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**Inequality of opportunity in Europe:
Economic and policy facts**

Gustavo A. Marrero
Juan G. Rodríguez

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Inequality of opportunity in Europe: Economic and policy facts*

Gustavo A. Marrero[†]
Universidad de La Laguna

Juan Gabriel Rodríguez
Instituto de Estudios Fiscales and Universidad Rey Juan Carlos

Abstract

In this paper we consider the main factors that have influenced inequality of opportunity (IO) in Europe. Based on the EU-SILC database, we find that the various levels of development, education and social protection expenditure in 23 European countries significantly affect IO. Dropping out from school, reaching at least secondary levels of education, social spending to promote social integration and child care are the most important variables of those analyzed. The functioning of the labor market and the tax structure, on the other hand, do not have a significant bearing on IO. Lastly, we note that IO and total inequality exhibit differentiated explanatory patterns, which signifies that means of redistribution that serve to reduce overall inequality do not necessarily reduce IO.

Keywords: inequality of opportunity; growth; education; public expenditure; labor market.

JEL classification: D63, E24, O15, O40.

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[†] **Address of correspondence:** Gustavo Marrero, Departamento de Análisis Económico (Universidad de La Laguna, Spain), FEDEA, ICAE and CAERP. +34 922 277798. gmarrero@ull.es
Juan Gabriel Rodríguez: Instituto de Estudios Fiscales and Departamento Economía Aplicada I (Universidad Rey Juan Carlos, Spain). +34 91 4888031. juangabriel.rodriguez@urjc.es

1. Introduction

Kuznets' (1955) pioneering work laid the foundation for explaining the long-term influence of economic growth on income distribution. His hypothesis envisages that the extent of a country's development determines the degree of income inequality, as related by an inverted U-shape. Although this hypothesis prevailed until the late 70s, it is currently under challenge. Specifically, there is a lack of consensus in the empirical literature on the validity of said hypothesis (Milanovic, 1994; Fields, 2001, among many others). Fields (2001) notes that the determining factor to explain the degree of inequality is not the growth phase a country is experiencing, but rather the *type* of growth present in said economy. Additionally, other factors aside from economic development have also been found to affect inequality, such as education, public policies and the functioning of the labor market. The incorporation of these factors into the analysis has given rise to an entire set of literature on the so-called *augmented* Kuznets hypothesis (Milanovic, 1994).

In parallel fashion, and based on the work by Roemer (1993) and Van de Gaer (1993), among others, a new field has developed around the concept of inequality of opportunity (IO). This field highlights how total inequality is, in reality, a combination of various types of inequalities: of opportunity, of effort and, perhaps less importantly, of luck (Lefranc et al., 2009). IO refers to those factors that are beyond individual control. These factors are referred to as circumstances, and relate to individuals' social roots, such as race, their parents' education and occupation, gender, place of birth, and so on.² As for effort inequality, this involves factors that are under the control of the individual, such as the number of hours worked, occupational choice, etc. It is important to distinguish between the various components of inequality, since the factors that determine it and their effect on the economy can be different. Along these lines, the World Bank (2006), Bourguignon et al. (2007a) and Marrero and Rodríguez (2010), have noted that IO, in addition to being the one inequality that is truly important from the standpoint of social justice, could exert a negative effect on growth. In this respect, and as applied to the economy of the United States, Marrero and Rodríguez (2010) have found that the impact of IO on growth is negative, while the effect of effort inequality is

² There is an alternative concept of inequality of opportunity that alludes to the degree of meritocracy (Lucas, 1995; Arrow et al., 2000). This notion regards individuals as being completely responsible for their income (or their health, utility, job, etc.), as a result of which total inequality is due exclusively to the disparity of personal choices. We see, therefore, that meritocracy is an extreme case of our concept of IO, in which there are no circumstances.

positive. If this result is confirmed, correcting a country's IO would not only result in a fairer society in terms of social equality, but it would also spur economic efficiency and growth.

In keeping with the above, and along the lines set out by Kuznets (1955) and Milanovic (1994), an understanding of the factors that explain IO and separating them from the determinants of aggregate inequality is fundamental to properly devising public policies. The ultimate goal of this paper is precisely that of studying these determining factors. Specifically, the purpose of our analysis is two-fold. First, we aim to obtain homogeneous estimates of IO for the main European countries. To this end, we use the statistics of the Survey on Income, Social Inclusion and Living Conditions in Europe (EU-SILC database). Our analysis focuses on the 2005 cross-section for 23 countries, this being the only one containing information on circumstances such as parents' occupation and education.

The second goal is to characterize the differences in IO among European countries based on factors related to the degree of economic development, the labor market, education, social protection and the tax structure. Taking as our reference the explanatory variables considered by Perugini and Martino (2008) in their paper on the determinants of income inequality among European regions, we study the explanatory capacity of a set of factors on IO and their differences with respect to total inequality. In this regard, we are aware of the limitations of our analysis in terms of the number of observations (a cross-section of 23 observations) resulting from the use of country data instead of regional data. Our objective, however, is to study those variables that, on a national level, have caused a greater or lesser level of IO so as to enable us to offer conclusions on economic policy at the national level. Moreover, numerous educational, labor and fiscal policies (both taxes and expenditures) are set at the national level. Also, the database used for this paper is probably the best currently available for obtaining a homogeneous estimate of IO for a broad range of countries.

Our main findings are as follows. First, as with previous studies (Roemer et al., 2003 and Rodríguez, 2008), we find that, in general, the Nordic countries have a lower IO, while Mediterranean countries have a greater IO. Central European countries occupy a central position, while those in Eastern Europe exhibit a broad range of IO. Secondly, the relationship between development and IO is negative and clearer than that between development and total inequality. Economic development is thus more

propitious to reduce IO than to reduce aggregate inequality. Thirdly, the aggregate variables of the labor market, such as employment or unemployment rates, have a very slight effect on IO. Variables that reflect the structure of the labor market, such as female employment rates, long-run unemployment rates or the difference between unemployment rates based on educational level have a greater influence on IO than aggregate variables. The effect of labor market variables on inequality is also ambiguous. Fourthly, the level of secondary education attained by individuals, and particularly dropout rates, has a significant effect on total inequality, although it is much more important on IO. According to our findings, avoiding dropouts and ensuring instruction through at least the secondary education level are the two most relevant aspects to reduce IO.

Fifthly, spending on social protection in its various forms helps to reduce disparity of opportunity. Among the various expenditure items, those that most help to explain the differences noted in IO are social protection expenditure against social exclusion and child care and, to a lesser extent, on health care. As for disability benefits, this is only significant in terms of total inequality, while unemployment and retirement benefits are not significant for any type of inequality. Sixthly, we note that the effect of the tax structure on IO, after accounting for public spending on social benefits, is negative for indirect taxes, and positive for direct taxes, although the extent of the significance is called into question once an analysis of robustness is performed. Lastly, we note the considerable differences among the factors that help to explain the differences in IO and aggregate inequality among countries, especially for the education and social protection spending variables, meaning that redistribution policies that favor global inequality do not necessarily favor IO.

This paper is structured as follows. Section 2 introduces the database used to measure IO in Europe, the methodology employed and the estimates found for IO. Section 3 offers a review of previous research into determinants of inequality. Section 4 strives to improve our understanding of the factors (labor market, education and policy) that explain the differences noted in IO in Europe. In Section 5 we consider the robustness of our results. Finally, Section 6 offers some public policy recommendations based on our findings.

2. Data, methodology and IO in Europe

In the first part of this section we present the database used to calculate IO in Europe. We then comment on the methodology employed before discussing our findings in the third part.

2.1. The EU-SILC European database

The availability of suitable data is crucial to a rigorous study of IO. The database must contain not only information on the income available to individuals, but also information on the individuals' social roots or circumstances.³ Unfortunately, there are few databases with this information, and even then, the number of circumstances tends to be limited.

The database used in this paper is the EU Survey on Income, Social Inclusion and Living Conditions, or EU-SILC. This survey is only recently implemented (in 2004), and only the data for 2005 is of use for our purposes, since this is the only year for which information is available on the occupation and level of education of parents, these variables being the most widely used in the related literature to measure IO (see, for example, Roemer et al., 2003, Checchi and Peragine, 2005, Bourguignon et al., 2007b, Lefranc et al., 2008, Rodríguez, 2008 and Ferreira and Gignoux, 2008). An initial benefit of this survey is that it offers information for a large number of countries (26 total), which gives its database sufficient heterogeneity in terms of economic features and public policies. The countries we use are: Germany, Austria, Belgium, Czech Republic, Denmark, Slovakia, Slovenia, Spain, Estonia, Finland, France, Greece, the Netherlands, Hungary, Ireland, Italy, Latvia, Lithuania, Norway, Poland, Portugal, the United Kingdom and Sweden.⁴ A second advantage is the considerable number of circumstances it contains. For our study, we use the educational levels and occupations of both parents, the origin (national, European or rest of the world) of the individual and, lastly, a qualitative variable that measures the prevalent economic conditions in the individual's home during his/her childhood.

³ For example, the studies presented in <http://www.econ.umn.edu/~fperri/Cross.html> consider databases with information on individual incomes, but without information on individual circumstances.

⁴ The EU-SILC database also contains information on Luxembourg, Iceland and Cyprus, though we opted not to use these countries due to the peculiarities they pose and to their small size.

The variable used to calculate inequality is the equivalent income for those households whose head is between 26 and 50 years of age.⁵ This way, we consider the cohorts with the highest proportion of employed persons and avoid the composition effect (individuals with different ages are in different phases of the wage-earning time series) while approaching the concept of permanent income (Grawe, 2005). In terms of the IO calculation, it must be noted that the circumstance vector observed is, by definition, a subset of the vector of all possible circumstances. The estimated IO values, then, will be a lower-bound of the true IO, and will increase with the number of circumstances observed (Ferreira and Gignoux, 2009).⁶ That is why, when measuring IO, it is important that a database containing sufficient information on the individuals' circumstances be employed. It is worth noting that, to the best of our knowledge, the 2005 EU-SILC database features the highest number of individual circumstances measured homogeneously for a large number of countries.

2.2. Methodology for computing IO

The modern economy of justice recognizes that an individual's income is a function of the effort exerted and of individual's initial circumstances.⁷ Individuals are only responsible for their efforts, however, since the circumstances are beyond their control. The first hurdle is defining the difference between effort and circumstances. To do this, we assume that society has reached a political agreement on the list of circumstances. A second hurdle is how to compare the results obtained by different individuals. This is done by grouping individuals according to circumstances and then comparing individuals under different circumstances. The final step is computing a policy for assigning resources among groups of circumstances.

⁵ The equivalence scale used in this paper is the same as that used in the EU-SILC database. Specifically, the equivalence scale is $e = 1 + 0.5(N_{14^+} - 1) + 0.3N_{13^-}$, where N_{14^+} is the number of household members 14 years of age or older and N_{13^-} is the number of household members 13 years of age or younger.

⁶ This problem is not unique to a study of IO, however, and is seen in practically every field of economics. For example, an analysis of salary discrimination must face the problem of a heterogeneity that is not explained by the individual characteristics observed. Worse yet, econometric modeling normally introduces a random variable to somehow account for all non-observed variables.

⁷ See, among others, Roemer (1993, 1996, 1998 and 2002), Van de Gaer (1993), Fleurbaey (1995 and 2008), O'Neill et al. (2000), Van de Gaer et al. (2001), Roemer et al. (2003), Ruiz-Castillo (2003), Peragine (2002 and 2004), Checchi y Peragine (2005), Betts and Roemer (2007), Moreno-Ternero (2007), Ooghe et al. (2007), Fleurbaey and Maniquet (2007), Bourguignon et al. (2007a and 2007b), Lefranc et al. (2008 and upcoming), Rodríguez (2008), Ferreira and Gignoux (2008) and Cogneau and Mesplé-Somps (2009).

