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# Inequality of educational opportunity and time-varying circumstances: Longitudinal evidence from Peru

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# Inequality of educational opportunity and time-varying circumstances: Longitudinal evidence from Peru

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**Abstract**

This document provides for the first time in the literature both lower and upper bounds estimates of inequality of opportunity on learning achievement in Peru. It exploits an unusual and rich longitudinal data set on a cohort of children who have been followed for fifteen years almost since they were born. This feature allows for studying empirically the role of time-varying circumstances, a problem that has been neglected until present in the inequality of opportunity literature. In this context, the sensitivity of the upper bound methodology proposed by Niehues and Peichl (2014) is evaluated.
**Keywords:** Inequality of opportunity, learning achievement
**JEL classification:** D63, I24

**Résumé**

Ce document fournit, pour la première fois dans la littérature, des estimations des limites inférieures et supérieures de l'inégalité des opportunités en matière des acquis scolaires au Pérou. Il exploite un ensemble de données longitudinales inhabituelles et riches sur des enfants suivis pendant quinze ans pratiquement depuis leur naissance. Cette particularité permet d'étudier empiriquement le rôle des circonstances qui varient dans le temps, un problème qui n'a pas été traité jusqu'à présent dans la littérature sur l'inégalité des opportunités. Dans ce contexte, est évaluée la sensibilité de la méthodologie proposée par Niehues et Peichl (2014).
**Mots-clés :** Inégalité des opportunités, acquis scolaires
**Classification J.E.L. :** D63, I24

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# 1 Introduction

Developing countries have experienced substantial increases in enrolment rates and years of schooling since 1960 (Lee & Lee, 2016). However, there still exists a serious problem concerning the quality of the educational provision: many pupils learn little while in school (Glewwe & Kremer, 2006). The vertiginous educational expansion has been accompanied by increasingly insufficient financial and human resources. As a consequence, the lack of infrastructure, equipment, and well-trained teachers –among other factors– became more apparent.

Peru has not been an exception. While the gross primary enrolment ratio was 99% in 2016 (INEI, 2018), the Student Assessment Census conducted by the Ministry of Education in the same year showed that only 34% and 46% of second grade primary students obtain satisfactory results in mathematics and reading tests, respectively (Minedu, 2017). International comparison studies such as the Programme for International Student Assessment (PISA) and the Latin American Laboratory for Assessment of the Quality of Education (LLECE) depict a similar reality (cf. OECD, 2016; Unesco, 2015). Certainly, it is worth mentioning that the evidence provided by both national and international assessments also suggests that there has been significant progress over the last years. Nevertheless, the indicators are still far from the expected standards for an upper-middle-income country.

Besides, the Peruvian educational system is considerably inequitable. The recent literature dealing with this topic has established some stylized facts.[1] In particular, poverty status, parental education, ethnic origins, and rural residence, are variables that are systematically correlated with both educational inputs (e.g. schools' characteristics, teachers' pedagogical content knowledge) and outcomes (e.g. completion, learning achievement).

Implicitly, previous works claim that the influence of the above-mentioned variables on educational outcomes of children is *unjust*. Likewise, previous literature has generally investigated the importance of those variables independently.

The present work aims to determine comprehensively the extent to which characteristics that are beyond individual responsibility of children affect their educational outcomes. In other words, I will address the problem of the distribution of educational opportunities. In this sense, relying on the philosophically meaningful distinction between *circumstances* and *efforts*, I will explicitly differentiate between fair and unfair sources of inequality.[2] In the inequality of opportunity (IOp) literature, *circumstances* can be seen as those aspects that are beyond individual control and thus for which individuals should not be held accountable. Genes, sex, and family background are some examples. On the other side, *effort* comprises persons' choices, and therefore individuals are held responsible for. In this context, both

[1] Recent reviews include Cueto and Felipe (2018), Guadalupe, León, Rodríguez, and Vargas (2017), Ñopo and Kitmang (2017), and Cueto, Miranda, and Vásquez (2016).

[2] It is noteworthy that the source of inequality matters from an ethical point of view. Indeed, most "would agree that effects of circumstances on persons' well-being that are beyond the control of individuals should be rectified, while at least some differential outcomes due to choice are not compensable at the bar of justice" (Roemer & Trannoy, 2015, p.294).

*circumstances* and *efforts* may influence relevant *outcomes*, such as income or welfare. Equality of opportunity is achieved when circumstances play no role in the determination of outcome levels (Roemer, 1998).

Analysing the distribution of educational opportunities is a matter of particular interest because it will shape the future outcomes of children, especially (but not exclusively) when they enter the labour market. Still, education might not be seen as an instrumental dimension of well-being, but as a dimension to which every child has the same right.[3]

Compared to the existing literature on inequality of opportunity, this document offers four important contributions. First, it studies educational inequality based on achievement, that is, educational disparities are addressed by means of standardized test scores, which are expected to reflect what children have really learned. This allows "for potentially much greater insight into the determinants of educational achievement, and might therefore contribute to the design of policies that raise average learning levels, or that reduce educational disparities" (Ferreira & Gignoux, 2014, p.241). It is noteworthy that in the IOp literature there are very few authors who analyse this type of inequality in the educational realm, and those who do so, are mainly concerned with outcomes such as "school completion" or "years of formal schooling". These kinds of outcomes do not allow to study the results of the learning process.

Second, I use a rich longitudinal database on children, which provides a very unusual set of "circumstance" variables, practically since the sampled infants were born. This database also brings the possibility to study the changes over time of variables that have been taken classically for granted as time-invariant in the IOp literature, which could potentially appear as a non-negligible mistake. In addition, it is important to note that the use of panel data has been acknowledged as a promising path to address the problem of "partial observability of circumstances"[4] (Balcázar, 2015), which yields to an unclear extent of underestimation bias for lower bound IOp measures using cross-sectional data.

Third, I provide both lower and upper bound estimates of educational IOp. Indeed, thanks to the longitudinal approach, I am able to account for unobserved circumstances and apply an adapted version of the upper-bound methodology proposed by Niehues and Peichl (2014).

Fourth, I tackle the *time-varying circumstances* problem. Indeed, due to the fact that the IOp literature has traditionally focused only on one specific stage of life (typically adulthood), it has been implicitly taken for granted that childhood circumstances do not vary over time. This is obviously not a problem when considering innate characteristics such as ethnic origin or sex. Nevertheless, some other circumstances might be more controversial, such as socioeconomic status background, nutritional status, or even parental education and occupation. All these variables

[3]As a matter of fact, the General Education Law N° 28044 (2003) states that education is a fundamental right and a free-cost public service when provided by the state, which ensures the right for an integral, high-quality, and universal education for every person.

[4]i.e. the fact that the full set of circumstances is not observed in the data.

can potentially vary over time. The rich longitudinal database that I use allows us to explore the impact of this kind of circumstances on IOp measures. Thus, I evaluate critically the methodology of Niehues and Peichl (2014).

The empirical analysis relies on the Young Lives Study (YLS). This is a multidisciplinary longitudinal research programme focusing on childhood poverty, coordinated by the University of Oxford, and carried out in Ethiopia, India, Peru, and Vietnam. This survey followed two cohorts of children for fifteen years since 2002. In each country, the sample is composed of approximately 1,000 children from the older cohort (born around 1994), and 2,000 children from the younger cohort (born around 2001). Five rounds of data collection have taken place since the first one. For my purposes, I focus only on the younger cohort because the rich set of circumstances is observed since they were one year old. In this way, I am able to identify unambiguously the evolution of the influence of circumstances over children's learning achievement as measured through reading and mathematics tests.

Following Hufe, Peichl, Roemer, and Ungerer (2017), the analysis relies on sets of circumstances. The sets under consideration include basic individual, household, and parental characteristics, as well as early childhood conditions, health-related variables, and shocks. Regarding the effort variables, they are proxied by the child's allocation of time: number of hours per day allocated to study at home, and also to leisure activities.

In order to provide an accurate estimation of the extent of IOp on learning achievement, I use two complementary methodologies. The first one follows Ferreira and Gignoux (2011) and serves as a lower bound estimate of IOp. Indeed, it is designed in such a way that adding new potentially non-observed circumstances can only increase the share of unjust inequalities. However, since the extent of the underestimation of this lower bound is unknown, providing an upper bound estimate becomes also relevant. Therefore, by exploiting the time-series dimension of the dataset cited above, I provide an upper bound of IOp, under the key assumption that circumstances are exogenous and do not vary over time. Using a fixed-effects model, the method claims that the time-constant individual effect is the maximum amount of circumstances which an individual should not be responsible for (Niehues & Peichl, 2014).

Since both methods were conceived to measure IOp on labour market earnings, I make a slight variation in order to apply them pertinently to the measure of IOp on standardized test scores. Indeed, unlike the original methods –which use the mean log deviation (MLD) as inequality index–, I make use of the simple variance as inequality index, which is the most appropriate choice for studying test scores constructed from item response theory models (Ferreira & Gignoux, 2014). Additionally, I do not proceed with the log-linearisation of the dependent variables, which is a common practice when analysing earnings, but not suitable for standardised test scores.

Finally, since my database permits to trace several circumstances over time, I am able to evaluate critically Niehues and Peichl (2014)'s upper bound method. As noted above, this methodology relies heavily on the assumption that circumstances do not vary over time. For the first time in the literature, this work empirically tests the importance of this assumption using real data.

The main findings suggest that inequality of opportunity on learning achievement is a relevant issue for the Peruvian educational system. A set of sixteen circumstances (coming almost exclusively from the child's first year of life) account for important shares of the variance in mathematics and reading tests scores: one-third at age 8, and one-fifth at age 15. Furthermore, the maximum amount of inequality attributable to unfair sources lies around 70%. The results are robust to different outcomes and inequality measures.

Regarding methodological issues, distinguishing the indirect effects of circumstances on learning outcomes makes little difference for IOp estimates: the philosophical debate on compensation approaches for the direct and indirect effects of circumstances on the outcome seems to be not a critical concern for practical purposes. Likewise, the Niehues and Peichl (2014)'s upper bound methodology proved to be robust to the inclusion of time-varying circumstances. This evidence suggests that the particular time-varying class of circumstances has a constant impact on the outcome of interest or, more generally, that the individual-specific effect is the most important component of learning achievement outcomes.

The rest of the dissertation is organized as follows. First is presented a brief state of the art (section 2). Then are described the data that is used (section 3) and the methods for estimating lower and upper bounds of IOp (section 4). After that, the main results are exposed (section 5) and some robustness checks are conducted (section 6). Finally, a discussion with concluding remarks and some implications for public policy are provided (section 7).

## 2 Related literature

Inequality of opportunity, inspired from the theoretical work of Rawls (1971), ceased to be a subject of exclusive domain of philosophers thanks to the formalization works of van de Gaer (1993) and Roemer (1993, 1998).[5] Consequently, in the last decade several studies have been carried out in the field of economics, and these have given rise to two different approaches to the topic: the ex-ante and the ex-post perspectives.[6] While the former analyses individuals who share the same circumstances, the latter focuses on individuals who exert the same degree of effort.

Most of the empirical work on inequality of opportunity has focused on the labour market, taking earnings as the relevant outcome. There are very few authors who analyse this type of inequality in the educational realm (for developing countries in general, and Andean countries in particular), and those who do, are mainly

[5] Some seminal philosophical works are those of Arneson (1989, 1990), Cohen (1989), and Dworkin (1981a, 1981b).

[6] cf. Fleurbaey and Peragine (2013) and Ramos and van de Gaer (2016) for a compelling discussion.

concerned with outcomes such as 'school completion' or 'years of formal schooling'. For instance, Yalonetzky (2012) develops two dissimilarity indices to measure IOp, and applies them to study IOp in Peru, in terms of educational attainment level (i.e. years of schooling). The author found that IOp on this outcome has reduced during the last decades, particularly among the younger cohorts.

Some exceptions include the work of Gamboa and Waltenberg (2012), who use a non-parametric approach inspired by Checchi and Peragine (2010). By exploiting the PISA 2006-2009 databases to study IOp for educational achievement in six Latin American countries, they found that IOp accounts for up to 25%, and established that parental education and school type are important sources of unfair inequality.

Ferreira and Gignoux (2014) study IOp in terms of learning achievement in mathematics, reading, and science. They use the 2006 PISA database, which includes 57 countries (but not Peru). Their lower bound methodology showed that IOp accounts for 35% of all disparities in educational achievement. In addition, they convincingly argue that the simple variance is the most suitable inequality measure for analysing standardized test scores. Indeed, unlike other widely used inequality measures, it is ordinally invariant to standardization.

Regarding the Peruvian educational system, evidence points that traditional school resources and teacher characteristics are important determinants of student performance. Furthermore, despite the fact that the schools are widely spread across the territory, "they are heterogeneous in terms of physical and human resources available, such as qualified teachers, school materials, and equipment" (León & Valdivia, 2015, p.83).

Evidence also shows that there is a strong positive association between socioeconomic status at early ages and teacher's knowledge of content and students. Furthermore, the latter variable is, in turn, positively correlated with pupil's educational achievement (Cueto, León, Sorto, & Miranda, 2017).

