Distr. Limited
E/ESCWA/EDID/2015/WP.7
24 December
Original: English

ECONOMIC AND SOCIAL COMMISSION FOR WESTERN ASIA (ESCWA)

Inequality of opportunity for educational achievement in Arab Region: Evidence from PISA 2006–2009-2012

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1. Introduction

In the last two decades, a new literature has flourished in the field of normative economics and distributional analysis: the equality of opportunity (EOp) literature[1]. This literature has developed concepts of fairness for the context in which individual achievements are partly the outcome of morally arbitrary circumstances (such as inherited endowments and social background) and partly the consequence of individual effort - or similar variables - of personal responsibility.[2]

Those concepts revolve around the idea that inequalities due to circumstances are unfair and should be eliminated as much as possible, while inequalities, which are results of unequal effort, should be considered acceptable. This literature has motivated a rapidly growing number of empirical applications interested in measuring the degree of inequality of opportunity (IOp) and in evaluating public policies in terms of EOp, mainly in the context of income distributions (see, among others, Aaberge et al. 2011, Björklund et al., (2010), Checchi and Peragine 2010, Lefranc et al 2009, Roemer et al 2003). Book-length collections of empirical analysis of equality of opportunity in developing countries can be found in World Bank (2006) and de Barros et al. (2009).

However, although the opportunity egalitarian perspective has gained a general consensus, both in the public debate and in the scientific literature, such consensus seems to be less robust when going from general concepts to more specific declinations.

This situation is even more striking in the field of education. In this field, the principle of equality of educational opportunities (EEOp) is often referred to as the leading normative principle; however, it is rarely spelt out. In fact, it is surprising that the model of equality of opportunity as formulated by Roemer (1993), Fleurbaey (1995) and the related literature, has been rarely applied to the field of education: notable exceptions are contained in Betts and Roemer (2005), Peragine and Serlenga (2008), Ferreira and Gignoux (2009). Hashemi and Intini (forthcoming) provide an interesting contribution applying a parametric method to the Arab region that complements to this study.

In this paper, building on the theory of EOp referred above, we propose a conceptual framework for the definition of EEOp and a consistent measurement strategy. Hence, we propose and justify some fairness criteria, based on the EOp theory that could be used to evaluate the degree of opportunity inequality in an educational system or to assess the effect of an educational reform.

Hence, we apply such framework to the measurement of inequality of opportunity in education in a subset of Arab countries. In particular, we focus on the countries that have taken part in the PISA survey.

In the first part of the paper, we discuss the concept of EEOp and propose a set of EEOp measures. The EOp literature has clarified that the ideal of equal opportunities is multifaceted leading to potential conflicts between various interpretations of the ideal and of its components. In particular, it has highlighted the distinction between the "compensation" principle - i.e. "inequalities due to circumstances should be eliminated" - and the "reward" or "responsibility" principle - i.e. "inequalities due to unequal effort should be considered acceptable"-, showing that the two principles actually tend to clash as soon as they are given precise expressions. The literature has showed that this incompatibility affects also the possibility to measure the degree of IOp. Hence, possible measures of inequality of opportunity are generally based on a compromise between the two principles: either one gives priority to the compensation or to the reward

[1]See Fleurbaey 2008 for a general treatment of the issues discussed in this literature.

[2]A seminal contribution is Roemer (1993, 1998). For the background philosophical literature see Dworkin (1981a,b), Arneson (1989), Cohen (1989).

principle. More precisely, the existing literature on the measurement of inequality of opportunity has proposed a two-step procedure: first, an artificial distribution is constructed in which only (and fully) the unfair inequalities are present, while the fair inequalities are removed; then, an inequality measure is applied to such artificial distribution. As for the first step, four different solutions (see Fleurbaey and Schokkaert (2009) and Checchi and Peragine (2005, 2010)) have recently been proposed: two of them give priority to the reward principle; the other two give priority to the compensation principle. In this paper we show how to adapt these solutions to the educational context and therefore we obtain four different criteria for evaluating the EEOp. As for the specific inequality measure to be applied to the artificial distribution, we apply in this exercise the MLD index.

In the second part of the paper we apply the proposed strategy in order to assess the recent evolution in the competences of students in a set of Arab countries, by using the PISA data.

The paper is organized as follows. In section 2 we introduce and discuss the concept of EEOp and we present a simple non-parametric model for the measurement of inequality of opportunity. In section 3 we present the empirical results. Section 4 concludes.

1. Measuring opportunity inequality: a simple model

Consider a distribution of outcome x in a given population. Suppose that all determinants of x, including the different forms of luck, can be classified into either a set of circumstances C that lie beyond individual control, or as responsibility characteristics, summarized by a variable[3] e, denoting effort. Circumstances belong to a finite set Ω. For example, suppose that the only circumstance variables are race, which can only take values in the set {black, white}, and parental education, that only takes values in the set {college education, high school education}. In this case the set Ω would be the following: Ω = ({black, parents with high school education}, {black, parents with college education}, {white, parents with high school education}, {white, parents with college education}).