We now briefly describe the theory behind the calculation of IO. Assume a discrete population of individuals of size N , indexed by $i \in \{1, \dots, N\}$. An individual's income y_i , is a function of his effort, e_i , and of his circumstances, C_i : $y_i = f(C_i, e_i)$.⁸ Assume the effort is a continuous and one-dimensional variable, although its definition in vector terms would not change our analysis (Roemer, 1998). We also have a vector C_i of J elements (circumstances) for each individual i . Finally, the circumstances are assumed to be exogenous while the effort exerted by the economic agents is influenced by, among other factors, the circumstances. The income of an individual i , then, is expressed as follows: $y_i = f(C_i, e_i(C_i))$.

We now divide the population into M mutually exclusive and exhaustive groups (or types), $\Gamma = \{H_1, \dots, H_M\}$, where all the individuals in the same group m have the same circumstances: $H_1 \cup H_2 \cup \dots \cup H_M = \{1, \dots, N\}$, $H_r \cap H_s = \emptyset$, $\forall r$ and s , and $C_i = C_k$, $\forall i$ and $k \mid i \in H_m$ and $k \in H_m$, $\forall m$. Moreover, we assume that the effort distribution for individuals of type m is F^m and that $e^m(\pi)$ represents the level of effort exerted by an individual in the π^{th} quintile of that effort distribution, with $\pi \in [0, 1]$. Given type m , we can then define the income level attained by the individual in the π^{th} quintile as $v^m(\pi) = y^m(e^m(\pi))$. In this manner, the order of incomes and efforts within each type coincide since, for a particular type, the income will be determined exclusively by the effort.⁹ In general, there is said to be equality of opportunity when an individual's income is independent of his social origins (Bourguignon et al., 2007a and Lefranc et al., 2008). Strictly speaking, this would translate into the following condition:

$$F^m(y) = F^k(y), \forall m, k \mid H_m \in \Gamma, H_k \in \Gamma. \quad (1)$$

Once income distribution is available by types, we can contrast first and second order stochastic dominance by types. The stochastic dominance criterion, however, is partial and incomplete, since the distribution functions can cross (Atkinson, 1970). What is more, when the number of circumstances is large, the number of observations

⁸ Talent could be considered a circumstance, however, this variable is controversial as it might reflect past effort of a person (while being a child) and hence is not obviously something for which a person should not be held accountable.

⁹ This property is equivalent to the *strictly increasing* axiom in the literature on IO (see O'Neill et al., 2000).

per type will be small, which, in practice, precludes an estimate of the distribution functions. One alternative to using income distributions is considering a particular moment of said distributions, such as the average. Thus, given $\pi \in [0, 1]$, let us consider

$$\mu = (\mu^1, \dots, \mu^M) = \left(\int_0^1 v^1(\pi) d\pi, \dots, \int_0^1 v^M(\pi) d\pi \right), \quad (2)$$

the M -dimensional vector of average incomes for the various types. Each element of vector μ would be the expected income for each origin category or type. Then, in order to be equality of opportunity, a necessary (though not sufficient) condition is that the elements of vector μ be equal, that is:

$$\mu^m(y) = \mu^k(y), \forall m, k | H_m \in \Gamma, H_k \in \Gamma. \quad (3)$$

Taking the average vector as a reference, Van de Gaer (1993) proposed maximizing the minimum average income:

$$\text{Min}(\mu) = \min_m \left\{ \int_0^1 v^m(\pi) d\pi \right\}. \quad (4)$$

Van de Gaer proposed using the minimum function to comply with the Rawlsian *maximin* principle. Many other authors, like Checchi and Peragine (2005), Moreno-Ternero (2007), Rodríguez (2008) and Ferreira and Gignoux (2008) have proposed using an inequality index, such as the Gini or the Theil 0. One advantage of this proposal is that the calculation, by taking into account every element in the average vector μ , and not just its minimum element, would be less subject to extreme values.

In summary, let χ be the space of joint income distributions and circumstances $\{y, C\}$ and δ the space of possible divisions of the population; then, given $IO: \chi \times \delta \rightarrow R^+$, we have that

$$IO = I(\mu) \quad (5)$$

is a measure of IO, where I is a specific inequality index. Of all the possible inequality indices that fulfill the basic principles found in the literature on inequality,¹⁰ we chose the Generalized Entropy class of inequality indices which are additively decomposable

¹⁰ The principle of progressive transfers, symmetry, invariance to changes in scale and replication of the population (Cowell, 1995; Sen and Foster, 1997).

(Bourguignon, 1979; Shorrocks, 1980; Cowell, 1980). In particular, we select the mean logarithmic deviation, or Theil 0, T_0 , since it uses weights based on the groups' population shares and has a path-independent decomposition (Foster and Shneyerov, 2000).¹¹ The decomposition of this index into between-group and within-group inequality components is

$$T_0(Y) = T_0(\mu) + \sum_{m=1}^M \frac{n^m}{N} T_0(y^m) \quad (6)$$

where n^m represents the population of type m . The between-group inequality index would be our IO index (actually, a lower bound of the IO), since the groups would be determined by the individual circumstances observed. As for the within-group inequality, this could be considered as that due to effort. However, we realize that it may contain other elements arising from non-observed circumstances and/or luck. That is why our analysis focuses on aggregate inequality and on the estimated IO.

The between-group component can be non-parametrically estimated (Checchi and Peragine, 2005; Lefranc et al., 2008; Marrero and Rodríguez, 2010). However, this approach presents a drawback when the number of circumstances is high, as in our case, because this could result in a small number of observations by type, with the concomitant lack of accuracy in the estimated values. One way to avoid this problem is to use parametric techniques, like those proposed by Bourguignon et al. (2007b) and Ferreira and Gignoux (2008), which yield reliable estimates. We will now summarize this method.

Parametric specifications rest on the assumption that the income of individual i is $y_i = f(C_i, e_i(C_i, u), v)$, where u and v represent random variables, like luck, as well as possible non-observed factors. If we now consider the reduced form of the above expression, $y = \Phi(C, \varepsilon)$, we can estimate the log-linear equation using ordinary least squares (OLS):

$$\ln y = C\lambda + \varepsilon . \quad (7)$$

¹¹ The Theil 0 index is positively related to total inequality and has a value between 0 and $\ln(N)$, where N is the sample size. For a distribution Y , with mean μ_Y , the Theil 0 index is defined as:

$$T(Y) = \frac{1}{N} \sum_{i=1}^N \ln \frac{\mu_Y}{y_i} .$$

The remaining Generalized Entropy indices use weights based not only on the population shares of each type, but also on their income shares. These indices, then, place greater importance on high incomes.

Thus, once the within-group dispersion is accounted for, the OLS estimate would yield an approximation $\hat{\mu}_i = \exp[C_i \hat{\lambda}]$ for the individual incomes. Based on the individual incomes thus estimated, we directly obtain the vector $\hat{\mu} = \left(\hat{\mu}^1, \dots, \hat{\mu}^M \right)$, which is a parametric version of the vector μ . Lastly, we compute IO as $IO = T_0(\hat{\mu})$.

2.3. IO in Europe

The IO estimates for the various EU countries are shown in Table 1 and Figure 1. Also shown are the standard error estimates given by the bootstrapping method using the formula (Davison and Hinkley, 2005):

$$\hat{\sigma}(\hat{T}) = \sqrt{\frac{1}{R-1} \sum_{r=1}^R \left(T_0^* - \bar{T}_0^* \right)^2}, \quad (8)$$

where R is the number of replicates.¹² To calculate the IO indices, we followed the methodology presented in the previous section, presenting the auxiliary regressions of (7) for each country in Appendix A.¹³ Based on the results of these regressions, we see that, in general, the parents' education has a positive influence on the children's income, which increases with the educational level of the father and/or mother. Taking workers in the farming, forestry and fishing sectors as a reference, all of the remaining occupations, except for the elementary occupation, have a positive effect on the children's incomes. On the other hand, having experienced financial difficulties in the household as a child, as well as, having roots outside the European Union, have clearly negative effects on income.

Table 1 shows total inequality using the Theil 0 index, the IO indices, the percentage of total inequality represented by IO, the ranking based on the two measures and, finally, the sample size. We note, first, how a country's rank can change significantly depending on whether total inequality or IO is considered. For example,

¹² For our calculation, we assumed $R = 1000$. Cowell and Flachaire (2007) find that, in general, the bootstrap technique improves the numerical performance of the significance tests. Moreover, for small sample sizes, this technique yields a closer margin to the nominal confidence intervals (Davison and Hinkley, 2005).

¹³ When an explanatory variable's estimated coefficient is not shown, that is because there are no observations with that circumstance in the sample.

Sweden, France, Ireland, Spain, Portugal and Slovenia rank worse in terms of IO than total inequality. The opposite is true for countries like Germany, Finland, Belgium, Slovakia, Norway and Latvia.

Secondly, we note how the Nordic countries are those with the lowest IO, while Mediterranean countries exhibit the largest.¹⁴ In an intermediate position are the central European countries, while the countries of Eastern Europe show a wide range of IO's. This arrangement can be easily seen in Figure 1, which ranks the European countries from smallest to largest IO. Lastly, we note that the average IO in Europe is approximately 9%, ranging from 2% in Denmark to 22% in Portugal.¹⁵ What is more, we see that in percentage terms, the relative positions of the countries hold, with the exception of Hungary.

Table 1. Inequality opportunity indices in Europe.
(Standard errors in parentheses)

Index	Austria	Belgium	Czec R.	Denmark	Estonia	Finland	France	Germany	Greece	Hungary	Ireland	Italy
Theil 0	0,1203 (0,0064)	0,2293 (0,1131)	0,1196 (0,0077)	0,0689 (0,0086)	0,1985 (0,0115)	0,1266 (0,0126)	0,1096 (0,0036)	0,1351 (0,0069)	0,2127 (0,0130)	0,1314 (0,0074)	0,1874 (0,0171)	0,1909 (0,0070)
IO	0,0063 (0,0012)	0,0127 (0,0029)	0,0072 (0,0016)	0,0013 (0,0009)	0,0218 (0,0047)	0,0038 (0,0011)	0,0097 (0,0011)	0,0028 (0,0006)	0,0230 (0,0034)	0,0156 (0,0018)	0,0250 (0,0035)	0,0222 (0,0021)
Ratio (%)	5,24 (0,99)	5,54 (4,31)	6,02 (1,30)	1,89 (0,96)	10,98 (1,96)	3,00 (0,89)	8,85 (1,00)	2,07 (0,45)	10,81 (1,53)	11,87 (1,30)	13,34 (1,97)	11,63 (1,00)
T0 position	7	20	6	1	15	8	5	12	17	10	13	14
IO position	7	12	8	1	15	3	11	2	17	13	19	16
N	2156	1839	1589	1241	1377	1981	3725	4256	2126	2590	1452	8640

	Latvia	Lithuania	ND	Norway	Poland	Portugal	Spain	Slovakia	Slovenia	Sweden	UK
Theil 0	0,2995 (0,0242)	0,2482 (0,0144)	0,0884 (0,0051)	0,1315 (0,0187)	0,2671 (0,0072)	0,2264 (0,0112)	0,2144 (0,0081)	0,1301 (0,0084)	0,1095 (0,0156)	0,0873 (0,0057)	0,2047 (0,0148)
IO	0,0239 (0,0078)	0,0358 (0,0065)	0,0042 (0,0011)	0,0048 (0,0035)	0,0276 (0,0027)	0,0503 (0,0060)	0,0286 (0,0023)	0,0047 (0,0014)	0,0087 (0,0070)	0,0084 (0,0016)	0,0201 (0,0034)
Ratio (%)	7,98 (2,48)	14,42 (2,15)	4,75 (1,17)	3,65 (2,36)	10,33 (0,94)	22,22 (2,21)	13,34 (1,06)	3,61 (0,97)	7,95 (4,61)	9,62 (1,84)	9,82 (1,54)
T0 position	23	21	3	11	22	19	18	9	4	2	16
IO position	18	22	4	6	20	23	21	5	10	9	14
N	1159	1702	1695	1424	6056	1654	5389	2293	1342	1393	1875