Likewise, it has been documented that cognitive gaps between advantaged and disadvantaged children appear early in life, and there are no substantial changes in this situation once they enter school (Schady et al., 2015). For the urban/rural case in Peru, Castro and Rolleston (2018) argue that the significant and persistent cognitive gaps do not reduce over time because the school environment reinforces them.

# 3 Data

The empirical analysis of the present work relies on the Young Lives Study (YLS). This is a multidisciplinary longitudinal research programme focusing on childhood poverty, coordinated by the University of Oxford, and carried out in Ethiopia, India, Peru, and Vietnam. This survey followed two cohorts of children for fifteen years since 2002. In each country, the sample is constituted by approximately 1,000 children from the older cohort (born around 1994), and 2,000 children from the younger cohort (born around 2001). Five rounds of data collection have taken place since the first one.[7]

The sampling strategy used in Peru is described in detail by Escobal et al. (2003). In broad terms, a hundred households within twenty sentinel sites were chosen using a multi-stage, cluster-stratified, random sampling approach. It has been shown that YLS households are very similar to the average household as depicted by other national-scale surveys. Indeed, the YLS sample "covers the full diversity of children in Peru in a wide variety of attributes and experiences. Therefore while not suited for simple monitoring of child outcome indicators, the Young Lives sample will be an appropriate and valuable instrument for analysing causal relations and modelling child welfare, and its longitudinal dynamics in Peru" (Escobal & Flores, 2008, p. iv).[8]

In the present document, the analysis relies only on the younger cohort because the rich set of circumstances is observed since they were one year old. In this way, I will be able to identify unambiguously the evolution of the influence of circumstances on children's learning achievement as measured through literacy and mathematics tests, which are the outcomes of interest.[9] It is noteworthy that these tests were inspired by traditional tests such as Early Grade Reading Assessment, Cloze, and PISA; they were administered in the preferred language of children, and contained items of increasing difficulty. Cueto and León (2012) provide a complete description and analyse their psychometric characteristics for YLS round 3.[10]

# 4 Methodology

In order to provide an accurate estimation of the extent of IOp on learning achievement, I use two complementary methodologies. The first one follows Ferreira and Gignoux (2011) and serves as a lower bound estimate of IOp. Indeed, it is designed in such a way that adding new potentially unobserved circumstances can only increase the share of unjust inequalities. However, since the extent of the underestimation of this lower bound is unknown, providing an upper bound estimate becomes also relevant. Therefore, by exploiting the time-series dimension of the dataset described above, I provide an upper bound of IOp, under the key assumption that circumstances are exogenous and do not vary over time. Using a fixed-effects model, the method claims that the time-constant individual effect is the maximum amount of circumstances which an individual should not be responsible for (Niehues & Peichl, 2014).

[7]The surveys were carried out in 2002, 2006, 2009, 2013, and 2016. Additionally, there was a school survey carried out in 2010 for a sub-sample of 572 children from the younger cohort distributed in 132 primary schools. For more details, cf. Appendix A.

[8]However, it is noteworthy that the richest five percent of districts were excluded from the sample with the purpose of over-sampling poor areas. As a consequence, our IOp estimates will likely be downward biased.

[9]It is important to mention that in this paper the outcomes are measured as z-values of the raw scores. Indeed, the Rasch scores are not available for rounds 4 and 5 on the Peruvian sample. Anyhow, rounds 2 and 3 show that both raw and Rasch scores are strongly correlated ($\rho > 0.95$).

[10]Similar technical notes for rounds 4 and 5 are forthcoming.

As a general framework, first let us consider two determinants of an individual outcome $y_{is}$ (in our case, mathematics and reading tests scores), for individual $i$ at time point $s$: (i) *circumstances* $C_i$, which are characteristics outside individual control (e.g. ethnic origin, gender, family background), and hence a source of *unjust* inequalities in outcomes; and (ii) *effort* $E_{is}$, which represents all factors affecting the outcome and that are assumed to be the result of personal responsibility. Hence:

$$y_{is} = f(C_i, E(C_i)_{is}) \tag{1}$$

Let then partition the population of individuals $i \in \{1, ...N\}$ into a set of disjunct *types* $\Pi = \{T_1, T_2, ...T_k\}$, i.e. subgroups of the population that are homogeneous in terms of their circumstances. According to the classic weak definition, perfect equality of opportunity is achieved if the mean advantage levels $\mu$ are identical across types: $\mu^l(y) = \mu^k(y)$, $\forall l, k | T_l, T_k \in \Pi$. Measuring IOp thus means capturing the extent to which $\mu^l(y) \neq \mu^k(y)$, for $l \neq k$.

The usual procedure consists of computing a measure of IOp by constructing a hypothetical smoothed distribution $\mu^k(y)$, which is obtained when each individual outcome $y_i^k$ is replaced by the group-specific mean for each type $\mu^k(y)$. Based on this smoothed distribution, it can be computed for any scale-invariant inequality index $I$[11] the absolute IOp level:

$$\theta_a = I(\{\mu_i^k\}) \tag{2}$$

Therefore, the relative share of total inequality that can be attributed to circumstances is given by:

$$\theta_r = \frac{I(\{\mu_i^k\})}{I(y)} \tag{3}$$

## 4.1 Lower bound

Ferreira and Gignoux (2011) proposed a log-linearization of equation (1). For our purposes, a logarithm on the dependent variable is not pertinent since the outcome of interest deals with standardized test scores.[12] Therefore, the equation writes:

[11] In fact, the only index that respects the axioms of anonymity, normalization, population replication, scale invariance, subgroup decomposability, path-independent decomposability, and the Pigou-Dalton transfer principle, is the *mean log deviation* $MLD = \frac{1}{N}\sum_i ln\frac{\mu_y}{y_i}$ (Foster & Shneyerov, 2000).

[12] The log transformation on income or earnings is a common practice since it is usually more normally distributed than the original variables, which are generally highly right-skewed. On the contrary, test scores and the normal distributions look usually alike. Moreover, test scores are typically "constructed from the raw results by means of Item Response Theory (IRT) models, which attempt to account for "test parameters", so as to better infer true learning. This process generates an arbitrary metric for test scores, which are then typically standardized to some arbitrary mean and standard deviation" (Ferreira & Gignoux, 2014, p.212).

$$y_{is} = \alpha C_i + \beta E_{is} + u_{is} \tag{4}$$

The indirect effect of circumstances on the outcome through effort is given by:

$$E_{is} = \kappa C_i + v_{is} \tag{5}$$

As noted by Niehues and Peichl (2014), "since it is unlikely that we will observe all relevant circumstance and effort variables that shape individuals' outcomes, estimating this model will likely yield biased estimates. However, to compute IOp shares it is not necessary to estimate the structural model and to derive causal relationships" (p.78). Therefore, by introducing the effort of equation (5) into equation (4), we obtain the reduced form depicted in equation (7):

$$y_{is} = (\alpha + \beta\kappa)C_i + \beta v_{is} + u_{is} \tag{6}$$

$$y_{is} = \psi C_i + \eta_{is} \tag{7}$$

Equation (7) can be straightforwardly estimated by OLS. Such a regression will display the fraction of variance explained by circumstances, including both their direct and indirect effects on learning achievement as captured by $\hat{\psi}$. Based on this result, a parametric estimate of the smoothed distribution, where all individuals sharing the same set of circumstances have the same advantage levels, can be computed as follows:

$$\tilde{\mu}^{LB} = \hat{\psi} C_i^K + \sigma^2/2 \tag{8}$$

In a situation of equality of opportunity, all predicted outcome levels would be identical, i.e. there would not be differences in outcomes due to the observed circumstances $C_i^K$. Thus, IOp can be measured as the degree of inequality of these counterfactual outcome levels, where differences are only due to differences in circumstances.

This procedure leads to lower-bound estimates because adding another circumstance variable to the analysis can only increase the explained variation. In other words, taking into account new previously unobserved circumstances, cannot decrease the share of inequality due to circumstances. However, in cross-sectional designs, it is ordinarily the case that not all potential circumstances can be observed. Therefore, the extent of this underestimation bias is unclear and an upper-bound estimate becomes relevant.

The lower bound strategy will be implemented using different sets of circumstances. Table 1 shows the list of circumstance variables that are considered.[13] It is worth noting that almost all of them are from the first round of the database, i.e. when the child was around one year old.

[13] In addition, some basic descriptive statistics are provided in Appendix C.

**Table 1:** Circumstance sets for the lower bound methodology

| Circumstance set | Variables |
|---|---|
| **Individual** | Gender, birth order |
| **Geography** | Area of residence (urban, rural), region (costa, sierra, selva) |
| **Household** | Size, dependency ratio |
| **Wealth** | Household wealth index |
| **Mother** | Mother's education, mother's age at birth, mother has indigenous tongue |
| **Health** | Vaccination, stunting |
| **Schooling** | Attended pre-school, age at start of grade 1, first attended school was public |
| **Community** | Population (log) |

Note: All variables are from round 1, except "attended pre-school" (round 2), "age at start of grade 1" (round 4), and "first school attended was public" (round 3). More details about the variables are provided in table B.1 in the Appendix.
Own elaboration.

## 4.2 Upper bound

The methodology detailed in section 4.1 yields to lower bounds because of the impossibility to observe the full set of circumstances. Niehues and Peichl (2014) –hereafter NP– provide a methodology to estimate upper bounds of IOp under the assumptions that circumstances are exogenous to the individual and do not vary over time nor their effects on the outcome of interest. Their approach consists of two steps: first, "estimate a FE [fixed-effects] model using panel data to derive a measure of time-constant unobserved heterogeneity. Second, (...) use this estimated unit effect to estimate the maximum extent of inequality which can be attributed to inequality due to circumstances" (NP, p.79).

NP contemplate two extreme possibilities in order to deal with the potential indirect effects of circumstances through effort on the outcome variable. The "responsibility cut" is therefore drawn in **step 1** according to two different approaches detailed below.

In the first approach, there is no compensation for the indirect effects of circumstances on the outcome, i.e. they are treated as effort, as suggested by Fleurbaey (2008). As a consequence, these indirect effects are captured by the $\beta$-coefficients in the following equation:[14]

$$y_{it} = \beta E_{it} + c_i^{(1)} + u_t + \varepsilon_{it} \tag{9}$$

Where $E_{it}$ are time-variant effort variables, $u_t$ captures time-specific effects common to all individuals, and $\varepsilon_{it}$ is the random error. All circumstances are accounted for

[14] Just as in section 4.1, the original logs are omitted for the dependent variable.

by the individual specific unit-effect $c_i^{(1)}$, which is the maximum amount of the effect attributable to circumstances. It yields unambiguously to an upper bound because potential non-observed time-invariant effort variables are also captured in this term.

In the second approach, full compensation is granted for the indirect effects of circumstances on the outcome, i.e. they are also treated as circumstances, in line with Roemer (1998). Therefore, it is needed to obtain a measure of efforts net of circumstances, which can be done through the following sequential system of equations:

$$y_{it} = u_i + u_t + \varepsilon_{it} \tag{10}$$

$$E_{it} = \gamma \hat{u}_i + u_t + e_{it} \tag{11}$$

$$y_{it} = \beta \hat{e}_{it} + c_i^{(2)} + u_t + \eta_{it} \tag{12}$$

Eq. (10) calls for a fixed-effects model without any effort variables. The estimation of the unit effect $u_i$ is then used in Eq. (11) "to sterilize all (observed) effort variables $E_{it}$ from the impact of all (observed and unobserved) circumstances by taking out the effect of $\hat{u}_i$" (NP, p.81). In the present work, only two effort variables $E_{it}$ are used, namely, the number of hours per day spent studying outside school, and the number of hours per day spent on leisure activities. Thence, the predicted residuals of Eq. (11), $\hat{e}_{it}$, can be seen as the sterilized effort variables. They are subsequently plugged into Eq. (12) in order to identify the unit effect $c_i^{(2)}$.

Finally, **step 2** is the same for both approaches. The unit effect $c_i^{(k)}, k \in \{1, 2\}$ is estimated by the following reduced-form model:

$$y_{is} = \psi \hat{c}_i^{(k)} + v_{is} \tag{13}$$

The term $\hat{c}_i^{(k)}$ is used "as the maximum extent of inequality which can be attributed to (time-invariant) circumstances" (NP, p.82). As in section 4.1, a parametric estimate of the smoothed distribution is constructed by replacing individual outcomes by their predictions. In our case, it would be:

$$\tilde{\mu}^{UB} = \hat{\psi} \hat{c}_i^{(k)} + \sigma^2/2 \tag{14}$$

Based on these predicted counterfactual levels, upper bound measures are derived for equations (2) and (3).

Finally, it is worth noting that since both methods detailed in sections 4.1 and 4.2 were conceived to measure IOp on labour market earnings, I make a slight variation in order to apply them pertinently to the measurement of IOp on standardized test scores. Indeed, unlike the original methodologies –which use the mean log deviation (MLD) as inequality index (because it satisfies a number of desired properties, especially path-independent decomposability)–, I make use of the simple variance as inequality index. As noted by Ferreira and Gignoux (2014, p.231), “the mean log deviation is not ordinally invariant in the standardization to which test scores are submitted” in the context of Item Response Theory (IRT) models. As a consequence, the MLD is not suitable for the present study.