Effort may be treated as either a continuous or a discrete variable belonging to the set Θ. The outcome of interest is generated by a function $g:\Omega\times\Theta\to R$ such that:

$$x = g(C,e) \tag{1}$$

This can be seen as a reduced-form model in which outcomes are exclusively determined by circumstances and effort, such that all individuals having the same circumstances and the same effort obtain the same outcome. Neither opportunities themselves, nor the process by which some particular outcomes are chosen, are explicitly modelled in this framework. The idea is to infer the opportunities available to individuals by observing joint distributions of circumstances, effort and outcomes. Roughly speaking, the source of unfairness in this model is given by the effect that circumstance variables (which lie beyond individual responsibility) have on individual outcomes.

Thus, we have a population of individuals, each of whom is fully characterised by the triple (x,C,e). For simplicity, treat effort e, as well as each element of the vector of circumstances, C, as discrete variables. Then this population can be partitioned in two ways: into types T_i, within which all individuals share the same circumstances, and into tranches T_j, within which everyone shares the same degree of effort. Denote by x_{ij} the outcome generated by circumstances C_i and effort e_j. Suppose in addition that there are n

[3] Effort could also be treated as a vector. However, we follow the literature and treat it as a scalar.

types, indexed by $i = 1,\ldots, n$, and m tranches, indexed by $j = 1,\ldots, m$. In this discrete setting[4], the population can be represented by a matrix $\left[\mathbf{X}_{ij}\right]$ with n rows, corresponding to types, and m columns, corresponding to tranches:

Table 1: Distribution of outcomes according to circumstances and effort.

	e_1	e_2	e_3	...	e_m
C_1	x_{11}	x_{12}	x_{13}	...	x_{1m}
C_2	x_{21}	x_{22}	x_{23}	...	x_{2m}
C_3	x_{31}	x_{32}	x_{33}	...	x_{3m}
...	...	...	...	...	...
C_n	x_{n1}	x_{n2}	x_{n3}	...	x_{nm}

To the $n \times m$ dimensional matrix $\left[\mathbf{X}_{ij}\right]$ in Table 1, let there be associated a $n \times m$ dimensional matrix $\left[\mathbf{P}_{ij}\right]$ where each element p_{ij} represents the proportion of total population with circumstances C_i and effort e_j.

Given this model, the measurement of inequality of opportunity can be thought of as a two-step procedure: first, the actual distribution $\left[\mathbf{X}_{ij}\right]$ is transformed into a counterfactual distribution $\left[\widetilde{\mathbf{X}}_{ij}\right]$ that reflects only and fully the unfair inequality in $\left[\mathbf{X}_{ij}\right]$, while all the fair inequality is removed. In the second step, a measure of inequality is applied to $\left[\widetilde{\mathbf{X}}_{ij}\right]$. The construction of the counterfactual distribution $\left[\widetilde{\mathbf{X}}_{ij}\right]$ should reflect the principle of equality of opportunity.

Within this framework, the opportunity egalitarian principle can be decomposed into two distinct and independent sub-principles: the Reward Principle, which is concerned with the apportion of outcome to effort and, in some of its formulations, requires to respect the outcome inequalities due to effort[5]; and the Compensation Principle, according to which all outcome inequalities due to C are unfair and should be compensated by society. Any satisfactory measure of opportunity inequality should respect both the compensation and the reward principles. The existing literature has developed two main versions of the compensation principle and two consequent approaches to the measurement of opportunity inequality, namely the ex-ante and the ex-post approach.

According to the ex-ante approach, there is equality of opportunity if the set of opportunities is the same for all individuals, regardless of their circumstances. Hence in the ex-ante version, the compensation principle is formulated with respect to individual opportunity sets: it requires reducing the inequality between opportunity sets. In the model introduced above, a given row i, that is the outcome distribution of a given type, is interpreted as the opportunity set of all individuals with circumstances C_i. Hence the focus is on the rows of the matrix above: the counterfactual distribution should eliminate the inequality within the rows (*reward*) and reflect the inequality between the rows (*ex-ante compensation*).

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[4] In an alternative formulation, that would treat effort as a continuous variable, $F_i(x)$ would denote the advantage distribution in type i and q_i denote its population share. The overall distribution for the population as a whole would be $F(x) = \sum_{i=1}^{n} q_i F_i(x)$.

[5] See Ferreira and Peragine (2015) for a discussion of the different formulations of the reward principle proposed in the literature. One of such formulations, *Utilitarian Reward*, states that society should express full neutrality with respect to inequalities due to effort; since in the ex-ante approach the outcome distribution of types is interpreted as the opportunity set of individuals in that type, it follows that, according to Utilitarian Reward, the social evaluation of the opportunity set is based on the means of the type distribution.

On the other side, according to the ex-post approach, there is equality of opportunity if and only if all those who exert the same effort end up with the same outcome. The compensation principle, in the ex-post version, is thus defined with respect to individuals with the same effort but different outcomes: it requires reducing outcome inequality among the individuals with the same effort. This means that opportunity inequality within this approach is measured as inequality within the columns of the matrix. Hence, the corresponding counterfactual distribution should reflect the inequality within the columns (*ex-post compensation*) but should eliminate the inequality between the columns (*reward*).

