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Essays on the determinants of educational achievements

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PhD Thesis

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Abstract

The goal of this dissertation is to analyze how students' circumstances such as their family background, school characteristics or peer groups, affect their educational achievements. The dissertation consists of three main chapters.

Chapters 2 and 3 aim at measuring inequality of opportunity in educational achievements in twenty European countries taking data from PISA 2012. We assume that students' attainments are determined by circumstance and effort variables, and we construct counterfactual distributions in which the inequality in achievements is only due to the differences in circumstances. Inequality of opportunity is measured as the inequality of those counterfactual distributions.

To construct the counterfactuals we follow two approaches proposed in the literature. In Chapter 2 we follow a parametric approach where we estimate a linear regression model for educational achievements on circumstance and effort variables, and we build counterfactuals based on those estimates. In Chapter 3, the counterfactuals are constructed following a non-parametric approach, where each student is assigned the average achievement of the group of students sharing either homogeneous circumstances or homogeneous efforts.

The results obtained in Chapters 2 and 3 confirm that the two approaches are in fact alternative methods to obtain a similar inequality of opportunity level. We find that, among the selected countries, Belgium, France, Germany, and Bulgaria get the highest levels for inequality of opportunity, whilst the lowest levels are for the Nordic countries. The results also show that peer groups are the greatest contributors to the inequalities, except for the Nordic countries, where efforts contribute more than circumstances.

Chapter 1 introduces the basic notions for the measurement of inequality of opportunity and the dataset that is used in Chapters 2 and 3.

Finally, Chapter 4 analyzes the influence of circumstances not only on students' achievements, but also on their attitude towards school. The aim is to contribute to the literature by analyzing the determinants of students' attitudes towards school in Spain. We take data from the 2009 wave of PISA and carry out the estimations using a multivariate multilevel approach. This methodology attempts to capture the hierarchical structure of the data and to take into account the existing correlation between attitude and educational achievements. The results show that the greatest proportion of the variance is explained by the students' personal and family characteristics. The only school-related variables that are statistically significant for attitude towards school are those related to the disciplinary climate. As a matter of fact, while achievements are strongly related to the socio-economic profile of the peer group, this factor does not seem to be important in determining their attitude.

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Introduction

This dissertation investigates to what extent students' educational achievements are conditioned by circumstances such as their family background, school characteristics and peer effects. Understanding how these factors affect the level of outcomes is important. Evidence indicates that individuals who get higher achievements are more likely to report higher subjective well-being (Oreopoulos, 2007), to participate more actively in society (Milligan et al., 2004; Dee, 2004) and to enjoy better health (Cutler et al., 2006; De Walque, 2007; Grimard and Parent, 2007; Grossman, 2008). Thus, investigating the explicative factors of achievements is important in order to mediate the educational policy aimed at improving students' performance.

All the chapters of the thesis are based on the data provided by OECD's Program for International Student Assessment (PISA). In the last two decades, this data has highlighted large differences in achievements, which result from different sources. Since the debate on 'equality of what?' pioneered by authors such as Rawls (1971); Dworkin (1981*a*,*b*); Sen (1970); Arneson (1989) and Cohen (1989), economists have started to shift the focus from overall inequality to inequality of opportunity. Despite the differences in the opinions of the authors, they all agree that individuals should have equal *opportunity* in order to get the desired achievements. Accordingly, once every individual has equal chances, the outcome level an individual reaches is their own responsibility and any existing inequality would be considered as 'fair'. Conversely, if individuals face different opportunities, the outcome level reached might be beyond their control and the outcome differences of this kind are considered as 'unfair'. Precisely, inequality of opportunity attempts to measure the extent of that unfair inequality.

In the first economic studies on the subject, opportunity was treated *directly* or explicitly. In this framework every individual faces some opportunity sets. Thus, there will be inequality of opportunity if the individuals are endowed with different sets, and some sets are likely to offer more advantages than others. Then, the measurement consists of comparing situations where individuals present different opportunity sets and ranking such situations according to the existing differences. Nevertheless, modelling opportunity sets explicitly requires much information that is hardly ever available due to its abstract quality. For a detailed literature review on ranking opportunities sets, see for instance Peragine (1999) and Barberà et al. (2004).

There is another branch of literature where unobservable opportunities are deduced *indirectly* from observable factors. Here, the opportunities are represented as a set of outcomes that individuals can reach subject to *circumstances* beyond their responsibility, such as socio-economic background, as well as their own *efforts*. See, for instance, the prominent models of Roemer (1993, 1998); Van de gaer (1993); Fleurbaey (1994) and Bossert (1995). In this setting, according to Roemer (1998), an opportunity-egalitarian policy should be focused on eliminating the consequences of circumstances, and respecting the influence of efforts on outcomes to the greatest extent possible.

Mark Fleurbaey, François Maniquet and Walter Bossert also propose several opportunity-egalitarian policies and allocation rules that are in line with the idea of Roemer's approach of compensating the effect of circumstances but not the influence of individual responsibility. This literature is summarized in Fleurbaey (2008). Since these important contributions, there has been a bloom of both theoretical and empirical literature aimed at measuring the extent of inequality of opportunity. For instance, Pignataro (2012); Roemer and Trannoy (2014); Van de gaer and Ramos (2015*a*); Ferreira and Peragine (2016) provide comprehensive surveys of recent research on this topic.

Taking these aspects together, Chapter 1, Chapter 2 and Chapter 3 analyze the inequality of opportunity in educational achievements for twenty European countries. Chapter 1 provides the basis for the two following chapters. First of all, it briefly summarizes the aspects of the measurement. In essence, we assume that students' achievements are determined by variables of *circumstances* and *effort*. The inequality of opportunity is measured as the inequality of the counterfactual distributions in which the achievement differences are uniquely due to circumstances. Next the chapter introduces the database provided by PISA 2012 that is used in the following two chapters. For the twenty European countries selected, it describes the educational outcomes represented by students' mathematical scores, as well as the chosen explanatory variables related with students' family background, school characteristics, peer influences, and students' motivation and attitude, which represent their circumstances and efforts.

Chapter 2 and Chapter 3 empirically measure the inequality of opportunity, each focusing on a different approach to construct counterfactual distributions. Chapter 2 follows a parametric approach, where we specify and estimate a linear functional form between achievements, and circumstances and effort variables. Then, counterfactuals are built based on those estimates.

In most studies in the field of education the inequality of opportunity hardly relies on counterfactual distributions, instead it is mainly measured as the association between parental background and students' performance (see for instance, Wößmann, 2004; Schütz et al., 2007; Wößmann and Peterson, 2007; Ammermueller, 2007; Raitano and Vona, 2016). As a matter of fact, the studies that do depend on parametrically constructed counterfactual distributions work only with certain circumstance variables (Martins and Veiga, 2010; Ferreira and Gignoux, 2014; Salehi-Isfahani et al., 2014).

Chapter 2 contributes to the empirical measurement of inequality of opportunity in different ways. First, we consider the proxy variables for effort in the construction of counterfactual distributions. The selection of these proxies is based on previous studies, such as Bozick and Depmsey (2010); de Fraja et al. (2010); Eren and Henderson (2011); Metcalfe et al. (2011) and Kuehn and Landeras (2014) which analyze how students' efforts affect their achievements. As circumstances may affect achievements both directly and through efforts, the specification that we propose captures their joint impact. Second, we account for students' peer effects on the side of circumstances. The rapidly growing literature finds that these effects are significant for individual student achievement (Hanushek et al., 2003; Hoxby, 2000; McEwan, 2003; Sacerdote, 2001; Schneeweis and Winter-Ebmer, 2007; Lavy et al., 2012; Boucher et al., 2014). In particular, if everyone in the group is high achieving, the performance of a student is likely to be positively affected by belonging to such a group, and simultaneously, that student might have an impact on the groups's average achievement. Therefore, the endogeneity of these peer effects is taken into account when estimating the models of interest. Finally, based on Van de gaer and Ramos (2015*b*), this study relies on counterfactual distributions that behave properly regarding one basic principle of the inequality of opportunity, so that our measures guarantee that a progressive transfer among students with the same effort will reduce inequality of opportunity.

In Chapter 3 the counterfactuals are constructed following two non-parametric approaches developed by Checchi and Peragine (2010). On the one hand, in the *ex ante* approach students are assigned the average achievement of their *type*, i.e., a group of students sharing homogeneous circumstances. In a counterfactual distribution built this way, achievements are entirely determined by circumstances in a manner that students of the same type obtain the same achievement regardless of the effort they exert. The inequality of opportunity is measured as the inequality of that distribution. On the other hand, in the *ex post* approach students are assigned the average achievement of their *tranche*, i.e., a group of students with homogeneous efforts. In this counterfactual distribution there is no room for circumstances-related inequalities. Hence, the inequality of opportunity is assessed as the distance between the actual and the counterfactual distribution.

Certainly, the definition of types and tranches condition the measures of inequality of opportunity. Nevertheless, in practice, there is no indication of how to classify the students into such groups. In most common procedures the students are sorted either according to their values in a limited number of categorical circumstance or effort variables, or according to their position in a single continuous circumstance variable. This study seeks to provide an alternative approach to define types and tranches, regardless of the nature and the number of variables under consideration. In particular, in both the above specifications, circumstances and efforts correspond to the estimated vectors obtained in the previous chapter.

The results obtained in Chapter 2 and Chapter 3 confirm that Belgium, France, Germany, and Bulgaria get the highest levels for inequality of opportunity, whilst the lowest levels are for Nordic countries and for Spain and Ireland. The results also indicate, for instance, that peer groups are the greatest contributors to the inequalities in the selected countries, except in Nordic countries and in Spain and Ireland, countries with the lowest between-school variance and the lowest inequality of opportunity.

Notwithstanding the importance of educational achievement, it is worth noting that this reflects just a part of the education received at school. That is, achievements are a way of evaluating cognitive processes which are related to the mental actions of acquiring knowledge, however, they do not capture the non-cognitive skills such as students' attitudes.

Studies like Kautz et al. (2014); Almlund et al. (2011) and Borghans and Schils (2012) show that non-cognitive skills play an important role in educational attaitment, labour market success, health and criminality, among other life outcomes. Nevertheless, non-cognitive skills have usually been neglected in the economic literature, despite their importance. The aim of Chapter 4 is to make a contribution to the literature on the relevance of non-cognitive aspects. In particular, for Spain we analyze and compare the determinants of students' achievements, or cognitive outcome, as well as their attitude towards school, or non-cognitive outcome.

Most studies that inquire about the main determinants of the educational achievements in Spain agree that inequality in educational achievements can be mainly attributed to the characteristics of students and their families, the role of school and peers being in the background (see the literature review of Ferrera et al., 2013, and the references therein). Our findings in the previous chapters coincide with these results.

This chapter seeks to investigate whether these conclusions can be carried over to attitudes towards school. Accordingly, the working hypothesis defends that for attitudes, as for achievements, the main determinants are individual and family factors, whilst the influence of the schools is relatively minor. At the same time, it presumes that among the school variables, those related to the peer learning environment have the largest influence on attitudes.

In order to test the hypothesis we take data from the 2009 wave of PISA for Spain and carry out the estimations following a multivariate multilevel approach. This methodology attempts to capture the hierarchical structure of educational data, and at the same time, to take into account the existing correlation between attitude and educational achievements. Accordingly, a multilevel bivariate regression model is estimated in which both the attitude towards school and the educational achievements are evaluated.

The results confirm the hypothesis and find that the greatest proportion of the variance is explained by the students' personal and family characteristics. In addition, the only school-related variables that are statistically significant for attitude towards school are those related to the prevailing disciplinary climate.

Chapter 1

Basic notions for the measurement of inequality of opportunity and the PISA database

1.1 Introduction

This chapter provides the background for the two following chapters in order to measure the educational inequality of opportunity in twenty European countries. It consists of two main parts. On the one hand, Section 1.2 briefly summarizes the basis for the measurement of the inequality of opportunity, by describing two basic principles that guarantee that a measure is able to capture inequality of opportunity. On the other hand, Section 1.3 introduces the database provided by the Program for International Student Assessment (PISA) 2012 which is used in the two following chapters. For the twenty European countries, this section describes the educational achievements that reflect individual outcomes as well as the selected variables related with students' family background, school characteristics, peer effects, and students' motivation and attitude, which taken together represent their circumstances and efforts. Finally, Section 1.4 summarizes the main conclusions.

1.2 Inequality of opportunity measurement

This section introduces the basis for the measurement of the inequality of opportunity. We consider a population of N students and denote by Y_i the educational achievement of student i. For each student $i = 1, \ldots, \mathsf{N}$, we assume that Y_i is completely determined by a vector $\mathbb{C}_i \in \mathbb{R}^{K_C}$ of circumstances and a vector $\mathbb{E}_i \in \mathbb{R}^{K_E}$ of efforts. We denote by $Y = [Y_1, \ldots, Y_{\mathsf{N}}]^T$, $\mathbb{C} = [\mathbb{C}_1, \ldots, \mathbb{C}_{\mathsf{N}}]$ and $\mathbb{E} = [\mathbb{E}_1, \ldots, \mathbb{E}_{\mathsf{N}}]$ the respective population matrices of achievements, circumstances and efforts, with $\mathcal{D}$ being the set of all possible population matrices, that is,

$$\mathcal{D} = \{(Y, \mathbb{C}, \mathbb{E}) : Y \in \mathbb{R}^{\mathsf{N}}, \mathbb{C} \in \mathbb{R}^{\mathsf{N} \times K_C}, \mathbb{E} \in \mathbb{R}^{\mathsf{N} \times K_E}\}$$

An inequality of opportunity measure is a function $\mathcal{M} : \mathcal{D} \to \mathbb{R}$. To guarantee that the measure $\mathcal{M}$ is able to capture inequality of opportunity, it should satisfy basic principles classified as *compensation* or *reward* (see for instance Fleurbaey and Peragine, 2013; Ramos and Van de gaer, 2016).

Among the different compensation principles, this thesis focuses only on the so-called *Ex-Post Compensation* (Fleurbaey and Peragine, 2013). It states that students that exert the same effort should obtain the same achievement. Thus, the differences in the outcomes of the students making the same effort should be compensated.

Formally, we consider two populations with the same number of students. In the first, students i and j make the same effort, but i gets a higher achievement than j. The difference in their achievements must be due to differences in their circumstances because they exert the same effort. In the second population, students i' and j' have the same circumstance and effort variables as students i and j respectively, but greater differences in their achievements. The rest of the students in the two populations are pairwise identical, meaning that for each of the rest of the students in the first population there is a student in the second population with exactly the same achievement, effort, and circumstance variables. According to the ex-post compensation principle the inequality of opportunity should be greater in the second population than in the first one.

> *Compensation principle.* A measure of inequality of opportunity $\mathcal{M}$ satisfies compensation if, for all $d^1 = (Y^1, \mathbb{C}, \mathbb{E})$, $d^2 = (Y^2, \mathbb{C}, \mathbb{E}) \in \mathcal{D}$, such that there are $\delta \in \mathbb{R}_{++}$ and $i, j \in \{1, \ldots, \mathsf{N}\}$ with $\mathbb{E}_i = \mathbb{E}_j$ and $Y_i^2 = Y_i^1 + \delta > Y_i^1 \geq Y_j^1 > Y_j^2 = Y_j^1 - \delta$, and for all $k \notin \{i, j\} : Y_k^2 = Y_k^1$, then $\mathcal{M}(d^1) < \mathcal{M}(d^2)$.

Among the different reward principles, only the *utilitarian reward* is considered in this study. It proposes respecting the outcome inequality between individuals with homogeneous circumstances, since these differences are derived from efforts for which individuals are responsible. Again we consider two populations with the same number of students. In the first population, students i and j have equal circumstances, but the achievement of student i is higher than that of student j. Since they are endowed with the same circumstances, the differences in achievements are due to differences in efforts. In the second population, students i' and j' have the same circumstances and efforts as i and j respectively and greater differences in their achievements. The rest of the students in the two populations are pairwise identical. According to the reward principle the inequality of opportunity in both populations should be the same.

> *Reward principle.* A measure of inequality of opportunity $\mathcal{M}$ satisfies reward principle if, for all $d^1 = (Y^1, \mathbb{C}, \mathbb{E})$, $d^2 = (Y^2, \mathbb{C}, \mathbb{E}) \in \mathcal{D}$, such that there are $\delta \in \mathbb{R}_{++}$ and $i, j \in \{1, \ldots, \mathsf{N}\}$ with $\mathbb{C}_i = \mathbb{C}_j$ and $Y_i^2 = Y_i^1 + \delta > Y_i^1 \geq Y_j^1 > Y_j^2 = Y_j^1 - \delta$, and for all $k \notin \{i, j\} : Y_k^2 = Y_k^1$, then $\mathcal{M}(d^1) = \mathcal{M}(d^2)$.

Therefore, whereas the compensation principle is formulated in terms of reducing the inequality between individuals with the same effort, the reward principle is formulated in terms of respecting the inequality between individuals with the same circumstances. Fleurbaey and Peragine (2013) have proved that the compensation and reward principles are not compatible.

In addition, a measure of inequality of opportunity should satisfy *anonymity* and *replication invariance*, which are two standard principles usually demanded of any inequality measure. Anonymity establishes that for each student only their own achievement and their corresponding vector of circumstances and efforts matter in evaluating inequality of opportunity. Replication invariance enables us to compare populations with different numbers of students. These two properties are formally stated as follows:

> *Anonymity.* The measure $\mathcal{M}$ is invariant under permutation of individuals with same achievements and same vectors of circumstances and efforts.
>
> *Replication invariance.* The measure $\mathcal{M}$ is invariant under replication of the population.

To empirically measure the inequality of opportunity in a given population, first we assume that the link between achievements, circumstances and efforts is as follows,

$$Y_i \quad = \quad G(\mathbb{C}_i, \mathbb{E}_i) \quad i = 1, \ldots, \mathsf{N} \quad G : \mathbb{R}^{K_C} \times \mathbb{R}^{K_E} \to \mathbb{R}_{++}. \tag{1.1}$$

Based on the above model, it is possible to build two different types of counterfactual distributions. The first type of distribution can be constructed such that they reflect only differences due to circumstances, i.e. counterfactuals in which all the differences due to efforts have been eliminated. Thus, given a population $d = (Y, \mathbb{C}, \mathbb{E})$, we denote by $Y^C(Y, \mathbb{C}, \mathbb{E})$ the counterfactual distribution constructed in this way. A 'direct' inequality of opportunity measure, denoted by $\mathcal{M}^D$ evaluates inequality of opportunity as follows:

$$\mathcal{M}^D(Y, \mathbb{C}, \mathbb{E}) \quad = \quad I(Y^C(Y, \mathbb{C}, \mathbb{E})) \tag{1.2}$$

where I is an inequality measure. The second type of counterfactual distribution consists of those in which the differences due to circumstances have been removed. We denote these counterfactuals by $Y^E(Y, \mathbb{C}, \mathbb{E})$. An 'indirect' measure, $\mathcal{M}^I$ evaluates inequality of opportunity as the difference between the inequality in the current distribution Y and the inequality in the counterfactual distribution Y^E, as follows:

$$\mathcal{M}^I(Y, \mathbb{C}, \mathbb{E}) = I(Y) - I(Y^E(Y, \mathbb{C}, \mathbb{E})). \tag{1.3}$$

In the following chapters we will discuss under which conditions the measures $\mathcal{M}^D$ and $\mathcal{M}^I$ fulfill the compensation and reward principles.

The selection of the inequality measure I depends on the characteristics of the variable of interest. In the dataset that will be described in the next section, the educational achievements are transformed through a standardization procedure that consists of both a translation and a rescaling by the ratio. Since standardization is just a change in the metric, there is no reason to change the inequality rankings between the countries after this transformation. However all the relative inequality measures violate this principle, that is, if inequality is measured according to any relative inequality index, the ranking between two countries before standardization may be reversed once achievements have been standardized. In contrast, the variance always preserves the rankings before and after this kind of transformation. Moreover, as shown by Zheng (2007), the variance is the *only* decomposable measure that preserves the rankings before and after standardization.[1] Consequently, if the idea is to avoid changes attributable to the standardization of the original data, the variance must be selected in the analysis. In addition, choosing the variance to evaluate the counterfactual distributions in Equations (1.2) and (1.3) guarantees that the direct and indirect approaches coincide.

The estimation of the counterfactual distributions depends on the model specified and the estimation procedure used. These distributions can be constructed following a parametric or non-parametric approach. Whereas the parametric approach imposes a functional form to estimate individuals' achievements as a function of circumstances and efforts, the non-parametric approach generally does not assume any functional form and typically relies on averaging procedures. Both approaches are followed in this thesis to construct counterfactual distributions and to measure the inequality of opportunity. In the chapters that follow both of them are explained and implemented individually. More precisely, Chapter 2 analyzes the inequality of opportunity based on parametrically constructed counterfactual distributions. Instead, in Chapter 3 the distributions are constructed based on the non-parametrical procedure developed by Checchi and Peragine

[1] A decomposable measure guarantees that if inequality in one population subgroup increases then overall inequality also increases.

(2010).

1.3 Dataset

To measure inequality of opportunity as defined in Equations (1.2) or (1.3) one needs to determine the outcome variable over which the inequality will be measured as well as the set of circumstances and effort variables. This section presents the database provided by the *Program for International Student Assessment*, PISA, which will be used in the following two chapters.

1.3.1 PISA database

We take data from the fifth round of PISA conducted in 2012. PISA is a worldwide study program supported by OECD and has been administered every three years since 2000. PISA 2012 provides internationally comparable insights into 15 year-old students in 65 countries.[2] The program primarily measures whether students about to conclude compulsory education are able to apply what they have learned in the school to real-life challenges OECD (2010). Accordingly, the assessment tests focus on core subjects such as mathematics, reading and science, and every three years one of them is evaluated more thoroughly, while the other two are tested as minor domains. In the PISA 2012 dataset the main focus is on mathematics, hence, the educational achievements in our study are represented by mathematical scores obtained by the students in the tests. It should also be noted that PISA tests are low-stakes, meaning that scores are anonymous and have no consequences for the test taker.

To measure the overall knowledge of students, PISA uses a complex technique that enables them to measure a wide coverage of competencies while maintaining a moderate testing time.[3] In particular, each student answers only a limited subset of the total number of questions and the responses of the questions that they did not have to answer

[2]The number of participating countries varies across PISA assessment cycles: 43 countries participated in 2000, 41 countries in 2003, 57 countries in 2006, and 65 countries in 2009 and 2012.

[3]PISA includes a *rotated test design* that consists of allocating the main study questions into thirteen clusters; seven of such clusters are used to assess the main competency — mathematics in PISA 2012— , and six to assess the remaining two competencies — reading and science in PISA 2012 —. Each student answers a booklet that contains four clusters. To avoid plagiarism between students, there are thirteen different booklets that vary according to the clusters included and their position within a booklet. Then each student is randomly assigned one of the thirteen booklets.

are inferred from their actual responses and characteristics. Thus, PISA follows the *Item Response Theory* (IRT) to estimate the whole distribution of the likely ability of each student based on the answered set of questions.[4] Then five plausible values are randomly drawn from each distribution to represent the likely performance of each student. These values are standardized so that the average score of OECD countries is 500 and standard deviation is 100. As mentioned in Section 1.2, this standardization procedure followed by PISA is a crucial point for choosing the variance, which is the only inequality measure that behaves properly under that linear transformation. The estimations that deal with students' achievements should be carried out for each plausible value separately, and then averaged to obtain the final estimate. However, to simplify the empirical analysis, the next two chapters focus on one, specifically the first, of the five plausible values. This procedure is superior to the calculating the average of the five (OECD, 2009*a*; Causa and Chapuis, 2011). As expected, results are robust to the use of either one of the values or all of them.

The procedure used by PISA intends to guarantee that the sample properly represents the target population. In this procedure, first of all, schools are sorted into *strata* (i.e. alike groups), according to certain variables such as region, language of instruction, proportion of immigrants and types of school, which are related to the characteristics of education system of each country. After this classification, PISA selects the participant students in two steps. At the first step, schools in each country are randomly chosen within each strata.[5] At the second step, 15 year-old students[6] attending grade 7 or higher are randomly selected from these schools.[7]

Dealing with survey data requires considering the sampling design. Therefore, the final sampling weights are used to adjust the results for the unequal probabilities of being

[4]Essentially, IRT models are based on a function of the form,

$$P(x|\theta, \delta).$$

This equation provides the probability of scoring x in a given question subject to the latent ability of a student θ and the test question parameter δ such as the difficulty of that question. Accordingly, the IRT is used to obtain the distribution of the ability θ.

[5]Schools are selected with probabilities proportional to their size, meaning that larger schools present a higher probability of being selected than smaller schools.

[6]PISA assesses students who are aged between 15 years and 3 (complete) months and 16 years and 2 (complete) months at the beginning of the assessment period.

[7]Usually 35 students are selected within the schools. If there are fewer than 35 fifteen-year-old students in a school, then all the students are invited to participate in the assessment. In any case at least 20 students need to be selected from each school.

selected and for the non-response of schools and students. Furthermore, due to the multi-stage sampling procedure, students should not be assumed as independent observations, as students attending the same school might be more similar than others attending a different school. If this specific dependence between observations is not taken into account, the standard errors of the regression estimations will be systematically underestimated. Consequently, in the two following chapters we estimate the clustered standard errors in the regressions to account for the nested sampling design.[8]

1.3.2 Selected countries

The analyses on inequality of opportunity in Chapters 2 and 3 are conducted in twenty European countries drawn from the four different geographical areas in Europe: Bulgaria (BGR), Croatia (HRV) and Romania (ROU) in Eastern Europe; Belgium (BEL), France (FRA), Germany (DEU), Ireland (IRL), Luxembourg (LUX), The Netherlands (NLD), Switzerland (CHE) and the United Kingdom (GBR) in Western Europe; Finland (FIN), Iceland (ISL), Lithuania (LTU), Norway (NOR) and Sweden (SWE) in Northern Europe; and Greece (GRC), Italy (ITA), Portugal (PRT) and Spain (ESP) in Southern Europe. Our database contains information on about 160,000 students, who represent a population of about four million. Education is compulsory for under 15s in all the countries considered in this study, so there is no bias in the analysis related to the school leaving rate.

Information for mathematical achievements is presented in the second column block in Table 1.1. It can be observed that only seven countries (Switzerland, The Netherlands, Finland, Belgium, Germany, France and Ireland) have mean scores higher than the OECD mean. By contrast, Bulgaria, Romania, Greece, Croatia and Sweden have the lowest average values. The sixth column shows the standard deviations of math scores. Belgium, France, Luxembourg and Germany have the highest values whereas the lowest can be found in Romania, Finland, Ireland, Greece and Spain. It can be easily checked that since the total standard deviation is 94.51, the total variance is 8931.64. From this value, more than 95% is attributable to the within-country variance.[9] This means that the greatest

[8] With the same purpose, Chapter 4 follows the multilevel regression analysis and the procedure is detailed therein.

[9] The variance may be decomposed by population subgroups as the sum of two components. The between-group component is the variance of a hypothetical distribution in which of the individuals in each group enjoy the same mean. The within-group component is a weighted average of the variance in each group where the weights are the population shares.

Table 1.1: Descriptive statistics for educational achievements

Countries		Sample and Population: Sample	Sample and Population: Weighted sample	Math score: Mean	Math score: Sd	Variance components (%): Between sch. variance	Variance components (%): Within sch. variance
Belgium	BEL	8401	114194	518.42	101.21	52.68	47.32
Bulgaria	BGR	5078	50617	444.70	92.05	52.65	47.35
Croatia	HRV	4951	44793	471.28	87.74	45.98	54.02
Finland	FIN	8670	58918	520.80	84.22	9.41	90.59
France	FRA	4220	631010	503.14	96.63	56.39	43.61
Germany	DEU	4802	720582	518.11	94.86	53.68	46.32
Greece	GRC	4945	91020	458.30	85.69	32.20	67.80
Iceland	ISL	3127	3718	494.92	92.57	12.39	87.61
Ireland	IRL	4979	53351	501.35	84.39	20.79	79.21
Italy	ITA	29486	487526	489.05	90.69	51.80	48.20
Lithuania	LTU	4132	28876	485.15	87.41	31.44	68.56
Luxembourg	LUX	5223	5484	489.84	95.37	32.05	67.95
Netherlands	NLD	4382	193212	522.52	91.66	66.70	33.30
Norway	NOR	4575	56941	489.73	89.53	14.76	85.24
Portugal	PRT	5495	92189	487.87	93.50	31.58	68.42
Romania	ROU	4875	130209	445.83	79.36	44.92	55.08
Spain	ESP	24686	364230	485.15	87.27	21.37	78.63
Sweden	SWE	4585	91713	477.38	90.25	15.00	85.00
Switzerland	CHE	10475	73963	532.13	94.51	38.07	61.93
United Kingdom	GBR	12538	679633	493.72	94.47	30.78	69.22
Total		159625	3972178	497.72	94.51		

Summary statistics are calculated using the final student weight and the first plausible value reported by PISA.

differences in the achievements in the selected countries are due to differences within each country. Therefore, it may be worth analyzing and comparing these differences using the same set of explanatory variables for each country.[10] As a first step we analyze the two last columns in Table 1.1 that report, for each country, the contribution of the between- and the within-school variance to the total variance. These contributions vary greatly between countries. For instance, in The Netherlands, France, Germany, Belgiumn, Bulgaria and Italy, the between-school variance represents more than half of the total variance, meaning that there are great disparities between schools. By contrast, in Nordic countries such as Finland, Iceland, Norway, Sweden and in Ireland and Spain the schools seems to be more homogeneous, with the highest contribution being due to the inequality within schools.

[10]We acknowledge that some important national features are not contemplated, for the set of expanatory variables are selected based on their general relevance in most countries rather than in each country individually. However, the main purpose of the study is to analyze the manner the same channels affect different countries, thus, we opt for the same set of variables.

These patterns on between and within-school variances among European countries are in line with those observed in Martins and Veiga (2010).

1.3.3 Selected variables

In addition to performing the tests, students answered a background questionnaire and school principals completed a questionnaire about their schools. Accordingly, our database is constructed by combining students' math scores with the variables that rely on students' and principals' responses. All the selected variables are briefly described in Table 1.2. For futher details on the definition and calculation of these variables, we suggest consulting the PISA 2012 report (OECD, 2014).

Circumstance variables

Students' circumstances, over which they have no control, are represented by their gender, and factors related with their families, schools and peer groups. The paragraphs that follow present the chosen circumstance variables and provide some motivation for their selection.

i) Family background

Numerous papers show the high effect of social origin on educational achievement (see for instance Sirin (2005) and references therein as well as more recent studies Pokropek et al. (2015); Schulz et al. (2017)). Social origin usually includes parental education, parental occupation, and income or home resources, which, although correlated, measure different aspects of family socio-economic status. In particular, the effect of household resources on educational achievements has received great attention (Spiezia, 2010; Traynor and Raykov, 2013) since it is believed that home possessions capture wealth better than income because they reflect a more stable source of wealth.

In addition, immigration status is also considered a relevant feature when measuring the influence of family background, since as stated by Hillmert (2013), the empirical studies indicate that migrants are often disadvantaged regarding their educational achievement, with their relative situation changing across countries.

Based on these references we select four indicators from the PISA database to represent social origin: 1) immigration status (NAT), if at least one parent is born in the country, 2)

Table 1.2: Description of explanatory variables

	CIRCUMSTANCE VARIABLES
PERSONAL CHARACTERISTICS	
MALE	Dummy variable equal to 1 if the student's gender is male, 0 otherwise.
FAMILY BACKGROUND	
NAT	Dummy variable equal to 1 if at least one student's parent is born in the country of the test, 0 otherwise.
PARED	*Highest level of parental education* Based on students' responses regarding parental education level, classified using the International Standard Classification of Education (ISCED), PISA estimates the number of years of schooling. The values range from 3 to 18.
HISEI	*Highest occupational status of parents* coded according to the International Standard Classification of Occupations (ISCO) and the international socio-economic index of occupational status (ISEI). The values of this variable ranges from 16 to 90, lower values representing lower socio-economic status and higher values representing higher socio-economic status.
HPOS	*Home possessions* is based on students' responses about the availability of 17 home items related to wealth (a room of their own, a dishwasher, a link to the Internet, a DVD player, and three other country-specic items), cultural possessions (classic literature, books of poetry and works of art), educational resources (a desk and a quiet place to study, a computer that students can use for schoolwork, educational software, books to help with students' school work, technical reference books and a dictionary) as well as the number of books at home. For more details on how this information is aggregated, see the footnote of this table. The values range from -6.69 to 4.15.
SCHOOL BACKGROUND	
SCEDUR	*School's educational resources* based on school principals' perceptions of potential factors facilitating instruction at their school, such as school laboratory equipment, didactic material, computers for instruction, internet connectivity, computer software for instruction and library materials. For more details on how this information is aggregated, see the footnote of this table. The values range between -3.59 and 1.97.
MACTIV	*Mathematics-related extra-curricular activities at school* indicates the number of extracurricular activities which are related with mathematics offered by the school (such as additional mathematics lessons and mathematics competitions). The values range from 0 to 5.
TCCLIM	*Teacher related factors affecting school climate* derived from school principals' reports on the extent to which teachers encourage students, cover students' needs, have good relationships with students, are not absent, are on time, are well prepared, etc. For more details on how this information is aggregated, see the footnote of this table. The values range from -3.27 to 2.85.
TCMOR	*Teacher morale* derived from school principals' reports on the extent to which teachers show high morale, high enthusiasm, pride in the school and positive valuation of academic achievement. For more details on how this information is aggregated, see the footnote of this table. The values range from -3.97 to 1.44.
TCSHORT	*Teacher shortage* indicates the presence of qualified teachers. For more details on how this information is aggregated, see the footnote of this table. The values range between -1.09 and 3.59.
PEER GROUP EFFECT	
P	Average mathematical achievements of students' schoolmates.

	EFFORT VARIABLES
HWORK	Average number of hours per week spent doing homework or other study set by teachers.
NSKIP	Dummy variable equal to 1 if the student has not skipped classes in the two weeks before the PISA test, 0 otherwise.
PERSEV	*Perseverance* constructed using student responses about their willingness to work on problems that are difficult, their interest in working on a task until it is perfectly accomplished, and their readiness to do more than is expected of them. For more details on how this information is aggregated, see the footnote of this table. The values range from -4.05 to 3.52.
ATSC	*Attitude towards school* constructed using student responses about their perception of the usefulness and benefits of school. For more details on how this information is aggregated, see the footnote of this table. The values range from -2.99 to 2.35.
NREP	Dummy variable equal to 1 if the student has never repeated any grade either at primary or secondary education, 0 otherwise.

HPOS, SCEDUR, TCCLIM, TCMOR, TCSHORT, PERSEV and ATSC are PISA's scale indices constructed by combining and coding different items from the context questionnaires based on the Item Response Theory (IRT) scaling procedure. IRT methodology attempts to infer the true value of latent traits from observed item responses, by taking into account the heterogeneity in the difficulty of given items. This complex technique makes it possible to summarize data instead of dealing with many single items. The estimated values are then standardized to scales with an OECD average of 0 and a standard deviation of 1. These scores can be interpreted by comparing them to the OECD mean (for more detais, see OECD, 2014).

the highest level of parental education (PARED), 3) the highest occupational status of the parents (HISEI), and 4) home possessions (HPOS), which is a summary index based on students' responses about 14 household items including wealth durables, cultural items, educational resources and number of books at home.[11]

ii) Characteristics of schools

There is also general agreement about the influence of the school in educational achievements. Since students spend a relatively large part of their time at school, the characteristics of schools and teachers appear to affect their learning. Therefore we consider the information on the availability of school resources that facilitate instruction (SCEDUR). These include factors such as access to laboratory equipment, didactic material, computers for instruction, Internet connectivity, computer software for instruction and library materials. The number of mathematics-related extra-curricular activities offered at school (MACTIV) is also included, since these can facilitate student learning. Regarding teacher-related aspects, we account for factors affecting school climate (TCCLIM) which reflect to what extent teachers encourage students, cover students' needs and relate well to them. In addition, we also consider teachers' morale, enthusiasm and pride in the school and their positive valuation of academic achievement (TCMOR). These variables may include not only norms and values, but also quality relationships and general atmosphere (OECD, 2012). Finally, the number of qualified teachers at school (TCSHORT) is also taken into account.[12]

iii) Peer effects

Growing literature on the economics of education find that the influence of peers is a powerful determinant of students' educational achievements. Students in a group help and interact with each other and contribute in the formation of group values. In that regard, high achieving peers may foster a more effective learning process where teachers are interrupted less frequently. Thus, students tend to perform better if their fellow students are high achievers. Sacerdote (2011) and Ewijk and Sleegers (2010) for instance,

[11]These variables are based on the information provided by the students rather than by their parents. In only a few countries (Belgium, Croatia, Germany, Italy and Portugal) the parents compleated a questionnaire.

[12]We are aware that in many countries the type of school is an important determinant of achievement. However, we are not able to include this kind of variable in our model. The reason is two-fold. First, there is no information in the PISA dataset about specific organization issues. For example, no information is provided about the different types of schools into which students are sorted in countries such as Belgium, Bulgaria, Croatia, Germany, Italy, Luxembourg, the Netherlands, Romania and Switzerland. Second, even if the type of school is provided, for instance public versus private, the classification of schools does not follow the same criterion across countries.

provide comprehensive surveys on this topic.

However, the choice of relevant groups is strictly constrained by data availability. In particular, the PISA datasets do not provide any information about students' social networks or about their classmates. Therefore, the peer groups are defined at school level. As a matter of fact, not all the students are sampled within a school and this generates a measurement error in the peer variable.[13] For this reason, we consider only schools for which at least 15 students have been interviewed, so that the sample size is large enough to build a peer variable that can be representative (Raitano and Vona, 2013, 2016). Another data limitation is that PISA does not give any prior information specifying the composition of peer groups. Nevertheless, despite the complexity involved in including peer group effects in the model, the conclusions obtained may help to better understand the differences in achievements. Therefore, following the related literature Hanushek et al. (2003); Entorf and Lauk (2008); Boucher et al. (2014) we capture the effect of peers by measuring the average level of achievement of the rest of the students attending the same school.

Econometric research on the identification of peer effects has been strongly influenced by the work of Manski (1993) which, among other problems, defines that of *reflection* or simultaneity. This emerges because the achievements of students in a peer group evolve in an interdependent manner: average performance of the peer group affects individual performance but, simultaneously, this last also affects the average of the group. Accordingly, the endogeneity of these peer effects is accounted for when estimating the models of interest. We provide more details on this in Chapter 2.

iv) Descriptive statistics for circumstance variables

Table 1.3 presents the descriptive statistics of circumstance variables. As is shown, in all countries the ratio between girls and boys is balanced. The percentage of students with at least one parent born in the country is higher than 85%, except for Luxembourg (54%) and Switzerland (76%). It is worth noting that in Bulgaria and Romania almost all the students are native, given that the migration patterns of both countries are characterized by emigration. The mean value for PARED for the countries in our dataset is 13.58.

[13] Micklewright et al. (2012) measure the case of error-in-variables by comparing the peer group measure based on administrative complete microdata and that based on peers in the PISA sample. They find that the estimated peer effect is biased downwards when drawing a measure for peers based on a PISA sample.

Portugal has the lowest value with 10.91, followed by Spain, France, and Italy. Iceland with 16.23 and Finland with nearly 15 have the highest values. The lowest values for HISEI are those of Portugal, Romania and Croatia, and the highest are those of Iceland and Norway. Romania, Croatia and Bulgaria are the lowest ranked countries according to HPOS while Iceland and Norway are the highest.

Table 1.3: Descriptive statistics for circumstance variables: Mean and standard deviation in parenthesis for continuous variables and percentage for dichotomous ones

Country	MALE	NAT	PARED	HISEI	HPOS	SCEDUR	MACTIV	TCCLIM	TCMOR	TCSHORT
Belgium	0.50	0.85	14.46	51.44	0.00	0.30	1.64	-0.25	-0.26	-0.27
			(2.69)	(21.74)	(0.81)	(0.96)	(1.04)	(0.83)	(0.89)	(0.96)
Bulgaria	0.50	0.99	13.91	48.44	-0.30	0.01	2.68	0.42	0.22	0.83
			(3.13)	(21.13)	(0.98)	(0.87)	(1.45)	(1.31)	(0.88)	(0.46)
Croatia	0.51	0.88	13.65	44.99	-0.41	-0.51	2.80	-0.32	-0.30	0.43
			(2.58)	(20.44)	(0.77)	(0.66)	(1.32)	(0.87)	(0.92)	(0.78)
Finland	0.51	0.97	14.97	55.59	0.15	-0.21	2.18	-0.08	0.33	0.45
			(2.10)	(20.32)	(0.77)	(0.82)	(1.06)	(0.77)	(0.83)	(0.66)
France	0.48	0.86	13.04	51.97	0.02	0.40	2.09	-0.16	-0.39	0.17
			(2.04)	(21.30)	(0.77)	(0.94)	(1.25)	(0.87)	(0.97)	(0.84)
Germany	0.50	0.87	14.05	50.59	0.25	0.11	2.33	-0.31	0.01	-0.37
			(3.06)	(19.42)	(0.78)	(0.85)	(1.31)	(0.68)	(0.87)	(0.83)
Greece	0.49	0.92	14.02	49.13	-0.18	-0.35	1.43	-0.17	-0.40	0.42
			(2.93)	(22.81)	(0.88)	(0.97)	(1.11)	(1.17)	(1.09)	(0.95)
Iceland	0.50	0.96	16.23	59.36	0.71	-0.34	1.89	-0.01	0.55	-0.15
			(2.39)	(19.30)	(0.86)	(0.88)	(1.24)	(0.86)	(0.92)	(0.84)
Ireland	0.51	0.90	13.56	52.34	0.21	0.12	1.82	0.11	0.51	0.14
			(2.31)	(20.98)	(0.87)	(0.94)	(1.26)	(0.94)	(0.93)	(0.81)
Italy	0.51	0.93	13.33	46.92	0.18	0.05	2.47	-0.31	-0.60	-0.26
			(3.27)	(20.77)	(0.86)	(0.87)	(1.03)	(0.91)	(0.90)	(0.89)
Lithuania	0.49	0.99	14.14	51.21	-0.15	0.15	2.95	0.54	0.38	0.68
			(2.31)	(23.24)	(0.84)	(0.68)	(1.16)	(0.77)	(0.80)	(0.58)
Luxembourg	0.51	0.54	13.57	49.00	0.26	0.04	2.50	-0.31	0.00	-1.12
			(3.83)	(21.79)	(0.97)	(0.78)	(1.09)	(0.72)	(0.76)	(0.92)
Netherlands	0.51	0.89	13.87	55.93	0.15	0.19	1.27	-0.84	-0.19	-0.58
			(2.26)	(20.08)	(0.68)	(0.91)	(0.93)	(0.51)	(0.81)	(0.85)
Norway	0.51	0.90	13.85	58.74	0.65	-0.18	1.00	-0.48	0.24	-0.30
			(1.84)	(19.15)	(0.92)	(0.80)	(0.99)	(0.75)	(0.88)	(0.85)
Portugal	0.51	0.93	10.91	42.24	0.10	0.17	3.27	0.13	-0.16	0.81
			(4.21)	(21.23)	(0.97)	(0.90)	(0.89)	(0.94)	(0.97)	(0.65)
Romania	0.50	0.99	13.64	42.41	-0.55	0.26	2.94	0.58	-0.03	0.55
			(2.26)	(21.35)	(1.04)	(0.80)	(1.14)	(0.98)	(0.87)	(0.72)
Spain	0.51	0.90	12.38	46.97	0.11	0.02	1.36	-0.19	-0.42	0.74
			(3.69)	(21.45)	(0.84)	(0.86)	(1.05)	(0.93)	(0.98)	(0.62)
Sweden	0.50	0.85	14.03	54.16	0.29	0.03	1.62	-0.11	0.38	0.05
			(2.32)	(20.59)	(0.85)	(0.82)	(1.08)	(1.02)	(0.88)	(0.84)
Switzerland	0.50	0.76	14.01	55.04	0.00	0.57	1.40	0.01	0.29	-0.05
			(2.97)	(21.07)	(0.75)	(0.90)	(0.94)	(0.74)	(0.87)	(0.87)
United Kingdom	0.49	0.87	14.14	54.96	0.19	0.51	3.95	0.38	0.45	0.19
			(1.96)	(20.56)	(0.92)	(1.02)	(1.03)	(1.02)	(0.89)	(0.86)
	0.50	0.89	13.58	50.86	0.11	0.20	2.40	-0.11	-0.09	0.06
			(2.84)	(21.05)	(0.86)	(0.93)	(1.42)	(0.94)	(0.98)	(0.91)

Data are weighted by the final student weight.

As regards school background, Table 1.3 shows that Croatia, Greece, and Iceland have the lowest values in SCEDUR, while Switzerland and the United Kingdom have the highest. The United Kingdom and Portugal offer the most extra-curricular activities, and Norway and The Netherlands offer the fewest. Moreover, Lithuania and Romania have the highest TCCLIM values, while The Netherlands and Norway have the lowest. Teachers in Iceland, Ireland, and the United Kingdom are considered as the most enthusiastic, while those in Italy, Spain, and Greece rank as the least. Portugal, Bulgaria, and Spain have the highest numbers of qualified teachers, while Luxembourg has the lowest.

Effort variables

In view of the richness of information provided by PISA, we propose introducing in the analyses variables that can be considered as proxies for efforts. We are aware of the challenge that our proposal entails. First of all, there are some views that consider all the actions of a child as determined by parental influence, and hence beyond the child's responsibility. Therefore, we need proxies that are to some extent within students' control. To tackle these issues we base our work on previous studies which seek to determine the extent to which students' efforts and socioeconomic conditions are in fact distinct variables. Bozick and Depmsey (2010) review studies that analyze student effort and, in addition, de Fraja et al. (2010), Eren and Henderson (2011), Metcalfe et al. (2011) and Kuehn and Landeras (2014) analyze the impact of efforts on educational achievements, focusing on students aged between twelve and sixteen. In line with these studies, we select some variables related to students' attitudes, perseverance and motivation as proxies for effort. In particular we select the five variables summarized in Table 1.4.