## 4.3 The role of time-varying circumstances

In order to assess the role of (observed) time-varying circumstances and their impact on the Niehues and Peichl (2014)'s upper bound method, I proceed as follows.

In the first approach, I add a vector of time-varying circumstances $C_{it}$ in Eq. (9). Thus, it becomes:

$$y_{it} = \beta E_{it} + \lambda C_{it} + c_i^{(1)} + u_t + \varepsilon_{it} \tag{15}$$

In the second approach, an analogous strategy is pursued:

$$y_{it} = u_i + \phi C_{it} + u_t + \varepsilon_{it} \tag{16}$$

$$E_{it} = \gamma \hat{u}_i + \hat{\phi} C_{it} + u_t + e_{it} \tag{17}$$

$$y_{it} = \beta \hat{e}_{it} + \lambda C_{it} + c_i^{(2)} + u_t + \eta_{it} \tag{18}$$

Finally, for both approaches a counterfactual for learning achievement is generated as follows:

$$y_{it} = \psi \hat{c}_i^{(k)} + \lambda C_{it} + v_{is} \tag{19}$$

$$\tilde{\mu}^{UBT} = \hat{\psi} \hat{c}_i^{(k)} + \hat{\lambda} C_{it} + \sigma/2 \tag{20}$$

The consequent IOp measures are computed in the same way as in the previous sections. It is worth to mention that this strategy will only be sensitive to observed time-varying circumstances. Thus, it may only be taken as informative of the extent to which the NP methodology is robust or not to the inclusion of such sort of variables. The list of time-varying circumstances that will be tested are detailed in table 2. Their main descriptive statistics are shown in table C.4 in the Appendix.

**Table 2:** Time-varying circumstance sets for the upper bound methodology

| Circumstance set | Variables (time-variant) |
|---|---|
| **Health** | Stunting, food security |
| **Geography** | Area of residence (urban, rural), region (costa, sierra, selva) |
| **Household** | Size, dependency ratio |
| **Wealth** | Household wealth index |
| **Schooling** | School type (public, private), commuting time to school |
| **Shocks** | Crime, economic, environmental, family (deaths, illnesses, etc.) |

Note: Each variable is observed in rounds 3, 4, and 5. More details about the variables are provided in table B.2 in the Appendix.
Own elaboration.

# 5 Results

This section presents first a non-parametric overview of the IOp problem (section 5.1), and then the results of the lower bound procedure (section 5.2), the upper bound estimation (section 5.3), and the role of time-varying circumstances (section 5.4).

## 5.1 A non-parametric overview

This subsection is devoted to providing some non-parametric empirical intuitions concerning the inequality of opportunity problem using the Young Lives database, before measuring IOp shares in the following subsections.

Figure 1 shows the conditional expectation functions of the child's score in mathematics and reading tests, when she was 15 years old (y-axis) and the household wealth index when she was 1 year old (x-axis).[15] The relationship is eloquent: on average, the wealthier the household where the child is born in, the better she performs in mathematics and reading tests fifteen years later.

Let us define *types* of children (i.e. individuals who share the same circumstances) based on the following three circumstance variables:[16] wealth index tercile in round 1 (3 categories: low, medium, high); mother education (2 categories: primary or less, more than primary); and first school (2 categories: public, private). The combination of these three circumstances yields to 12 possible disjunct children *types*, as shown in table 3.

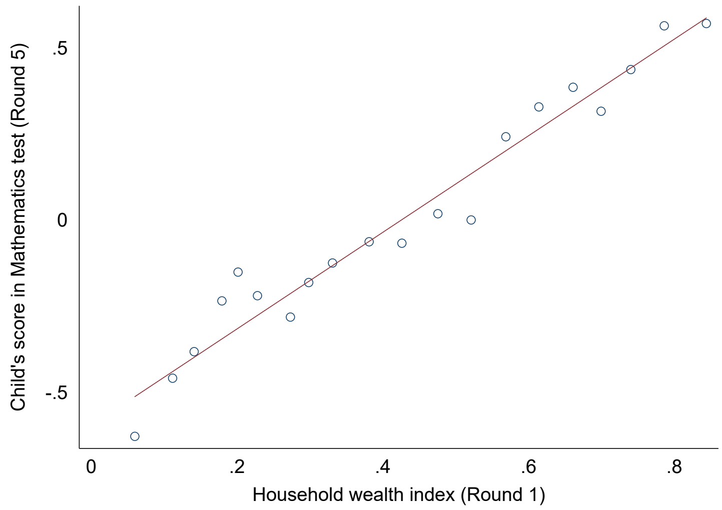
Based on this classification, 85% of the sample is contained in five out of the twelve types (CPU, BPU, BSU, ASI, and ASU). Three types are particularly rare in the

[15]The details of the wealth index construction and its properties are provided by Briones (2017).

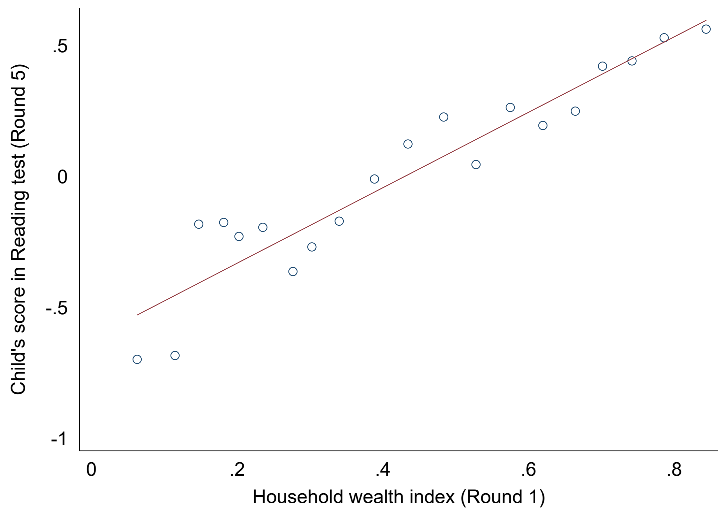
[16]These circumstances are chosen conveniently for illustrative purposes because they explain relevant shares of the variance in test scores, as it will be shown in section 5.2.

**Figure 1:** Mathematics and Reading tests scores (Round 5) and household wealth index (Round 1)

**(a)** Mathematics




**(b)** Reading




Note: Non-parametric representation of the conditional expectation function with 20 equal-sized bins (quantiles of the household wealth index in round 1).
Source: Young Lives Study 2002-2016. Own elaboration.

**Table 3:** Types of children based on three circumstances: wealth index tercile (round 1), mother's education, and child's first school

| **Wealth index tercile (R1)** | **Mother's education** | **First school** | **Child type code** | **Obs.** | **%** |
|---|---|---|---|---|---|
| C | P | I | CPI | 1 | 0.1 |
| C | P | U | CPU | 506 | 26.7 |
| C | S | I | CSI | 5 | 0.3 |
| C | S | U | CSU | 114 | 6.0 |
| B | P | I | BPI | 12 | 0.6 |
| B | P | U | BPU | 311 | 16.4 |
| B | S | I | BSI | 48 | 2.5 |
| B | S | U | BSU | 260 | 13.7 |
| A | P | I | API | 25 | 1.3 |
| A | P | U | APU | 80 | 4.2 |
| A | S | I | ASI | 208 | 11.0 |
| A | S | U | ASU | 323 | 17.1 |

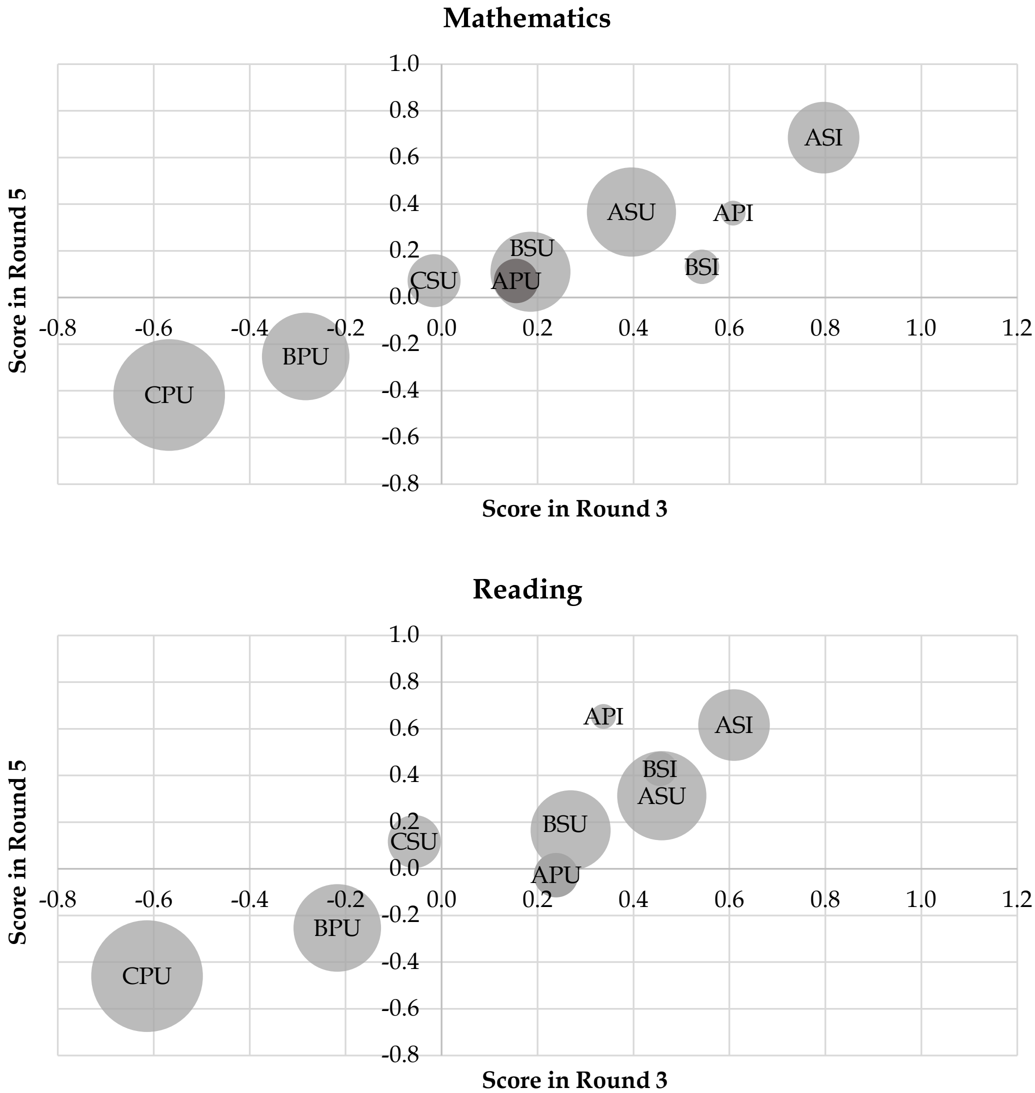
Note: A: High wealth, B: Medium wealth, C: Low wealth, P: Primary or less, S: More than primary, U: Public, I: Private.

Source: Young Lives Study 2002-2016. Own elaboration.

population of Peruvian children. They are related to pupils born in medium and low wealth households attending private schools as first schooling experience (CPI, CSI, BPI). These three types account for less than 1% of the population. Since the number of observations in these cases is very poor, these types will be excluded from the analysis in what follows.

Figure 2 shows the scores in rounds 3 and 5 by type, where the size of each bin is proportional to the size of the type it represents (cf. table 3). A positive correlation can immediately be noticed: the types that performed worst in round 3, did also perform the worst in round 5. This non-parametric representation does not suggest any pattern of mobility between types. Indeed, a scenario of equal opportunity in round 5 would display a zero-slope pattern: all types of children would perform equally on average, i.e. exogenous circumstances would play no role in determining the outcome. It is worth noting that the two types at the bottom are related to children born in poor households, whose mother's education is low (primary at most), and whose first school is public. On the contrary, the most well placed types are formed of children born in wealthier households, whose mothers have at least some secondary education, and usually have started school in a private institution.

**Figure 2:** Children's types: Mathematics and Reading tests scores in rounds 3 and 5




Note: Each bin represents a type, i.e. children who share the same circumstances (cf. table 3 for details). The size of each bin is proportional to the relative size of each type. Types with less than 25 observations are omitted.
Source: Young Lives Study 2002-2016. Own elaboration.

## 5.2 Lower bound

The illustrative exercise carried out in the previous subsection is interesting for that it brings some intuitions about the inequality of opportunity problem in a clear way. However, a non-parametric approach is very data-intensive for estimating IOp measures. As it has been shown in the schematic definition of types with only 3 circumstances (cf. table 3), some cases end with very few observations and no consistent estimates can be computed. For this reason, a parametric approach is prioritized in the present work. In this context, the variables that are going to be used in what follows are detailed along with their basic descriptive statistics in appendices B and C.