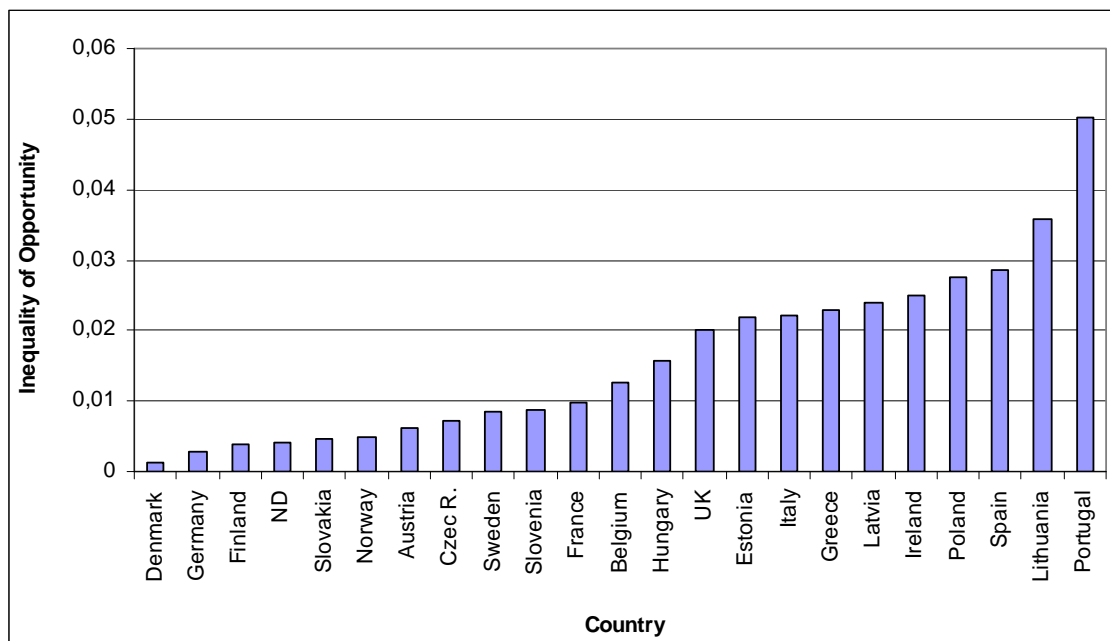
In light of these results, there is ample margin in Europe for implementing policies to reduce IO while at the same time maintaining individual effort and, by

¹⁴ A similar result using other databases was presented by Roemer et al. (2003) and Rodríguez (2008).

¹⁵ It is interesting to note that Checchi and Peragine (2005) calculated a value below 10% for Italy, while Ferreira and Gignoux (2009) found percentages between 20% and 33% for six Latin American countries (Brazil, Colombia, Ecuador, Guatemala, Panama and Peru).

extension, economic growth. In Section 4 we evaluate some potential policies in view of events in Europe in the last decade, but before we offer a brief summary of the literature on the relationship between inequality and development.

Graph 1. Inequality of opportunity in Europe (2005)



3. Background: the Kuznets hypothesis and the augmented Kuznets hypothesis

The Kuznets hypothesis (1995) holds that economic development is a long-term determining factor in the inequality levels of an economy, this relationship having an inverted U shape. There is no theory, however, on which to base the long-term relationship that exists between development and IO. That is why, even though it is not the main goal of this article, we will make a few observations in this regard based on the arguments used by Kuznets in his proposal on total inequality.

In the first stages of development, the important resources are land first, and then physical capital. These resources are highly concentrated, meaning that the output is obtained by few people. In this early stage, the aggregate inequality is small, but largely explained by IO since income is determined primarily by the initial conditions or the social origin of the individuals. As the economy develops, there is a shift in workers toward the industrial sector, which offers a greater range of salaries and opportunities. This results in wider salary dispersion and therefore increases total inequality

(representing the upslope portion of the inverted U), whereas IO decreases because individuals are given more opportunities. In this initial segment, an increase in inequality due to effort (and other possible factors) would more than offset the drop in IO.

Later, the decreasing marginal productivity of capital (accumulated by a few) would diminish its performance, resulting in more capital being distributed to the population and in the salary difference between skilled and unskilled workers dropping. At the same time, IO would continue falling. The total inequality would thus decrease, since its two primary components would also be falling. This represents the downward slope of the inverted U.

In the last three decades, however, aggregate inequality in the most developed countries has undergone an increase (see, for example, Atkinson, 1996). The proliferation of technology (Eicher, 1996, Aghion et al., 2002) and international trade deregulation (Wood and Ridao, 1996) are some of the factors used to explain this widening of salary differences. The factors that have served to trigger this increase in aggregate inequality, however, are more related to effort inequality than to IO. Our premise, then, is that IO always decreases with development. Kuznets' inverted U (and the subsequent upturn in inequality) would then be explained by the trend in the effort-driven inequality, and not so much by the trend in IO.

In addition to a country's degree of development, the evidence points to other factors that help to explain the inequality differences observed among countries. Along these lines, Milanovic (1994) proposed an *augmented Kuznets hypothesis*, in which inequality would be determined by 'given' (long-term) factors involving the country's resources, the degree of development, social norms, etc., and by short-term factors, such as education, the functioning of the labor market, spending and tax policies, and so on. The 'given' factors would change slowly and would be difficult to modify in the short term, while the short-term factors would be more flexible and have potentially permanent effects. Milanovic's work concluded that these short-term factors are more relevant in more developed countries, meaning less developed countries have a reduced capacity to lower aggregate inequality in the short term, since the 'given' factors are

more important.¹⁶ Besides, the more advanced societies reduce their level of inequality not only for economic reasons, but also because they decide to have less inequality and implement policies to that end. Recently, Perugini and Martino (2008) characterized the factors that explain aggregate inequality among European regions, distinguishing also between long- and short-term factors.

The goal of our work is to characterize those factors that exert the greatest influence on the IO levels observed in European countries. Unfortunately, there are no theoretical models available to us that distinguish among factors that affect aggregate inequality versus IO. Nor are there any empirical references that characterize the factors affecting IO. As a result, we will focus on those factors that have traditionally been used to characterize aggregate inequality: extent of economic development, public policies, education and the functioning of the labor market. So as to better understand our findings, we will compare them with those obtained for total inequality while noting the main differences found.

4. Economic and Policy Patterns of IO

Our study considers *INEQ*, an index of inequality (total and IO) for 23 European countries in 2005 (see Section 2), as a dependent variable. Since our goal is to understand the explanatory factors of the differences observed in inequality among countries, the explanatory variables were measured prior to 2005. Specifically, we took 1998 as a reference year, since numerous series started in that year.¹⁷ See Appendix B for greater detail on the data used in this part of our research. This strategy also reduces any possible bias arising from problems with endogeneity and measurement errors (Barro and Sala-i-Martin, 1991, and Partridge, 1997, among others), meaning the OLS procedure will be suitable.

¹⁶ Along similar lines, Tanzi (1998) writes on the determinants of inequality and distinguishes between market forces, social norms, the role of the government and ownership of capital (physical and human). He also underscores how the factors that determine inequality change as the country develops. In poor countries, social norms, economic development and ownership of tangible goods (land and physical capital) explain the inequality, while in rich countries, these factors become less important and are replaced by factors such as the distribution of human capital, economic changes (privatization, technical development, trade deregulation, etc.) and governmental policies.

¹⁷ Whenever possible, we considered 1995 or 2000, though the results are very similar.

Due to our reduced sample size, we will estimate very parsimonious models. Based on the Kuznets hypothesis, we begin with the simplest model, which will include only the level of development of the countries (DEV) and a quadratic term:

$$INEQ_i = \alpha + \beta_1 \cdot DEV_i + \beta_2 DEV_i^2 + \varepsilon_i \quad (9)$$

In the second group of models, in addition to the level of development, we will include each of the short-term factors to be considered, but on an individual basis. There are four of these factors in all: the functioning of the labor market, education levels, social protection spending and the tax system. In these ‘augmented models’, then, we will estimate a model for each factor X :

$$INEQ_i = \alpha + \beta_1 \cdot DEV_i + \beta_2 DEV_i^2 + \delta \cdot X_i + \varepsilon_i \quad (10)$$

Note that the interpretation of coefficient δ in (10) differs from that in a fully specified model, in which δ would measure the *partial* effect that variable X exerts on inequality while keeping the remaining variables constant. In (10), however, δ measures the *global* effect of X , corrected only by DEV and its quadratic term. The global effect is the sum of the partial effect and of all the other indirect effects arising from the correlation that exists between X and other variables affecting inequality and which are not included in the model.

For our purpose, which is merely to characterize the differences in inequality based on policy, education, and other variables, the interpretation of these global coefficients is sufficient. Nevertheless, at the end of this section we will, for illustrative purposes, present the results of a more complete model where more explanatory variables are specified.¹⁸ Lastly, in Section 5 we will conduct a statistical analysis, comparing the residuals of models (9) and (10) for the different explanatory variables considered, so as to add robustness to the results achieved in this section.

4.1. Development

There are many variables that can be used to reflect a country’s level of development. The most utilized are PPP-adjusted (purchasing power parity) per capita GDP, the percentage of jobs concentrated in the agriculture sector and the percentage of jobs

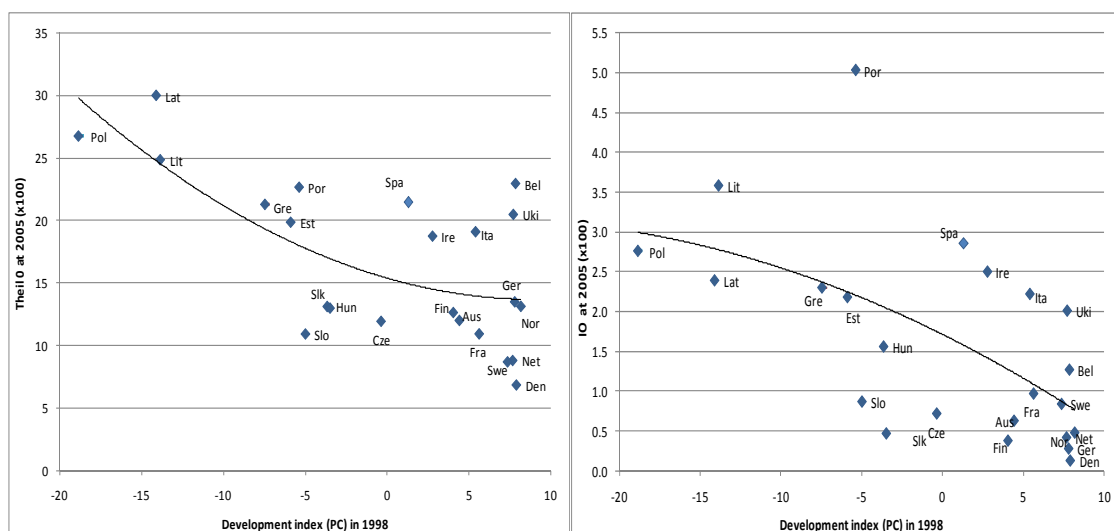
¹⁸ Due to the small number of degrees of freedom and to the possible colinearity among the factors considered, of vital importance will be noting the global adjustment attained by our regressions, since said adjustment is not affected by the low number of degrees of freedom.

concentrated in the services sector. Given these indicators' high correlation, we will follow the strategy of Perugini and Martino (2008), who use the first principal component (PC) of these variables as an indicator of development. In our case, the first PC accounts for almost 90% of the joint variability seen in 1998.¹⁹

Figures 2a and 2b show the scatter plots between total inequality and the development indicator, and the IO and the development indicator, respectively. Table 2 shows the estimates for model (9). Based on these analyses, there is a negative relationship between inequality and development, which is consistent with being on the downslope of Kuznets' inverted U. The quadratic fit, convex for total inequality and concave for IO, is not significant. If, however, we omit the countries with the least inequality (Sweden, Denmark, the Netherlands and Norway), the convex relationship for total inequality becomes significant, while the relationship for IO remains linear and negative. These findings are consistent with the arguments given in the previous section on IO and on a possible upturn of total inequality by countries with high levels of development. These results are boosted when we include other explanatory variables in the model, as we will see in the following sub-sections.