Different measures, which are either consistent with the ex-ante or the ex-post approaches, have been proposed in the literature (see Ferreira and Peragine (2015), Ramos and Van de Gaer (2015)): they express different and sometimes conflicting views on equality of opportunity and in fact the rankings they generate may be different.[6] In addition, their informational requirements are quite different: while for the ex-ante approach one needs to observe the individual outcome and the set of circumstances, for the ex-post approach a measure of individual effort is required. Therefore, in addition to normative considerations, the choice of the methodology to adopt should reflect also the data availability. In our case, as will be discussed in the next section, the database we use does not contain a satisfactory measure of effort: for this reason in the rest of the paper we focus on the ex-ante approach.

In particular, the measure we use, Between-Types Inequality, was variously proposed by Peragine (2002), Checchi and Peragine (2010) and Ferreira and Gignoux (2011). It relies on a counterfactual distribution $\left[\widetilde{\mathbf{X}}_{BT}\right]$, which is obtained by replacing each individual outcome x_{ij} by the average outcome of the type she belongs to (μ_i), abstracting from individual level of effort[7]. This smoothing transformation is intended to remove all inequality within types. Formally:

Between-types counterfactual distribution $\left[\widetilde{\mathbf{X}}_{BT}\right]$: $\forall j \in \{1,...,m\}$, $\forall i \in \{1,...,n\}$, $\tilde{x}_{ij} = \mu_i = \frac{\sum_{j=1}^{m} p_{ij}\, x_{ij}}{\sum_{j=1}^{m} p_{ij}}$.

Table 2: Measuring between-types inequality ($n = m = 3$).

	e_1	e_2	e_3
C_1	μ_1	μ_1	μ_1
C_2	μ_2	μ_2	μ_2
C_3	μ_3	μ_3	μ_3

Once the smoothed distribution $\left[\widetilde{\mathbf{X}}_{BT}\right]$ is obtained, any inequality measure I applied to such a distribution, $I\left(\widetilde{\mathbf{X}}_{BT}\right)$ is to be interpreted as a measure of inequality of opportunity. Following Aaberge et al. (2011) in this paper we use the Gini coefficient and the mean logarithmic deviation, which is an additively decomposable inequality index (Theil, 1979a,b) and therefore allows obtaining an exact decomposition of overall inequality (I) into two terms: the between-types inequality (I_{BT}), to be interpreted as inequality of opportunity, and the within-types inequality (I_{WT}), interpreted as inequality due to effort.

3. Inequality of educational opportunity in Arab countries

[6] See Fleurbaey and Peragine (2013) for a discussion of the clash between ex-ante and ex-post equality of opportunity.
[7] Hence the between-types measure satisfies *ex-ante compensation* and *utilitarian reward*. See Ferreira and Peragine (2015).

3.1. Data

The analysis is based on data from the program PISA (Program for International Student Assessment), sponsored by OECD and conducted every three years in more than 30 countries. This survey was conducted for the first year in 2000 to assess reading ability of 15-year-old students; the test score is standardized to an international mean of 500 and a standard deviation of 100.

In particular, in this paper we consider the last three available surveys: 2006-2009-2012[8]. PISA dataset includes test scores of representative samples of students, in three different subjects: Mathematics, Science and Reading[9]. Only three Arab countries have taken part to the PISA test in 2006, 2009, and 2012 namely Tunisia, Qatar Jordan; the United Arab Emirates (UAE) joined the PISA survey in 2012.

Table 3 reports the average results by country, for each subject and for all the periods considered. Tunisia and Qatar seem the best performing over time, in fact in these countries the average scores increased for all subjects between 2006 and 2012. Whereas for Jordan, only the average score of Math slightly increased, while it decreased for Science and Reading. If we focus on 2012, the last year of the survey for which data are available, it is possible to observe that United Arab Emirates are the best performing in all the subjects considered. Furthermore, in these countries the average scores are considerably higher than in the other three. Hence, overall Tunisia, Qatar, and Jordan appear quite homogeneous in terms of average scores, while there is a clear heterogeneity between Arab Emirates and the group of the other three countries.

Table 3: PISA test scores 2006-2009-2012.

	TUNISIA			QATAR			JORDAN			UNITED ARAB EMIRATES		
	2006	**2009**	**2012**	**2006**	**2009**	**2012**	**2006**	**2009**	**2012**	**2006**	**2009**	**2012**
MATH	365	371	388	318	368	376	384	387	386	-	-	434
SCIENCE	386	401	398	349	379	384	422	415	409	-	-	448
READING	380	404	404	312	372	388	401	405	399	-	-	442

Source: Authors' computation based on PISA.

Pupils' educational achievements are determined by the combination of several factors (ability, socioeconomic status, family background, etc.). We then proceed by investigating whether exogenous factors, such as gender and parental background, play a role in determining students' test scores.[10] To do this we consider a set of circumstances composed by gender (two categories: *i.* Male, *ii.* Female), parental education (3 categories: *i.* No education or unknown level, primary education, and lower secondary education; *ii.* Upper secondary and post-secondary non-tertiary education; *iii.* First and second stage of tertiary education), parental jobs (2 categories: *i.* blue collar, low- and high-skilled; *ii.* white collar, low- and high-skilled)[11].