Tables 4 and 5 implement equation (7) for mathematics and reading tests, respectively, considering the circumstance variables detailed in table 1. Some interesting relations can be noticed immediately. Having lived in rural areas during the first year of life (which is a proxy for being born there) has a strong negative and persistent impact on learning outcomes in adolescence. Likewise, having started schooling in a public institution has an impact in the same direction. In contrast, the level of wealth that the household had around the child's first year of life strongly increases learning achievement at 12 and 15 years. A greater education of the mother also points in the same direction.

Based on these results, the lower bound estimates of IOp are shown in figure 3. As one might notice from table 1, almost all the circumstances considered are obtained from Round 1 (i.e. when the child was around one year old). These circumstances explain around one-third of total variance in learning achievement when children are eight years old, and their influence decreases to one-fifth when they are fifteen years old. This is the case for both mathematics and reading tests. The observed decreasing influence of the same set of circumstances is not surprising since other circumstance variables are expected to be more relevant at later ages. In particular, variables from the educational context such as school and teachers' characteristics.[17] Nevertheless, the fact that circumstances from virtually child's birth can explain a substantial part of learning outcomes fifteen years later is a matter of particular interest for public policy. Especially considering the fact that a sober set of sixteen circumstance variables taken into account in the analysis does this job (cf. table 1).

It is worth noting that these results are consistent with the findings of Ferreira and Gignoux (2014), who estimate lower bound IOp shares for some Latin American countries (but not for Peru, which was not included in the sample). Indeed, based on the PISA 2006 database, the authors conclude that IOp shares in Brazil, Chile, and Mexico were around 0.26 for reading and 0.30 for mathematics (Ferreira & Gignoux, 2014, p.235).

In order to get an idea about the different relative importance of the distinct circumstance sets, figure 4 shows the decomposition of the share of explained variances

[17] For instance, using a Peruvian sub-sample of the Young Lives Study, Cueto et al. (2017) found that "students' socioeconomic status at age 1 and maternal education were positively associated with their teachers' PCK [*pedagogical content knowledge*] by the time students were enrolled in fourth grade" (Cueto et al., 2017, p.329).

**Table 4:** Mathematics scores in Rounds 3 to 5 and circumstances (OLS estimates)

| | (1) Maths R3 | (2) Maths R4 | (3) Maths R5 |
|---|---|---|---|
| Female | -0.143*** | -0.069 | -0.214*** |
| | (0.040) | (0.043) | (0.042) |
| Birth order | -0.059** | -0.023 | -0.027 |
| | (0.022) | (0.024) | (0.023) |
| Rural (R1) | -0.227*** | -0.387*** | -0.227*** |
| | (0.063) | (0.067) | (0.066) |
| Sierra (R1) | -0.047 | 0.123* | 0.117* |
| | (0.055) | (0.058) | (0.057) |
| Selva (R1) | 0.106 | 0.098 | 0.026 |
| | (0.068) | (0.072) | (0.071) |
| Household size (R1) | 0.014 | 0.007 | 0.012 |
| | (0.010) | (0.010) | (0.010) |
| Dependency ratio (R1) | -0.396* | -0.243 | -0.176 |
| | (0.155) | (0.165) | (0.162) |
| Wealth index (R1) | 0.420** | 0.415** | 0.516*** |
| | (0.131) | (0.139) | (0.138) |
| Mother education (R1) | 0.045*** | 0.060*** | 0.050*** |
| | (0.007) | (0.007) | (0.007) |
| Mother age at birth | 0.012** | 0.012** | 0.016*** |
| | (0.004) | (0.005) | (0.005) |
| Mother has indig. tongue | 0.040 | 0.047 | 0.058 |
| | (0.056) | (0.059) | (0.058) |
| Stunting (R1) | -0.081* | -0.096* | -0.076* |
| | (0.035) | (0.038) | (0.037) |
| Vaccins (R1) | 0.062* | 0.038 | 0.007 |
| | (0.027) | (0.028) | (0.028) |
| Attended pre-school (R2) | 0.147* | 0.092 | 0.007 |
| | (0.062) | (0.066) | (0.065) |
| First school public (R3) | -0.315*** | -0.169** | -0.213** |
| | (0.062) | (0.065) | (0.065) |
| Age at start of grade 1 | -0.417*** | -0.129** | -0.030 |
| | (0.039) | (0.041) | (0.041) |
| Com. population log (R1) | -0.071*** | -0.093*** | -0.111*** |
| | (0.021) | (0.022) | (0.022) |
| Constant | 2.418*** | 0.688 | 0.430 |
| | (0.330) | (0.351) | (0.346) |
| N | 1,638 | 1,638 | 1,638 |
| R2 | 0.328 | 0.244 | 0.189 |
| R2-adj. | 0.321 | 0.236 | 0.180 |

Standard errors in parentheses

Source: Young Lives Study 2002-2016. Own elaboration.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table 5:** Reading scores in Rounds 3 to 5 and circumstances (OLS estimates)

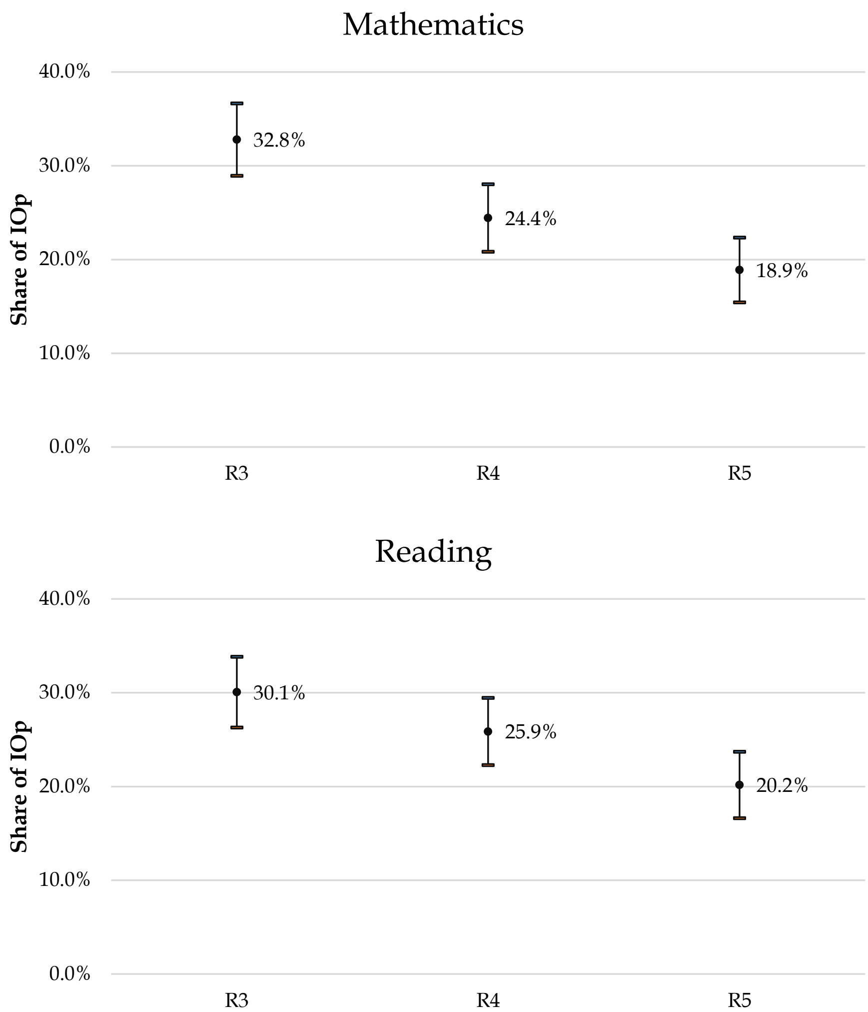
| | (1) Read. R3 | (2) Read. R4 | (3) Read. R5 |
|---|---|---|---|
| Female | 0.003 | 0.037 | 0.010 |
| | (0.041) | (0.042) | (0.044) |
| Birth order | -0.100*** | -0.037 | -0.041 |
| | (0.023) | (0.023) | (0.024) |
| Rural (R1) | -0.403*** | -0.175** | -0.288*** |
| | (0.065) | (0.066) | (0.069) |
| Sierra (R1) | 0.053 | -0.047 | 0.059 |
| | (0.056) | (0.058) | (0.060) |
| Selva (R1) | 0.245*** | 0.092 | 0.111 |
| | (0.070) | (0.072) | (0.074) |
| Household size (R1) | 0.008 | 0.013 | 0.007 |
| | (0.010) | (0.010) | (0.011) |
| Dependency ratio (R1) | 0.127 | -0.213 | -0.159 |
| | (0.159) | (0.163) | (0.169) |
| Wealth index (R1) | 0.538*** | 0.539*** | 0.320* |
| | (0.135) | (0.138) | (0.143) |
| Mother education (R1) | 0.036*** | 0.056*** | 0.056*** |
| | (0.007) | (0.007) | (0.007) |
| Mother age at birth | 0.017*** | 0.014** | 0.013** |
| | (0.004) | (0.005) | (0.005) |
| Mother has indig. tongue | -0.153** | 0.008 | 0.112 |
| | (0.057) | (0.059) | (0.061) |
| Stunting (R1) | -0.083* | -0.099** | -0.086* |
| | (0.036) | (0.037) | (0.039) |
| Vaccins (R1) | 0.029 | 0.025 | 0.032 |
| | (0.027) | (0.028) | (0.029) |
| Attended pre-school (R2) | 0.234*** | 0.135* | 0.071 |
| | (0.064) | (0.065) | (0.068) |
| First school public (R3) | -0.085 | -0.180** | -0.204** |
| | (0.063) | (0.065) | (0.067) |
| Age at start of grade 1 | -0.221*** | -0.169*** | -0.161*** |
| | (0.040) | (0.041) | (0.042) |
| Com. population log (R1) | -0.064** | -0.060** | -0.068** |
| | (0.021) | (0.022) | (0.023) |
| Constant | 0.929** | 0.570 | 0.747* |
| | (0.339) | (0.347) | (0.361) |
| N | 1,638 | 1,638 | 1,638 |
| R2 | 0.301 | 0.259 | 0.202 |
| R2-adj. | 0.293 | 0.251 | 0.193 |

Standard errors in parentheses

Source: Young Lives Study 2002-2016. Own elaboration.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Figure 3:** Lower bound estimates of inequality of educational opportunity




Note: Confidence intervals at the 95% level, based on 1,000 replications bootstraps.
Source: Young Lives Study 2002-2016. Own elaboration.

measured by R-squared in tables 4 and 5 into contributions of groups of circumstances by means of the Shapley value (Huettner & Sunder, 2012). Among the different circumstance sets, the mother's characteristics are those that account for the largest share. Likewise, school characteristics and household wealth accounts for important contributions. In broad terms, the shares are distributed similarly for rounds 4 and 5, between and within both mathematics and reading tests. However, in round 3 the share of circumstances corresponding to the mother set is less sizeable than in later rounds.

### 5.3 Upper bound

Regarding the upper bound estimation procedure, table 6 shows the first step for the first approach detailed in section 4.2, where no compensation is granted to the indirect effects of circumstances on the outcome (cf. Eq. (9)). The two effort variables under consideration –hours per day spent studying outside school, and hours per day spent on leisure activities– display the expected signs. Indeed, studying more hours at home increases the scores in both mathematics and reading tests, while the opposite relation is observed for spending more time in leisure activities.

