Educational Quality and Deprivation: Elasticity Comparisons Based on Reading Test Scores from PISA 2000 and 2009

submitted to the European Population Conference (EPC) 2012
Stockholm, June 13-16

Eduardo L. G. Rios-Neto
Centre for Regional and Development Planning (CEDEPLAR)
eduardo@cedeplar.ufmg.br

Clarissa G. Rodrigues
Vienna University of Economic and Business (WU)
Wittgenstein Centre for Demography and Global Human Capital (WiC)
cguimara@wu.ac.at

Abstract

The goal of this paper is to analyze the link between average, deprivation and inequality of reading test scores from 38 countries evaluated by the Programme for International Student Assessment (PISA), for the years 2000 and 2009. As proficiency data has statistical properties similar to income data, the primary contribution of the current study is to apply well-developed indices and techniques used in economic studies of poverty and inequality to some education data. One hypothesis is that the growth elasticity of educational deprivation reduction is greater than that typically found in economic studies. The reason for this is that the distribution of test scores tends to be more homogeneous as compared to income distributions. To measure deprivation in education we use the poverty metrics developed by Foster, Greer and Thorbecke (1983, 2010) including: 1) educational deprivation headcount index; 2) educational deprivation gap index; and 3) educational deprivation severity index. We define as 'poor in education' students who have neither acquired fundamental knowledge nor mastered the basic skills corresponding to their level of schooling. Our findings suggest that ambitious strategies to reduce educational deprivation might have to combine both the increase in the average quality of educational system and some kind of distributive policy focusing on the lowest-skilled students.

1 Introduction

The main goal of this paper is to analyze the link between average, deprivation and inequality of test scores from 38 countries for the years 2000 and 2009, evaluated by the Programme for International Student Assessment (PISA). The date from PISA enables comparative analysis within and across countries, by having a large sample of countries and a historic time series which comprises a decade of testing.

The proficiency data has statistical properties similar to income data. Proficiency and income are both classified as individual and continuous observations. Moreover, these two variables are important predictors of individual and collective well-being. The main insight of this paper is to base on the well developed indices and techniques applied to economics studies about poverty and inequality in order to adapt it to some features of the educational data. Improving the quality of education and reducing the number of low-skilled students is one of the most important goals in many countries.

A large debate in labor economics concerns which kind of policies, whether income distribution or income growth, are more effective to reduce poverty. Many studies show that the growth elasticity of poverty reduction depends on the degree of income inequality (Deininger and Squire, 1996; Bourguignon, 2002; Ravallion, 2005). In other words, the higher is the income inequality, the smaller is the effect of economic growth (per-capita income growth) on poverty reduction (decline in the proportion of persons below the poverty line). The approach followed here is similar, but it is centered on educational data and indicators.

One hypothesis is that the growth elasticity of educational deprivation reduction is greater than the usual one found in economic studies. The reason for this expected sign is that the distribution of test scores tends to be more homogeneous when compared with the distribution of income. As previously mentioned, the per-capita income growth impact on poverty reduction is lower on societies that are more unequal.

Pending on the confirmation of our hypothesis, we can suggest different policy implications that go from an improvement in the average quality of education of a country, with or without a combination of explicitly distributive policies in the way that educational achievement is acquired.

2 Data

We use the Programme for International Student Assessment (PISA) data collected every three years since 2000 by the Organisation for Economic Cooperation and Development (OECD). PISA evaluates the 15-year-old student performance on reading, science and mathematics in OECD member and partners countries.