[8] The first round of PISA took place in 2000 and after that it has been conducted every three years: 43 countries took part in PISA 2000, 41 in PISA 2003, 58 in PISA 2006, 74 in PISA 2009, and 65 in PISA 2012 (see OECD 2003, 2006, 2009, 2013).

[9] Reading refers to the performance of different kinds of reading tasks, such as forming a broad general understanding retrieving specific information, developing an interpretation or reflecting on the content or form of the text." (OECD-PISA 2000, p.13).

[10] Note that the choice of focusing on these two factors only is due to data availability.

11 The analysis distinguishes between two different categories of occupations by the major groups identified by the ISCO coding of the highest parental occupation. Blue Collar: Elementary (ISCO 9), semi-skilled blue-collar (ISCO 6, 7 and 8) ; White Collar :semi-skilled white-collar (ISCO 4 and 5), skilled (ISCO 1, 2 and 3). This classification follows the same methodology used in other OECD publications such as Education at a Glance (2013b) and the OECD Skills Outlook (2013c).

Tables 4, 5, 6, and 7 report the opportunity profiles[12] of each year respectively for Tunisia, Qatar, Jordan, and Arab Emirates United. Types are ranked according to their average scores (μ_i). Some important features stand out. In particular, the types' ranking is similar across countries and it is mostly determined by parental education, in fact, all the bottom ranked types encompass individuals whose parents have the lowest level of education, while parental job exerts a less strong influence on children's achievement. As for the best performing types, it is possible to observe that, in all the countries considered, the best results are achieved by the type encompassing female individuals, with highly educated parents and with a blue collar professional job. In the interpretation of this last result, it is important to notice that the population share of this type is one of the lowest in Tunisia, while it is the highest in Qatar and Arab Emirates.

12 See Ferreira and Gignoux (2011).

Table 4: Tunisia. PISA 2006-2009–2012: Descriptive Statistics and Partition in Type.

Gender	Education Parents	Occupation Parents	Pisa 2006				Pisa 2009				Pisa 2012			
			$rank^{06}$	$sample^{06}$	q_i^{06}	μ_i^{06}	$rank^{09}$	$sample^{09}$	q_i^{09}	μ_i^{09}	$rank^{12}$	$sample^{12}$	q_i^{12}	μ_i^{12}
Male	No-Edu/Elementary	White Collar	11	893.00	0.19	355.13	11	1012.00	0.21	371.792	10	630.00	0.14	372.7977
Male	Secondary	White Collar	7	515.00	0.11	371.89	7	651.00	0.13	392.3147	8	675.00	0.15	391.1129
Male	Higher	White Collar	8	274.00	0.06	366.2	8	278.00	0.06	380.046	9	324.00	0.07	381.3108
Female	No-Edu/Elementary	White Collar	9	1085.00	0.24	359.15	9	1195.00	0.25	372.8808	11	785.00	0.18	371.4261
Female	Secondary	White Collar	5	656.00	0.14	379.63	6	741.00	0.15	398.2734	6	932.00	0.21	398.354
Female	Higher	White Collar	6	207.00	0.04	374.77	5	228.00	0.05	400.381	7	239.00	0.05	395.3263
Male	No-Edu/Elementary	Blue Collar	10	69.00	0.01	357.75	12	57.00	0.01	356.3018	12	12.00	0.00	370.6604
Male	Secondary	BlueCollar	4	96.00	0.02	401.41	4	72.00	0.01	405.1656	4	86.00	0.02	423.3377
Male	Higher	Blue Collar	2	322.00	0.07	414.73	2	243.00	0.05	427.0579	2	290.00	0.07	448.3487
Female	No-Edu/Elementary	Blue Collar	12	73.00	0.02	352.13	10	72.00	0.01	372.4084	5	5.00	0.00	420.8997
Female	Secondary	BlueCollar	3	111.00	0.02	414.73	3	102.00	0.02	424.9322	3	118.00	0.03	428.2208
Female	Higher	Blue Collar	1	313.00	0.07	445.77	1	218.00	0.04	443.9899	1	311.00	0.07	458.6967

Note: Sample indicates the number of observations, q_i indicates the population share of each type, μ_i indicates the average PISA scores in Math, Reading and Science. Source: Authors' computation based on PISA.

Table 5: Jordan. PISA 2006-2009–2012: Descriptive Statistics and Partition in Type.