**Table 6:** Mathematics and reading FE estimates: First approach (cf. equation 9)

| | (1)<br>Maths | (2)<br>Read. |
|---|---|---|
| Hours/day studying outside school | 0.022 | 0.043** |
| | (0.012) | (0.013) |
| Hours/day leisure activities | -0.020** | -0.007 |
| | (0.008) | (0.008) |
| Constant | 0.100* | -0.005 |
| | (0.044) | (0.049) |
| Time fixed effects | Yes | Yes |
| N | 4,872 | 4,872 |
| N_g | 1,624 | 1,624 |
| rho | 0.665 | 0.605 |
| r2_w | 0.006 | 0.004 |
| r2_o | 0.004 | 0.025 |
| r2_b | 0.004 | 0.062 |
| F | 4.502 | 3.134 |

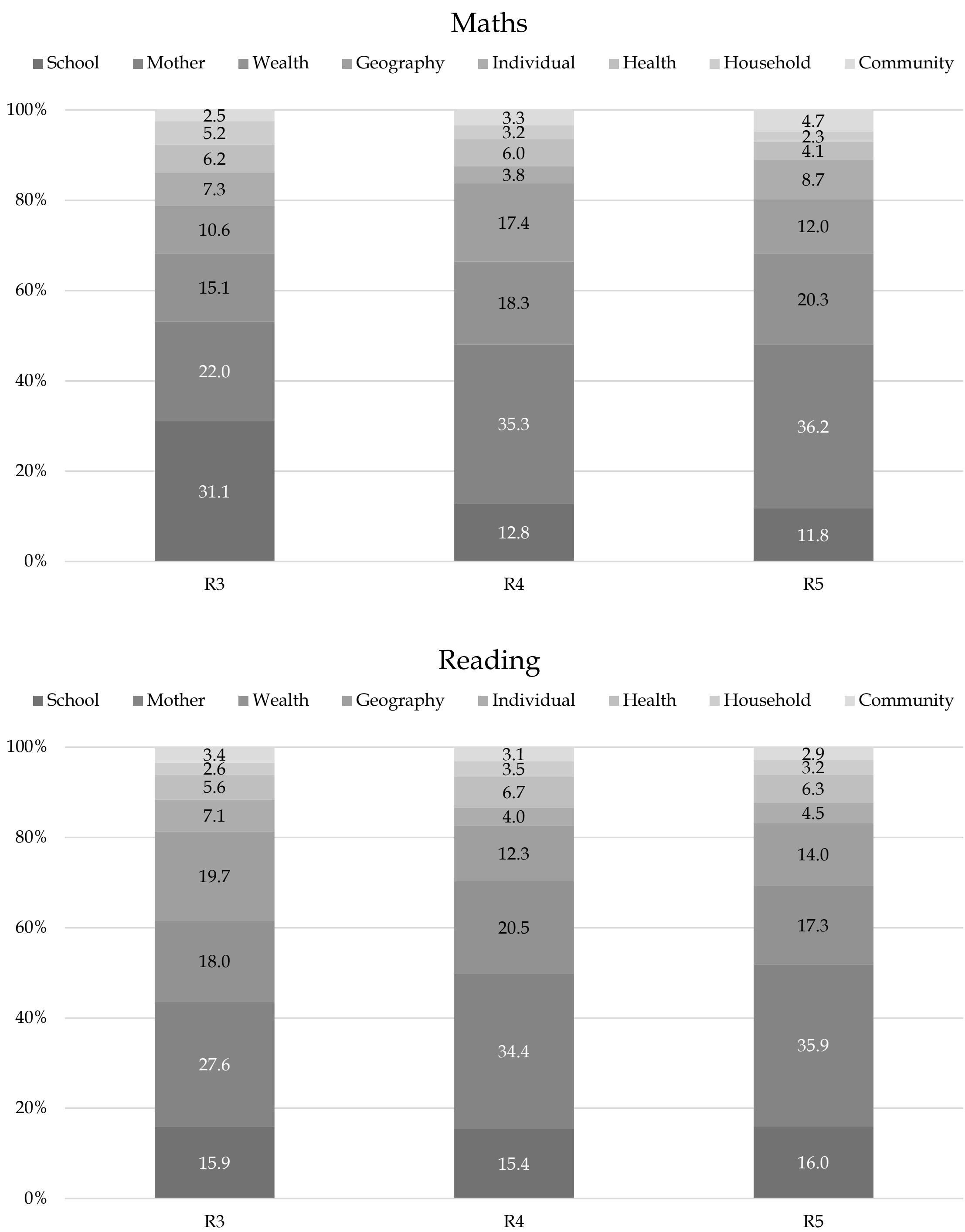
Standard errors in parentheses

Source: Young Lives Study 2002-2016. Own elaboration.

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

The details of the second upper bound approach –where the indirect effects of circumstances are also treated as circumstances– are depicted in tables 7 and 8 for mathematics and reading tests, respectively. The procedure consists of a system of three equations. In both tables, column (1) implements Eq. (10), columns (2) and (3) implement Eq. (11) for each effort variable, and column (4) does the same for

**Figure 4:** Variance decomposition by circumstance sets




1/ Decomposition from regressions shown in tables 4 and 5.
2/ The variables that compose each circumstance set are detailed in table 1.
Source: Young Lives Study 2002-2016. Own elaboration.

Eq. (12). The specific individual unit effect that results from column (4) is then used to estimate the maximum extent of IOp.

**Table 7:** Mathematics FE estimates: Second approach (cf. equations 10, 11, and 12)

| | (1) Maths | (2) Hours study | (3) Hours leisure | (4) Maths |
|---|---|---|---|---|
| Individual effect from col.(1) | | 0.194*** | 0.121*** | |
| | | (0.016) | (0.025) | |
| Residuals from col.(2) | | | | 0.022 |
| | | | | (0.012) |
| Residuals from col.(3) | | | | -0.020** |
| | | | | (0.008) |
| Constant | 0.060*** | 1.901*** | 4.133*** | 0.060*** |
| | (0.015) | (0.023) | (0.036) | (0.015) |
| Time fixed effects | Yes | Yes | Yes | Yes |
| N | 4,872 | 4,872 | 4,872 | 4,872 |
| N_g | 1,624 | | | 1,624 |
| rho | 0.665 | | | 0.665 |
| r2_w | 0.002 | | | 0.006 |
| r2_o | 0.000 | | | 0.001 |
| r2_b | . | | | 0.000 |
| F | 2.948 | 83.598 | 81.185 | 4.502 |

Standard errors in parentheses

Source: Young Lives Study 2002-2016. Own elaboration.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This being said, table 9 summarizes the upper bound IOp estimates following the two approaches. They are very close and consistent at around 70%. This is the maximum amount of inequality that can be attributed to circumstances, which are assumed to be time-invariant. Not surprisingly, the second approach yields higher values “due to the inclusion of the indirect effects of circumstances on the observed effort variables” (Niehues & Peichl, 2014, p.87). However, the two special extreme treatments for the indirect effects of circumstances on efforts make little difference. This suggests that circumstances and efforts are likely to be, to a large extent, orthogonal for educational achievement. This result is in line with the findings of Asadullah, Trannoy, Tubeuf, and Yalonetzky (2018), according to whom the correlation between overall effort and circumstances is negligible for performance scores among secondary school pupils in rural Bangladesh.

### 5.4 Time-varying circumstances and upper bound IOp estimates

The impact of the inclusion of time-varying circumstances on the upper bound estimates is explored in this subsection. All the regressions used for the calculations

**Table 8:** Reading FE estimates: Second approach (cf. equations 10, 11, and 12)

| | (1)<br>Read. | (2)<br>Hours study | (3)<br>Hours leisure | (4)<br>Read. |
|---|---|---|---|---|
| Individual effect from col.(1) | | 0.212*** | 0.166*** | |
| | | (0.016) | (0.026) | |
| Residuals from col.(2) | | | | 0.043** |
| | | | | (0.013) |
| Residuals from col.(3) | | | | -0.007 |
| | | | | (0.008) |
| Constant | 0.051** | 1.901*** | 4.133*** | 0.051** |
| | (0.016) | (0.023) | (0.036) | (0.016) |
| Time fixed effects | Yes | Yes | Yes | Yes |
| N | 4,872 | 4,872 | 4,872 | 4,872 |
| N_g | 1,624 | | | 1,624 |
| rho | 0.608 | | | 0.609 |
| r2_w | 0.000 | | | 0.004 |
| r2_o | 0.000 | | | 0.001 |
| r2_b | . | | | 0.000 |
| F | 0.001 | 91.999 | 87.763 | 3.134 |

Standard errors in parentheses

Source: Young Lives Study 2002-2016. Own elaboration.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table 9:** Upper bound estimates of inequality of educational opportunity

| | **Approach 1** | **Approach 2** |
|---|---|---|
| **Mathematics** | 68.55 | 68.80 |
| | [64.13 ; 72.96] | [64.34 ; 73.24] |
| **Reading** | 65.40 | 66.48 |
| | [61.41 ; 69.38] | [62.41 ; 70.53] |

Note: Confidence intervals at the 95% level in brackets, based on 1,000 replications bootstraps.
Source: Young Lives Study 2002-2016.
Own elaboration.

are presented in Appendix D.

Regarding the first upper bound approach, Table D.1 displays the regression presented in Eq. (15). Most of the time-varying circumstances do not appear as statistically significant. Even the two effort variables are not simultaneously significant for both mathematics and reading tests, despite the fact that they do show the expected signs. This result probably suggests that the unobserved heterogeneity (which includes circumstances such as innate intelligence) is the critical element when analysing learning achievements. Note that this component is controlled for in the context of fixed-effects regressions.

This being said, the counterfactuals generated from these regressions yield to IOp upper bounds of 70.17% and 66.15%, respectively for mathematics and reading tests, as shown in the first column of table 10. These magnitudes are very close to those previously calculated without considering time-varying circumstances (cf. table 9). Actually, they are statistically identical, as the confidence intervals from both tables put in evidence.

The results of the second IOp upper bound approach including time-varying circumstances point in the same direction. Indeed, the maximum amount of inequality is similar to that previously calculated where time-varying circumstances are not considered. Furthermore, their confidence intervals are virtually the same.

**Table 10:** Upper bound estimates of inequality of educational opportunity, including time-varying circumstances

| | **Approach 1** | **Approach 2** |
|---|---|---|
| **Mathematics** | 70.17 | 70.38 |
| | [65.66 ; 74.66] | [65.86 ; 74.88] |
| **Reading** | 66.15 | 67.30 |
| | [62.10 ; 70.18] | [63.19 ; 71.39] |

Note: Confidence intervals at the 95% level in brackets, based on 1,000 replications bootstraps.
Source: Young Lives Study 2002-2016.
Own elaboration.

These findings might suggest that the Niehues and Peichl (2014)'s methodology is robust to the issue of omitted time-varying circumstances when studying learning achievement outcomes. After all, it could be the case that this kind of circumstances has a constant impact on the outcome of interest, and thus it is already captured through the specific unit effect $c_i^{(k)}$. Nevertheless, at the present stage of research, this result should be taken with caution since the set of time-varying circumstances considered here does not appear systematically as statistically significant in the models.

# 6 Robustness checks

For robustness checks, I proceed by using a different outcome first and then using different inequality measures. Appendix E provides all the material used for the discussion in this section.

In addition to the mathematics and reading tests, during the Young Lives Study surveys was also administered the Peabody Picture Vocabulary Test (PPVT).[18] It is a test of receptive vocabulary ability constituted of 204 items, which is individually and orally administered, "untimed, and norm-referenced. The task of the test taker is to select the picture that best represents the meaning of a stimulus word presented orally by the examiner" (Cueto & León, 2012, p.6).

Certainly, the PPVT is not intended to provide estimates of learning achievement. However, it is informative of receptive vocabulary ability, which is also a relevant outcome for individuals during their childhood.

In this context, the OLS estimates of the PPVT scores on circumstances (cf. table E.1) are remarkably similar to those shown previously in section 5.2 for mathematics and reading test scores: the set of circumstances under consideration has similar explanatory power on the variance of the three tests. As a consequence, it is not surprising that the correspondent lower-bound estimates are also congruent. Indeed, the lower bound IOp shares for PPVT scores decrease from 35% in round 3 to 24% in round 5. Both the shares and the sense of the evolution of IOp are alike to the previous findings. Regarding the upper bound IOp estimates, the counterfactuals constructed from the results shown in tables E.2 and E.3 yield to IOp shares of 75% at most, for both approaches. These numbers are slightly higher than those previously found in section 5.3, however, they depict similar conclusions.

Finally, the second robustness check involves the use of different inequality measures. Although it has been shown that the variance is the most suitable inequality measure for analysing standardized test scores (cf. Ferreira & Gignoux, 2014), I provide results using other well-known inequality indices. It is important to mention that, since the outcomes used in previous sections include zero and negative values, some inequality indices are not defined because of those ranges. For this reason, I re-centered the distribution of the test scores in order to have 1 as minimum value.

This being said, table 11 presents the results for the lower bound estimates using the Gini index and indices from the Generalized Entropy class, with values -1, 0 (mean logarithmic deviation), 1 (Theil index), and 2 (half the square of the coefficient of variation). Some regularities are noticed. IOp shares are consistently the highest in round 3, and the lowest in round 5. This means that the unfair source of inequality coming from the circumstances under consideration (cf. table 1) decreases over time. As it was mentioned before, other circumstances might become more relevant as the child advances in her schooling life. Furthermore, the values of the Generalized Entropy class' indices are near to the IOp shares calculated with the simple variance in section 5.2. This is not the case for the Gini coefficient, which depicts sizeable

[18] cf. Cueto and León (2012) for more details.

higher values. The Lorenz curves for mathematics test scores shown in figure E.2 might be useful to understand the issue: the smoothed distribution built from the circumstances is very close to the original distribution in round 3. It is worthwhile to mention that the Gini coefficient has some well-known limitations; for instance, it can give the same value to two different distributions, is most sensitive to inequalities in the middle portion of the distributions, and it fails to satisfy the diminishing transfers axiom. Moreover, the Gini coefficient, as well as the Theil indices, are not ordinally invariant to the standardization of test scores (Ferreira & Gignoux, 2014, p.242).

