Mortality', *American Journal of Public Health*, 87(9), pp. 1491–1498. Available at: https://ajph.aphapublications.org/doi/pdf/10.2105/AJPH.87.9.1491 (Accessed: 12 May 2021).

Kaztman, F. and Retamoso, A. (2007) 'Efectos de la segregación urbana sobre la educación en Montevideo', *Revista de la CEPAL*, 2007(91), pp. 133–152. doi: 10.18356/81526422-es.

Kelly, M. (2000) 'Inequality and crime', *The Review of Economics and Statistics*, 82(4), pp. 530–539. doi: 10.4324/9781843926634.

Kenworthy, L. (2007) 'Inequality and Sociology', *American Behavioral Scientist*, 50, pp. 584–602. doi: 10.1177/0002764206295008.

Kingston, P. W. (2008) 'The Unfulfilled Promise of Cultural Capital', *Sociology of*

Education, 74(2001), pp. 88–99.

Klein, C. (2013) 'Social Capital or Social Cohesion: What Matters For Subjective Well-Being?', *Soc Indic Res*, 110, pp. 891–911. doi: 10.1007/s11205-011-9963-x.

Kohlberg, L. (1981) 'The philosophy of moral development : moral stages and the idea of justice', p. 441.

Korpershoek, H. *et al.* (2019) 'The relationships between school belonging and students' motivational, social-emotional, behavioural, and academic outcomes in secondary education: a meta-analytic review', *https://doi.org/10.1080/02671522.2019.1615116*, 35(6), pp. 641–680. doi: 10.1080/02671522.2019.1615116.

Krivo, L. J. *et al.* (2013) 'Social isolation of disadvantage and advantage: The Reproduction of Inequality in Urban Space', *Social Forces*, 92(1), pp. 141–164. doi: 10.1093/sf/sot043.

Krueger, A. B. and Lindahl, M. (2001) 'Education for growth: Why and for whom?', *Journal of economic literature*, 39(4), pp. 1101–1136.

Kuhn, A. (2019) 'The subversive nature of inequality: Subjective inequality perceptions and attitudes to social inequality', *European Journal of Political Economy*, 59, pp. 331–344. doi: 10.1016/j.ejpoleco.2019.04.004.

Kyriacou, A. and Trivin, P. (2020) 'Economic development, inequality and generalized trust', *Economics Bulletin*, 40(1). Available at: https://dugi-doc.udg.edu/handle/10256/17722 (Accessed: 9 November 2021).

Lakner, C. *et al.* (2019) *How Much Does Reducing Inequality Matter for Global Poverty?*, *How Much Does Reducing Inequality Matter for Global Poverty?* 8869. doi: 10.1596/33902.

Lalive, R. and Cattaneo, M. A. (2009) 'Social interactions and schooling decisions', *Review of Economics and Statistics*, 91(3), pp. 457–477. doi: 10.1162/rest.91.3.457.

Layte, R. (2012) 'The association between income inequality and mental health: Testing status anxiety, social capital, and neo-materialist explanations', *European Sociological Review*. Oxford Academic, pp. 498–511. doi: 10.1093/esr/jcr012.

Lee, J.-S. and Bowen, N. K. (2006) 'Parent Involvement, Cultural Capital, and the Achievement Gap Among Elementary School Children', *American Educational Research Journal*, 43(2), pp. 193–218. doi: 10.3102/00028312043002193.

Lee, S. S. and Von Davier, M. (2020) 'Improving measurement properties of the PISA home possessions scale through partial invariance modeling', *Psychological Test and Assessment Modeling*, 62(1), pp. 55–83. Available at: https://repository.upenn.edu/edissertations/3310/ (Accessed: 1 January 2021).

Lenzi, M. *et al.* (2012) 'Family Affluence, School and Neighborhood Contexts and Adolescents' Civic Engagement: A Cross-National Study', *American Journal of Community Psychology*, 50(1–2), pp. 197–210. doi: 10.1007/s10464-012-9489-7.

Lindemann, K. and Saar, E. (2014) 'Contextual effects on subjective social position: Evidence from European countries', *International Journal of Comparative Sociology*, 55(1), pp. 3–23. doi: 10.1177/0020715214527101.

LINDENBERG, S. (1977) 'The Direction of Ordering and Its Relation to Social Phenomena', *Zeitschrift für Soziologie*, 6(2), pp. 203–221.

Logan, J. R. and Burdick-Will, J. (2017) 'School Segregation and Disparities in Urban, Suburban, and Rural Areas', *Annals of the American Academy of Political and Social Science*, 674(1), pp. 199–216. doi: 10.1177/0002716217733936.

MacIntyre, A. (2020) *Whose justice? Which rationality?* Edited by Routledge.

Mackie, J.L.: The cement of the universe. A study of causation. Clarendon Press, Oxford (1974)

MacNeil, A. J., Prater, D. L. and Busch, S. (2009) 'The effects of school culture and climate on student achievement', *International Journal of Leadership in Education*, 12(1), pp. 73–84. doi: 10.1080/13603120701576241.

Maddox, S. J. and Prinz, R. J. (2003) 'School bonding in children and adolescents: Conceptualization, assessment, and associated variables', *Clinical Child and Family Psychology Review*, 6(1), pp. 31–49. doi: 10.1023/A:1022214022478.

Malatinszky, A. and Armor, D. J. (2021) 'Comment on M.G. Sciffer, L.B. Perry, & A.M. McConney, "critiques of socio-economic school compositional effects: are they valid?"', *British Journal of Sociology of Education*. doi: 10.1080/01425692.2021.1929843.

Mang, J. *et al.* (2021) 'Sampling weights in multilevel modelling: an investigation using PISA sampling structures', *Large-Scale Assessments in Education*, 9(1). doi: 10.1186/s40536-021-00099-0.

Marks, G. N. (2006) 'Are between- and within-school differences in student performance largely due to socio-economic background? Evidence from 30 countries', *Educational Research*, 48(1), pp. 21–40. doi: 10.1080/00131880500498396.

Marks, G. N. (2021) 'School socioeconomic-background effects are generally small: a response to Sciffer, Perry, and McConney', *British Journal of Sociology of Education*. doi: 10.1080/01425692.2021.1929842.

Massey, D. S. and Denton, N. A. (1988) 'The dimensions of residential segregation', *Social Forces*, 67(2), pp. 281–315. doi: 10.1093/sf/67.2.281.

Mayer, S. E. (1997) *What money can't buy: Family income and children's life chances*. Harvard University Press.

McKenzie, D. J. (2005) 'Measuring inequality with asset indicators', *Journal of Population Economics*, 18, pp. 229–260. doi: 10.1007/s00148-005-0224-7.

McLoyd, V. C. (1990) 'The Impact of Economic Hardship on Black Families and Children: Psychological Distress, Parenting, and Socioemotional Development', *Child Development*, 61(2), pp. 311–346. doi: 10.1111/J.1467-8624.1990.TB02781.X.

Merlo, J., Viciana-Fernández, F. J. and Ramiro-Fariñas, D. (2012) 'Bringing the individual back to small-area variation studies: A multilevel analysis of all-cause mortality in Andalusia, Spain', *Social Science and Medicine*, 75(8), pp. 1477–1487. doi: 10.1016/j.socscimed.2012.06.004.

Merrell, K. W. *et al.* (2008) 'How Effective Are School Bullying Intervention

Programs? A Meta-Analysis of Intervention Research', *School Psychology Quarterly*, 23(1), pp. 26–42. doi: 10.1037/1045-3830.23.1.26.

Merton, R. K. (1957) 'Social structure and anomie', *Social Theory and*.

Mickelson, R. A. and Nkomo, M. (2012) 'Integrated Schooling, Life Course Outcomes, and Social Cohesion in Multiethnic Democratic Societies', *Review of Research in Education*, 36(1), pp. 197–238. doi: 10.3102/0091732X11422667.

Mikulyuk, A. B. and Braddock, J. H. (2018) *K-12 School Diversity and Social Cohesion: Evidence in Support of a Compelling State Interest*, *Education and Urban Society*. doi: 10.1177/0013124516678045.

Mill, J. S. *et al.* (2003) *Utilitarianism: and, On liberty: including Mill's Essay on Bentham' and selections from the writings of Jeremy Bentham and John Austin.* Oxford : Blackwell, 2003. Available at: http://search.ebscohost.com/login.aspx?direct=true&db=cat01883a&AN=uea.003067596&authtype=sso&custid=s8993828&site=eds-live&scope=site.

Mochizuki, Y. (2016) 'Educating for Transforming Our World: Revisiting International Debates Surrounding Education for Sustainable Development', *Current Issues in Comparative Education*, 19(1), pp. 109–125. Available at: http://libproxy.library.wmich.edu/login?url=https://search.proquest.com/docview/1895975872?accountid=15099.

Mooij, T., Smeets, E. and de Wit, W. (2011) 'Multi-level aspects of social cohesion of secondary schools and pupils' feelings of safety', *British Journal of Educational*

Psychology, 81(3), pp. 369–390. doi: 10.1348/000709910X526614.

Morande, P. (1996) 'Social inequality in the Social Sciences', in *The Study of the Tension Between Human Equality and Social Inequalities. From the Perspective of the Various Social Sciences*. Vatican City.

Morris, K. S. *et al.* (2020) 'Racial discrimination stress, school belonging, and school racial composition on academic attitudes and beliefs among black youth', *Social Sciences*, 9(11), pp. 1–20. doi: 10.3390/socsci9110191.

Morrison, T. G., Morrison, M. A. and McCutcheon, J. M. (2017) 'Best Practice Recommendations for Using Structural Equation Modelling in Psychological Research', *Psychology*, 08(09), pp. 1326–1341. doi: 10.4236/psych.2017.89086.

Muraki, E. (1992) *A generalized partial credit model: Application of an EM algorithm*, *ETS Research Report Series*. Princeton.

Napoletano, A. *et al.* (2016) 'The View From the Bottom: Relative Deprivation and Bullying Victimization in Canadian Adolescents', *Journal of Interpersonal Violence*, 31(20), pp. 3443–3463. doi: 10.1177/0886260515585528.

Nash, R. (1990) 'Bourdieu on Education and Social and Cultural Reproduction', *British Journal of Sociology of Education*, 11(4), pp. 431–447. doi: 10.1080/0142569900110405.

Nash, R. (2003) 'Inequality/difference in education: Is a real explanation of primary and secondary effects possible?', *British Journal of Sociology*, 54(4), pp. 433–451. doi: 10.1080/0007131032000143537.

Nieuwenhuis, J. *et al.* (2013) 'Neighbourhood effects on school achievement: The mediating effect of parenting and problematic behaviour?', *Environment and Planning A*, 45(9), pp. 2135–2153. doi: 10.1068/a45367.

Nozick, R. (1974) *Anarchy, state, and utopia*. New York: Basic Books.

Nygärd, F. and Sandström, A. (1985) 'The estimation of the Gini and the entropy inequality parameters in finite populations', *Journal of Official Statistics*, 1(4), pp. 399–426.

O'Neill, J. and Vogel, M. (2020) 'School Cohesion Perception Discrepancy and Student Delinquency', *Journal of Youth and Adolescence*, 49(7), pp. 1492–1502. doi: 10.1007/s10964-019-01170-4.