The first one is Homework, denoted by HWORK, which is based on the number of hours of study per week. This is the most common proxy for effort in all the studies that assess the impact of effort on education outcomes (see for instance Stinebrickner and Stinebrickner, 2004; de Fraja et al., 2010; Kuehn and Landeras, 2014). The second effort variable is No Truancy, NSKIP, which is also frequently used in empirical studies (Schuman et al., 1985; Bonesrønning and Opstad, 2012, 2015, for instance) and seeks to reflect the responsibility of students and the interest shown in lessons. We also select Perseverance, PERSEV, which is an aggregated index based on students' responses about their willingness to work on problems that are difficult and their interest in working on assignments until they are fully completed. The fourth variable is Attitude towards School, ATSC, which describes how students perceive the usefulness and benefits of school, and can be considered a proxy for effort since students who are more interested will tend to exert more effort. These last two variables are closely related to non-cognitive aspects of students and are frequently used in psychological studies (see for instance Rosen et al., 2010) and are quite similar to the proxies introduced by de Fraja et al. (2010) to evaluate students' efforts.

The last variable considered as a proxy for effort is Non Repeater, NREP. It should be mentioned that there are major differences in education policies between the countries analyzed in regard to this variable. In Norway, for instance, students go forward automatically regardless of their academic performance. In Iceland the decision is taken by students themselves, while elsewhere, e.g. in Spain, it is taken by the faculty (for more details on the different regulations see Borodankova and Coutinho, 2011). However, since the regressions are estimated for each country separately, the different policies do not affect the final results. We consider it of interest to include this variable in the study, since in those countries where students do not go forward automatically the fact of repeating a grade involves perseverance, attitude, and motivation towards schoolwork to some extent.

As shown in many empirical studies, efforts generally depend to a large extent on circumstances. Given the nature of the data under analysis, we consider that students' efforts must be cleaned from the circumstance effects, so that the vector of circumstances incorporates the direct effect of circumstances and their indirect effect through the students' efforts. As will be explained in Chapter 2, the cleansing process can be tracked by following the proposal of Jusot et al. (2013) and dealing with the correlation between effort and circumstance variables on the circumstance side.[14]

i) Descriptive statistics for effort variables

As shown in Table 1.4, students from Italy, Ireland, and Romania spend most hours doing homework and those from Finland spend the fewest. Students from Belgium, Germany, and Luxembourg are least likely to skip classes whereas more than 40% of students from Greece and Romania have recently done so. The least persevering students are those from France, Norway, and Belgium while the most persevering are those from Bulgaria. Moreover, The Netherlands and Norway have the lowest ATSC values, while students from Lithuania have the highest. Finally, whereas the lowest rate of non-repeater students are observed in Belgium, Luxembourg, Portugal and Spain, the highest are found

[14] Actually, Jusot et al. (2013) also propose the alternative way to deal with the correlation, that is, adding all the correlation to efforts. However, we have decided not to present the results obtained under this approach since the efforts of 15-year-old students are deemed to be highly influenced by parents' pressure.

in Norway, Iceland, Greece, Croatia and Romania.

Table 1.4: Descriptive statistics for effort variables: Mean and standard deviation in parenthesis for continuous variables and percentage for dichotomous ones

Country	HWORK	NSKIP	PERSEV	ATSC	NREP
Belgium	5.42	0.92	-0.34	-0.11	0.65
	(4.09)		(0.82)	(0.75)	
Bulgaria	5.62	0.67	0.59	-0.10	0.97
	(4.71)		(1.00)	(0.82)	
Croatia	5.93	0.76	0.10	0.09	0.98
	(4.85)		(0.88)	(0.84)	
Finland	2.79	0.85	-0.01	0.05	0.96
	(2.03)		(0.78)	(0.82)	
France	5.09	0.83	-0.47	0.10	0.76
	(3.59)		(0.91)	(0.85)	
Germany	4.60	0.92	-0.02	-0.06	0.80
	(3.04)		(0.73)	(0.83)	
Greece	5.30	0.57	-0.09	-0.18	0.98
	(4.89)		(0.86)	(0.83)	
Iceland	4.11	0.88	-0.11	0.04	0.99
	(3.04)		(0.84)	(0.85)	
Ireland	7.29	0.87	0.14	0.12	0.91
	(4.71)		(0.89)	(0.89)	
Italy	8.73	0.66	0.04	0.00	0.85
	(6.20)		(0.88)	(0.80)	
Lithuania	6.76	0.68	0.17	0.43	0.98
	(4.66)		(0.72)	(1.00)	
Luxembourg	4.51	0.93	-0.07	-0.07	0.65
	(3.37)		(0.82)	(0.88)	
Netherlands	5.78	0.89	-0.13	-0.36	0.72
	(4.15)		(0.70)	(0.61)	
Norway	4.78	0.88	-0.37	-0.27	1.00
	(3.61)		(0.97)	(0.78)	
Portugal	3.72	0.71	0.35	0.22	0.65
	(3.19)		(0.91)	(0.89)	
Romania	7.11	0.55	0.03	-0.02	0.98
	(5.58)		(0.82)	(0.88)	
Spain	6.33	0.68	0.09	0.27	0.67
	(4.78)		(0.84)	(0.92)	
Sweden	3.55	0.79	-0.28	-0.15	0.96
	(2.85)		(0.87)	(0.81)	
Switzerland	4.00	0.89	-0.14	0.05	0.81
	(2.97)		(0.77)	(0.85)	
United Kingdom	4.94	0.88	0.12	0.13	0.97
	(3.76)		(0.87)	(0.87)	
	5.58	0.81	-0.06	0.03	0.83
	(4.44)		(0.87)	(0.85)	

Data are weighted by the final student weight.

1.3.4 Missing values

Finally, we indicate the manner in which we have addressed the issue of missing values in the PISA 2012 database. All the information used in this study is reported by students who failed to complete all the items in their respective questionnaires. In particular there are some variables, such as parents' education, where missing values are concentrated more in the questionnaires of students with below-average achievements. This means that the missing data in our database is not completely random, so the systematic difference between missing values and observed values can be explained by differences in the observed data. Based on this assumption, we impute missing values through the procedure introduced by Buuren et al. (1999), known as *Multiple Imputations Chained Equations* (MICE).

This approach imputes missing datasets on a variable by variable basis, specifying an imputation model for each of them. That is, in a set of variables with missing values, these are ordered from those with the least to those with most missing values. Then, the one with the least is regressed on the rest of the variables and its missing values are replaced by simulated draws from the posterior predicted distribution. This process is repeated until all the missing values are replaced with their imputed values in all the variables. Following Royston and White (2011), we choose 50 cycles for the imputations that are needed for the convergence of the sampling distribution of imputed values. The entire procedure is repeated independently five times, yielding five imputed datasets. Finally, we compute the average of the five imputed values to obtain the final dataset on which the study is based. Taking into consideration that efforts are assumed to be influenced by circumstances, the imputation is carried out in two steps. First, we impute the values for the missing observations in circumstance variables. Then we impute the missing values for effort variables based on the circumstance variables with no missing observations obtained in the first step. Thus effort variables may be influenced by circumstances, but not the other way around.

1.4 Conclusions

In this chapter we describe the basic notions of inequality of opportunity. It is stated that any measure should satisfy either compensation or reward principles. In addition, most empirical studies in this field use parametric or non-parametric approaches for constructing counterfactual distributions in order to measure inequality of opportunity.

Furthermore, we present the variables of interest from the PISA 2012 dataset and we provide their descriptive statistics for twenty European countries. It is observed that from the total variance in achievements, more than 95% is attributable to the within-country variance. Hence, it is worthwhile to evaluate the differences in the achievements within each country, and in particular, to analyze and compare the channels of the differences using the same set of explanatory variables for each country. We find that in Western countries such as The Netherlands, France, Germany and Belgium as well as in Bulgaria and Italy, the largest differences are observed between schools. Contrastingly, in Nordic countries such as Finland, Iceland, Norway and Sweden, and in Ireland and Spain the variation is larger within schools. Therefore, it seems that in the latter countries the schools are more homogeneous than in the former ones.

The circumstances are selected such that they capture the factors beyond students' control, such as their families' social origin, the school- and teacher-background as well as their peers' characteristics. We find three main limitations for their identification in PISA datasets. First, the information on family background is reported by the students rather than by their parents. In fact, in only a few countries (Belgium, Croatia, Germany, Italy and Portugal) the parents compleated a questionnaire. Second, the information on teacher-related background is reported by the school principals rather than by the teachers themselves. Finally, class-level information is not available for identifying peers' features, and thus, the peer group of a student is determined as the rest of students attending the same school.

With regard to efforts, we select proxies that appear to be within students' control to some considerable extent, based on previous studies. The main disadvantage of our effort variables is that they rely on the self-reported information from students. As Swerdzewski et al. (2011) warned, self-reported measures suffer from limitations; for instance, they require that students accurately be able to report their level of motivation, and in addition, it is difficult to ascertain whether students are being truthful when reporting their effort.

In addition to these limitations, PISA has also been subject to some criticisms in the literature. First, the PISA tests are independent of the participating countries' school curricula, because the focus is on assessing students' abilities to apply their skills to everyday life situations. This fact limits the possibility to establish clear relationships between schools' educational practices and students' performance. Therefore, it is difficult to draw conclusions about school-related factors.

Furthermore, the degree of interest in succeeding in a low-stake assessment such as PISA might be cultural, and may vary across countries (see Hambleton et al., 2004). For instance, some governments or schools may have attempted to make students aware of the honor of being chosen to represent their country or school, and hence, these students may have the responsibility to perform well. Instead, for students in other countries or schools, PISA assessment may have been seen as just an irrelevant activity, because this has no impact on their course grade. According to Wainer (1993), the differential motivation to perform on the test could lead to distort the findings.

Another criticism concerns the linguistic equivalence and cultural relevance of PISA assessment materials. Due to the poor translation as well as the differences in language, culture and curriculum coverage, the adapted forms may not be comparable to the source versions (English and French). This could be a source of bias (Grisay et al., 2007; Nardi, 2008; Hopfenbeck et al., 2018).

Despite these limitations, PISA has been a major instrument in providing data for European education systems. Although the program could be improved, it provides rich information in order to investigate inequalities related with family and school backgrounds across countries.

Chapter 2

Re-examining the inequality of opportunity measurement following a parametric approach

2.1 Introduction

In this chapter we use a parametric approach to build counterfactual distributions. Our procedure consists of estimating a linear model for each country, regressing achievements over the whole set of circumstance and effort variables presented in Chapter 1. Then we build up a counterfactual distribution for each country in which the differences due to effort are removed. The inequality of opportunity is measured by the variance applied to the counterfactual distributions.

There are numerous papers that assess inequality of opportunity in education using parametric procedures. Most of them are based on the regression analysis that estimates the direct association between parental background and students' performance rather than being based on counterfactual distributions (see for instance Wößmann, 2004; Schütz et al., 2007; Wößmann and Peterson, 2007; Ammermueller, 2007; Raitano and Vona, 2016). In addition, the few studies that do depend on parametrically constructed counterfactual distributions take into account only certain circumstance variables, related to personal characteristics, family and school background (Martins and Veiga, 2010; Ferreira and Gignoux, 2014; Salehi-Isfahani et al., 2014). The only exception, as far as we know, is the study of Asadullah et al. (2018) where in fact effort variables are considered together with circumstance ones.

As mentioned in the introduction, this chapter contributes to the empirical measurement of inequality of opportunity in different ways. First, we consider the proxy variables for effort in the construction of counterfactual distributions. The proxies are chosen based on previous studies which analyze how students' efforts affect their achievements, focusing on students aged between twelve and sixteen. Furthermore, as achievements may be affected by circumstances both directly and indirectly through efforts, we follow the procedure implemented by Jusot et al. (2013) to clean the contribution of efforts of that impact. The correlation is transferred to the side of circumstances. This specification enables us to capture the direct and indirect impact of those variables.

Second, the side of circumstances also comprises the students' peer effects. The literature indicates that outcomes may be influenced not only by students social origin and by their school background but also by their schoolmates' behaviour (see for instance, Hanushek et al., 2003; Hoxby, 2000; McEwan, 2003; Sacerdote, 2001; Schneeweis and

Winter-Ebmer, 2007; Lavy et al., 2012; Boucher et al., 2014). In particular, if everyone in the group is high achieving, the achievement of a student is likely to be positively affected by belonging to such a group. However, that student may simultaneously have an impact on the other team members' average achievement. Therefore, considering the endogeneity of peer effects, we use an instrumental variables based estimator to reach consistency. Although the inclusion of these effects is limited by the lack of information on students' social networks and classmates, the obtained results may help to better understand the differences in achievements.

Thirdly, as recently shown by Van de gaer and Ramos (2015*b*), evaluating inequality of opportunity by applying a standard inequality measure to a counterfactual distribution does not guarantee that a progressive transfer among individuals exerting the same effort will reduce inequality of opportunity. However, this 'transfer principle' is a crucial property in the measuring of inequality. The authors show that this problem is closely related to the treatment of the residuals obtained in a parametric estimation, and identify counterfactual distributions that behave properly as regards the transfer principle. The results presented in this paper are based on the counterfactuals for which the transfer property is guaranteed and, in consequence, the measure we obtain is a 'true' inequality measure. Moreover, since the side of circumstances includes both the correlation with the efforts as well as the residuals, the values obtained are indeed upper-bounds of the actual inequality of opportunity.

Finally, we evaluate the contributions of different circumstances to the overall achievement inequality.

The rest of the chapter is organized as follows. Section 2.2 describes the estimation strategy, Section 2.3 presents the results, and Section 2.4 concludes.

2.2 The estimation strategy

In this section we describe the estimation strategy for building counterfactuals. First we specify the model and present the estimation procedure used to estimate the effect of circumstances on achievements. Then, we describe the method used to construct counterfactual distributions. Finally, we indicate how to measure the contributions of different sources to achievement inequality.

2.2.1 Model specification

Let y_i be the educational achievement of student i, $i = 1, \ldots, N$, $\mathrm{C}_i = (c_{1i}, \ldots, c_{k_c i})$ the vector of $k_c \leq K_C$ observed circumstances and $\mathrm{E}_i = (e_{1i}, \ldots, e_{k_e i})$ the vector of $k_e \leq K_E$ observed effort variables. Assuming a lineal relation, Model (1.1) presented in Chapter 1 can be rewritten as follows:

$$y_i \;=\; \alpha + \beta\ \mathrm{C}_i + \gamma\ \mathrm{E}_i + u_i \qquad i = 1, \ldots, N, \tag{2.1}$$

where the coefficients β and γ measure the marginal effects of circumstances and efforts, respectively, and u_i is a zero-mean error that captures random effects, factors such as preferences or luck, the influence of non-measurable or unobserved variables, and also errors derived from possible misspecification of the functional forms. Since efforts are usually influenced by circumstances, these last can affect achievements both directly and indirectly through efforts. According to Roemer's definition of inequality of opportunity (see for instance Roemer, 1998), students' efforts should be cleaned from any influence of circumstances, and the influence of the common part between circumstances and efforts must be attributed to the former. This is particularly uncontroversial in our analysis of educational achievements, where the variables that we take as proxies for effort can be highly influenced by personal characteristics, by family and school background and by peer effects. Assuming a linear relationship between circumstances and efforts leads to the following equation:

$$\mathrm{E}_i = \delta + \phi C_i + \mathcal{E}_i \tag{2.2}$$

where δ is the constant term, ϕ is a matrix of coefficients linking circumstance variables to effort variables and $\mathcal{E}_i$ is the part of effort that is not explained by circumstances.

Inserting Equation (2.2) into Equation (2.1) it follows that

$$y_i = \alpha + \beta \mathrm{C}_i + \gamma(\delta + \phi C_i + \mathcal{E}_i) + u_i = (\alpha + \gamma\delta) + (\beta + \gamma\phi)\mathrm{C}_i + \gamma\mathcal{E}_i + u_i, \tag{2.3}$$

which can be rewritten as,

$$y_i = \alpha^R + \beta^R \mathrm{C}_i + \gamma^R \mathcal{E}_i + u_i \tag{2.4}$$

leading to a model that fits Roemer's framework indicated by the superscript R. Note that Equation (2.3), which is non linear in coefficients, allows us to compare the coefficients of Models (2.1) and (2.4). Both models use the same information so that the predicted achievement is the same. It can be observed that the marginal influences of efforts are the same, i.e. $\gamma^R = \gamma$ and that the overall effect of circumstances, β^R, is the sum of their marginal effect β, and the effect derived from the common part $\gamma\phi$. That is, β^R measures the total effect of circumstances on achievements,[1] including the impact of effort variables or unobserved variables correlated with the circumstance variables used. Finally, α^R is the sum of the constant term α and the effect derived from the common part $\gamma\delta$. Theoretically, better circumstances should contribute positively to achievements and efforts, and higher efforts should translate into better achievements. Consequently, the estimated total effects for circumstances in Model (2.4) should not be smaller than the marginal effects estimated in (2.1).

In practice, estimating Equation (2.4) requires $\mathcal{E}$ to be calculated. This can be done by linearly regressing efforts on circumstances using an appropriate estimator according to the characteristics of each effort variable. Formally,

$$E_i = \delta + \phi \mathrm{C}_i + \epsilon_i. \tag{2.5}$$

The residuals ($\hat{\epsilon}_i$) obtained in these regressions are orthogonal to circumstances when the effort variable is continuous. However, when the effort variable is not continuous the estimation procedure is non-linear, therefore, we compute generalized residuals (see Gourieroux et al., 1987) in order to preserve the orthogonality conditions between the residuals and circumstances. Thus, in any case, the residuals ($\hat{\epsilon}_i$) are adequate proxies for $\mathcal{E}_i$ in Equation (2.4), as they capture the part of effort that is not explained by circumstances. This estimation strategy is also used in Jusot et al. (2013), among others, to analyze inequality of opportunity in health.

2.2.2 Model estimation

In this study the peer group variable, denoted by P, is the last circumstance variable in the data matrix $X = (\mathbb{1}, \mathrm{C}_1, \ldots, \mathrm{C}_{k_c-1}, P, \mathcal{E}_1, \ldots, \mathcal{E}_{k_e})$. This is defined as the average achievement of the ith student's schoolmates,

$$P_i = \frac{1}{N_{S_i} - w_i^s} \sum_{j=1, j\neq i}^{N} y_j w_j^s \mathcal{I}_{ij}, \tag{2.6}$$

[1]If standard desirable regression assumptions hold, then $E(\hat{\beta}^R) = \beta + \gamma\phi$.

where w_i^s is the within school weight for the ith student[2], N_{S_i} is the number of students in the school S_i to which student i belongs, and $\mathcal{I}_{ij}$ is the indicator that takes value one if the jth student goes to the same school as the ith student.

The estimation of Equation (2.4) should take into account that the above mentioned peer variable P may be endogenous due to the simultaneity problem, and in that case, the OLS estimator would be inconsistent. One common strategy to adequately address endogeneity is to use an estimation procedure based on instrumental variables (IV hereafter) methods. This estimation procedure relies on some *instruments* labelled Z_i, which must satisfy two conditions in order to reach consistency. First, these must be correlated with the regressor which presents endogeneity problems (P_i in our case). Second, they must be conditionally uncorrelated with the error term. These conditions are known as relevance and exogeneity conditions respectively.

In our study, we propose to use an Instrument Variable Efficient Feasible Generalized Methods of Moments (IV-EFGMM) estimator. This provides an efficiency gain compared to OLS and IV estimators in the presence of valid instruments, and the unknown heteroskedasticity pattern emerged from the clustered nature of the error term (see Baum et al., 2003; Davidson and MacKinnon, 2004). The IV-EFGMM estimator is based on some moment conditions assuming the incorrelation between instruments and the error term,

$$g_i(\beta) = E(z_i(y_i - x_i\beta)) = 0, \tag{2.7}$$

where y_i is the ith observation of y, and the vectors x_i and z_i are the ith rows of the data matrix X and the instrumental matrix Z, respectively. Given a sample, the estimator is derived as the solution to the analogous sample moments,

$$\bar{g}(\beta) = N^{-1}\sum_{i}^{N}(z_i(y_i - x_i\beta)) = 0. \tag{2.8}$$

If X and Z are of the same order, there are as many equations as unknown coefficients, and thus, the system of equations is exactly identified. In this case, the estimator is denoted as the method of moments estimator, and it has a unique closed form expression. Nevertheless, when the rank of Z is larger than the rank of X, the system is overidentified, since there are more equations than unknown coefficients. In such cases, although the estimator cannot fulfill the condition (2.8), this is obtained such that it is as close to zero

[2]See OECD (2009*b*).

as possible. Thus, the estimator is that which minimizes the distance, measured by the quadratic form, from $\bar{g}(\beta)$ to zero,

$$\hat{\beta}_{IV-EFGMM}(W) = \arg\min_{\beta}\ N^{-1}\bar{g}(\beta)'W\bar{g}(\beta), \tag{2.9}$$

where the positive definite weight matrix W accounts for heteroskedasticity and correlations in the error term. Even though the estimator can sometimes be derived analitically from the optimization problem, often the estimations must be obtained through numerical methods. The following paragraphs explain the basic steps of the estimation procedure of this kind.

First step: Instruments and initial consistent estimator.

In the presence of more than one available instrument, the best choice in terms of efficiency is to use a combination of the whole set of instruments. To that end, we run an auxiliary regression of the peer variable P_i on the whole set of instruments Z_i,

$$P_i = \pi_0 + \sum_{\ell=1}^{k_c-1} Z^c_{\ell i}\pi^c_\ell + \sum_{\ell=1}^{k_e} Z^e_{\ell i}\pi^e_\ell + \sum_{\ell=1}^{k_c-1} \mathrm{C}_{\ell i}\delta^c_\ell + \sum_{\ell=1}^{k_e} \mathcal{E}_{\ell i}\delta^e_\ell + v_i. \tag{2.10}$$

In this equation, our instruments are defined as peers' average circumstances (Z^c_ℓ) and orthogonalized efforts (Z^e_ℓ), which are calculated similarly to peers' average achievements. That is, the instrument for the ℓth circumstance is obtained as,

$$Z^c_{\ell i} = \frac{1}{N_{S_i} - w^s_i} \sum_{j=1, j\neq i}^{N} \mathrm{C}_{\ell j} w^s_j \mathcal{I}_{ij} \qquad \ell = 1, \dots, k_c - 1, \tag{2.11}$$

and for ℓth orthogonalized efforts as,

$$Z^e_{\ell i} = \frac{1}{N_{S_i} - w^s_i} \sum_{j=1, j\neq i}^{N} \mathcal{E}_{\ell j} w^s_j \mathcal{I}_{ij} \qquad \ell = 1, \dots, k_e. \tag{2.12}$$

Whereas $\{\mathrm{C}_\ell\}_{\ell=1}^{k_c-1}$ and $\{\mathcal{E}_\ell\}_{\ell=1}^{k_e}$ are known as *included* instruments, Z^c_ℓ and Z^e_ℓ are denoted as *excluded* ones, referring to whether they are regressors which are included in the main model (2.4) or not.

The estimation of Equation (2.10) gives the best instrument as the linear combination of the multiple available instruments ($\hat{P}$). Thus the instrumental matrix, $Z = (\mathbb{1}, \mathrm{C}_1, \dots, \mathrm{C}_{k_c-1}, \hat{P}, \mathcal{E}_1, \dots, \mathcal{E}_{k_e})$, enables us to estimate consistently model (2.4) by using the generalized Instrumental Variable Estimator (GIVE)

$$\tilde{\beta}_{GIVE} = (X'Z(Z'Z)^{-1}Z'X)^{-1}X'Z(Z'Z)^{-1}Z'Y. \tag{2.13}$$

When only one instrument is valid, the order of the instrument matrix and the data matrix is the same, and hence, there is no need to run the auxiliary regression (2.10). In this case the matrix $Z'X$ is square and non-singular, so the resulting estimator becomes the usual Instrumental Variable (IV) estimator. In the case that all explanatory variables are exogenous, the OLS estimator is reached.

Second step: Initial consistent estimator for the variance covariance matrix of the errors.

Although the presence of heteroskedasticity or clustered errors does not affect the consistency property of instrumental variable estimators, their standard errors are not efficient (given the instruments) and the usual diagnostic tests are affected. The efficient GMM estimator has the smallest possible asymptotic variance when the optimal weight matrix (W) converges in the probability to the inverse of the variance-covariance matrix of the errors.

Since all the students in the same school (S_m) interact with each other and have same number of peers (N_{S_m}), the variance covariance matrix has a block diagonal structure that takes into account the clustered structure of the data (Baum et al., 2003), which is given by,

$$\Sigma_{CL} = \begin{bmatrix} \Sigma_1 & & & & \\ & \ddots & & & \\ & & \Sigma_m & & \\ & & & \ddots & \\ & & & & \Sigma_M \end{bmatrix} \tag{2.14}$$

where each submatrix Σ_m corresponds to the variance-covariance matrix between errors associated to students in same school. That is, it measures the relation between students in the same school. A natural estimator of each submatrix is calculated by crossing the instrumental variable residuals of the schools. Hence,

$$\widehat{\Sigma}_m = \sum_{j \in S_m} \tilde{u}_j \tilde{u}_j' \qquad \text{where} \quad \tilde{u}_j = (y_j - x_j \tilde{\beta}) X'Z(Z'Z)^{-1} z_j, \tag{2.15}$$

where all elements have been defined above, except $\tilde{\beta}$ which indicates the coefficients of model (2.4), estimated using the GIVE estimator defined in (2.13).

Last step: Consistent and efficient estimator for coefficients in model (2.4).

Once instruments are selected and given the estimator for the variance-covariance matrix of the errors ($\widehat{\Sigma}_{CL}$), a consistent and efficient estimation of model (2.4) is obtained by the IV-EFGMM estimator,

$$\hat{\beta}_{IV-EFGMM} = (X'Z\widehat{\Sigma}_{CL}^{-1}Z'X)^{-1}X'Z\widehat{\Sigma}_{CL}^{-1}Z'Y. \tag{2.16}$$

Since estimator (2.16) depends on the variance-covariance matrix obtained in the second step and this last depends on the coefficients of interest, these last two steps can be iterated until convergence is reached.

Endogeneity of the suspected explanatory variable can be tested using the C statistic of (Baum et al., 2007) that generalizes the endogeneity test of Haussman to the context of heteroskedasticity. The test is based on the difference between two Sargan-Hansen statistics (Sargan, 1958; Hansen, 1982), where the suspected variable has been treated as endogenous and exogenous respectively. Under the null hypothesis the regressor is considered exogenous. Hence, when the null is not rejected, coefficients are estimated by an Efficient Feasible Generalized Method of Moments (EFGMM) estimator given by equation (2.16), assuming $Z \equiv X$, since there is no need for instruments. Besides, when the null is rejected, coefficients are estimated by (2.16) to guarantee consistency. In this case some validation tests are required in order to confirm the adequancy of the instruments since they are the base of the estimation procedure (see Davidson and MacKinnon, 2004, for more details).

Testing the relevance and exogeneity of instruments

Estimator (2.16) is consistent and efficient only if the instruments are both relevant and exogenous. Firstly, instruments are considered relevant if they are correlated with the explanatory variable considered endogenous. We propose to test the relevance of instruments using the LM and Wald versions of the Kleibergen-Paap rk statistic (Kleibergen and Paap, 2006), which are valid in the case of non i.i.d. errors. On the one hand, a rejection of the null in the LM indicates that the equation is *identified*, i.e., the excluded instruments are correlated with the endogenous regressors. On the other hand, values larger than 10 for Kleibergen-Paap Wald rk F statistic indicate that the instruments are relevant and strong. Thus these two tests account for the first condition that instruments have to satisfy.

Secondly, the instruments are exogenous if they are not conditionally correlated with the error term. Exogeneity tests, also called tests of *overidentifying restrictions*, require more instruments than endogenous regressors (i.e. the equation is overidentified) and assume that at least one instrument is exogenous (Wooldridge, 2006, 2010). Among the main overidentification tests, the Hansen J statistic (Sargan, 1958; Hansen, 1982), also known as the Sargan-Hansen statistic, is robust to heteroskedasticity. The null hypothesis is that the instruments are exogenous and that the excluded instruments are correctly excluded from the estimated equation. Rejection of the null means that the instruments can not be considered as exogenous because they are conditionally correlated with the error term. Consequently estimator (2.16) using those instruments is not consistent.

2.2.3 Inequality of opportunity measure

We now proceed to estimate the counterfactual distributions. According to Van de gaer and Ramos (2015*b*), to guarantee that the inequality of opportunity measure M, as defined in Equation (1.2) in Chapter 1, satisfies the compensation principle one should only use

$$y^{C,R} \;=\; \hat{\alpha}^R + \hat{\beta}^R \mathrm{C} + \hat{\gamma}^R \bar{\mathcal{E}} + \hat{u} \tag{2.17}$$

for fixed values of cleaned efforts ($\bar{\mathcal{E}}$). Note that the residuals $\hat{u}$ are by construction uncorrelated to the observed circumstances and efforts. Using the variance for measuring inequality of opportunity, the corresponding measure of inequality of opportunity is found to be:

$$\mathcal{M}(y, C, E) = V(y^{C,R}) = V(\hat{\beta}^R \mathrm{~C}) + V(\hat{u}). \tag{2.18}$$

In the case of IV based estimation, the residual vector is orthogonal to the instrument matrix (Z) but not to the data matrix of circumstances and efforts. In that case Equation (2.18) should consider that the residuals might not be orthogonal to the data matrix. Hence, the correlation between the residual vector and the circumstances matrix should be accounted as follows,

$$\mathcal{M}(y, C, E) = V(y^{C,R}) = V(\hat{\beta}^R \mathrm{~C}) + V(\hat{u}) + 2cov(\hat{\beta}^R \mathrm{~C}, \hat{u}).$$

2.2.4 Decomposition of achievement inequality

The last point to discuss is how to measure the contributions of different sources to achievement inequality. In particular, based on Equation (2.4), we use the predicted educational achievement $\hat{y}_i$ as a linearly decomposable measure,

$$\hat{y}_i = \hat{\alpha}^R + \hat{\beta}^R \mathrm{C}_i + \hat{\gamma}^R \mathcal{E}_i. \tag{2.19}$$

In order to measure the inequality in the predicted achievements which is attributable to either circumstances or effort, we follow the natural decomposition of the variance proposed by Shorrocks (1982). The author shows that the contribution of a specific source is given by the covariance between that source and the outcome of interest. In particular, since the vector of circumstances and that of efforts are uncorrelated, we get the following expression,

$$\begin{aligned} V(\hat{y}) &= cov(\hat{\beta}^R \mathrm{C}, \hat{y}) + cov(\hat{\gamma}^R \mathcal{E}, \hat{y}) \\ &= V(\hat{\beta}^R \mathrm{C}) + V(\hat{\gamma}^R \mathcal{E}). \end{aligned} \tag{2.20}$$

The contribution share of circumstances is given by the ratio of the variance of achievements predicted by circumstances, $V(\hat{\beta}^R \mathrm{C})$, and the variance of the predicted achievement, $V(\hat{y})$. In a similar manner, the contribution share of efforts is given by the ratio of the variance of achievements predicted by efforts, $V(\hat{\gamma}^R \mathcal{E})$ and the variance of the predicted achievement, $V(\hat{y})$.

We are also interested in quantifying the contribution of certain circumstances to overall inequality. To that end, we decompose the variance of achievements into that related to each component,

$$V(\hat{\beta}^R \mathrm{C}) = \sum_{j}^{k_c} V(\hat{\beta}_j^R \mathrm{C}^j) + \sum_{k \neq j}^{k_c} \sum_{j}^{k_c} cov(\hat{\beta}_k^R \mathrm{C}^k, \hat{\beta}_j^R \mathrm{C}^j), \tag{2.21}$$

where C^j and C^k are the students' column vectors of circumstances j and k from the matrix of circumstances $C = [C^1, ..., C^{k_c}]$. Then, according to the natural decomposition of the variance, the contribution of each circumstance j can be obtained as,

$$S(C^j) = cov(\hat{\beta}_j^R \mathrm{C}^j, \hat{y}) = V(\hat{\beta}_j^R \mathrm{C}^j) + \sum_{k \neq j}^{k_c} cov(\hat{\beta}_k^R \mathrm{C}^k, \hat{\beta}_j^R \mathrm{C}^j). \tag{2.22}$$

Here the circumstance j is assigned the half value of all interaction terms involving that variable in Equation (2.21) such that the sum of all the contributions over the k_c variables gives the aggregate inequality due to the circumstances. Finally, the partial shares of inequality explained by each circumstance j is given by the ratio of the covariance in Equation (2.22) to the variance of achievements, $V(y)$. These partial shares are a simple example of a Shapley decomposition.[3]

[3]There are other methods to measure the contribution of the explanatory variables based on their contribution to an overall model fit statistic which are equivalent to Shapley values (see Grömping, 2007,

It should be noted that the estimates of the partial contributions rely on the validity of the specific coefficients $\hat{\beta}_j^R$. Thus, these contributions are valid only under the assumption that $\hat{\beta}_j^R$ are unbiased. In practice, however, especially when instrumental variables based estimators are used to account for endogeneity problems, there might be a sample bias. Moreover, it is possible that certain circumstance variables may be correlated with some omitted or unobserved circumstances. Therefore, given our model, we provide lower and upper bounds for the contributions.

In order to compute an upper bound for the contribution of a circumstance or a set of circumstances C^J, we run an auxiliary regression of y on the subset of circumstances of interest,

$$y_i = \eta + \varphi C_i^J + \omega_i \tag{2.23}$$

where the vector of coefficients φ captures the total effect of the subset of circumstances C^J. That is, φ reflects not only the direct influence of C^J, but also any effect of these circumstances through their effect on omitted variables. Then we use the upper 95% confidence interval of the coefficients $\hat{\varphi}^U$, to obtain the respective vector of fitted values $\hat{\varphi}^U C^J$, and compute its variance, denoted by $V(\hat{\varphi}^U C^J)$. This measure gives the overall contribution of the subset of circumstances C^J on achievements, because both their *direct* contribution, and their *indirect* contribution through the rest of omitted variables, are captured. Finally, the upper bound of the contribution share is given by the ratio of $V(\hat{\varphi}^U C^J)$ to the variance of achievements $V(y)$.

A potential lower bound of the contribution of the subset of circumstances, C^J, is just the achievement variance they explain, $V(\hat{\beta}_J^R C^J)$, since it captures its 'pure' contribution and disregards all the potential interaction effects. It would correspond to a hypothetical distribution in which the only changes we consider are those that occur in the circumstances of interest, while the rest remains unchanged. In particular we use the

for a discussion). One approach of that kind is the *general dominance analysis* of Budescu (1993), in which the contribution of a variable is computed by aggregating results across multiple models. This method requires that the ensemble of models contain each possible combination of the explanatory variables in the full model (in a full model with k_c independent variables, alterating between included versus excluded variables, all possible combinations ensemble results in 2^{k_c-1} estimated models). Then, the contribution of a variable is derived as its weighted average incremental contribution to the overall fit statistic across all models in which that variable is included. These statistics can be summed to obtain the value of the full model's fit statistic. Nevertheless, and as far as we are concerned, there has not yet been developed any programme in Stata for estimating the ensemble of models with the IV-GMM estimator. As a consequence, we opt for the natural decomposition of the variance so that we can estimate our model with that estimator.

lower 95% confidence intervals of the corresponding coefficients $\hat{\beta}_J^{R,L}$ in the computations, denoted by $V(\hat{\beta}_J^{R,L} C^J)$. The lower bound of the contribution share is given by the ratio of $V(\hat{\beta}_J^{R,L} C^J)$ to the achievement variance $V(y)$.

2.3 Results and discussion

In this section we check the endogeneity of the peer group variable as well as the validity of our instruments. Next we analyze the total effects and marginal effects of circumstance and effort variables, respectively. Then we evaluate the contribution of these sources to achievement inequality, and finally, we assess inequality of opportunity.

2.3.1 Checking the endogeneity and validity of instruments

We begin by considering the results of the diagnostic tests associated with our results, which are presented in columns 12 - 15 of Table 2.1. The p-values for C statistic in the last column indicates that the average achievement of peers is endogenous in Belgium, Croatia, Finland, Greece, Iceland, Ireland, Italy, The Netherlands, Portugal, Romania, Spain and Switzerland. Therefore, in these countries valid instruments are needed in order to obtain consistent estimates. For the rest of the countries the peer group variable can be considered exogenous and consequently the estimation of the models in these countries is carried out by EFGMM.

In what follows we describe the selected instrumental variables and discuss their diagnostic results, which are available for those countries in which the IV-EFGMM estimator is used.

The average achievement of peers is instrumented by different variables. The first is the average occupational status of peers, which indicates their socio-economic status, and the rest reflect the average effort of peers (orthogonalized with respect to the circumstances). All of them are constructed based on Equations (2.11) and (2.12). The choice of this set of instruments is motivated by the idea that a greater share of students with high socio-economic status and high effort levels results in a better learning environment. Hence, those variables are likely to be correlated with the average achievements of peers, as is required for instruments to be relevant. To test this fact we use the results from the Kleibergen and Paap (2006) statistics presented in columns 12 and 13 of Table 2.1. First, the LM test, known as the underidentification test, indicates that the model is always identified for the different countries. Second, the F statistic of the Wald test is at least 20, indicating that our instruments are relevant and strong for all the countries.

With regard to exogeneity, once the effect that students' family background, school characteristics and peer performance have on their achievements is controled for, their schoolmates' parental occupation and effort may not directly affect students' individual achievement. This is confirmed by the p-values for the Hansen J statistic of the overidentification test, shown in column 14 of Table 2.1, in the sense that the null hypothesis that the instruments are exogenous is not rejected. Therefore, all these tests show that the instruments satisfy the conditions of relevance and exogeneity and, as a result, they are valid.

2.3.2 Total and marginal effects of circumstance and effort variables

Columns 1 - 11 of Table 2.1 presents the total effects of circumstance variables obtained by estimating linear regression model (2.4) by the EFGMM or IV-EFGMM estimators discussed in Subsection 2.2.2, and also by using the first plausible value that represents the mathematics achievement in PISA tests. Clustered standard errors are in parentheses.[4]

The regression results in Table 2.1 point out that in general boys are expected to obtain a higher achievement than girls, the exception being Iceland.[5] Only in Finland, Norway, and Sweden is gender not significant. In line with previous findings, our results confirm that students with at least one parent born in the country have higher expected scores than immigrant students in 75% of the countries. Note that in Bulgaria, Lithuania and Romania, for which this variable is non-significant, less than 1% of students are non-native.

The effects of the variables linked to socio-economic status are in general highly significant with a high positive impact on students' achievements. As expected, the effects of the highest occupational status of parents (HISEI) and the home ownership index (HPOS) variables are positively significant for all countries, whereas the highest educational level

[4]For the estimations we use the Stata's module `ivreg2` provided by Baum et al. (2010).

[5]Schneeweis and Winter-Ebmer (2007) also found that boys are expected to perform better than girls in maths whereas the opposite is true for reading. Similarly, Entorf and Lauk (2008) found significant results for girls in reading.

of parents (PARED) is significant for 75% of the countries.

By contrast, as has been found in the literature, school characteristics factors are in general insignificant when family- and peers-related factors are taken into consideration. In fact, in Croatia, Finland, Greece, Iceland, Lithuania, Luxembourg, Romania, Spain and Sweden none of these variables is significant to explain students' outcomes. This group includes Bulgaria, France and Portugal if we demand a significance level of 1%.[6] Educational resources are positively related to scores only in Portugal. The effect of extra-curricular activities is positive in Belgium, Bulgaria, Germany, Italy, The Netherlands and Switzerland, whereas the effect is negative in the United Kingdom.[7] The school climate has a significant positive effect in the students' scores only in Ireland and Norway, while the effect is negative in France.[8] Teachers' morale is positively related to scores in Italy, while negatively related in Switzerland. Finally, the number of qualified teachers positively affects the performance of students in Belgium and the United Kingdom.

Regarding peer effects, the higher average achievement of peers affects students' individual performance significanly in all the countries. The largest effect is observed in The Netherlands, Croatia, Italy and Germany, whilst the lowest is found in Finland, Spain, Ireland and Iceland.

The results for the effort variables, once cleaned of the correlation with the circumstance variables, are presented in Table 2.2. These estimates are the same as the marginal effects estimated in Equation (2.1) as mentioned before. As expected, when they are significant the relation is generally positive. Specifically, in Belgium, Bulgaria, Finland, Italy, Lithuania, Luxembourg, Norway, Spain, Switzerland and the United Kingdom all the selected effort variables are significant.[9] In addition, the coefficients for perseverance and not having repeated are significantly positive in all countries. The effect of the hours that students devote to homework is significantly positive except for the Nordic countries of Finland, Iceland and Sweden. In the latter two this effect is not statistically significant, whereas it is strongly negative in Finland. In Finnish schools, there is notably less home-

[6] Ammermueller (2007), Entorf and Lauk (2008), among others, obtain similar conclusions.

[7] In the United Kingdom there is a high number of extra-curricular activities offered at school (indeed the UK has the highest mean at 3.95) which are carried out by teachers from the schools and not by external staff.

[8] The correlations between achievements and TCCLIM in France, as well as between achievements and PARED in Croatia, Italy and The Netherlands are positive. Hence, the unexpected negative effects must be due to the multicollinearity between these variables and other circumstances.

[9] Remember that in Norway students never repeat a year.

work than in other countries because according to Finnish education ideology, pupils are supposed to be taught in school, not at home. Therefore, one plausible explanation for the negative association of homework time and mathematics achievement could be that students who spend more time on homework are likely to be those who need to study more because of poor performance. This result is consistent with Brookhart (1997) and Liang (2010). Finally, in 65% of the countries, students who do not skip classes have higher expected achievements. Similar result is found in students with a good attitude accounting for 75% of the countries.

Table 2.1: Estimation results for circumstance variables in Roemer's framework and results of the diagnostic tests

	Male	NAT	PARED	HISEI	HPOS	SCEDUR	MACTIV	TCCLIM	TCMOR	TCSHORT	PEERS	Kleibergen-Paap rk LM (p-value)	Kleibergen-Paap rk Wald (F statistic)	Hansen J (p-value)	C statistic (p-value)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Belgium	16.93**	30.15**	-0.212	0.625**	6.116**	0.0915	1.794**	0.259	-0.747	1.306*	0.840**	0.00	270.4	0.68	0.03
	(1.472)	(2.535)	(0.347)	(0.0472)	(1.184)	(0.648)	(0.640)	(0.889)	(0.771)	(0.617)	(0.0124)				
Bulgaria	11.76**	21.72	0.109	0.400**	8.459**	0.159	0.754*	0.251	1.067	-0.473	0.847**				0.32
	(1.744)	(12.86)	(0.347)	(0.0558)	(1.182)	(0.930)	(0.365)	(0.602)	(0.724)	(1.058)	(0.0140)				
Croatia	20.16**	4.952	-1.313**	0.519**	5.542**	-0.0709	0.242	-0.453	-0.313	0.943	0.914**	0.00	109.3	0.17	0.01
	(1.910)	(2.737)	(0.441)	(0.0726)	(1.462)	(0.732)	(0.471)	(0.589)	(0.545)	(0.631)	(0.0158)				
Finland	0.503	61.50**	2.756**	0.749**	10.97**	0.511	-0.385	0.415	-0.689	0.966	0.357**	0.00	46.72	0.83	0.01
	(2.074)	(3.513)	(0.429)	(0.0572)	(1.136)	(0.888)	(0.838)	(1.281)	(1.142)	(1.311)	(0.0683)				
France	19.83**	19.45**	1.795**	0.410**	13.06**	0.608	0.706	-1.883*	0.681	1.337	0.840**				0.55
	(2.073)	(2.545)	(0.521)	(0.0533)	(1.408)	(0.776)	(0.590)	(0.901)	(0.786)	(0.785)	(0.0133)				
Germany	24.33**	17.73**	0.924*	0.420**	5.369**	0.740	2.425**	-0.421	0.212	0.882	0.859**				0.21
	(1.655)	(2.786)	(0.396)	(0.0587)	(1.293)	(0.774)	(0.574)	(0.800)	(0.701)	(0.907)	(0.0135)				
Greece	19.61**	10.36**	1.326**	0.537**	6.506**	-1.160	-0.0641	-0.0404	0.180	0.628	0.763**	0.00	104.8	0.19	0.02
	(2.006)	(3.426)	(0.448)	(0.0634)	(1.350)	(0.801)	(0.856)	(0.693)	(0.637)	(0.842)	(0.0279)				
Iceland	-7.211*	31.74**	1.773**	0.902**	6.254**	0.190	1.943	-3.041	1.234	0.753	0.486**	0.00	22.80	0.37	0.05
	(3.518)	(8.007)	(0.643)	(0.0831)	(1.671)	(1.284)	(1.113)	(1.625)	(1.742)	(1.691)	(0.0598)				
Ireland	13.11**	-2.050	2.539**	0.738**	11.46**	-0.0526	-0.0105	4.355**	-1.006	0.684	0.485**	0.00	29.76	0.58	0.01
	(2.004)	(3.252)	(0.587)	(0.0612)	(1.403)	(1.014)	(0.744)	(1.260)	(1.166)	(1.276)	(0.0608)				
Italy	20.66**	15.07**	-0.867**	0.332**	5.767**	0.335	1.488**	-0.248	1.089*	-1.044	0.878**	0.00	336.2	0.13	0.00
	(0.965)	(1.963)	(0.209)	(0.0288)	(0.734)	(0.506)	(0.495)	(0.637)	(0.489)	(0.584)	(0.0108)				
Lithuania	9.944**	-5.232	1.619**	0.495**	7.853**	0.908	0.155	-0.181	1.228	-0.753	0.785**				0.76
	(2.253)	(8.333)	(0.575)	(0.0571)	(1.590)	(0.880)	(0.530)	(1.096)	(0.771)	(1.091)	(0.0185)				
Luxembourg	18.96**	14.49**	-0.0975	0.817**	3.094*	-0.947	-0.811	-1.877	-0.0410	1.365	0.781**				0.36
	(2.254)	(2.754)	(0.329)	(0.0824)	(1.445)	(1.602)	(1.123)	(1.271)	(1.692)	(1.467)	(0.0324)				
Netherlands	17.77**	20.64**	-1.006*	0.287**	3.733**	0.0999	2.011**	-0.409	0.468	-0.625	0.945**	0.00	229.4	0.50	0.01
	(1.709)	(3.255)	(0.444)	(0.0517)	(1.432)	(0.449)	(0.715)	(0.947)	(0.573)	(0.571)	(0.00876)				
Norway	2.328	28.81**	1.720*	0.848**	5.360**	-0.497	1.426	3.869**	0.388	0.840	0.595**				0.82
	(2.329)	(4.368)	(0.685)	(0.0738)	(1.424)	(1.210)	(0.965)	(1.367)	(1.123)	(1.073)	(0.0321)				
Portugal	14.42**	19.73**	1.025**	0.826**	13.48**	2.852*	0.483	-0.430	1.516	2.106	0.571**	0.00	86.46	0.31	0.00
	(1.689)	(4.780)	(0.284)	(0.0613)	(1.256)	(1.440)	(1.384)	(1.411)	(1.589)	(1.822)	(0.0364)				
Romania	11.12**	-18.34	-0.994*	0.555**	7.109**	0.148	0.568	-0.0879	0.516	-0.626	0.811**	0.00	145.9	0.19	0.09
	(2.014)	(20.20)	(0.433)	(0.0507)	(0.989)	(0.827)	(0.531)	(0.759)	(0.653)	(0.788)	(0.0186)				
Spain	15.59**	30.32**	2.358**	0.647**	13.86**	1.220	0.0683	0.346	0.858	-1.064	0.462**	0.00	101.9	0.59	0.00
	(1.341)	(2.601)	(0.232)	(0.0403)	(0.967)	(0.982)	(0.778)	(1.246)	(1.022)	(1.522)	(0.0352)				
Sweden	-0.709	37.87**	0.137	0.887**	10.52**	-1.509	1.531	-1.097	0.506	0.376	0.552**				0.26
	(2.403)	(3.933)	(0.569)	(0.0665)	(1.426)	(1.039)	(0.829)	(1.127)	(1.155)	(1.142)	(0.0385)				
Switzerland	16.14**	37.64**	1.546**	0.454**	9.864**	1.126	2.264*	0.871	-2.199**	1.702	0.754**	0.00	36.48	0.18	0.01
	(1.941)	(2.115)	(0.345)	(0.0507)	(1.612)	(0.965)	(0.921)	(1.268)	(0.838)	(0.974)	(0.0274)				
United Kingdom	10.84**	7.450*	0.997	0.719**	10.07**	0.466	-1.575*	0.774	1.576	2.416**	0.725**				0.22
	(2.097)	(3.791)	(0.626)	(0.0556)	(1.236)	(0.721)	(0.684)	(0.920)	(0.927)	(0.879)	(0.0177)				

Regression coefficients of circumstantial variables obtained through the estimation of equation (2.4) for each country separately. Significance levels:* 5%, ** 1%.