**Table 11:** Lower bound relative shares of IOp: Different inequality measures (cf. Equation 3)

| | **Gini** | **GE(-1)** | **GE(0)** | **GE(1)** | **GE(2)** |
|---|---|---|---|---|---|
| **Mathematics** | | | | | |
| Round 3 | 0.543 | 0.236 | 0.265 | 0.284 | 0.295 |
| Round 4 | 0.475 | 0.157 | 0.184 | 0.204 | 0.218 |
| Round 5 | 0.380 | 0.101 | 0.121 | 0.133 | 0.137 |
| **Reading** | | | | | |
| Round 3 | 0.445 | 0.148 | 0.170 | 0.187 | 0.198 |
| Round 4 | 0.485 | 0.180 | 0.203 | 0.218 | 0.228 |
| Round 5 | 0.397 | 0.117 | 0.133 | 0.145 | 0.153 |
| **PPVT** | | | | | |
| Round 3 | 0.583 | 0.222 | 0.263 | 0.294 | 0.315 |
| Round 4 | 0.562 | 0.238 | 0.270 | 0.290 | 0.301 |
| Round 5 | 0.481 | 0.150 | 0.183 | 0.204 | 0.218 |

Note: GE(a) are inequality indexes from the Generalized Entropy class for a = -1, 0 (mean logarithmic deviation), 1 (Theil index), 2 (half the square of the coefficient of variation).
Source: Young Lives Study 2002-2016. Own elaboration.

Regarding the upper bound IOp shares calculated with other inequality measures, table 12 shows the results of an analogous exercise. Once again, the estimates are similar to those previously shown in section 5.3. Among the different indices, the mean value is 0.70, with a range from a minimum of 0.61 and a maximum of 0.85. The results also put in evidence that the fact of taking into account or not the set of time-varying circumstances does not make a difference.

# 7 Concluding remarks

This document explores the problem of inequality of educational opportunity in Peru for the period 2002-2016 using a unique longitudinal database of children followed since they were around one year old. It offers, for the first time in the literature, both lower and upper bounds of IOp for learning achievement using standardized test scores. In addition, it explores a previously neglected problem:

**Table 12:** Upper bound relative shares of IOp: Different inequality measures (cf. Equation 3)

| | Gini | GE(-1) | GE(0) | GE(1) | GE(2) |
|---|---|---|---|---|---|
| ***Without time-varying circumstances*** | | | | | |
| **First approach** | | | | | |
| Mathematics | 0.85 | 0.65 | 0.68 | 0.70 | 0.72 |
| Reading | 0.82 | 0.61 | 0.64 | 0.66 | 0.67 |
| **Second approach** | | | | | |
| Mathematics | 0.85 | 0.65 | 0.68 | 0.70 | 0.72 |
| Reading | 0.82 | 0.61 | 0.64 | 0.66 | 0.67 |
| ***With time-varying circumstances*** | | | | | |
| **First approach** | | | | | |
| Mathematics | 0.85 | 0.65 | 0.69 | 0.71 | 0.72 |
| Reading | 0.82 | 0.61 | 0.64 | 0.66 | 0.68 |
| **Second approach** | | | | | |
| Mathematics | 0.85 | 0.65 | 0.69 | 0.71 | 0.72 |
| Reading | 0.82 | 0.62 | 0.64 | 0.66 | 0.68 |

Note: GE(a) are inequality indexes from the Generalized Entropy class for a = -1, 0 (mean logarithmic deviation), 1 (Theil index), 2 (half the square of the coefficient of variation).
Source: Young Lives Study 2002-2016. Own elaboration.

the role of time-varying circumstances.

The methods rely on Ferreira and Gignoux (2014) and Niehues and Peichl (2014). Certainly, there is a large number of IOp measures that have been proposed in the literature and it also has been shown that the methodological choice is not innocuous.[19] However, since the objective of the present work was to establish lower and upper bounds of educational IOp (and not its exact *true* share) the mentioned warning does not pose a critical problem.

Furthermore, some authors argue that "all measurable achievement and behaviours of children, before an age of consent is attained, are the result of their circumstances. (...) [*i.e.*] children should not be held responsible for any of their accomplishments before that age" (Hufe et al., 2017, p.501). According to this view, there is no place for *effort* when analysing childhood outcomes. However, there is evidence suggesting that pupil's overall effort explains a large extent of within-school variations in test scores, whereas circumstances are more important to explain between-school variations (Asadullah et al., 2018, pp.4-5). Anyhow, it is worth noting that I used

[19] According to Ramos and van de Gaer (2017), among the three main measurement criteria – ex-ante/ex-post, direct/indirect, and parametric/non-parametric– it seems that the former choice is the most relevant since it substantially influences IOp orderings.

only two effort variables: number of hours allocated to study at home, and to leisure activities. They seem to be reasonable for this study.[20]

In this context, the results suggest that circumstances related to the first year of life account, at least, for one-third of total variance in learning achievement when children are eight years old, and their influence decreases to, at least, one-fifth at age fifteen. Likewise, the maximum amount attributable to *unjust* inequalities lies around 70%. In this context, educational IOp shares are important and are consistent with the view according to which "breaking the strong association between socio-economic characteristics, educational opportunities, and educational outcomes is, perhaps, the main challenge of Peruvian education" (Cueto & Felipe, 2018, p.67, *own translation*).

Furthermore, the distinction between the two extreme positions of reward principles for the indirect effect of circumstances on outcomes proved to make little difference. Likewise, time-varying circumstances seem to be a minor problem when measuring upper bounds of IOp using panel data. A plausible reason might be that their effect on the outcome is constant in practice.

For future research, regarding the lower bound procedure, it would be important to include particular circumstances that are relevant for each stage of the life path, for example, school and teachers' characteristics for secondary education. This may be possible by matching the YLS database with the school census and other surveys carried out by the Peruvian Ministry of Education.[21] On the other hand, more evidence is needed regarding the impact of time-varying circumstances on upper bound estimates of IOp. The present work studied this issue for the first time, but more research in different contexts is needed. Finally, besides the measure of the extent of IOp, the most promising research path involves the underlying process and mechanisms that determine IOp, which are still poorly understood, especially with respect to the effect of preferences and aspirations. Making a link with the theory of intergenerational mobility could be a promising avenue to fill this gap.

[20]It may also be noticed that time-varying effort variables are needed in order to compute upper bounds of IOp within the Niehues and Peichl (2014) framework, otherwise, they would be 100%.

[21]Unfortunately, I was not given access to the YLS database with the child's school identifier, but it does exist.

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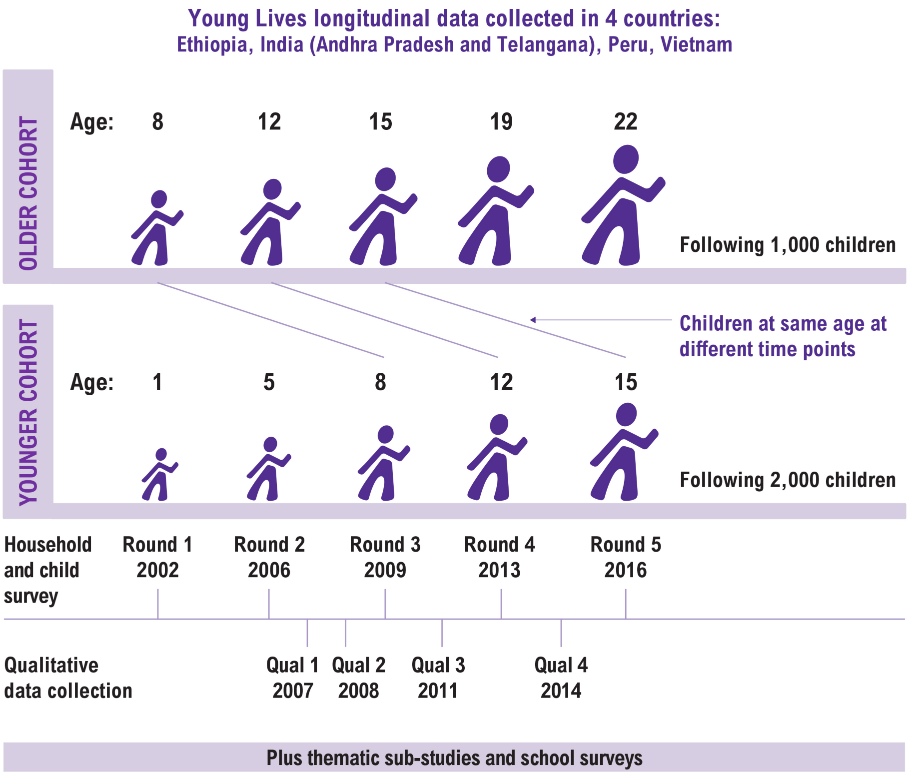
# Appendices

## A The Young Lives Study

**Figure A.1:** The Young Lives Study




Source: http://younglives.org.uk/content/our-research-methods

# B Variables detail

**Table B.1:** Circumstance variables used for lower bound estimates

| Variable | Description | Values taken from |
|---|---|---|
| Gender | 0 = Male; 1 = Female | Round 1 |
| Birth order | Order the child is born in his family: 1 = first-born, 2 = second-born, and so on. | Round 1 |
| Area | 0 = Urban; 1 = Rural | Round 1 |
| Region | Dummies for Costa (reference), Sierra, and Selva | Round 1 |
| Household size | Number of members of the household | Round 1 |
| Dependency ratio | Ratio of household members aged 0 to 14 and 65 or more, and those aged 15 to 64 | Round 1 |
| Wealth index | Ranges from 0 to 1, a higher value indicates a higer socio-economic status. It is constructed from three indices: housing quality, access to services, and ownership of consumer durables. All the details are provided in Briones (2017). | Round 1 |
| Mother's education | Continous variable from 0 (none) to 16 (complete undergraduate) | Round 1 |
| Mother's age at birth | Mother's age at child's birth | Round 1 |
| Mother has indigenous tongue | 0 = Spanish; 1 = Quechua, Aymara, Nomatsiguenga, Other native from jungle | Round 1 |
| Stunting | Short height for age (z-score): 0 = not stunted (2 sd or more), 1 = moderately stunted (-3 to -2 sd), 2 = severly stunted (less than -3 sd) | Round 1 |
| Vaccination | Number of vaccines the child received from the following list: BCG, Measles, Polio, DPT, HIB, and tetanus (mother during pregnancy) | Round 1 |
| Attended pre-school | Child ever attended pre-school between 3 and 5 years-old | Round 2 |
| First school public (proxy) | The school the child attended at 8 years old was public | Round 3 |
| Age at start of grade 1 | Child's age at start of grade 1 | Round 3 |
| Community's population (log) | Size of the child's local community in log | Round 1 |

Own elaboration.

**Table B.2:** Some circumstance variables used for upper bound estimates

| Variable | Description |
|---|---|
| Food security | Household's declared food situation in the last 12 months: 1 = "We always eat enough of what we want", 2 = "We eat enough but not always what we want"; 3 = "We sometimes do not eat enough"; 4 = "We frequently do not eat enough" |
| Shock - crime* | Destruction/theft of tools for production, housing/consumer goods; theft of cash, crops, livestock; crime that resulted in death/disablement |
| Shock - regulation* | Land redistribution, resettlement or forced migration, forced contributions, eviction, invasion of property |
| Shock - economic* | Increase in input prices, decrease in output prices, death of livestock, closure place of employment, loss of job / source of income / family enterprise, industrial action, contract disputes, disbanding credit, confiscation of assets, disputes abouth assets, decrease in food availability |
| Shock - environment* | Drought, flooding, erosion, frost, pests on crops/storage/livestock, crop failure, natural disaster, earthquake, forest fire, pollution caused by mining |
| Shock - house* | Fire or collapse affecting house/building |
| Shock - family* | Death/illness of a household member, divorce or separation, imprisonment, discrimination |

* Measured as the total number of events.
Note: The values taken of each variable are from rounds 3, 4, and 5.
Own elaboration.

# C Descriptive statistics

**Table C.1:** Younger cohort: Descriptive statistics, Rounds 1 to 5

| | Frequency | | | | | Percentage | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Round 1** | **Round 2** | **Round 3** | **Round 4** | **Round 5** | **Round 1** | **Round 2** | **Round 3** | **Round 4** | **Round 5** |
| ***Area*** | | | | | | | | | | |
| **Total** | **2,052** | **1,963** | **1,943** | **1,902** | **1,860** | **100.00** | **100.00** | **100.00** | **100.00** | **100.00** |
| Urban | 1,406 | 1,360 | 1,390 | 1,393 | 1,385 | 68.52 | 69.28 | 71.54 | 73.24 | 74.46 |
| Rural | 646 | 603 | 553 | 509 | 475 | 31.48 | 30.72 | 28.46 | 26.76 | 25.54 |
| ***Region*** | | | | | | | | | | |
| **Total** | **2,052** | **1,963** | **1,943** | **1,902** | **1,860** | **100.00** | **100.00** | **100.00** | **100.00** | **100.00** |
| Costa | 709 | 719 | 718 | 760 | 774 | 34.55 | 36.63 | 36.95 | 39.96 | 41.61 |
| Sierra | 1,035 | 948 | 924 | 828 | 796 | 50.44 | 48.29 | 47.56 | 43.53 | 42.80 |
| Selva | 308 | 296 | 301 | 314 | 290 | 15.01 | 15.08 | 15.49 | 16.51 | 15.59 |
| ***Gender*** | | | | | | | | | | |
| **Total** | **2,052** | **1,963** | **1,943** | **1,902** | **1,860** | **100.00** | **100.00** | **100.00** | **100.00** | **100.00** |
| Male | 1,027 | 990 | 980 | 957 | 938 | 50.05 | 50.43 | 50.44 | 50.32 | 50.43 |
| Female | 1,025 | 973 | 963 | 945 | 922 | 49.95 | 49.57 | 49.56 | 49.68 | 49.57 |
| ***Ethnic origin*** | | | | | | | | | | |
| **Total** | **2,052** | **1,963** | **1,943** | **1,902** | **1,860** | **100.00** | **100.00** | **100.00** | **100.00** | **100.00** |
| White | 117 | 110 | 109 | 107 | 100 | 5.70 | 5.60 | 5.61 | 5.63 | 5.38 |
| Mestizo | 1,881 | 1,800 | 1,781 | 1,743 | 1,711 | 91.67 | 91.70 | 91.66 | 91.64 | 91.99 |
| Native | 44 | 44 | 44 | 43 | 41 | 2.14 | 2.24 | 2.26 | 2.26 | 2.20 |
| Other | 10 | 9 | 9 | 9 | 8 | 0.49 | 0.46 | 0.46 | 0.47 | 0.43 |

Source: Young Lives Study 2002-2016. Own elaboration.