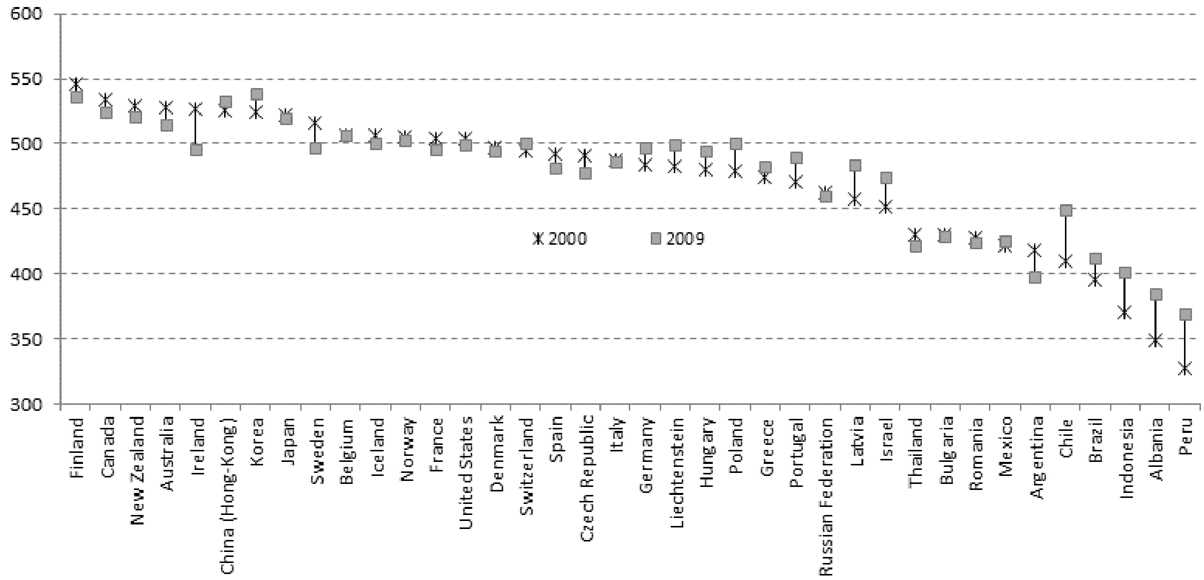
We chose the years 2000 and 2009 in order to evaluate changes in the educational performance for the last decade. We calculate the statistics based on the reading test scores, as it was the major domain in those two rounds. Thirty-eight countries where the test scores are comparable over time were included in our study, as shown in the Appendix I

3 Trends in cognitive achievement

3.1 Average test scores

Since the implementation of the test scores evaluation, the average has been the most common measure used as an indicator of the global level of learning acquired by the students in a country or region. As shown in Figure 1, Finland has the highest level of cognitive achievement, being followed by South Korea in 2009. At the bottom of this ranking, Brazil, Indonesia, Albania and Peru are highlighted as having the worst results. The average reached by the latter countries is nearly, or even below, the minimum level of learning expected at the age 15, according to PISA report (2010), which is equal to 407 score-point. However, as might be expected from the low average score countries, the improvements over time are largest, but still not enough to catch up with OCDE average equal to 493 on the reading scale.

Figure 1. Average of test score, 2000 and 2009



3.2 Educational deprivation

We develop an idea of educational deprivation which is similar to the concept of poverty line in the economic literature. In general, the latter is defined by an amount of income capable of satisfying the individual's basic needs - in most cases, nutritional demands. The economically poor are those individuals or families who are below this amount. Following this approach, we assume as 'poor in education' those students who have neither acquired fundamental knowledge nor mastered the basic skills corresponding to their age and level of schooling – at age 15 they are supposed to be near the end of their compulsory education. Therefore, educational deprivation defines all students whose school performance lies below some predetermined limit.