Figure 2a. Development and inequality

Figure 2b. Development and IO



¹⁹ Perugini and Martino (2008) also use population density as a development indicator. At the country level, however, we believe density is an inadequate indicator of development, given its dependence on the country's surface area and the geographical dispersion among its regions. The density in regions of Finland, Sweden or Norway may be high, for example, but at the national level it is very low. In fact, their densities are much lower than those of Greece, Portugal or Spain, though they are by no means any less developed than the latter.

Table 2. Development and Inequality

	Total inequality	Inequality of Opportunity
Const.	15.3930 (***) (1.4552)	1.7131 (***) (0.3688)
DEV	-0.3744 (**) (0.1432)	-0.10123 (***) (0.0285)
DEV^2	0.0205 (0.0155)	-0.0018 (0.0032)
R2	0.4582	0.3500
R2-adj.	0.4040	0.2850

Standard deviation in parentheses
Significant at 1% (***), 5% (**) and 10% (*)

In terms of IO, the focus of our attention, we note that every country in Eastern Europe, except for Lithuania, is below the regression curve, meaning that its IO levels are below what would be expected for their levels of development. Their Communist roots and the great opportunities created in these economies after the expansion of the EU could explain this situation, though factors involving education, the labor market and others could also have an effect, as we shall see in the following sub-sections. Among the most developed countries, there are three clearly distinguishable groups: Denmark, Finland, Austria, Germany, Norway and the Netherlands, whose IO levels are less than expected based on their levels of development; the United Kingdom, Italy, Ireland, Spain, Portugal and, to a lesser extent, Belgium, whose IO levels are higher than expected; and, Sweden, France and Greece, which are very close to regression. Despite having found certain geographical and developmental patterns common among European countries, much remains to be explained in terms of the differences noted in inequality and IO for these countries.

4.2. Labor market performance

From a theoretical standpoint, the relationship between the labor market and inequality is complex and inconclusive (Burniaux et al., 2006). On the one hand, better functioning of the labor market involves less exclusion, and therefore less inequality. This same reasoning could be applied to IO if the labor market favored the inclusion of those population sectors that had, a priori, fewer opportunities, such as immigrants, youth and women. On the other hand, labor inclusion could place pressure on less-qualified

employees as a whole, increasing salary differences between this group and that of more qualified workers (Topel, 1994).

There is a large number of variables involving the functioning of the labor market (see Appendix B). Following Perugini and Martino (2008), we consider as an aggregate measure of the functioning of this market the first principal component (*Labor_MK_PC*) of the following four variables: total employment rate, total unemployment rate, female employment rate and long-term unemployment.²⁰ We note, however, that the first two reflect aggregate aspects of the labor market, while the last two capture more concrete and structural aspects. Distinguishing between them is an interesting undertaking, since those policies aimed at people with worse circumstances should have a greater influence on IO. That is why we have also conducted a detailed analysis for each of these four variables separately. In addition, we consider the following differential unemployment rates: for those aged above and below 40 and for workers with considerable schooling (secondary or university education) and those with little education (primary or none).²¹ These differentials may be interpreted as proxies for premiums to age (or experience) and education, respectively.

Graphs 3a and 3b show the relationship between total inequality and IO with *Labor_MK_PC*. Note that for IO, Portugal is far above the regression line, which could affect the parameter estimates. That is why Tables 3a and 3b show the estimates of model (10) for aggregate inequality and IO, respectively, with and without the Portugal dummy variable.

Firstly, we note how, in effect, the model with the Portugal dummy variable considerably improves the significance of the labor market variables with respect to IO. Secondly, the results when using the aggregate variable *Labor_MK_PC* indicate that a better functioning of the labor market would help to reduce inequality and IO. Thirdly, female employment and long-term unemployment, with negative and positive coefficients, respectively, are clearly more significant and robust to the inclusion or omission of the Portugal dummy variable than are the total unemployment and employment rates. Our results, therefore, indicate that those variables associated with

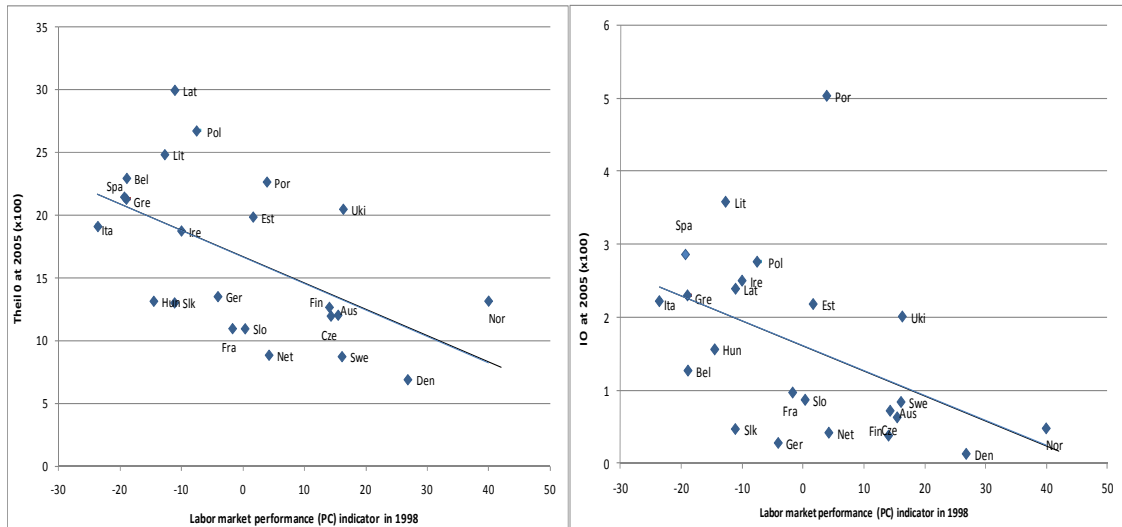
²⁰ The first principal component accounts for almost 90% of the joint variability in these variables for 1998.

²¹ We have also considered the difference in unemployment between men and women, though the results were not significant.

the structure of the labor market have a greater effect on IO than the aggregate variables. To comment further on this, we also note the results for the differences in unemployment rate by age groups and educational level (see the last four columns of Tables 3a and 3b).

Figure 3a. Labor market and inequality

Figure 3b. Labor market and IO



The difference in unemployment rate by age exhibits a positive coefficient in both cases, but is significant for IO only when the Portugal dummy variable is included. This result, although weak, indicates that combatting unemployment among the young and reducing any potential gap that may exist with adult unemployment figures could help to improve IO. As for the unemployment rate between more and less educated individuals, the coefficient is negative in both cases, though it is especially significant for IO. One conclusion that may be drawn from this is that a labor market that favors better educated workers would promote the acquisition of human capital, would reduce its dispersion and would indirectly help to lower IO.

Table 3a. Labor market and total inequality

	Labor Mk PC		Unempl. rate		Empl. rate		Empl. rate fem.		Long-run unemp.		Dif. unemp. Age		Dif. unemp. Education	
Const.	14.923*** (1.2596)	14.153*** (1.3798)	10.421** (3.1763)	7.134** (3.0543)	28.954** (11.300)	34.769*** (9.2826)	29.206*** (4.257)	30.112*** (4.2575)	7.115* (3.8434)	6.2023 (3.8879)	13.671*** (1.8864)	12.618*** (2.2915)	17.140*** (1.699)	16.353*** (2.5567)
DEV	-0.1952 (0.1559)	-0.1052 (0.1799)	-0.2555 (0.1616)	-0.1108 (0.190)	-0.2320 (0.1954)	-0.0805 (0.2148)	-0.2301 (0.1663)	-0.1453 (0.1896)	-0.2346 (0.1538)	-0.1752 (0.1802)	-0.3266** (0.1414)	-0.2549 (0.1739)	-0.457*** (0.1481)	-0.4033*** (0.1979)
DEV^2	0.0280* (0.0157)	0.0350** (0.0161)	0.0226 (0.0149)	0.0315** (0.0155)	0.0277 (0.0194)	0.0385* (0.0195)	0.0316 (0.0190)	0.0391** (0.0185)	0.0233 (0.0140)	0.0282* (0.0156)	0.0235 (0.0161)	0.0296* (0.0170)	0.0175 (0.0140)	0.0212 (0.0169)
X	-0.1525** (0.0614)	-0.1717*** (0.0597)	0.5492* (0.3204)	0.8092** (0.2831)	-0.2058 (0.1683)	-0.3071** (0.1374)	-0.2615*** (0.0858)	-0.2922*** (0.0858)	0.1812** (0.0854)	0.1888** (0.0849)	0.3377 (0.2100)	0.4202* (0.2243)	-0.1595** (0.0640)	-0.1189** (0.1004)
Dum_Por	--	7.5849*** (1.7835)	--	9.9547*** (2.4577)	--	9.166*** (2.5914)	--	7.6248*** (1.8397)	--	6.0314*** (1.7682)	--	6.7485*** (2.274)	--	3.6409*** (2.9145)
R2	0.581	0.636	0.524	0.608	0.506	0.578	0.594	0.650	0.563	0.598	0.491	0.534	0.489	0.500
R2-adj.	0.515	0.555	0.449	0.521	0.428	0.484	0.530	0.572	0.493	0.509	0.410	0.430	0.408	0.389

Standard deviation in parentheses
Significant at 1% (***), 5% (**) and 10% (*)

Table 3b. Labor market and inequality of opportunity

	Labor Mk PC		Unempl. rate		Empl. rate		Empl. rate fem.		Long-run unemp.		Dif. unemp. Age		Dif. unemp. Education	
Const.	1.6576*** (0.3685)	1.2951*** (0.3132)	1.6538* (0.9804)	0.3928 (0.5162)	1.8841 (2.9186)	4.2723*** (1.4811)	3.4785*** (0.7751)	3.9050*** (0.7215)	0.5332 (0.5841)	0.0300 (0.5025)	1.4218** (0.5256)	0.8664* (0.4742)	2.5683*** (0.3902)	2.0235*** (0.3965)
DEV	-0.0800** (0.0381)	-0.0377 (0.0342)	-0.0998** (0.0395)	-0.0442 (0.0297)	-0.0994** (0.0490)	-0.0372 (0.0315)	-0.0827** (0.0378)	-0.0429 (0.0337)	-0.0813** (0.0337)	-0.0485 (0.0338)	-0.0931*** (0.0315)	-0.0553** (0.0274)	-0.1414*** (0.0305)	-0.1045*** (0.0279)
DEV^2	-0.0009 (0.0035)	0.0024 (0.0031)	-0.0017 (0.0033)	0.0017 (0.0029)	-0.0016 (0.0038)	0.0027 (0.0031)	-0.0003 (0.0039)	0.0031 (0.0031)	-0.0014 (0.0030)	0.0013 (0.0031)	-0.0012 (0.0035)	0.0019 (0.0031)	-0.0032 (0.0021)	-0.0007 (0.0025)
X	-0.0180 (0.0110)	-0.0271*** (0.0091)	0.0065 (0.1003)	0.1063* (0.0582)	-0.0026 (0.0445)	-0.0442** (0.0196)	-0.0334* (0.0171)	-0.0478*** (0.0139)	0.0258** (0.0102)	0.0300*** (0.0106)	0.0571 (0.0599)	0.1006** (0.0457)	-0.0780*** (0.0215)	-0.0499*** (0.0136)
Dum_Por	--	3.5689*** (0.3746)	--	3.8192*** (0.4160)	--	3.7645*** (0.3967)	--	3.5896*** (0.3768)	--	3.3249*** (0.3906)	--	3.5582*** (0.4586)	--	2.5204*** (0.4291)
R2	0.3948	0.7130	0.3502	0.6705	0.3502	0.6654	0.4079	0.7304	0.4054	0.6899	0.3743	0.6877	0.5431	0.6823
R2-adj.	0.2992	0.6492	0.2476	0.5972	0.2476	0.5910	0.3144	0.6705	0.3115	0.6210	0.2755	0.6184	0.4710	0.6117