Gender	Education Parents	Occupation Parents	Pisa 2006				Pisa 2009				Pisa 2012			
			$rank^{06}$	$sample^{06}$	q_i^{06}	μ_i^{06}	$rank^{09}$	$sample^{09}$	q_i^{09}	μ_i^{09}	$rank^{12}$	$sample^{12}$	q_i^{12}	μ_i^{12}
Male	No-Edu/Elementary	White Collar	9	391.00	0.06	387.4592	11	383.00	0.06	368.0194	12	480.00	0.07	320.982
Male	Secondary	White Collar	6	567.00	0.09	409.5586	8	712.00	0.11	384.4907	9	773.00	0.11	361.5689
Male	Higher	White Collar	7	568.00	0.09	393.2634	5	764.00	0.12	406.9911	10	988.00	0.14	355.9439
Female	No-Edu/Elementary	White Collar	4	474.00	0.07	411.7967	7	464.00	0.07	396.1768	7	464.00	0.07	381.3389
Female	Secondary	White Collar	5	749.00	0.12	411.7967	4	863.00	0.14	413.8319	4	1046.00	0.15	405.6517
Female	Higher	White Collar	2	684.00	0.11	436.3468	2	750.00	0.12	437.2152	2	1045.00	0.15	418.1294
Male	No-Edu/Elementary	Blue Collar	12	204.00	0.03	330.8069	12	105.00	0.02	335.0191	11	804.00	0.11	330.9185
Male	Secondary	BlueCollar	11	244.00	0.04	373.8603	10	173.00	0.03	376.6306	8	28.00	0.00	375.5309
Male	Higher	Blue Collar	3	956.00	0.15	417.7477	3	898.00	0.14	418.2656	3	154.00	0.02	411.295
Female	No-Edu/Elementary	Blue Collar	10	270.00	0.04	386.1149	9	120.00	0.02	379.1342	6	1000.00	0.14	398.6669
Female	Secondary	BlueCollar	8	338.00	0.05	392.9486	6	207.00	0.03	404.3781	5	39.00	0.01	405.1612
Female	Higher	Blue Collar	1	1033.00	0.16	453.5496	1	911.00	0.14	458.9565	1	193.00	0.03	450.0314

Note: Sample indicates the number of observations, q_i indicates the population share of each type, μ_i indicates the average PISA scores in Math, Reading and Science. Source: Authors' computation based on PISA.

Table 6: Qatar. PISA 2006-2009–2012: Descriptive Statistics and Partition in Type.

Gender	Education Parents	Occupation Parents	Pisa 2006				Pisa 2009				Pisa 2012			
			$rank^{06}$	$sample^{06}$	q_i^{06}	μ_i^{06}	$rank^{09}$	$sample^{09}$	q_i^{09}	μ_i^{09}	$rank^{12}$	$sample^{12}$	q_i^{12}	μ_i^{12}
Male	No-Edu/Elementary	White Collar	10	133.00	0.02	297.4643	11	224.00	0.03	327.3486	12	579.00	0.05	295.8324
Male	Secondary	White Collar	9	152.00	0.03	300.6693	8	389.00	0.04	336.9934	11	579.00	0.05	314.4122
Male	Higher	White Collar	6	309.00	0.05	322.6479	4	711.00	0.08	364.9144	10	1569.00	0.14	324.9273
Female	No-Edu/Elementary	White Collar	5	148.00	0.02	324.4296	7	286.00	0.03	344.4657	9	526.00	0.05	347.356
Female	Secondary	White Collar	3	306.00	0.05	338.931	6	590.00	0.07	351.8442	7	696.00	0.06	366.0421
Female	Higher	White Collar	2	347.00	0.06	352.4384	2	723.00	0.08	390.7158	4	1109.00	0.10	386.4205
Male	No-Edu/Elementary	Blue Collar	12	283.00	0.05	277.8148	12	236.00	0.03	307.3433	8	100.00	0.01	351.1978
Male	Secondary	BlueCollar	11	468.00	0.08	285.1189	10	414.00	0.05	334.7333	5	344.00	0.03	381.6497
Male	Higher	Blue Collar	7	1470.00	0.25	322.3964	3	2405.00	0.27	374.6868	2	2490.00	0.23	411.9265
Female	No-Edu/Elementary	Blue Collar	8	358.00	0.06	320.9846	9	230.00	0.03	336.708	6	127.00	0.01	367.2139
Female	Secondary	BlueCollar	4	512.00	0.09	325.6299	5	513.00	0.06	358.0042	3	365.00	0.03	401.0718
Female	Higher	Blue Collar	1	1450.00	0.24	358.2905	1	2206.00	0.25	408.9507	1	2482.00	0.23	435.8855

Note: Sample indicates the number of observations, q_i indicates the population share of each type, μ_i indicates the average PISA scores in Math, Reading and Science. Source: Authors' computation based on PISA.

Table 7: Arab Emirates United. PISA 2012: Descriptive Statistics and Partition in Type.

Gender	Education Parents	Occupation Parents	Pisa 2012			
			rank[12]	sample[12]	q_i^{12}	μ_i^{12}
Male	No-Edu/Elementary	White Collar	12	483.00	0.04	367.08
Male	Secondary	White Collar	10	808.00	0.07	377.0597
Male	Higher	White Collar	9	1202.00	0.10	401.6897
Female	No-Edu/Elementary	White Collar	8	520.00	0.05	405.9559
Female	Secondary	White Collar	5	860.00	0.07	420.1218
Female	Higher	White Collar	3	1016.00	0.09	451.0168
Male	No-Edu/Elementary	Blue Collar	11	115.00	0.01	368.6546
Male	Secondary	BlueCollar	7	509.00	0.04	410.9808
Male	Higher	Blue Collar	2	2591.00	0.23	459.2721
Female	No-Edu/Elementary	Blue Collar	6	126.00	0.01	413.1023
Female	Secondary	BlueCollar	4	603.00	0.05	432.43
Female	Higher	Blue Collar	1	2667.00	0.23	482.2144

Note: Sample indicates the number of observations, q_i indicates the population share of each type, μ_i indicates the average PISA scores in Math, Reading and Science. Source: Authors' computation based on PISA.