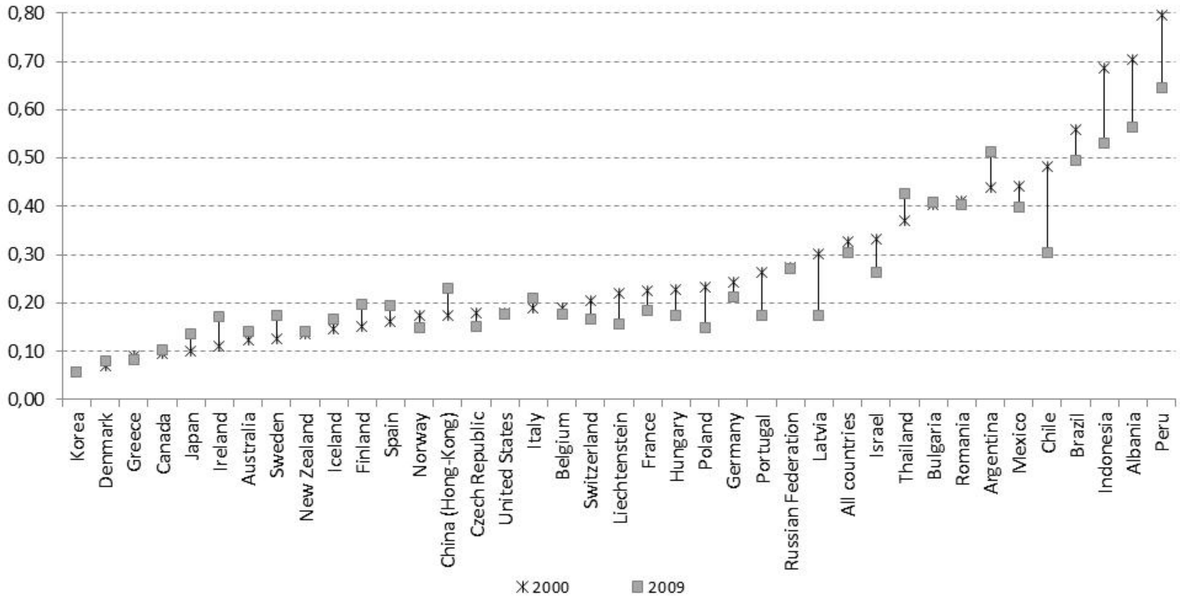
According to the PISA (2010, vol.1) report, this threshold is given by a proficiency score equal to 407 and it corresponds to the lowest limit of level 2 in an ordered scale that goes from 1b (low-skilled readers) to 6 (highly-skilled readers) proficiency levels. This baseline is assumed to be constant during the period being analyzed, as the PISA scores are comparable accross the surveys.

Using this baseline, we estimate three educational deprivation indices following the methodology developed by Foster, Greer and Thorbecke (1983). The first index (educational deprivation headcount) is a very simple measure and tells us the proportion of students who are below the educational deprivation line. The second (educational deprivation gap) considers the student's gap (analogous to the income gap) from the educational deprivation line, thus, if a student has improved his/her performance, but he/she still continues below the educational deprivation line, that improvement will be recorded in the index. The third and last index (educational deprivation severity) attributes a different weight to the students, depending on their placement below the educational deprivation line. The greatest weight is given to the changes in the performance of those students who suffer more deprivation in educational terms, within the group of deprived students. In other words, it captures those that are situated furthest from the education deprivation line.