Table 2.2: Estimation results for effort variables in Roemer's framework

Country	HWORK	NSKIP	PERSEV	ATSC	NREP
Belgium	1.841**	9.179**	11.58**	3.668**	56.97**
	(0.219)	(2.840)	(0.988)	(1.012)	(1.987)
Bulgaria	2.660**	6.842**	5.883**	4.335**	44.86**
	(0.255)	(1.768)	(1.019)	(1.135)	(8.324)
Croatia	1.626**	8.547**	5.764**	-1.733	20.61**
	(0.215)	(2.345)	(1.067)	(1.078)	(7.076)
Finland	-1.466**	11.44**	38.13**	12.84**	85.60**
	(0.491)	(2.658)	(1.484)	(1.389)	(4.601)
France	1.644**	3.313	21.18**	2.720*	32.64**
	(0.318)	(2.468)	(1.276)	(1.205)	(4.667)
Germany	0.694*	6.758	21.05**	-0.180	37.52**
	(0.298)	(3.986)	(1.497)	(1.130)	(2.542)
Greece	2.815**	-1.939	19.78**	-2.058	46.56**
	(0.247)	(2.004)	(1.324)	(1.146)	(7.787)
Iceland	-0.646	14.33**	36.53**	16.24**	41.37*
	(0.532)	(5.016)	(1.595)	(1.603)	(17.03)
Ireland	3.115**	-2.826	21.08**	1.644	44.46**
	(0.244)	(3.365)	(1.187)	(1.169)	(3.496)
Italy	1.332**	5.459**	11.31**	1.756**	32.14**
	(0.0989)	(1.093)	(0.642)	(0.614)	(1.556)
Lithuania	1.804**	13.16**	9.733**	5.824**	66.87**
	(0.254)	(2.595)	(1.689)	(1.205)	(8.620)
Luxembourg	2.766**	14.75**	10.30**	5.580**	58.97**
	(0.386)	(3.142)	(1.262)	(1.294)	(3.873)
Netherlands	1.595**	-4.253	4.659**	3.504*	27.63**
	(0.217)	(2.817)	(1.053)	(1.441)	(2.360)
Norway	1.612**	24.00**	36.74**	9.689**	:
	(0.319)	(3.276)	(1.276)	(1.389)	:
Portugal	2.898**	3.267	15.41**	4.147**	80.36**
	(0.330)	(2.173)	(1.180)	(1.139)	(3.171)
Romania	3.057**	-0.0558	4.866**	1.710	17.10**
	(0.202)	(1.650)	(0.832)	(1.078)	(6.501)
Spain	1.723**	8.843**	16.42**	3.874**	74.03**
	(0.163)	(1.446)	(0.915)	(0.815)	(1.868)
Sweden	-0.0394	17.34**	33.80**	8.969**	64.17**
	(0.351)	(2.863)	(1.523)	(1.436)	(6.617)
Switzerland	1.852**	9.284**	17.37**	5.388**	45.99**
	(0.314)	(3.267)	(1.260)	(1.321)	(2.662)
United Kingdom	4.382**	17.39**	22.50**	4.944**	56.11**
	(0.330)	(3.549)	(1.329)	(1.238)	(5.821)

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

2.3.3 Contribution of circumstances and efforts to achievement inequality

Having estimated the coefficients of the educational equation for each country, we can now calculate the contribution of the circumstance and effort related sources to the explained inequality in educational achievements.

First of all, we analyze the contribution of the estimated vectors of circumstance and the effort variables to the differences in the predicted achievements. Table 2.3 presents these contributions. The second column in the table shows the percentage of the inequality of educational achievements, as measured by the variance, which is jointly explained by circumstances and efforts. The percentages are quite high. In fact more than 50% of the variance is explained in The Netherlands (62.49%), France (62.33%), Belgium (62.12%), Germany (58.67%), Italy (54.98%), Bulgaria (54.89%) and Portugal (52.66%). Only in Iceland (29.09%) is the percentage of explained variance less than 30%.

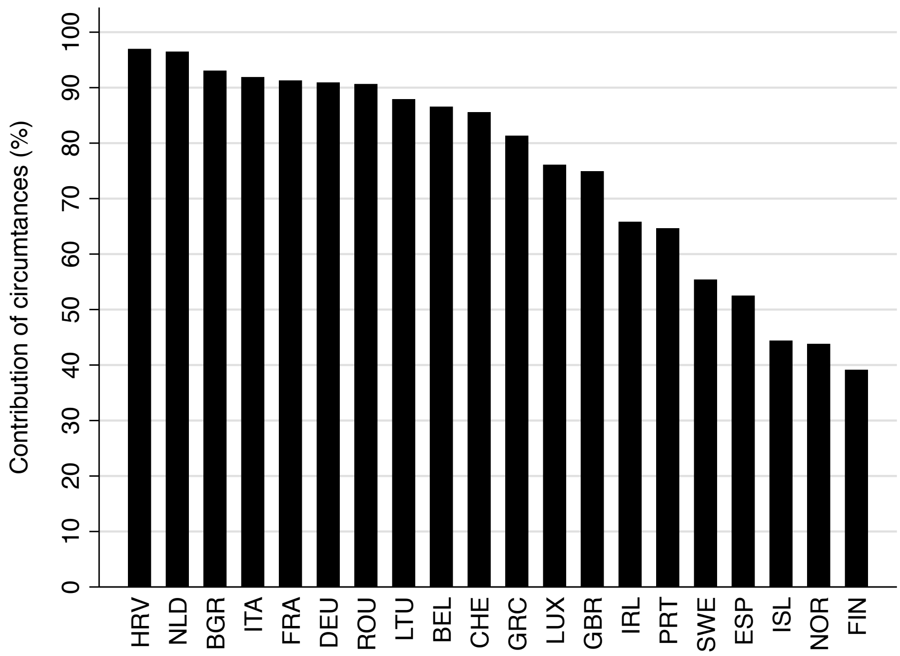
Table 2.3: Contribution of circumstance and effort related sources to the explained achievement inequality, $V(\hat{y})$

Country	R^2	Correlation	Contributions (%)	
			Circumst.	Efforts
Belgium	0.62	0.44	86.54	13.46
Bulgaria	0.55	0.43	93.02	6.98
Croatia	0.47	0.26	96.95	3.05
Finland	0.32	0.17	39.11	60.89
France	0.62	0.53	91.26	8.74
Germany	0.59	0.25	90.90	9.10
Greece	0.40	0.29	81.30	18.70
Iceland	0.29	0.18	44.37	55.63
Ireland	0.33	0.22	65.77	34.23
Italy	0.55	0.29	91.87	8.13
Lithuania	0.34	0.19	87.87	12.13
Luxembourg	0.48	0.35	76.05	23.95
Netherlands	0.68	0.33	96.45	3.55
Norway	0.35	0.08	43.77	56.23
Portugal	0.53	0.38	64.62	35.38
Romania	0.49	0.35	90.62	9.38
Spain	0.46	0.27	52.48	47.52
Sweden	0.34	0.12	55.38	44.62
Switzerland	0.48	0.21	85.53	14.47
United Kingdom	0.40	0.27	74.89	25.11

Before looking at the contributions of the circumstances and cleaned efforts, it may be interesting to analyze the correlation between them, shown in the third column of Table 2.3. Lowest values are observed for Norway, Sweden, Finland, Iceland and Lithuania with the correlation coefficient lower than 0.2. Conversely, the highest values are observed in France, Belgium and Bulgaria with the coefficient higher than 0.4.

The share of the education inequality explained by circumstances and cleaned effort are presented in the fourth and the fifth columns respectively. These contributions have been calculated by Equation (2.20). In addition, for illustrative purposes, the contribution share of circumstances has been graphically displayed in Figure 2.1. As can be seen, more than 90% of the explained variance is due to the circumstance variables in Croatia (96.95%), The Netherlands (96.45%), Bulgaria (93.02%), Italy (91.87%), France (91.26%), Germany (90.90%) and Romania (90.62%). In all these countries the between-school variance is relatively high. In contrast there is a group of countries in which the contribution of the cleaned efforts to the explained variance is more than 44%. These countries are Finland (60.89%), Norway (56.23%), Iceland (55.63%), Spain (47.52%) and Sweden (44.62%), which correspond to those with the lowest between-school contribution values.

Figure 2.1: Contribution of circumstances to the explained achievement inequality



Moreover, we are interested in analyzing which type of circumstance is the most influential in explaining the overall achievement inequality. In Table 2.4 the first column of each column block indicates the contribution shares of peer effects, family background and parental occupational status (HISEI) measured based on Equation (2.22).[10] This information is graphically shown in Figure 2.2.

Table 2.4: Contribution of circumstance blocks to the achievement inequality, $V(y)$

Country	Contributions (%)								
	Peers			Family			HISEI		
		Lower bound	Upper bound		Lower bound	Upper bound		Lower bound	Upper bound
Belgium	43.35	35.10	50.00	10.16	2.56	33.94	5.65	1.31	21.05
Bulgaria	42.73	35.42	50.20	7.20	1.01	33.30	3.62	0.45	20.37
Croatia	41.08	35.88	43.48	4.81	0.68	23.18	4.35	0.77	17.83
Finland	1.71	0.48	4.76	10.57	6.93	15.89	4.82	2.36	8.80
France	45.63	37.40	53.03	10.66	2.34	38.49	3.64	0.45	20.48
Germany	44.29	37.27	50.14	6.89	0.96	30.20	3.50	0.39	20.37
Greece	22.07	16.18	28.95	8.66	2.05	24.92	5.11	1.21	16.30
Iceland	4.18	1.70	9.14	7.68	3.19	15.58	5.15	2.38	9.75
Ireland	7.75	2.79	16.39	11.18	5.13	21.76	6.06	2.36	13.48
Italy	42.61	38.09	48.81	3.42	0.74	15.02	2.21	0.40	10.17
Lithuania	22.51	17.69	27.32	7.16	1.89	20.27	4.13	1.04	12.58
Luxembourg	24.67	16.52	31.47	10.52	2.39	38.29	8.21	2.24	26.01
Netherlands	62.35	57.43	64.43	3.62	0.44	24.08	2.07	0.17	14.71
Norway	6.68	4.23	9.62	7.91	3.53	16.01	4.81	2.27	9.22
Portugal	15.31	7.90	28.11	15.62	6.70	33.40	8.08	2.57	22.38
Romania	34.18	27.01	42.21	8.69	2.27	29.79	6.01	1.50	21.88
Spain	7.15	3.32	16.63	14.34	8.57	23.35	5.53	1.95	13.64
Sweden	6.38	3.44	10.20	12.24	6.41	22.14	6.22	2.99	11.63
Switzerland	25.49	18.71	34.55	11.51	5.10	25.00	3.19	0.63	12.91
United Kingdom	20.20	14.75	26.29	8.47	2.93	21.35	5.17	1.76	13.81

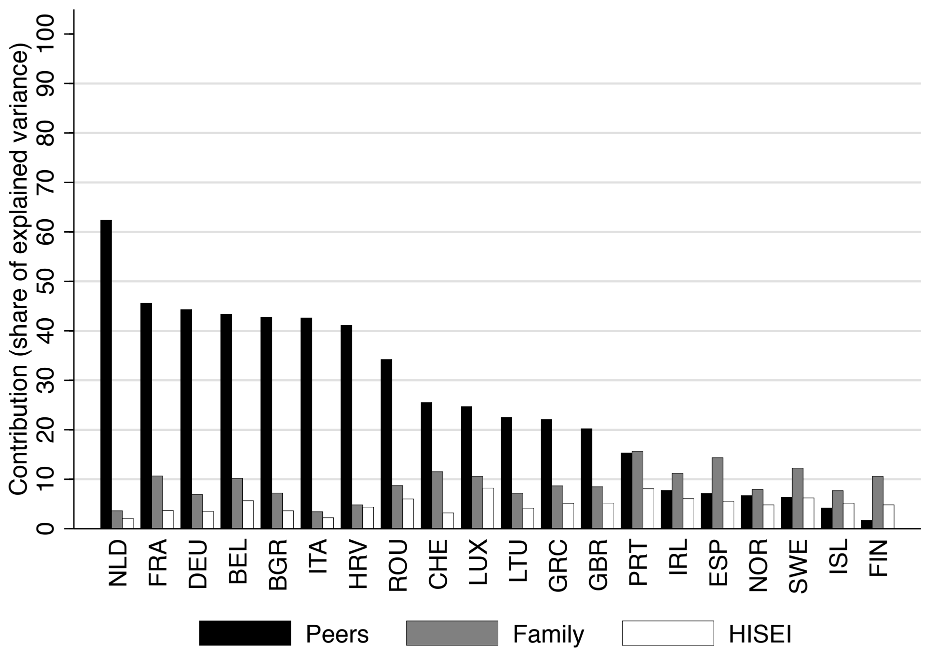
The first column in the column blocks indicates the contribution defined in Equation (2.22) whereas the second and the third columns indicate their respective lower and upper bounds.

As can be observed, in most countries peer performance is the greatest contributor to the overall variance, explaining between 20% and 63% of achievement inequality. In fact, the shares are higher than 40% for The Netherlands (62.35%), France (45.63%), Germany (44.29%), Belgium (43.35%), Bulgaria (42.73%), Italy (42.61%) and Croatia (41.08%), which are the countries with the largest shares of inequality explained by circumstances, and with the largest between-school variances. However, this is not the case for the Nordic countries of Finland, Sweden and Iceland, nor for Spain and Ireland, for which the family

[10] The contribution of school characteristics is not reported because it is lower than 1% for all the countries.

background is the most prominent circumstance, accounting for between 7% and 15% of achievement inequality.[11] Similar results are presented in Causa and Chapuis (2011) in terms of the relative importance of the family with respect to peer-related background. In Portugal and Norway the contributions of peers and family are almost equal. Among the variables representing the family background, HISEI is the most significant for all countries (except for Switzerland and France, for which NAT and HPOS are more important, respectively). These contribution shares vary between 2.07% in The Netherlands to 8.21% in Luxembourg.[12]

Figure 2.2: Contribution of peer effects, family background and parental occupational status to the achievement inequality



To conclude with this part of the study, we look at the potential lower and upper bounds of the contributions presented in the second and third columns in each column block. Regarding the contributions of peer effects, both lower and upper bounds indicate that the lowest shares are for the Nordic countries of Finland, Iceland, Sweden and Norway, and for Spain and Ireland, whereas the highest shares are for The Netherlands, France, Germany, Belgium, Bulgaria, Italy and Croatia. As for the contribution of family background and HISEI, lower bounds are in line with the rankings of the contributions

[11]Keep in mind that these shares are computed with regard the overall variance $V(y)$ rather than the explained variance $V(\hat{y})$.

[12]The contribution shares presented in the first column of the column blocks in Table 2.4 are similar to those obtained using the general dominance analysis of Budescu (1993).

themselves. According to these rankings, the lowest values for family background are found in Italy, The Netherlands and Croatia, while highest are found in Sweden, Spain and Portugal. Regarding HISEI, the lowest shares are observed for The Netherlands and Italy, whilst the highest are for Portugal and Sweden. On the contrary, upper bounds provide different rankings. According to them, the lowest values for family background are found for Italy and the Nordic countries of Iceland, Finland and Norway whereas the highest are for France and Luxembourg. Regarding the upper bounds of HISEI, the lowest contributions are observed also for Finland, Norway, Iceland and Italy, while Luxembourg shows the highest.

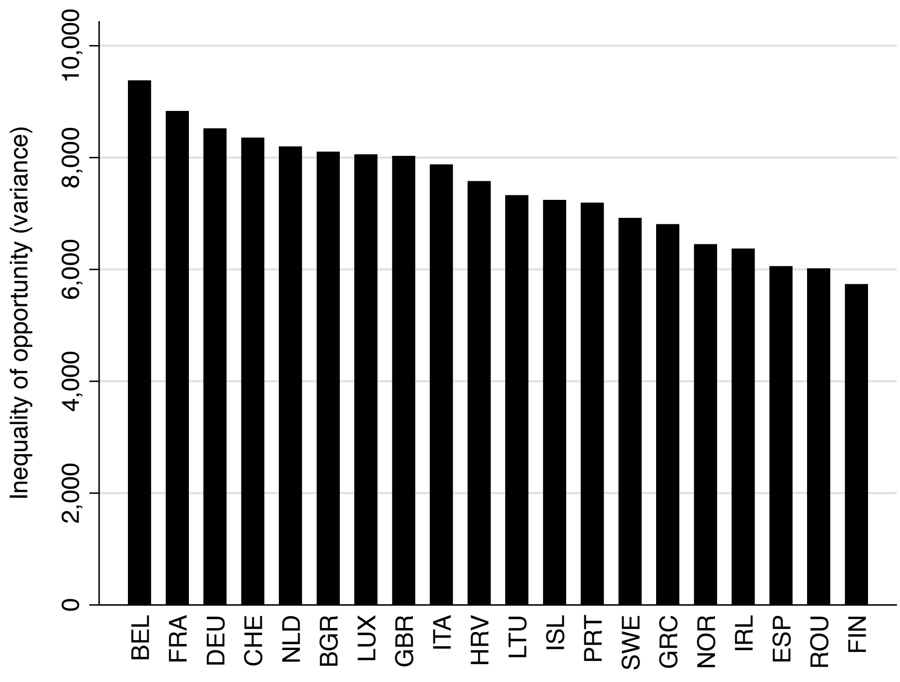
2.3.4 Inequality of opportunity

Now we asses inequality of opportunity in the countries selected. To that end, we compute the variance in the counterfactual distribution constructed according to Equation (2.17). As explained above, these counterfactuals are characterized by three features: First, correlation between circumstances and efforts is attributed to the side of circumstances; second, differences due to efforts have been removed; and finally the residual term is included in the estimated achievement in order to guarantee that the compensation principle is satisfied. The results are displayed in the first column of Table 2.5 and in Figure 2.3. As shown can be seen, there is a wide variation in inequality of opportunity across countries ranging from 5734.45 in Finland to 9377.20 in Belgium. In particular, Belgium, France, Germany, Switzerland, The Netherlands and Bulgaria have the highest figures for inequality of opportunity, while Finland, Romania, Spain, Ireland, Norway, Greece and Sweden have the lowest. These rankings are in line with those reported by Ferreira and Gignoux (2014), where relatively lower levels of inequality of opportunity are observed in the Nordic countries, Spain and Ireland, and the higher levels in the Western countries (Belgium, France, Germany, Luxembourg, the Netherlands and Switzerland) and Bulgaria.

Table 2.5: Inequality of opportunity, total variance and share.

Country	$M^D(Y, C, E)$	Total variance	Inequality of Opportunity Share (%)
Belgium	9377.20	10244.42	91.53
Bulgaria	8101.55	8473.54	95.61
Croatia	7576.07	7698.89	98.40
Finland	5734.45	7093.42	80.84
France	8829.50	9337.97	94.55
Germany	8518.88	8999.19	94.66
Greece	6806.30	7342.72	92.69
Iceland	7237.50	8569.77	84.45
Ireland	6369.28	7122.10	89.43
Italy	7872.68	8224.06	95.73
Lithuania	7324.02	7641.03	95.85
Luxembourg	8054.90	9094.57	88.57
Netherlands	8195.17	8401.07	97.55
Norway	6448.08	8015.46	80.45
Portugal	7189.94	8742.41	82.24
Romania	6014.66	6298.59	95.49
Spain	6055.47	7616.66	79.50
Sweden	6916.50	8145.16	84.92
Switzerland	8353.26	8931.44	93.53
United Kingdom	8026.11	8923.94	89.94

Figure 2.3: Inequality of opportunity



The second column gives the variance of the achievements and the third one presents the share of the total variance explained by inequality of opportunity. Regarding this share, the highest percentages correspond to Croatia, The Netherlands, Lithuania, Italy, Bulgaria and Romania, with more than 95% of total inequality captured by inequality of opportunity. In contrast, in Spain, Portugal, and the Nordic countries of Norway, Finland, Iceland and Sweden inequality of opportunity represents between 79% and 85% of overall inequality.[13]

Figure 2.4: Overall inequality and inequality of opportunity

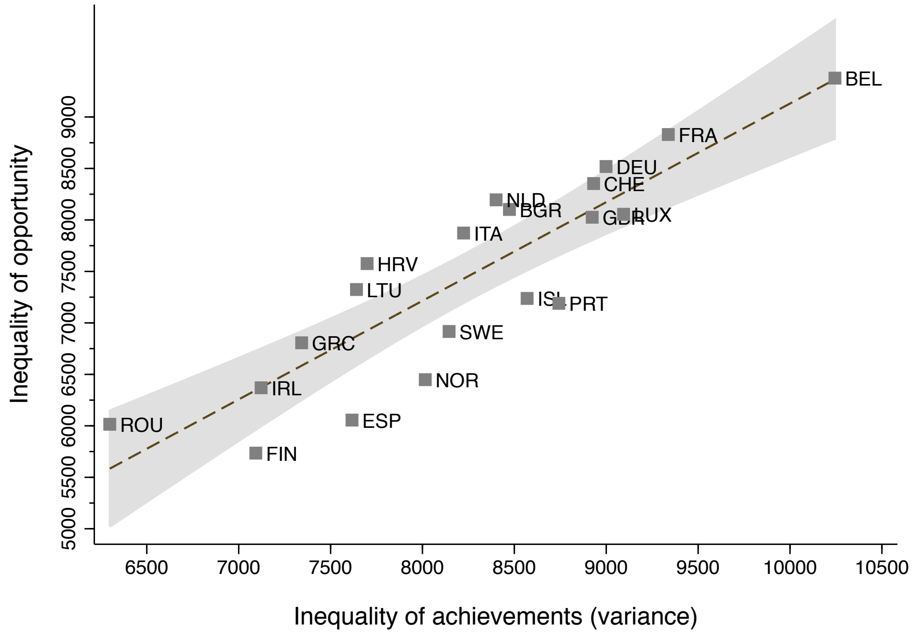
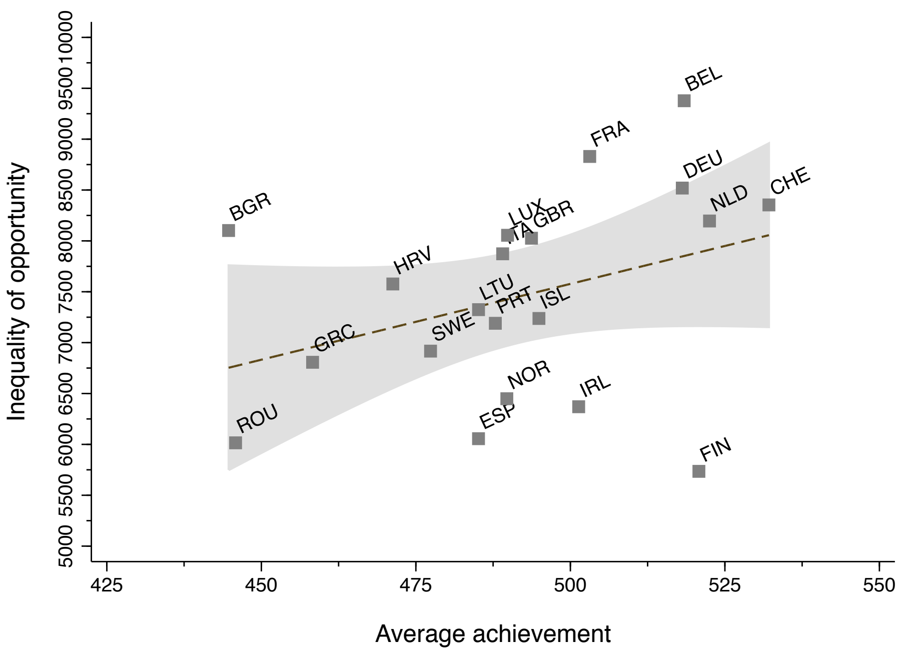


Figure 2.4 illustrates the relationship between overall inequality and inequality of opportunity. The regression line and a 95% confidence interval for the mean of the achievements are shown. As expected, there is a positive correlation between the two inequalities. The coefficient of correlation is estimated at 0.87. Romania, Finland, Spain, Ireland, Greece and Norway are the countries with the highest levels of equality in terms of both overall inequality and inequality of opportunity, while Belgium is at the opposite end of the scale. We also find that Spain, Portugal and the Nordic countries of Finland, Norway, Iceland and Sweden lie below the line, with lower-than-expected levels of inequality of opportunity, while Germany, the Netherlands, Bulgaria, Italy, Lithuania and Croatia are positioned above it.

[13]The reader should keep in mind that the levels of inequality of opportunity estimated in this paper are upper-bounds of the real inequality of opportunity.

A final issue of interest is to compare inequality of opportunity with mean educational achievements. As can be observed in Figure 2.5, there is considerable variation across countries and there seems to be no clear relationship between both measures. We find, for instance, that Bulgaria and Switzerland have similar levels of inequality of opportunity but extreme values of average achievements. Romania, with a low level of inequality, and inequality of opportunity, is among the countries with the lowest mean scores. In contrast Croatia and Bulgaria, which also have low scores, have high levels of inequality. We also find differences in inequality levels among the countries with high mean scores. Switzerland, Germany, The Netherlands, and Belgium, all of which have high mean scores, have relatively high inequality levels. Finland, however, has a low inequality of achievement distribution, and is the best-positioned country.

Figure 2.5: Average achievements and inequality of opportunity



Moreover, the relationship between inequality of opportunity and average achievement could be used for deeper analysis. For instance, we find that the students in the least privileged group[14] in Switzerland, a country with a high level of inequality of opportunity and a high average achievement, enjoy a higher education level than that of students in Romania, a country with lower inequality of opportunity and also a lower average. Furthermore, we find that students in Finland, which shows a low level of inequality

[14]Least and most privileged groups are defined as students located at the first and the last quartiles of $\hat{\beta}^R$C, respectively.

of opportunity and high achievement, do better than the most advantaged students in Romania, also with low levels of inequality but low average achievement. On the contrary, the more privileged students in Bulgaria, with high inequality of opportunity and low average achievement, do worse than students in Switzerland, also with high inequality of opportunity but high average achievement.

2.4 Conclusions

In this chapter we analyze educational achievement inequality in twenty European countries taking data from PISA 2012 using parametric procedures. For each country, we first estimate a model, then measure the contributions of circumstances and efforts to inequality in achievements, and finally assess inequality of opportunity.

Our model provides the total effects of the circumstances. Furthermore, we consider for students' peer effects as an additional circumstance, and due to the endogeneity of this variable we use instrumental variables to obtain consistent estimates. These things considered, the whole set of variables is able to explain more than 50% of the variation for most countries, and in any case, this percentage is higher than 29%. Within these shares, the contribution of circumstances is more than half for all the countries except for the Nordic countries of Finland, Norway and Iceland.

Regarding the contribution of different circumstances to overall achievement inequality, peer effects are the most important circumstance for most countries. Indeed, for The Netherlands, France, Germany, Belgium, Bulgaria, Italy and Croatia, peer performance explains more than 40% of overall achievement inequality. On the contrary, for the Nordic countries of Finland, Sweden and Iceland, and for Spain and Ireland, the contribution of family background is notably larger than that of peer effects. As a matter of fact, in these countries between-school variance is relatively lower compared to the rest. Among the aspects of students' family background, parental occupational status is the most important for almost all the countries. Additionally, we provide lower and upper bounds of these contributions' shares.

Concerning inequality of opportunity, the results show great disparities from one country to another. Achievement inequality is higher in Belgium, France, Luxembourg and Germany and is lower in Romania, Finland, Ireland, Greece and Spain. In general, countries with high inequality levels have greater inequality of opportunity, but there is no evidence that inequality of opportunity is related to achievement levels.

Chapter 3

Re-examining the inequality of opportunity measurement following a non-parametric approach

3.1 Introduction

This chapter measures inequality of opportunity following the *ex-ante* and *ex-post* non-parametric approaches developed by Checchi and Peragine (2010). In the ex-ante approach the population is partitioned into *types*, each of which consists of students who share homogeneous circumstances. In the ex-post approach the population is partitioned into *tranches* composed by students who share homogeneous efforts. Inequality of opportunity is measured either as the inequality between the types or as the inequality within the tranches.

The definition of types and tranches is at the core of the measurement. In the usual procedures researchers are normally forced to work with limited numbers of categorical variables (see for instance, Checchi and Peragine, 2010; Gamboa and Waltenberg, 2012; Salehi-Isfahani et al., 2014), or with a single continuous one (as in O'Neill et al., 2000). This study seeks to provide another approach to define types and tranches that allows us to consider any number of both categorical and continuous variables.

The rest of the chapter is organized as follows. Section 3.2 describes the procedure followed in order to construct counterfactual distributions to measure inequality of opportunity using a non-parametric approach. Section 3.3 offers a review of the literature on the most commonly used methods to define types and tranches, and proposes a new procedure for their empirical definition. Section 3.4 presents the results and Section 3.5 concludes.

3.2 Framework for the inequality of opportunity and its measurement from a non parametric approach

This section introduces the non-parametric procedure used to build up counterfactual distributions in order to assess the inequality of opportunity in a given population.

Assuming that the educational achievements are completely determined by circumstances and efforts, as previously stated in Equation (1.1),

$$Y_i \;=\; G(\mathbb{C}_i, \mathbb{E}_i) \quad i = 1, \ldots, \mathsf{N} \quad G : \mathbb{R}^{K_C} \times \mathbb{R}^{K_E} \to \mathbb{R}_{++},$$

the population can be grouped according to either circumstances or efforts. As regards the former partition, students that share homogeneous circumstances are grouped into n *types* that are mutually exclusive. Accordingly, the overall outcome distribution can be rewritten as,

$$Y = \{Y^{1\cdot}, \cdots, Y^{k\cdot}, \cdots, Y^{n\cdot}\}, \tag{3.1}$$

where $Y^{k\cdot} = \{y_1^{k\cdot}, \cdots, y_i^{k\cdot}, \cdots, y_{N_k}^{k\cdot}\}$ is the achievement distribution of the students in type k and N_k is the number of students in that type.

Regarding the partition in terms of efforts, students that share homogeneous efforts are grouped into m mutually exclusive *tranches*. Hence, the overall achievement distribution can also be rewritten as,

$$Y = \{Y^{\cdot 1}, \cdots, Y^{\cdot l}, \cdots, Y^{\cdot m}\}, \tag{3.2}$$

where $Y^{\cdot l} = \{y_1^{\cdot l}, \cdots, y_i^{\cdot l}, \cdots, y_{N^l}^{\cdot l}\}$ is the achievement distribution of the students in tranche l and N^l is the number of students in that tranche.

Students that share homogeneous circumstances and efforts belongs to the same *cell*, thus, the outcome distribution can also be rewritten in terms of these cells as,

$$Y = \{Y^{11}, \cdots, Y^{kl}, \cdots, Y^{nm}\}, \tag{3.3}$$

where $Y^{kl} = \{y_1^{kl}, \cdots, y_i^{kl}, \cdots, y_{N_k^l}^{kl}\}$ is the achievement distribution of the students in type k and tranche l and N_k^l is the number of students in cell kl.

Table 3.1 represents the distribution of outcome Y where each column of the matrix corresponds to a type and each row to a tranche.

Table 3.1: Achievement distribution in terms of cells

	$c = 1$	$\cdots$	$c = k$	$\cdots$	$c = n$
$e = 1$	Y^{11}	$\cdots$	Y^{k1}	$\cdots$	Y^{n1}
$\vdots$	$\vdots$		$\vdots$		$\vdots$
$e = l$	Y^{1l}	$\cdots$	Y^{kl}	$\cdots$	Y^{nl}
$\vdots$	$\vdots$		$\vdots$		$\vdots$
$e = m$	Y^{1m}	$\cdots$	Y^{km}	$\cdots$	Y^{nm}

In the studies with categorical circumstance variables (see for instance, Checchi and Peragine, 2010; Ferreira and Gignoux, 2011; Gamboa and Waltenberg, 2012) and categorical effort variables (such as, Li Donni et al., 2014), the number of types (n) and tranches (m) are determined by the number of values that each variable can take. However, in this study types and tranches are defined according to the variables that are categorical as well as continuous, and both n and m are determined exogenously. This will be explained in Section 3.3.2.

Checchi and Peragine (2010) propose two distinct measures of inequality of opportunity that are obtained through the *ex-ante* and *ex-post* approaches. Both of them are explained in the paragraphs that follow.

Ex-ante approach

The ex-ante approach described in Checchi and Peragine (2010) relies on Van de gaer's formal definition of equal opportunity policy (Van de gaer, 1993) and is compatible with the reward principle. After partitioning the population into n types, the value of an individual's opportunity set is measured by the average achievement of their type.[1] Hence, inequality of opportunity is measured as the inequality between the values of opportunity sets.

The counterfactual in the ex-ante approach is given by the *smoothed* distribution in which each individual achievement in type k, $y_i^{k\cdot}$, is replaced by the mean of their type, $\bar{Y}^{k\cdot}$,

$$Y_{EA} = \{\bar{Y}^{1\cdot}1_{N_1}, ..., \bar{Y}^{k\cdot}1_{N_k}, ..., \bar{Y}^{n\cdot}1_{N_n}\} \tag{3.4}$$

where 1_{N_k} is the unit vector of length N_k. Only inequality between types, which is due to circumstances, remains in the given distribution. Then, a direct measure $\mathcal{M}^D(Y, C, E)$, evaluates inequality of opportunity as follows:

$$\mathcal{M}^D(Y, C, E) \quad = \quad I(Y_{EA}), \tag{3.5}$$

where I is a standard inequality measure. As stated in Van de gaer and Ramos (2015*b*), if there is a Pigou-Dalton transfer between two students in the same type, the counterfactual defined in (3.4) is unchanged, thus, the measure of inequality of opportunity (3.5) satisfies the reward principle.

Ex-post approach

The ex-post approach described in Checchi and Peragine (2010) is in line with Roemer's concept of equality of opportunity (Roemer, 1998) and is compatible with the compensation principle. Once the population is partitioned into m tranches, inequality of

[1] Some other studies have proposed the use of distinct features of types' outcome distributions. For instance, Lefranc et al. (2009) relies on the stochastic dominance conditions of the outcome distributions of types.

opportunity depends on the achievement inequality amongst individuals within the same tranche.

The counterfactual in the ex-post approach is obtained by replacing the achievements of the students in tranche l, $y_i^{\cdot l}$, by the arithmetic mean achievement[2] of that tranche, $\bar{Y}^{\cdot l}$,

$$Y_{EP} = \{\bar{Y}^{\cdot 1} 1_{N^1}, ..., \bar{Y}^{\cdot l} 1_{N^l}, ..., \bar{Y}^{\cdot m} 1_{N^m}\} \tag{3.6}$$

where 1_{N^l} is the unit vector of length N^l. Counterfactual distribution (3.6) represents the smoothed distribution in which students in tranche l are assigned the same achievement, $\bar{Y}^{\cdot l}$, regardless of their circumstances. Hence, in counterfactual (3.6) there is no inequality of opportunity. An indirect measure, $\mathcal{M}^I(Y, \mathbb{C}, \mathbb{E})$, evaluates inequality of opportunity as the difference between the inequality in the actual distribution Y and the inequality in the counterfactual distribution, Y_{EP}, as follows,

$$\mathcal{M}^I(Y, C, E) \quad = \quad I(Y) - I(Y_{EP}). \tag{3.7}$$

If there is a Pigou-Dalton transfer between two students in the same tranche, the inequality in the actual income distribution decreases whereas the counterfactual defined in (3.6) is unchanged. Thus, the measure of inequality of opportunity (3.7) satisfies the compensation principle (see Van de gaer and Ramos, 2015*b*).

The inequality measure I selected for this analysis is the variance due to the reasons previously explained in Section 1.2 of Chapter 1.

Accordingly, equations (3.5) and (3.7) can respectively be reformulated as,

$$\mathcal{M}^D(Y, C, E) \quad = \quad V(Y_{EA}), \tag{3.8}$$

$$\mathcal{M}^I(Y, C, E) \quad = \quad V(Y) - V(Y_{EP}). \tag{3.9}$$

Since the variance can be decomposed into population subgroups as the sum of between-group and within-group components, the expression in Equation (3.8) is equivalent to the between-type component of overall inequality. In a similar way, the expression in Equation (3.9) is equivalent to within-tranches inequality, that is, a weighted average of the variance in each tranche where the weights are the population shares.

[2]Any other "representative achievement" such as the geometric or harmonic mean or the equally distributed equivalent achievement could be formulated as well. Nevertheless, we follow Checchi and Peragine (2010) who use the arithmetic mean in order to preserve the same total achievement.

3.3 Empirical definition of types and tranches

The definition of types and tranches is at the heart of the measures of inequality of opportunity in non-parametric approaches. Nonetheless, no consensus has been reached so as to provide an unanimous criterion for their construction in a given sample. This section first describes the most common procedures used to build up types and tranches, and then we propose another approach.

3.3.1 Literature review

With regard to types, they have usually been determined by the number of values that each circumstance variable can take.

The main disadvantage here is that as the vector of the observed circumstances and the number of categories within each variable increase, the number of types grows geometrically. This fact leads to types with very few observations, with large sampling variances and unreliably imprecise estimates. This is particularly problematic in the case of non-parametric approaches to inequality of opportunity, as large datasets are required in order to yield reliable estimates.[3] A common approach used to avoid the vast variety of types with very few observations has been to ignore a large number of circumstances, and to provide ad hoc definitions of types based on a small number of categorical circumstances. As a consequence, a large part of the variation in outcomes due to circumstances has been erroneously attributed to efforts.

As a way out for such cases, Li Donni et al. (2015) propose an alternative to the empirical definition of types. The authors propose an econometric strategy for identifying social types based on estimation of latent class models, where the composition and number of these types are endogenously determined by the model. Their empirical strategy develops in three stages. First they identify the number of unobserved types in the data. Second, they estimate the probability of each individual belonging to each type, given their observed set of circumstances. Then, individuals are assigned to social types according to the highest probability criterion. This technique makes possible the use of a wide set of circumstances while maintaining a fixed number of social types, from which each individual can be treated as a random draw. In the case of the continuous circum-

[3]This problem is carefully analyzed in Ferreira and Gignoux (2011).

stance variables, they are first categorized in order to avoid numerical problems in the computations. Therefore, continuous variables are first transformed so as to estimate the probabilities.

There are also some procedures that allows us to use exclusively the continuous variables. For instance, the study of O'Neill et al. (2000) evaluates inequality of opportunity in the context of intergenerational income mobility using a conditional Kernel density estimator. It evaluates the impact of a father's income (the only circumstance variable) on his son's income (the outcome of interest). The opportunity sets are estimated using the conditional Kernel density of sons' incomes on fathers' incomes. Then, the authors categorize the circumstance variable for illustration purposes. Specifically, they extract those fathers who belong to percentiles 25, 50 and 75 of the fathers' income distribution, and illustrate how having "poor", "average" or "rich" fathers requires different amounts of effort on the part of the sons to reach average income. The main shortcoming of the model in O'Neill et al. (2000) is that only the income of the father is included as a circumstance, whereas the rest of the variation in income is attributed to effort. Consequently, the term which represents the effort becomes unreliable for it comprises numerous relevant circumstances that are left out in the analysis. Including additional variables in the conditional Kernel density estimations is, however, hardly feasible due to the slow convergence of non-parametric estimators.

In sum, many attempts have been made to tackle the issue of how to construct types and tranches when a set of circumstance and effort variables is available, especially when these variables are continuous.

Regarding tranches, their construction depends on the availability of effort variables. In the studies where no effort variables are available, tranches are usually determined as the quantiles of the type-specific outcome distributions under two assumptions: first, the achievements are monotonically related to effort within a type, and second, the degrees of effort are by definition orthogonal to circumstances. This method, inspired by Roemer's model (Roemer, 1998), is known as Roemer's Identification Axiom.

When effort variables are at least partly observable, there are different procedures to define tranches as is explained by Brunori (2016). For instance, if one or more categorical variables are available (see for instance, Li Donni et al., 2014), tranches can be defined as the number of all the possible combinations of values taken by each effort variable, in the same way as in the definition of types. Nevertheless, this partition depends on the effort which is likely to be affected by the circumstances and cannot be considered as freely chosen effort. Therefore, this technique does not hold the orthogonality assumption between effort and circumstances. If contrastingly, one continuous effort variable is available, then tranches can be defined as the quantiles of that effort distribution of types in concordance with Roemer's Identification Axiom. However, no more than one continuous effort variables have been used in the contruction of tranches so far.

3.3.2 Empirical methodology to define types and tranches

Considering the limitations of the above mentioned methods, in this section we propose a methodology in order to define types and tranches. Our proposal enables us to consider any number of both categorical and continuous variables by using non-parametric techniques. In the same way as O'Neill et al. (2000), our approach lets us work with continuous variables, but instead of being focused on only one circumstance, we consider multiple variables all together. This also makes it possible to use a wide set of circumstances while maintaining a fixed number of types, as in Li Donni et al. (2015), but we do not need first to categorize the continuous variables.

The procedure consists of two steps, a parametric step to estimate the achievement distributions conditional on observed circumstances and efforts, and a non-parametric step to partition the population into types and tranches subject to students' positions in those distributions.

Parametric step: Estimation of the conditional achievement distribution.

To estimate students' achievements as a function of circumstances and cleaned efforts, we recall Equation (2.19) previously defined in Section 2.2.4 of Chapter 2,

$$\hat{y}_i = \hat{\alpha}^R + \hat{\beta}^R \mathrm{C}_i + \hat{\gamma}^R \mathcal{E}_i,$$

Note that efforts $\mathcal{E}_i$ are orthogonal to circumstances C_i, so that the constant term $\hat{\alpha}^R$ and coefficients $\hat{\beta}^R$ comprise the common part between circumstances and efforts, i.e. $E(\hat{\alpha}^R) = \alpha + \gamma\phi$ and $E(\hat{\beta}^R) = \beta + \gamma\delta$. Thus, $\hat{y}_i$ can be linearly decomposed into a part that is exclusively conditional on circumstances, and another on orthogonalized efforts. The former is defined as the first two summands of the right-hand side of Equation (2.19):

$$\hat{y}_i^c = \hat{\alpha}^R + \hat{\beta}^R \mathrm{C}_i. \quad (3.10)$$

Therefore, $\hat{y}_i^c$ indicates the achievement that student i is expected to reach given their circumstances. Specifically, it aggregates the direct and indirect influence of the whole set of circumstance variables.[4]

In a similar way, the achievement conditional on orthogonalized efforts is defined as the last summand of the right-hand side of Equation (2.19):

$$\hat{y}_i^e \quad = \quad \hat{\gamma}^R \mathcal{E}_i. \tag{3.11}$$

Thus, $\hat{y}_i^e$ represents the achievement student i is expected to obtain conditional on their efforts. This aggregates the direct influence of the set of efforts, which are cleaned of the impact of circumstances.

We denote by $\hat{Y}^{\mathrm{C}} = \{\hat{y}_1^c, \cdots, \hat{y}_i^c, \cdots, \hat{y}_N^c\}$ and $\hat{Y}^{\mathcal{E}} = \{\hat{y}_1^e, \cdots, \hat{y}_i^e, \cdots, \hat{y}_N^e\}$ the respective distributions of estimated achievements conditional either on circumstances or efforts, respectively. These distributions represent the circumstances-related and effort-related sources of inequality. Therefore, the population is fully characterized by $(\hat{Y}, \hat{Y}^{\mathrm{C}}, \hat{Y}^{\mathcal{E}})$. In this context, we propose to define types and tranches as a combination of different circumstances or efforts, in an analogous manner to the social types defined in Li Donni et al. (2015). The idea is that the students that are close-equals in terms of $\hat{Y}^{\mathrm{C}}$ should be in the same type, whereas students that are close-equals in terms of $\hat{Y}^{\mathcal{E}}$ should be in the same tranche. In this way, these groups would be formed by students whose achievements are homogeneously affected by their circumstances or efforts. Note that $\hat{y}_i^e$ is by construction orthogonal to the observed circumstances. Hence, it is not necessary to partition the sample into types as a first step in defining the tranches.

Non-parametric step: Definition of types and tranches based on conditional achievement distributions

To define types and tranches, first students are ordered from those that have the lowest to those that have the highest values in the distribution of $\hat{Y}^{\mathrm{C}}$ and $\hat{Y}^{\mathcal{E}}$, respectively. For sake of simplicity, let $x_{(1)} \leq \cdots \leq x_{(N)}$ denote the corresponding order statistics of the estimated achievement distribution conditional on circumstances, and that conditional on efforts, where $x = \hat{Y}^{\mathrm{C}}, \hat{Y}^{\mathcal{E}}$. Then, we suggest partitioning the population according to the quantiles of x into groups of students who have similar values of $x = \hat{Y}^{\mathrm{C}}, \hat{Y}^{\mathcal{E}}$.