Oder, E. (2005) 'The Social Cohesion Role of Educational Organizations: Primary and Secondary Schools', *Peabody Journal of Education*, 80(4), pp. 78–88. doi: 10.1287/isre.

OECD (2009) *PISA Data Analysis Manual*. 2nd edn. doi: 10.1109/ICBN.2005.1589722.

OECD (2014) *PISA 2012 Technical Report Programme for International Student Assessment*.

OECD (2016) *PISA 2015 Results (Volume I): Excellence and Equity in Education*. Paris.

OECD (2017a) *PISA 2015 Results (Volume III): Students' well-being*. Paris. doi: 10.1787/9789264273856-en.

OECD (2017b) *PISA 2015 Technical Report, OECD Publishing*. Paris.

OECD (2018) *Equity in Education: Breaking down barriers to social mobility*. Paris: OECD publishing. doi: 10.1787/9789264073234-en.

OECD (2019a) *PISA 2018 Results: combined executive summaries*. Paris.

OECD (2019b) *PISA 2018 Results (Volume III): What school life means for students' lives*, *Oecd*. Paris: OECD publishing. doi: https://doi.org/10.1787/acd78851-en.

OECD (2020) *PISA 2018 Technical Report*. Available at: https://www.oecd.org/pisa/data/pisa2018technicalreport/ (Accessed: 11 September 2021).

Oppedisano, V. and Turati, G. (2015) 'What are the causes of educational inequality and of its evolution over time in Europe? Evidence from PISA', *Education Economics*, 23(1), pp. 3–24. doi: 10.1080/09645292.2012.736475.

Osterman, K. F. (2016) 'Students' Need for Belonging in the School Community:', *http://dx.doi.org.uea.idm.oclc.org/10.3102/00346543070003323*, 70(3), pp. 323–367. doi: 10.3102/00346543070003323.

Oyserman, D. (2013) 'Not just any path: Implications of identity-based motivation for disparities in school outcomes', *Economics of Education Review*, 33, pp. 179–190. doi: 10.1016/j.econedurev.2012.09.002.

Pabayo, R. *et al.* (2014) 'School social fragmentation, economic deprivation and social cohesion and adolescent physical inactivity: A longitudinal study', *PLoS ONE*, 9(6). doi: 10.1371/journal.pone.0099154.

Passas, N. (1997) 'Anomie, reference groups and relative deprivation', in Passas, N. and Agnew, R. (eds) *The Future of Anomie Theory*. Boston: Northeastern University Press. doi: 10.2307/2654956.

Perotti, R. (1993) 'Political Equilibrium, Income Distribution, and Growth', *The Review of Economic Studies*, 60(4), pp. 755–776. doi: 10.2307/2298098.

Perry, L. B. and McConney, A. (2010) 'Does the SES of the school matter? An examination of socioeconomic status and student achievement using PISA 2003', *Teachers College Record*, 112(4), pp. 1137–1162.

Pickett, K. E. and Wilkinson, R. G. (2015) 'Income inequality and health: A causal review', *Social Science and Medicine*, 128, pp. 316–326. doi: 10.1016/j.socscimed.2014.12.031.

Piketty, T. (2015) 'About Capital in the Twenty-First Century', *American Economic Review*, 105(5), p. pp.48-53.

Pohl, S. and Becker, B. (2020) 'Performance of missing data approaches under nonignorable missing data conditions', *Methodology*, 16(2), pp. 147–165.

Pokropek, A. (2015) 'Phantom Effects in Multilevel Compositional Analysis: Problems and Solutions', *Sociological Methods & Research*, 44(4), pp. 677–705. doi: 10.1177/0049124114553801.

Preacher, K. J., Zyphur, M. J. and Zhang, Z. (2010) 'A general multilevel SEM framework for assessing multilevel mediation.', *Psychological methods*, 15(3), pp. 209–233. doi: 10.1037/a0020141.

Putnam, R. D. (2007) 'E Pluribus Unum: Diversity and Community in the Twenty-first Century The 2006 Johan Skytte Prize Lecture.', *Scandinavian Political Studies*, 30(2), pp. 137–174. Available at: http://10.0.4.87/j.1467-9477.2007.00176.x.

R Core Team (2020) 'R: A language and environment for statistical computing. R Foundation for Statistical Computing'. Vienna, Austria: R Foundation for Statistical Computing.

Rabe-Hesketh, S. and Skrondal, A. (2006) 'Multilevel modelling of complex survey data', *Journal of the Royal Statistical Society. Series A: Statistics in Society*, 169(4), pp. 805–827. doi: 10.1111/j.1467-985X.2006.00426.x.

Rasch, G. (1960) *Studies in mathematical psychology: I. Probabilistic models for some intelligence and attainment tests.* Copenhagen: Danmarks Paedag-ogiske Institut.

Ravallion, M. and Chen, S. (2007) 'China's (uneven) progress against poverty', *Journal of Development Economics*, 82(1), pp. 1–42. doi: 10.1016/j.jdeveco.2005.07.003.

Reimer, J. (1977) 'A Structural Theory of Moral Development', 16(2), pp. 60–66.

Roberts, B. R. (2011) 'The consolidation of the Latin American city and the undermining of social cohesion', *City and Community*, 10(4), pp. 414–423. doi: 10.1111/j.1540-6040.2011.01378.x.

Robitzsch, A. and Oberwimmer, K. (2015) 'BIFIEsurvey: tools for survey statistics in educational assessment', *R package version*, pp. 1–2.

Rose, P. (2015) 'Three lessons for educational quality in post-2015 goals and targets: Clarity, measurability and equity', *International Journal of Educational Development*, 40, pp. 289–296. doi: 10.1016/j.ijedudev.2014.11.006.

Rosseel, Y. (2012) 'lavaan: An R Package for Structural Equation Modeling.', *Journal of Statistical Software*, 48(2), pp. 1–36.

RStudio Team (2020) 'RStudio: Integrated Development Environment for R'. Boston, MA. Available at: http://www.rstudio.com/.

Rubin, D. (1987) *Multiple imputation for nonresponse in sample surveys*. New York: John Wiley.

Rumberger, R. W. and Palardy, G. J. (2005) 'Does segregation still matter? The impact of student composition on academic achievement in high school', *Teachers College Record*, 107(9), pp. 1999–2045. doi: 10.1111/j.1467-9620.2005.00583.x.

Runciman, W. G. (1966) *Relative deprivation and social justice: A study of attitudes to social inequality in twentieth-century England*. Routledge & Kegan Paul.

Rutkowski, D. *et al.* (2018) 'Poverty and educational achievement in the US: A less-biased estimate using PISA 2012 data', *Journal of Children and Poverty*, 24(1), pp. 47–67. doi: 10.1080/10796126.2017.1401898.

Rutkowski, D. and Rutkowski, L. (2013) 'Measuring socioeconomic background in PISA: One size might not fit all', *Research in Comparative and International Education*, 8(3), pp. 259–278. doi: 10.2304/rcie.2013.8.3.259.

Rutkowski, L. *et al.* (2010) 'International Large-Scale Assessment Data: Issues in

Secondary Analysis and Reporting', *Educational Researcher*, 39(2), pp. 142–151. doi: 10.3102/0013189X10363170.

Rutkowski, L. (2011) 'The Impact of Missing Background Data on Subpopulation Estimation', *Journal of Educational Measurement*, 48(3), pp. 293–312. doi: 10.1111/j.1745-3984.2011.00144.x.

Rutkowski, L. (2014) 'Applied Measurement in Education Sensitivity of Achievement Estimation to Conditioning Model Misclassification'. doi: 10.1080/08957347.2014.880440.

Rutkowski, L. and Rutkowski, D. (2010) 'Getting it "better": The importance of improving background questionnaires in international large-scale assessment', *Journal of Curriculum Studies*, 42(3), pp. 411–430. doi: 10.1080/00220272.2010.487546.

Rutkowski, L. and Zhou, Y. (2015) 'The Impact of Missing and Error-Prone Auxiliary Information on Sparse-Matrix Sub-Population Parameter Estimates', *Methodology*, 11(3), pp. 89–99. doi: 10.1027/1614-2241/a000095.

Ryabov, I. and Van Hook, J. (2007) 'School segregation and academic achievement among Hispanic children', *Social Science Research*, 36(2), pp. 767–788.

Salahuddin, M. *et al.* (2016) 'Does Parents' Social Cohesion Influence Their Perception of Neighborhood Safety and Their Children's Active Commuting to and From School?', *Journal of Physical Activity and Health*, 13(12), pp. 1301–1309. doi: 10.1123/jpah.2016-0148.

Sampson, R. J. and Groves, W. B. (1989) ‘Community Structure and Crime: Testing Social-Disorganization Theory’, *American Journal of Sociology*, 94(4), pp. 774–802.

Sandoval-Hernandez, A. *et al.* (2019) ‘“Back to the drawing board: Can we compare background scales?”’, *Revista de Educación*, 383, pp. 37–61. doi: 10.4438/1988-592X-RE-2019-383-400.

Scherer, R. (2020) ‘The Case for Good Discipline? Evidence on the Interplay Between Disciplinary Climate, Socioeconomic Status, and Science Achievement from PISA 2015’, in *Equity, Equality and Diversity in the Nordic Model of Education*. Springer International Publishing, pp. 197–224. doi: 10.1007/978-3-030-61648-9_8.

Schiefer, D. and van der Noll, J. (2017) ‘The Essentials of Social Cohesion: A Literature Review’, *Social Indicators Research*, 132(2), pp. 579–603. doi: 10.1007/s11205-016-1314-5.

Schleicher, A. (2019) ‘PISA 2018. Insights and interpretations’, *OECD Publishing*, p. 61. Available at: https://www.oecd.org/pisa/PISA 2018 Insights and Interpretations FINAL PDF.pdf.

Schneider, S. M. (2012) ‘Income Inequality and its Consequences for Life Satisfaction: What Role do Social Cognitions Play?’, *Social Indicators Research*, 106(3), pp. 419–438. doi: 10.1007/s11205-011-9816-7.

Schneider, S. M. (2016) ‘Income Inequality and Subjective Wellbeing: Trends, Challenges, and Research Directions’, *Journal of Happiness Studies*, 17(4), pp. 1719–1739. doi: 10.1007/s10902-015-9655-3.

Schneider, S. M. (2019) ‘Why Income Inequality Is Dissatisfying - Perceptions of Social Status and the Inequality-Satisfaction Link in Europe’, *European Sociological Review*, 35(3), pp. 409–430. doi: 10.1093/esr/jcz003.

Schulz, W. *et al.* (2017) *Becoming Citizens in a Changing World. IEA International Civic and Citizenship Education Study 2016 International Report*. Springer. doi: 10.1007/978-3-319-73963-2.

Sciffer, M. G., Perry, L. B. and McConney, A. (2020) ‘Critiques of socio-economic school compositional effects: are they valid?’, *British Journal of Sociology of Education*, 41(4), pp. 462–475. doi: 10.1080/01425692.2020.1736000.

Sciffer, M. G., Perry, L. B. and McConney, A. (2021) ‘Appropriate modelling of school compositional effects: a response to Malatinszky and Armor, and Marks’, *British Journal of Sociology of Education*, 42, pp. 627–632. doi: 10.1080/01425692.2021.1959301.