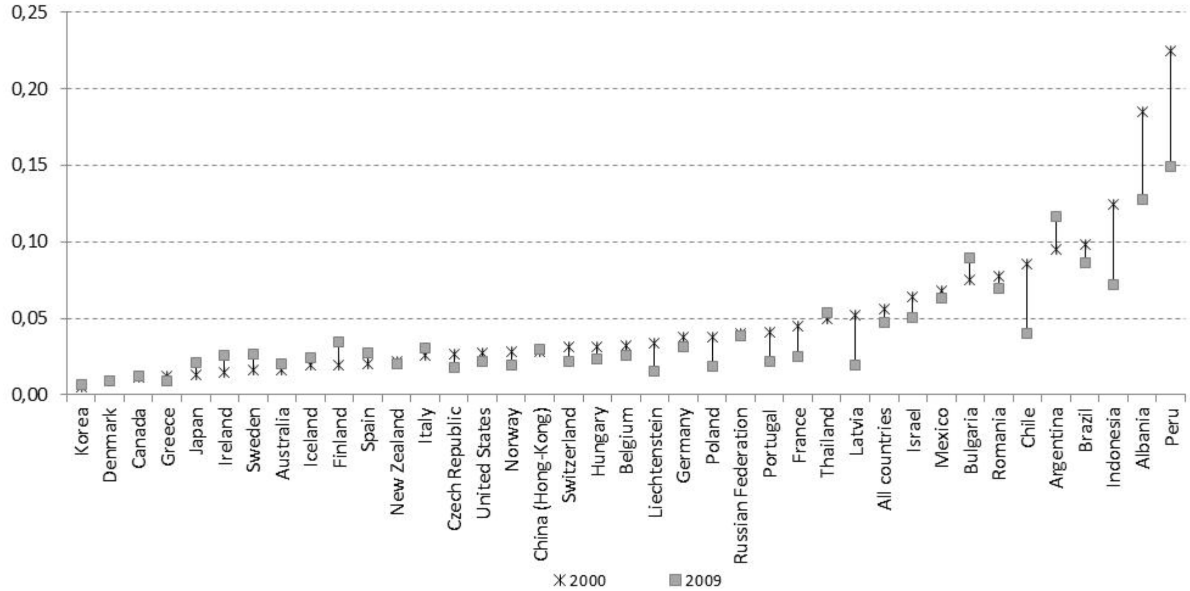
Results are shown in Figure 2. The magnitude of educational deprivation reduction is more pronounced in countries in the bottom of the educational outcomes: Peru, Albania, Indonesia and Brazil. Not only the share of those students poorest in education has decreased over time in these countries, but also its depth has diminished, which means that the distance between poorly performing students and educational deprivation line narrowed over time.

Figure 2. Educational deprivation indices, 2000 and 2009

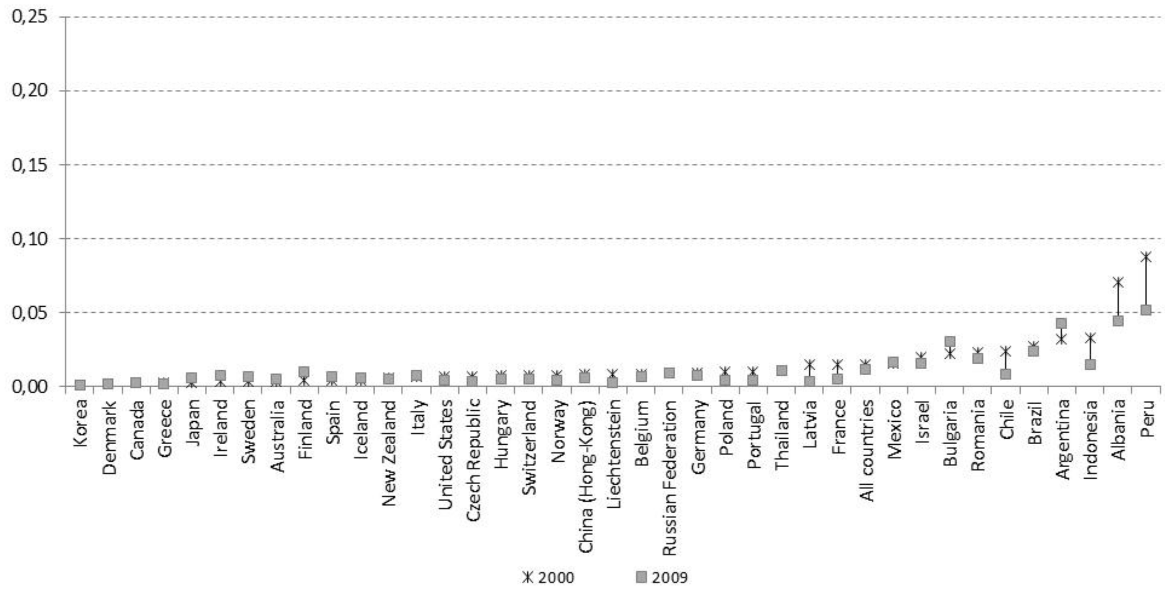
Educational Deprivation Headcount Index



Educational Deprivation Gap Index



Educational Deprivation Severity Index



Source: PISA, 2000 and 2009.