[4]Note that even if the constant term $\hat{\alpha}^R$ were dismissed in Equation (3.10) the results on inequality of opportunity would not change, since these are measured by the variance.

The τth quantile associated to distribution $F(x)$ is given by,

$$q_\tau = inf\{x : F(x) \geq \tau\} = F^{-1}(\tau), \qquad 0 \leq \tau \leq 1. \tag{3.12}$$

The traditional estimator of q_τ is the empirical quantile function estimator

$$\tilde{q}_\tau = inf\{x : \tilde{F}(x) \geq \tau\} \quad \text{where} \quad \tilde{F}(x) = \frac{1}{N}\sum_{i=1}^{N} I(x_i \leq x),$$

with $\tilde{F}(x)$ being the empirical distribution function.

Nevertheless, $\tilde{q}_\tau$ suffers a lack of efficiency (Azzalini, 1981) that comes from the variability of individual order statistics, especially in the case of continuous variables. A way to improve this efficiency is to form a weighted average of the order statistics using a smooth weighting function. Accordingly, in this study, the quantiles are estimated based on smooth quantile estimator, provided by Yang (1985) and which is traced to Parzen (1979):

$$\hat{q}_\tau = \sum_{i=1}^{N}\left[\int_{\frac{i-1}{N}}^{\frac{i}{N}} \frac{1}{h}K\left(\frac{t-\tau}{h}\right)dt\right]x_{(i)}, \tag{3.13}$$

where $K(\cdot)$ is the kernel weight function and h is the bandwidth or smoothing parameter. The role of h is to select the number of individuals to be taken into account in a type (tranche) through the kernel weight, which gives the highest weight to the order statistics $x_{(i)}$ for which $\frac{i}{N}$ is the closest to τ.

In the empirical application we compute the non-parametric deciles from the univariate distribution function of $\hat{Y}^{\mathrm{C}}$ ($\hat{Y}^{\mathcal{E}}$) using the Gaussian kernel, and the bandwidth selection method proposed by Li and Racine (2013) and Li et al. (2017) which has recently been introduced in the R project's `np` package by Hayfield et al. (2008). Thus, students that are located in the τth decile of given distributions are assumed to belong to the τth type (tranche), such that students in each type (tranche) are close-equals in the way their achievements are influenced by circumstances (efforts).

3.4 Results

The first part of this section gives the descriptive statistics of types and tranches and the second part presents the results on inequality of opportunity for each country.

3.4.1 Descriptive Statistics of types and tranches

The types are defined according to the kernel smoothed deciles of the estimated achievement distribution conditional on circumstances $\hat{Y}^{C}$ obtained from Equation (3.10). Accordingly, each type is composed by students that are close-equals in terms of the overall expected influence of the circumstances on the achievements. The parameters $\hat{\beta}^{R}$ used for the construction of $\hat{Y}^{C}$ are defined in Equation (2.19) and presented in Table 2.1 in Chapter 2. In general, the estimations of these parameters are significantly positive, except for some school background variables which are not statistically significant. Therefore, the students with higher values in the selected circumstance variables, C, are likely to be located in the types associated with higher deciles of the estimated circumstance variable, $\hat{Y}^{C}$, i.e. higher-order types, and vice versa. In essence, the lower-order types generally present a higher share of non-native girls with lower average values for family background and peer performance. On the contrary, the higher-order types exhibit a higher share of native boys with higher average values for family background and peer performance.

As regards the tranches, they are defined according to the kernel smoothed deciles of the proxy variables for efforts $\hat{Y}^{\mathcal{E}}$ obtained from Equation (3.11). The coefficients $\hat{\gamma}^{R}$ on which $\hat{Y}^{\mathcal{E}}$ rely on are estimated from Equation (2.19). As can be seen in Table 2.2 in Chapter 2, these coefficients are significantly positive.[5] Thus, the students with higher values in the orthogonalized efforts are located in the tranches associated with higher deciles of $\hat{Y}^{\mathcal{E}}$ and vice versa. As a result, in the tranches of higher order there is generally a higher share of students that have never repeated, have not skipped classes, present higher level of perseverance and attitude towards school, and spend more time doing homework, whereas it is the opposite case for the tranches of lower order.

Individuals that share the same type and tranche belong to the same cell. The tables for each country in Appendix I provide the means of expected achievements of the cells together with their standard error, the number of observations, and the confidence intervals for the mean. The values in the column that corresponds to type $k \in n$, and in the row that corresponds to tranche $l \in m$ represent the values for the students in cell k, l. As can be seen, the higher-order types and tranches result in higher values for the means of expected achievements than those of lower order. That is, the means are increasing in

[5] The only exception is the effect of studying time in Finland.

circumstances and in efforts.[6]

The graphs in Appendix II provide a display of the information in the tables in Appendix I for each country. The graphs on the left display the information organized in columns, such that each line represents the mean expected achievement of students in the same type along different tranches. As can be observed, the slopes of the lines are generally positive. This indicates that within each type the mean expected achievements are increasing in efforts. Also, the lines associated to the higher-order types are placed above the lines corresponding to the lower-order types, hence, the means are increasing in circumstances as well. The vertical distance between the lines reflects the mean differences between students with homogeneous efforts located in different types. The greater the distance between the lines, the greater the differences in average achievements due to circumstances. At first sight, it seems that the largest differences are found in Belgium, Bulgaria, France and Germany. In contrast, the smallest differences are observed in Finland, Iceland and Norway. On the other hand, although the distance between the lines is quite homogeneous in most countries, that corresponding to the first and the last types are further apart from the rest, indicating a rather more different pattern.

The graphs on the right for each country in Appendix II depict the information organized in rows in the tables in Appendix I. Each line of the graphs describes the mean expected achievement of students in the same tranche along different types. The positive slopes in the graphs suggest that the mean achievements are increasing in circumstances within each tranche. At first glance, the steepest slopes are observed in Belgium, Bulgaria, France and Germany; this hints that differences due to circumstances within tranches are likely to be greater in those countries. Additionaly, the lines that correspond to the upper-order tranches are placed above those that correspond to the lower-order ones, such that the mean achievements are increasing in efforts as well. Also, the distance between the lines that correspond to the first and the last tranches are at a greater distance from the rest. However, given the similar pattern and the small distance between some lines associated either to types or tranches in some countries, it seems that the number of these groups could be reduced. Future work may consider a procedure to test equality of types and tranches in order to optimize the number of groups. This may be the case, for

[6]In the few cases where the mean is lower for a lower-order type or tranche, that difference is not statistically significant according to the confidence intervals derived from Balance Repeated Replication variance estimation.

instance, for the Nordic countries of Finland, Iceland, Norway and Sweden, and for Bulgaria, Croatia, Germany, Greece, Ireland, Italy, Lithuania, The Netherlands, Romania, Switzerland and the United Kingdom.

Regarding the within-cells standard deviation in the tables in Appendix I, the greatest values are observed in the cells corresponding to the first and the tenth types and tranches in all the countries. For instance, focusing on the cells corresponding to each type (the information in column blocks), the variation is notably higher in the first and the tenth tranches. In a similar way, in the cells corresponding to each tranche (the information in rows), the largest variation is found between the students in the first and the last types.

To better understand what is happening within the types and tranches, we analyze the $\hat{Y}^{\mathcal{E}}$ distribution of types and $\hat{Y}^{\mathrm{C}}$ distribution of tranches. Appendix III gives the corresponding density functions that are estimated based on a kernel density estimator which is given by,

$$\hat{f}(x) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{h}K\left(\frac{x - x_i}{h}\right) \quad x = \hat{Y}^{\mathrm{C}}, \hat{Y}^{\mathcal{E}} \tag{3.14}$$

where $K(\cdot)$ is a kernel function with bandwidth h. $K(\cdot)$ places a greater weight on points x_i that are closer to x. In practice, among all possible kernel weightening functions, we use the Epanechnicov kernel,

$$K(v) = \begin{cases} \frac{3}{4}(1 - v^2), & \text{for } |v| \leq 1 \\ 0 & \text{otherwise.} \end{cases}$$

We select the bandwidth h proposed by Silverman (1986) which is more robust against outliers in the sample, and it is formulated as $h = 0.9AN^{-1/5}$, where $A = min(\sigma_x, IRQ/1.349)$ and σ_x and IRQ are the standard deviation and the interquantile range of x, respectively.

As can be seen from the graphs on the left, the density functions are bimodal for all types in Belgium, France, Germany, Luxembourg, Portugal, Spain, Italy, The Netherlands and Switzerland. Bimodal distributions usually indicate that there are two different population subgroups. These countries have the highest grade-repetition rate, and whereas the first subgroup is mostly composed by students that have repeated a grade with a lower mean for $\hat{Y}^{\mathcal{E}}$, the second group is mainly formed by those that have not, with a higher mean for $\hat{Y}^{\mathcal{E}}$. For the rest of the countries, the $\hat{Y}^{\mathcal{E}}$ distribution of types is generally unimodal and they are reasonably homogeneous.

The graphs on the right in Appendix III display the density function of $\hat{Y}^{\mathrm{C}}$ of tranches.

On the whole, the tranches in different countries display different patterns of the distributions of $\hat{Y}^{C}$. In countries such as the Nordic countries of Finland, Iceland, Norway and Sweden, and in Croatia, Ireland, Lithuania, Switzerland and the United Kingodm these distributions are rather similar for the tranches. This indicates that the students' circumstances are homogeneously distributed, regardless of how their expected achievements are being affected by the orthogonalized efforts. Particularly, in the Nordic countries all the $\hat{Y}^{C}$ distributions are somehow left-skewed, indicating higher probalities of having values above the mean. On the other hand, in Belgium, France, Luxembourg, Portugal and Spain, the students that exert relatively low and high values in $\hat{Y}^{\mathcal{E}}$ (students in tranches 2 and 3, and tranches 9 and 10, respectively) are generally the ones whose achievements conditional on circumstances are less favourably affected. Contrastingly, the students with medium values of $\hat{Y}^{\mathcal{E}}$ (those in tranches 5 and 6) appear to be those whose expected achievements are most favourably affected by circumstances. It seems that, in general, students with worse circumstances opt for exerting either low or high levels of effort, and those with the best circumstances exert medium effort level. Interestingly, by looking at the $\hat{Y}^{C}$ distribution of the first tranche we observe that students that exert the lowest effort are equally distributed across types. For the rest of the countries we do not find any clear association between the order of the tranches and the characteristics of the distribution. Nevertheless, a deeper analysis may provide some insights into which circumstance or effort is the main determinant for classifying students into types or tranches.

3.4.2 Inequality of opportunity

Table 3.2 presents the results on inequality of opportunity in educational achievements in the selected European countries. The first column presents the ex-ante measures and the second column displays the ex-post ones.

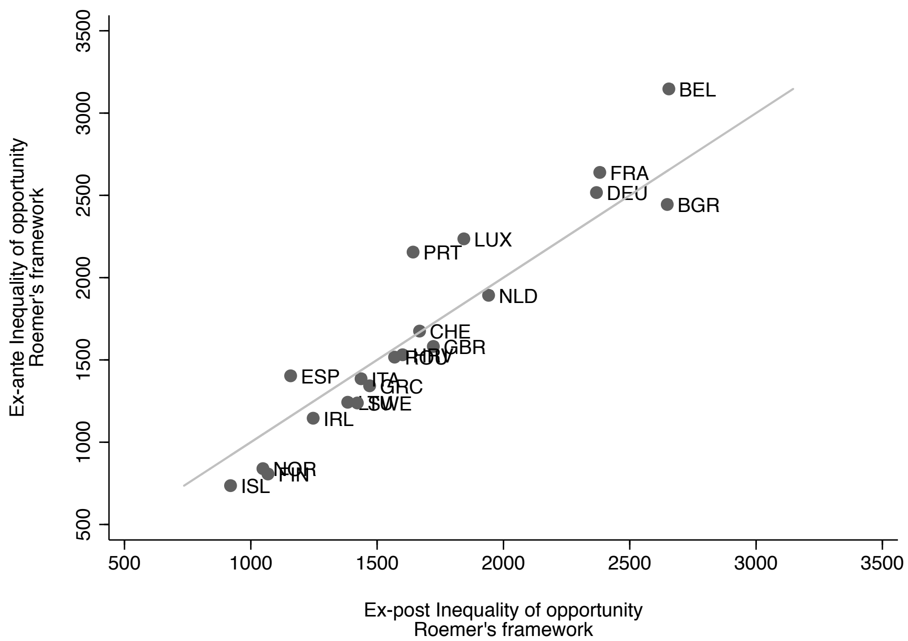
Table 3.2: Ex-ante and ex-post inequality of opportunity

Country	Inequality of opportunity			
	Ex-ante	%	Ex-post	%
Belgium	3146.66	30.72	2654.91	25.92
Bulgaria	2444.32	28.85	2648.57	31.26
Croatia	1530.99	19.89	1600.83	20.79
Finland	806.62	11.37	1067.93	15.06
France	2639.20	28.26	2381.48	25.50
Germany	2516.85	27.97	2368.34	26.32
Greece	1342.35	18.28	1470.41	20.03
Iceland	735.81	8.59	919.88	10.73
Ireland	1145.46	16.08	1246.91	17.51
Italy	1385.28	16.84	1436.52	17.47
Lithuania	1242.45	16.26	1383.64	18.11
Luxembourg	2235.48	24.58	1843.43	20.27
Netherlands	1892.45	22.53	1941.39	23.11
Norway	839.12	10.47	1047.99	13.07
Portugal	2155.19	24.65	1642.30	18.79
Romania	1516.63	24.08	1569.15	24.91
Spain	1403.10	18.42	1157.75	15.20
Sweden	1237.96	15.20	1421.72	17.45
Switzerland	1675.02	18.75	1667.98	18.68
United Kingdom	1581.79	17.73	1722.46	19.30

As shown in the table, although there is a wide variation in inequality of opportunity across countries, there are not great differences between the ex-ante and ex-post approaches. In both approaches, and in terms of both absolute values and percentages, the countries with the lowest figures for inequality of opportunity are the Nordic countries of Iceland, Finland and Norway, while those with the highest are the Western countries of Belgium, France and Germany, and Bulgaria.

Figure 3.1 diplays the relationship between the ex-post and ex-ante measures of inequality of opportunity. As can be observed, these measures are positively correlated and the countries stand close to the identity line. Most countries lie below the line meaning that the ex-post values are higher than the ex-ante ones. The exceptions are Belgium, France, Germany, Luxembourg, Portugal and Spain, with higher values for the ex-ante measure. It is worth noting that these countries are those that have a bimodal distribution of $\hat{Y}^{\mathcal{E}}$.

Figure 3.1: Relationship between ex-post and ex-ante measures of Inequality of opportunity



3.4.3 Comparison of the ex-post measures of inequality of opportunity obtained following the parametric and non-parametric approaches

Figure 3.2 displays the relationship between the parametric and non-parametric measures of inequality of opportunity that satisfy the compensation principle. The regression line and the 95 % confidence interval for the mean is shown in the graph. As can be observed, there is a positive correlation between both measures. Finland, Spain, Norway and Ireland present relatively low values for both measures. Contrastingly, Belgium, Bulgaria, France and Germany present the highest values. It is also observed that Iceland lies far below the line with lower-than-expected values in the non-parametric approach. On the other hand, Bulgaria and Romania stand notably above the line with higher-than-expected values in the non-parametric approach.

It seems that when the residual is not attributed to the circumstances, Iceland is the country with the lowest inequality of opportunity. However, that value increases significantly when it so. This fact was expected since in Iceland the unexplained part accounts for 70% of the achievement inequality, and so, the unfair inequality should rise

Figure 3.2: Relationship between parametric and non-parametric ex-post measures of Inequality of opportunity

considerably when it is assigned to the circumstances. Contrastingly, Romania presents an intermediate position when the residual is not accounted as a circumstance, but ranks among the countries with the lowest inequality of opportunity when it is considered so. This must be because the circumstances explain a relatively large share of the explained inequality. Hence, inequality of opportunity is also larger when only this explained part is accounted for. Contrastingly, inequality of opportunity in the parametric approach is in line with the overall inequality, and since Romania is one of the countries with the lowest overall inequality, the given measure is also relatively low.

3.5 Conclusions

In this study we propose an alternative method for defining types and tranches to construct counterfactual distributions using a mix of parametric and non-parametric approach. By means of this methodology, types and tranches are composed by the students whose achievements are being homogeneously conditioned by their circumstances or efforts. In contrast to the existing methods, this one allows us to work with multiple continuous variables all together. It also enables us to use a wide set of variables while maintaining a fixed number of groups, but with no need to categorize the continuous variables first.

The results point out that the lowest values for inequality of opportunity are for the Nordic countries of Iceland, Finland and Norway, while the highest figures are for the Western countries of Belgium, France and Germany, and for Bulgaria. This is so according to both ex-ante and ex-post measures. Although the results obtained in both approaches are positively correlated, the rankings of the countries are different. In general, the ex-post figures are higher than the ex-ante ones. The exceptions are Belgium, France, Germany, Luxembourg, Portugal and Spain, with greater figures for the ex-ante measure. These countries are the ones with a bimodal estimated effort distribution and the ones with the largest grade retention rate.

Finally, we observe that there is a positive correlation between the parametric and non-parametric measures of inequality of opportunity that satisfy the compensation principle.

Chapter 4

Beyond cognitive-skills: the attitude towards school and its determinants in Spain

(A summarized version of this chapter has been published, jointly with María Marta Formichella and Natalia Krüger in Revista de Educación, 367, 10–35, 2015)

4.1 Introduction

Does school help students to prepare for adult life, giving confidence to make decisions and teaching useful skills for a job? Or is it rather a waste of time? These ingredients of students' attitudes towards school are influenced by their personal characteristics, socioeconomic and cultural background of their family, and their centre's disciplinary climate. The objective of this chapter is to analyze how the characteristics of students, their families and schools influence their attitudes.

Attitude towards school encompasses students' beliefs regarding the utility, enjoyment and attachment to their school. Their perception of the usefulness of attending school may indicate the predisposition of the students towards studying, their degree of responsibility, valuing of knowledge and expectations regarding their future educational career.

Despite the significant role of the attitudes and other affective aspects of students, they have usually been neglected in the economic literature. This is mainly due to the difficulty in reaching an agreement on the definition of attitudinal characteristics that do not belong to the dimension of cognitive skills. In addition, as Heckman and Rubinstein (2001) and Levin (2012) stated, the lack of trustworthy methods available to measure these characteristics has constituted another limitation for research.

Therefore, the aim of this chapter is to make a contribution to the economic literature on the importance of the affective characteristics of students. In particular we intend to analyze the determinants of students' attitude towards school in Spain. The working hypothesis defends that the main determinants of this attitude towards school are individual and family factors, whilst the influence of the schools is relatively minor. At the same time it presumes that among the school variables, those related to the social-affective environment have the largest influence on attitudes.

In order to test this hypothesis we take data from the 2009 wave of the OECD's Program for International Student Assessment (PISA) and we carry out the estimations following a multivariate multilevel approach. This methodology attempts to capture the hierarchical structure of educational data, and at the same time, to take into account the existing correlation between attitude—non-cognitive skills— and educational achievements — cognitive skills. Accordingly, a multilevel bivariate regression model is estimated in which both attitude towards school and educational achievements are evaluated.

The chapter is organized as follows. Section 4.2 presents an overview of the lines of research on attitudes towards school. Section 4.3 gives details on the PISA 2009 dataset and the variables we have used. Section 4.4 explains the multilevel and multivariate multilevel approaches and presents the estimated models. Section 4.5 shows the empirical results and Section 4.6 concludes.

4.2 Literature Review

Attitudes towards school, and attitudes in a broader sense, have been long studied in psychological and sociological research, but they have hardly been the focus of economic studies until recent years.

Ajzen and Fishbein (1977) state that countless definitions of attitudes have been proposed in the literature, but most researchers agree that a person's attitude represents their *evaluation* of somebody or something. Similarly, attitude *towards an object* reflects the emotional predisposition to act in some way toward that object. Attitude towards school, therefore, is related to the way students value the schooling and it may indicate their perception of school as being interesting and important for their future (Davalos et al., 1999). In addition, Ajzen and Fishbein (1977) show that attitude and behavior are highly correlated, and this fact leads us to understand that students' attitudes towards school are likely to influence the overall pattern of how they respond to that school and school-related activities.

The desire to conceptualize and examine parts of the literature under the label of *attitudes towards school* presents some difficulties because there is a proliferation of definitions and measures of concepts that are very similar and interrelated. In psychology, there is a considerable amount of research on how students behave, feel, think and perform, which leads us to harmonized conclusions, but they use slightly different concepts. In the paragraphs that follow we introduce some studies that deal either directly or indirectly with attitudes.

The main purpose of some studies is to make a contribution in the measurement of attitudes themselves. For instance, Thornburg (1980) provides a method to assess adolescents' attitudes by emphasizing the scaling techniques, reliability and validity. Valeski and Stipek (2001) construct a measure known as Feelings About School (FAS) to assess children's perceptions of academic competence, their feelings about the teacher, and their general attitudes toward school. McCoach and Siegle (2003) revise an instrument to measure adolescents' attitudes toward school, attitudes toward teachers, goal-valuation, motivation, and general academic self-perceptions, which is known as The final School Attitude Assessment Survey-Revised (SAAS-R). Hannula (2002) conceptualizes attitudes towards mathematics using four different evaluative processes related to students' emotions, stimulation and expectations towards a situation. The study of Osborne et al. (2003) reviews the attitudes towards science as a concept that includes students' anxiety, motivation, valuation and enjoyment of the topic. Fredricks et al. (2004) analyze the multifaceted nature of school-engagement, and they analyze the attitudes towards school as a portion of *emotional* engagement.

In all the mentioned studies, attitudes are not studied as an isolated process but as a portion of a broader dimension where different emotional factors such as attitudes, motivation and feelings, are dynamically interrelated. This broad dimension related to students' emotions and affection is better known as the *non-cognitive* dimension. The concept 'non-cognitive' was introduced by sociologists Bowles and Gintis (1976) to focus on factors other than those measured by cognitive assessments such as Intelligence Quotient (IQ) tests, standardized achievement tests and school grades. These latter tests are designed to evaluate cognitive processes, which are related to mental actions of acquiring knowledge and understanding. Some examples of cognitive processes are memory, reasoning, problem solving, comprehension and use of language. However, the aforementioned tests by themselves do not capture attitudes or, more generally, non-cognitive skills.

Heckman and Rubinstein (2001) point out that due to the lack of agreement on the definition and measurement of factors within the non-cognitive dimension, economic literature has almost exclusively focused on measures of cognitive abilities, whilst the non-cognitive dimension has been neglected until recently.

Nevertheless, there are an increasing number of measures of non-cognitive skills available, and correspondingly, there has been a growth in the number of studies that examine their consequences on different outcomes. James Heckman, together with colleges, is the academic who has worked the most towards understanding of the role that non-cognitive skills play in educational attainment, labour market success, health, and criminality, among other outcomes. His studies have demonstrated that the predictive power of non-cognitive skills exceeds that of cognitive ones (Kautz et al., 2014; Almlund et al., 2011; Borghans et al., 2008). In addition, the authors show that both cognitive and non-cognitive skills are correlated.

The influence of attitude towards school has been measured in many studies in a quite different way. Despite the differences in the measurement, these studies coincide in the conclusion that favourable attitudes impact positively on multiple outcomes. For instance, Ames and Archer (1988) find that positive valuing of school has a significant role in academic success. Ekstrom et al. (1986); Cairns and Cairns (1994) and Fredricks et al. (2004) show that negative attitudes are associated with higher dropout rates. McCoach and Siegle (2003) ascertain that negative attitudes towards school are associated with educational underachievement. The relationship between attitude towards school and educational achievements does not determine any flow of causality between these two variables, but they are correlated (e.g. McCoach and Siegle, 2003) and this fact should be taken into account. All in all, these studies emphasize the importance of boosting positive attitudes towards school.

Non-cognitive skills, and hence attitudes, can be shaped by families, schools and social environments, and furthermore, these skills are more malleable than cognitive skills at later ages (Kautz et al., 2014). Therefore, it is essential to analyze the determinants that boost students' positive attitudes towards school. There are several studies in psychology that examine how school characteristics influence the students' attitudes towards their place of study (Valeski and Stipek, 2001), but as far as we are concerned, there are not many studies that analyze the influence of students' personal and family characteristics.

In Spain, the empirical evidence indicates that the main determinants of cognitive educational achievements are personal and family variables, while the influence of schools is relatively minor. Similarly, the school variables that positively affect achievements are those linked to the centre's socio-economic and disciplinary environment (Ferrera et al., 2013). Our study is interested in testing whether the same case applies in attitudes towards school. The aim is to test whether individual characteristics and family background are more influential than school background in boosting attitudes towards school. Similarly, we are interested in comparing the difference of the influence of these determinants on attitudes towards school and educational achievements.

4.3 Dataset

As already mentioned in the previous section, the main interest of this chapter is, on the one hand, to analyze whether the primary determinants of attitudes towards school are individual and family factors (characteristics at student-level), rather than attributes related to school (school-level); and on the other hand, to analyze the nature of the most relevant attributes. In addition, the aim is to analyze how the influence of given determinants varies between attitudes towards school and educational achievements.

With this purpose, we take data from the fourth round of PISA, conducted in 2009. It provides information on students representing 15-year-old students from 65 participant countries. During this round, Reading comprehension is studied in depth, keeping Mathematics and Science as supplementary.[1]. This chapter focuses on Spain and the final dataset contains information about 18,043 students at 840 schools.

The dependent variables considered for the analysis are the index *attitude towards school* (`ATSCHL`) and the average achievement in Reading, Science and Mathematics tests (`SCORE`). The former stands for non-cognitive achievements of the students while the latter embodies cognitive ones. Table 4.1 shows a brief description of each response variable.

The explanatory variables are selected on the basis of previous studies such as Battistich et al. (1995); Cervini (2003); Ferrera et al. (2013) and Opdenakker and Damme (2000). For the purpose at hand, they are sorted into *student-level* variables and *school-level* variables. The first type includes students' personal and family characteristics and they are described in Table 4.2; the latter type comprises school-related characteristics and they are described in Table 4.3. Descriptive statistics of all the variables are presented in Table 4.4.

Students' personal characteristics include gender, age, immigration status, language spoken at home and two variables that represent students' prior academic career: attendance at the pre-primary education and course repetition. Empirical literature shows that the influence of gender varies according to the evaluated competency. Age is usually

[1]Further details on PISA are provided in Section 1.3 in Chapter 1

Table 4.1: Description of dependent variables

Non-cognitive achievements:	***Attitude towards school index*** **(ATSCHL)**
	An index variable that describes the perception of students towards the usefulness and benefits of school. This index is based on the opinion of students regarding: i) school preparation for adult life; ii) usefulness of school; iii) contribution of school when making appropriate decisions; and iv) usefulness of school to find a job. These items are combined and coded based on the Item Response Theory (IRT) scaling procedure, and then standardized to scales with an OECD average of 0 and a standard deviation of 1(OECD, 2012).
Cognitive achievements:	**Average achievement in Reading, Science and Mathematics tests (SCORE)**
	This is the average of Reading, Science and Mathematics standardized tests scores. It is calculated by taking the average of the first plausible values in the three subjects, PV1READ, PV1MATH and PV1SCI. Its role is to take into account the possible correlation between cognitive and non-cognitive results when calculating the determinants of the latter.

When the sample contains more than 6400 observations, there is no significant difference between employing only one plausible value or all five, in the estimation of the mean and the standard error, or in the probability of committing a type I error (OECD (2012)). Thus, we have chosen to average the PV1 values for all three competencies to calculate the SCORE variable.

included as a control variable to take into account the *calendar effect* — the youngest students within a school have more difficulties in the learning processes, as is stated by Calero et al. (2009). Students with immigrant origin have on average lower achievements in any cognitive competencies (see for instance Calero et al., 2010; Ferrera et al., 2013; OECD, 2010). In this study 7.41% of students present an immigrant condition as can be observed in Table 4.4.

Although Spanish is the official national language in Spain, there are other co-official languages in specific regions. Therefore, there are regions in which the language of instruction is Spanish, but there are other regions in which it can be either the co-official language, Spanish, or a mix of both. In addition there are students with a foreign mother language. These facts are considered by including a variable that indicates whether the language spoken at home coincides with the language used in the PISA test. All in all, 14.23% of the students did the tests in a language that was not the one spoken at home.

Various authors are in favor of including some indicators of students' previous educational achievements, because ignoring them could bias the influence of contemporaneous variables (e.g. Ewijk and Sleegers, 2010). Therefore, in our study, the early academic career is embodied with variables referring to pre-school attendance and grade repetition. These variables intend to reflect both the academic path and the unobservable attributes of family background that are likely to have an impact on the performance and the attitude of students. Almost 95% of students received pre-school education for at least one year. Considering grade repetition, it is a policy that is applied to the students that do not reach certain academic level; 18.49% of students in the sample have repeated at least one grade.

As regards the family related aspects, family structures that do not consist of two parents might reflect the presence of a certain disruptive event in a student's life, such as a separation or divorce. Such experiences might affect negatively their attitude and the learning process. 12.66% of students did not live with two parents at the moment of the test.

The empirical literature emphasizes the influence of socio-economic and cultural factors in students' performance (see for example Ferrera et al., 2013; Sirin, 2005). In our study, the socioeconomic (SES) and cultural background of a student are presented using PISA indices which are constructed combining students' responses. Basically, the chosen indices gather information on three dimensions: i) parents' education, ii) parents' occupational status and iii) cultural climate at home. Parents' education is defined according to the International Standard Classification of Education (ISCED) of 1997. This is a scale index ranging from zero to six, with zero meaning no education and six referring to second stage tertiary education (master's degree and doctorate). PISA provides a variable that shows the maximum ISCED level of either parent (`HISCED`) and based on it, we create a new variable with three categories: i) *primary education* (base category in the regressions; ISCED 0,1 or 2) ii) *secondary education* (ISCED 3 or 4) and iii) *tertiary education* (ISCED 5 or 6). It is interesting to mention that more than 50% of parents reached tertiary education level.

The occupational status of parents is shown with the index `HISEI`, and a categorical variable related to the mothers' employment status. Parental occupational status provides information on the socioeconomic status of the family (Sirin, 2005). Parents in high-status occupations might be an example for their children to follow, thus enhancing their ambitions and attitudes towards school (Kohn, 1989). The values of this index range from 16 to 90, higher values representing higher socio-economic status. In Spain, the average of the index is 48.06 mainly representing middle class families. Regarding the working status, only the mother's activity level is considered in the literature because, historically, it has been the main agent of socialization and the transmission of education. As can be seen only the 49.35% of mothers work full-time.

The cultural climate at home is embodied with the PISA constructed index `CULTPOS`. Its aim is to capture family lifestyles and cultural resources which establish the intellectual climate for children's educational anspirations, and motivation and performance in schools (see Nonoyama-Tarumi, 2008, and the references therein). The PISA index `CULTPOS` is standardized so that the mean value of OECD countries is 0 and the standard deviation is 1. Higher values of the index indicate higher possession of cultural items. The Spanish mean for the same (0.27) is somewhat above the OECD mean. To finish with family background aspects, households' educational resources are considered indicating their availability (`HEDRES`) and usage (`HOMESCH`). The former aims to reflect expenditure decisions related to education at home, and the latter shows the effort parents and students make to use these resources properly for education related tasks. The average values of these indices (-0.01 `HEDRES` and -0.04 for `HOMESCH`) are very slightly below the average for OECD countries.

School-level variables are related to the type of administration, resource availability, and peers' socioeconomic status and perception of disciplinary climate. As can be observed in Table 4.4, 42.97% of the schools are private. School resources are symbolized with the proportion of computers with access to the Internet (`COMPWEB`). In fact, having a greater share of computers with access to the Internet might be an indicator of the availability of financial and educational resources in the school. The average value of this variable (0.98) is higher than the OECD average.

In the literature, the influence of peers' socio-economic status is usually measured by average background characteristics of peers (see for instance the survey provided by Sacerdote, 2001). In this line, the peer-group contextual effects on students' school performance have been discussed widely. The meta-analysis of Ewijk and Sleegers (2010) shows that students generally perform better in school if their own socio-economic background is higher. To test whether this influence is also perceived in attitude towards school, we include the school average of the *Economic, Social and Cultural Status Cultural*(`ESCS`) PISA index. The country average of the same (-0.20) is lower than the OECD average.

Table 4.2: Description of student-level explanatory variables

Student-level	
Personal characteristics	
Female	Dummy variable equal to 1 if the student's gender is female, 0 otherwise.
Age	Discrete variable that ranges between 15.3 and 16.3. It is calculated as the difference between the year and month of the test, and the year and month of the student's birth.
Native	Dummy variable equal to 1 if at least one student's parent is born in the country of the test, 0 otherwise.
Language	Dummy variable equal to 1 if the language at home is the same as the language of assessment for that student, 0 otherwise.
Prior academic career	
Preprimary	Dummy variable equal to 1 if the student attended at least one year of pre-school program, 0 otherwise.
Repeater	Dummy variable equal to 1 if the student has repeated a grade at primary or secondary school, 0 otherwise.
Family background	
Family structure	
Nuclear family	Dummy variable equal to 1 if the household consists of a traditional two-parent family, 0 otherwise.
Socio-economic and cultural background	
Parents education	
Secondary	Dummy variable equal to 1 if the highest education level of either parent is high-school graduate or the formative levels (ISCED 3 of 4), 0 otherwise.
Tertiary	Dummy variable equal to 1 if the highest education level of either parent is at least the first stage of tertiary education level (ISCED 5 or 6), 0 otherwise.
Mother full-time	Dummy variable equal to 1 if the mother has a full-time job.
`HISEI`	The index *highest occupational level of parents* corresponds to the higher ISEI (International Socio-Economic Index of occupational status) score of either parent or to the only available parent's ISEI score.
`CULTPOS`	The index of *cultural possessions* is based on students' responses to whether they have classic literature, books of poetry and works of art among other cultural items.
Availability and use of educational resources	
`HOMSCH`	The index of *Employment of ICT in school tasks* represents the frequency in the use of information and communication technologies for studying.
`HEDRES`	The index of *home educational resources* is derived from the students' responses to whether they have some educational resources at home including a desk and a quiet place to study, and some educational material to help with school work.

All these variables are readily available in the PISA 2009 dataset. `CULTPOS`, `HOMSCH` and `HEDRES` are scale indices constructed by combining categorical items from the context questionnaires using IRT modelling. These are transformed to scales with an OECD average of 0 and a standard deviation of 1 (with equally weighted samples). It is possible to interpret these scores by comparing them to the OECD mean (OECD, 2014).

Furthermore, we consider Lavy et al. (2012) who find positive associations between classroom disciplinary environment, student-teacher relationships and students test scores. Hence, we use two PISA indices that are related to students' perceptions about their relationships with the teachers (`average DISCLIM`) and the disciplinary climate in class (`average STUDREL`) to analyze their influence in students' attitudes. Whereas the average value of the former is slightly above the OECD average, that of the latter is slightly below.

Table 4.3: Description of school-level explanatory variables

School-level	
Type of school administration	
Private	Dummy equal to 1 if the school is private (school managed directly or indirectly by a non-government organization; e.g. a church, trade union, business, or other private institution), 0 otherwise.
Resources availability	
`COMPWEB`	The index of *computers connected to the Internet* is defined as the proportion of computers for educational purposes connected to the Internet at the school.
Socioeconomic and cultural composition	
Average `ESCS`	This reflects the social composition of the student population. We have calculated it by taking the school averages of the PISA index of Economic, Social and Cultural Status (ESCS). This indicator summarizes the information about the parents' occupational status, their educational level, and home durables (OECD, 2010). The greater the value, the higher the average socio-economic status.
Climate	
Average `STUDREL`	The average of the index of a schools' *quality of student-teacher relationship*. We have calculated it by taking the school averages of the PISA index `STUDREL`. This refers to the students' average perception of the attitude and treatment on the part of the teachers. The greater the value, the better the relationship is perceived.
Average `DISCLIM`	The average of the index of schools' *disciplinary climate in the classroom*. We have calculated it by taking the school averages of the PISA index `DISCLIM`. This indicates the students' perception of the order and organization existing in the classroom during language lessons. The greater the value, the better the perceived disciplinary climate.

We have constructed the Average `ESCS`, Average `STUDREL` and Average `DISCLIM` based on the variables `ESCS`, `DISCLIM` and `ESCS`, which are readily available from the PISA 2009 database. These indices (`ESCS`, `STUDREL` and `DISCLIM`), as well as `COMPWEB`, are constructed by combining categorical items from the context questionnaires using IRT modelling, and then transformed to scales with an OECD average of 0 and a standard deviation of 1 (OECD, 2014).

Table 4.4: Summary statistics for the variables

Variables			Frequency (%)	Mean	Std. Dev.
Variables-level	Response	ATSCHL		0.15	0.99
		SCORE		508.55	77.37
Student-level	Student	Female	51.37		
		Age		15.82	0.28
		Native	92.59		
		Language	85.77		
		Preprimary	94.77		
		Repeater	18.49		
	Family	Nuclear family	87.34		
		Parents' education:			
		secondary	26.40		
		tertiary	52.12		
		Mother works full-time	49.35		
		HISEI		48.06	17.40
		CULTPOS		0.27	0.84
		HOMSCH		−0.01	0.91
		HEDRES		−0.04	0.87
School-Level	School	Private	42.97		
		COMPWEB		0.98	0.09
		Average ESCS		−0.20	0.56
		Average STUDREL		−0.03	0.33
		Average DISCLIM		0.07	0.44

4.4 Methodology

This study follows a multivariate multilevel approach in order to analyze the determinants of the ATSCHL of students while its interaction with the cognitive achievements is accounted for. This approach is appropriate to deal with data that presents hierarchical structure, as well as to take into account the interaction between multiple dependent variables in the regression analysis. The paragraphs that follow, briefly introduce the multilevel approach and then define the multivariate multilevel models of interest.

4.4.1 Multilevel models

The data provided by PISA is collected by means of a two-stage sampling procedure: schools are selected first and then students within those schools are randomly sampled. This sampling procedure is chosen in response to the hierarchical structure of the educational context where the students (*student-level*) are nested in schools (*school-level*).

Therefore, there is one population in which the observation units are the schools, and another in which the observations are the students; so each level corresponds to a population.

Students selected with a two-stage or a random sampling procedure have different chances of being selected. That is, a student within a school that has been selected — via two-stage sampling — have more chances of being selected than a student that has been selected randomly from the whole population — via random sampling. In addition students attending the same school tend to be more similar than students in different schools, among other reasons, because they share more resources and background characteristics. Consequently, the assumption about the independence between observations might not be satisfied when we handle data with clustered structure. The consequence of using conventional regression analysis with such data is that standard errors of the regression coefficients might be underestimated; this could lead us to conclude that some effects are statistically significant when they are not. To obtain consistent and efficient estimates of parameters, the data structure should be accounted for.[2]

The multilevel approach is one way of taking into account the hierarchical form of the data because it allows us to estimate equations at each level. With this approach, in addition to the unexplained variability between students, that between schools is also regarded as random. This can be indicated by models with random coefficients. These are appropiate if the schools are regarded as a sample from a population, and if the interest is in drawing conclusions pertaining to the population rather than to the observed specific schools (Snijders and Bosker, 1999). In this line, these models assume that unexplained group variability is driven by a mechanism that is similar from one school to another, and which operates independently between schools. That is, schools are *exchangeable*.

To analyze the data, first we define a *student-level* equation that defines the relationships among student-level characteristics and the outcome of interest. Hence, we estimate a regression equation for each school,

$$y_{ij} = \beta_{0j} + \sum_{p=1}^{P} \beta_p X_{pij} + \sum_{q=1}^{Q} \beta_{qj} Z_{qij} + e_{ij} \tag{4.1}$$

for $i = 1, ..., n_j$ students in school $j = 1, ..., J$. Where,

[2]The previous chapters use the two-step Efficient Feasible Generalized Method of Moments in order to obtain consistent and efficient estimates in the presence of non independent and identically distributed (i.i.d.) errors.

y_{ij} is the outcome of student i at school j,

β_{0j} is the intercept or the average outcome of school j,

X_{pij} $(p = 1, ...P)$ represents the value of the p^{th} student-level variable for individual i at school j,

β_p is the regression coefficient that is common to all the schools,

Z_{qij} $(q = 1, ..., Q)$ represents the value of q^{th} student-level variable included with random effects for individual i at school j,

β_{qj} is the regression coefficient with a random part and it is allowed to vary across schools according to that random part,

e_{ij} is the random deviation of student i from the average outcome of school j.

Then, we define *school-level* equations where the variability in the regression parameters is a function of the characteristics of schools. Firstly, for each intercept β_{0j} in equation (4.1) we assume that,

$$\beta_{0j} = \beta_{00} + \sum_{m=1}^{M} \beta_{0m} S_{mj} + r_{0j} \tag{4.2}$$

where,

S_{mj} $(m = 1, ..., M)$ indicates the value of the m^{th} school-level variable for school j,

β_{00} is the general mean for all the schools adjusted for S,

β_{0m} are the regression coefficients that capture the effects of school-level variables on the within-school intercept (β_{0j}),

r_{0j} is random error in the school-level equation.

Secondly, for the regression coefficients that belong to the variables included with random effects, we pose the following equation,

$$\beta_{qj} = \beta_{q0} + r_{qj} \tag{4.3}$$

where,

β_{q0} is the overall mean intercept on the within-school structural relationships (β_{qj}),

r_{qj} is the random error in this school-level equation.

Finally, we include Equations (4.2) and (4.3) in (4.1), so that we can observe how the dependent variable can be decomposed as a sum of a fixed and a random part,

$$\begin{aligned} y_{ij} = & \underbrace{\beta_{00} + \sum_{m=1}^{M} \beta_{0m} S_{mj} + \sum_{p=1}^{P} \beta_p X_{pij} + \sum_{q=1}^{Q} \beta_{q0} Z_{qij}}_{\text{Fixed part}} \\ & \underbrace{+ r_{0j} + \sum_{q=1}^{Q} r_{qj} Z_{qij} + e_{ij}}_{\text{Random part}} \end{aligned} \tag{4.4}$$

In this equation regression coefficients β_{00}, β_{0m}, β_p and β_{q0} are not assumed to vary across schools, they are fixed coefficients that belong to the fixed part of the equation, because they are applied to all the schools. The errors or random effects in school-level r_{0j} — in the intercept — and r_{qj} — in the slope — capture the between-school variation. The latter components and the student-level error, e_{ij}, represent the random part of the equation. It is assumed that r_{0j}, r_{qj} and e_{ij} have zero means given the values of explanatory variables X_{pij}, Z_{qij} and S_{mj}.[3] It is also assumed that r_{0j} and r_{qj} are independent from e_{ij}. These errors are normally distributed with their variances specified as $\sigma^2_{r_0}$ (indicating the variability in schools' intercepts), $\sigma^2_{r_q}$ (indicating the variability in schools' slopes) and σ^2_e (indicating variability betwen students within schools).

4.4.2 Multivariate multilevel models

Multivariate multilevel models are the extention of multilevel regression models which combine two or more outcome variables in one model. Snijders and Bosker (1999) provide some reasons why it is sensible to analyze data jointly. First, it allows us to evaluate the covariances between the outcome variables and to decompose them over the student- and school-levels. Furthermore, the tests of specific effects for a single dependent variable are more powerful in multivariate analysis, which is reflected in the consistency and reduction of the standard errors. This fact is more considerable if the outcome variables are strongly correlated. In addition, it is possible to test whether the effect of an explanatory variable on one outcome variable is larger than its effect on the other.

Dependent variables are included into a multilevel model by creating an additional *variables-level* below the original student-level. Hence, after this adjustment, there are three nesting levels: *level 1* with dependent variables indexed by h, *level 2* with students i, and *level 3* with schools j. Therefore, technically, level 1 exists exclusively to define

[3]This implies that random intercepts and slopes are uncorrelated with all explanatory variables.

the multivariate structure (see for instance Snijders and Bosker, 1999; Hox et al., 2010).

Our model has two response variables `ATSCHL` ($h = 1$), and `SCORE` ($h = 2$). Both dependent variables are included into a multilevel model using a dummy variable for each of them, d_{1hij} for `ATSCHL` and d_{2hij} for `SCORE`. Thus, on the lowest level we have,

$$y_{hij} = \pi_{1ij} d_{1hij} + \pi_{2ij} d_{2hij} \tag{4.5}$$

for $h = 1, 2$, where,

y_{hij} indicates the outcome h of student i at school j.

π_{1ij} *and* π_{2ij} refers to the student-level equations for $h = 1$ and $h = 2$ respectively. The symbol π is used so that we can continue employing β for student-level and school-level regression coefficients.

d_{1hij} takes a value of 1 if $h = 1$ and 0 if $h = 2$.

d_{2hij} is defined as $1 - d_{1hij}$.

The specification of the final model is carried out in the conventional form (e.g. Bryk and Raudenbush, 1992; Hox et al., 2010). That is, we start with the null model (Model 0) which does not include any explanatory variables, in order to evaluate the variance decomposition of the dependent variables between the proposed levels. Next, in Model 1, all the student-level variables are incorporated as independent variables with fixed effects. In this step, we assess the contribution of each individual-level explanatory variable and we evaluate the changes which have occurred in both the first-level and second-level variance terms compared to Model 0. In Model 2 we include variables at the school-level and we analyze whether they explain between-school variation in the dependent variable. Finally in Model 3 we incorporate new elements in the random part, allowing that the slopes of certain variables vary across schools. In the paragraphs that follow each model is explained in detail.

Model 0: Null model

This model is used to test whether there are any differences at the school-level in the outcome variables, and confirms whether a multilevel approach is necessary. It also serves as a benchmark to compare the residual variances with latter models in which we add explanatory variables.