Sempé, L. (2021) ‘School-level inequality measurement based categorical data: a novel approach applied to PISA’, *Large-Scale Assessments in Education*, 9(1), pp. 1–31. doi: 10.1186/s40536-021-00103-7.

Sen, A. and Foster, J. (1997) *On economic inequality*. Oxford University Press.

Siddiqi, A. *et al.* (2012) ‘Education determines a nation’s health, but what determines educational outcomes? A cross-national comparative analysis’, *Journal of Public Health Policy*, 33(1), pp. 1–15. doi: 10.1057/jphp.2011.52.

Sirin, S. R. (2005) ‘Socioeconomic status and academic achievement: a meta-analytic review of research', *Review of Educational Research*, 75(3), pp. 417–453. doi: 10.3102/00346543075003417.

Sjøberg, S. (2015) 'PISA and Global Educational Governance – A Critique of the Project, its Uses and Implications', *Eurasia Journal of Mathematics, Science and Technology Education*, 11(1), pp. 111–127. doi: 10.12973/eurasia.2015.1310a.

Slaten, C. D. *et al.* (2016) 'School belonging: A review of the history, current trends, and future directions', *Educational and Developmental Psychologist*, 33(1), pp. 1–15. doi: 10.1017/edp.2016.6.

Smith, E. (2003) 'Ethos, Habitus and Situation for Learning: An ecology', *British Journal of Sociology of Education*, 24(4), pp. 463–470. doi: 10.1080/01425690301916.

Smith, N. L. (1994) 'Clarifying and Expanding the Application of Program Theory-driven Evaluations', *American Journal of Evaluation*, 15(1), pp. 83–87. doi: 10.1177/109821409401500110.

Springer, A. E. *et al.* (2016) 'School social cohesion, student-school connectedness, and bullying in Colombian adolescents', *Global Health Promotion*, 23(4), pp. 37–48. doi: 10.1177/1757975915576305.

Stewart, F. (2002) *Horizontal Inequalities : A Neglected Dimension of Development*, *QEH Working Paper Series*. doi: 10.1057/9780230501850_5.

Stewart, F. (2014) 'Why Horizontal Inequalities are Important for a Shared Society', *Development*, 57(1), pp. 46–54. doi: 10.1057/dev.2014.30.

Strulik, H. (2013) 'School Attendance and Child Labor—A Model Of Collective

Behavior', *Journal of the European Economic Association*, 11(2), pp. 246–277. doi: 10.1111/JEEA.12008.

Sullivan, A. (2002) 'Bourdieu and education: How useful is Bourdieu's theory for researchers?', *The Netherlands' Joumal of Social Sciences*, 38(2), pp. 144–166.

Suls, J., Martin, R. and Wheeler, L. (2002) 'Social comparison: Why, with whom, and with what effect?', *Current Directions in Psychological Science*, 11(5), pp. 159–163. doi: 10.1111/1467-8721.00191.

Tabane, R. and Human-Vogel, S. (2010) 'Sense of belonging and social cohesion in a desegregated former House of Delegates school', *South African Journal of Education*, 30(3), pp. 491–504. Available at: http://www.scielo.org.za/scielo.php?script=sci_arttext&pid=S0256-01002010000300010.

Taylor, C. (1992) *The ethics of authenticity*. Edited by H. U. Press.

Thapa, A. *et al.* (2013) 'A Review of School Climate Research', *Review of Educational Research*, 83(3), pp. 357–385. doi: 10.3102/0034654313483907.

Thomas, V., Wang, Y. and Fan, X. (2001) *Measuring Education Inequality. Gini Coefficients of Education*. 2525.

Thorbecke, E. and Charumilind, C. (2002) 'Economic inequality and its socioeconomic impact', *World Development*, 30(9), pp. 1477–1495. doi: 10.1016/S0305-750X(02)00052-9.

Thrupp, M., Lauder, H. and Robinson, T. (2002) 'School composition and peer effects', *International Journal of Educational Research*, 37(5), pp. 483–504. doi: 10.1016/S0883-0355(03)00016-8.

Tivadar, M. (2019) 'OasisR: An R Package to Bring Some Order to the World of Segregation Measurement', *Journal of Statistical Software*, 89(7), pp. 1–39.

Tzanakis, M. (2011) 'Bourdieu's social reproduction thesis and the role of cultural capital in educational attainment: A critical review of key empirical studies', *Educate~*, 11(1), pp. 76–90. doi: 10.1080/0142569900110405.

UNESCO (2015) 'Incheon Declaration. Education 2030'.

UNESCO (2016) *New agreement to measure global citizenship and sustainable development education*. Available at: https://en.unesco.org/news/new-agreement-measure-global-citizenship-and-sustainable-development-education (Accessed: 6 December 2017).

UNESCO (2021) *Education: From disruption to recovery*. Available at: https://en.unesco.org/covid19/educationresponse (Accessed: 23 November 2021).

United Nations (2015) 'Transforming our world: the 2030 Agenda for Sustainable Development', *General Assembly 70 session*, 16301(October), pp. 1–35. doi: 10.1007/s13398-014-0173-7.2.

United Nations Development Program (2019) *Human Development Report 2019: beyond income, beyond averages, beyond today*.

Valenzuela, J. P., Bellei, C. and Ríos, D. de los (2014) 'Socioeconomic school segregation in a market-oriented educational system. The case of Chile', *Journal of* *education Policy*, 29(2), pp. 217–241.

Walford, G. and Pickering, W. S. F. (1998) *Durkheim and modern education.* London : Routledge, 1998 (Routledge international studies in the philosophy of education: 6). Available at: http://search.ebscohost.com/login.aspx?direct=true&db=cat01883a&AN=uea.001058344&authtype=sso&custid=s8993828&site=eds-live&scope=site.

Walker, S. P. *et al.* (2011) 'Inequality in early childhood: Risk and protective factors for early child development', *The Lancet*. Lancet, pp. 1325–1338. doi: 10.1016/S0140-6736(11)60555-2.

Walsemann, K. M. and Bell, B. A. (2010) 'Integrated schools, segregated curriculum: effects of within-school segregation on adolescent health behaviors and educational aspirations', *American journal of public health*, 100(9), pp. 1687–1695.

Wang, M.-T. and Degol, J. L. (2016) *School Climate: a Review of the Construct, Measurement, and Impact on Student Outcomes*, *Educational Psychology Review*. Educational Psychology Review. doi: 10.1007/s10648-015-9319-1.

Ward, M. (2018) 'PISA for development: Results in focus'.

Warm, T. A. (1989) 'Weighted likelihood estimation of ability in item response theory', *Psychometrika*, 54(3), pp. 427–450.

Wentzel, K. R. and Looney, L. (2007) 'Socialization in school settings', *Handbook of socialization: Theory and research*, (2014), pp. 382–403.

van de Werfhorst, H. G. (2010) 'Cultural capital: Strengths, weaknesses and two advancements', *British Journal of Sociology of Education*, 31(2), pp. 157–169. doi: 10.1080/01425690903539065.

Wilkinson, R. G. and Pickett, K. E. (2006) 'Income inequality and population health: A review and explanation of the evidence', *Social Science and Medicine*, 62(7), pp. 1768–1784. doi: 10.1016/j.socscimed.2005.08.036.

Wilkinson, R. G. and Pickett, K. E. (2007) 'The problems of relative deprivation: Why some societies do better than others', *Social Science and Medicine*, 65(9), pp. 1965–1978. doi: 10.1016/j.socscimed.2007.05.041.

Willms, D. (2006) *Learning Divides: Ten policy questions about the performance and equity of schools and schooling systems*. t. Montreal. doi: 10.1369/jhc.5A6745.2005.

Willms, J. D. (2010) 'School composition and contextual effects on student outcomes', *Teachers College Record*, 112(4), pp. 1008–1037.

Willms, J. D. and Somer, M.-A. (2001) 'Family, Classroom, and School Effects on Childrens Educational Outcomes in Latin America', *School Effectiveness and School Improvement*, 12(4), pp. 409–445. doi: 10.1076/sesi.12.4.409.3445.

World Bank (2018) *World development report 2018. Learning to realise education´s promise*. Washington D.C. doi: 10.1596/978-1-4648-1097-8.

Wright, E. O. and Rogers, J. (2011) *American Society: how it really works*. New York: WW Norton & Company.

Yitzhaki, S. (1979) ‘Relative Deprivation and the Gini Coefficient’, *The Quarterly Journal of Economics*, 93(2), p. 321. doi: 10.2307/1883197.

Zeileis, A. (2014) ‘ineq: Measuring Inequality, Concentration, and Poverty’.

Zheng, B. (2008) *Measuring inequality with ordinal data: A note, Research on Economic Inequality*. Elsevier. doi: 10.1016/S1049-2585(08)16008-2.

Zheng, B. (2011) ‘A new approach to measure socioeconomic inequality in health’, *Journal of Economic Inequality*, 9(4), pp. 555–577. doi: 10.1007/s10888-010-9148-x.

Zheng, X. and Yang, J. S. (2016) ‘Using sample weights in item response data analysis under complex sample designs’, in *Springer Proceedings in Mathematics and Statistics*. Springer New York LLC, pp. 123–137. doi: 10.1007/978-3-319-38759-8_10.

8. Annexes

8.1. Chapter 2

Table 22: Country ISO Code

CNT	Country Name	CNT	Country Name
AZE	Azerbaijan	CHE	Switzerland
ARG	Argentina	THA	Thailand
AUS	Australia	TUN	Tunisia
AUT	Austria	TUR	Turkey
BEL	Belgium	GBR	United Kingdom
BRA	Brazil	USA	United States
BGR	Bulgaria	URY	Uruguay
CAN	Canada	ALB	Albania
CHL	Chile	QCN	Shanghai-China
TAP	Chinese Taipei	KAZ	Kazakhstan
COL	Colombia	PAN	Panama
HRV	Croatia	PER	Peru
CZE	Czechia	SGP	Singapore
DNK	Denmark	TTO	Trinidad & Tobago
EST	Estonia	CRI	Costa Rica
FIN	Finland	GEO	Georgia
FRA	France	MDA	Moldova
DEU	Germany	MLT	Malta
GRC	Greece	MUS	Mauritius
HKG	Hong Kong SAR China	MYS	Malaysia
HUN	Hungary	QHP	Himachal Pradesh-India
ISL	Iceland	QTN	Tamil Nadu-India

IDN	Indonesia	QVE	Miranda-Venezuela
IRL	Ireland	ARE	United Arab Emirates
ISR	Israel	QRS	Perm(Russian Federation)
ITA	Italy	VNM	Vietnam
JPN	Japan	DZA	Algeria
JOR	Jordan	DOM	Dominican Republic
KOR	South Korea	KSV	Kosovo
KGZ	Kyrgyzstan	LBN	Lebanon
LVA	Latvia	MKD	Macedonia
LIE	Liechtenstein	QCH	B-S-J-G (China)
LTU	Lithuania	QES	Spain (Regions)
LUX	Luxembourg	QAR	Argentina (Ciudad Autónoma de Buenos)
MAC	Macau SAR China	QUC	Massachusettes (USA)
MEX	Mexico	QUE	North Carolina (USA)
MNE	Montenegro	QUD	Puerto Rico (USA)
NLD	Netherlands	BIH	Bosnia & Herzegovina
NZL	New Zealand	BLR	Belarus
NOR	Norway	BRN	Brunei
POL	Poland	MAR	Morocco
PRT	Portugal	PHL	Philippines
QAT	Qatar	QAZ	Baku (Azerbaijan)
ROU	Romania	QCI	B-S-J-Z (China)
RUS	Russia	QMR	Moscow Region (RUS)
SRB	Serbia	QRT	Tatarstan (RUS)
SVK	Slovakia	SAU	Saudi Arabia
SVN	Slovenia	UKR	Ukraine
ESP	Spain	ROM	Romania