Standard deviation in parentheses
Significant at 1% (***), 5% (**) and 10% (*)

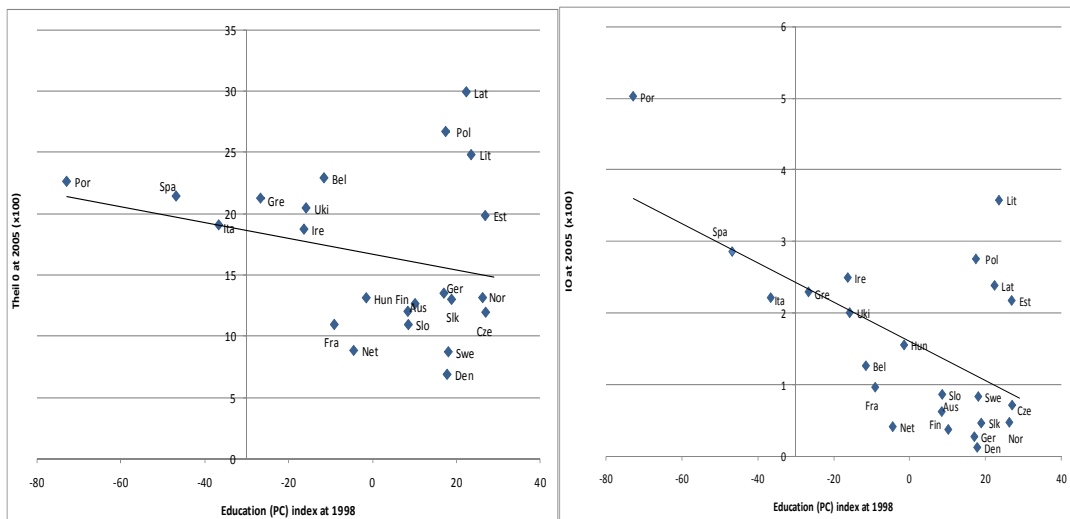
4.3. Education

In theory, higher levels of education should help to balance the initial distribution of human capital, and thereby to reduce one of the main causes of inequality in developed economies (Tanzi, 1998). The variables considered for measuring education are those commonly employed in the literature (see, for example, Barro, 2000): the population with at least a secondary level of education as a percentage of the population older than

15, which we call *Second* (ISCED levels 3-6); the population with at least a university education as a percentage of the population older than 15, which we call *Tertiary* (ISCED levels 5-6); the percentage of women who attain secondary education (*Second Fem.*); lastly, we also consider a less used, but very important, variable, that of dropouts (*Early Leaves*), which measures the percentage of the population between the ages of 18-24 with only some or no secondary education. As in the above cases, we can summarize the trend in these variables through their first principal component (Education PC).²²

Figure 4a. Education and total inequality

Figure 4b. Education and IO



Graphs 4a and 4b show the scatter plots for *Education PC*, total inequality and IO. The fit is negative in both cases, though it is much better for IO. We note the good fit for IO for Greece, Spain, the United Kingdom and Hungary, as well the improvement for Ireland and especially Portugal, the result for which was clearly anomalous in Graph 3b. Although no scatter plot is shown for the *Early Leaves* variable, the nearly perfect fit for Portugal is worth noting. Tables 4a and 4b summarize the results of the regressions. As in the previous cases, we consider the development variable, its quadratic term and we include the education variables one by one.

²² The first main component accounts for almost 90% of the joint variability in these variables for 1998.

Table 4a. Education and total inequality

	Education PC	Secondary	Secondary Fem.	Early Leaves	Tertiary
Const.	14.5134*** (1.1284)	25.203*** (2.1876)	24.231*** (2.3383)	9.370*** (1.2524)	8.8386*** (2.2231)
DEV	-0.3257** (0.1485)	-0.3312** (0.1444)	-0.3405** (0.1522)	-0.2466* (0.1407)	-0.4266** (0.1237)
DEV^2	0.03455** (0.0156)	0.0344** (0.0154)	0.0341* (0.0170)	0.0317** (0.0114)	0.0201 (0.0131)
X	-0.1088*** (0.0245)	-0.1609*** (0.0353)	-0.1508*** (0.0409)	0.3383*** (0.0741)	1.2595** (0.4555)
R2	0.640	0.643	0.612	0.691	0.511
R2-adj.	0.583	0.587	0.551	0.642	0.433

Standard deviation in parentheses

Significant at 1% (***), 5% (**) and 10%(*)

Table 4b. Education and IO

	Education PC	Secondary	Secondary Fem.	Early Leaves	Tertiary
Const.	1.4475*** (0.2249)	4.6642*** (0.4977)	4.4398*** (0.5752)	-0.0155 (0.2385)	0.4094 (0.6108)
DEV	-0.086*** (0.0241)	-0.0882*** (0.0232)	-0.0907*** (0.0256)	-0.0645*** (0.021)	-0.1116*** (0.0286)
DEV^2	0.0024 (0.0026)	0.0024 (0.0026)	0.0024 (0.0030)	0.0014 (0.0017)	-0.0018 (0.0029)
X	-0.0328*** (0.0058)	-0.0484*** (0.0086)	-0.0465*** (0.0104)	0.0971*** (0.0078)	0.2505* (0.1286)
R2	0.7843	0.7871	0.7328	0.8509	0.4042
R2-adj.	0.7503	0.7535	0.6906	0.8274	0.3101

Standard deviation in parentheses

Significant at 1% (***), 5% (**) and 10%(*)

We note first how, once educational levels are taken into account, the relationship between development and total inequality is U-shaped (see the positive and significant quadratic term), while the relationship between development and IO remains negative and significant, though the quadratic term is clearly not significant. This result is consistent with the argument made in Section 3 and sub-section 4.1. Secondly, we note how most of the coefficients associated with the education variables are very

significant, especially those involving academic dropouts. This is reflected in the elevated values of R^2 (and adjusted R^2) and in its notable improvement attained when included the education variables (compare with results in Table 2). In general, these differences are much more salient in the case of IO. For example, the R^2 for the IO model when the *Early Leaves* variable is included in the regression exceeds 85%. Tertiary education is the only variable that is more significant in explaining the differences in terms of total inequality than in terms of IO. Nevertheless, its sign is positive in both cases, in contrast to the sign for secondary education.

In light of these results, preventing dropouts and attaining a level of secondary education would help to balance the initial distribution of human capital and to significantly reduce total inequality, and especially IO. Tertiary education, however, by complementing innovation and technological change (Aghion et al., 1999), would increase income differences (Perugini and Martino, 2008). This variable would have a small effect on IO, though it would influence total inequality by increasing the effort component of inequality.

4.4. Public Expenditure in Social Protection and Taxes

Public spending on social protection is the most direct way available to the public sector to reduce inequality. What is not as obvious is whether the various outlays (unemployment benefits, child care, health care, disability, etc.) have the same effect on inequality. It might even be the case that some have an effect on total inequality but not on IO. As an aggregate variable, we consider the total spending on social protection as a percentage of the GDP. Moreover, we consider the different items of expenditure individually, all measured as a percentage of GDP: child care, disability, social exclusion, health care, pensions and unemployment.

Graphs 5a and 5b show the scatter plots between total spending, total inequality and IO. Note that for both aggregate inequality and IO, the fit is negative and significant. For IO, the case of Portugal stands out once more, since it is far above the regression line. On this occasion, however, the inclusion of the Portugal dummy variable does not significantly change the estimates for the public spending variable,

and so it was not included in the analysis. Tables 5a and 5b show the estimates of model (10) for total inequality and IO, respectively.

Figure 5a. Total social expenditure and total inequality

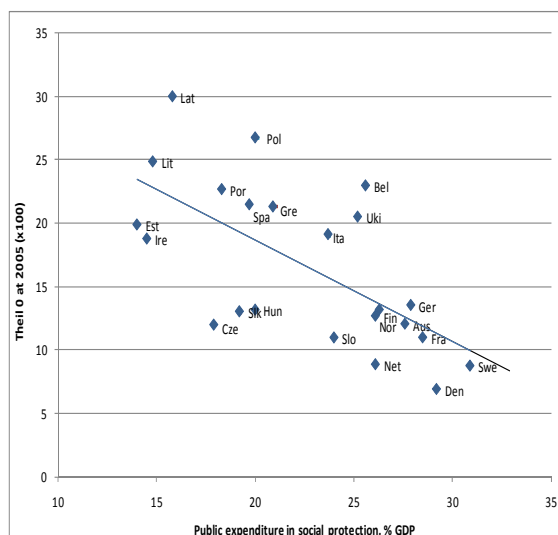
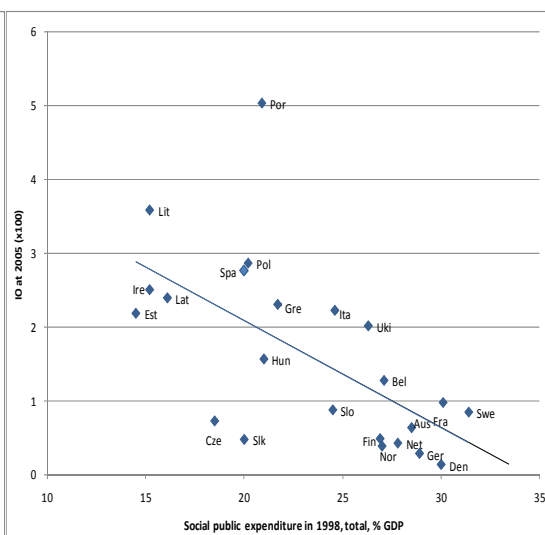


Figure 5b. Total social expenditure and IO



We first see that some items have a greater explanatory power than others. If we focus on IO, the expenditures that best explain the differences are for child care, social inclusion and health care. The remaining items (unemployment benefits, pensions, disability and work leave) are not significant. For total inequality, the significant items are disability and work leave, in addition to those for IO. Once again unemployment benefits and pensions are not significant. It should be noted, therefore, that child care, social inclusion and health care are the most important items to improve opportunities. In contrast, unemployment benefits, pensions and expenses incurred by disability and work leave influence not so much opportunity, as they do the redistribution of income in general.

In the last part of this sub-section we analyze the possible effect of the tax scheme. Once again, for reasons of parsimony, we will simplify the exercise and consider only two types of tax, grouping indirect taxes on consumption (VAT) and imports on one side, which represented an average of approximately 7.4% of the GDP

in 1998 for the countries analyzed, and income and capital taxes on the other, representing 14.5% of the GDP on average.