So, we start with variables-level equation (4.5) to define the multilevel structure, and then, the student-level equation is defined in order to estimate a separate equation for each school,

$$\pi_{hij} = \beta_{h0j} + e_{hij} \tag{4.6}$$

for $h = 1, 2$

$$\begin{bmatrix} e_{1ij} \\ e_{2ij} \end{bmatrix} \sim \mathcal{N}(0, \Omega_e) \qquad \Omega_e = \begin{bmatrix} \sigma^2_{e_1} & \\ \sigma_{e_{12}} & \sigma^2_{e_2} \end{bmatrix}, \qquad \forall i, \forall j.$$

Next, the school-level equation is posed to allow the variation in the intercepts of schools,

$$\beta_{h0j} = \beta_{h00} + r_{h0j} \tag{4.7}$$

$$\begin{bmatrix} r_{10j} \\ r_{20j} \end{bmatrix} \sim \mathcal{N}(0, \Omega_r) \qquad \Omega_r = \begin{bmatrix} \sigma^2_{r_1} & \\ \sigma_{r_{12}} & \sigma^2_{r_2} \end{bmatrix}, \qquad \forall j.$$

Inserting equation (4.7) into equation (4.6), and this in turn into equation (4.5), we obtain the composite equation,

$$y_{hij} = \beta_{h00} d_{hij} + r_{h0j} d_{hij} + e_{hij} d_{hij} \tag{4.8}$$

Model 1: Random intercepts model with student-level variables

Model 1 also starts by defining the equation in the variables-level, (4.5), and subsequently all the student-level variables, X_{pij}, are incorporated as independent variables with fixed effects in student-level equation (4.6),

$$\pi_{hij} = \beta_{h0j} + \sum_{p=1}^{P} \beta_{hp} X_{pij} + e_{hij}. \tag{4.9}$$

The school-level equation is the same as equation (4.7). Finally, the composite equation in Model 1 is the following,

$$y_{hij} = \beta_{h00} d_{hij} + \sum_{p=1}^{P} \beta_{hp} d_{hij} X_{pij} + r_{h0j} d_{hij} + e_{hij} d_{hij} \tag{4.10}$$

Model 2: random intercepts model with student-level and school-level variables

In this model, in addition to the student-level variables included in the previous model, the school-level variables are included to test whether they explain between-school variation in the dependent variables. On the one hand, the variables-level and student-level equations are the same as (4.5) and (4.9), respectively. On the other hand, school characteristics, S_{mj} are included in the school-level equations,

$$\beta_{h0j} = \beta_{h00} + \sum_{m=1}^{M} \beta_{h0m} S_{mj} + r_{h0j} \tag{4.11}$$

Combining the three equations —(4.5), (4.9) and (4.11) — the composite equation in Model 2 is,

$$Y_{hij} = \beta_{h00} d_{hij} + \sum_{m=1}^{M} \beta_{h0m} d_{hij} S_{mj} + \sum_{p=1}^{P} \beta_{hp} d_{hij} X_{pij} + r_{h0j} d_{hij} + e_{hij} d_{hij} \tag{4.12}$$

Model 3: Random intercepts and slopes model

To conclude, in Model 3, random effects are included in the regression coefficients of the student-level equations. The equations used to construct this model are the following. The equation (4.5) to describe the multilevel structure,

$$y_{hij} = \pi_{1ij} d_{1hij} + \pi_{2ij} d_{2hij}$$

Next, the student-level equation with the variables embodying students' characteristics with fixed effects, X_{pij}, and random effects, Z_{qij},

$$\pi_{hij} = \beta_{h0j} + \sum_{p=1}^{P} \beta_{hp} X_{pij} + \sum_{q=1}^{Q} \beta_{hqj} Z_{qij} + e_{hij}. \tag{4.13}$$

Then, in school-level or between-school equations, there are two distinct equations, the first to define the random intercept (equation 4.11),

$$\beta_{h0j} = \beta_{h00} + \sum_{m=1}^{N} \beta_{h0m} S_{mj} + r_{h0j}$$

and the second to define the random slopes,

$$\beta_{hqj} = \beta_{hq0} + r_{hqj}. \tag{4.14}$$

Bringing these equations together, the composite equation in Model 3 is the following,

$$\begin{aligned} y_{hij} = {} & \underbrace{\beta_{h00} d_{hij} + \sum_{m=1}^{M} \beta_{h0m} d_{hij} S_{mj} + \sum_{p=1}^{P} \beta_{hp} d_{hij} X_{pij} + \sum_{q=1}^{Q} \beta_{hq0} d_{hij} Z_{qij}}_{\text{Fixed part}} \\ & \underbrace{+ r_{h0j} d_{hij} + \sum_{q=1}^{Q} r_{hqj} d_{hij} Z_{qij} + e_{hij} d_{hij},}_{\text{Random part}} \end{aligned} \tag{4.15}$$

which is the multivariate generalization of equation (4.4).

4.4.3 Additional information about multilevel models

This section presents additional calculations frequently used in multilevel approaches to analyze the proportion of the variance explained by the clustered structure in the population, as well as by the included explanatory variables at each level. In multilevel regression analysis the unexplained variance is exposed at different levels, hence, first we present the intraclass correlation formula used to compute the proportion of the school-level variance compared to the total variance. Then, we present the formulas of a statistic analogous to the R^2 for multilevel models[4] in order to calculate the proportion of variance explained using the explanatory variables at the different levels (see Raudenbush and Bryk, 2002). Finally, to facilitate interpretation of the coefficients at different levels, we provide the formula to derive standardized regression coefficients.

Intraclass correlation

The intraclass correlation coefficient, ρ_h, is computed using the variance components of the null model. It provides the proportion of total variance attributable to the differences between schools, or what is equivalent, it provides the percentage of the variance in the outcomes that is due to the school membership. It is computed with the following formula,

$$\rho_h = \frac{\sigma^2_{r_h}}{(\sigma^2_{e_h} + \sigma^2_{r_h})}, \qquad \text{for } h = 1, 2. \tag{4.16}$$

In contrast, the proportion of the variance attributable to student-level characteristics can be computed as $1 - \rho_h$.

Percentage of variance accounted for by variables over the null model

Multilevel analyses provide information about the unexplained variance at each level. The models that add explanatory variables over the null model should have a smaller residual variance, since their aim is to explain variation in the outcome. Likewise, models that incorporate random effects in the intercept and slopes should also present smaller residual variance. Accordingly, it is advisable to compare each model with respect to the null model in order to analyze the decrease in the unexplained variance. In general, models with the lowest residual variance fit better than models with higher residual variances. The proportion of the variance that is explained over the null model is computed as

[4] In multilevel regression analyisis, the concept of explained variance has no unique definition as in the single-level regression analysis, since the unexplained variation is expressed at different levels.

follows:

Student-level	$1 - (e_{hij})_{\text{model}} / (e_{hij})_{\text{null model}}$
School-level	$1 - (r_{h0j})_{\text{model}} / (r_{h0j})_{\text{null model}}$
Total	$1 - (r_{h0j} + e_{hij})_{\text{model}} / (r_{h0j} + e_{hij})_{\text{null model}}$

Standardization of regression coefficients

When the interest is in comparing the effects of different variables within one sample, the regression coefficients are often standardized because that facilitates their interpretation.[5] Since the value of the unstandardized regression coefficients depends on the choice of units used to measure the explanatory variables, it is often difficult to say which of these variables is the most important in determining the value of the outcome variable. Alternatively, standardized coefficients ignore the explanatory variables' scale of units. Essentially, these coefficients refer to how many standard deviations an outcome variable will change per standard deviation increase in the explanatory variable. They can be derived from unstandardized coefficients using the following formula,

$$\text{Standardized coeff.} = \text{unstandardized coeff.} \times \frac{\text{S.D. explanatory variable}}{\text{S.D. dependent variable}}. \tag{4.17}$$

4.5 Results

The software `Stata 12` together with the computational program `MLwiN` is used for the estimation of the models by following Leckie and Charlton (2013) and Rasbash et al. (2015). Accordingly, the coefficients that accompany the explanatory variables and the variance components are estimated simultaneously through iterative methods that maximize the function of maximum likelihood. The observations are weighted by the standardized final weights per student (`W_FSTUWT`) as well as per school (`W_FSCHWT`), provided by the PISA dataset. These weights attempt to compensate the possible biases arising from the sampling methods or from the non-response on the part of the school and students, and their use enables us to derive appropriate estimations of population values.

[5]If the focus is on comparing parameter estimates from different samples to each other (as it is the case in Chapters 2 and 3), one should always use the unstandardized coefficients.

Table 4.5 shows the decomposition of the variance in the null model which is calculated using the formula of intraclass correlation (4.16). Only 7.76% of the total variance in `ATSCHL` is attributable to the variation between schools. The remaining variation is due to differences among students within schools. This fact is also verified for educational achievements, since 20.41% of the variance in the `SCORE` is due to the variation at school level. Indeed, it can be observed that the relative role that personal and family differences play is greater in the case of the non-cognitive results studied here, which is coherent with the conclusions of Cervini (2003) and Opdenakker and Damme (2000).

Table 4.5: Intraclass correlation and covariance

	`ATSCHL`	`SCORE`	**Covariance**	
	(%)	(%)	Par.	S.E.
ρ_h	7.76	20.58		
$1 - \rho_h$	92.24	79.42		
$\sigma^2_{r_h}$	0.075**	1227.296 **		
$\sigma^2_{e_h}$	0.8697**	4735.097 **		
$\sigma_{r_1 r_2}$			−0.130	0.458
$\sigma_{e_1 e_2}$			4.759**	0.498

Significance level:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Despite the relatively low variation between schools for `ATSCHL`, $\sigma^2_{r_1}$, it is statistically significant at 0.05 level. In the same way, the between-schools residual variation for `SCORE`, $\sigma^2_{r_2}$, is also significant at 0.05 level. Accordingly, it is convenient to use the multilevel approach for the estimations.

Furthermore, although the covariance between the dependent variables, $\sigma_{r_1 r_2}$, is not statistically significant at the school-level, it is at the student-level, $\sigma_{e_1 e_2}$, as is shown in Table 4.5. This shows that the correlation between students' attitudes towards school and their achievement is larger within schools than between schools. Accordingly, the use of a multivariate approach is pertinent, given that it takes into account the correlation between dependent variables in the model. All in all, multivariate multilevel approaches are appropriate with our data.

Table 4.6 presents the results of the estimated models. It starts with the null model, and then explanatory variables are added gradually in an attempt to account for some of the variation at both levels. Initially, these variables are incorporated with fixed effects, first at student-level (Model 1) and then at school-level (Model 2). Finally, Model 3

Table 4.6: Parameter estimates for multivariate multilevel models for ATSCHL and SCORE

	ATSCHL				SCORE				
	Model 0	Model 1	Model 2	Model 3	Model 0	Model 1	Model 2	Model 3	
Fixed effects									
constant	0.145***	0.357	0.535	0.513	506.317***	342.447***	352.294***	353.362***	
Students' characteristics									
Female		0.148***	0.146***	0.144***		−9.408***	−9.355***	−9.438***	
Age		−0.021	−0.021	−0.020		7.627***	7.610***	7.714***	
Native		−0.087***	−0.095***	−0.090***		21.063***	20.613***	20.847***	
Language		0.059**	0.040*	0.043*		5.356***	5.090***	5.011***	
Preprimary		0.129***	0.144***	0.142***		6.507***	6.442***	6.395***	
Repeater		−0.162***	−0.157***	−0.156***		−79.650 ***	−79.186 ***	−79.103 ***	
Family background									
Nuclear family		0.056***	0.054**	0.051**		1.117	1.145	1.147	
Mother full-time		−0.024	−0.029**	−0.023*		1.979**	1.921**	1.898**	
HISEI		0.000	0.000	0.000		0.512***	0.464***	0.461***	
Par. educ. secondary		−0.451**	−0.045**	−0.046**		3.798***	3.201**	3.152**	
Par. educ. tertiary		−0.093***	−0.090***	−0.089***		4.296***	3.070**	3.059**	
HEDRES		0.117***	0.115***	0.113***		3.781***	3.887***	3.784***	
CULTPOS		0.062***	0.063***	0.062***		11.620***	11.305***	11.275***	
HOMESCH		0.081***	0.081***	0.084***		−8.391***	−8.414***	−8.349***	
School background									
Private			−0.018	−0.017			−2.486	−2.549	
COMPWEB			−0.158	−0.143			−1.419	−3.847	
Average ESCS			−0.012	−0.012			19.639***	19.877***	
Average STUREL			0.531***	0.528***			−11.746 ***	−11.666 ***	
Average DISCLIM			0.033	0.030			14.926***	14.814***	
Random effects									
Between-schools									
$\sigma^2_{r_h} = var(r_{h0})$	0.075**	0.070**	0.038**	0.038**	1227.296 **	665.027**	522.755**	520.911**	
	(0.005)	(0.005)	(0.004)	(0.004)	(71.950)	(40.887)	(33.859)	(33.858)	
$\sigma^2_{r_{h_{HED}}} = var(r_{h,HEDRES})$				0.005				10.691	
				(0.002)				(11.247)	
$\sigma^2_{r_{h_{HOM}}} = var(r_{h,HOMESCH})$				0.010**				23.282**	
				(0.002)				(10.949)	
Within-schools									
$\sigma^2_{e_h} = var(e_{hij})$	0.897**	0.860**	0.860**	0.848**	4735.097 **	3401.775 **	3399.179 **	3372.988 **	
	(0.009)	(0.009)	(0.009)	(0.009)	(51.040)	(36.671)	(36.640)	(37.770)	
Covariances[a]									
$\sigma_{r_{1HOM},r_{20}} = cov(r_{1HOMESCH}, r_{20})$									0.715**
									(0.023)
$\sigma_{r_{10},r_{2HED}} = cov(r_{10}, r_{2HEDRES})$									0.374**
									(0.151)
$\sigma_{r_{20},r_{2HOMESCH}} = cov(r_{20}, r_{HOMESCH})$									30.22**
									(13.94)

Standard errors in parentheses
Significance level:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[a]Only statistically significant covariances are included.

includes the same explanatory variables as Model 2 together with random effects for two variables, `HEDRES` and `HOMSCH`. These family background variables are the ones related to the availability and use of educational resources. Hence, by including random slopes, we wish to know whether the influence of these resources varies between schools. That is, we want to know whether the schools have different capacities for compensating for the diffences that emerge from the availability and use of these resources at home. In the following lines, we briefly introduce the principal findings in each model, and then we focus more carefully on the results of Model 3.

The results of **Model 1** indicate that among personal characteristics, being a girl is positively associated with attitudes towards school, whereas on average, girls have worse achievement scores. Doing the tests in the language that is spoken at home positively affects both `ATSCHL` and `SCORE`. In the same manner, having attended two or more years at pre-school level also influences both types of results positively. Meanwhile, having repeated at least one grade significantly reduces not only the `ATSCHL` value but also the `SCORE`. This can be reflected in the impact of repeating itself – an experience that could lead to a loss of motivation and a feeling of failure or detachment by interrupting the school career continuity and separating the student from their group of peers – or it can be capturing the effect of personal and family variables that have an incidence on academic performance and attitude at the same time.

Regarding family factors, results suggest that the parents' occupational status is not relevant for determining `ATSCHL`, but their education level is. However, the effect is not the expected one: the parents' higher education level decreases their children's valuing of school. On the contrary, the effect on performance is positive. Even though this result deserves further investigation, the following hypothesis is posed: parents that have not had access to higher education value more the fact that their children can study, transferring to them such enthusiasm; at the same time, in comparison with the more educated parents, they possess fewer competencies to help their children on their student path. Also, it can be observed that having educational resources, as well as materials and an appropriate place for studying, and having access to works of art or literature, are positively associated with attitude towards school. It is probable that, to a great extent, these factors are reflected in the family attitude – the role given to education at home, and the effort parents make to guarantee that their children have the necessary resources, regardless of their income. These results coincide with those referred to in the `SCORE`, with the exception that, in this case, the parents' occupational status is significant. In the same way, having computer resources to carry out school tasks has a positive incidence on motivation as well as on academic results.

As regards family structure, we find that belonging to a two-parent family allows us to expect greater valuing of school. Probably, this is due to the fact that the presence of disruptive episodes in the dynamics of the family, such as a separation, may affect the educational process and interest for the same. However, this variable is not significant in order to explain performance.

Model 2 is extended by including school factors. The amount of material resources and the socioeconomic profile of the group of peers do not seem to have a relevant impact on the determination of a positive attitude towards school. On the contrary, the socioeconomic composition of a student population influences cognitive results significantly.

Students' perception of their teachers' attitude does have an incidence on the `ATSCHL` index. Thus when, on average, students consider that their relationship with teachers is positive, and that they worry about their learning and well-being, they value school more. Lastly, it is worth pointing out that the type of school management does not present a significant association with the students' interest in school or with their academic performance.

In **Model 3** random effects are incorporated for two variables. For home educational resources (`HEDRES`) the random effects are not statistically significant; however, they are in the case of technological resources aimed at school tasks (`HOMSCH`). This means that the use of ICT – or the family attitude towards education that it may be capturing — does not have the same effect on student attitudes in all the centers, and thus, schools seem to have a role as mediators, modifying the students' initial situation to a certain extent.

If we compare the results between the models, the significance of the student-level and school-level variables have not been generally altered (except for having a mother working full-time in `ATSCHL`), and the effects of the variables are slightly reduced in the last model with respect to the previous ones.

The successive inclusion of explanatory variables increases the explanatory power of the models. Table 4.7 shows the gradual reduction of the residual variance of each model with respect to the null model. Model 3 is the one that explains most of the residual variance in each dependent variable and at each level. Our explanatory variables are able to explain 5.46 % of the variation of `ATSCHL` within the school and 49.33% of the variation between schools. In total, 8.85% of the total inequalities in `ATSCHL` are explained over the null model. According to `SCORE`, the residual variance is decreased by 28.77 % at student level and 57.56% at school level. These results are consistent with the literature on the topic (Cervini, 2003).

Table 4.7: Residual variance that is explained over the null model (%)

	`ATSCHL`			`SCORE`		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Student-level	4.12	4.24	5.46	28.16	28.21	28.77
School-level	6.67	49.33	49.33	45.81	57.41	57.56
Total	4.32	7.72	8.85	31.79	34.22	34.69

In multilevel models the deviance indicates how well the model fits the data (Hox et al., 2010). In general, models with a lower deviance fit better than models with a higher deviance. Table 4.8 shows that Model 3 is the one with the lowest deviance[6] among all the models presented, and thus, it is the one that fits the best.

Table 4.8: Deviance of the models

	Model 0	**Model 1**	**Model 2**	**Model 3**
Deviance	255 443	248 582	248 122	248 061

Taking into account that the last model is the one that explains most of the variation in both dependent variables and also has the lowest deviance, we focus our attention on the results obtained in this model.

The coefficients of the explanatory variables that are statistically significant to explain the variation of `ATSCHL` are standardized to facilitate the interpretation when comparing the effects of different variables. These coefficients, which are presented in Table 4.9, indicate the number of standard deviations in which `ATSCHL` will change per standard deviation increase in the explanatory variable.

It can be observed that among the individual variables, having repeated a school year presents a greater impact on the attitude towards school, decreasing the `ATSCHL` index

[6] The difference in deviance has a chi-square distribution with degrees of freedom equal to the difference in the number of parameters that are estimated in the models. The differences in deviance between the adjacent models are statistically significant at 99%.

Table 4.9: Standardized coefficients with respect to ATSCHL

Variable	Stand. coeff.
Female	1.355
Preprimary	1.334
Repeating student	−1.459
Nuclear family	0.483
Par. educ. secondary	−0.432
Par. educ. tertiary	−0.831
HEDRES	0.954
CULTPOS	0.502
HOMESCH	0.753
Average STUDREL	1.633

value by 1.5 standard deviations (SD). Girls, on the other hand, are expected to have 1.35 SD higher attitude towards school. In the same way, having attended pre-school increases the index by 1.33 SD, and belonging to a nuclear family by 0.5 SD. The effect of parents' secondary and tertiary education is minor and negative.

Regarding the variables related to home resources, an increment of one SD of educational resources, cultural possessions, or employment of the ICT, is associated with an increment of 0.9; 0.5 and 0.7 SD of the ATSCHL variable, respectively.

The only variable at school level that is statistically significant is the index that reflects the average quality of the relationship between students and teachers: if it increases in one SD, the attitude towards school improves in 1.6 SD.

4.6 Conclusions

To summarize, there are many psychological and sociological studies that analyze attitudes towards school, and currently there are more available instruments for their measurement. The studies presented in the literature review have shown that attitudes towards school have a significant impact on many life outcomes, and hence, they are valuable in themselves. In addition, empirical evidence points out that attitudes are still malleable at adolescence. Given the importance and the relative flexibility of attitudes towards school, it is essential to identify the factors that help improve them. However, there is a substantial gap in the economic literature which analyzes the influence of personal and family characteristics in addition to school-related characteristics in these attitudes. Accordingly, this study is aimed at contributing to the economic literature on attitudes towards school.

The hypothesis has been that, in Spain, the variables that influence the most on attitudes towards school correspond to both the individual and family levels and that, among school variables, the most influential are linked to their socio-affective climate.

The evidence is in favor of the hypothesis. The results show that the greater proportion of the variance of attitudes towards school is explained by the students' personal characteristics, such as gender and previous academic career, and by the family characteristics such as family structure, parents' education and possession of educational resources. On the other hand, the only school-related variables that are statistically significant are factors that refer to the atmosphere students breathe at school. Therefore, a better school climate affects students' attitude positively.

Among the statistically significant variables related to family background, we highlight the role of those that indicate the possession of educational and cultural resources. These variables would evince a double effect. On the one hand, it would seem that if students have the necessary resources to carry out their educational activity, their attitude towards school improves. On the other hand, the fact that a home has the educational resources implies that in the expenditure decisions of such a home, the purchase of these resources has been valued. This reflects the positive attitude of adults in the home towards education, which may influence the students positively.

Nevertheless, this does not mean that nothing can be done by schools, since the model also shows that the inclusion of random effects in the variable that reflects the use of ICT for studying has been significant. Thus, the centers are likely to differ in their capacity to compensate for the inequalities of origin. Given that some schools have a better performance than others when equating initial differences, there is room for seeking improvements in educational policies that attempt to match the results of different institutions.

Conclusions and further research

This thesis analyzes to what extent students' educational outcomes are conditioned by circumstances such as their family background, school characteristics and peer effects, using data provided by the OECD's Program for International Student Assessment (PISA). While being aware of the limitations of the PISA program, this has been a major resource that provides information about education systems and allows us to make comparisons between European countries.

Chapter 1, Chapter 2 and Chapter 3 analyze the educational inequality of opportunity for twenty European countries. At first glance, the data shows that from the total variance in achievements, more than 95% is attributable to the within-country variance, and that in the Nordic countries of Finland, Iceland, Norway and Sweden, and in Ireland and Spain, schools are more homogeneous than in the Western countries of The Netherlands, France, Germany and Belgium, and in Bulgaria and Italy.

In order to better understand the sources of inequality, we select circumstances which are intended to capture the factors beyond students' control such as their families' social origin, the school- and teacher-background, as well as their peers' characteristics. Finally, efforts are proxied by aspects that seem to be within students' control to some extent.

Although the effort proxies provided by PISA present many advantages, they rely on self-reported information from students, and so, suffer from some limitations. Therefore, in future research, it would be desirable to complement our work by including effort variables as measured in Zamarro et al. (2016) and in the references therein. These authors evaluate the effort students make in completing surveys and tests, by analyzing the survey-taking and test-taking behaviours of students in the PISA datasets. Since PISA tests and background questionnaires are low-stakes, the effort differences across students are not due to individual incentives. Therefore, effort is defined by careless answering patterns and item non-response within background questionnaires. In addition, effort is also defined as the rate of decline in the performance in the test as it progresses. Then the authors bring together these measures and analyze the share of the observed differences across countries that could be attributed to differences in students' efforts.

In Chapter 2 we specify a linear regression model for achievements on circumstance and effort variables. To address the potential endogeneity bias arising from the simultaneity problem of peer effects, as well as the clustered structure of the data, we use an efficient IV-GMM estimation procedure. Additionally, in line with Roemer's definition of inequality of opportunity (Roemer, 1998), our model provides the direct and indirect effects of circumstances. The counterfactuals are built based on those estimates.

In broad strokes, as expected, having at least one parent born in the country, belonging to a family with a higher socio-economic background, or to a school with a better peer performance, all affect mathematical achievements positively. Regarding efforts, having spent more time studying, not having skipped classes within a school day, having been perseverant, having shown a positive attitude towards school or not having repeated a grade, all also result in higher average achievements. The whole set of circumstances and efforts can account for more than 50% of achievement inequality for the Western countries of The Netherlands, France, Belgium and Germany, and also for Italy, Bulgaria and Portugal. This share exceeds 29% for all the countries. Within these percentages, the circumstances explain more than half of the variation for all the countries, except for the Nordic countries of Finland, Norway and Iceland.

Furthermore, we find that among the circumstances, peer effects contribute the most to overall achievement inequality. The exceptions are the Nordic countries of Finland, Sweden and Iceland, and Spain and Ireland, for which the contribution of family background exceeds that of peer effects. As expected, in the latter countries the between-school variance is lower than the within-school variance, whereas the opposite is true for the countries with a higher contribution of peer effects. Among the variables representing family background, parental occupational status is the most significant for nearly all countries. Finally, to deal with the consequences of potential omitted variables bias, we provide potential lower and upper bounds of partial contributions of circumstances.

The inequality of opportunity is measured as the variance in the counterfactual distributions where first, the correlation between circumstances and efforts is treated as circumstances, secondly, differences due to efforts have been removed, and finally the residual term is included. This measure satisfies the compensation principle. The results show that Belgium, France, Germany, Switzerland, The Netherlands and Bulgaria have the highest figures for inequality of opportunity, while Finland, Romania, Spain, Ireland, Norway, Greece and Sweden show the lowest. In general, the countries with high inequality levels have greater figures of inequality of opportunity, but there is no evidence that inequality of opportunity is related to achievement levels.

There are some natural extensions of our work which could be addressed in future research. On the one hand, all the results presented in this chapter rely on the estimation of the regression parameters. As in any empirical study, it might be that achievement depends non-linearly on the considered variables, or other variables which have been omitted from our model. An interesting task for future work would be to estimate non-parametrically the respective model, without a linear assumption, as well as to explore the likely magnitude of the potential biases in the estimation, as in Bourguignon et al. (2007, 2013) using Monte-Carlo methods. In addition, it would be worthwhile to explore the methods for measuring the relative importance of correlated regressors discussed in Grömping (2007) and Bi (2012) in order to measure the contribution of particular circumstance and effort variables. Furthermore, it could be of interest to estimate the model by means of quantile regressions to calculate the effects of circumstances and efforts for students in different positions on the conditional test score distribution.

Chapter 3 follows a combination of parametric and non-parametric approaches in order to construct counterfactual distributions. The main aim is to propose the use of a methodology that enables us to consider any number of categorical and continuous variables when defining types and tranches. Specifically, each student is assigned to types or tranches according to the kernel smoothed deciles on achievement distributions which are conditional either on circumstances or on efforts. The idea is to group students that are close-equals by how their achievements are conditioned by either of the above two sources.

Our proposal enables us to mix both parametric and non-parametric approaches in order to benefit from the advantages of each. That is, it allows us to maintain an adequate number of observations, so as to enhance the accuracy of the estimations of the achievement means in these groups. Furthermore, it lets us hold Roemer's assumption of orthogonality of circumstances and efforts while defining tranches based on more than one effort variable.

The analysis of descriptive statistics of cells indicates that the means of expected educational achievements are increasing in circumstances and efforts. Also, it is observed that there is a greater variation of expected achievements in the cells that correspond to the first and last types and tranches in all the countries. Future research would be desirable to understand the determinants of that greater within-cell variation. It would also be interesting for future investigation to estimate the posterior probability of belonging to a type and tranche, and to identify the main determining factors for sorting students into these groups.

The results on ex-ante and ex-post inequality of opportunity indicate that the lowest figures are for the Nordic countries of Iceland, Finland and Norway, whereas the highest ones are for the Western countries of Belgium, France and Germany, and for Bulgaria. Even though the results obtained in both approaches are positively correlated, the rankings of the countries are different. In general, the ex-post values are larger than the ex-ante ones, except for the countries with the highest grade-retention rate. Finally, we observe that the parametric and non-parametric measures of inequality of opportunity are positively correlated.

Notwithstanding the importance of comparing the results, the number of countries selected for these chapters might be too large if a researcher is interested in accurately analyzing inequality of opportunity. Since each country has a particular education system, some important issues have not been taken into account in comparing the results across countries.

Chapter 4 aims to contribute to the literature on the relevance of non-cognitive aspects. Using data from PISA 2009, for Spain we analyze and compare the determinants of students' achievements, or cognitive outcome, as well as their attitudes towards school, or non-cognitive outcome.

Our findings in Chapters 2 and 3 point to the fact that in Spain inequality in educational achievements is mainly due to the characteristics of students and their families, and not that much due to the role of schools and peers. Therefore, Chapter 4 analyzes whether these conclusions can be transferred into attitudes towards school.

To test this, we estimate a multivariate multilevel model, which enables us to consider the hierarchical structure of educational data, and the interaction between attitudes and educational achievements.

The results reveal that the greatest proportion of the variation is explained by students' personal and family characteristics. In addition, it follows that the only school-related variable that is statistically significant for attitude towards school is that related to the disciplinary climate. Indeed, unlike for educational achievements, the socio-economic profile of peer groups does not seem to be important for determining students' attitudes.

Nevertheless, the inclusion of random effects at school level reveals that schools are likely to differ in their capacity to compensate for inequalities of origin. Therefore, there still is some room for seeking improvements in education policies that attempt to equate the results of different institutions.

With regards to future research, it may be worth analyzing the determinants of attitudes using more recent waves of PISA. Moreover, it would be desirable to extend the analysis to other non-cognitive skills such as motivation, self-confidence, perseverance and so on. It would also be worthwhile to analyze how these non-cognitive aspects affect other life outcomes such as future educational and professional careers, and also self-satisfaction.

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Appendix I

Table 1: Descriptive statistics for expected educational achievements per cells for Belgium

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	348.41	20.53	288	343.27	352.62	380.62	14.70	921	377.56	383.14	402.06	13.44	842	400.37	404.43	417.38	13.67	1185	416.10	419.76	432.70	14.73	1463	431.50	434.24
2	365.00	22.25	1065	362.20	367.93	401.79	8.31	1761	401.02	402.77	422.27	6.83	1922	421.71	422.80	440.48	6.25	1739	439.82	440.98	455.67	6.07	1489	455.00	456.16
3	377.62	24.01	2442	375.37	380.54	417.02	8.94	2742	416.39	417.77	438.83	7.58	2082	438.24	439.48	455.13	6.46	1472	454.42	455.70	472.08	7.32	1154	471.36	472.90
4	391.60	22.83	2667	389.13	393.62	435.53	9.58	1690	434.45	436.37	458.22	8.42	850	457.44	459.17	475.21	9.18	765	473.99	476.45	496.59	8.68	406	495.03	498.28
5	394.53	33.79	467	387.34	402.90	457.22	9.56	257	454.61	459.03	481.02	6.60	241	479.41	482.63	497.48	5.22	485	496.76	498.26	514.23	5.98	557	513.30	515.11
6	422.49	36.53	353	415.92	432.43	468.09	6.36	219	466.44	469.58	490.87	7.18	588	489.56	492.59	508.37	5.52	809	507.57	508.99	525.52	4.96	1000	524.89	526.08
7	433.30	21.97	286	427.38	438.58	481.24	7.85	357	479.60	482.87	500.64	6.35	904	500.01	501.59	518.13	5.26	1181	517.83	518.90	534.15	5.58	1354	533.56	534.68
8	451.05	19.01	478	447.25	454.63	489.25	6.54	817	488.14	490.10	509.01	5.98	1175	508.14	509.73	527.74	5.70	1453	527.20	528.23	542.85	5.67	1734	542.41	543.34
9	460.63	23.05	1027	456.96	464.00	499.96	8.28	1383	499.10	500.85	520.32	6.18	1555	519.71	520.92	538.58	6.17	1493	537.95	539.25	554.87	6.31	1590	554.35	555.54
10	477.75	30.12	2745	474.91	480.93	518.62	14.31	1629	517.28	519.90	543.98	17.29	1631	542.12	545.64	560.45	15.60	1209	559.66	562.67	574.69	14.56	1101	573.16	576.33

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	449.35	12.94	1613	447.97	450.76	462.31	13.53	1582	461.34	463.85	478.56	14.07	1463	477.06	480.35	492.63	18.04	1156	490.54	494.72	520.48	21.95	1287	518.54	522.99
2	470.25	6.45	1355	469.58	470.94	486.75	6.94	950	485.83	487.61	501.91	6.82	750	500.97	502.77	516.82	8.79	467	515.20	518.49	542.28	10.48	310	539.82	544.65
3	486.99	6.91	626	486.06	488.12	502.78	8.23	501	501.05	504.02	518.32	7.83	294	516.31	519.91	537.64	9.50	241	535.80	539.71	573.48	22.83	257	568.25	579.52
4	512.58	9.32	635	511.41	513.81	529.29	8.27	529	528.03	530.67	545.73	7.10	757	544.85	546.71	564.48	8.67	1370	563.61	565.60	595.99	17.93	2075	593.28	598.57
5	530.96	4.89	1065	530.57	531.40	544.87	5.40	1595	544.40	545.45	561.14	5.87	1917	560.75	561.56	579.28	6.59	2390	578.86	579.70	609.10	14.86	2825	607.96	610.48
6	541.54	5.22	1284	540.99	541.94	556.68	5.21	1677	556.18	557.08	571.76	5.37	1870	571.21	572.26	588.97	6.20	2073	588.34	589.61	619.37	15.45	1956	617.68	621.06
7	550.66	5.35	1587	550.08	551.15	565.73	5.08	1778	565.20	566.28	581.08	5.17	1707	580.67	581.51	598.77	6.29	1539	598.27	599.26	624.95	15.02	1093	622.33	626.46
8	559.87	5.59	1261	559.33	560.38	573.63	5.31	1382	573.06	574.19	590.43	5.42	1417	589.87	591.07	609.01	6.23	1100	608.44	609.70	636.17	15.40	903	634.12	638.41
9	569.99	5.52	1356	569.40	570.59	585.86	6.14	1185	585.25	586.28	602.50	5.73	849	601.79	603.11	617.25	6.97	802	616.65	618.04	641.62	9.85	579	640.01	642.94
10	589.92	12.12	938	588.54	591.36	612.85	19.17	710	610.70	615.00	622.05	13.83	664	620.25	623.32	642.31	16.81	641	640.16	644.26	674.17	19.02	501	671.47	678.34

Data are weighted by the final student weight. Confidence intervals for the mean are derived from balanced repeated replication (BRR) variance estimation.

Table 2: Descriptive statistics for expected educational achievements per cells for Bulgaria

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	294.30	25.66	803	289.14	299.21	326.57	18.66	460	323.34	330.50	343.93	21.17	439	341.25	347.02	366.66	17.90	447	364.17	369.44	374.15	22.78	498	370.76	377.32
2	321.59	30.04	419	314.41	329.27	362.57	5.99	322	361.50	363.63	379.02	5.00	504	378.05	379.83	390.40	4.90	487	389.84	390.99	403.61	5.83	736	402.81	404.32
3	336.37	26.09	332	330.34	342.47	369.01	6.19	615	368.22	369.83	386.35	4.39	695	385.79	386.93	399.17	4.29	737	398.59	399.73	412.73	4.64	580	412.15	413.31
4	340.75	23.43	376	336.38	345.00	374.52	5.36	499	373.54	375.63	391.97	4.16	583	391.39	392.54	407.02	4.06	519	406.52	407.49	419.89	3.85	679	419.43	420.34
5	350.10	20.79	291	347.16	353.38	383.43	5.38	698	382.78	384.18	398.12	4.67	480	397.58	398.57	412.72	4.49	632	412.03	413.32	425.80	4.51	550	425.31	426.36
6	347.89	42.31	729	342.17	352.81	387.10	5.34	493	386.41	387.77	404.52	4.61	614	403.94	405.02	418.41	4.04	587	417.83	419.04	432.15	4.41	642	431.68	432.68
7	361.44	21.21	550	358.76	363.91	395.46	5.95	784	394.78	396.14	411.93	3.58	672	411.42	412.45	425.72	4.18	474	425.20	426.12	438.24	4.86	357	437.40	438.99
8	368.65	18.94	535	366.41	371.27	401.66	6.27	549	400.77	402.49	419.46	5.70	558	418.88	420.17	434.60	5.13	527	433.76	435.26	448.62	5.36	509	447.96	449.29
9	378.09	24.75	726	373.86	381.90	411.79	6.67	621	410.66	412.64	431.85	5.55	504	430.92	432.65	444.94	5.56	588	444.18	445.69	458.66	5.57	422	457.94	459.53
10	389.59	30.48	648	385.31	393.42	445.60	24.23	385	441.69	448.78	455.10	13.39	378	453.13	456.81	475.06	19.57	445	471.91	477.63	495.56	27.17	439	491.40	499.51

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	394.53	19.66	441	391.38	398.21	406.14	24.11	402	402.97	410.50	428.99	17.85	554	426.04	431.51	449.71	17.20	656	447.35	451.76	478.91	22.21	715	475.44	482.26
2	418.33	4.89	541	417.64	419.03	433.11	5.81	665	432.14	433.79	447.94	6.11	543	447.28	448.63	467.17	7.54	476	466.01	468.23	497.18	15.23	676	494.83	498.99
3	426.91	5.08	504	426.30	427.70	442.53	5.10	549	441.91	443.16	460.23	4.82	648	459.60	460.81	477.62	6.80	687	476.71	478.61	500.25	12.06	618	498.68	502.13
4	433.41	4.66	540	432.84	433.98	448.47	4.88	623	447.76	449.18	465.19	5.23	478	464.57	465.93	481.98	6.30	414	481.41	482.64	508.22	12.69	398	506.44	510.20
5	439.25	4.20	611	438.79	439.76	456.12	5.14	440	455.24	456.96	471.37	4.39	458	470.71	472.21	489.89	5.89	509	489.09	490.56	515.66	12.04	482	513.52	517.58
6	447.25	4.36	533	446.69	447.76	462.11	5.11	587	461.61	462.91	478.25	4.96	468	477.61	478.85	495.31	5.23	392	494.61	495.99	523.39	16.80	391	520.81	525.71
7	453.75	4.06	444	453.26	454.30	467.19	5.25	468	466.38	467.85	484.65	4.94	585	484.02	485.48	502.49	6.80	512	501.20	503.66	525.26	10.27	549	524.10	526.97
8	461.41	4.56	532	460.64	462.10	477.02	5.37	630	476.30	477.58	493.14	5.43	554	492.52	493.79	510.05	6.67	456	509.01	510.97	541.81	18.51	493	539.08	544.68
9	472.09	5.74	616	471.21	472.82	487.91	6.76	521	486.99	488.62	503.36	6.66	567	502.51	504.41	521.90	7.04	669	520.84	523.07	549.68	17.65	430	546.09	552.68
10	503.94	21.59	669	501.59	507.10	515.87	20.84	549	513.04	519.05	533.80	19.06	577	531.39	535.93	552.86	20.44	660	550.11	555.60	585.04	27.27	652	581.00	588.12

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 3: Descriptive statistics for expected educational achievements per cells for Croatia

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	373.71	15.49	354	371.30	376.12	394.28	10.93	449	393.01	395.79	408.41	11.24	400	406.43	410.42	419.89	9.34	412	418.30	421.18	429.37	9.53	536	428.15	430.38
2	386.64	11.55	516	384.78	388.09	408.29	5.18	454	407.45	408.97	421.45	4.53	414	420.69	422.19	432.39	4.35	443	431.83	432.99	442.61	4.18	448	442.07	443.18
3	397.27	9.86	495	395.78	398.74	417.34	4.19	376	416.66	417.91	430.54	4.01	574	430.00	431.15	440.31	3.14	415	439.71	440.78	450.12	3.63	441	449.64	450.59
4	405.14	9.70	278	403.12	407.47	422.06	4.64	417	421.37	422.63	435.37	4.07	430	434.79	435.80	445.83	2.81	420	445.39	446.21	454.67	2.60	493	454.38	454.97
5	405.06	11.03	475	403.28	406.64	426.92	4.72	330	426.44	427.39	439.46	3.75	500	438.93	439.90	450.96	2.94	645	450.64	451.31	460.51	2.96	470	460.13	460.88
6	407.27	13.29	533	405.27	409.37	430.83	4.37	521	430.27	431.61	443.86	3.15	411	443.42	444.41	454.83	3.37	537	454.29	455.28	464.39	3.19	498	464.02	464.84
7	408.50	13.65	568	406.14	410.65	434.46	4.65	579	433.86	435.10	447.51	3.78	520	447.04	448.04	458.57	3.20	389	458.17	459.02	468.03	3.43	397	467.50	468.65
8	415.63	13.03	500	413.67	418.03	439.97	5.18	437	439.07	440.72	452.89	4.37	472	452.30	453.62	463.35	3.42	528	462.91	463.74	473.01	3.21	465	472.61	473.40
9	423.15	12.38	506	420.97	426.04	447.38	4.96	607	446.83	448.02	460.95	4.90	484	460.20	461.62	469.90	4.08	334	469.12	470.71	480.51	3.79	385	479.84	481.09
10	445.64	23.47	359	441.55	449.80	471.12	18.87	366	469.19	473.29	482.02	15.06	370	480.08	484.11	497.66	15.55	402	495.63	500.24	506.53	19.06	426	503.95	508.52

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	441.25	7.56	444	440.26	442.32	451.85	8.26	501	450.81	452.76	462.29	12.25	415	460.60	464.25	481.30	7.69	446	480.24	482.44	512.68	17.89	610	509.69	515.05
2	453.20	3.57	476	452.60	453.61	464.71	4.20	339	464.06	465.29	478.29	5.49	532	477.52	478.99	494.20	5.02	379	493.35	495.06	521.43	15.19	531	519.56	523.28
3	461.70	3.35	363	461.19	462.22	472.60	3.76	458	471.98	473.12	487.91	4.32	461	487.27	488.51	500.67	5.42	480	499.99	501.29	529.29	13.23	479	527.31	531.38
4	466.64	3.10	514	466.24	467.02	478.08	3.72	643	477.60	478.46	492.11	4.98	528	491.39	492.74	508.40	5.92	425	507.37	509.30	534.24	13.09	437	532.29	536.36
5	471.24	3.49	545	470.69	471.63	482.90	4.14	435	482.32	483.62	495.93	4.56	411	495.21	496.56	513.25	5.16	407	512.66	514.07	539.47	12.31	298	536.54	541.52
6	475.50	2.87	410	475.14	475.90	486.00	3.62	375	485.56	486.61	500.84	4.50	496	500.21	501.44	516.54	6.01	382	515.74	517.55	541.62	15.59	394	538.55	544.62
7	480.32	3.47	505	479.80	480.79	490.37	3.51	352	489.83	491.12	503.41	4.56	427	502.70	504.01	520.14	5.37	453	519.46	520.80	551.75	13.90	363	549.75	553.66
8	484.08	3.42	414	483.58	484.54	495.42	4.39	411	494.77	496.22	509.30	4.72	413	508.61	509.96	526.02	4.90	486	525.31	526.71	554.14	13.59	416	552.59	556.14
9	490.83	4.33	419	490.33	491.59	503.96	4.68	496	503.22	504.64	516.85	4.98	404	516.21	517.53	533.52	5.54	413	532.69	534.20	559.31	15.55	507	556.64	561.51
10	511.23	14.60	502	509.69	513.04	525.53	16.09	502	523.97	527.16	536.88	14.94	458	535.31	538.78	563.99	20.53	658	561.49	566.70	583.07	23.51	515	579.82	587.01

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 4: Descriptive statistics for expected educational achievements per cells for Finland

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	379.56	34.83	906	376.59	383.62	413.20	27.80	635	409.48	417.23	430.59	26.44	557	428.12	434.05	431.39	32.80	562	427.12	435.86	444.85	29.83	557	441.19	448.61
2	434.80	21.16	476	432.96	436.67	459.79	5.48	442	458.75	460.62	469.15	5.36	496	468.41	469.71	478.33	5.40	560	477.68	479.24	487.28	4.99	520	486.53	487.83
3	450.78	16.68	384	448.29	452.82	471.76	4.51	505	471.17	472.38	481.13	3.35	572	480.74	481.57	490.96	3.65	632	490.31	491.45	499.28	3.58	797	498.88	499.72
4	452.36	22.57	440	449.98	454.24	478.46	4.28	621	477.83	479.00	489.37	3.36	667	488.91	489.87	499.20	3.36	628	498.73	499.62	507.30	3.38	668	506.76	507.80
5	459.89	23.25	408	456.86	462.14	487.42	4.12	509	486.90	487.88	497.09	3.77	812	496.59	497.59	505.94	3.08	461	505.58	506.33	515.34	3.01	642	514.87	515.79
6	464.86	24.61	643	462.81	467.23	493.94	3.80	618	493.47	494.48	504.75	3.53	594	504.23	505.08	513.95	3.35	558	513.50	514.48	522.24	3.11	661	521.90	522.65
7	476.82	21.67	677	475.18	478.72	501.52	3.76	607	501.04	501.94	511.69	3.56	570	511.28	512.07	522.10	4.09	630	521.64	522.57	530.60	3.44	575	530.11	531.16
8	482.00	26.74	598	479.55	484.35	510.69	4.69	744	510.06	511.35	521.35	4.31	665	521.00	521.74	529.95	4.09	658	529.24	530.60	540.46	3.68	551	540.05	541.00
9	493.64	30.62	942	490.93	496.17	523.34	4.91	716	522.72	523.84	534.24	5.25	584	533.52	534.98	543.77	4.73	783	543.19	544.49	553.63	5.17	455	552.85	554.19
10	519.22	41.61	674	515.14	523.25	558.62	24.82	580	555.71	561.81	559.12	16.85	483	557.43	560.85	578.56	25.14	510	574.76	582.24	589.35	30.61	561	585.17	593.98