SWE	Sweden	YUG	Yugoslavia

Table 23: Frequency per country

Country	Freq		Country	Freq
ARE	12,695		KSV	4,013
AUS	6,398		LBN	3,374
AUT	6,494		LTU	5,170
BEL	9,273		LUX	5,204
BGR	5,393		LVA	3,660
BRA	19,440		MAC	4,419
CAN	17,791		MDA	4,293
CHE	5,241		MEX	6,667
CHL	6,634		MKD	5,214
COL	10,896		MLT	3,524
CRI	6,471		MNE	5,400
CZE	4,828		NLD	5,172
DEU	4,949		NOR	4,940
DNK	5,346		NZL	3,431
DOM	4,167		PER	6,112
DZA	5,207		POL	4,248
ESP	6,384		PRT	6,680
EST	4,819		QAR	1,520
FIN	5,735		QAT	11,719
FRA	5,245		QCH	9,632
GBR	13,214		QES	31,066
GEO	3,884		ROU	4,610
GRC	5,117		RUS	5,240

HKG	5,270		SGP	6,084
HRV	5,679		SVK	4,722
HUN	5,124		SVN	5,338
IDN	5,966		SWE	5,019
IRL	5,654		TAP	7,617
ISL	2,819		THA	7,542
ISR	6,413		TTO	4,381
ITA	10,030		TUN	4,939
JOR	6,928		TUR	5,664
JPN	6,614		URY	5,428
KOR	5,411		USA	5,539
			VNM	5,624

Source: OECD (2017)

Table 24: Correlation between HOMEPOS and replication per country

CNT	Correlation		CNT	Correlation
ARE	0.993		KSV	0.985
AUS	0.989		LBN	0.996
AUT	0.982		LTU	0.970
BEL	0.946		LUX	0.991
BGR	0.977		LVA	0.963
BRA	0.995		MAC	0.994
CAN	0.991		MDA	0.996
CHE	0.975		MEX	0.998
CHL	0.999		MKD	0.989
COL	0.998		MLT	0.981

CRI	0.998		MNE	0.983
CZE	0.962		NLD	0.953
DEU	0.964		NOR	0.955
DNK	0.941		NZL	0.994
DOM	0.992		PER	0.994
DZA	0.999		POL	0.980
ESP	0.988		PRT	0.984
EST	0.984		QAR	0.998
FIN	0.943		QAT	0.988
FRA	0.974		QCH	0.997
GBR	0.986		QES	0.987
GEO	0.992		ROU	0.996
GRC	0.987		RUS	0.980
HKG	0.986		SGP	0.990
HRV	0.950		SVK	0.985
HUN	0.979		SVN	0.940
IDN	0.998		SWE	0.981
IRL	0.987		TAP	0.983
ISL	0.947		THA	0.998
ISR	0.961		TTO	0.995
ITA	0.971		TUN	0.993
JOR	0.996		TUR	0.996
JPN	0.981		URY	0.988
KOR	0.973		USA	0.996
			VNM	0.998

Source: own calculations based on OECD (2017)

Table 25: Percentage of schools above mean country inequality

CNT	# schools > national	average # schools < national	average proportion schools > national average
ARE	96	255	27.35
AUS	68	187	26.67
AUT	55	151	26.7
BEL	61	190	24.3
BGR	43	101	29.86
BRA	83	517	13.83
CAN	190	398	32.31
CHE	52	121	30.06
CHL	32	150	17.58
COL	21	288	6.8
CRI	31	154	16.76
CZE	46	116	28.4
DEU	54	137	28.27
DNK	62	155	28.57
DOM	13	123	9.56
DZA	38	104	26.76
ESP	54	130	29.35
EST	45	91	33.09
FIN	52	101	33.99
FRA	41	149	21.58
GBR	162	342	32.14
GEO	37	93	28.46
GRC	51	111	31.48

HKG	31	106	22.63
HRV	50	104	32.47
HUN	45	122	26.95
IDN	9	181	4.74
IRL	56	106	34.57
ISL	25	44	36.23
ISR	3	161	1.83
ITA	98	255	27.76
JOR	51	173	22.77
JPN	67	129	34.18
KOR	47	111	29.75
KSV	46	85	35.11
LBN	23	120	16.08
LTU	49	130	27.37
LUX	13	26	33.33
LVA	43	98	30.5
MAC	9	30	23.08
MDA	55	88	38.46
MEX	10	176	5.38
MKD	33	70	32.04
MLT	16	33	32.65
MNE	15	26	36.59
NLD	42	132	24.14
NOR	62	134	31.63
NZL	41	74	35.65

PER	4	191	2.05
POL	42	102	29.17
PRT	52	138	27.37
QAR	11	39	22
QAT	54	83	39.42
QCH	3	252	1.18
QES	291	604	32.51
ROU	35	102	25.55
RUS	47	103	31.33
SGP	52	123	29.71
SVK	29	116	20
SVN	56	147	27.59
SWE	51	114	30.91
TAP	50	158	24.04
THA	9	194	4.43
TTO	36	93	27.91
TUN	16	130	10.96
TUR	15	139	9.74
URY	51	123	29.31
USA	56	106	34.57
VNM	20	146	12.05

Source: own calculations based on OECD (2017)

Table 26: Correlation between the Gini Coefficient and Alpha Inequality in each country

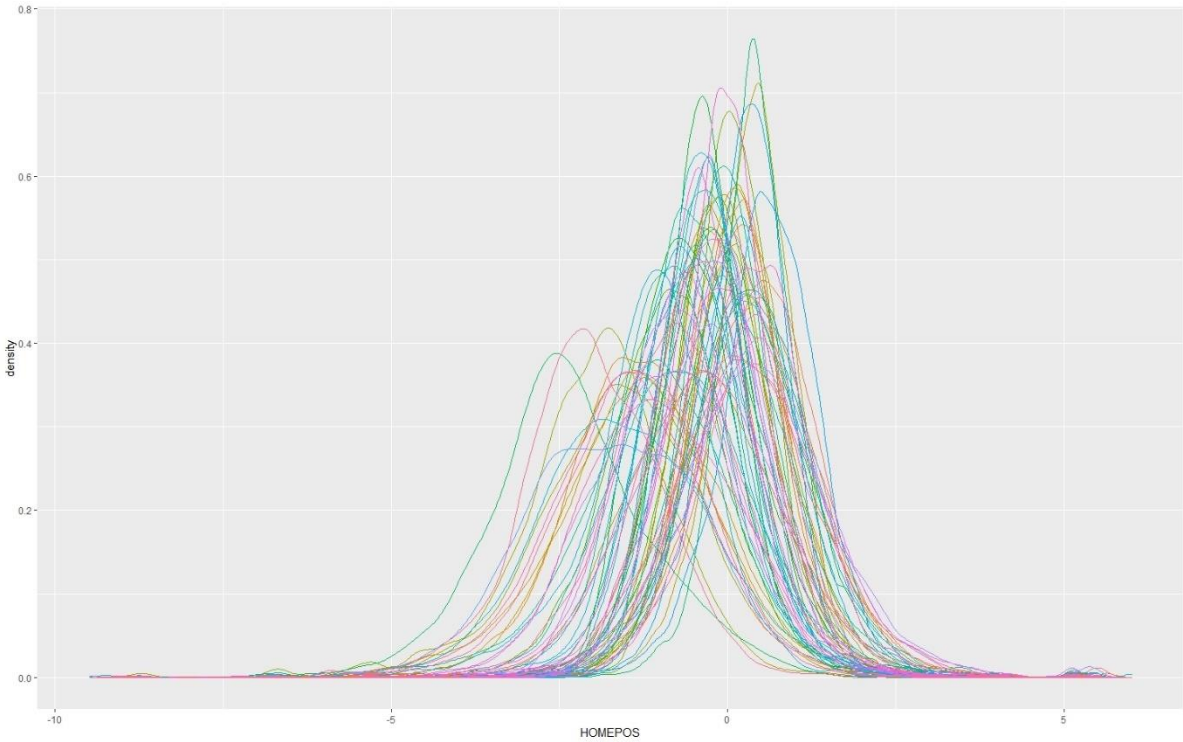
CNT	Correlation		CNT	Correlation

ARE	0.771		KSV	0.479
AUS	0.761		LBN	0.525
AUT	0.603		LTU	0.633
BEL	0.757		LUX	0.555
BGR	0.665		LVA	0.276
BRA	0.576		MAC	0.563
CAN	0.632		MDA	0.691
CHE	0.649		MEX	0.626
CHL	0.611		MKD	0.687
COL	0.722		MLT	0.611
CRI	0.771		MNE	0.583
CZE	0.303		NLD	0.687
DEU	0.618		NOR	0.584
DNK	0.626		NZL	0.733
DOM	0.567		PER	0.635
DZA	0.61		POL	0.609
ESP	0.638		PRT	0.658
EST	0.559		QAR	0.759
FIN	0.58		QAT	0.847
FRA	0.654		QCH	0.531
GBR	0.337		QES	0.615
GEO	0.76		ROU	0.684
GRC	0.544		RUS	0.54
HKG	0.706		SGP	0.84
HRV	0.627		SVK	0.757
HUN	0.533		SVN	0.387
IDN	0.39		SWE	0.664

IRL	0.533		TAP	0.692
ISL	0.479		THA	0.6
ISR	0.11		TTO	0.541
ITA	0.678		TUN	0.71
JOR	0.766		TUR	0.604
JPN	0.768		URY	0.634
KOR	0.671		USA	0.511
			VNM	0.533

Source: own calculations based on OECD (2017)

Figure 17: Density distribution HOMEPOS per country



Source: own calculations based on OECD (2017). Original in colour.