2.3 Educational inequality

Educational inequality is measured by using the traditional Gini index that represents the extent to which the distribution of educational scores among students within a country deviates from a perfectly equal distribution. The index is the area between Lorenz curve (the cumulative shares of test scores against the cumulative shares of students, starting with the lowest skilled student) and a hypothetical line of absolute equality expressed by a 45^{o}.

Figure 3 shows that the index ranged from 0.08, being South Korea the lowest educational inequality country, to 0.15 in Argentina and Bulgaria in 2009. Educational inequality had a big drop between 2000 and 2009 in some countries, such as Latvia and Chile.

It is worth mentioning that educational inequality is lower than income inequality, as shown in Table 1 for a selected list of countries available in the World Bank data source.

Figure 3. Educational Gini index, 2000 and 2009,

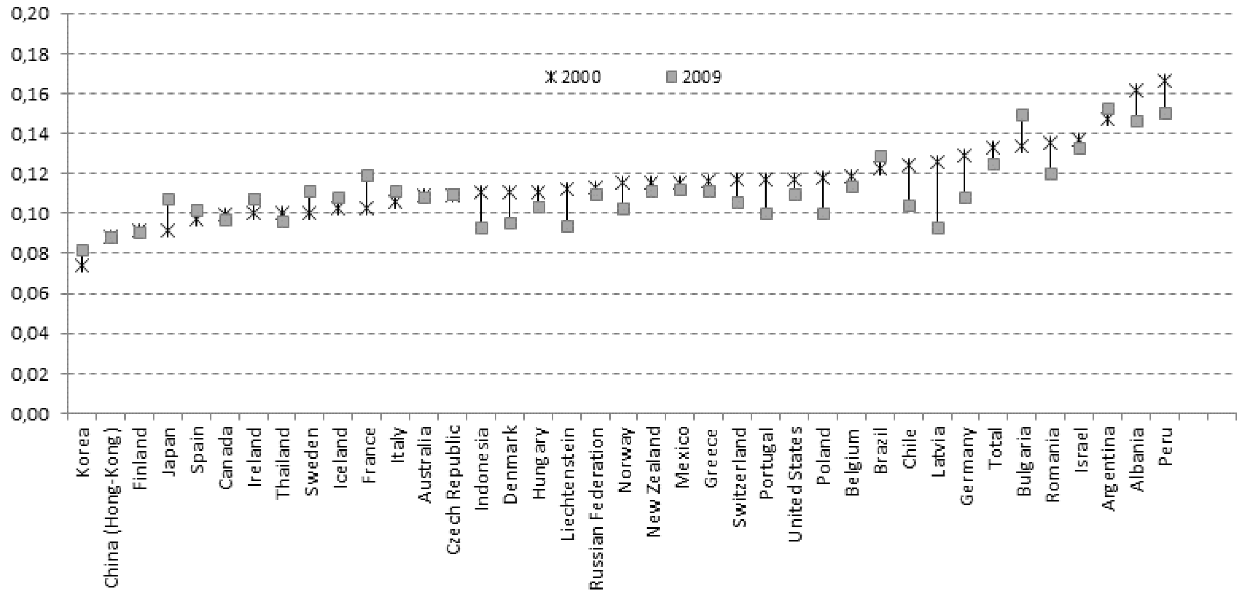


Table 1. Income Gini Index

Countries	2000	2009	Countries	2000	2009
Argentina		0.46	Mexico	0.52	
Belgium	0.33		Norway	0.26	
Brazil		0.54	Peru		0.48
Chile	0.55	0.52	Poland	0.33	
Finland	0.27		Romania	0.30	
Germany	0.27		Spain	0.35	
Greece	0.34		Sweden	0.25	
Indonesia		0.37	Switzerland	0.34	
Ireland	0.34		Thailand	0.43	0.54
Italy	0.36		United States	0.41	

Source: World Bank.