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	462.88	27.46	656	459.80	466.80	466.80	26.77	500	462.41	470.51	470.71	31.48	609	467.21	475.23	492.63	17.65	472	490.04	495.15	497.69	28.60	566	493.14	501.80
2	495.37	5.11	743	494.98	495.93	502.35	4.73	748	501.86	502.88	510.12	4.81	708	509.50	510.70	516.77	4.48	615	516.12	517.32	526.49	8.25	726	525.60	527.48
3	507.07	3.91	538	506.60	507.56	515.45	3.78	645	514.96	515.90	521.43	3.38	659	521.02	521.83	528.55	3.80	692	528.04	528.96	540.36	7.00	541	539.45	541.32
4	515.68	3.33	610	515.13	516.16	523.09	3.13	579	522.65	523.55	530.46	2.92	583	530.08	530.72	536.82	3.06	592	536.52	537.17	548.94	7.77	677	547.91	549.92
5	523.01	3.22	540	522.62	523.34	530.27	2.83	617	529.85	530.57	537.45	2.86	608	537.07	537.81	544.22	3.42	624	543.77	544.56	555.97	6.85	792	555.25	556.77
6	530.13	3.30	608	529.73	530.46	538.54	3.25	680	538.09	538.84	545.33	2.78	606	544.93	545.77	551.26	2.81	578	550.89	551.62	561.96	5.48	514	561.19	562.65
7	538.40	3.03	574	538.07	538.80	546.62	2.72	569	546.27	546.90	552.74	3.12	574	552.34	553.17	559.97	3.09	595	559.47	560.42	569.80	5.96	491	568.97	570.61
8	547.30	3.64	539	546.82	547.71	554.65	3.98	559	554.11	555.16	562.94	3.53	536	562.54	563.30	568.48	3.50	569	567.90	568.88	579.08	6.13	652	578.30	579.87
9	560.42	5.36	457	559.90	561.40	566.34	4.42	522	565.67	566.86	574.95	4.94	555	574.37	575.47	581.69	4.73	495	581.08	582.49	592.65	9.28	435	591.15	593.39
10	592.24	23.59	728	589.18	594.71	601.00	24.03	582	597.84	604.49	613.27	30.91	547	609.19	617.51	620.13	30.56	794	617.14	624.40	638.78	35.42	553	633.75	643.04

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 5: Descriptive statistics for expected educational achievements per cells for France

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	318.43	28.75	4261	314.18	324.39	349.88	17.29	5294	346.80	353.25	371.13	18.71	8107	367.63	373.86	383.93	16.02	8121	382.07	386.04	403.35	12.77	9516	401.86	404.82
2	345.80	24.79	7621	342.66	349.62	382.29	9.73	13348	380.95	383.04	398.05	8.45	13341	397.19	398.94	415.96	7.86	12273	414.99	416.86	429.70	8.68	7450	428.49	430.97
3	368.80	22.14	17497	367.08	371.02	403.39	10.02	11540	402.32	404.84	423.00	8.23	8446	421.71	423.91	438.48	10.79	4663	436.88	440.51	455.91	9.73	4417	454.18	457.49
4	386.65	26.00	5481	382.86	390.66	434.70	6.17	3859	433.48	435.97	450.32	7.89	2977	449.17	452.52	469.08	6.54	2439	467.71	470.35	481.99	6.86	4499	480.78	483.40
5	402.14	30.72	2797	395.17	408.67	446.92	8.46	1750	444.46	449.49	467.26	5.76	3784	465.53	467.92	482.29	5.60	4297	481.40	483.18	495.12	5.30	5704	494.34	495.79
6	408.64	24.57	1634	402.77	415.48	454.81	6.65	2001	452.91	456.45	475.63	5.91	4201	474.54	476.58	490.23	5.22	6431	489.53	490.94	504.56	5.48	7449	503.82	505.43
7	431.74	15.72	2762	427.27	435.24	466.30	6.95	4038	464.98	467.74	483.87	4.99	4595	482.81	484.74	498.33	5.19	7656	497.57	499.03	513.94	4.88	8387	513.30	514.58
8	439.47	18.27	4443	435.78	443.22	474.90	6.99	7112	473.91	475.89	494.19	6.10	8905	493.40	495.11	510.03	6.09	7407	509.30	510.82	524.47	5.23	8495	523.74	524.97
9	459.15	15.84	7150	456.53	461.35	488.30	7.97	8720	487.43	489.24	506.84	5.51	8795	506.32	507.66	521.72	5.76	9334	520.96	522.37	538.57	6.35	8083	537.69	539.46
10	475.15	28.35	16587	472.97	478.21	514.52	22.65	12063	511.97	516.64	529.79	17.40	6967	527.67	532.48	548.65	22.17	7228	545.18	550.88	562.89	22.14	5897	559.10	566.12

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	412.23	13.04	10141	410.65	413.82	424.44	21.36	8014	421.03	427.29	438.59	16.98	6256	436.00	441.01	450.91	16.32	5088	447.57	453.58	479.69	20.98	5260	476.01	483.56
2	444.44	7.83	5429	443.07	446.01	458.51	9.57	5525	457.03	459.93	466.65	8.00	2190	464.53	468.59	486.80	7.66	2210	484.89	488.51	526.28	41.62	633	513.49	544.65
3	475.23	11.17	3253	473.18	476.86	491.32	9.12	2452	488.66	493.66	504.48	10.66	4055	502.42	506.47	525.60	7.55	5775	524.15	526.64	557.90	19.28	7899	555.76	560.41
4	496.31	6.55	7700	495.39	497.35	510.54	7.26	6845	509.42	511.53	525.57	6.74	9424	524.87	526.16	542.97	8.10	10210	542.09	543.92	574.36	18.79	16328	572.57	576.07
5	509.30	5.03	10102	508.76	509.85	524.06	5.18	9878	523.37	524.65	539.51	5.14	10445	538.87	540.18	556.73	6.74	10844	555.91	557.35	584.40	14.35	11048	582.88	585.88
6	519.36	4.67	7966	518.62	519.86	532.64	5.07	9507	532.04	533.09	547.76	5.11	10625	547.25	548.27	565.02	6.74	9550	564.38	565.98	593.45	15.60	10447	591.62	595.76
7	528.02	5.12	7685	527.34	528.73	542.60	5.55	7694	541.96	543.49	557.63	5.18	10168	557.06	558.18	575.49	5.77	9178	574.83	576.28	599.55	13.50	7496	597.87	601.49
8	539.44	5.29	6218	538.66	540.22	551.02	4.71	8888	550.29	551.72	568.55	5.84	7060	567.47	569.43	586.22	7.01	7182	585.19	587.36	616.29	17.31	4388	613.15	619.18
9	550.40	5.41	6642	549.51	551.15	563.97	6.44	7464	563.10	564.86	580.26	5.62	5488	579.33	581.16	598.60	7.26	5081	597.44	599.58	621.89	15.22	3179	619.67	624.26
10	574.84	14.85	5107	572.52	577.69	594.40	19.69	3883	590.77	598.25	600.94	12.01	4082	598.68	603.33	628.59	20.91	4898	624.94	632.35	654.05	25.93	3078	648.49	659.63

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 6: Descriptive statistics for expected educational achievements per cells for Germany

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	372.49	15.76	6640	370.07	375.17	398.50	12.34	7374	397.23	399.83	415.66	11.59	8852	414.09	417.43	429.41	11.59	9689	427.30	431.15	440.02	18.16	9566	437.25	442.75
2	385.49	20.34	20088	383.63	387.38	419.20	8.86	11323	418.40	420.32	436.84	7.56	8859	435.86	437.72	450.66	7.56	7204	449.60	451.87	464.51	8.37	7007	463.07	465.61
3	409.42	16.34	4046	405.62	412.47	445.36	9.54	4489	443.58	447.55	465.49	7.57	5471	464.26	466.38	478.16	7.57	5049	476.80	479.31	491.95	7.44	5750	490.85	492.98
4	427.19	11.08	2448	424.93	429.52	457.10	7.48	5407	455.84	458.81	476.73	4.94	5315	476.04	477.35	490.15	4.94	6652	489.34	491.10	505.25	4.82	5715	504.57	506.08
5	438.08	10.43	2433	435.49	440.73	463.81	6.49	4539	462.58	465.06	482.03	5.09	6821	481.28	482.63	497.37	5.09	6504	496.68	497.92	510.16	4.25	8183	509.51	510.76
6	443.05	13.51	4210	440.20	445.52	468.84	5.99	4734	467.86	469.97	488.01	4.82	7429	487.24	488.75	501.34	4.82	6704	500.71	501.87	514.64	4.20	7307	513.99	515.28
7	441.44	13.95	7322	439.65	443.13	472.66	6.11	9745	471.92	473.50	492.64	4.79	9414	492.02	493.13	506.76	4.79	6928	506.27	507.29	520.48	4.77	8044	519.83	521.12
8	443.02	16.00	8623	440.73	445.55	478.19	6.26	9165	477.45	479.00	497.94	4.40	7115	497.28	498.62	512.24	4.40	8486	511.65	512.79	526.08	4.90	7089	525.24	526.90
9	453.80	19.03	10126	451.25	456.30	484.96	6.43	9751	484.13	485.82	503.13	5.39	8191	502.34	503.92	519.42	5.39	8852	518.85	519.94	532.95	4.94	9171	532.44	533.71
10	465.42	30.00	9814	462.14	469.17	501.71	18.67	9228	499.03	504.78	524.50	18.47	8881	521.78	527.23	538.46	18.47	8820	536.25	540.88	551.20	17.08	8124	549.01	553.06

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	455.41	10.49	6413	454.29	456.45	468.33	11.59	7607	467.19	469.71	484.53	11.44	6642	483.29	485.92	506.32	11.72	6555	504.89	507.81	535.47	20.97	6419	532.26	538.53
2	476.31	8.36	6056	474.90	477.77	490.47	7.49	3965	488.80	491.92	511.00	8.62	3943	509.26	512.81	532.14	10.30	4580	530.34	533.85	561.26	16.18	2651	556.63	564.83
3	506.76	6.39	6724	505.57	507.90	521.59	8.55	6629	520.24	522.81	539.48	7.97	10160	538.28	540.67	556.54	7.46	12809	555.69	557.47	586.57	15.22	14521	585.05	588.03
4	518.82	4.35	8409	518.23	519.33	533.26	5.39	9193	532.70	533.99	548.21	5.43	10733	547.60	548.89	571.03	5.21	8715	570.44	571.77	597.25	13.73	13094	595.41	599.47
5	524.63	4.34	8871	524.09	525.16	539.51	4.68	10474	538.86	540.09	554.96	5.67	9164	554.29	555.58	573.15	6.14	9129	572.66	574.00	603.63	14.94	9605	601.36	605.81
6	530.04	4.05	9232	529.42	530.43	544.31	4.60	9167	543.93	544.81	560.37	5.32	8546	559.58	561.13	578.65	6.31	10056	577.87	579.41	608.77	14.43	8344	606.46	611.07
7	534.48	3.92	8887	534.01	534.93	549.77	4.51	6815	549.05	550.35	566.06	5.43	7368	565.26	566.91	583.41	6.12	7407	582.47	584.25	609.68	12.04	3684	606.67	611.84
8	539.40	4.44	7239	538.83	539.88	555.49	4.81	9008	554.75	556.24	570.10	4.45	6186	569.50	570.66	586.71	5.86	7185	586.05	587.62	620.70	18.33	5571	617.58	624.32
9	547.28	5.48	6881	546.50	547.90	561.45	4.62	5691	560.74	562.26	576.98	5.83	6185	576.11	577.78	596.83	6.72	5001	595.58	598.14	622.30	13.05	6075	620.25	624.23
10	564.00	12.22	6669	562.12	565.62	583.40	16.34	7311	580.90	585.76	600.24	16.30	6833	597.83	602.45	619.94	19.63	4259	616.75	623.40	640.37	19.63	5554	637.30	643.07

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 7: Descriptive statistics for expected educational achievements per cells for Greece

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	333.55	14.35	1548	331.02	334.77	347.57	27.24	1159	344.44	351.94	360.82	19.43	1102	357.70	363.05	378.58	21.33	894	375.79	381.87	386.65	25.47	1034	382.12	390.86
2	364.43	18.71	528	361.97	367.38	388.10	5.40	502	387.08	389.32	402.68	3.98	740	402.02	403.21	411.94	3.84	596	411.46	412.58	422.95	3.59	1124	422.61	423.46
3	378.90	9.84	390	377.03	380.93	398.02	4.43	806	397.33	398.61	409.48	3.51	956	408.86	409.88	420.07	3.71	879	419.56	420.55	430.66	3.68	1250	430.14	431.30
4	382.76	11.78	531	381.86	384.89	402.78	4.75	817	401.97	403.58	416.57	3.61	1034	416.06	416.93	426.99	3.38	1195	426.53	427.63	436.91	3.74	984	436.22	437.64
5	387.47	11.60	750	385.42	389.79	409.47	4.65	975	408.84	410.13	421.63	4.20	989	421.01	422.29	432.12	3.17	1093	431.79	432.51	443.87	3.62	1207	443.43	444.38
6	392.55	10.86	1048	391.45	393.90	414.21	5.00	1206	413.61	414.87	426.33	3.74	911	425.58	427.00	437.61	3.43	1168	437.20	438.01	448.18	3.59	956	447.55	448.79
7	396.26	11.80	1000	394.33	398.17	420.68	5.15	1244	419.87	421.28	433.85	3.58	1256	433.44	434.38	444.38	3.72	1163	443.89	444.87	454.44	3.46	660	453.94	455.00
8	402.94	14.74	1134	400.99	404.78	427.23	5.19	1102	426.54	427.82	442.06	4.14	1169	441.48	442.52	452.72	3.79	927	452.09	453.26	462.18	4.30	671	461.57	462.66
9	415.73	14.86	1394	413.70	417.24	441.64	7.63	1005	440.57	442.98	454.75	5.68	698	453.91	455.45	464.16	6.16	956	463.52	465.02	475.43	6.01	889	474.55	476.39
10	454.59	24.78	1370	451.14	457.84	475.45	24.46	839	471.40	478.84	487.19	22.08	860	484.00	490.99	494.25	16.60	765	491.65	496.95	509.52	20.88	883	506.37	513.01

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	400.86	27.43	638	396.36	405.30	419.97	19.98	781	416.81	422.63	430.19	24.86	656	425.03	434.59	449.21	19.46	979	446.71	452.13	472.80	19.65	885	470.20	475.59
2	432.97	4.40	921	432.30	433.75	446.41	5.06	1238	445.91	447.05	457.12	4.56	1279	456.67	457.63	469.99	4.61	1510	469.41	470.62	489.18	9.83	1204	487.82	490.46
3	442.21	3.36	1009	441.89	442.58	453.64	3.41	1114	453.32	454.02	466.25	4.36	1232	465.69	466.71	477.88	4.36	1038	477.43	478.31	496.89	10.55	1017	495.61	498.16
4	448.41	3.47	1387	448.06	448.74	460.22	4.39	1080	459.78	460.97	471.51	4.14	1026	471.14	472.02	484.51	3.98	757	483.95	485.09	503.83	9.96	885	502.42	505.41
5	453.96	3.77	1009	453.47	454.52	465.59	3.39	912	465.12	466.08	477.63	3.84	1033	477.07	478.10	490.87	4.18	903	490.36	491.41	509.06	7.59	741	508.09	510.14
6	460.63	3.99	1031	460.27	461.12	471.72	3.79	860	471.18	472.41	483.52	4.36	919	482.82	484.08	496.83	4.59	757	496.03	497.60	514.84	8.61	815	514.08	515.76
7	466.32	4.28	882	465.79	466.80	477.89	3.75	986	477.26	478.46	489.91	4.13	1019	489.48	490.41	502.88	4.32	745	502.12	503.52	520.49	9.22	738	519.21	521.45
8	474.39	4.55	888	473.76	475.17	485.04	4.28	906	484.39	485.68	496.72	5.26	907	495.74	497.53	511.06	3.93	1021	510.54	511.60	529.91	10.74	918	528.83	531.10
9	486.23	5.62	920	485.38	487.25	498.42	5.95	887	497.66	499.29	510.58	5.65	947	509.73	511.31	523.90	6.66	932	523.12	524.79	545.06	13.50	1039	543.13	546.46
10	518.75	19.94	986	516.28	520.75	531.14	18.27	893	528.18	533.98	543.95	20.95	658	540.55	547.27	554.96	24.94	1023	551.52	559.19	574.10	22.77	1373	571.50	576.39

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 8: Descriptive statistics for expected educational achievements per cells for Iceland

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	380.82	29.06	25	374.15	387.66	395.69	24.98	38	390.57	400.93	409.30	27.26	39	405.06	413.31	419.96	27.33	49	416.52	423.78	423.23	36.29	44	417.67	427.52
2	407.99	15.19	44	405.38	410.50	431.19	5.84	47	430.36	432.10	440.94	5.16	34	439.93	441.76	451.29	4.83	48	450.61	452.01	458.49	4.01	38	457.88	459.10
3	416.30	15.81	39	412.84	419.13	439.51	4.02	46	438.84	440.16	451.96	4.36	40	451.16	452.78	463.33	3.94	36	462.65	463.97	470.98	3.08	35	470.42	471.49
4	427.67	11.48	40	425.43	429.49	448.95	4.52	48	448.26	449.64	461.15	4.25	45	460.39	462.03	470.59	3.29	34	470.04	471.16	479.53	3.44	49	478.98	480.04
5	432.79	17.02	49	429.98	435.53	457.12	4.75	36	456.20	458.19	468.16	3.09	35	467.70	468.71	478.08	3.45	49	477.54	478.59	486.65	2.79	38	486.21	487.09
6	441.94	15.14	50	439.91	444.36	463.24	4.60	57	462.50	463.81	475.33	3.80	44	474.76	475.84	486.48	3.87	46	485.95	487.16	495.16	3.19	44	494.72	495.71
7	448.69	15.03	42	446.37	451.06	472.29	4.52	42	471.62	473.00	483.47	3.90	49	482.87	484.03	494.30	3.61	40	493.72	494.97	502.99	3.90	37	502.33	503.61
8	461.81	16.61	45	458.83	464.36	483.15	6.17	33	481.90	484.57	495.23	5.14	43	494.35	496.13	504.53	4.86	38	503.45	505.40	512.44	4.57	44	511.73	513.05
9	479.30	13.81	36	476.60	481.99	496.27	5.79	50	495.34	497.11	508.92	5.50	48	508.21	509.82	517.71	6.27	44	516.68	518.68	528.14	5.65	46	527.12	529.08
10	509.09	24.10	44	505.60	513.14	530.81	23.57	31	526.06	535.36	550.75	33.03	31	544.30	556.87	554.95	32.70	41	549.87	560.35	563.68	26.45	28	559.09	568.83

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	444.64	18.87	41	441.55	447.71	445.26	19.98	50	442.39	448.66	455.32	21.27	41	452.24	458.35	453.09	33.84	47	447.18	458.73	469.52	26.13	44	465.70	473.10
2	467.61	4.85	51	466.81	468.48	475.41	4.83	40	474.34	476.30	481.66	4.16	36	480.94	482.20	489.89	4.15	42	489.28	490.58	502.16	8.44	39	500.96	503.40
3	477.97	3.41	40	477.36	478.52	485.03	2.73	39	484.58	485.47	492.83	3.36	42	492.16	493.35	499.41	3.70	50	498.80	499.97	511.60	7.37	37	510.59	512.72
4	486.55	3.17	51	486.10	487.00	494.14	2.34	47	493.84	494.51	500.88	3.24	36	500.40	501.41	507.79	3.65	37	507.05	508.34	521.16	6.79	41	520.00	521.87
5	492.92	2.54	35	492.52	493.31	501.40	3.18	54	500.96	501.89	508.30	2.99	38	507.64	508.70	515.63	3.91	32	515.02	516.30	527.85	7.11	37	526.73	529.18
6	501.44	3.09	35	500.82	501.86	508.67	2.89	39	508.11	509.11	515.45	3.26	42	514.95	515.94	523.47	3.49	38	523.01	524.14	535.34	5.24	40	534.44	536.36
7	510.81	3.34	36	510.15	511.40	517.61	3.15	41	516.95	518.05	524.25	3.50	42	523.68	524.84	531.97	3.14	47	531.50	532.47	546.05	6.96	31	544.81	547.48
8	520.80	4.15	43	520.27	521.28	528.27	3.36	38	527.76	528.90	534.98	3.94	54	534.37	535.55	541.91	4.16	38	541.21	542.72	553.58	6.93	45	552.41	554.53
9	536.42	5.62	35	535.46	537.28	542.44	5.19	32	541.44	543.62	549.75	5.33	44	548.89	550.57	556.43	4.92	48	555.51	557.10	569.84	8.22	44	568.75	570.92
10	574.21	29.03	47	568.86	579.50	576.70	22.69	48	573.44	579.71	583.39	26.04	50	579.82	586.73	600.44	29.52	44	595.66	605.39	606.69	32.16	41	601.29	611.35

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 9: Descriptive statistics for expected educational achievements per cells for Ireland

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	387.12	21.05	614	384.31	389.52	409.05	16.77	637	406.17	411.60	423.47	12.52	568	422.12	425.31	430.43	19.15	518	428.36	432.99	441.66	15.18	400	439.42	443.94
2	415.38	10.57	538	413.59	416.73	435.67	5.31	408	434.87	436.63	449.48	4.38	496	448.73	450.01	458.41	4.73	554	457.88	459.01	468.32	5.43	589	467.49	469.06
3	425.00	12.06	417	422.99	427.11	444.84	4.15	645	444.26	445.33	458.32	4.16	573	457.61	458.90	468.43	4.11	640	467.86	468.96	479.66	4.12	391	478.94	480.33
4	434.61	9.70	524	433.00	436.34	453.10	4.74	519	452.51	453.60	465.86	3.98	534	465.39	466.35	475.17	3.67	504	474.43	475.67	485.47	3.27	506	484.95	485.96
5	440.00	13.03	575	438.13	441.87	460.01	4.41	515	459.35	460.64	472.63	3.57	603	472.21	473.02	483.03	3.50	471	482.47	483.46	493.08	3.79	643	492.56	493.52
6	443.63	11.41	494	442.05	445.14	465.08	4.34	484	464.50	465.59	479.44	3.44	380	478.89	479.97	489.42	3.69	690	488.92	489.90	499.36	3.86	579	498.92	500.06
7	452.91	11.89	569	451.06	454.41	473.67	4.61	629	473.14	474.30	486.76	3.63	485	486.19	487.43	495.92	3.22	507	495.48	496.38	505.71	3.94	586	505.13	506.33
8	459.67	13.77	556	457.63	462.05	481.69	4.92	559	480.94	482.18	492.36	4.37	515	491.74	493.04	503.27	3.72	488	502.86	503.90	515.04	4.07	638	514.52	515.62
9	473.96	11.76	554	472.17	475.67	492.78	5.54	522	492.04	493.41	503.99	5.43	651	503.29	504.67	514.55	5.13	536	513.60	515.39	523.48	5.07	558	522.88	524.17
10	493.52	16.10	556	491.57	495.70	513.07	11.09	493	511.44	514.70	524.98	13.45	587	522.60	526.76	536.29	14.69	484	534.07	539.05	548.57	15.45	519	546.12	550.70

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	451.67	18.70	552	448.31	454.19	465.17	15.83	419	462.37	467.75	474.48	14.47	492	471.76	476.75	492.30	13.83	690	490.34	494.13	509.40	20.58	517	506.44	512.18
2	477.90	4.92	521	477.11	478.69	488.19	4.72	545	487.41	488.76	498.60	4.95	572	497.91	499.30	509.68	4.97	630	509.00	510.46	533.54	12.77	593	532.05	534.82
3	489.29	3.83	612	488.81	489.85	498.57	4.30	461	497.90	499.13	509.33	3.76	497	508.66	509.85	522.67	4.77	547	521.87	523.29	542.59	12.68	665	540.71	544.06
4	497.17	3.81	561	496.57	497.76	506.61	3.61	600	506.16	507.05	517.49	3.57	461	516.94	518.04	528.87	3.85	587	528.28	529.41	550.36	14.87	571	548.07	552.17
5	502.61	3.33	495	502.06	503.15	513.42	3.39	464	512.85	513.91	524.00	3.87	637	523.46	524.52	535.75	3.64	421	535.07	536.40	558.17	12.14	561	556.19	560.04
6	509.11	3.32	593	508.57	509.65	519.91	3.13	614	519.46	520.37	531.03	4.15	458	530.34	531.75	541.19	3.71	631	540.65	541.67	561.16	11.76	450	559.25	563.48
7	515.83	3.37	404	515.23	516.36	526.13	3.42	623	525.63	526.67	536.84	4.32	622	536.26	537.39	548.42	4.05	451	547.82	549.09	566.38	11.84	531	564.76	567.98
8	524.11	3.58	571	523.55	524.55	534.20	3.83	578	533.64	534.70	544.26	4.22	567	543.45	544.88	556.97	3.96	452	556.39	557.48	574.78	10.01	463	573.20	576.16
9	534.65	4.76	665	534.10	535.23	545.00	4.63	518	544.42	545.56	553.66	4.40	489	552.88	554.31	567.52	4.74	433	566.93	568.11	587.61	13.51	487	585.88	589.70
10	558.02	13.69	463	556.14	560.20	571.83	21.14	552	568.34	575.14	578.17	13.73	607	576.20	580.10	590.79	15.09	563	588.83	592.46	609.19	17.51	557	607.16	611.16

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 10: Descriptive statistics for expected educational achievements per cells for Italy

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	362.96	13.52	6451	361.95	363.89	384.06	10.72	6681	383.05	385.09	395.45	11.51	6648	394.79	396.23	405.43	12.17	5710	404.43	406.36	416.80	10.92	5517	416.10	417.48
2	383.29	14.73	7724	382.25	384.32	406.36	7.81	5456	405.68	406.91	423.24	7.83	4954	422.23	424.05	433.17	7.55	4638	432.43	434.04	444.24	7.68	4143	443.62	445.22
3	403.07	14.54	3872	401.88	404.96	426.38	5.57	4429	425.88	426.84	440.92	4.62	4334	440.51	441.33	450.92	4.35	4231	450.56	451.35	461.92	4.26	4831	461.61	462.19
4	412.21	12.90	3617	410.78	413.37	436.12	5.29	4211	435.66	436.53	449.16	4.14	3796	448.80	449.50	460.70	3.77	5749	460.46	461.01	470.90	3.49	5113	470.63	471.16
5	421.25	12.08	3826	420.16	422.28	444.39	4.96	4853	443.96	444.83	456.92	3.96	5352	456.60	457.21	468.17	3.56	5083	467.90	468.48	477.98	3.26	5352	477.75	478.18
6	426.18	13.79	4368	424.59	427.69	450.46	5.10	4358	450.11	450.90	463.27	3.78	5522	462.96	463.59	474.53	3.51	6400	474.30	474.75	484.94	3.51	5361	484.74	485.17
7	434.91	11.93	4690	433.79	436.08	457.09	4.89	5648	456.74	457.40	470.95	4.06	5271	470.55	471.22	482.02	3.70	5071	481.75	482.36	491.50	3.56	5444	491.20	491.78
8	439.81	14.30	6142	438.68	440.97	465.05	4.92	5059	464.73	465.40	478.86	4.05	5271	478.52	479.27	490.44	4.25	4878	490.13	490.77	500.20	3.86	5446	499.94	500.46
9	450.08	16.14	5974	448.56	450.88	476.23	5.74	5490	475.75	476.57	490.17	5.46	5419	489.58	490.65	500.23	5.01	4645	499.75	500.66	510.80	4.69	5712	510.45	511.19
10	477.79	20.53	5603	476.06	479.25	502.33	16.17	6101	501.11	503.41	517.09	16.13	5365	515.53	518.60	526.41	15.30	5989	525.07	527.67	535.18	14.22	4828	534.18	536.16
	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	425.41	11.54	5340	424.41	426.45	433.56	11.97	4716	432.73	434.53	444.71	13.69	3674	443.76	446.30	458.23	13.47	4061	456.75	459.53	479.75	19.79	3305	477.93	481.39
2	456.12	7.81	4438	455.45	456.89	467.16	7.71	5050	466.53	468.01	476.96	7.95	4858	476.38	477.53	492.34	8.10	4477	491.84	492.97	520.04	14.58	6418	519.20	520.79
3	471.46	4.39	5560	471.03	471.89	481.61	4.43	5433	481.31	481.92	493.45	4.74	6281	493.07	493.76	507.76	5.95	6460	507.32	508.19	535.30	14.92	6723	534.39	536.61
4	480.08	3.61	4972	479.83	480.33	491.05	4.01	5915	490.80	491.36	502.71	4.46	5688	502.38	502.96	517.26	5.53	6676	516.91	517.56	543.14	14.47	6386	541.92	544.11
5	488.11	3.40	5453	487.85	488.35	498.18	3.74	6103	497.86	498.46	509.59	3.91	5571	509.39	509.94	524.47	5.18	5255	524.18	524.94	550.09	13.34	5307	549.16	550.97
6	494.60	3.40	5474	494.35	494.81	505.58	3.62	5637	505.31	505.85	517.01	4.39	4890	516.71	517.32	531.87	5.52	5699	531.34	532.33	556.12	14.61	4936	554.52	557.87
7	502.33	3.44	5133	502.01	502.63	512.59	4.11	4879	512.19	512.93	524.08	4.24	5127	523.76	524.42	538.81	5.91	4941	538.10	539.30	563.12	12.61	5486	562.34	563.89
8	509.56	4.03	4962	509.23	509.87	520.30	4.10	4504	520.03	520.65	531.87	4.50	6404	531.59	532.12	546.28	5.31	4859	545.84	546.66	571.48	12.70	4544	570.40	572.30
9	520.89	4.70	5227	520.59	521.24	531.07	5.04	4893	530.68	531.45	542.86	5.65	4804	542.36	543.37	556.91	6.21	4980	556.52	557.41	583.54	14.43	5031	582.44	584.59
10	544.85	14.19	5629	544.08	546.08	555.53	14.02	5254	554.71	556.70	567.75	14.86	4736	566.69	568.95	582.19	14.44	4606	581.32	583.47	604.60	15.96	3955	603.14	606.04

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 11: Descriptive statistics for expected educational achievements per cells for Lithuania

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	354.29	30.99	455	351.22	358.26	384.00	26.04	332	380.22	387.33	407.39	22.76	317	404.06	410.09	418.83	20.71	314	415.75	421.65	423.13	29.28	318	419.38	426.24
2	395.83	10.28	340	394.40	397.12	417.25	4.99	317	416.47	417.89	430.12	4.23	341	429.46	430.64	440.55	4.32	268	439.88	441.11	450.57	3.86	352	449.96	451.13
3	405.04	12.66	275	402.73	407.28	425.92	4.76	345	425.25	426.55	436.47	3.65	257	435.83	437.11	448.77	4.04	315	448.17	449.37	459.10	3.95	342	458.56	459.61
4	411.67	9.94	323	410.46	412.85	431.35	4.93	275	430.71	432.00	444.60	3.79	351	444.12	445.26	455.95	3.55	309	455.31	456.47	464.71	3.29	382	464.29	465.17
5	418.00	13.27	273	416.41	419.83	437.99	4.36	391	437.38	438.61	449.22	3.24	365	448.81	449.66	460.46	3.24	285	459.91	460.99	471.70	3.61	347	471.27	472.21
6	420.82	13.41	242	418.30	423.58	442.29	4.44	314	441.65	442.92	455.64	3.67	337	455.04	456.09	466.27	3.73	323	465.73	466.87	477.09	3.98	353	476.62	477.75
7	428.98	14.22	215	426.48	431.45	448.22	4.43	328	447.42	448.84	460.38	3.11	329	459.93	460.76	471.75	3.78	339	471.23	472.32	481.87	3.32	315	481.40	482.39
8	433.01	9.91	390	431.71	434.13	455.11	4.36	374	454.45	455.61	467.49	4.07	282	466.74	468.11	478.30	3.68	324	477.70	478.88	488.44	3.89	311	487.79	489.02
9	441.72	13.05	364	439.89	443.49	462.16	4.85	307	461.39	462.82	474.93	4.14	352	474.24	475.59	486.28	4.53	416	485.69	486.97	496.45	4.25	295	495.91	497.17
10	456.33	21.19	448	454.66	458.78	478.03	11.81	318	475.83	479.44	490.45	8.14	359	489.22	491.69	504.09	11.81	396	502.59	506.13	513.48	10.51	297	512.20	514.53
	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	440.11	22.08	252	436.25	443.72	450.01	20.11	338	446.57	453.21	461.59	21.89	311	457.28	464.40	475.32	20.45	312	472.48	478.15	500.75	20.77	366	497.51	503.53
2	462.15	3.31	352	461.78	462.65	472.10	3.46	287	471.55	472.75	481.76	4.25	338	481.17	482.39	495.33	4.64	310	494.55	495.95	516.22	13.64	391	514.34	518.02
3	470.19	3.89	414	469.75	470.71	480.40	2.74	332	480.06	480.74	491.42	3.67	402	490.97	491.86	504.26	4.26	310	503.71	504.83	523.33	11.56	313	522.18	524.68
4	476.47	3.13	322	475.95	476.91	487.78	3.72	343	487.21	488.28	497.09	4.52	257	496.47	497.83	511.65	3.72	300	511.06	512.20	533.51	11.98	441	531.36	535.02
5	481.55	3.43	415	480.92	482.02	492.43	3.17	288	491.89	492.97	503.62	3.83	239	502.80	504.27	514.80	3.98	385	514.50	515.27	536.74	12.39	325	534.92	538.64
6	487.28	3.73	320	486.82	487.76	498.39	3.63	380	497.90	498.90	508.14	3.41	374	507.74	508.70	521.80	3.82	330	521.21	522.27	540.89	11.29	371	539.20	542.32
7	493.51	3.94	304	492.99	493.98	504.04	3.57	346	503.57	504.51	514.12	3.48	342	513.49	514.49	526.68	4.45	369	526.10	527.22	547.50	13.41	382	545.80	549.38
8	498.63	3.35	351	498.12	499.10	509.02	4.21	273	508.37	509.67	520.47	3.36	334	520.00	521.03	533.49	4.80	396	532.98	534.19	550.58	12.37	259	547.95	553.22
9	507.14	4.25	323	506.55	507.82	518.56	3.94	367	518.13	519.10	528.95	4.67	351	528.30	529.73	541.04	4.07	295	540.52	541.59	561.51	10.88	254	559.80	563.53
10	524.06	12.76	243	521.70	526.21	533.42	10.01	340	531.85	534.57	545.91	10.56	352	544.62	547.31	556.44	8.78	318	555.09	557.49	574.39	11.08	208	572.67	576.45

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 12: Descriptive statistics for expected educational achievements per cells for Luxembourg

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	353.96	8.84	30	352.39	355.48	371.38	8.92	32	369.81	373.06	387.46	9.44	28	385.45	389.11	398.52	11.21	61	397.09	399.77	413.75	11.59	69	412.54	415.00
2	369.77	8.98	71	368.40	370.70	388.37	6.00	78	387.66	388.98	402.87	5.44	73	402.17	403.66	417.47	5.71	91	416.93	418.03	433.18	6.41	69	432.37	433.93
3	381.69	8.72	141	380.95	382.40	401.98	6.32	109	401.29	402.62	416.55	5.41	102	416.08	417.03	429.69	5.36	80	429.26	430.32	445.62	5.59	45	444.63	446.43
4	398.41	10.70	65	397.10	399.77	419.10	8.00	49	417.81	420.21	432.59	7.53	43	431.22	433.77	449.27	8.10	33	447.94	450.50	468.95	8.07	33	467.35	470.73
5	417.38	9.47	14	414.20	420.05	440.28	5.97	11	438.42	441.90	456.94	3.95	13	455.79	457.91	470.31	5.60	20	469.00	471.48	486.21	5.54	35	485.45	487.13
6	427.01	7.11	11	425.10	429.08	450.45	5.12	17	449.49	451.69	461.48	5.41	16	460.25	463.12	479.54	5.01	37	478.80	480.46	495.84	4.45	41	495.24	496.71
7	436.72	8.78	21	434.64	438.76	458.39	4.24	28	457.59	459.09	472.86	4.26	56	472.34	473.35	487.47	5.58	68	486.80	488.08	501.55	5.06	72	501.00	501.99
8	444.94	8.38	42	443.63	446.54	465.41	4.42	46	464.77	466.19	479.20	4.69	58	478.65	479.69	494.73	5.74	52	493.87	495.63	510.23	4.73	71	509.62	510.77
9	453.69	7.63	72	452.61	454.52	474.87	6.01	89	474.24	475.50	489.04	4.58	85	488.58	489.52	503.96	5.57	65	503.31	504.62	520.02	5.37	64	519.44	520.74
10	472.49	17.17	101	471.05	474.24	493.60	13.63	101	492.13	495.02	509.12	15.25	68	506.87	510.09	525.96	14.75	63	524.18	528.30	538.43	14.38	46	536.43	540.90

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	429.05	11.54	68	427.99	430.69	443.50	10.61	79	442.08	444.66	457.10	14.43	67	455.31	458.78	473.73	12.72	70	472.26	475.17	494.88	17.99	60	492.50	497.50
2	445.47	6.13	58	444.52	446.36	462.53	5.63	47	461.67	463.57	481.59	5.43	29	480.34	482.71	493.73	7.17	21	492.31	495.38	524.15	4.68	6	522.62	525.85
3	463.17	5.33	28	462.13	464.49	478.90	6.39	24	477.57	480.08	493.13	7.10	13	491.01	495.29	511.06	8.27	13	509.37	513.69	540.35	19.72	8	534.90	543.07
4	484.75	9.49	34	483.20	486.61	503.97	7.87	42	503.11	505.34	520.24	8.65	52	519.21	521.31	536.40	8.16	78	535.38	537.23	564.61	15.28	113	563.26	565.96
5	501.10	5.21	64	500.42	501.67	517.38	5.12	80	516.76	518.03	532.54	5.86	86	531.94	533.09	549.53	5.78	117	549.00	550.11	574.79	11.84	104	573.66	575.71
6	510.26	5.68	73	509.60	510.82	525.33	5.00	77	524.71	525.85	542.62	5.04	90	542.14	543.17	558.63	5.83	111	558.02	559.09	582.06	11.89	80	580.99	583.21
7	517.41	4.46	53	516.74	518.11	532.95	4.68	71	532.46	533.53	549.16	5.16	72	548.62	549.68	565.67	5.81	68	565.26	566.43	590.12	12.21	58	588.49	591.34
8	524.92	5.22	61	524.31	525.58	541.60	4.73	58	541.05	542.10	556.22	4.65	50	555.68	556.78	574.31	5.63	41	573.23	575.13	596.10	9.72	50	594.83	597.51
9	535.57	6.11	64	534.98	536.47	552.60	5.55	39	551.84	553.81	568.06	5.89	44	567.09	569.08	585.87	6.50	29	584.65	586.81	605.36	11.22	25	602.79	607.72
10	557.76	15.83	47	555.77	559.51	573.09	20.12	31	568.58	577.22	586.00	12.20	49	584.77	587.87	605.43	10.40	18	603.07	607.89	630.85	13.74	18	627.43	634.35

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 13: Descriptive statistics for expected educational achievements per cells for The Netherlands

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	392.17	16.38	1903	389.66	394.65	422.23	10.30	1992	420.49	423.94	439.05	10.63	2131	437.24	440.52	450.27	9.53	1958	449.22	451.79	464.52	9.87	1810	463.29	465.96
2	405.48	17.38	2836	403.54	407.32	436.98	6.92	3504	436.28	437.90	455.32	6.36	2401	454.41	456.24	470.32	6.19	2342	469.00	471.39	482.69	5.97	1576	481.82	483.54
3	416.61	17.08	2332	414.78	419.05	452.19	5.45	1649	451.37	453.20	471.16	6.32	1999	470.26	472.04	486.66	5.69	1575	485.88	487.71	497.54	5.57	1966	496.79	498.35
4	432.96	15.98	1507	430.50	434.94	465.43	6.44	986	464.18	466.31	483.61	4.94	1919	482.78	484.42	497.49	4.08	1815	496.70	498.07	508.57	3.99	2391	508.11	509.03
5	432.14	22.11	926	427.02	437.61	473.02	6.65	1585	471.95	473.88	491.93	5.29	1851	491.10	492.81	505.00	4.84	2107	504.24	505.74	517.29	3.25	1403	516.69	517.96
6	449.22	17.98	1625	446.22	452.34	480.43	7.03	1775	479.13	481.56	497.40	5.33	1662	496.41	498.42	512.43	4.00	1615	511.82	513.15	524.06	3.91	2060	523.49	524.67
7	451.11	17.32	1677	448.77	453.56	484.33	6.99	1867	482.92	485.59	505.48	4.75	1784	504.92	506.11	517.96	3.99	1792	517.39	518.63	531.24	4.23	2253	530.63	532.04
8	461.79	14.06	2260	459.71	463.80	494.27	6.83	2155	493.22	495.06	511.24	6.32	2086	510.04	512.09	525.85	4.27	2431	525.13	526.41	539.76	4.67	1770	538.99	540.18
9	468.71	21.58	2017	464.24	472.78	505.57	6.50	2226	504.77	506.37	522.06	5.46	1814	521.15	522.96	535.99	5.58	1741	534.87	536.87	548.89	5.30	2103	548.12	549.88
10	502.91	26.50	2539	500.31	506.14	531.53	17.34	1951	528.47	535.03	549.27	24.91	1931	545.24	553.40	563.65	21.51	2326	560.29	566.55	575.13	18.24	2282	572.56	577.71

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	473.71	9.87	2257	472.20	475.35	485.20	9.74	1967	483.92	486.60	496.13	7.41	1659	494.98	497.50	511.58	9.09	2170	509.89	512.55	537.53	17.42	1840	534.71	539.69
2	493.16	5.85	1579	492.56	493.93	505.09	5.57	1299	504.27	506.19	519.19	6.36	1318	516.94	520.26	532.47	6.76	1560	531.29	533.34	554.76	9.45	1152	551.26	556.92
3	508.92	6.18	1419	507.74	509.92	521.63	5.27	2397	520.75	522.50	533.38	4.98	2203	532.71	534.14	548.51	5.14	1672	548.13	549.58	574.94	12.23	2464	573.22	576.89
4	522.51	5.02	1895	521.76	523.25	533.54	4.25	1811	533.04	534.16	544.83	4.85	2850	544.15	545.54	559.18	4.77	2124	558.45	560.03	588.75	14.61	2327	586.42	591.13
5	530.43	4.14	2703	529.83	531.05	539.68	4.06	2426	539.26	540.24	554.59	4.18	2371	553.53	555.09	568.29	5.32	1956	567.71	569.24	591.08	10.53	2341	589.17	592.72
6	535.62	3.60	2403	535.19	536.07	548.47	3.62	2161	547.84	549.05	559.65	4.15	1633	559.21	560.26	574.85	5.01	2350	574.02	575.56	597.66	10.58	2284	596.21	599.17
7	542.48	4.76	2218	541.77	543.28	553.32	3.65	2270	552.77	553.85	567.06	3.33	2089	566.41	567.59	579.90	5.36	1645	578.83	580.77	603.02	9.80	1997	601.14	604.90
8	551.41	4.33	1779	550.86	552.04	563.03	4.07	1745	562.22	563.70	575.19	4.66	1586	574.43	576.09	589.21	6.54	1983	588.35	590.18	609.68	8.85	1822	607.44	611.43
9	561.82	5.50	1983	561.08	563.00	572.59	5.27	2058	571.65	573.35	586.56	6.15	2103	585.42	587.61	602.19	6.32	2117	601.01	603.17	623.31	12.05	1478	620.99	624.63
10	588.46	19.59	1425	585.20	591.88	598.34	21.68	1439	597.82	601.91	615.75	29.27	1817	611.04	620.08	623.98	18.48	2029	622.04	626.28	646.63	24.29	1882	643.01	651.36

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 14: Descriptive statistics for expected educational achievements per cells for Norway

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	362.34	31.69	573	358.42	366.43	380.14	29.77	622	375.96	384.30	390.00	33.14	449	384.88	395.77	403.50	35.09	704	398.79	408.46	415.88	22.15	471	412.48	419.30
2	393.83	19.27	540	390.09	396.51	420.27	6.59	632	419.43	421.08	433.17	6.77	650	432.40	434.10	444.99	5.43	599	444.22	445.82	453.41	6.18	554	452.54	454.39
3	411.43	15.40	632	409.99	414.16	435.91	4.35	588	435.38	436.52	445.32	4.45	538	444.31	446.21	458.43	4.18	546	457.70	459.02	467.68	4.27	575	467.21	468.25
4	418.69	18.18	640	416.12	421.70	444.86	4.96	505	444.21	445.61	457.94	4.41	666	457.34	458.36	467.60	4.63	722	466.91	468.26	477.08	3.31	823	476.91	477.66
5	427.28	16.23	543	425.34	429.53	454.48	5.08	621	453.87	455.29	466.70	3.62	468	466.21	467.23	477.58	3.75	528	477.03	478.16	486.35	3.11	677	485.87	486.71
6	439.95	13.88	641	438.18	441.97	463.79	4.89	477	462.93	464.66	475.50	4.48	562	474.80	476.20	485.57	3.68	726	485.03	486.14	494.06	3.73	512	493.45	494.70
7	449.15	18.74	535	446.42	452.50	471.87	4.37	588	471.14	472.50	483.90	4.67	572	483.16	484.51	494.19	3.79	620	493.73	494.76	503.24	3.90	646	502.86	503.85
8	458.92	15.15	704	456.95	460.90	481.71	5.12	846	481.14	482.50	494.87	3.90	590	494.41	495.34	505.72	4.37	469	505.05	506.43	513.56	3.87	553	512.98	513.95
9	467.38	21.69	545	464.82	469.79	495.71	6.67	697	494.59	496.42	508.40	5.63	689	507.75	509.26	517.78	6.07	487	516.93	518.82	527.17	5.39	574	526.56	527.98
10	506.34	34.81	588	500.75	512.19	530.92	28.01	366	525.67	535.61	545.60	32.72	754	541.74	548.78	554.94	26.47	551	551.44	558.71	556.69	22.02	595	553.84	559.32

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	420.30	28.14	716	416.20	424.62	426.58	32.70	664	421.87	430.64	431.54	35.93	572	426.59	436.77	445.74	27.46	654	442.09	449.60	464.57	26.83	527	460.45	469.41
2	459.73	6.00	538	458.64	460.72	467.94	5.29	603	467.33	468.66	473.93	5.70	636	473.25	474.77	481.04	7.28	641	479.99	482.16	498.88	9.95	536	497.52	500.46
3	473.81	3.51	524	473.28	474.19	480.79	3.89	440	480.24	481.39	488.07	3.70	840	487.58	488.52	495.41	3.88	619	494.81	495.99	514.26	10.35	643	512.43	515.95
4	484.27	3.43	806	483.86	484.70	490.08	3.47	407	489.58	490.61	498.13	2.99	394	497.65	498.68	505.66	4.06	527	504.94	506.37	523.44	12.69	469	520.90	525.94
5	493.14	3.68	526	492.51	493.71	499.57	2.93	689	499.24	499.89	505.99	3.46	641	505.53	506.42	514.60	3.90	580	514.00	515.13	534.12	13.04	674	531.65	536.41
6	501.73	3.21	617	501.22	502.16	508.43	3.16	723	508.03	508.77	515.19	3.52	591	514.67	515.80	523.87	3.41	572	523.41	524.50	538.44	10.77	515	536.91	540.24
7	510.63	3.05	641	510.20	511.12	516.45	3.32	668	515.99	516.93	524.56	3.93	653	524.02	525.09	533.10	4.02	525	532.51	533.69	547.83	9.49	616	546.45	549.51
8	519.52	3.39	360	518.99	520.21	528.99	3.32	556	528.56	529.62	534.62	3.88	626	534.03	535.13	542.14	5.14	538	541.19	543.20	555.97	8.97	566	554.39	557.58
9	533.68	5.25	532	532.93	534.41	540.94	5.10	536	540.05	541.62	548.36	5.32	509	547.66	549.04	556.92	4.60	681	556.37	557.38	569.85	9.37	697	568.46	571.07
10	567.64	25.56	682	564.54	570.95	574.86	21.76	634	571.05	577.67	586.39	34.36	484	581.68	591.65	593.35	29.54	609	589.33	597.75	610.95	32.59	678	607.58	615.42