8.2. Chapter 3

Table 27: Frequencies per country – PISA 2012, 2015, 2018

CNT	2018	2015	2012
ALB	6256		4408
ARE	18778	14143	11410
ARG	11902		5864
AUS	12907	14465	14219
AUT	6750	6993	4728
BEL	8399	9648	8498
BGR	5168	5928	5215
BIH	6384		
BLR	5775		
BRA	10518	22782	18832
BRN	6804		
CAN	21565	19981	21162
CHE	5755	5859	11175
CHL	7466	7047	6766
COL	7199		8975
CRI	7186	6866	4499
CZE	6961		5307
DEU	4761	6497	4240
DNK	7478		7392
DOM	5543	4740	
ESP	35474	6601	25095
EST	5210	5582	4735
FIN	5574		8732
FRA	6227	6095	4543
GBR	13375	14080	12538

GEO	5474	5314	
GRC	6365	5525	5103
HKG	5879	5359	4579
HRV	6579	5809	4996
HUN	5089	5643	4754
IDN	12009	6513	5613
IRL	5548	5741	4987
ISL	3217	3371	3407
ISR	6494		0
ITA	11505	11521	30900
JOR	8944	7266	6976
JPN	6091	6647	6255
KAZ	19457		5803
KOR	6633	5581	5029
KSV	5000	4823	
LBN	5544		
LIE			
LTU	6782	6525	4604
LUX	5198	5299	5244
LVA	5217	4868	4280
MAC	3774	4476	5319
MAR	6738		
MDA	5352		
MEX	6468	7566	33455
MKD	5486		
MLT	3314	3633	
MNE	6615	5662	4696
MYS	6042		5182
NLD	4692	5384	4404

NOR	5645		0
NZL	6077	4519	4240
PAN	6105		
PER	6035	6971	5981
PHL	7189		
POL	5582	4472	4582
PRT	5651	7323	5644
QAR		1626	
QAT	13521	12083	10744
QAZ	6606		
QCH		9841	
QCI	11992		
QCN			
QES		32330	
QMR	1995		
QRS			
QRT	5706		
QUC		1652	
QUD		1398	
QUE		1887	
ROU	5066	4872	5057
RUS	7454	6031	5198
SAU	6100		
SGP	6657		5528
SRB	6529		4631
SVK	5891		4629
SVN	6319	6394	5828
SWE	5421	5452	4645
TAP	7180	7708	6027

THA	8581	8243	6599
TTO		4663	
TUN		5375	
TUR	6857	5889	4809
UKR	5985		
URY	5076	6062	5259
USA	4799	5710	4937
VNM	5376	5826	4954

Source: PISA 2015 (OECD, 2017b)

Table 28: Multilevel models of reading attainment – Robustness checksPISA 2018

Parameter	Est	SE	t	df	p
Alpha Inequality	-48.8375	1.1469	-42.58	Inf	0
Sex	-19.5701	0.2125	-92.11	107.27	0
HISCED	1.6283	0.0726	22.44	58.43	0
IMMIG	1.3702	0.4354	3.15	Inf	0.0016
Language	-23.2055	0.4428	-52.41	181.36	0
AGE	3.3989	0.1147	29.63	215.78	0
REPEAT	-50.4989	0.418	-120.8	456.41	0
School type	-3.5279	0.7008	-5.03	Inf	0
Area	6.4764	0.2233	29	Inf	0
HOMEPOS	7.2754	0.1217	59.79	223.1	0
School HOMEPOS	37.9293	0.206	184.15	Inf	0
(Intercept)	506.994	1.6097	314.96	418.64	0
Var (Intercept)	2099.207	15.4955	135.47	146.82	0
Resid Var	5451.898	6.505	838.11	12.39	0
Resid Var_Lev2	2099.207	15.4955	135.47	146.82	0
Expl Var_Lev1_Fixed	371.3477	37.8979	9.8	Inf	0
Resid Var_Lev1	5451.898	6.505	838.11	12.39	0
Var Total	7922.453	44.184	179.31	Inf	0
R2 Lev1	0.0638	0.0029	22.05	Inf	0
R2 Total	0.0469	0.0026	18.07	Inf	0
ICC Uncond	0.265	0.0013	199.32	185.05	0
ICC Cond	0.278	0.0017	167.53	402.82	0

Parameter	est	SE	t	df	p
Gini	-12.4002	0.4998	-24.81	Inf	0

School HOMEPOS	37.1274	0.2707	137.15	Inf	0
School HOMEPOS*Gini	-6.8792	0.26	-26.46	Inf	0
Sex	-19.6477	0.2126	-92.4	107.35	0
HISCED	1.6466	0.0742	22.2	63.41	0
IMMIG	1.2824	0.4344	2.95	Inf	0.0032
Language	-23.164	0.4442	-52.15	182.01	0
AGE	3.4226	0.1144	29.91	212.12	0
REPEAT	-50.6639	0.4256	-119.04	484.23	0
School type	0.8635	0.7918	1.09	Inf	0.2757
Area	7.9039	0.2291	34.5	Inf	0
HOMEPOS	7.2571	0.1216	59.7	220.81	0
(Intercept)	450.9627	2.0073	224.67	Inf	0
Var (Intercept)	2104.829	14.6474	143.7	148.74	0
Resid Var	5452.08	6.4913	839.9	12.22	0
ResidVar Lev2	2104.829	14.6474	143.7	148.74	0
ExplVar Lev1_Fixed	373.2626	37.6582	9.91	Inf	0
ResidVar Lev1	5452.08	6.4913	839.9	12.22	0
Var Total	7930.172	40.405	196.27	Inf	0
R2 Lev1	0.0641	0.0029	22.41	Inf	0
R2 Total	0.0471	0.0027	17.68	Inf	0
ICC Uncond	0.2654	0.0014	189.88	251.39	0
ICC Cond	0.2785	0.0015	181.07	348.03	0

PISA 2015

Parameter	**Est**	**SE**	**t**	**df**	**p**
Alpha Inequality	-48.8375	1.1469	-42.58	Inf	0
Sex	-19.5701	0.2125	-92.11	107.27	0
HISCED	1.6283	0.0726	22.44	58.43	0
IMMIG	1.3702	0.4354	3.15	Inf	0.0016

Language	-23.2055	0.4428	-52.41	181.36	0
AGE	3.3989	0.1147	29.63	215.78	0
REPEAT	-50.4989	0.418	-120.8	456.41	0
School type	-3.5279	0.7008	-5.03	Inf	0
Area	6.4764	0.2233	29	Inf	0
HOMEPOS	7.2754	0.1217	59.79	223.1	0
School HOMEPOS	37.9293	0.206	184.15	Inf	0
(Intercept)	506.994	1.6097	314.96	418.64	0
Var (Intercept)	2099.207	15.4955	135.47	146.82	0
Resid Var	5451.898	6.505	838.11	12.39	0
ResidVar Lev2	2099.207	15.4955	135.47	146.82	0
ExplVar Lev1 Fixed	371.3477	37.8979	9.8	Inf	0
ResidVar Lev1	5451.898	6.505	838.11	12.39	0
Var Total	7922.453	44.184	179.31	Inf	0
R2 Lev1	0.0638	0.0029	22.05	Inf	0
R2 Total	0.0469	0.0026	18.07	Inf	0
ICC Uncond	0.265	0.0013	199.32	185.05	0
ICC Cond	0.278	0.0017	167.53	402.82	0

Parameter	**Est**	**SE**	**t**	**df**	**p**
Gini	-12.4002	0.4998	-24.81	Inf	0
School HOMEPOS	37.1274	0.2707	137.15	Inf	0
School HOMEPOS*Gini	-6.8792	0.26	-26.46	Inf	0
Sex	-19.6477	0.2126	-92.4	107.35	0
HISCED	1.6466	0.0742	22.2	63.41	0
IMMIG	1.2824	0.4344	2.95	Inf	0.0032
Language	-23.164	0.4442	-52.15	182.01	0

AGE	3.4226	0.1144	29.91	212.12	0
REPEAT	-50.6639	0.4256	-119.04	484.23	0
School type	0.8635	0.7918	1.09	Inf	0.2757
Area	7.9039	0.2291	34.5	Inf	0
HOMEPOS	7.2571	0.1216	59.7	220.81	0
(Intercept)	450.9627	2.0073	224.67	Inf	0
Var (Intercept)	2104.829	14.6474	143.7	148.74	0
ResidVar	5452.08	6.4913	839.9	12.22	0
ResidVar Lev2	2104.829	14.6474	143.7	148.74	0
ExplVar Lev1 Fixed	373.2626	37.6582	9.91	Inf	0
ResidVar Lev1	5452.08	6.4913	839.9	12.22	0
Var Total	7930.172	40.405	196.27	Inf	0
R2 Lev1	0.0641	0.0029	22.41	Inf	0
R2 Total	0.0471	0.0027	17.68	Inf	0
ICC Uncond	0.2654	0.0014	189.88	251.39	0
ICC Cond	0.2785	0.0015	181.07	348.03	0

PISA 2012

Parameter	**Est**	**SE**	**t**	**df**	**p**
Alpha Inequality	-35.2542	2.3995	-14.69	Inf	0
Sex	-27.6073	0.1517	-182.04	217.64	0
HISCED	3.7379	0.1066	35.06	Inf	0
IMMIG	-3.3331	0.4838	-6.89	211.92	0
Language	-15.4701	0.3616	-42.79	27.51	0
AGE	2.7851	0.0754	36.94	47.87	0
REPEAT	-52.8951	0.3787	-139.67	Inf	0
School type	3.4243	0.6142	5.58	Inf	0
Area	5.3519	0.3072	17.42	Inf	0
HOMEPOS	4.6942	0.1162	40.41	42.91	0

School HOMEPOS	43.0843	0.3675	117.23	Inf	0
(Intercept)	544.2095	2.5206	215.91	Inf	0
Var (Intercept)	2434.635	12.3005	197.93	51.41	0
ResidVar	4488.936	6.9908	642.12	4.75	0
ResidVar Lev2	2434.635	12.3005	197.93	51.41	0
ExplVar Lev1 Fixed	507.2038	103.5142	4.9	Inf	0
ResidVar Lev1	4488.936	6.9908	642.12	4.75	0
Var Total	7430.775	103.2435	71.97	Inf	0
R2 Lev1	0.1015	0.0078	13.02	Inf	0
R2 Total	0.0683	0.0071	9.56	Inf	0
ICC Uncond	0.3276	0.0026	123.68	586.39	0
ICC Cond	0.3516	0.0014	250.61	35.67	0

Parameter	**Est**	**SE**	**t**	**df**	**p**
Gini	-10.4744	0.3775	-27.74	Inf	0
School HOMEPOS	41.7634	0.4196	99.53	747.16	0
School HOMEPOS*Gini	-4.2862	0.3708	-11.56	Inf	0
Sex	-27.6495	0.1515	-182.56	215.39	0
HISCED	3.7508	0.1038	36.14	Inf	0
IMMIG	-3.4088	0.4657	-7.32	183.58	0
Language	-15.5652	0.3669	-42.42	29.42	0
AGE	2.8064	0.0748	37.52	46.9	0
REPEAT	-53.0902	0.3819	-139	Inf	0
School type	6.8267	0.4701	14.52	929.21	0
Area	5.9981	0.29	20.68	Inf	0
HOMEPOS	4.672	0.1157	40.38	42.34	0
(Intercept)	505.289	1.3605	371.4	183.47	0

Var(Intercept)	2420.162	12.5338	193.09	46.15	0
ResidVar	4489.671	6.9862	642.65	4.74	0
ResidVar Lev2	2420.162	12.5338	193.09	46.15	0
ExplVar Lev1 Fixed	510.1525	103.653	4.92	Inf	0
ResidVar Lev1	4489.671	6.9862	642.65	4.74	0
Var Total	7419.985	101.4951	73.11	Inf	0
R2 Lev1	0.102	0.0078	13.12	Inf	0
R2 Total	0.0688	0.0072	9.58	Inf	0
ICC Uncond	0.3262	0.0028	116.21	554.75	0
ICC Cond	0.3502	0.0014	243.54	29.84	0