Table 5a. Social public expenditure and total inequality

	Total	Child care	Disability	Social exclusion	Health	Senior	Unemploy.
Const.	32.909*** (4.7827)	21.278*** (2.587)	19.990*** (1.4219)	18.758*** (1.4707)	30.559*** (6.2332)	19.502*** (2.9788)	16.604*** (2.1039)
DEV	0.1679 (0.2258)	-0.1619 (0.2213)	-0.092 (0.1884)	-0.1685 (0.1479)	-0.0913 (0.1923)	-0.2965 (0.1711)	-0.2909* (0.1673)
DEV^2	0.0446** (0.0158)	0.0260 (0.0169)	0.0407** (0.0164)	0.0281* (0.0158)	0.0168 (0.0118)	0.0261 (0.0165)	0.0231 (0.0162)
X	-0.8478*** (0.2266)	-3.0031** (1.2031)	-2.7437*** (0.7351)	-8.8394*** (2.2314)	-2.4449** (0.9299)	-0.5098 (0.4122)	-0.9112 (1.3881)
R2	0.628	0.590	0.571	0.663	0.602	0.484	0.471
R2-adj.	0.569	0.525	0.503	0.610	0.540	0.403	0.387

Standard deviation in parentheses
Significant at 1% (***), 5% (**) and 10%(*)

Table 5b. Social public expenditure and IO

	Total	Child care	Disability	Social exclusion	Health	Senior	Unemploy.
Const.	4.5068*** (0.7586)	3.1631*** (0.6349)	2.1656*** (0.4058)	2.2043*** (0.4235)	3.5235*** (1.0376)	2.4810*** (0.8510)	1.9367*** (0.4067)
DEV	-0.0147 (0.0348)	-0.0489 (0.0411)	-0.0735 (0.0533)	-0.0711** (0.0306)	-0.0674* (0.0372)	-0.0867*** (0.0245)	-0.0858** (0.0394)
DEV^2	0.0021 (0.0030)	-0.0004 (0.0032)	0.0002 (0.0044)	-0.0006 (0.0032)	-0.0022 (0.0029)	-0.0007 (0.0031)	-0.0013 (0.0035)
X	-0.1352*** (0.0293)	-0.7398*** (0.2584)	-0.2700 (0.2475)	-1.2900** (0.6257)	-0.2918* (0.1522)	-0.0953 (0.0870)	-0.1682 (0.2213)
R2	0.463	0.559	0.378	0.464	0.404	0.374	0.361
R2-adj.	0.378	0.489	0.280	0.379	0.310	0.275	0.261

Standard deviation in parentheses
Significant at 1% (***), 5% (**) and 10%(*)

If we focus solely on the relationship that exists between inequality (total and IO) and these tax items, we find a weak connection, the corresponding scatter plots (not shown) exhibit a large dispersion. When we estimate the linear model using only the development variables and the tax items (not shown), we find that these are not significant in any of the cases. What is relevant, however, is analyzing the effect of the tax structure not by itself, but with reference to the total amount of social protection spending. The regression results in these cases are shown in Table 5c.

Table 5c. Social public expenditure, taxes and inequality

	Total inequality	IO
Const.	51.046*** (4.8408)	7.8077*** (1.3359)
DEV	0.0626 (0.2135)	-0.0529 (0.0343)
DEV^2	0.0406** (0.0160)	0.0003 (0.0029)
Social expenditure	-1.0062*** (0.1794)	-0.1753*** (0.0345)
Tax income and weath	0.1964 (0.1836)	0.0714*** (0.0217)
Tax VAT and imports	-2.0576*** (0.3886)	-0.3984*** (0.0937)
R2	0.7938	0.6288
R2-adj.	0.7331	0.5196

Standard deviation in parentheses
Significant at 1% (***), 5% (**) and 10% (*)

First, we find that the total expenditure variable remains negative, with similar coefficients and very significant. Secondly, given the country's level of development and the extent of social protection spending, those countries with a tax structure based primarily on indirect taxes tend to exhibit a lower IO, while those countries that rely more heavily on financing through direct taxes show a greater IO. Lastly, for total inequality, the effect of taxes on indirect taxes persists, while that of income taxes becomes non-significant.

4.5. A *fully* specified model for IO

Despite the existing problems involving degrees of freedom and colinearity, it is still illustrative to present the results of a *fully*-specified model that includes the aggregate variables corresponding to each of the factors considered over the course of this section. In Table 6 we show the regressions for total inequality and for IO. We first note the very high value of the adjusted R^2 , which exceeds 85% for the IO model and reaches almost 70% for the total inequality model. If we compare the adjusted R^2 for the complete IO model with just the development variable (Table 2), its value has more than doubled.

The development coefficient is negative and significant for both total inequality and IO. *Labor_MK_PC*, on the other hand, is not significant in either case. If we compare this result with that obtained in Section 4.2, the negative sign and the significance found in that section resulted from the indirect effect of the labor market variable (through its relationship with educational levels and/or spending policies), since the partial effect of this variable on inequality appears to be non-significant. The negative effect of the education variable remains for IO, while results non-significant for total inequality. Improving education, therefore, is one of the keys to reducing IO. The social spending item has a negative bearing on total inequality and IO. Yet again, as noted in Section 4.4, we see that public spending policy can have a notable impact on reducing both total inequality and IO. Lastly, taxes lose their explanatory power, save for that of indirect taxes on total inequality, though the signs remain the same.

Colinearity affects the estimates and significance of the individual variables, but not the R^2 statistics or OLS residuals. The interpretation of the residuals in these broader models is interesting. They show what is left to explain for IO and total inequality once the aggregate labor market, education and policy variables are taken into consideration. Accordingly, we conclude this section comparing the residuals of the complete model for total inequality and IO (Figure 6). We note first a positive correlation between these residuals. This means that there are factors common to both total inequality and IO that could help to explain what remains to be explained for both inequality measures. However, we also see a notable dispersion, symptomatic of elements that are exclusive to each inequality type. Also evident is the fact that the

countries are fairly well mixed, a sign that there are no geographical patterns or fixed factors by country groups like those found in Figures 2a and 2b.

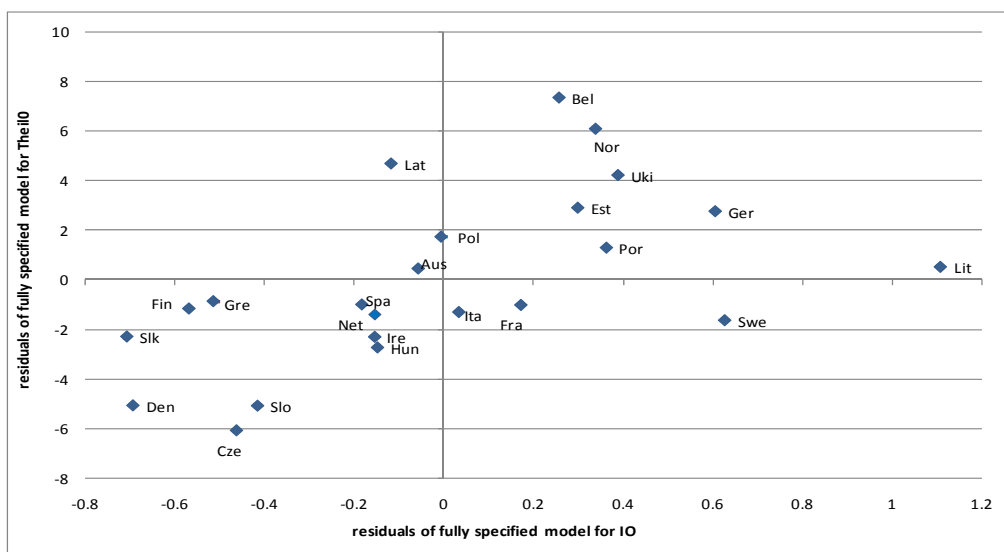
Table 6. A *fully*-specified model for total inequality and IO

	Theil 0	IO
Const	43.1823*** (14.7773)	3.7808*** (1.0956)
DEV	-0.4143*** (0.1293)	-0.0891*** (0.0162)
Labor_MK_PC	-0.0237 (0.1323)	0.0129 (0.0099)
Education_PC	-0.0104 (0.0355)	-0.0319*** (0.0058)
Social expenditure	-0.7379** (0.3413)	-0.1153*** (0.0340)
Tax income and wealth	0.4379 (0.2617)	0.0587 (0.0376)
Tax VAT and imports	-1.9517* (0.9955)	-0.0531 (0.0832)
R ²	0.6988	0.8634
R ² -adj.	0.5859	0.8121

Standard deviation in parentheses

Significant at 1% (***), 5% (**) and 10% (*)

Figure 6. Residuals of the Total Inequality and IO model



In summary, we have a set of countries on the one hand for which the complete model helps to explain practically all of its inequality and IO (those about the origins of the X-Y axes). These include Poland, Austria, France, Italy, Ireland, Hungary, the Netherlands and Spain. On the other, there is a set of countries whose inequality and IO are below those predicted by the models, such as the Czech Republic, Slovenia, Denmark and Slovakia. The opposite occurs in Estonia, Belgium, Norway, the United Kingdom and Germany. And, finally, there are countries whose residuals are well behaved for only one of the inequality variables, such as Sweden, Lithuania, Greece and Finland.

5. Robustness and comparison of results

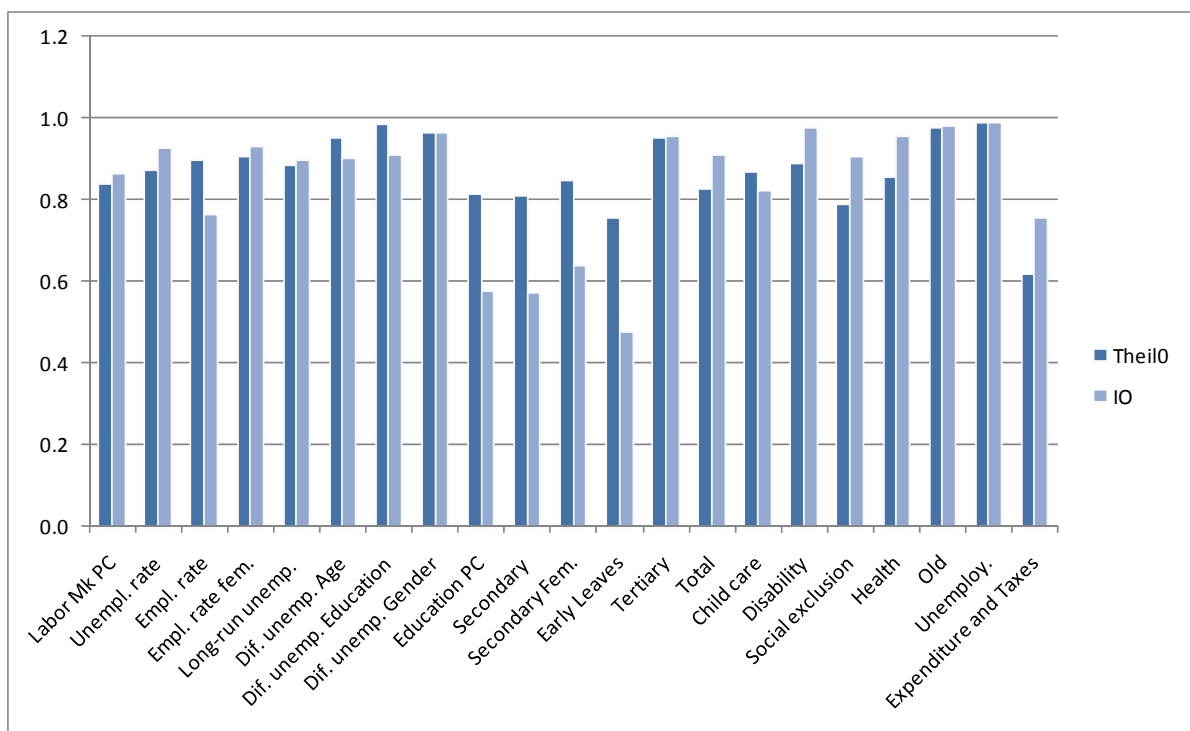
The purpose of this section is to offer an alternative analysis to that made in the previous section so as to provide the results with robustness. In each case, we will compare the residuals of model (9) with those of model (10) for every one of the explanatory variables considered. When the residuals are plotted on a scatter plot, the bisector indicates that the variable X included in (10) adds no information to the development indicator (model (9)). On the other hand, the distance to the bisector indicates the additional explanatory capacity of the variable X . In addition to complementing the contrasts of the individual significances, these graphs also illustrate each country's particular cases by enabling a country-by-country comparison of the change in the residuals. Due to space considerations, the similarities in these two sets of residuals are summarized in a statistic for each case, with the scatter plots only being shown for the more significant cases in Appendix C. Figure 7 shows the Spearman rank correlation coefficient between the residuals of the basic model (9) and the augmented model (10) for the different explanatory variables considered.²³

The correlations are expected to be positive, and indeed they are, but the less the correlation, the greater the explanatory capacity of variable X . Based on these correlations, we can draw the following conclusions. In general, the labor market variables have a similar effect on total inequality and IO. Moreover, their effect is the least relevant of all those studied. The main differences are evident in the age- and education-related unemployment rate differentials, where the correlation is lower for IO.