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 15: Descriptive statistics for expected educational achievements per cells for Portugal

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	343.68	12.15	216	339.78	347.32	361.93	14.76	464	359.11	365.10	374.83	6.53	521	373.86	376.11	383.99	6.02	1094	383.23	384.74	390.03	10.89	952	388.30	391.95
2	362.55	9.95	1192	361.24	363.84	381.03	6.29	1538	380.18	381.76	391.71	6.54	1551	390.94	392.43	402.85	5.73	1403	401.89	403.54	413.63	5.33	1382	412.90	414.35
3	377.86	12.33	2379	376.72	378.86	397.27	7.25	2530	396.65	397.99	409.48	7.29	2052	408.64	410.46	420.37	6.68	972	419.31	421.44	428.27	6.90	589	427.07	429.53
4	388.93	15.74	2172	387.39	390.55	416.33	9.21	882	414.67	418.27	428.29	5.67	364	427.81	429.39	439.99	10.40	186	436.68	443.11	453.47	7.89	430	451.86	455.08
5	411.23	8.80	157	409.04	414.49	441.15	6.94	109	438.54	443.72	454.20	7.93	224	451.50	455.98	466.33	7.71	268	463.76	468.80	478.30	5.05	313	476.97	479.52
6	417.78	36.06	101	402.28	426.60	453.06	4.75	139	450.27	455.26	469.95	3.83	254	468.73	471.06	478.18	3.77	620	477.54	478.81	489.98	3.88	786	489.57	490.68
7	454.85	6.52	66	453.07	457.77	463.50	6.30	304	461.97	464.91	478.17	4.31	820	477.49	478.96	488.55	3.91	1084	488.06	489.03	499.40	4.54	1129	498.85	499.94
8	461.43	7.11	513	460.11	462.68	476.87	5.32	870	476.02	477.70	488.55	4.46	1066	487.90	489.18	499.27	4.03	1159	498.61	499.75	511.17	3.97	1393	510.65	511.58
9	469.16	9.89	815	467.50	471.09	489.68	6.28	1224	488.82	490.50	502.51	5.40	1227	501.79	503.38	512.08	4.39	1689	511.54	512.61	523.07	5.40	1395	522.29	523.72
10	491.98	21.17	1993	489.22	495.39	515.92	18.48	1508	514.23	517.59	523.72	13.34	1533	522.04	525.88	536.29	17.16	1138	534.82	538.41	544.98	14.75	1179	542.89	546.88

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	401.65	15.27	1527	399.75	403.74	415.60	11.55	1706	414.28	416.94	430.28	13.38	1620	429.07	431.64	447.06	12.47	970	445.45	448.93	475.10	17.12	526	471.40	479.09
2	423.69	6.38	1259	422.96	424.41	436.10	6.09	850	435.17	437.27	451.89	6.00	350	450.56	453.40	473.24	2.27	45	472.46	474.05	516.78	18.52	86	509.70	524.02
3	442.86	7.29	505	440.85	444.42	454.25	10.13	176	451.11	457.52	469.36	8.85	73	467.09	472.19	496.09	5.24	37	493.84	498.11	541.44	22.79	243	535.26	547.58
4	464.97	6.13	197	463.70	466.29	489.30	6.65	423	488.36	490.19	506.17	7.64	699	505.13	507.10	528.78	9.65	1635	527.69	530.39	562.88	19.69	2603	561.04	564.48
5	489.45	6.23	787	488.39	490.49	504.64	6.65	907	503.75	505.88	522.51	7.36	1968	521.88	523.22	545.19	8.67	2422	544.49	546.01	576.83	15.73	2479	575.52	577.59
6	502.51	4.68	820	501.65	503.49	515.07	5.81	1673	514.60	515.73	534.63	5.65	1718	534.04	535.45	555.98	7.98	1932	555.06	556.77	589.06	13.12	1554	586.85	591.14
7	512.83	5.16	1245	512.19	513.41	525.99	5.52	1519	525.30	526.53	543.67	6.99	1170	542.79	544.37	566.11	8.01	1245	565.09	567.30	601.07	15.02	1026	598.71	603.26
8	522.46	4.74	1638	521.76	523.06	535.30	5.49	1138	534.43	536.21	554.90	6.80	782	553.59	556.30	577.70	7.93	659	575.98	579.24	613.34	14.31	448	610.21	617.36
9	533.37	6.16	953	532.68	534.29	547.83	6.84	841	547.19	548.58	565.20	7.24	841	564.16	566.18	589.40	8.46	286	586.57	592.16	617.86	9.61	294	616.07	619.81
10	554.87	10.21	749	553.32	556.60	571.26	10.37	337	568.58	573.12	591.87	11.42	440	589.61	594.11	616.58	10.21	341	614.43	619.11	651.73	17.83	351	648.15	656.53

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 16: Descriptive statistics for expected educational achievements per cells for Romania

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	346.23	15.20	1154	343.11	349.02	371.04	7.51	912	369.59	372.25	385.38	4.63	836	384.49	386.28	390.70	7.66	912	389.54	392.20	400.51	6.09	1257	399.97	401.31
2	364.16	13.57	734	361.10	366.85	384.07	4.31	1274	383.45	384.65	395.21	2.77	1141	394.80	395.71	402.68	2.81	1897	402.32	403.06	410.09	3.24	1546	409.63	410.59
3	371.54	13.77	1187	368.52	373.53	390.28	3.70	1533	389.62	390.84	400.62	2.53	1802	400.30	400.98	408.97	2.47	1429	408.67	409.34	417.08	2.84	1753	416.80	417.45
4	372.82	15.56	1730	370.36	375.43	395.76	4.09	1556	395.31	396.24	405.96	2.68	1331	405.62	406.38	414.41	2.55	1526	414.08	414.72	421.84	2.76	1630	421.40	422.24
5	382.12	10.55	1781	380.38	383.57	401.46	3.52	2042	401.07	401.87	410.84	3.10	1634	410.48	411.24	418.75	3.10	1491	418.32	419.17	427.13	2.58	1216	426.72	427.43
6	381.44	17.45	1623	378.48	384.50	406.43	4.41	1768	406.03	407.11	416.09	3.06	1735	415.76	416.44	424.69	3.17	895	424.14	425.16	432.67	2.81	1738	432.41	433.13
7	386.58	17.45	1879	384.68	389.06	412.98	4.18	1603	412.43	413.42	422.78	2.88	1928	422.43	423.08	430.90	3.29	1511	430.49	431.26	438.95	3.27	1175	438.57	439.26
8	388.08	25.73	1498	382.95	393.83	420.83	4.49	1091	420.32	421.49	430.20	4.27	1500	429.70	430.66	438.87	3.86	1592	438.21	439.36	446.29	3.70	1538	445.80	446.82
9	406.24	24.32	1814	402.72	409.88	430.55	4.64	1254	430.00	431.26	442.80	5.39	796	441.90	443.91	450.56	5.33	1529	449.94	451.07	459.68	5.61	1027	458.70	460.41
10	434.78	32.48	671	427.58	441.56	464.27	20.97	1240	462.01	467.13	470.70	20.26	1273	467.90	473.06	486.14	20.05	1408	483.31	489.01	491.57	21.50	1166	488.84	495.18

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	409.21	6.24	1066	408.21	410.12	419.05	9.55	1536	417.58	420.78	436.55	9.35	1727	435.28	437.96	456.76	8.34	2389	455.75	457.79	488.41	18.35	2408	485.56	490.98
2	420.51	3.74	1577	420.04	420.96	431.54	4.86	1261	430.83	432.15	448.19	5.93	1725	447.33	448.96	467.28	5.76	1278	466.41	468.10	492.53	12.41	1560	490.94	494.48
3	425.80	3.79	1338	425.21	426.31	436.97	4.28	1262	436.32	437.60	454.63	5.49	1505	454.01	455.31	471.75	5.75	1221	470.91	472.49	501.31	15.75	1147	498.32	503.81
4	430.54	3.20	1354	430.11	431.00	441.77	4.22	1293	441.18	442.45	459.93	5.91	1293	459.05	460.79	478.40	4.71	1232	477.70	479.13	508.02	19.04	1046	505.00	511.25
5	436.28	3.21	1494	435.87	436.68	448.03	4.73	1224	447.32	448.54	464.39	4.74	1185	463.84	465.03	481.81	5.77	1023	480.65	482.89	512.37	16.33	1174	509.80	515.18
6	441.06	3.24	1516	440.70	441.48	454.32	4.35	1613	453.84	454.93	469.98	6.29	1259	469.06	470.80	489.11	5.85	817	488.03	490.31	517.90	16.29	985	515.79	519.59
7	447.61	3.28	1078	447.16	448.08	461.72	4.86	1378	461.08	462.44	476.26	5.25	1107	475.27	477.06	495.64	5.92	1353	494.76	496.57	527.97	15.49	1066	525.55	530.32
8	456.04	4.13	1488	455.45	456.60	469.47	4.58	1467	468.90	469.99	484.21	6.12	1109	482.97	485.10	504.11	5.89	1430	503.22	505.03	532.63	15.66	1362	530.17	535.26
9	466.77	4.80	1773	466.19	467.37	480.31	7.14	1567	479.05	481.48	495.27	7.66	1601	494.40	496.32	514.74	6.54	1532	513.93	515.78	543.33	17.58	1220	540.92	545.60
10	507.42	23.63	1232	503.27	511.40	516.71	22.28	1517	512.35	519.93	530.36	21.80	1584	527.97	533.41	547.36	19.79	1835	545.55	548.90	574.63	23.42	2155	570.65	576.78

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 17: Descriptive statistics for expected educational achievements per cells for Spain

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	360.29	12.02	1099	357.49	362.69	375.10	12.11	1855	373.68	376.54	386.97	8.94	3379	386.11	387.98	394.61	9.09	3785	393.78	395.44	406.24	9.01	4348	405.44	407.01
2	374.74	12.12	4902	373.31	375.97	393.06	6.47	6035	392.39	393.84	405.13	6.06	6057	404.84	405.84	414.78	5.68	5593	414.43	415.27	424.48	5.51	5094	423.88	425.00
3	386.49	14.53	10148	385.68	387.47	410.93	6.97	8128	410.44	411.31	423.18	6.38	6069	422.58	423.73	433.45	6.90	4672	432.63	434.10	441.03	6.57	2714	440.11	441.68
4	400.40	17.57	6006	398.64	402.49	430.19	8.14	2019	428.97	431.46	444.31	7.28	1690	443.41	445.38	457.46	7.11	1297	456.42	458.72	469.09	7.22	1329	467.72	470.79
5	416.84	24.17	1133	412.47	420.80	447.00	5.53	796	445.57	448.49	462.86	4.26	586	461.99	463.68	473.23	4.38	1232	472.44	474.18	482.93	3.68	2619	482.55	483.31
6	430.71	16.00	678	427.31	433.83	459.47	4.41	1557	458.72	460.13	471.89	3.77	2533	471.42	472.33	481.37	4.16	2885	480.87	481.84	491.33	3.47	3008	490.99	491.63
7	449.79	7.93	571	448.66	450.76	466.90	5.10	1926	466.03	467.65	478.84	3.59	2772	478.39	479.30	489.78	3.52	4151	489.50	490.07	499.15	3.75	4847	498.90	499.44
8	457.74	9.00	1963	456.56	458.96	475.55	5.00	3577	475.04	476.18	488.47	4.11	3509	488.08	488.81	498.79	4.07	4774	498.54	499.09	508.92	3.84	5069	508.65	509.21
9	464.24	15.28	3386	462.27	466.11	485.81	5.75	4878	485.35	486.23	498.69	4.23	5078	498.42	499.03	508.87	4.69	4969	508.45	509.27	518.90	4.76	4717	518.53	519.39
10	480.86	19.54	7682	479.92	482.29	506.14	12.87	6765	505.35	506.84	517.99	13.52	5303	516.52	519.47	529.00	12.34	4025	527.68	529.84	539.51	14.31	3581	537.95	540.98

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	415.89	9.01	5966	415.24	416.58	425.04	10.22	5091	424.13	425.93	436.14	11.95	4526	434.79	437.07	448.12	11.97	3387	446.52	449.39	463.88	15.28	3926	462.58	465.10
2	435.04	5.78	3786	434.37	435.76	444.16	5.75	2844	443.52	444.87	458.60	5.97	1587	457.77	459.52	471.62	6.53	952	470.52	472.77	490.52	9.18	476	488.17	492.71
3	453.79	6.31	1764	452.91	454.65	467.89	6.83	1307	466.82	469.00	479.09	8.64	931	477.37	480.70	499.15	7.87	627	497.31	500.54	527.13	16.02	1156	524.62	529.41
4	481.78	4.91	1661	481.22	482.40	493.78	5.75	2542	493.27	494.23	504.43	6.13	5252	504.05	504.86	518.95	6.55	6932	518.51	519.42	540.78	13.22	8879	539.83	541.73
5	494.13	3.94	3868	493.86	494.38	504.86	4.65	4947	504.45	505.24	517.52	4.93	5870	517.25	517.84	531.62	5.36	8168	531.32	531.94	552.18	9.02	7959	551.68	552.74
6	502.47	3.76	3678	502.14	502.77	513.97	4.23	5451	513.64	514.26	526.23	4.38	6215	525.89	526.62	540.84	4.87	6305	540.35	541.06	561.47	10.10	5165	560.21	562.23
7	510.28	4.04	5116	509.91	510.61	521.73	3.88	4800	521.41	522.01	534.41	4.32	4783	533.94	534.69	548.30	5.48	3990	547.86	548.81	569.71	10.62	4193	568.93	570.59
8	518.40	4.20	4362	518.08	518.79	530.27	4.26	4927	529.94	530.60	542.61	4.04	3363	542.42	543.11	557.59	5.15	3673	557.09	558.25	576.95	9.78	2135	575.87	578.51
9	528.78	4.04	4457	528.56	529.17	538.97	4.44	3165	538.68	539.45	553.04	5.48	2587	552.57	553.52	566.36	6.23	2105	565.62	567.10	589.39	9.31	2031	588.20	590.36
10	549.96	13.77	2919	548.51	551.33	562.75	14.76	2104	560.98	564.32	573.06	11.81	2230	571.63	574.54	588.55	16.51	1342	585.66	591.40	611.37	13.10	1404	608.86	613.25

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 18: Descriptive statistics for expected educational achievements per cells for Sweden

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	332.87	29.72	1324	329.50	337.26	373.74	25.70	1154	370.57	376.60	386.09	29.87	784	381.26	390.29	392.12	22.49	941	388.51	395.55	406.39	28.28	895	400.15	411.60
2	368.64	16.70	760	365.55	371.58	408.66	7.31	913	407.69	409.71	420.19	6.39	1057	419.36	420.90	431.58	5.58	893	430.97	432.34	443.62	5.58	999	442.86	444.30
3	387.07	16.41	623	383.47	389.92	419.44	7.25	718	418.13	420.41	432.79	4.11	999	432.31	433.21	447.24	4.62	959	446.51	447.82	457.24	4.76	981	456.51	457.76
4	399.47	12.89	813	397.23	401.37	429.52	5.95	1150	428.82	430.20	443.48	4.30	1222	442.92	444.06	454.52	4.39	985	453.74	455.19	468.28	3.83	900	467.73	468.76
5	405.81	12.84	962	404.05	407.47	437.01	6.38	736	435.79	438.11	452.04	4.31	804	451.05	452.66	464.18	4.13	1269	463.71	464.59	476.83	3.64	1149	476.43	477.30
6	413.14	14.30	938	410.66	415.71	446.13	4.71	954	445.32	446.86	460.05	3.42	953	459.52	460.53	472.27	4.03	742	471.53	472.97	483.00	3.04	848	482.52	483.47
7	417.82	13.43	769	415.78	420.98	452.81	5.55	1123	452.04	453.53	466.21	4.05	956	465.64	466.79	477.94	4.06	1087	477.25	478.45	490.49	3.49	1057	490.06	491.00
8	425.92	12.08	963	424.09	427.79	460.85	6.86	845	459.49	461.87	475.26	4.24	801	474.64	475.87	486.66	4.03	773	486.10	487.23	497.97	4.34	1028	497.48	498.44
9	440.06	16.11	1146	437.73	442.62	473.90	7.49	1116	472.86	474.99	487.32	5.54	1124	486.72	488.09	499.55	6.32	1066	498.81	500.38	512.14	5.65	779	511.35	512.93
10	474.78	35.27	1198	470.29	478.79	510.16	26.11	766	505.78	513.84	521.52	28.28	819	517.23	525.98	533.40	24.10	788	530.66	537.13	545.19	31.51	909	540.51	549.87

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	421.88	26.72	629	417.57	426.70	435.76	19.65	802	433.08	438.27	441.86	18.71	885	438.88	445.39	444.44	26.98	882	440.92	447.85	462.83	26.87	1199	459.94	465.80
2	454.61	5.33	857	453.85	455.26	462.95	5.70	1061	462.16	463.76	471.73	5.32	926	470.90	472.47	479.79	4.54	981	479.12	480.51	494.16	11.20	1148	492.49	496.25
3	467.56	3.60	1189	467.20	467.98	476.49	3.50	857	475.90	476.94	483.72	3.97	994	483.13	484.25	493.07	4.15	1165	492.63	493.62	507.24	8.89	891	505.88	508.61
4	476.94	4.34	853	476.35	477.46	485.54	3.87	770	484.97	486.11	493.64	4.14	901	493.03	494.14	503.15	3.54	905	502.51	503.76	519.74	9.57	1046	518.56	520.93
5	486.10	3.04	1139	485.65	486.58	494.42	3.48	932	493.89	494.86	502.17	3.54	1105	501.67	502.71	511.56	4.27	735	511.04	512.17	524.87	8.31	769	523.61	526.14
6	493.18	2.84	1261	492.81	493.50	502.28	3.68	1022	501.76	502.85	510.97	2.98	1087	510.59	511.40	519.32	3.09	964	518.85	519.72	533.73	8.06	755	532.70	534.90
7	500.34	3.47	901	499.88	500.85	509.94	2.88	943	509.56	510.30	518.82	3.93	736	518.01	519.50	526.70	3.81	978	526.17	527.22	542.76	10.93	772	541.19	544.54
8	508.70	3.83	802	508.15	509.36	517.81	3.60	1184	517.35	518.28	527.76	4.45	1116	527.10	528.38	535.13	4.04	1022	534.53	535.74	550.68	9.04	957	549.40	551.85
9	521.09	5.12	866	520.16	522.09	530.23	4.86	928	529.68	530.82	538.30	4.85	830	537.56	539.32	548.53	5.32	755	547.68	549.27	562.51	9.17	881	561.12	563.62
10	551.09	19.06	940	548.70	553.72	564.82	30.07	1017	561.63	570.31	569.94	26.42	876	565.60	573.94	584.91	30.38	1126	580.42	590.09	594.44	26.72	1054	590.04	597.93

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 19: Descriptive statistics for expected educational achievements per cells for Switzerland

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	381.98	18.91	803	380.00	384.08	417.57	12.12	1032	416.10	418.63	437.85	11.54	844	436.67	438.98	449.82	13.16	900	448.58	451.34	462.22	12.05	849	460.88	463.49
2	406.87	17.88	1571	404.92	408.61	443.43	9.87	1097	442.54	444.28	464.29	10.04	919	463.10	465.35	477.62	8.56	844	476.69	478.52	489.44	8.51	657	488.34	490.73
3	439.31	13.49	483	437.30	441.62	470.51	10.06	500	468.65	471.92	491.57	6.56	441	490.53	492.35	505.35	6.28	750	504.49	506.04	517.51	6.50	842	516.73	518.43
4	454.30	11.25	309	451.72	456.98	481.55	8.37	438	480.07	482.71	503.45	4.37	669	502.74	504.05	517.16	3.88	696	516.62	517.64	527.97	4.28	765	527.51	528.56
5	462.54	13.49	327	460.07	464.65	486.97	6.78	532	485.69	488.08	508.78	5.13	940	508.26	509.53	523.39	3.83	880	523.06	523.83	534.11	3.89	1060	533.58	534.66
6	460.19	13.74	491	458.59	461.76	493.37	8.25	706	492.29	494.39	514.22	4.55	910	513.66	514.78	527.82	3.99	744	527.23	528.34	539.57	3.64	801	539.09	539.94
7	466.93	13.91	573	465.08	468.70	498.21	6.78	828	497.20	499.24	519.20	5.11	840	518.76	519.90	533.05	3.69	927	532.66	533.44	544.61	3.75	798	543.98	544.90
8	469.93	18.34	920	467.58	472.61	506.90	7.49	854	505.79	508.18	526.42	5.35	716	525.73	527.04	538.73	3.01	724	538.40	539.12	550.35	3.53	859	549.82	550.91
9	476.68	14.92	1056	475.54	478.08	512.04	7.27	893	511.28	512.61	532.74	4.72	911	532.32	533.15	548.08	4.75	771	547.58	548.48	558.57	3.91	749	558.07	559.05
10	494.69	19.16	1418	492.40	496.55	533.17	17.12	1072	531.71	534.36	549.49	14.31	779	547.98	550.98	563.76	10.25	705	562.85	564.90	576.62	12.40	629	575.24	577.88

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	472.11	12.70	755	470.78	473.38	480.39	12.96	539	478.73	482.17	491.02	13.21	825	489.57	492.17	505.01	11.38	710	503.68	506.43	523.08	16.93	715	521.34	525.13
2	498.97	9.70	701	497.48	500.68	508.82	8.56	688	507.71	509.90	520.02	8.71	567	518.99	521.36	533.86	11.09	416	531.18	536.04	557.79	18.68	496	555.55	560.50
3	529.06	5.14	746	528.43	529.61	538.02	5.73	948	537.31	538.78	548.66	5.61	931	548.21	549.22	560.60	6.42	1077	559.99	561.10	581.95	13.22	1309	580.55	583.36
4	538.77	3.40	982	538.44	539.17	546.98	3.72	1051	546.56	547.46	558.45	4.07	964	557.95	559.03	569.55	4.40	901	569.08	570.07	593.84	13.30	1133	592.42	595.04
5	545.08	3.77	727	544.55	545.49	554.12	3.68	1008	553.75	554.51	564.82	3.62	688	564.39	565.34	578.35	4.38	857	577.83	578.84	598.24	11.66	925	596.43	599.73
6	550.00	2.94	880	549.73	550.25	559.67	3.37	941	559.28	559.99	571.03	3.41	884	570.38	571.59	583.16	4.42	872	582.54	583.67	606.13	15.98	761	604.32	608.11
7	554.12	3.14	824	553.71	554.54	565.32	3.28	659	564.94	565.70	575.40	3.78	995	575.01	575.81	588.60	4.10	708	587.92	589.19	607.85	10.30	788	606.31	609.26
8	560.29	2.78	853	559.99	560.67	570.29	3.10	754	569.90	570.68	580.65	3.65	620	580.11	581.05	593.37	4.26	992	592.76	593.78	611.61	10.86	778	610.67	612.64
9	568.32	4.14	694	567.78	568.94	578.74	3.99	740	578.26	579.24	588.14	4.42	819	587.59	588.66	600.63	5.00	720	600.11	601.27	618.57	10.20	506	617.44	619.85
10	588.09	12.33	792	586.48	589.43	596.97	12.45	615	595.73	598.67	606.60	13.27	704	604.94	608.55	616.91	11.78	677	615.77	618.26	637.43	16.63	562	635.45	639.55

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Table 20: Descriptive statistics for expected educational achievements per cells for the United Kingdom

	Type 1					Type 2					Type 3					Type 4					Type 5				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	361.33	25.42	5811	356.83	367.61	393.68	21.69	6075	391.11	396.72	402.79	24.39	6431	399.88	406.00	413.00	23.88	7341	409.91	415.49	426.38	27.46	5596	422.11	430.21
2	394.47	12.28	6310	392.85	396.49	420.14	6.64	7295	419.46	420.78	434.52	5.29	5581	433.55	435.43	446.81	4.46	6267	446.29	447.44	458.59	4.89	7425	458.06	459.01
3	404.40	12.23	6130	402.57	406.14	431.28	4.67	7537	431.00	432.08	444.58	4.84	7571	443.96	445.06	456.81	4.16	6980	456.35	457.35	468.06	4.47	7830	467.49	468.60
4	413.24	12.48	8769	411.94	414.90	437.83	4.93	6800	437.12	438.42	451.58	4.99	7527	451.10	452.10	464.86	4.28	6266	464.31	465.38	476.84	3.92	8284	476.43	477.29
5	422.12	11.88	7140	421.39	424.03	443.81	5.14	8003	442.87	444.50	458.72	3.50	6856	458.16	459.21	471.29	3.91	6195	470.81	472.00	484.53	3.90	6789	484.20	485.06
6	427.26	12.32	9441	424.64	428.34	452.33	5.15	6332	451.65	453.23	465.90	3.97	7452	465.49	466.30	478.23	4.29	6999	477.62	478.71	490.22	3.97	6167	489.58	490.57
7	434.61	13.70	6860	432.56	436.32	459.10	5.64	7326	458.45	459.83	472.71	4.46	7308	472.16	473.47	485.39	4.18	7543	484.77	486.00	498.42	3.70	6291	497.86	498.84
8	439.99	15.01	5846	437.80	441.63	467.18	5.61	6399	466.41	467.90	482.04	5.11	7890	481.37	482.66	494.38	4.68	6319	493.81	495.04	507.28	3.81	7344	506.81	507.70
9	459.06	13.19	7454	458.18	461.13	481.16	6.45	6569	480.29	482.15	495.53	6.32	6189	494.63	496.29	507.81	5.97	6710	507.01	508.38	519.81	6.89	6745	518.96	520.98
10	494.01	27.49	5105	489.99	497.19	513.22	25.76	6527	509.58	516.17	531.20	26.59	6000	527.90	535.31	544.36	25.26	8147	541.91	546.15	552.58	21.68	6313	550.02	554.68

	Type 6					Type 7					Type 8					Type 9					Type 10				
Tranches	Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI		Mean	Sd	N_k^l	CI	
1	445.73	19.62	9256	443.47	447.68	452.23	20.55	6166	449.85	454.33	464.16	29.90	7121	461.01	467.44	480.74	21.37	7583	478.87	483.17	507.72	22.49	7857	505.43	510.46
2	470.19	4.72	4923	469.55	470.80	481.99	4.96	6848	481.33	482.56	494.23	5.19	8424	493.57	494.88	508.04	5.48	8478	507.48	508.64	532.51	13.11	7263	530.60	534.00
3	480.37	3.88	6688	479.91	480.86	492.80	4.25	6805	492.14	493.30	504.19	4.31	5469	503.62	504.71	517.08	4.88	7668	516.52	517.58	540.00	10.63	5775	538.55	541.18
4	488.42	4.42	7594	487.84	489.00	500.44	4.14	7347	499.87	500.91	511.72	3.48	5788	511.22	512.16	524.91	4.87	5168	524.13	525.53	553.86	16.48	6486	551.49	556.06
5	494.97	4.23	7074	494.51	495.47	507.24	4.04	7622	506.82	507.71	518.34	4.05	6469	517.82	518.78	532.94	4.36	6050	532.35	533.36	556.36	12.41	5363	555.01	557.94
6	502.44	3.88	5735	501.85	502.99	513.28	3.57	5429	512.87	513.81	525.82	4.05	7631	525.13	526.43	539.02	4.90	6614	538.29	539.76	561.95	12.08	6964	560.56	563.64
7	510.22	3.86	8040	509.69	510.71	520.93	4.06	8212	520.57	521.34	532.59	4.62	7490	532.11	533.13	546.17	5.40	4982	545.07	547.12	567.97	12.42	5785	566.48	569.23
8	518.64	3.53	5783	518.16	519.02	530.88	4.36	6427	530.28	531.39	543.04	4.55	6474	542.49	543.67	555.14	5.70	7669	554.37	556.12	579.44	12.09	7695	578.18	580.51
9	531.40	6.36	7406	530.62	532.27	544.23	6.86	6424	543.45	545.27	554.99	6.17	6187	554.22	555.77	569.87	6.13	7121	569.02	570.67	591.27	11.90	8313	589.70	593.01
10	569.70	26.63	6359	566.13	574.06	579.68	30.00	7527	576.12	584.16	589.59	23.72	7734	587.20	591.89	603.08	21.02	7731	600.82	604.94	621.94	25.10	7134	618.68	625.04

Data is weighted by the final student weight. The confidence intervals for the mean are derived from Balanced Repeated Replication (BRR) variance estimation.