**Table C.2:** Mathematics scores by circumstances

| | Score in Mathematics | | | | | |
|---|---|---|---|---|---|---|
| | Round 3 | | Round 4 | | Round 5 | |
| | **Mean** | **s.d.** | **Mean** | **s.d.** | **Mean** | **s.d.** |
| **Total** | **0.000** | **1.000** | **0.000** | **1.000** | **0.000** | **1.000** |
| **Gender** | | | | | | |
| Male | 0.069 | 0.988 | 0.027 | 1.004 | 0.103 | 1.040 |
| Female | -0.069 | 1.008 | -0.028 | 0.996 | -0.105 | 0.946 |
| **Area (R1)** | | | | | | |
| Urban | 0.238 | 0.915 | 0.226 | 0.906 | 0.184 | 0.991 |
| Rural | -0.504 | 0.985 | -0.500 | 1.018 | -0.394 | 0.901 |
| **Region (R1)** | | | | | | |
| Costa | 0.331 | 0.873 | 0.221 | 0.902 | 0.161 | 0.994 |
| Sierra | -0.202 | 1.033 | -0.113 | 1.055 | -0.066 | 1.018 |
| Selva | -0.063 | 0.966 | -0.130 | 0.941 | -0.150 | 0.903 |
| **Mother's tonge** | | | | | | |
| Spanish | 0.173 | 0.952 | 0.148 | 0.936 | 0.111 | 0.980 |
| Indigenous | -0.399 | 1.001 | -0.356 | 1.062 | -0.255 | 0.989 |
| **Stunting (R1)** | | | | | | |
| Not stunted | 0.129 | 0.960 | 0.130 | 0.959 | 0.117 | 0.990 |
| Moderately stunted | -0.238 | 1.025 | -0.277 | 1.008 | -0.212 | 0.960 |
| Severly stunted | -0.504 | 0.975 | -0.452 | 1.066 | -0.474 | 0.967 |
| **Attended pre-school (R2)** | | | | | | |
| No pre-school | -0.551 | 0.962 | -0.434 | 1.009 | -0.354 | 0.961 |
| Pre-school | 0.103 | 0.975 | 0.078 | 0.978 | 0.067 | 0.988 |
| **First school (R3)** | | | | | | |
| Private | 0.716 | 0.797 | 0.561 | 0.816 | 0.544 | 1.030 |
| Public | -0.129 | 0.974 | -0.105 | 0.998 | -0.092 | 0.947 |

Source: Young Lives Study 2002-2016. Own elaboration.

**Table C.3:** Reading scores by circumstances

| | Score in Reading | | | | | |
|---|---|---|---|---|---|---|
| | **Round 3** | | **Round 4** | | **Round 5** | |
| | **Mean** | **s.d.** | **Mean** | **s.d.** | **Mean** | **s.d.** |
| **Total** | **0.000** | **1.000** | **0.000** | **1.000** | **0.000** | **1.000** |
| **Gender** | | | | | | |
| Male | 0.006 | 0.977 | -0.017 | 0.982 | 0.002 | 1.010 |
| Female | -0.007 | 1.023 | 0.018 | 1.018 | -0.002 | 0.990 |
| **Area (R1)** | | | | | | |
| Urban | 0.281 | 0.857 | 0.228 | 0.915 | 0.203 | 0.922 |
| Rural | -0.596 | 1.021 | -0.503 | 0.997 | -0.452 | 1.020 |
| **Region (R1)** | | | | | | |
| Costa | 0.316 | 0.813 | 0.310 | 0.907 | 0.205 | 0.928 |
| Sierra | -0.221 | 1.076 | -0.193 | 1.005 | -0.121 | 1.029 |
| Selva | 0.029 | 0.927 | -0.067 | 1.014 | -0.074 | 0.988 |
| **Mother's tonge** | | | | | | |
| Spanish | 0.219 | 0.888 | 0.178 | 0.949 | 0.129 | 0.934 |
| Indigenous | -0.505 | 1.060 | -0.420 | 1.006 | -0.310 | 1.089 |
| **Stunting (R1)** | | | | | | |
| Not stunted | 0.139 | 0.956 | 0.151 | 0.948 | 0.115 | 0.962 |
| Moderately stunted | -0.226 | 0.997 | -0.317 | 1.043 | -0.238 | 1.053 |
| Severly stunted | -0.641 | 1.015 | -0.522 | 0.979 | -0.425 | 0.991 |
| **Attended pre-school (R2)** | | | | | | |
| No pre-school | -0.572 | 0.990 | -0.463 | 1.044 | -0.385 | 1.039 |
| Pre-school | 0.106 | 0.965 | 0.085 | 0.971 | 0.067 | 0.978 |
| **First school (R3)** | | | | | | |
| Private | 0.564 | 0.702 | 0.613 | 0.787 | 0.543 | 0.809 |
| Public | -0.102 | 1.011 | -0.113 | 0.994 | -0.107 | 1.000 |

Source: Young Lives Study 2002-2016. Own elaboration.

**Table C.4:** Panel time-varying circumstances: Descriptive statistics

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| **Stunting** | | | | |
| overall | 0.22 | 0.49 | 0.00 | 2.00 |
| between | | 0.43 | 0.00 | 2.00 |
| within | | 0.24 | -1.11 | 1.55 |
| **Food security** | | | | |
| overall | 1.75 | 0.66 | 1.00 | 4.00 |
| between | | 0.49 | 1.00 | 4.00 |
| within | | 0.46 | -0.25 | 3.75 |
| **Rural** | | | | |
| overall | 0.27 | 0.44 | 0.00 | 1.00 |
| between | | 0.43 | 0.00 | 1.00 |
| within | | 0.13 | -0.40 | 0.94 |
| **Sierra** | | | | |
| overall | 0.45 | 0.50 | 0.00 | 1.00 |
| between | | 0.48 | 0.00 | 1.00 |
| within | | 0.13 | -0.22 | 1.11 |
| **Selva** | | | | |
| overall | 0.16 | 0.37 | 0.00 | 1.00 |
| between | | 0.36 | 0.00 | 1.00 |
| within | | 0.08 | -0.51 | 0.83 |
| **Household size** | | | | |
| overall | 5.30 | 1.87 | 2.00 | 18.00 |
| between | | 1.60 | 2.00 | 14.33 |
| within | | 0.98 | -0.70 | 12.30 |
| **Dependency ratio** | | | | |
| overall | 0.25 | 0.17 | 0.00 | 0.75 |
| between | | 0.15 | 0.00 | 0.70 |
| within | | 0.09 | -0.17 | 0.62 |
| **Household wealth index** | | | | |
| overall | 0.59 | 0.20 | 0.00 | 0.95 |
| between | | 0.18 | 0.03 | 0.94 |
| within | | 0.08 | 0.17 | 1.03 |
| **Public school** | | | | |
| overall | 0.83 | 0.38 | 0.00 | 1.00 |
| between | | 0.33 | 0.00 | 1.00 |
| within | | 0.18 | 0.16 | 1.49 |
| **Commuting time to school** | | | | |
| overall | 15.12 | 16.35 | 0.00 | 420.00 |
| between | | 11.63 | 0.67 | 150.00 |
| within | | 11.76 | -119.88 | 285.12 |
| **Shock: crime** | | | | |
| overall | 0.16 | 0.44 | 0.00 | 4.00 |

*Continues on next page...*

Table C.4 – *...Continued from previous page*

| | **Mean** | **Std. Dev.** | **Min** | **Max** |
|---|---|---|---|---|
| between | | 0.28 | 0.00 | 2.00 |
| within | | 0.35 | -1.50 | 2.50 |
| **Shock: regulation** | | | | |
| overall | 0.01 | 0.09 | 0.00 | 2.00 |
| between | | 0.05 | 0.00 | 0.67 |
| within | | 0.07 | -0.66 | 1.34 |
| **Shock: economic** | | | | |
| overall | 0.19 | 0.48 | 0.00 | 5.00 |
| between | | 0.30 | 0.00 | 2.00 |
| within | | 0.38 | -1.81 | 3.53 |
| **Shock: environment** | | | | |
| overall | 0.42 | 0.90 | 0.00 | 7.00 |
| between | | 0.67 | 0.00 | 4.67 |
| within | | 0.61 | -3.25 | 4.42 |
| **Shock: house** | | | | |
| overall | 0.01 | 0.17 | 0.00 | 2.00 |
| between | | 0.09 | 0.00 | 1.00 |
| within | | 0.14 | -0.99 | 1.35 |
| **Shock: family** | | | | |
| overall | 0.42 | 0.66 | 0.00 | 4.00 |
| between | | 0.42 | 0.00 | 2.00 |
| within | | 0.52 | -1.58 | 3.08 |

Source: Young Lives Study, 2002-2016 - Rounds 3, 4, and 5. Own elaboration.

# D Regressions for the analysis of time-varying circumstances

## D.1 Upper bound first approach

**Table D.1:** Mathematics and reading FE estimates including time-varying circumstances: First approach (cf. equation 15)

| | (1) Mathematics | (2) Reading |
|---|---|---|
| Hours/day studying outside school | 0.020 | 0.044*** |
| | (0.012) | (0.013) |
| Hours/day leisure activities | -0.019* | -0.005 |
| | (0.008) | (0.008) |
| Stunting | -0.035 | -0.050 |
| | (0.036) | (0.040) |
| Food security | 0.035 | 0.005 |
| | (0.018) | (0.020) |
| Rural | -0.087 | -0.176* |
| | (0.073) | (0.081) |
| Sierra | -0.240*** | -0.149 |
| | (0.071) | (0.079) |
| Selva | 0.095 | -0.053 |
| | (0.114) | (0.128) |
| Household size | 0.010 | -0.008 |
| | (0.009) | (0.010) |
| Dependency ratio | -0.410*** | 0.048 |
| | (0.094) | (0.105) |
| Wealth index | 0.015 | -0.049 |
| | (0.117) | (0.130) |
| Public school | -0.018 | 0.015 |
| | (0.046) | (0.052) |
| Commuting time to school | 0.001 | 0.002* |
| | (0.001) | (0.001) |
| Shock: crime | 0.013 | -0.065* |
| | (0.024) | (0.027) |
| Shock: regulation | -0.093 | -0.124 |
| | (0.110) | (0.123) |
| Shock: economic | 0.011 | 0.049* |
| | (0.022) | (0.025) |
| Shock: environment | 0.006 | -0.022 |
| | (0.014) | (0.016) |
| Shock: house | 0.055 | 0.037 |
| | (0.060) | (0.067) |
| Shock: family | 0.019 | -0.044* |
| | (0.017) | (0.018) |

| | | |
|---|---|---|
| Constant | 0.196 | 0.163 |
| | (0.117) | (0.131) |
| Time fixed effects | Yes | Yes |
| N | 4,872 | 4,872 |
| N_g | 1,624 | 1,624 |
| rho | 0.656 | 0.580 |
| r2_w | 0.021 | 0.015 |
| r2_o | 0.046 | 0.130 |
| r2_b | 0.055 | 0.195 |
| F | 3.516 | 2.505 |

Standard errors in parentheses

Source: Young Lives Study 2002-2016. Own elaboration.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## D.2 Upper bound second approach