4 Explaining the changing of educational deprivation between 2000 and 2009

Table 2 shows the growth-inequality elasticity of poverty reduction results. Three models were estimated for each one of the three educational deprivation measures. The simplest Model 1 analyzes only the relationship between changes in the educational deprivation indices and changes in the average of reading test scores over time. Model 2 gives us additional information by taking into account the effect of changes in the educational inequality on educational deprivation. The idea is to explore how the intensity of the inequality degree can affect the association between average and educational deprivation. In the economic literature, the higher is the inequality, the lower is the effect of the economic growth on the poverty reduction. Model 3 adds two more variables – average and inequality in 2000 - in order to control for the initial level of the educational development.

Also in the Table 2, there is a reproduction of the Bourguignon's (2002) results for comparison purposes. The approach followed here is similar to that by Bourguignon (2002), but less complex, because we don't need the assumption that the underlying distribution of scores is Log-normal.

Table 1. OLS regression results

Dependend variable: percentage change in deprivation headcount index P(0)

	Model 1				Model 2				Model 3	
	Education		Income[a]		Education		Income[a]		Education	
	Coef.	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*
Intercept	2,38	2,50	0,08	0,04	4,54**	1,80	0,10	0,04	43,45	42,23
Percentage change in average test score	-4,17*	0,58	-1,65*	0,26	-2,54*	0,49	-2,01*	0,22	-3,09*	0,65
Percentage change in educational Gini					1,25*	0,20	4,72*	0,67	1,20*	0,22
Initial average test score									-0,07	0,06
Initial educational Gini									-49,76	149,18
Adj. R^2	0,58		0,27		0,79		0,49		0,79	
N	38		114		38		114		38	

Dependend variable: percentage change in deprivation gap index P(1)

	Model 1				Model 2				Model 3	
	Education		Income[a]		Education		Income[a]		Education	
	Coef.	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*
Intercept	1,21	4,55	0,14	0,09	5,97**	2,33	0,17	0,08	51,92	55,17
Percentage change in average test score	-5,91*	1,06	-1,24*	0,51	-2,33*	0,63	-1,80*	0,47	-2,93*	0,85
Percentage change in educational Gini					2,74*	0,26	7,30*	1,44	2,69*	0,28
Initial average test score									-0,08	0,08
Initial educational Gini									-69,28	194,92
Adj. R^2	0,45		0,05		0,86		0,23		0,86	
N	38		114		38		114		38	

Dependend variable: percentage change in deprivation severity index P(2)

	Model 1		Model 2		Model 3	
	Education		Education		Education	
	Coef.	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*
Intercept	4,57	7,58	12,21	4,27	56,20	102,46
Percentage change in average test score	-7,67*	1,76	-1,91	1,16	-2,45	1,57
Percentage change in educational Gini			4,41*	0,48	4,35*	0,52
Initial average test score					-0,07	0,15
Initial educational Gini					-75,55	361,95
Adj. R^2	0,33		0,79		0,78	
N	38		38		38	

Source: PISA 2000 and 2009.

Note: * significantly different from zero at the 1%; ** significantly different from zero at the 5%.

[a] Bourguignon's (2002) results for the income context.

Model 1 prediction shows a strong relationship between changes in educational deprivation indices and changes in the average of reading test scores over time. The negative association is found for all the three indices.