4. Results: inequality of educational opportunities

In this section, we turn to the assessment of inequality of educational opportunity in each different subject. In particular, we focus on ex-ante inequality of opportunity and measure it using the Mean Logarithmic Deviation (MLD).

The results of inequality of educational opportunity in Mathematics, for the different countries and years, are reported in Table 8. Tunisia, Qatar, and Jordan show some similarities in the trend of inequality of educational opportunity over time. In particular, while inequality of opportunity in level (IOp, first column in the table for each year) appears to be quite stable, relative inequality of opportunity (Relative IOp, third column in the table for each year) increases and this increase is remarkable in Qatar and Jordan. It is also interesting to notice that while inequality of opportunity in level is similar in the four countries, relative inequality of opportunity varies considerably across them. In 2006 and 2009 Tunisia is the worst performing country, with a level of Relative IOp equal to 38.1 in 2006 and 31.9 in 2009. The second worst ranked is Jordan (31.7 in 2006 and 26.8 in 2009), while Qatar ranks the best (22.4 in 2006 and 23.6 in 2009) in both years. In 2012, Tunisia together with Jordan shows the highest relative IOp (38.3 and 38.3, respectively). Arab Emirates are the country with the second highest relative IOp (32.74), while Qatar confirms its best performance in terms of inequality of educational achievement in Mathematics (23.42), although it is the worst performing country in terms of overall educational inequality.

Table 8: Inequality of Educational Opportunity, Mathematics.

Countries	**Pisa 2006**			**Pisa 2009**			**Pisa 2012**		
	IOp	IO	Relative IOp	IOp	IO	Relative IOp	IOp	IO	Relative IOp
Tunisia	0.05	0.14	38.12	0.04	0.12	31.92	0.04	0.11	38.33
	(0.03)	(0.12)	(0.03)	(0.05)	(0.03)	(0.13)	(0.02)	(0.03)	(0.25)
Qatar	0.03	0.15	22.41	0.03	0.15	23.64	0.03	0.15	23.42
	(0.12)	(0.03)	(0.01)	(0.03)	(0.03)	(0.04)	(0.08)	(0.03)	(0.014)
Jordan	0.04	0.12	31.73	0.03	0.12	26.76	0.04	0.11	38.34
	(0.03)	(0.08)	(0.03)	(0.07)	(0.03)	(0.09)	(0.02)	(0.02)	(0.06)
Arab Emirates	-	-	-	-	-	-	0.04	0.12	32.79
							(0.03)	(0.02)	(0.16)

Notes: Estimations obtained using sample weights through bootstrap procedure. Standard Errors shown in Parentheses. IOp indicates inequality of opportunity measured through MLD. IO indicates total Inequality measured through MLD. Realtive IOp indicates relative inequality of opportunity, measured as the ration between IOp and IO. Source: Authors' computation based on PISA.

The results of inequality of educational opportunity for reading are reported in Table 9 and are somehow different from those concerning Mathematics, discussed above. First, the trend of both IOp in level and relative IOp varies by country. As for Tunisia, we observe that IOp in level, after a decrease between 2006 and 2009, increases between 2009 and 2012. A similar trend is shown by relative IOp, whose rise between 2009 and 2012 is however much more remarkable: relative IOp is about 31 in 2006, about 31 in 2009, and is about 37 in 2012. As for Qatar, we observe a reduction of both IOp in level and relative IOp between 2006 and 2009. In particular, for this country, relative IOp is about 33 in 2006, about 28 in 2009 and about 30 in 2012. It is Jordan, however, the country with the worst performance over time. In fact, both IOp in level and relative IOp experience a big rise in the period considered: relative IOp increases from 38 in 2006 to 39 in 2009 to about 53 in 2012. Thus, Jordan results to be the country with the highest relative IOp in reading in

all years considered. When we focus on 2012, the last year available, we find that the second highest unequal country, in terms of education opportunity, is UAE (39.7), closely followed by Tunisia and then Qatar, the latter being again the worst performing country in terms of overall educational inequality.

Table 9: Inequality of Educational Opportunity, Reading.

Countries	Pisa 2006			Pisa 2009			Pisa 2012		
	IOp	IO	Relative IOp	IOp	IO	Relative IOp	IOp	IO	Relative IOp
Tunisia	0.044	0.142	31.039	0.037	0.120	30.925	0.048	0.124	38.641
	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.13)	(0.07)	(0.01)	(0.02)
Qatar	0.063	0.193	32.795	0.049	0.175	28.012	0.049	0.165	29.818
	(0.03)	(0.02)	(0.07)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.25)
Jordan	0.048	0.125	38.196	0.047	0.121	39.011	0.068	0.129	52.985
	(0.03)	(0.05)	(0.06)	(0.03)	(0.09)	(0.08)	(0.02)	(0.01)	(0.15)
Arab Emirates	-	-	-	-	-	-	0.050	0.126	39.705
							(0.08)	(0.02)	(0.19)

Notes: Estimations obtained using sample weights through bootstrap procedure. Standard Errors shown in Parentheses. IOp indicates inequality of opportunity measured through MLD. IO indicates total Inequality measured through MLD. Realtive IOp indicates relative inequality of opportunity, measured as the ration between IOp and IO. Source: Authors' computation based on PISA.