Table 29: Multilevel models of mathematics attainment using different inequality measures – PISA 2018Atkinson

Parameter	Est	SE	t	df	p
Atkinson.05	-2.2308	0.2796	-7.98	759.74	0
Sex	12.163	0.3473	35.02	15.84	0
HISCED	1.9782	0.1268	15.6	15.12	0
IMMIG	0.7232	0.3911	1.85	41.83	0.0714
Language	-11.9143	0.6033	-19.75	98.44	0
AGE	3.3501	0.1335	25.1	24.4	0
REPEAT	-55.4789	0.5797	-95.7	24.62	0
School type	2.0691	0.8695	2.38	Inf	0.0173
Area	3.5237	0.2325	15.15	776.24	0
HOMEPOS	8.3986	0.1615	52	19.16	0
School HOMEPOS	38.882	0.3135	124.04	31.48	0
(Intercept)	397.9074	2.3483	169.44	33.52	0
Var (Intercept)	2207.196	20.1463	109.56	82.27	0
ResidVar	4961.423	10.9056	454.94	9.68	0

ExplVar Lev2 Fixed	2905.446	46.8485	62.02	Inf	0
ResidVar Lev2	2207.196	20.1463	109.56	82.27	0
ExplVar Lev1 Fixed	363.9269	40.6029	8.96	Inf	0
ResidVar Lev1	4961.423	10.9056	454.94	9.68	0
Var Total	10437.99	63.1309	165.34	Inf	0
R2 Lev2	0.5683	0.004	143.06	570.8	0
R2 Lev1	0.0683	0.0037	18.72	Inf	0
R2 Total	0.3132	0.0028	113.75	880.54	0
ICC Uncond	0.4898	0.0025	198.92	144.04	0
ICC UncondWB	0.5266	0.0026	205.24	154.54	0
ICC Cond	0.3079	0.0021	143.35	76.59	0

Parameter	**Est**	**SE**	**t**	**df**	**p**
School HOMEPOS	38.7645	0.3356	115.52	42.37	0
Atkinson.05	-10.6247	0.6446	-16.48	Inf	0
School HOMEPOS*Atkinson.05	-4.4629	0.2643	-16.88	Inf	0
Sex	12.1821	0.347	35.11	15.8	0
HISCED	1.9751	0.1268	15.58	15.1	0
IMMIG	0.7461	0.3894	1.92	41.21	0.0618
Language	-11.9222	0.6003	-19.86	97.55	0
AGE	3.3507	0.1338	25.04	24.65	0
REPEAT	-55.4956	0.5765	-96.26	24.1	0
School type	1.3484	0.8783	1.54	Inf	0.1236
Area	3.6726	0.2226	16.5	694.08	0
HOMEPOS	8.4024	0.1616	52.01	19.19	0
(Intercept)	396.5686	2.3696	167.36	34.82	0

Var (Intercept)	2131.485	19.4937	109.34	90.87	0
ResidVar	4961.553	10.9075	454.87	9.71	0
ExplVar Lev2 Fixed	2990.48	47.8525	62.49	Inf	0
ResidVar Lev2	2131.485	19.4937	109.34	90.87	0
ExplVar Lev1 Fixed	364.1599	40.5449	8.98	Inf	0
ResidVar Lev1	4961.553	10.9075	454.87	9.71	0
Var Total	10447.68	63.487	164.56	Inf	0
R2 Lev2	0.5839	0.004	146.72	552.25	0
R2 Lev1	0.0684	0.0036	18.76	Inf	0
R2 Total	0.3211	0.0028	113.46	858.15	0
ICC Uncond	0.4902	0.0024	203.16	135.9	0
ICC UncondWB	0.5266	0.0026	205.24	154.54	0
ICC Cond	0.3005	0.0021	140.92	84.58	0

Theil

Parameter	**Est**	**SE**	**t**	**df**	**p**
Theil.0	-3.0177	0.2683	-11.25	419.59	0
Sex	12.1664	0.3473	35.03	15.83	0
HISCED	1.978	0.1268	15.6	15.1	0
IMMIG	0.7287	0.3911	1.86	41.82	0.0699
Language	-11.892	0.6034	-19.71	98.63	0
AGE	3.351	0.1335	25.1	24.41	0
REPEAT	-55.4635	0.5796	-95.7	24.57	0
School type	2.1262	0.8687	2.45	Inf	0.0143
Area	3.5352	0.231	15.31	752.67	0
HOMEPOS	8.3997	0.1615	52.02	19.15	0
School HOMEPOS	38.473	0.318	120.99	33.3	0
(Intercept)	397.7622	2.3426	169.79	33.18	0
Var (Intercept)	2202.649	20.0573	109.82	81.53	0

ResidVar	4961.43	10.9052	454.96	9.68	0
ExplVar Lev2 Fixed	2911.313	46.5165	62.59	Inf	0
ResidVar Lev2	2202.649	20.0573	109.82	81.53	0
ExplVar Lev1 Fixed	363.7732	40.5246	8.98	Inf	0
ResidVar Lev1	4961.43	10.9052	454.96	9.68	0
Var Total	10439.16	62.8467	166.11	Inf	0
R2 Lev2	0.5693	0.0039	144.76	567.8	0
R2 Lev1	0.0683	0.0036	18.74	Inf	0
R2 Total	0.3137	0.0027	114.99	887.02	0
ICC Uncond	0.4899	0.0025	199.19	143.65	0
ICC UncondWB	0.5266	0.0026	205.24	154.54	0
ICC Cond	0.3075	0.0021	143.61	75.92	0

Parameter	**Est**	**SE**	**t**	**df**	**p**
School HOMEPOS	38.1919	0.3407	112.11	45.65	0
Theil.0	-12.7704	0.5066	-25.21	Inf	0
School HOMEPOS*Theil.0	-5.1012	0.2282	-22.36	Inf	0
(Intercept)	395.9537	2.3433	168.97	33.35	0
Sex	12.1916	0.3468	35.15	15.78	0
HISCED	1.9731	0.1268	15.56	15.09	0
IMMIG	0.7603	0.3891	1.95	41.14	0.058
Language	-11.8889	0.6004	-19.8	97.84	0
AGE	3.352	0.1339	25.04	24.73	0
REPEAT	-55.4738	0.576	-96.31	23.99	0
School type	1.2996	0.8832	1.47	Inf	0.1416
Area	3.7308	0.2206	16.91	665.55	0
HOMEPOS	8.4046	0.1615	52.05	19.17	0
Var (Intercept)	2105.439	19.1612	109.88	87.45	0

ResidVar	4961.62	10.9052	454.98	9.71	0
ExplVar Lev2 Fixed	3021.303	47.0593	64.2	Inf	0
ResidVar Lev2	2105.439	19.1612	109.88	87.45	0
ExplVar Lev1 Fixed	363.9396	40.5277	8.98	Inf	0
ResidVar Lev1	4961.62	10.9052	454.98	9.71	0
Var Total	10452.3	63.2278	165.31	Inf	0
R2 Lev2	0.5893	0.0039	152.26	517.43	0
R2 Lev1	0.0683	0.0036	18.75	Inf	0
R2 Total	0.3239	0.0028	115.61	903.58	0
ICC Uncond	0.4905	0.0024	204.34	133.4	0
ICC UncondWB	0.5266	0.0026	205.24	154.54	0

Alpha Inequality

Parameter	**Est**	**SE**	**t**	**df**	**p**
Alpha Inequality	-41.2822	2.0231	-20.41	50.84	0
Sex	19.1858	0.4451	43.1	18.69	0
HISCED	0.8423	0.1615	5.21	15.76	0.0001
IMMIG	-6.7456	1.4031	-4.81	42.58	0
Language	-13.9477	1.6692	-8.36	19.17	0
AGE	2.9849	0.2596	11.5	13.54	0
REPEAT	-50.2053	0.9357	-53.65	15.03	0
School type	-11.1727	1.0541	-10.6	164.82	0
Area	0.3438	0.3995	0.86	92.45	0.392
HOMEPOS	6.9529	0.397	17.51	13.23	0
School HOMEPOS	36.3577	0.8298	43.81	32.24	0
(Intercept)	457.5856	6.3996	71.5	23.32	0
Var (Intercept)	946.9448	23.3283	40.59	25.8	0
ResidVar	3842.523	23.9252	160.61	9.17	0
ExplVar Lev2 Fixed	2671.606	46.4564	57.51	70.81	0

ResidVar Lev2	946.9448	23.3283	40.59	25.8	0
ExplVar Lev1 Fixed	512.993	32.2971	15.88	291.66	0
ResidVar Lev1	3842.523	23.9252	160.61	9.17	0
Var Total	7974.067	54.6592	145.89	150.56	0
R2 Lev2	0.7383	0.0077	95.38	60.23	0
R2 Lev1	0.1178	0.0049	23.9	128.68	0
R2 Total	0.3994	0.0048	83.89	122.17	0
ICC Uncond	0.4538	0.0046	99.61	35.29	0
ICC UncondWB	0.4622	0.0043	107.76	30.62	0
ICC Cond	0.1977	0.0045	43.94	23.28	0

Parameter	**Est**	**SE**	**t**	**df**	**p**
School HOMEPOS	25.3575	1.2826	19.77	143.54	0
Alpha Inequality	-27.0159	2.0607	-13.11	88.87	0
School HOMEPOS * *Alpha Inequality*	14.9417	1.5542	9.61	58.72	0
Sex	19.1623	0.4443	43.13	18.64	0
HISCED	0.8605	0.1615	5.33	15.74	0.0001
IMMIG	-6.769	1.4022	-4.83	42.56	0
Language	-13.8913	1.6672	-8.33	19.08	0
AGE	2.99	0.26	11.5	13.6	0
REPEAT	-50.2149	0.9343	-53.75	15.01	0
School type	-9.459	1.0659	-8.87	330.92	0
Area	0.5805	0.3956	1.47	101.61	0.1447
HOMEPOS	6.9431	0.3971	17.49	13.19	0
(Intercept)	446.2006	6.1906	72.08	28.68	0
Var (Intercept)	929.8198	23.0928	40.26	28.37	0
ResidVar	3842.629	23.917	160.67	9.19	0

ExplVar Lev2 Fixed	2669.341	46.5819	57.3	71.2	0
ResidVar Lev2	929.8198	23.0928	40.26	28.37	0
ExplVar Lev1 Fixed	513.0459	32.2686	15.9	291.74	0
ResidVar Lev1	3842.629	23.917	160.67	9.19	0
Var Total	7954.835	54.3709	146.31	142.5	0
R2 Lev2	0.7417	0.0079	94.44	65.97	0
R2 Lev1	0.1178	0.0049	23.92	128.95	0
R2 Total	0.4001	0.0048	83.65	125.64	0
ICC Uncond	0.4525	0.0045	101.29	34.83	0
ICC UncondWB	0.4622	0.0043	107.76	30.62	0
ICC Cond	0.1948	0.0045	43.7	25.35	0

Table 30: Multilevel models of mathematics attainment (schools > median size) – Gini: PISA 2018