Regarding the educational deprivation headcount index, we can see through the fitted OLS straight line that a 1% increase in average test scores in this set of countries reduces the proportion of poor in education by 4.5%. Moreover, changes in the average test scores explain 56% of the headcount index variance. Comparing these results with those found in the economic literature, we would confirm that, in the education field, the growth elasticity of educational deprivation reduction seems to be more intense. Regarding the educational deprivation gap index, the result shows that a 1% increase in the average test scores is enough to reduce the magnitude of this index by 6.4% percent. Finally, the last fitted OLS regression has the steepest slope, indicating that a 1% increase in the average test scores would reduce educational deprivation severity by 8.2%.

Model 2 predictions improve substantially with respect to its explanatory power, by adding inequality measure to the regression equation. It suggests that the heterogeneity in the test score's distribution is also important to reduce educational deprivation. Moreover, it shows that the effect is not the same among those three educational deprivation measures. The worst the student's performance in the PISA evaluation, the highest the importance of having a more homogeneous test scores' distribution to reduce the number of poorly performing students.

5 Simulations

The prior analysis provides an indication of the link between the changing of educational deprivation and its association with both the variation over time in the test score's average and inequality. Using the regression results from Model 2, we performed some simple simulations in order to assess what would be the magnitude of the deprivation reduction if a low educated country had both a considerable increase in the average quality of education and a more equitable distribution of the cognitive achievement.

To do that, we selected three countries which have both the lowest average of cognitive achievement and the highest level of educational deprivation. For each country, we set up two scenarios. The first scenario brings each selected country to the average level of Korean in 2009. The second scenario brings each selected country to the educational inequality level of Korea in 2009. Korean was chosen as the standard country due to its desirable results on the PISA evaluation as well as its impressive development of education in the last decades.

Results show that the average growth would have an important impact on the reduction of the proportion of students below the educational deprivation line, while the inequality reduction would be more important for reducing educational deprivation gap and severity indices.

Table 2. Simulated educational deprivation reduction

	Scenarios	Δ Mean	Δ Gini	Δ P(0)	Δ P(1)	Δ P(2)
ALBANIA	Current	10,31%	-9,56%	-19,68%	-31,00%	-36,67%
	If Albaniareached Korean's 2009 average test scores, but kept Gini index variation constant between 2000 and 2009.	54,58%	-9,56%	-146,06%	-147,18%	-134,32%
	If Albania reached Korean's 2009 Gini index, but kept average test scores variation constant between 2000 and 2009	10,31%	-49,29%	-83,27%	-153,27%	-224,86%
BRAZIL	Current	3,97%	5,42%	-11,38%	-11,79%	-12,56%
	If Brazil reached Korean's 2009 average test scores, but kept Gini index variation constant between 2000 and 2009.	32,50%	5,42%	-71,24%	-54,73%	-26,06%
	If Brazil reached Korean's 2009 Gini index, but kept average test scores variation constant between 2000 and 2009	3,97%	-32,85%	-46,62%	-93,42%	-140,24%
PERU	Current	13,03%	-9,41%	-18,73%	-33,39%	-41,46%
	If Peru reached Korean's 2009 average test scores, but kept Gini index variation constant between 2000 and 2009.	64,87%	-9,41%	-172,00%	-170,68%	-153,33%
	If Peru reached Korean's 2009 Gini index, but kept average test scores variation constant between 2000 and 2009	13,03%	-50,55%	-91,74%	-163,04%	-235,59%

Discussion

Would educational policies towards improving the global quality of the educational system enrich the learning of those disadvantaged students? Taking seriously our empirical findings, the answer would be "it depends on the degree of their learning deficiency". Looking at the average of those thirty eight countries from different regions in the world, 1% increase in the average of reading test scores between 2000 and 2009 would reduce the deprivation headcount and gap in 2.5% and 2.3%, respectively. However, when the analysis is performed for students of extreme education disadvantage, *i.e.*, those who are located at the bottom of the test scores distributions, being furthest from the education deprivation line, the average increase would have any effect. For those cases, the heterogeneity in distributional changes accounted by educational Gini is totally responsible for variation in educational deprivation reductions over time.