We conclude our analysis by estimating inequality of educational opportunity in Science, with results reported in Table 10. As one could expect, the results are similar to the case of Mathematics. In all countries, both IOp in level and relative IOp experience a rise between 2006 and 2012, this rise being the highest for Jordan. As for Tunisia, relative IOp decreases from 29 in 2006 to 26 in 2009, but it increases to 31.5 in 2012. In Qatar, this measure is about 23.8 in 2006, increasing to about 24.9 in 2009 and decreasing to 24.3 in 2012. In Jordan, instead, it decreases from 33.8 in 2006 to 32 in 2009, but increases to 42.6 in 2012, the highest value for relative IOp in this year across all countries. UAE are the second country with highest relative inequality of educational opportunity (35.8), followed by Tunisia and Qatar.

Table 10: Inequality of Educational Opportunity, Science.

Countries	Pisa 2006			Pisa 2009			Pisa 2012		
	IOp	IO	Relative IOp	IOp	IO	Relative IOp	IOp	IO	Relative IOp
Tunisia	0.035	0.120	29.254	0.030	0.116	26.073	0.035	0.112	31.579
	(0.03)	(0.05)	(0.12)	(0.03)	(0.02)	(0.12)	(0.03)	(0.02)	(0.13)
Qatar	0.031	0.130	23.850	0.038	0.152	24.926	0.038	0.156	24.322
	(0.02)	(0.05)	(0.07)	(0.08)	(0.03)	(0.14)	(0.03)	(0.07)	(0.15)
Jordan	0.039	0.116	33.801	0.038	0.118	32.007	0.049	0.115	42.608
	(0.03)	(0.09)	(0.08)	(0.03)	(0.02)	(0.12)	(0.03)	(0.02)	(0.02)
Arab Emirates	-	-	-	-	-	-	0.043	0.120	35.812
							(0.03)	(0.02)	(0.27)

Notes: Estimations obtained using sample weights through bootstrap procedure. Standard Errors shown in Parentheses. IOp indicates inequality of opportunity measured through MLD. IO indicates total Inequality measured through MLD. Realtive IOp

indicates relative inequality of opportunity, measured as the ration between IOp and IO. Source: Authors' computation based on PISA.

Some concluding remarks are in order here. First, in 2012 Qatar ends up to be the country with the lowest inequality of educational opportunity in all subjects considered, while the country with highest inequality of educational opportunity depends on the subject. Second, there seems to be an inverse relationship between overall educational inequality and inequality of educational opportunity. Last, although UAE rank the best in terms of average test scores, they are in general one of the worst performing countries in terms of inequality of educational opportunity.

4.1. Inequality of educational opportunity and immigration

In this section, we extend the analysis of inequality of educational opportunity in the Arab countries considered in this paper by introducing an additional circumstance, that is, immigration status. This variable is coded into two categories: being native and being immigrant. Note that, the use of this circumstance forces us to make some additional treatment to the data, necessary to allow for estimate reliability. This is because the number of observations categorized as immigrant is very low with respect to the number of observations categorized as native. For this reason, we cannot perform the analysis for each subject specifically, but we have to merge the results of Mathematics, Reading, and Science and perform the analysis on the overall result. Furthermore, in order to obtain type with a sufficient sample size we do not consider education. Therefore, our analysis is performed assuming three circumstances: gender, parental occupation status, and immigration status.

Tables 11, 12, and 13 report the new opportunity profiles of each year respectively for Qatar, Jordan, and UAE. The types' ranking is similar across countries and it is mostly determined by gender and immigration status, in fact, all the bottom ranked types encompass female individuals that are immigrant, while, as for the previous partition, parental job exerts a less strong influence on children's achievement. As for the best performing types, it is possible to observe that, in all the countries considered, these are represented by types encompassing male and native individuals.

Table 14 reports the results of overall educational inequality and ex-ante inequality of educational opportunity for the different countries and years. First, it deserves to be noted that the values of overall educational inequality are consistently lower than those obtained in the analysis proposed in the previous section. This is because many individuals report missing information concerning their immigration status and all these observations are obviously dropped from our analysis. In particular, overall inequality ranges from 0.02 to 0.04, with Qatar experiencing a slight increase from 0.03 to 0.04 between 2006 and 2012, while Jordan experiencing a stable pattern around 0.02. 0.02 is also the value of overall educational opportunity in the Arab Emirates, for which we have observations only in 2012.

The inclusion of immigration status as a circumstance variable also affects our estimations of inequality of opportunity in education, which appear to be different from those obtained using gender, parental education, and parental occupation as circumstances. Qatar is the most opportunity unequal country in all the periods considered (in 2012 is the most opportunity unequal together with UAE), its level of educational opportunity inequality decreases from 0.01 to 0.007 between 2006 and 2009, but increases again to 0.01 in 2012. Inequality of educational opportunity is, instead, stable at 0.001 in Jordan between 2006 and 2009 and increases up to 0.002 in 2012. As for Arab Emirates, inequality of opportunity is 0.01 in 2012.