Parameter	**Est**	**SE**	**t**	**df**	**p**
Gini	-10.0201	0.4378	-22.89	403.18	0
Sex	13.6522	0.4556	29.96	15.1	0
HISCED	1.7112	0.1325	12.92	27.65	0
IMMIG	2.8109	0.6262	4.49	159.24	0
Language	-12.9523	0.7621	-17	84.41	0
AGE	3.5107	0.1522	23.06	17.96	0
REPEAT	-55.8015	0.6254	-89.23	62.83	0
School type	1.8801	1.6641	1.13	Inf	0.2585
Area	3.0721	0.5541	5.54	Inf	0
HOMEPOS	8.0579	0.2239	35.99	20.43	0
School HOMEPOS	39.5533	0.4373	90.46	26.54	0
(Intercept)	400.0239	4.3341	92.3	107.16	0
Var (Intercept)	2347.973	28.35	82.82	124.35	0
ResidVar	4920.67	16.732	294.09	9.92	0

ExplVar Lev2 Fixed	3264.866	64.7537	50.42	Inf	0
ResidVar Lev2	2347.973	28.35	82.82	124.35	0
ExplVar Lev1 Fixed	380.4149	71.0518	5.35	Inf	0
ResidVar Lev1	4920.67	16.732	294.09	9.92	0
Var Total	10913.92	79.6892	136.96	298.22	0
R2 Lev2	0.5817	0.0053	110.1	Inf	0
R2 Lev1	0.0718	0.0065	11.03	Inf	0
R2 Total	0.334	0.0037	91.24	936.83	0
ICC Uncond	0.5143	0.0042	123.25	Inf	0
ICC UncondWB	0.5269	0.0045	116.04	Inf	0
ICC Cond	0.323	0.0026	121.9	374.99	0

Parameter	**Est**	**SE**	**t**	**df**	**p**
School HOMEPOS	41.3899	0.4563	90.71	27.99	0
Gini	-14.4799	0.4399	-32.92	449.27	0
School HOMEPOS * Gini	-7.2875	0.2458	-29.65	631.99	0
(Intercept)	396.5863	4.0234	98.57	79.97	0
Sex	13.6697	0.4556	30	15.11	0
HISCED	1.6965	0.1324	12.81	27.65	0
IMMIG	2.8396	0.6292	4.51	163.25	0
Language	-13.0652	0.7666	-17.04	87.27	0
AGE	3.5154	0.1521	23.11	17.97	0
REPEAT	-55.8768	0.624	-89.55	62.07	0
School type	0.6059	1.5743	0.38	Inf	0.7039
Area	3.1041	0.499	6.22	Inf	0
HOMEPOS	8.0624	0.224	35.99	20.46	0
Var (Intercept)	2267.359	29.2804	77.44	166.2	0

ResidVar	4920.767	16.7375	294	9.93	0
ExplVar Lev2 Fixed	3297.442	58.741	56.14	Inf	0
ResidVar Lev2	2267.359	29.2804	77.44	166.2	0
ExplVar Lev1 Fixed	381.3045	71.3212	5.35	Inf	0
ResidVar Lev1	4920.767	16.7375	294	9.93	0
Var Total	10866.87	78.8181	137.87	303.6	0
R2 Lev2	0.5926	0.0049	119.9	817.83	0
R2 Lev1	0.0719	0.0065	11.03	Inf	0
R2 Total	0.3385	0.0037	90.48	941.57	0
ICC Uncond	0.5121	0.0041	125.61	Inf	0
ICC UncondWB	0.5269	0.0045	116.04	Inf	0
ICC Cond	0.3154	0.0028	111.72	514.33	0

Table 31: Multilevel models of reading attainment – Alpha Inequality with PLS

Coef.	**Estimate**	**SE**	**t-stat**	**p-val (z)**	**Sig.**
Alpha Inequality	-50.502	1.235	-40.891	< 0.001	***
School HOMEPOS	32.502	1.151	28.235	< 0.001	***
Alpha Inequality * school HOMEPOS	-2.918	1.243	-2.348	0.01889	*
(Intercept)	424.412	3.122	135.929	< 0.001	***
Sex Male	12.161	0.241	50.532	< 0.001	***
HISCED ISCED 1	1.316	1.08	1.218	0.22315	
HISCED ISCED 2	-1.434	1.006	-1.425	0.15403	
HISCED ISCED 3B-C	5.196	1.072	4.847	< 0.001	***
HISCED ISCED 3A-4	6.173	0.996	6.196	< 0.001	***
HISCED ISCED 5B	4.282	1.018	4.205	< 0.001	***
HISCED ISCED 5A-6	10.429	1.005	10.379	< 0.001	***

IMMIG Second.generation	-2.518	0.619	-4.067	< 0.001	***
IMMIG First.generation	4.184	0.773	5.41	< 0.001	***
Language Other language	-11.293	0.47	-24.011	< 0.001	***
AGE	3.354	0.112	29.981	< 0.001	***
REPEAT Yes	-56.072	0.469	-119.637	< 0.001	***
School type Private	-1.972	0.889	-2.217	0.02664	*
Area3k>15k	0.946	0.974	0.971	0.33137	
Area15k>100k	4.275	0.948	4.507	< 0.001	***
Area100k>1m	9.087	0.993	9.153	< 0.001	***
Area>1m	11.208	1.183	9.477	< 0.001	***
HOMEPOS	8.05	0.148	54.56	< 0.001	***

8.3. Chapter 4

I model three univariate causal mediation analysis models to explore the relationship between wealth inequality, mediating variables as proxies of inequality mechanisms and *learning scores*. I use 100 simulations to estimate Quasi-Bayesian Confidence Intervals. The mediating variables were the following:

For social isolation: "How satisfied are you with the friends you have"; for anomie: Index of Student's experience of being bullied; and, for interpersonal comparisons: "Importance for decisions about the future occupation: The plans my close friends have for their future". Table 32 presents summary statistics. In the majority of cases (see Table 33), I find evidence of negative associations between these variables and also a negative mediation effect of them on *learning scores*. This suggests congruence between the previous theory and the empirical evidence.

Table 32: Descriptive statistics – analysis of potential mechanisms of inequality

Characteristic	N = 473,312[1]
How satisfied are you with the friends you have	
"Not at all dissatisfied"	1,691 (3.2%)
"Not satisfied"	4,159 (8.0%)
"Satisfied"	26,240 (50%)
"Totally satisfied"	19,973 (38%)
Alpha Inequality	0.84 (0.70, 0.98)
PV1READ	464 (388, 540)
Importance for decisions about the future occupation: The plans my close friends have for their future	
"Not important"	51,285 (28%)
Somehow important"	63,684 (34%)
"Important"	55,671 (30%)
"Very important"	15,473 (8.3%)
BEINGBULLIED	-0.78 (-0.78, 0.82)
[1]n (%); Median (IQR)	

The effect of *school inequality* on *learning scores* was partially mediated via all variables. Table 33 shows the indirect effect for all variables. I tested the significance of this indirect effect using bootstrapping procedures. Unstandardised indirect effects were computed for each of 100 bootstrapped samples, and the 95% confidence interval was computed by determining the indirect effects at the 2.5th and 97.5th percentiles. All indirect effects were statistically significant ($p<.001$).

Table 33: Mediation analysis results – potential mechanisms of inequality –

Social isolation

	Estimate	95% CI Lower	95% CI Upper	p-value
ACME	-2.2790	-2.6470	-1.94	<2e-16 ***
ADE	-151.9673	-154.74	-148.88	<2e-16 ***
Total Effect	-154.2463	157.1505	-151.29	<2e-16 ***
Prop. Mediated	0.0147	0.0126	0.02	<2e-16 **

Note: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Sample Size Used: 52059

Anomie:

	Estimate	95% CI Lower	95% CI Upper	p-value
ACME	-8.5786	-8.9997	-8.16	<2e-16 ***
ADE	-121.4066	-123.0650	-119.97	<2e-16 ***
Total Effect	-129.9852	-131.7290	-128.47	<2e-16 ***
Prop. Mediated	0.0661	0.0632	0.07 *	<2e-16 **

Note: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Sample Size Used: 186103

Interpersonal comparisons:

	Estimate	95% CI Lower	95% CI Upper	p-value
ACME	-3.4378	-3.6042	-3.27	<2e-16 ***
ADE	-121.0896	-122.3131	-119.89	<2e-16 ***
Total Effect	-124.5274	-125.6892	-123.24	<2e-16 ***
Prop. Mediated	0.0277	0.0262	0.03	<2e-16 **

Note: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Sample Size Used: 431753

8.4. Chapter 5

Table 34: Coefficients for regression models – Country Gini and School Gini

Parameters	(10)	(11)	(12)	(13)
Sex Male	8.100***	8.500***	8.900***	9.400***
	(0.25)	(0.25)	(0.25)	(0.25)
HISCED ISCED 1	-0.062	-(1.6	0.18	1.6
	(1.4)	(1.4)	(1.4)	(1.4)
HISCED ISCED 2	-8.000***	-9.700***	-6.800***	(2.2
	(1.3)	(1.3)	(1.3)	(1.3
HISCED ISCED 3B-C	-4.500***	-6.600***	-3.700***	2.500*
	(1.4)	(1.4)	(1.4)	(1.4)
HISCED ISCED 3A-4	-1.2	-3.100**	(0.4	5.200***
	(1.3)	(1.3)	(1.3)	(1.3)
HISCED ISCED 5B	-1.4	-3.300**	-0.69	4.800***
	(1.3)	(1.3)	(1.3)	(1.3)
HISCED ISCED 5A-6	8.700***	7.100***	9.100***	12.000***
	(1.3)	(1.3)	(1.3)	(1.3)
IMMIG Second generation	4.900***	4.400***	5.000***	6.100***
	(0.58)	(0.58)	(0.58)	(0.58)
IMMIG First generation	24.000***	23.000***	23.000***	22.000***
	(0.63)	(0.63)	(0.63)	(0.62)
Language Other language	-12.000***	-12.000***	-12.000***	-12.000***
	(0.44)	(0.44)	(0.44)	(0.43)
AGE	3.700***	3.700***	3.600***	3.600***
	(0.13)	(0.13)	(0.13)	(0.12)
REPEAT Yes	- 58.000***	-57.000***	-57.000***	-56.000***
	(0.44)	(0.44)	(0.44)	(0.43)
School Type Private	-0.6	-1.800***	-1.700***	-4.000***
	(0.4)	(0.4)	(0.39)	(0.4)
School Area 3k> 15k	-1.200**	(-1.100**	(0.39	0.78

	(0.52)	(0.52)	(0.52)	(0.51)
School Area 15k> 100k	1.700***	1.500***	1.600***	2.700***
	(0.5)	(0.5)	(0.5)	(0.5)
School Area 100k> 1m	7.000***	6.600***	6.900***	7.200***
	(0.51)	(0.51)	(0.51)	(0.51)
School Area > 1m	6.300***	5.900***	6.200***	5.200***
	(0.58)	(0.58)	(0.57)	(0.57)
HOMEPOS	7.300***	7.300***	7.400***	7.500***
	(0.16)	(0.15)	(0.15)	(0.15)
School HOMEPOS	43.000***	40.000***	42.000***	74.000***
	(0.26)	(0.27	(0.27)	(0.6)
Country Gini HOMEPOS	85	160	139	127
	(179)	(176	(174)	(178)
Gini		-7.400***	-30.000***	-13.000***
		(0.17)	(0.4)	(0.49)
School HOMEPOS * Country Gini HOMEPOS				-450.000***
				(8.1)
School HOMEPOS * Gini				-12.000***
				(0.35)
Country Gini HOMEPOS * Gini			350.000***	-18.000**
			(5.7)	(8.7)
School HOMEPOS * Country Gini HOMEPOS * Gini				60.000***
				(4.1)
Constant	385.000***	383.000***	375.000***	364.000***
	(10)	(10)	(10)	(10)