²³ The results do not change when the Pearson correlation coefficient is used. Both coefficients range from -1 to 1.

For IO in particular, the education variables have a very noticeable effect on the model residuals, such that the estimated correlations are the smallest from among all the cases considered. In this regard, the variables that exhibit the lowest correlations are those for secondary education and dropout rate. These are also the variables that have the largest difference between the total inequality model and IO. As for the tertiary education variable, it does not appear as though the residuals differ much from those of the model without this variable. With regard to social public spending, there is a noticeable heterogeneity in the estimated correlations by type of expenditure. Spending on child care has the greatest effect on the range of residuals for IO, and is the only item whose correlation is less for IO than for total inequality. Unemployment and retirement spending, the correlations are very high (very close to 1) and similar in both cases. Lastly, once the total expenditure is included, the tax structure seems to have an effect on the correlations for both total inequality and IO. All of these findings appear to confirm the main results from the previous section.

Figure 7. Spearman rank correlation between the basic and augmented models



6. Concluding remarks

Traditionally public economic policies have been evaluated from two perspectives: efficiency, which attempts to determine which policies have the greatest effect on productivity and economic growth; and equality, which studies, for example, the effects of a fiscal system on the final income distribution. Both approaches are based on the assumption that efficiency and equality are two components of the economy that can be analyzed separately. In general, equality is disregarded in efficiency analyses, while economic incentives and the level of effort are not considered in studies on equality. A new concept, however, which first appeared in the economic literature in the early nineties, attempts to combine these two aspects.

The modern economy of justice recognizes an individual's income as being a function of the effort made and of the initial circumstances affecting the individual. And yet, individuals are only responsible for their own efforts, since the circumstances remain beyond their control. Thus, a greater inequality in the distribution of income does not imply, *per se*, that the course of the economy in general, or the redistributive capacity of a public policy in particular, is bad. It may happen that the level of effort made by individuals is different. In fact, a country's fiscal policy could correct the uneven distribution of initial circumstances while at the same time respecting the individual labor supply. For this to happen, a public policy must be implemented that, far from simply redistributing income, provides every individual with the same initial conditions without modifying the economic incentives to maximize effort.

With regard to this kind of policy, our findings highlight educational policies first and foremost. In particular, a reduction in the academic dropout rate constitutes a fundamental tool to increasing the opportunities available in an economy. Reaching secondary education levels would also help to reduce IO indices. Tertiary education does not seem to have a significant impact on IO, though it would on aggregate inequality, though its impact would be positive, thus promoting inequality arising from effort instead of from opportunity.

A second pillar on which any policy aimed at reducing IO should be based is social protection spending, though not all items of expenditure would have the same effect. Spending to reduce social exclusion and on child and health care would have the greatest effect in terms of reducing IO, while expenses on unemployment benefits, retirement and disability do not appear to have any significance on improving IO. With

respect to financing these expenses, both direct and indirect taxes appear to have little effect on IO. Variables that consider the functioning of the labor market do not help to explain the differences in IO among the European countries analyzed. Nevertheless, increasing female employment rate, reducing long-term unemployment and increasing the differential between poorly and highly educated individuals would prove beneficial for an economy's IO. Lastly, a country's level of development has a clearly negative influence on IO, though no evidence was noted to suggest a quadratic inverted-U relationship.

This paper have attempted to lay the empirical foundations for a theoretical study that will help us to understand the various mechanisms through which educational, economic and policy factors might explain the levels of IO that exist among countries. In addition to continuing to enhance the empirical evidence, the development of this theoretical framework would naturally be the most promising and ambitious extension of this paper.

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APPENDIX A

Table 1A. Reduced-form OLS regression of household income on circumstances

Variables	Austria	Belgium	Czec R.	Denmark	Estonia	Finland	France
Primary education (F)		-0.018 (0.062)			0.182 (0.278)	0.506 (0.379)	0.072* (0.041)
Secondary education (F)	1.111** (0.516)	0.013 (0.061)	0.240 (0.186)	-0.015 (0.047)	0.141 (0.276)	0.553 (0.390)	0.091** (0.043)
Tertiary education (F)	1.031* (0.525)	0.028 (0.070)	0.318 (0.192)		0.308 (0.281)	0.629 (0.391)	0.152*** (0.052)
Primary education (M)		0.058 (0.060)		0.198 (0.341)	-0.107 (0.217)	-0.296 (0.388)	0.077* (0.041)
Secondary education (M)		0.136** (0.058)	0.174 (0.185)	0.070* (0.041)	0.094 (0.215)	-0.228 (0.399)	0.142*** (0.044)
Tertiary education (M)		0.152** (0.067)	0.273 (0.191)		0.229 (0.219)	-0.201 (0.399)	0.205*** (0.051)
Manager (F)	0.134** (0.058)	0.047 (0.070)	0.182** (0.083)	0.068 (0.059)	0.220* (0.124)	0.168*** (0.049)	0.202*** (0.034)
Professional (F)	0.225* (0.119)	0.045 (0.073)	0.222** (0.083)	0.030 (0.067)	0.167 (0.131)	0.073 (0.054)	0.150*** (0.037)
Technician (F)	0.128*** (0.043)	-0.027 (0.075)	0.136** (0.065)	0.014 (0.060)	0.241* (0.135)	0.063 (0.042)	0.191*** (0.034)
Clerk (F)	0.110** (0.053)	0.014 (0.070)	0.246** (0.089)	-0.013 (0.075)	0.309 (0.225)	0.048 (0.084)	0.114*** (0.038)
Salesman (F)	0.033 (0.044)	0.020 (0.075)	0.050 (0.083)	0.031 (0.066)	0.341* (0.203)	0.077 (0.060)	0.057 (0.045)
Craft trade worker (F)	0.015 (0.036)	-0.019 (0.062)	0.066 (0.061)	-0.058 (0.047)	0.115 (0.113)	0.023 (0.033)	0.057** (0.026)
Machine operator (F)	-0.025 (0.049)	-0.027 (0.069)	0.064 (0.064)	-0.051 (0.060)	0.002 (0.113)	0.037 (0.036)	0.049* (0.027)
Elementary occupation (F)	-0.087** (0.041)	-0.038 (0.068)	-0.106 (0.076)	-0.008 (0.055)	-0.045 (0.127)	-0.023 (0.064)	-0.007 (0.034)
Armed occupation (F)	0.528 (0.362)	0.033 (0.097)	0.102 (0.130)	0.072 (0.157)	-0.129 (0.190)	0.224 (0.133)	0.148*** (0.046)
Difficulties most of the time		-0.385*** (0.069)	-0.198*** (0.066)	-0.032 (0.098)	-0.152 (0.127)	0.001 (0.056)	
Difficulties often		-0.151*** (0.055)	-0.080* (0.045)	0.031 (0.071)	-0.127* (0.068)	-0.036 (0.044)	
Difficulties occasionally		-0.14137** (0.037)	-0.034 (0.031)	0.040 (0.040)	0.031 (0.048)	0.012 (0.028)	
Difficulties rarely		-0.085** (0.038)	0.003 (0.031)	0.023 (0.037)	0.073 (0.052)	-0.009 (0.028)	
EU	0.041 (0.067)	-0.028 (0.052)	0.050 (0.091)	0.178 (0.151)		0.015 (0.104)	-0.021 (0.039)
Other	-0.288*** (0.040)	-0.347*** (0.051)	-0.294*** (0.126)	-0.095 (0.103)	-0.056 (0.062)	-0.222* (0.114)	-0.238*** (0.031)
Constant	8.654*** (0.517)	9.748*** (0.070)	7.924*** (0.231)	9.995*** (0.068)	7.648*** (0.308)	9.448*** (0.314)	9.470*** (0.044)
Observations	2156	1839	1589	1241	1377	1981	3725
R-squared	0.05	0.10	0.06	0.01	0.09	0.03	0.09

Standard errors in parenthesis. * significant at 10 %; ** significant at 5 %; *** significant at 1 %.

Omitted categories are: less than primary education; skill agricultural, forestry and fishery worker; never; local.

Table 1A. Reduced-form OLS regression of household income on circumstances (Cont.)

Variables	Germany	Greece	Hungary	Ireland	Italy	Latvia	Lithuania
Primary education (F)	-0.127* (0.064)	0.105* (0.054)	-0.003 (0.135)	0.125 (0.155)	0.186*** (0.032)	-0.342 (0.310)	0.371*** (0.105)
Secondary education (F)	0.048** (0.020)	0.231*** (0.073)	0.017 (0.135)	0.247 (0.156)	0.226*** (0.037)	-0.112 (0.311)	0.377*** (0.110)
Tertiary education (F)		0.086 (0.104)	0.041 (0.142)	0.216 (0.160)	0.373*** (0.068)	0.078 (0.326)	0.511*** (0.126)
Primary education (M)		0.084 (0.051)	0.391*** (0.114)	-0.082 (0.167)	0.127*** (0.028)	0.899*** (0.277)	-0.023 (0.096)
Secondary education (M)	0.192*** (0.049)	0.147* (0.073)	0.493*** (0.114)	0.100 (0.167)	0.190*** (0.034)	0.932*** (0.273)	0.012 (0.101)
Tertiary education (M)	0.150*** (0.053)	0.365*** (0.100)	0.574*** (0.119)	0.076 (0.172)	0.294*** (0.079)	1.023*** (0.285)	0.256** (0.110)
Manager (F)	0.139*** (0.046)	0.169*** (0.060)	0.358*** (0.055)	0.272* (0.141)	0.075* (0.038)	0.252 (0.209)	0.288** (0.126)
Professional (F)	0.145*** (0.042)	0.232** (0.105)	0.395*** (0.061)	0.378** (0.151)	0.092 (0.063)	0.280 (0.209)	0.127 (0.124)
Technician (F)	0.052 (0.041)	0.302** (0.125)	0.275*** (0.053)	0.353** (0.162)	0.098** (0.042)	0.282 (0.211)	0.165 (0.149)
Clerk (F)	0.026 (0.045)	0.172* (0.085)	0.209*** (0.062)	0.342** (0.149)	0.055 (0.045)	-0.287 (0.302)	0.397** (0.161)
Salesman (F)	0.108* (0.057)	0.003 (0.083)	0.168** (0.062)	0.330** (0.151)	-0.023 (0.049)	0.311 (0.255)	0.401** (0.169)
Craft trade worker (F)	0.005 (0.037)	0.124** (0.051)	0.146*** (0.035)	0.214 (0.141)	0.003 (0.030)	0.104 (0.180)	0.153 (0.097)
Machine operator (F)	0.015 (0.042)	0.064 (0.069)	0.099** (0.038)	0.217 (0.144)	0.102*** (0.034)	0.191 (0.179)	0.015 (0.099)
Elementary occupation (F)	0.077 (0.049)	0.005 (0.062)	-0.040 (0.042)	0.152 (0.141)	-0.138*** (0.034)	0.139 (0.191)	-0.035 (0.099)
Armed occupation (F)	0.077 (0.084)	0.153 (0.181)	0.176** (0.081)	0.173 (0.172)	0.182** (0.067)	0.168 (0.272)	0.094 (0.243)
Difficulties most of the time			-0.102** (0.038)	-0.271*** (0.061)	-0.196*** (0.033)	-0.003 (0.136)	-0.15* (0.083)
Difficulties often			-0.090*** (0.031)	-0.264*** (0.059)	-0.166*** (0.030)	0.003 (0.095)	-0.042 (0.066)
Difficulties occasionally			-0.017 (0.031)	-0.155*** (0.040)	-0.081*** (0.027)	-0.039 (0.073)	-0.028 (0.054)
Difficulties rarely			-0.024 (0.026)	-0.139*** (0.038)	-0.065** (0.029)	0.011 (0.080)	0.013 (0.060)
EU		0.132 (0.113)	0.026 (0.173)	-0.147 (0.049)	-0.455*** (0.073)		0.006 (0.340)
Other	-0.111** (0.040)	-0.495*** (0.067)	-0.062 (0.067)	-0.265*** (0.076)	-0.270*** (0.037)	-0.137 (0.088)	0.006 (0.089)
Constant	9.528*** (0.062)	8.934*** (0.039)	7.547*** (0.138)	9.672*** (0.180)	9.3568*** (0.040)	6.747*** (0.354)	7.139*** (0.143)
Observations	4256	2126	2590	1452	8640	1159	1702
R-squared	0.02	0.07	0.12	0.14	0.07	0.05	0.10

Standard errors in parenthesis. * significant at 10 %; ** significant at 5 %; *** significant at 1 %.