A similar trend characterizes relative IOp, which is decreasing for Qatar between the first two periods from 33.33% to 17.5% and increasing again up to 25.0% between 2009 and 2012. Whereas in Jordan relative IOp is stable at 5.0% in the first two periods and increases up to 10.0% in 2012. Again, Qatar is the country showing, in every period, the highest share of IOp in education. In 2012, UAE is the country with the lowest share, around 5.0%. Hence, differently from the previous analysis, when we focus on immigration status, Qatar ends up being the country with the highest level of inequality of education and inequality of educational opportunities. Jordan, instead, shows the lowest level of educational opportunity inequality but intermediate level of overall educational inequality.

Table 11: Qatar. PISA 2006-2009–2012: Descriptive Statistics and Partition in Type.

Gender	Occupation	Immigrant status	Pisa 2006				Pisa 2009				Pisa 2012			
			$rank^{06}$	$sample^{06}$	q_i^{06}	μ_i^{06}	$rank^{09}$	$sample^{09}$	q_i^{09}	μ_i^{09}	$rank^{12}$	$sample^{12}$	q_i^{12}	μ_i^{12}
Male	Blue Collar	Native	7	320	0.07	290	8	667	0.08	318	8	1469	0.142386	250
Female	Blue Collar	Native	6	231	0.05	326	6	897	0.10	344	6	1389	0.134632	353
Male	White Collar	Native	8	405	0.09	280	7	1574	0.18	320	7	939	0.091015	348
Female	White Collar	Native	5	1426	0.31	328	5	1623	0.19	355	4	1174	0.113793	380
Male	Blue Collar	Immigrant	3	256	0.05	368	4	619	0.07	388	5	867	0.084036	374
Female	Blue Collar	Immigrant	2	301	0.06	369	3	677	0.08	400	3	868	0.084133	404
Male	White Collar	Immigrant	4	888	0.19	358	2	1334	0.15	428	2	1887	0.182902	438
Female	White Collar	Immigrant	1	829	0.18	379	1	1280	0.15	446	1	1724	0.167103	462

Table 12: Jordan. PISA 2006-2009–2012: Descriptive Statistics and Partition in Type.

Gender	Occupation	Immigrant status	Pisa 2006				Pisa 2009				Pisa 2012			
			$rank^{06}$	$sample^{06}$	q_i^{06}	μ_i^{06}	$rank^{09}$	$sample^{09}$	q_i^{09}	μ_i^{09}	$rank^{12}$	$sample^{12}$	q_i^{12}	μ_i^{12}
Male	Blue Collar	Native	8	1197	0.19	384	8	1557	0.25	389	8	1767	0.27	358
Female	Blue Collar	Native	5	1476	0.24	414	5	1785	0.28	416	5	2001	0.30	404
Male	White Collar	Native	7	1092	0.17	399	6	957	0.15	401	6	974	0.15	403
Female	White Collar	Native	3	1276	0.20	427	2	1011	0.16	440	2	1085	0.16	441
Male	Blue Collar	Immigrant	6	290	0.05	412	7	290	0.05	397	7	236	0.04	379
Female	Blue Collar	Immigrant	2	389	0.06	430	4	288	0.05	429	4	250	0.04	426
Male	White Collar	Immigrant	4	235	0.04	426	3	198	0.03	430	3	160	0.02	427
Female	White Collar	Immigrant	1	312	0.05	454	1	219	0.03	449	1	190	0.03	451

Table 13: United Arab Emirates. PISA 2006-2009–2012: Descriptive Statistics and Partition in Type.

Gender	Occupation	Immigrant status	Pisa 2012			
			$rank^{12}$	$sample^{12}$	q_i^{12}	μ_i^{12}
Male	Blue Collar	Native	8	1298	0.12	367
Female	Blue Collar	Native	6	1343	0.12	416
Male	White Collar	Native	7	1178	0.11	402
Female	White Collar	Native	4	1298	0.12	436
Male	Blue Collar	Immigrant	5	1006	0.09	423
Female	Blue Collar	Immigrant	3	991	0.09	451
Male	White Collar	Immigrant	2	1941	0.17	479
Female	White Collar	Immigrant	1	2040	0.18	493

Table 14: Inequality of Educational Opportunity, Average Scores (Math, Reading, Science)

Countries	Pisa 2006			Pisa 2009			Pisa 2012		
	Iop	IO	Relative Iop	Iop	IO	Relative Iop	Iop	IO	Relative Iop
Qatar	0.01 (0.002)	0.03 (0.0002)	33.33%	0.007 (0.001)	0.04 (0.0036)	17.5%	0.01 (0.001)	0.04 (0.001)	25.00%
Jordan	0.001 (0.0001)	0.02 (0.002)	5.00%	0.001 (0.001)	0.02 (0.0036)	5.0%	0.002 (0.0001)	0.02 (0.004)	10.0%
Arab Emirates	-	-	-	-	-	-	0.01 (0.0001)	0.02 (0.001)	5.0%

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