**Table D.2:** Mathematics FE estimates including time-varying circumstances: Second approach (cf. equations 16, 17, and 18)

| | (1) Maths | (2) Hours study | (3) Hours leisure | (4) Maths |
|---|---|---|---|---|
| Stunting | -0.034 | | | -0.034 |
| | (0.036) | | | (0.036) |
| Food security | 0.036* | | | 0.035 |
| | (0.018) | | | (0.018) |
| Rural | -0.082 | | | -0.085 |
| | (0.073) | | | (0.073) |
| Sierra | -0.244*** | | | -0.236*** |
| | (0.071) | | | (0.071) |
| Selva | 0.086 | | | 0.094 |
| | (0.115) | | | (0.114) |
| Household size | 0.009 | | | 0.010 |
| | (0.009) | | | (0.009) |
| Dependency ratio | -0.409*** | | | -0.404*** |
| | (0.094) | | | (0.094) |
| Wealth index | 0.037 | | | 0.015 |
| | (0.117) | | | (0.117) |
| Public school | -0.024 | | | -0.018 |
| | (0.046) | | | (0.046) |
| Commuting time to school | 0.001 | | | 0.001 |
| | (0.001) | | | (0.001) |
| Shock: crime | 0.016 | | | 0.013 |
| | (0.024) | | | (0.024) |
| Shock: regulation | -0.097 | | | -0.091 |
| | (0.110) | | | (0.110) |
| Shock: economic | 0.009 | | | 0.011 |
| | (0.022) | | | (0.022) |
| Shock: environment | 0.007 | | | 0.006 |
| | (0.014) | | | (0.014) |
| Shock: house | 0.056 | | | 0.054 |
| | (0.060) | | | (0.060) |
| Shock: family | 0.018 | | | 0.019 |
| | (0.017) | | | (0.017) |
| Individual effect from col.(1) | | 0.172*** | 0.047 | |
| | | (0.016) | (0.026) | |
| Time-varying circumstances prediction | | 0.613*** | 1.442*** | |
| | | (0.075) | (0.119) | |
| Residuals from col.(2) | | | | 0.020 |
| | | | | (0.012) |
| Residuals from col.(3) | | | | -0.019* |
| | | | | (0.008) |

| | | | | |
|---|---|---|---|---|
| Constant | 0.154 | 1.958*** | 4.269*** | 0.154 |
| | (0.109) | (0.024) | (0.037) | (0.109) |
| Time fixed effects | Yes | Yes | Yes | Yes |
| N | 4,872 | 4,872 | 4,872 | 4,872 |
| N_g | 1,624 | | | 1,624 |
| rho | 0.655 | | | 0.657 |
| r2_w | 0.018 | | | 0.021 |
| r2_o | 0.045 | | | 0.042 |
| r2_b | 0.055 | | | 0.049 |
| F | 3.275 | 71.517 | 94.452 | 3.516 |

Standard errors in parentheses

Source: Young Lives Study 2002-2016. Own elaboration.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table D.3:** Reading FE estimates including time-varying circumstances: Second approach (cf. equations 16, 17, and 18)

| | (1) Read. | (2) Hours study | (3) Hours leisure | (4) Read. |
|---|---|---|---|---|
| Stunting | -0.049 | | | -0.051 |
| | (0.040) | | | (0.040) |
| Food security | 0.005 | | | 0.005 |
| | (0.020) | | | (0.020) |
| Rural | -0.173* | | | -0.180* |
| | (0.081) | | | (0.081) |
| Sierra | -0.154 | | | -0.152 |
| | (0.079) | | | (0.079) |
| Selva | -0.057 | | | -0.054 |
| | (0.128) | | | (0.128) |
| Household size | -0.010 | | | -0.009 |
| | (0.010) | | | (0.010) |
| Dependency ratio | 0.046 | | | 0.049 |
| | (0.105) | | | (0.105) |
| Wealth index | -0.027 | | | -0.050 |
| | (0.130) | | | (0.130) |
| Public school | 0.010 | | | 0.015 |
| | (0.052) | | | (0.052) |
| Commuting time to school | 0.002** | | | 0.002** |
| | (0.001) | | | (0.001) |
| Shock: crime | -0.062* | | | -0.066* |
| | (0.027) | | | (0.027) |
| Shock: regulation | -0.139 | | | -0.127 |
| | (0.123) | | | (0.123) |
| Shock: economic | 0.043 | | | 0.050* |
| | (0.025) | | | (0.025) |

| | | | | |
|---|---|---|---|---|
| Shock: environment | -0.022 | | | -0.023 |
| | (0.016) | | | (0.016) |
| Shock: house | 0.037 | | | 0.038 |
| | (0.067) | | | (0.067) |
| Shock: family | -0.044* | | | -0.045* |
| | (0.018) | | | (0.019) |
| Individual effect from col.(1) | | 0.172*** | 0.070* | |
| | | (0.018) | (0.028) | |
| Time-varying circumstances prediction | | 0.716*** | 1.365*** | |
| | | (0.096) | (0.152) | |
| Residuals from col.(2) | | | | 0.044*** |
| | | | | (0.013) |
| Residuals from col.(3) | | | | -0.005 |
| | | | | (0.008) |
| Constant | 0.231 | 2.030*** | 4.378*** | 0.229 |
| | (0.121) | (0.028) | (0.045) | (0.121) |
| Time fixed effects | Yes | Yes | Yes | Yes |
| N | 4,872 | 4,872 | 4,872 | 4,872 |
| N_g | 1,624 | | | 1,624 |
| rho | 0.581 | | | 0.583 |
| r2_w | 0.011 | | | 0.015 |
| r2_o | 0.121 | | | 0.111 |
| r2_b | 0.180 | | | 0.164 |
| F | 2.068 | 76.257 | 82.393 | 2.505 |

Standard errors in parentheses

Source: Young Lives Study 2002-2016. Own elaboration.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

# E Robustness checks material

**Table E.1:** PPVT z-scores in Rounds 3 to 5 and circumstances (OLS estimates)

| | (1)<br>PPVT R3 | (2)<br>PPVT R4 | (3)<br>PPVT R5 |
|---|---|---|---|
| Female | -0.079* | -0.180*** | -0.158*** |
| | (0.038) | (0.041) | (0.043) |
| Birth order | -0.067** | -0.082*** | -0.073** |
| | (0.021) | (0.023) | (0.024) |
| Rural (R1) | -0.271*** | -0.214** | -0.152* |
| | (0.062) | (0.067) | (0.070) |
| Sierra (R1) | 0.013 | 0.041 | 0.104 |
| | (0.050) | (0.054) | (0.056) |
| Selva (R1) | 0.083 | 0.060 | 0.119 |
| | (0.063) | (0.068) | (0.070) |
| Household size (R1) | 0.006 | -0.003 | -0.000 |
| | (0.009) | (0.010) | (0.010) |
| Dependency ratio (R1) | 0.020 | 0.013 | -0.012 |
| | (0.146) | (0.158) | (0.164) |
| Wealth index (R1) | 0.844*** | 0.757*** | 0.715*** |
| | (0.120) | (0.130) | (0.135) |
| Mother education (R1) | 0.041*** | 0.044*** | 0.038*** |
| | (0.006) | (0.007) | (0.007) |
| Mother age at birth | 0.013** | 0.017*** | 0.014** |
| | (0.004) | (0.004) | (0.005) |
| Mother has indig. tongue | 0.021 | 0.060 | 0.034 |
| | (0.053) | (0.057) | (0.059) |
| Stunting (R1) | -0.120** | -0.137*** | -0.070 |
| | (0.037) | (0.040) | (0.041) |
| Vaccins (R1) | 0.103*** | 0.091*** | 0.065* |
| | (0.025) | (0.027) | (0.028) |
| Attended pre-school (R2) | 0.124* | 0.143* | 0.187** |
| | (0.063) | (0.068) | (0.071) |
| First school public (R3) | -0.213*** | -0.259*** | -0.245*** |
| | (0.055) | (0.060) | (0.062) |
| Age at start of grade 1 | -0.210*** | -0.121** | -0.125** |
| | (0.037) | (0.040) | (0.042) |
| Com. population log (R1) | -0.049* | -0.044 | -0.053* |
| | (0.021) | (0.022) | (0.023) |
| Constant | 0.698* | 0.198 | 0.365 |
| | (0.322) | (0.349) | (0.361) |
| N | 1,401 | 1,401 | 1,401 |
| R2 | 0.355 | 0.315 | 0.241 |
| R2-adj. | 0.347 | 0.307 | 0.231 |

Standard errors in parentheses

Source: Young Lives Study 2002-2016. Own elaboration.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table E.2:** PPVT FE estimates: First approach (cf. equation 9)

| | (1)<br>PPVT |
|---|---|
| Hours/day studying outside school | -0.005 |
| | (0.011) |
| Hours/day leisure activities | -0.016* |
| | (0.007) |
| Constant | 0.121** |
| | (0.041) |
| Time fixed effects | Yes |
| N | 4,773 |
| N_g | 1,591 |
| rho | 0.720 |
| r2_w | 0.002 |
| r2_o | 0.012 |
| r2_b | 0.056 |
| F | 1.601 |

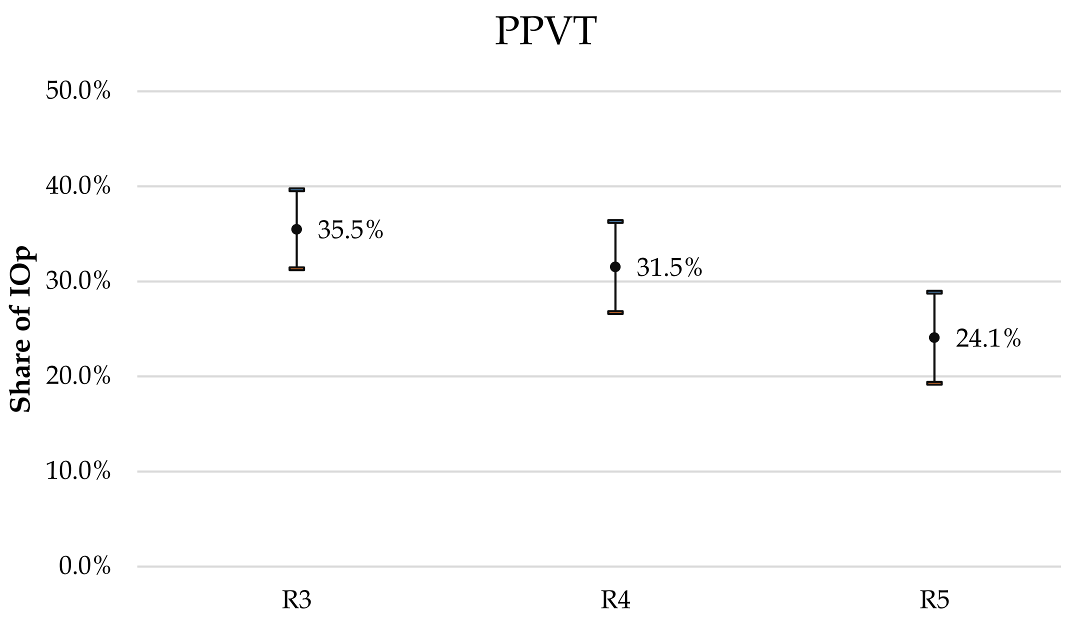
Standard errors in parentheses
Source: Young Lives Study 2002-2016. Own elaboration.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table E.3:** PPVT FE estimates: Second approach (cf. equations 10, 11, and 12)

| | (1) PPVT | (2) Hours study | (3) Hours leisure | (4) PPVT |
|---|---|---|---|---|
| Individual effect from col.(1) | | 0.235*** | 0.188*** | |
| | | (0.015) | (0.025) | |
| Residuals from col.(2) | | | | -0.005 |
| | | | | (0.011) |
| Residuals from col.(3) | | | | -0.016* |
| | | | | (0.007) |
| Constant | 0.045*** | 1.899*** | 4.133*** | 0.045*** |
| | (0.014) | (0.023) | (0.037) | (0.014) |
| Time fixed effects | Yes | Yes | Yes | Yes |
| N | 4,773 | 4,773 | 4,773 | 4,773 |
| N_g | 1,591 | | | 1,591 |
| rho | 0.718 | | | 0.718 |
| r2_w | 0.000 | | | 0.002 |
| r2_o | 0.000 | | | 0.000 |
| r2_b | . | | | 0.000 |
| F | 0.466 | 114.219 | 88.023 | 1.601 |

Standard errors in parentheses
Source: Young Lives Study 2002-2016. Own elaboration.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

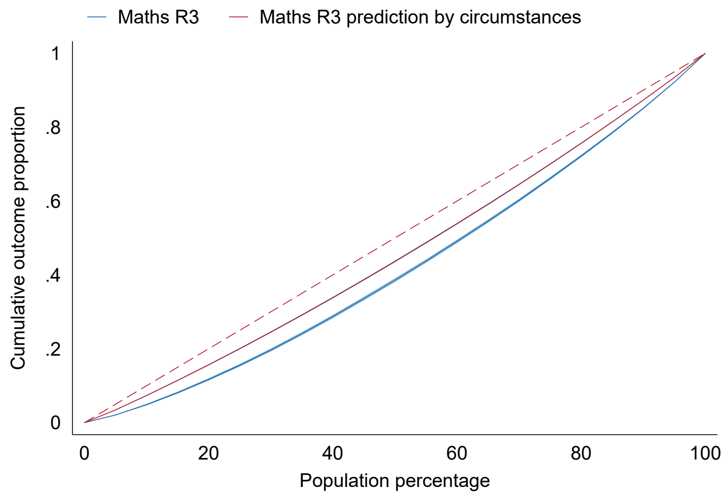
**Figure E.1:** PPVT: Lower bound estimates of inequality of educational opportunity




Note: Confidence intervals at the 95% level, based on 1,000 replications bootstraps.
Source: Young Lives Study 2002-2016. Own elaboration.

**Figure E.2:** Lorenz curves for mathematics test scores

(a) Matematics Round 3




(b) Matematics Round 5