Appendix II

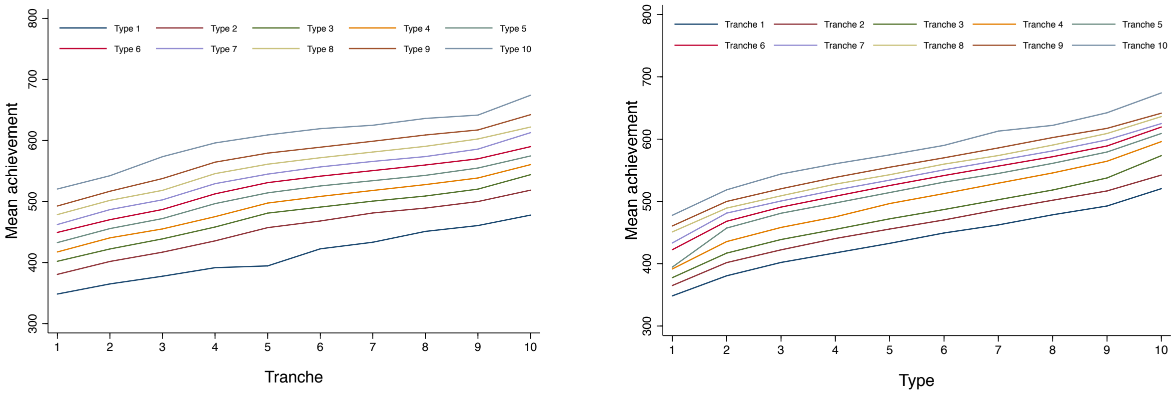

Figure 1: Mean achievement of cells per tranches and types for Belgium

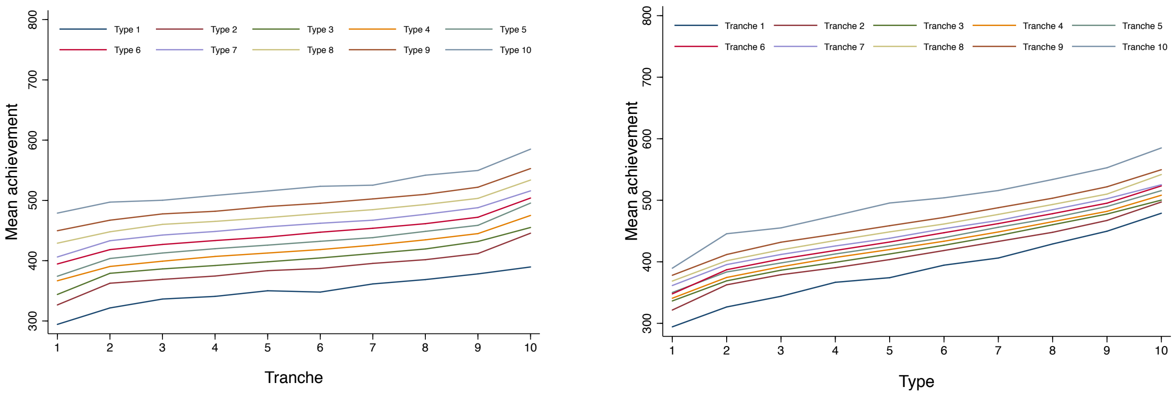

Figure 2: Mean achievement of cells per tranches and types for Bulgaria

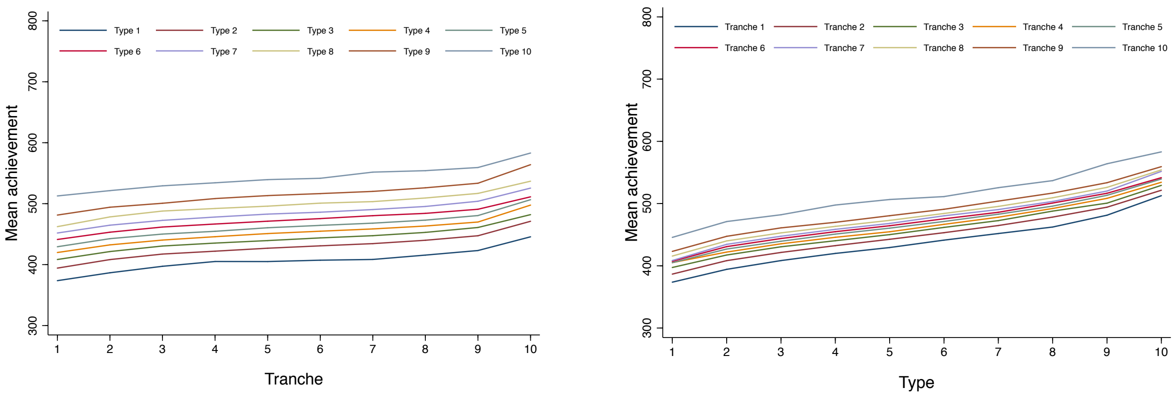

Figure 3: Mean achievement of cells per tranches and types for Croatia

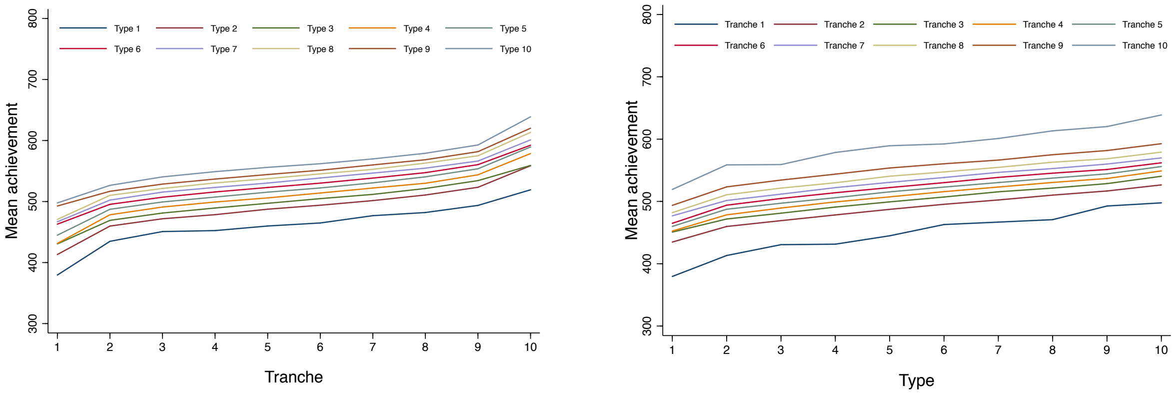

Figure 4: Mean achievement of cells per tranches and types for Finland

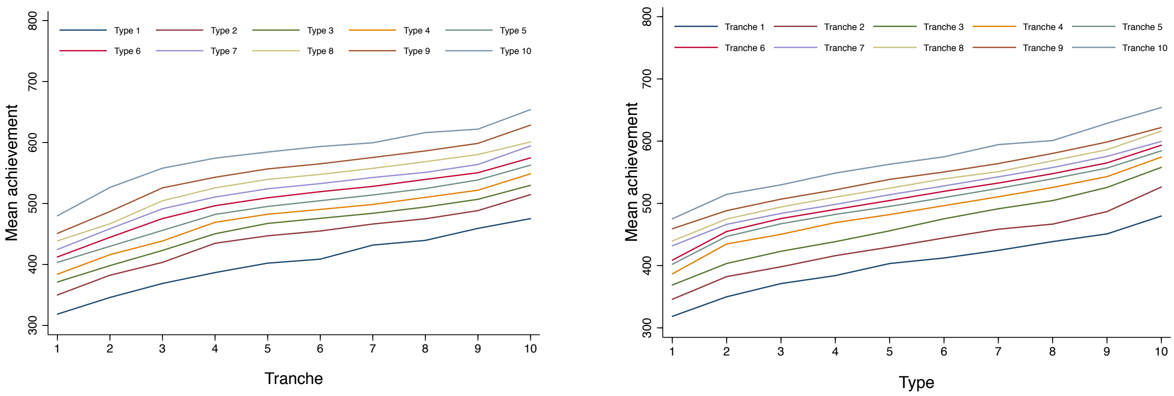

Figure 5: Mean achievement of cells per tranches and types for France

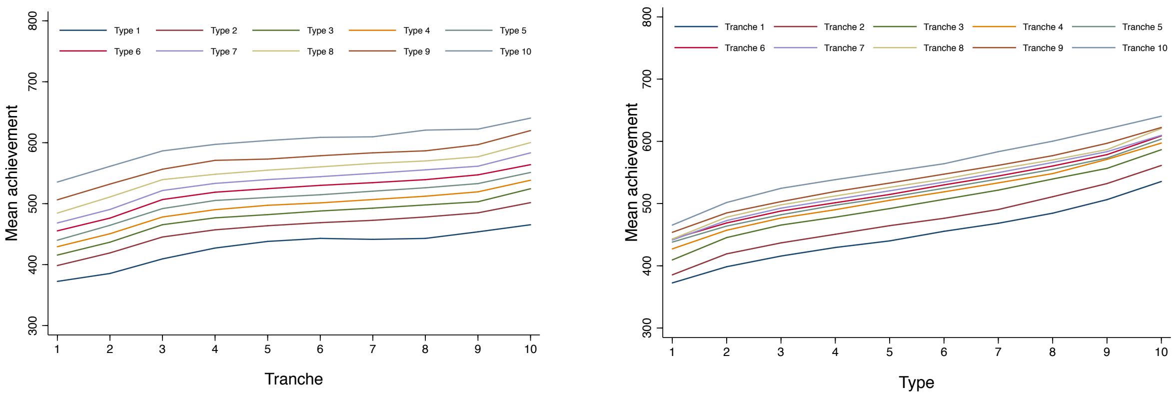

Figure 6: Mean achievement of cells per tranches and types for Germany

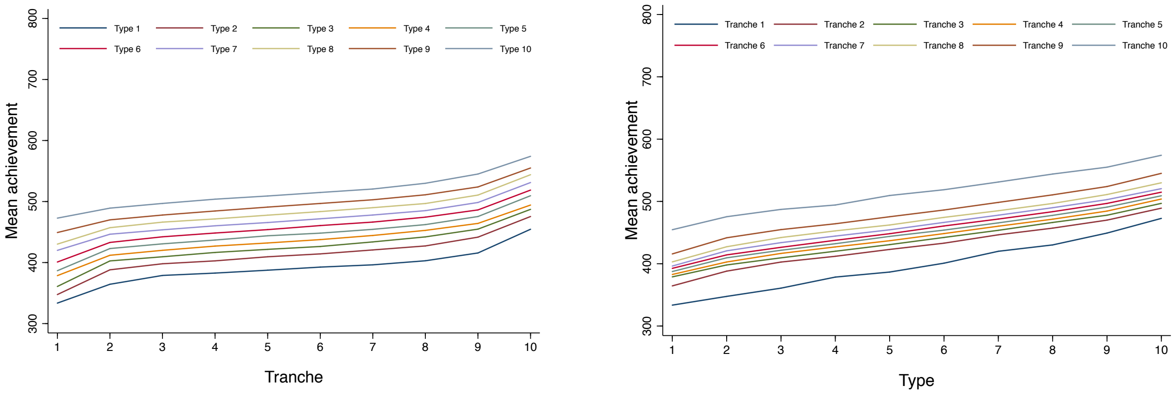

Figure 7: Mean achievement of cells per tranches and types for Greece

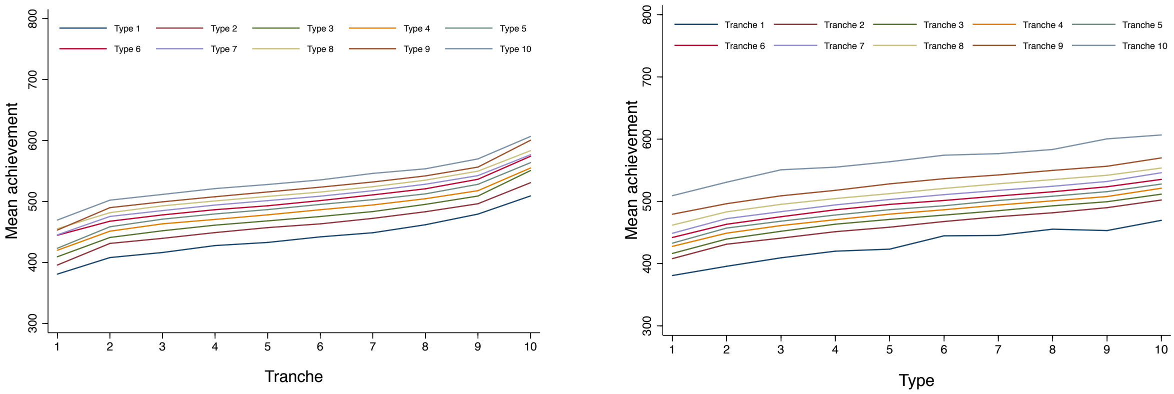

Figure 8: Mean achievement of cells per tranches and types for Iceland

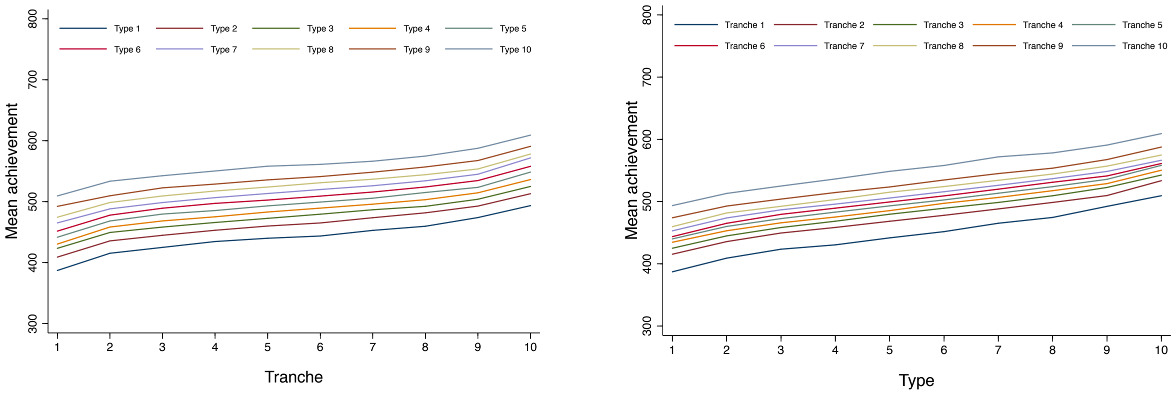

Figure 9: Mean achievement of cells per tranches and types for Ireland

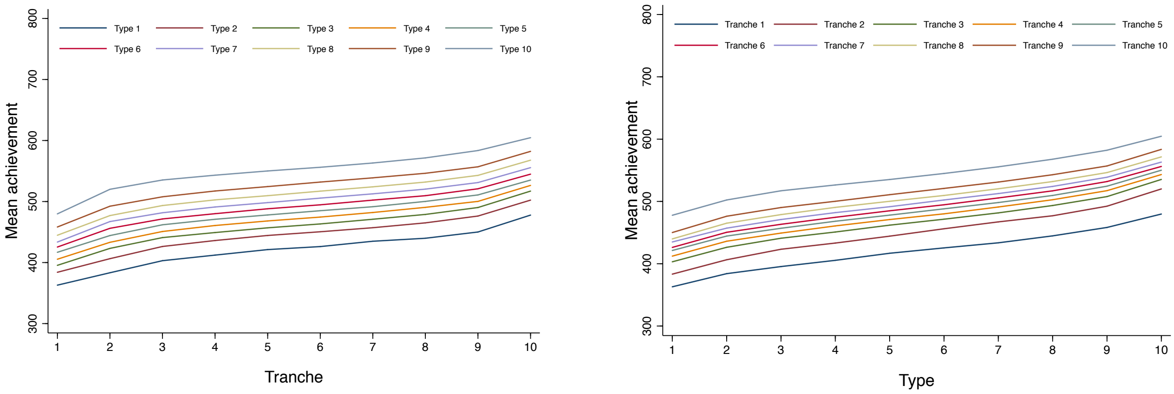

Figure 10: Mean achievement of cells per tranches and types for Italy

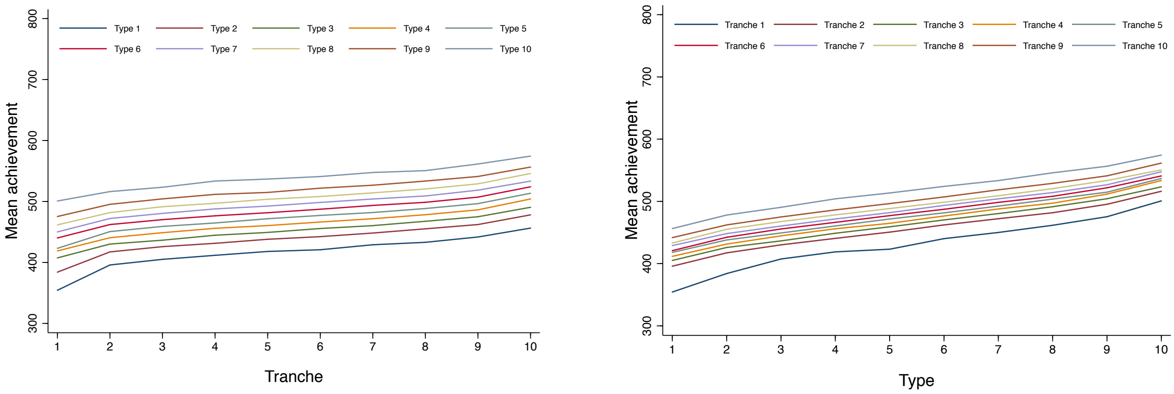

Figure 11: Mean achievement of cells per tranches and types for Lithuania

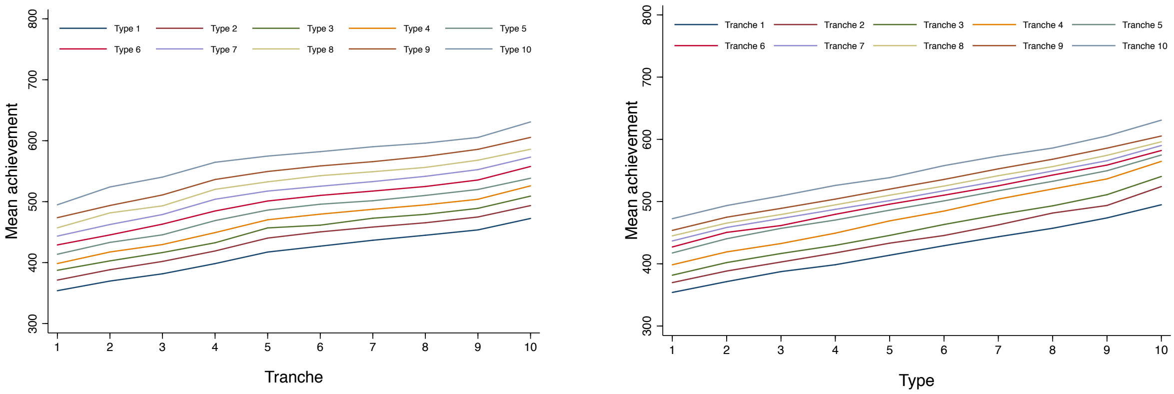

Figure 12: Mean achievement of cells per tranches and types for Luxembourg

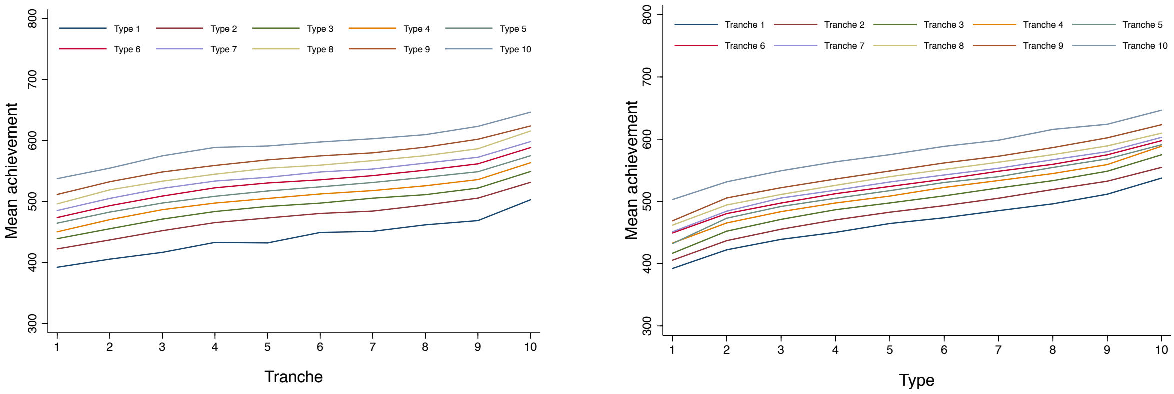

Figure 13: Mean achievement of cells per tranches and types for The Netherlands

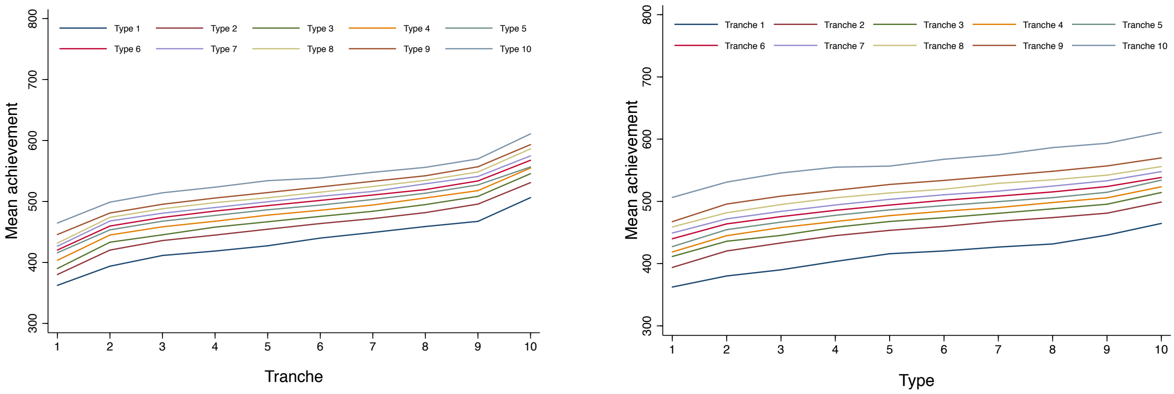

Figure 14: Mean achievement of cells per tranches and types for Norway

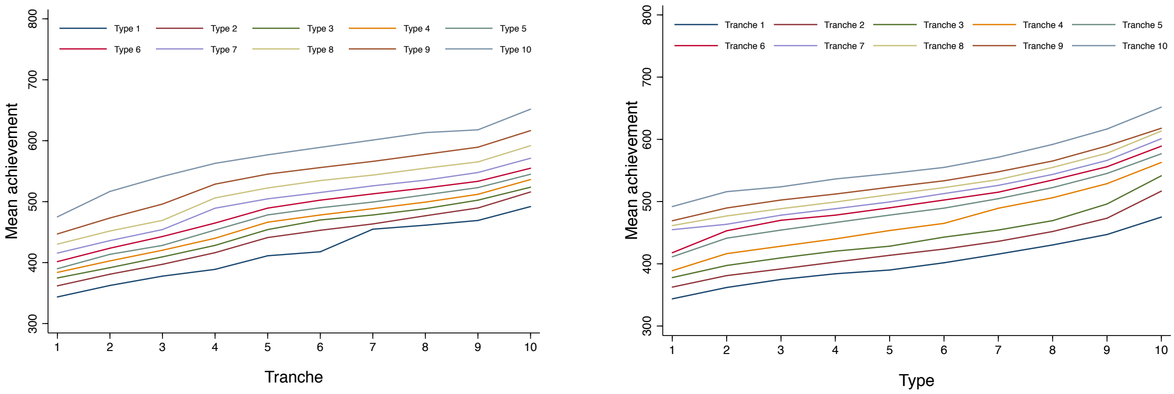

Figure 15: Mean achievement of cells per tranches and types for Portugal

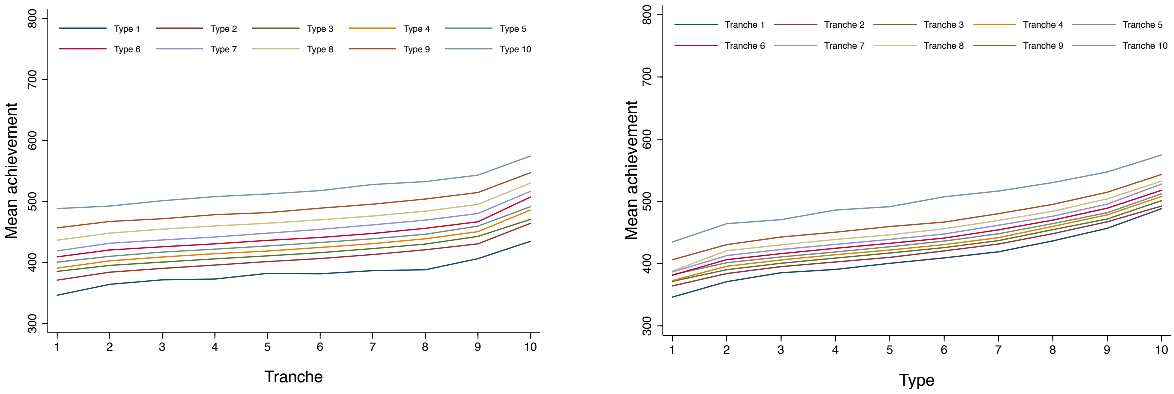

Figure 16: Mean achievement of cells per tranches and types for Romania

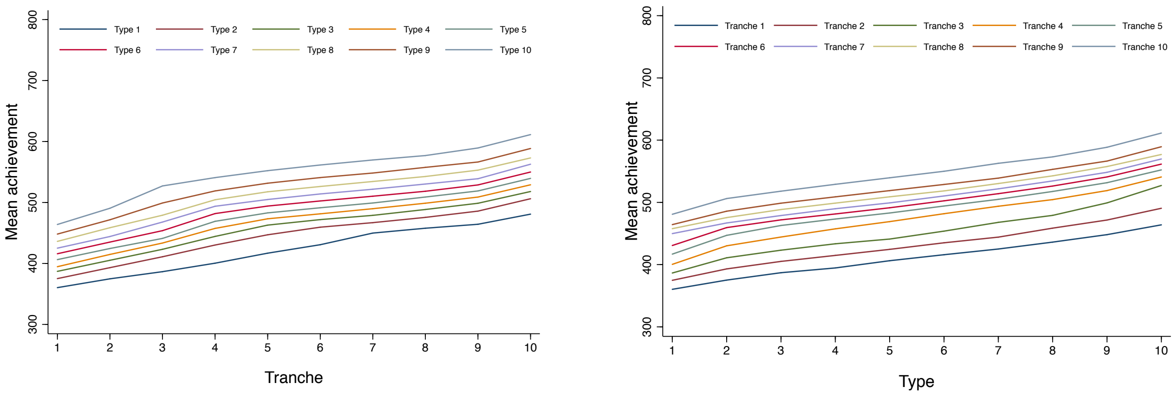

Figure 17: Mean achievement of cells per tranches and types for Spain

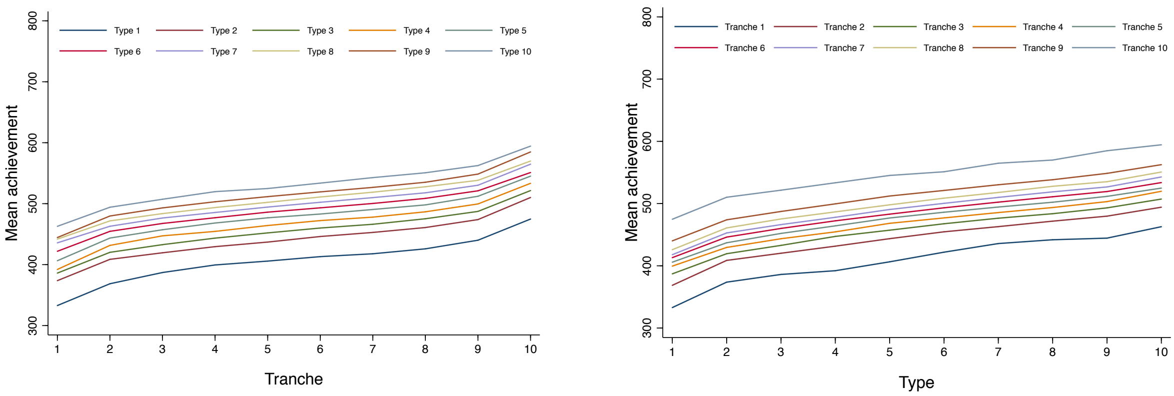

Figure 18: Mean achievement of cells per tranches and types for Sweden

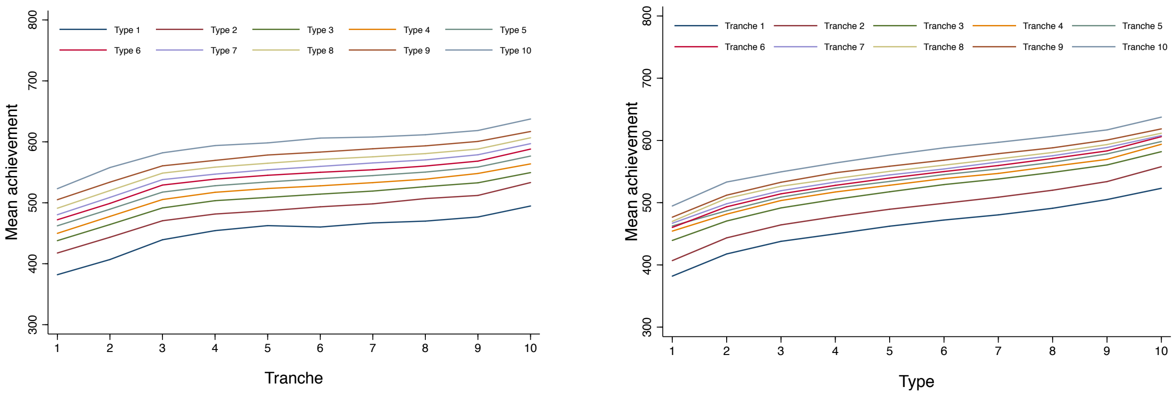

Figure 19: Mean achievement of cells per tranches and types for Switzerland

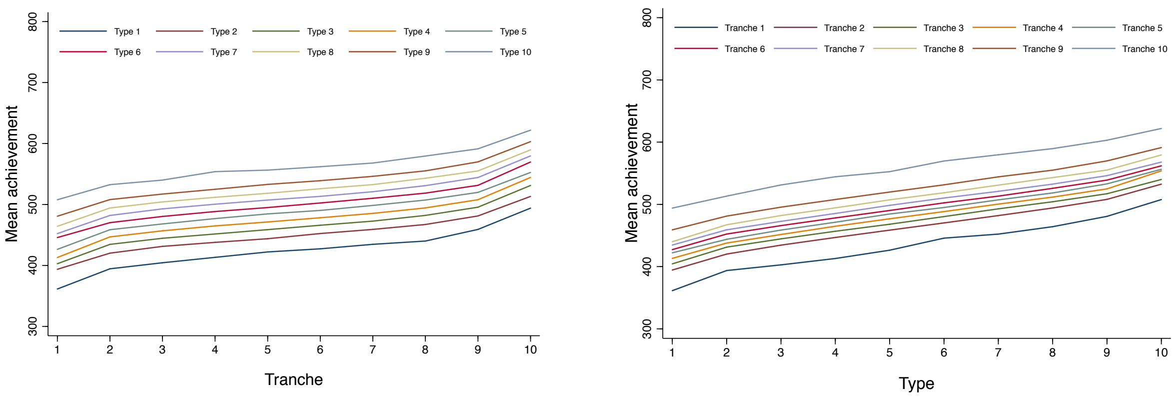

Figure 20: Mean achievement of cells per tranches and types for the United Kingdom

Appendix III

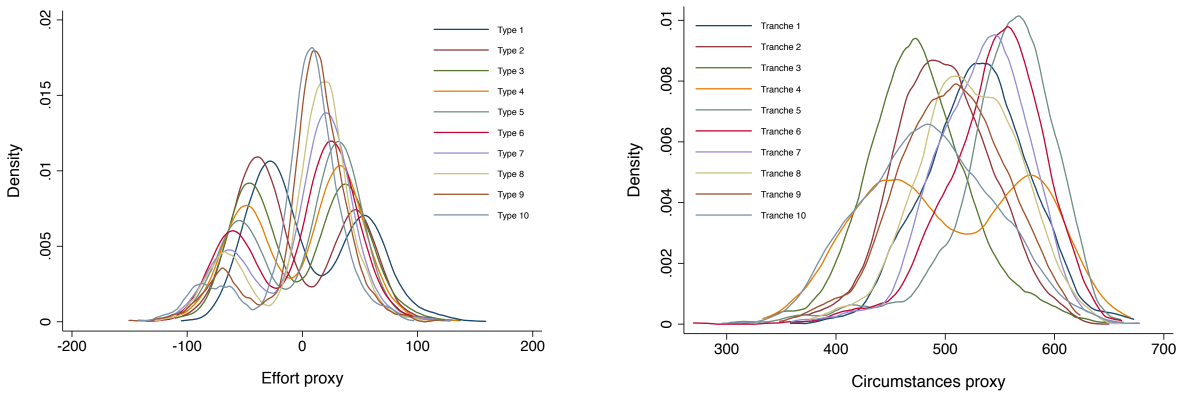

Figure 1: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{C}$ for Belgium

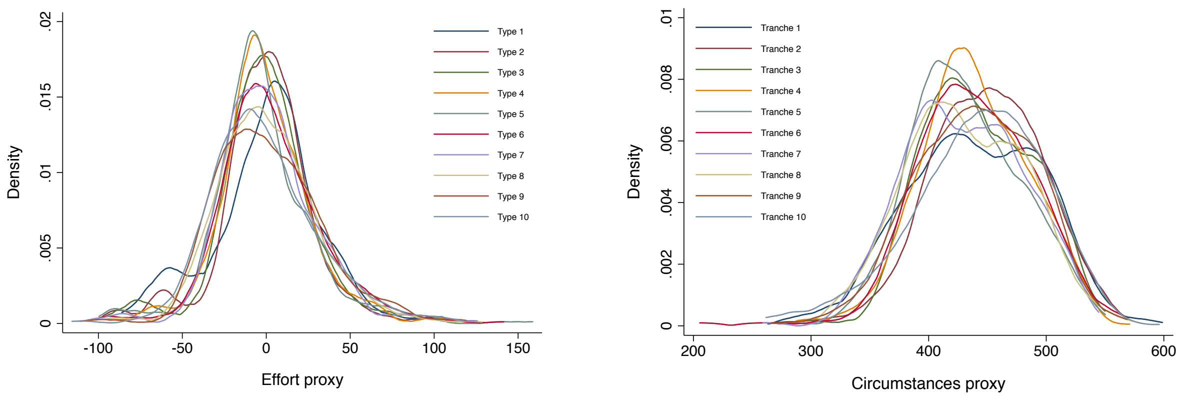

Figure 2: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{C}$ for Bulgaria

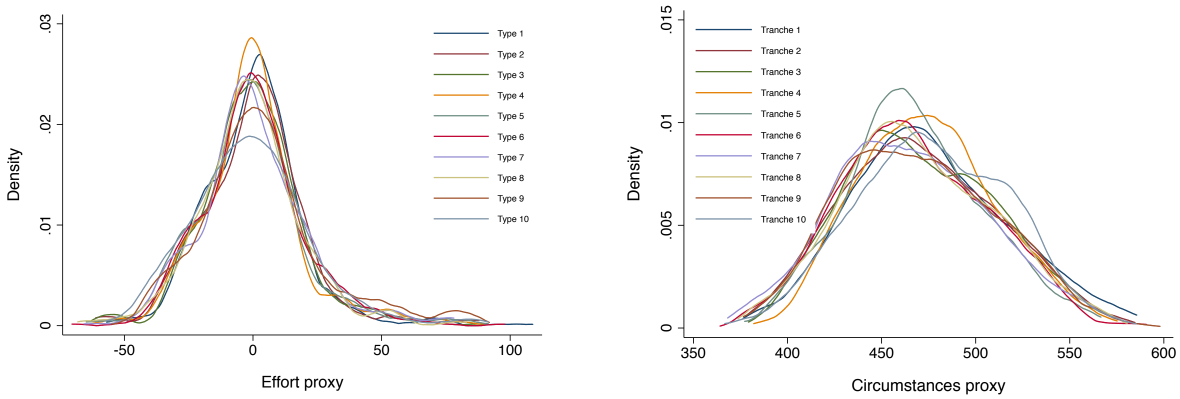

Figure 3: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{C}$ for Croatia

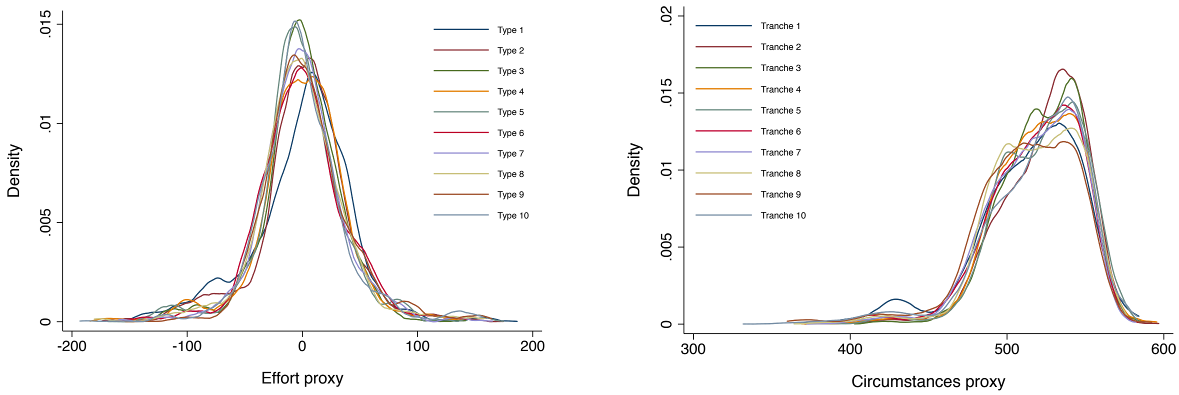

Figure 4: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for Finland

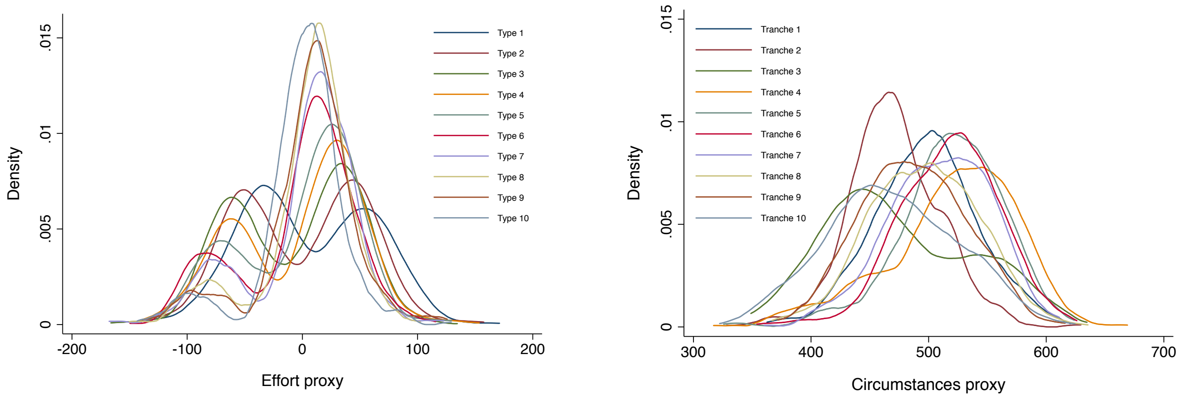

Figure 5: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for France

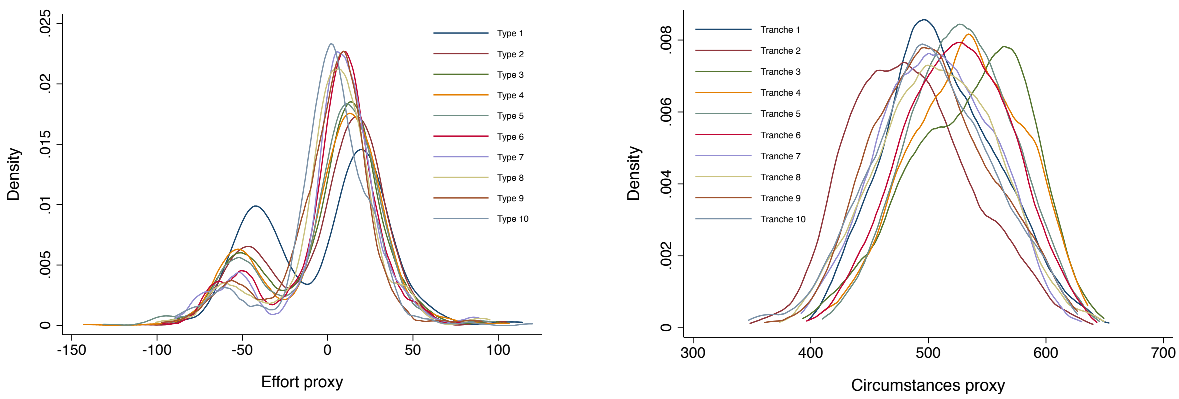

Figure 6: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for Germany

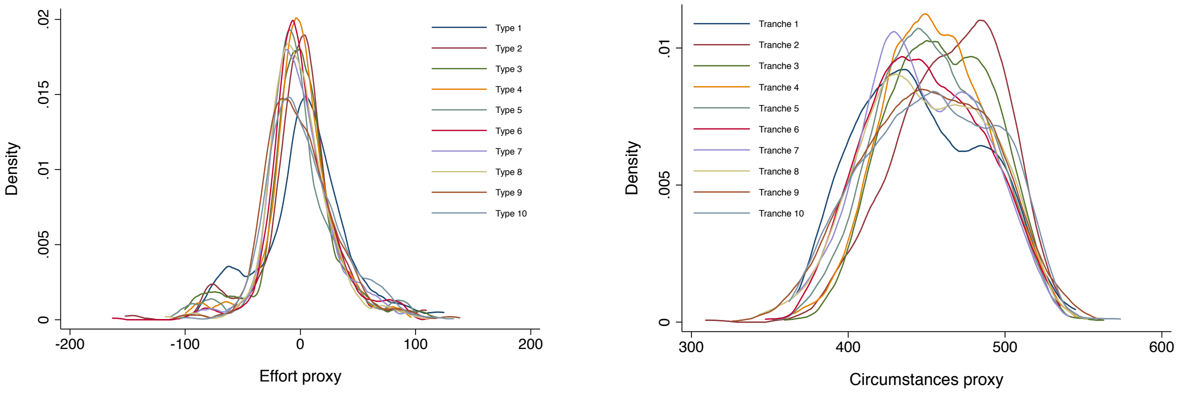

Figure 7: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for Greece

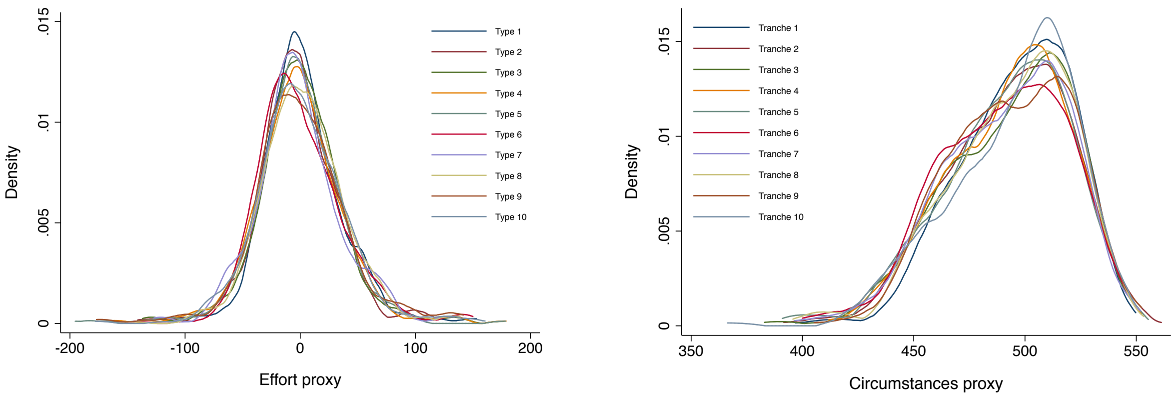

Figure 8: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for Iceland

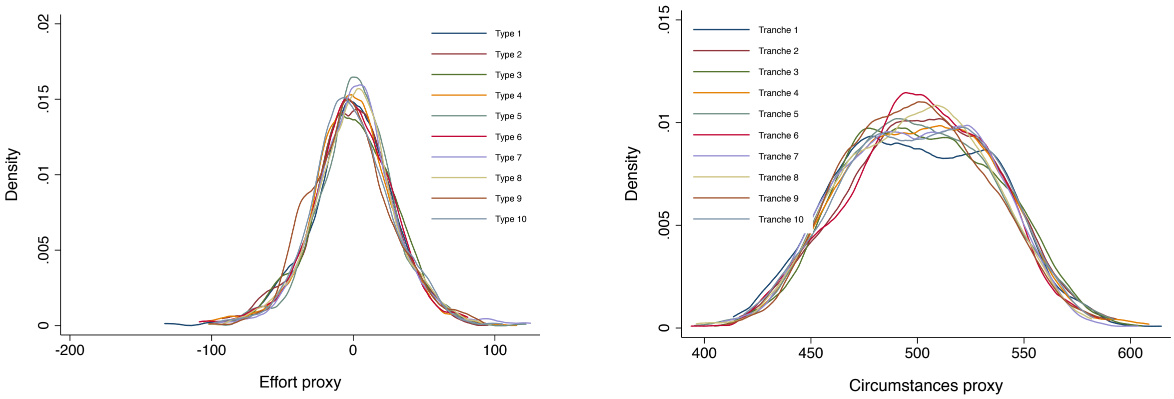

Figure 9: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for Ireland

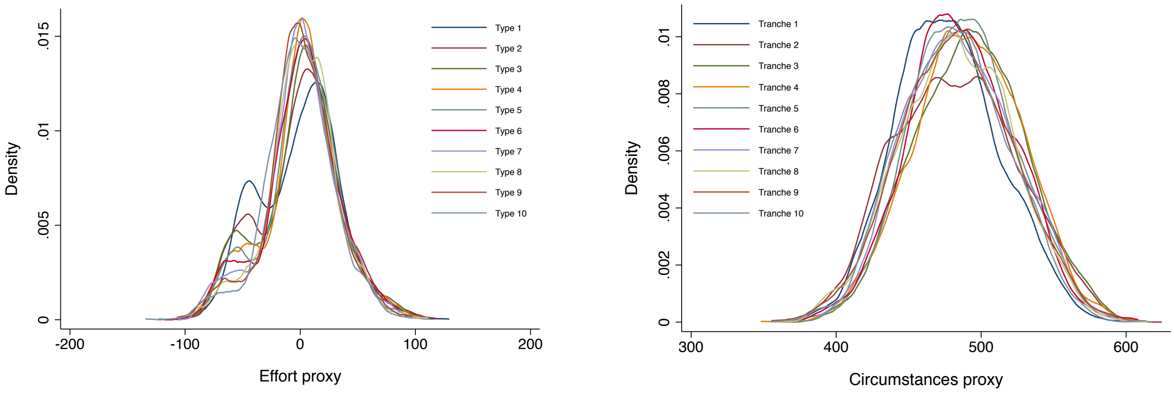

Figure 10: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for Italy

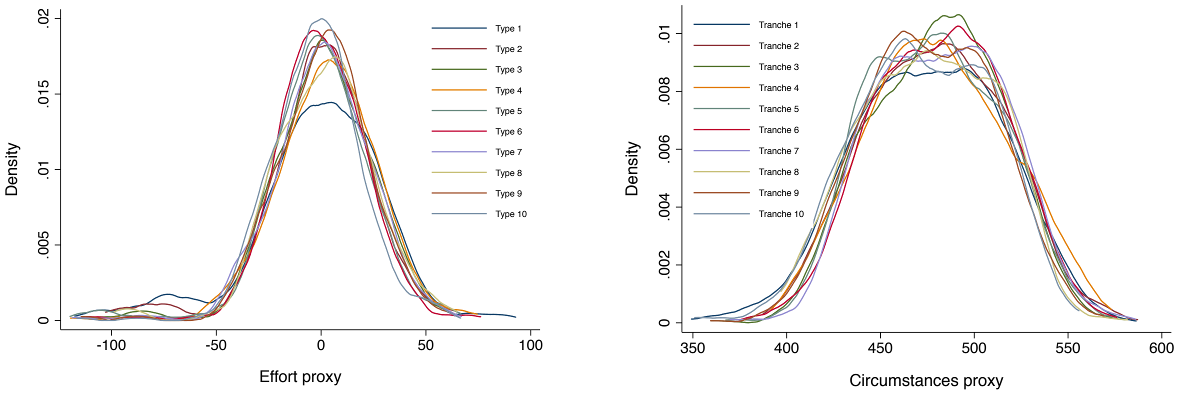

Figure 11: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for Lithuania

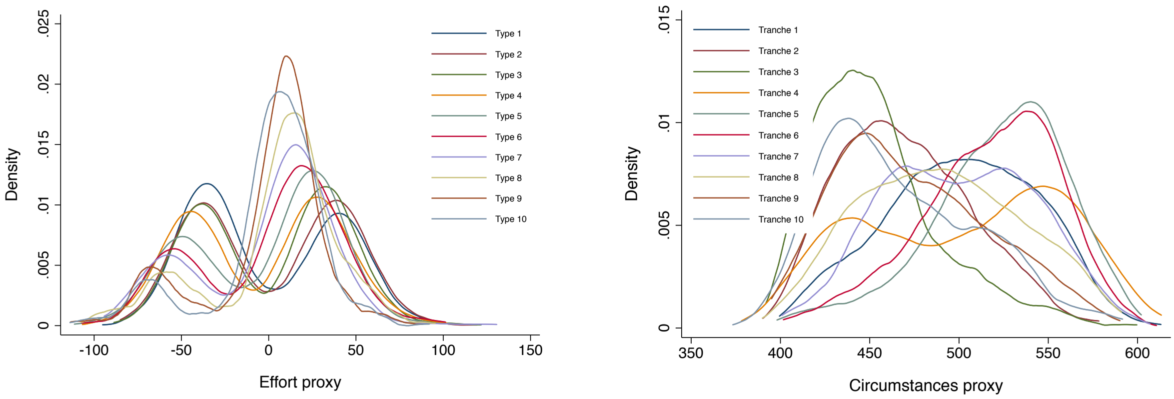

Figure 12: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for Luxembourg

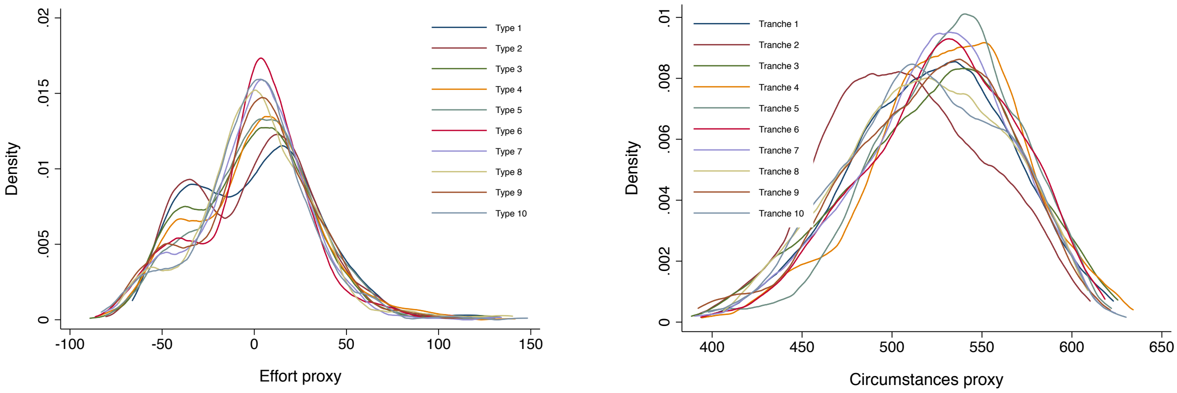

Figure 13: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{C}$ for The Netherlands

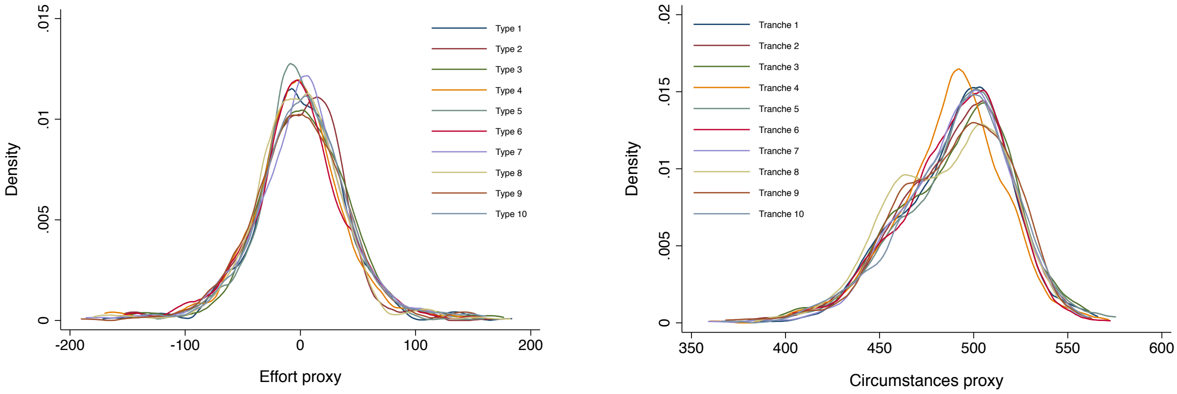

Figure 14: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{C}$ for Norway

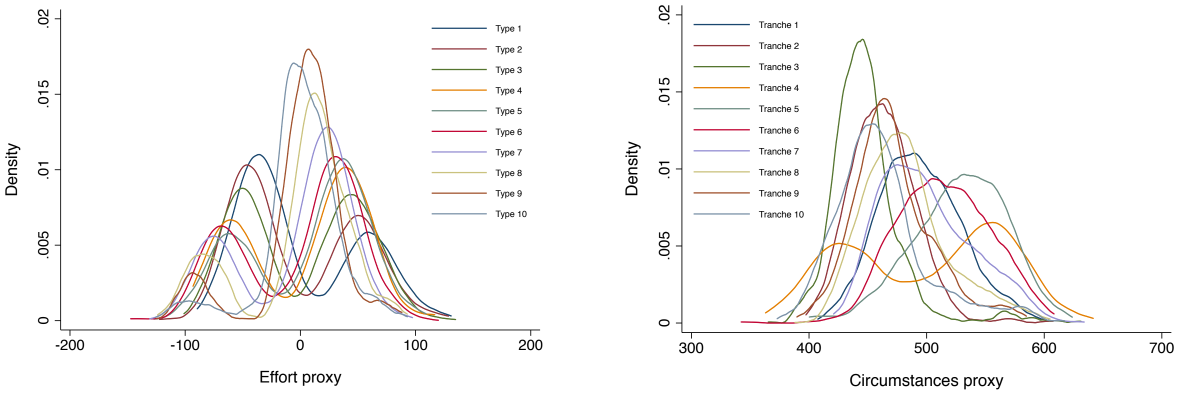

Figure 15: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{C}$ for Portugal

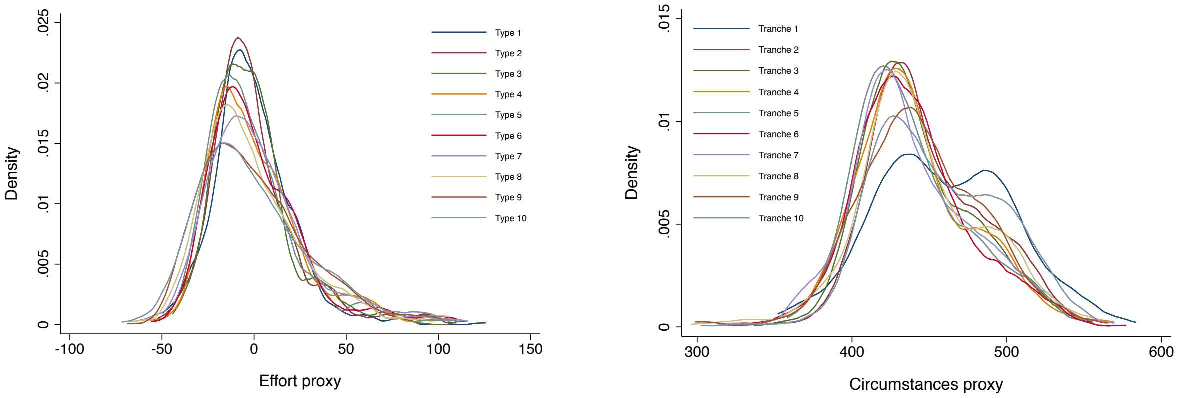

Figure 16: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for Romania

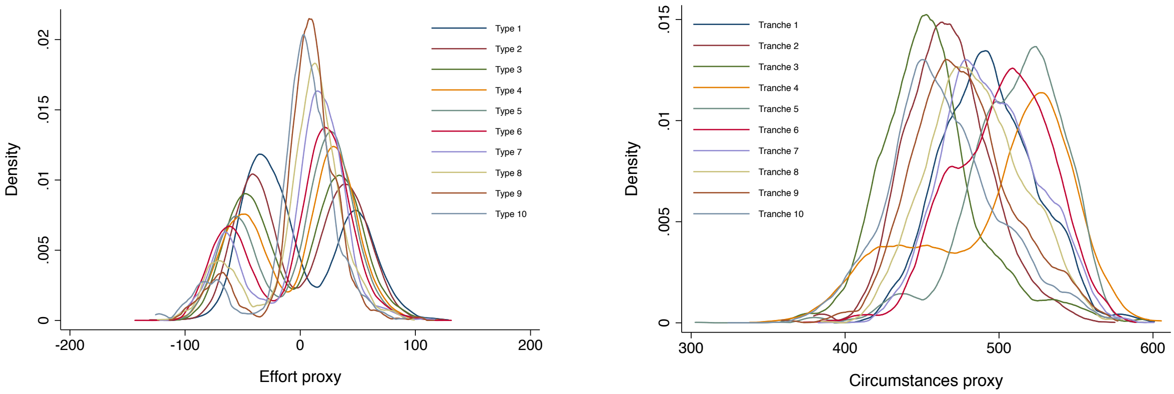

Figure 17: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for Spain

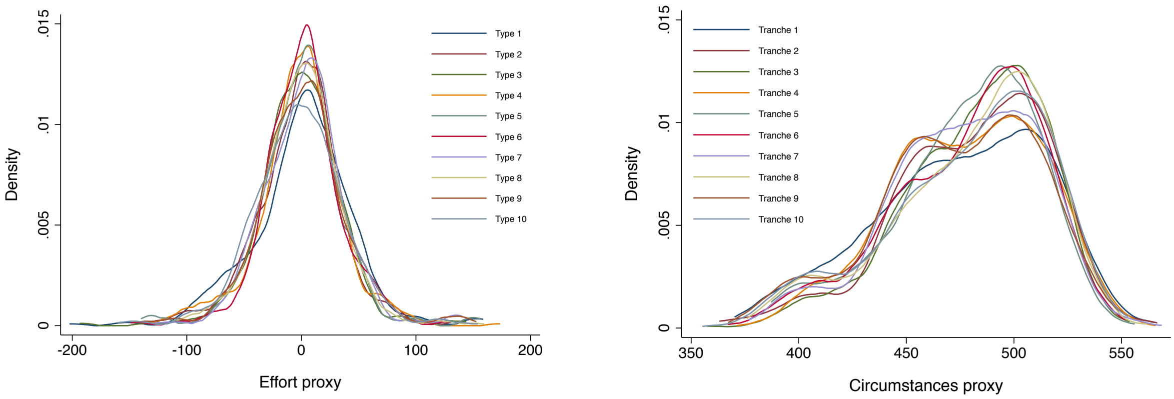

Figure 18: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for Sweden

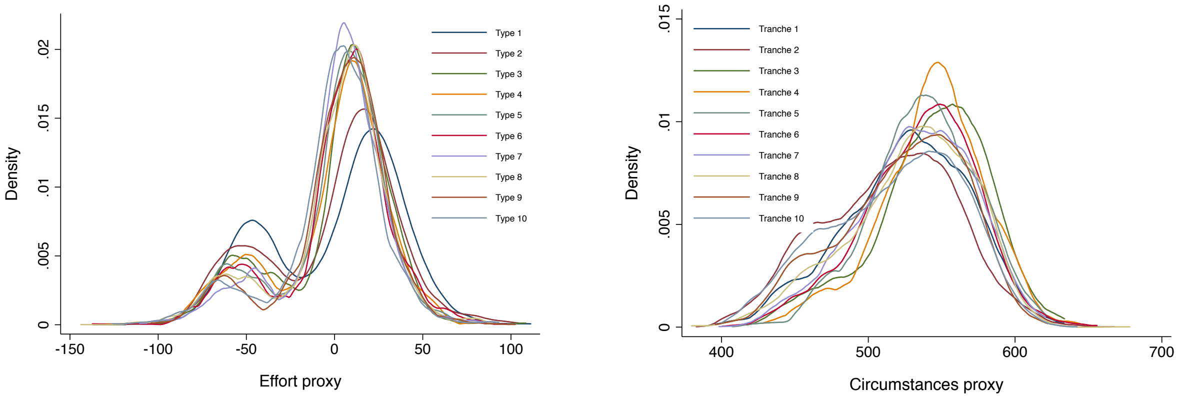

Figure 19: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for Switzerland

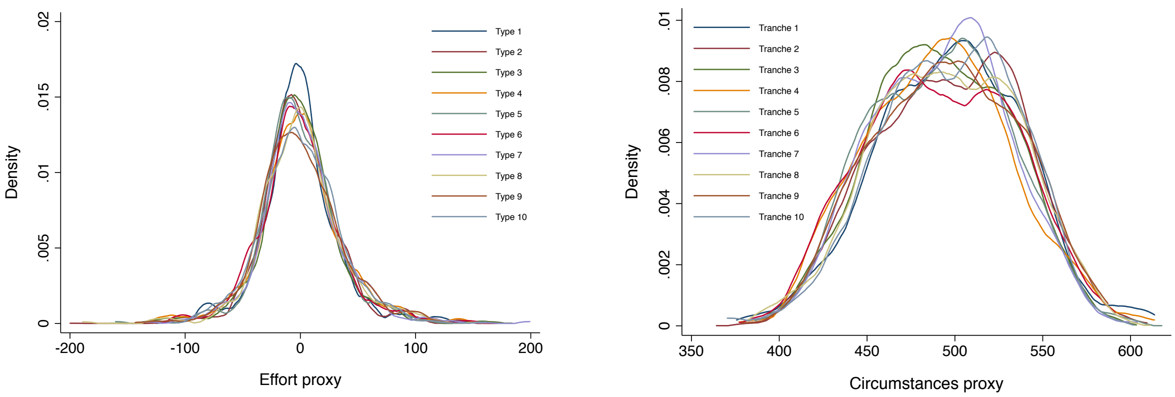

Figure 20: Kernel densities for $\hat{Y}^{\mathcal{E}}$ and $\hat{Y}^{\mathrm{C}}$ for the United Kingdom