For many reasons, the most disadvantaged students might not respond straightforwardly to the policies addressed to the amelioration of school system, such as the improvement of the teacher working conditions, school infra-structure, pedagogic plans, among others, because their lack of learning comes specially from the family environment. The literature focusing on the effects of the socioeconomic background versus school quality on the children's school performance has overwhelmingly showed the strong importance of the former variable.

In that case, a special treatment, like reinforcement class policies, would be necessary to push them into an appropriate level of learning. Therefore, the importance relies on the target policies aimed at the elimination of the barriers which hampers their process of learning.

Nonetheless, universal policies seem to be important to improve the performance of those who are alongside with deprivation educational line, as results show a significant negative elasticity of deprivation headcount and gap indices with respect to the general educational quality growth.

Obviously, these results are very preliminary and this discussion is far from being conclusive. Estimates are based on a limited sample of countries and include countries fairly different in terms of their educational and economic development. Further explorations are necessary and the improvement would be done either by using the spells variation from the four PISA's rounds or splitting the set of countries by their similarities in terms of educational development. Nonetheless, this first general view of the growth-inequality elasticity of deprivation reduction suggest that ambitious strategies to reduce educational deprivation might have to combine both the increase in the average quality of educational system and some kind of distributive policy focusing on the lowest-skilled students.

References

Bourguignon, F. (2002). "The growth elasticity of poverty reduction: explaining heterogeneity across countries and time periods. *Forthcoming in T. Eichler and S. Turnovsky (eds), Growth and Inequality, MIT Press.*

Deininger, K. and Squire, L. (1996). "A New Dataset Measuring Income Inequality." *World Bank Economic Review,* 10(3), pp. 65-91, Sep.

Foster, J.; Greer, J. and Thorbecke, E. (1984). "A class of decomposable poverty measures". In: *Econometrica*, vol. 52, n. 3, May.

Foster, J.; Greer, J. and Thorbecke, E. (2010). "The Foster-Greer-Thorbecke (FGT) poverty measures: twenty-five years later". In: *Journal of Economic Inequality*, 2010.

OECD (2010), PISA 2009 Results: What Students Know and Can Do – Student Performance in Reading, Mathematics and Science (Volume 1). Available in: http://dx.doi.org/10.1787/9789264091450-en.

Ravallion, M. (2005). "Inequality is bad for the poor? In: *World Bank Policy Research Working Paper* No. 3677, pp. 1-50, Aug.

Appendix I

Figure 1. Selected countries and sample size

Country	2000	2009	Country	2000	2009
Albania	4980	4.596	**Israel**	**4498**	5.761
Argentina	3983	4.774	**Italy**	**4984**	30.905
Australia	**5176**	14.251	**Japan**	**5256**	6.088
Belgium	**6670**	8.501	**Korea**	**4982**	4.989
Brazil	4893	20.127	Latvia	3893	4.502
Bulgaria	4657	4.507	Liechtenstein	314	329
Canada	**29687**	23.207	**Mexico**	**4600**	38.250
Chile	**4889**	5.669	**New Zealand**	**3667**	4.643
Czech Republic	**5365**	6.064	**Norway**	**4147**	4.660
Denmark	**4235**	5.924	Peru	4429	5.985
Finland	**4864**	5.810	**Poland**	**3654**	4.917
France	**4673**	4.298	**Portugal**	**4585**	6.298
Germany	**5073**	4.979	Romania	4829	4.776
Greece	**4672**	4.969	Russian Federation	6701	5.308
China (Hong-Kong)	4405	4.837	**Spain**	**6214**	25.887
Hungary	**4887**	4.605	**Sweden**	**4416**	4.567
Iceland	**3372**	3.646	**Switzerland**	**6100**	11.812
Indonesia	7368	5.136	Thailand	5340	6.225
Ireland	**3854**	3.937	**United States**	**3846**	5.233

Note: Bold countries are those which are OCDE members.