Observations	395,508	395,508	395,508	395,508
Log Likelihood	-2,286,845.00	-2,285,899.00	-2,284,020.00	-2,280,680.00
Akaike Inf. Crit.	4,573,735.00	4,571,846.00	4,568,089.00	4,561,416.00
Bayesian Inf. Crit.	4,573,986.00	4,572,108.00	4,568,361.00	4,561,721.00

Note: *p<0.1; **p<0.05; ***p<0.01

Table 35: Variance inflation factor for regression models – Country Gini and School Gini

Parameters	**(10)**	**(11)**	**(12)**	**(13)**
Sex	1.01	1.01	1.01	1.01
HISCED	1.23	1.24	1.24	1.26
IMMIG	1.08	1.09	1.09	1.09
Language	1.06	1.06	1.06	1.06
AGE	1.00	1.00	1.00	1.00
REPEAT	1.05	1.05	1.05	1.05
School Type	1.17	1.17	1.17	1.20
School Area	1.17	1.17	1.17	1.18
HOMEPOS	1.48	1.48	1.48	1.48
School HOMEPOS	1.72	1.87	1.91	9.47
Country Gini HOMEPOS	1.00	1.00	1.00	1.00
Gini		1.20	6.63	10.11
Country Gini HOMEPOS * Gini			6.84	16.33
School HOMEPOS * Country Gini HOMEPOS				9.66
School HOMEPOS * Gini				16.81
School HOMEPOS * Country Gini HOMEPOS * Gini				20.83

Source: own calculations based on PISA 2018 (OECD, 2020)

Table 36: Coefficients for regression models – Country Duncan and School Alpha Inequality

Parameters	(14)	(15)	(16)
Sex Male	9.400***	9.400***	9.600***
	(0.25)	(0.25)	(0.25)
HISCED ISCED 1	0.23	0.2	(0.19
	(1.4)	(1.4)	(1.4)
HISCED ISCED 2	-5.600***	-5.600***	-4.400***
	(1.3)	(1.3)	(1.3)
HISCED ISCED 3B-C	(1.8	(1.8	0.026
	(1.4)	(1.4)	(1.4)
HISCED ISCED 3A-4	1.1	1.2	2.800**
	(1.3)	(1.3)	(1.3)
HISCED ISCED 5B	0.8	0.85	2.500*
	(1.3)	(1.3)	(1.3)
HISCED ISCED 5A-6	10.000***	10.000***	11.000***
	(1.3)	(1.3)	(1.3)
IMMIG Second generation	4.300***	4.300***	4.500***
	(0.58)	(0.58)	(0.58)
IMMIG First generation	22.000***	22.000***	22.000***
	(0.62)	(0.62)	(0.62)
Language Other language	-11.000***	-11.000***	-11.000***
	(0.43)	(0.43)	(0.43)
AGE	3.500***	3.500***	3.500***
	(0.12)	(0.12)	(0.12)
REPEAT Yes	-55.000***	-56.000***	-56.000***
	(0.43)	(0.43)	(0.43)
School Type Private	-3.200***	-3.000***	-3.500***
	(0.39)	(0.39)	(0.39)
School Area 3k> 15k	0.41	0.28	0.37
	(0.51)	(0.51)	(0.51)

School Area 15k> 100k	2.400***	2.300***	2.400***
	(0.5)	(0.5)	(0.5)
School Area 100k> 1m	7.200***	7.000***	7.100***
	(0.51)	(0.51)	(0.51)
School Area > 1m	6.300***	6.300***	6.100***
	(0.57)	(0.57	(0.57
HOMEPOS	7.400***	7.400***	7.500***
	(0.15)	(0.15)	(0.15)
School HOMEPOS	34.000***	34.000***	54.000***
	(0.27)	(0.27	(2.5)
Country segregation Duncan	-37	-84	-43
	(63)	(63)	(63)
School HOMEPOS * Country segregation Duncan			-29.000***
			(6.2
School HOMEPOS * Alpha inequality			29.000***
			(3)
Alpha inequality	-63.000***	-83.000***	-25.000***
	(0.6)	(2.7)	(3.2)
Country segregation Duncan * Alpha inequality		59.000***	-109.000***
		(8)	(9.3)
School HOMEPOS * Country segregation Duncan * Alpha inequality			-102.000***
			(7.8)
Constant	451.000***	467.000***	418.000***
	(22)	(22)	(22)
Observations	395,508	395,508	395,508

Log Likelihood	-2,281,341.00	-2,281,311.00	-2,280,573.00
Akaike Inf. Crit.	4,562,730.00	4,562,671.00	4,561,202.00
Bayesian Inf. Crit.	4,562,992.00	4,562,943.00	4,561,506.00

Note: *p<0.1; **p<0.05; ***p<0.01

Table 37: VIF for regression models – Country Duncan and School Alpha Inequality

Parameters	(14)	(15)	(16)
Sex	1.01	1.01	1.01
HISCED	1.24	1.24	1.25
IMMIG	1.09	1.09	1.09
Language	1.06	1.06	1.07
AGE	1.00	1.00	1.00
REPEAT	1.05	1.05	1.05
School Type	1.17	1.18	1.19
School Area	1.17	1.18	1.18
HOMEPOS	1.48	1.48	1.48
School HOMEPOS	1.92	1.96	166.93
Country segregation Duncan	1.00	1.01	1.01
School HOMEPOS * Country segregation Duncan			167.72
Alpha Inequality	1.25	26.43	35.76
Country segregation Duncan * Alpha Inequality		27.40	37.60
School HOMEPOS * Alpha Inequality			167.23
School HOMEPOS * Country segregation Duncan * Alpha Inequality			180.18

Source: own calculations based on PISA 2018 (OECD, 2020)

Table 38: Coefficients for regression models including macroeconomic parameters – Country S_c and School Alpha Inequality

Parameters	(17)	(18)	(19)	(20)

Sex Male	8.307***	9.762***	9.767***	9.923***
	(0.286)	(0.283)	(0.283)	(0.283)
HISCED ISCED 1	2.436	1.779	1.842	1.82
	(1.702)	(1.679)	(1.679)	(1.677)
HISCED ISCED 2	-6.587***	-5.083***	-4.954***	-3.367**
	(1.587)	(1.566)	(1.566)	(1.565)
HISCED ISCED 3B-C	-2.687*	-0.555	-0.431	1.73
	(1.627)	(1.605)	(1.605)	(1.604)
HISCED ISCED 3A-4	1.901	3.622**	3.725**	5.804***
	(1.545)	(1.524)	(1.524)	(1.523)
HISCED ISCED 5B	0.493	2.125	2.25	4.388***
	(1.574)	(1.553)	(1.553)	(1.552)
HISCED ISCED 5A-6	13.262***	14.274***	14.372***	15.759***
	(1.549)	(1.529)	(1.529)	(1.527)
IMMIG Second generation	7.026***	6.328***	6.383***	7.037***
	(0.633)	(0.625)	(0.625)	(0.624)
IMMIG First generation	27.639***	25.418***	25.486***	25.883***
	(0.682)	(0.673)	(0.673)	(0.673)
Language Other language	-13.868***	-12.932***	-12.971***	-13.545***
	(0.494)	(0.488)	(0.487)	(0.487)
AGE	3.942***	3.705***	3.714***	3.724***
	(0.144)	(0.143)	(0.143)	(0.142)
REPEAT Yes	-59.799***	-57.400***	-57.478***	-57.279***
	(0.491)	(0.485)	(0.485)	(0.484)
School Type Private	1.690***	-1.241***	-1.009**	-1.642***
	(0.439)	(0.435)	(0.436)	(0.438)

School Area 3k> 15k	-1.187**	0.138	-0.117	0.377
	(0.603)	(0.595)	(0.596)	(0.597)
School Area 15k> 100k	1.836***	2.222***	1.889***	2.641***
	(0.584)	(0.577)	(0.578)	(0.579)
School Area 100k> 1m	7.397***	7.211***	6.896***	7.743***
	(0.606)	(0.598)	(0.599)	(0.6)
School Area > 1m	6.628***	6.421***	6.185***	6.584***
	(0.686)	(0.677)	(0.677)	(0.677)
School HOMEPOS	42.239***	33.485***	33.808***	38.992***
	(0.294)	(0.305)	(0.308)	(1.549)
HOMEPOS	7.519***	7.600***	7.601***	7.628***
	-0.179	-0.176	-0.176	-0.176
Alpha Inequality		(61.565***	(72.825***	(45.102***
		(0.676)	(1.496)	(1.806)
Country segregation	46.55	-39.454	-113.816	25.905
	(93.468)	(94.161)	(94.798)	(92.575)
GDP per capita	0.0002	0.0004	0.0004	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Country Gini	0.285	-0.046	-0.041	-0.063
	(0.822)	(0.828)	(0.83)	(0.809)
School HOMEPOS * Country segregation				12.146
				(8.216)
School HOMEPOS * Alpha Inequality				16.117***
				(1.794)
Country segregation * Alpha Inequality			95.954***	-130.252***

			(11.368)	(14.313)
School HOMEPOS * Country segregation * Alpha Inequality				(-57.180***
				(11.048)
Constant	362.701***	431.354***	440.497***	418.315***
	(29.057)	(29.277)	(29.367)	(28.636)
Observations	304315	304315	304315	304315
Log Likelihood	-1760215	-1756124	-1756086	-1755618
Akaike Inf. Crit.	3520480	3512301	3512225	3511296
Bayesian Inf. Crit.	3520745	3512577	3512512	3511614

Note: *p<0.1; **p<0.05; ***p<0.01

Table 39: VIF for regression models including macroeconomic parameters – Country Sc and School Alpha Inequality

Parameters	**(17)**	**(18)**	**(19)**	**(20)**
Sex	1.01	1.01	1.01	1.01
HISCED	1.24	1.24	1.24	1.26
IMMIG	1.12	1.12	1.12	1.12
Language	1.09	1.09	1.09	1.09
AGE	1.00	1.00	1.00	1.00
REPEAT	1.04	1.05	1.05	1.05
School Type	1.17	1.17	1.18	1.19
School Area	1.16	1.16	1.17	1.18
School HOMEPOS	1.69	1.88	1.91	48.57
HOMEPOS	1.49	1.49	1.49	1.49
Country segregation	1.32	1.32	1.33	1.34
GDP per capita	1.11	1.11	1.11	1.11
Country Gini	1.26	1.26	1.26	1.26

Alpha Inequality		1.24	6.09	8.91
Country segregation * Alpha Inequality			6.27	9.98
School HOMEPOS * Country segregation				48.45
School HOMEPOS * Alpha Inequality				44.52
School HOMEPOS * Country segregation * Alpha Inequality				52.51

Source: own calculations based on PISA 2018 (OECD, 2020)