Omitted categories are: less than primary education; skill agricultural, forestry and fishery worker; never; local.

Table 1A. Reduced-form OLS regression of household income on circumstances (Cont.)

Variables	ND	Norway	Poland	Portugal	Spain	Slovakia
Primary education (F)	-0.161*** (0.041)		0.067 (0.055)	0.219*** (0.041)	0.178*** (0.039)	
Secondary education (F)	-0.094*** (0.033)		0.087 (0.058)	0.365*** (0.086)	0.234*** (0.053)	0.006 (0.074)
Terciary education (F)		-0.016 (0.041)	0.094 (0.086)	0.728*** (0.149)	0.254*** (0.064)	0.085 (0.086)
Primary education (M)			0.057 (0.052)	0.116*** (0.038)	0.155*** (0.037)	
Secondary education (M)	0.016 (0.028)	-0.037 (0.040)	0.209*** (0.054)	0.179* (0.101)	0.237*** (0.053)	0.089 (0.070)
Terciary education (M)	-0.022 (0.047)		0.348*** (0.072)	0.308*** (0.111)	0.302*** (0.070)	0.176** (0.086)
Manager (F)	0.110 (0.091)	0.027 (0.073)	0.256*** (0.064)	0.385*** (0.068)	0.108* (0.055)	0.150** (0.075)
Professional (F)	0.087 (0.096)	0.011 (0.080)	0.445*** (0.077)	0.256 (0.159)	0.256*** (0.080)	0.200** (0.079)
Technician (F)	0.173* (0.093)	-0.003 (0.068)	0.257*** (0.050)	0.446*** (0.092)	0.329*** (0.063)	0.177** (0.072)
Clerk (F)	0.187* (0.097)	0.152 (0.096)	0.204*** (0.063)	0.287*** (0.079)	0.210*** (0.058)	0.193** (0.089)
Salesman (F)	0.004 (0.101)	-0.018 (0.095)	0.085 (0.072)	0.331*** (0.073)	0.107** (0.051)	0.144 (0.089)
Craft trade worker (F)	0.106 (0.091)	-0.038 (0.065)	0.132*** (0.031)	0.125*** (0.043)	0.056 (0.038)	0.103 (0.067)
Machine operator (F)	0.102 (0.094)	0.039 (0.071)	0.140*** (0.034)	0.100* (0.055)	0.169*** (0.045)	0.080 (0.067)
Elementary occupation (F)	0.076 (0.102)	0.004 (0.178)	0.031 (0.041)	0.127** (0.056)	0.043 (0.040)	0.000 (0.070)
Armed occupation (F)	0.067 (0.127)	-0.076 (0.185)	0.350*** (0.089)	0.534*** (0.139)	0.228** (0.092)	
Difficulties most of the time	-0.148** (0.072)	-0.041 (0.130)	-0.240*** (0.044)		-0.089* (0.045)	-0.007 (0.070)
Difficulties often	-0.057 (0.045)	-0.029 (0.092)	-0.163*** (0.034)		-0.098** (0.042)	-0.017 (0.069)
Difficulties occasionally	-0.056* (0.032)	-0.103* (0.053)	-0.057** (0.027)		-0.162*** (0.031)	-0.051 (0.069)
Difficulties rarely	-0.022 (0.028)	-0.046 (0.040)	-0.047 (0.031)		-0.051 (0.030)	-0.062 (0.073)
EU	0.106 (0.099)	0.101 (0.093)	0.252 (0.459)	-0.173 (0.129)	-0.349*** (0.046)	0.161 (0.106)
Other	-0.213*** (0.055)	-0.373*** (0.084)	-0.372 (0.282)	-0.147 (0.101)	-0.673*** (0.159)	-0.137 (0.159)
Constant	9.798*** (0.096)	10.209*** (0.067)	7.544*** (0.040)	8.543*** (0.036)	8.960*** (0.041)	7.771*** (0.102)
Observations	1695	1424	6056	1654	5389	2293
R-squared	0.04	0.03	0.08	0.20	0.08	0.04

Standard errors in parenthesis. * significant at 10 %; ** significant at 5 %; *** significant at 1 %.

Omitted categories are: less than primary education; skill agricultural, forestry and fishery worker; never; local.

Table 1A. Reduced-form OLS regression of household income on circumstances (Cont.)

Variables	Slovenia	Sweden	UK
Primary education (F)	-0.150 (0.237)	0.176** (0.087)	
Secondary education (F)	-0.204 (0.239)	0.246** (0.088)	0.153*** (0.051)
Tertiary education (F)	-0.064 (0.241)	0.210* (0.109)	0.194*** (0.046)
Primary education (M)	-0.011 (0.198)	-0.126 (0.074)	
Secondary education (M)	0.072 (0.200)	-0.062 (0.077)	0.161*** (0.044)
Tertiary education (M)	0.026 (0.203)	-0.064 (0.096)	0.116** (0.049)
Manager (F)		0.284*** (0.077)	0.261** (0.103)
Professional (F)		0.127 (0.087)	0.188* (0.105)
Technician (F)		0.173*** (0.057)	0.111 (0.109)
Clerk (F)		0.088 (0.065)	0.007 (0.124)
Salesman (F)		0.115* (0.063)	0.178 (0.123)
Craft trade worker (F)		0.008 (0.044)	0.082 (0.098)
Machine operator (F)		0.029 (0.043)	0.085 (0.100)
Elementary occupation (F)		0.009 (0.058)	0.043 (0.102)
Armed occupation (F)		0.243* (0.134)	
Difficulties most of the time	0.122 (0.108)	0.010 (0.049)	-0.104 (0.065)
Difficulties often	0.041 (0.088)	0.026 (0.042)	-0.001 (0.058)
Difficulties occasionally	0.032 (0.061)	0.024 (0.038)	0.073 (0.043)
Difficulties rarely	0.022 (0.050)	0.067 (0.040)	-0.035 (0.042)
EU	-0.157 (0.096)		-0.007 (0.230)
Other	-0.474*** (0.083)	-0.179*** (0.043)	-0.228*** (0.052)
Constant	9.889*** (0.171)	8.942*** (0.082)	9.750*** (0.096)
Observations	1342	1393	1875
R-squared	0.04	0.08	0.08

Standard errors in parenthesis. * significant at 10 %; ** significant at 5 %; *** significant at 1 %.

Omitted categories are: less than primary education; skill agricultural, forestry and fishery worker; never; local. United Kingdom: occupation variables are referred to mother's occupation.

APPENDIX B

Table 1B. Descriptive statistics for the independent variables

Year	Development indicators				Labor Market indicator									
	GDP per capita (PPP adjusted) 1998	Employ. in agriculture 1998	Employ. in service 1998	Develop. PC 1998	Employment rate 1998	Female employ. rate 1998	Unempl. rate 1998	Long-term unempl. (12 months or more) 1998	Market PC 1998	Unemploy. rate difference by age 2000	Unemploy. rate difference by education 2000	Unemploy. rate difference by sex 2000	Year	
Source	Eurostat (National accounts)	Eurostat (Labour Force Survey)	Eurostat (Labour Force Survey)	--	Eurostat (Labour Force Survey)	Eurostat (Labour Force Survey)	Eurostat (Labour Force Survey)	Eurostat (Labour Force Survey)	--	Eurostat (Labour Force Survey)	Eurostat (Labour Force Survey)	Eurostat (Labour Force Survey)	Year	
Units	Millions of PPS/habitant	% over total	% over total	--	% population 15-64	% female population 15-64	% active population	% of total unemployment	--	years old - p.p <40	educated - p.p. lower tertiary	p.p. female - male	Units	
Bel	0.0208	2.5	74.2	7.85	62.4	47.6	9.3	61.7	-18.89	4.4	7.6	3.0	Bel	
Cze	0.0120	5.6	53.0	-0.37	74.6	58.7	6.4	31.5	14.33	3.2	19.6	3.2	Cze	
Den	0.0224	3.8	72.6	7.89	81.4	70.2	4.9	26.9	26.84	1.2	3.6	1.0	Den	
Ger	0.0208	2.5	67.1	7.79	71.5	55.8	9.1	52.6	-4.06	-2.0	8.2	0.7	Ger	
Est	0.0072	8.8	58.2	-5.89	68.9	60.3	9.2	46.3	1.68	2.5	20.4	-3.1	Est	
Ire	0.0205	9.0	62.4	2.78	64.5	49.0	7.5	52.0	-9.99	1.2	6.2	-0.1	Ire	
Gre	0.0141	17.0	62.5	-7.46	60.2	40.5	10.8	55.0	-18.97	10.3	1.1	9.6	Gre	
Spa	0.0162	7.1	63.7	1.31	58.1	35.8	15.0	49.9	-19.29	11.9	4.3	10.8	Spa	
Fra	0.0195	4.3	73.2	5.62	62.9	53.1	11.0	41.7	-1.68	6.6	9.8	3.7	Fra	
Ita	0.0203	5.3	64.5	5.40	61.2	37.3	11.4	59.6	-23.60	12.0	6.0	6.6	Ita	
Lat	0.0060	18.7	55.9	-14.10	64.4	55.1	14.3	56.5	-11.07	2.9	14.1	-1.6	Lat	
Lit	0.0069	19.1	52.2	-13.85	66.2	58.6	13.2	62.6	-12.71	6.6	14.3	-4.6	Lit	
Hun	0.0093	7.6	58.0	-3.65	54.7	47.2	8.4	50.8	-14.50	3.9	10.1	-1.4	Hun	
Net	0.0218	3.6	76.5	7.67	75.9	60.1	3.8	47.9	4.26	1.6	2.7	1.3	Net	
Aus	0.0223	8.4	65.0	4.42	72.7	58.8	4.5	29.2	15.49	0.0	5.9	-0.2	Aus	
Pol	0.0080	26.8	44.6	-18.85	60.6	51.7	10.2	47.6	-7.53	5.8	16.3	3.7	Pol	
Por	0.0130	13.2	53.8	-5.37	74.4	58.2	5.0	45.8	3.92	2.5	1.1	1.6	Por	
Slo	0.0134	13.0	48.9	-4.98	65.9	58.6	7.4	45.4	0.36	4.7	8.6	0.3	Slo	
Slk	0.0088	7.0	56.3	-3.48	59.4	53.5	12.6	52.7	-11.12	6.3	35.1	-0.8	Slk	
Fin	0.0194	6.3	65.9	4.04	67.0	61.2	11.4	28.1	14.07	6.9	13.5	1.7	Fin	
Swe	0.0208	3.1	71.8	7.35	78.6	67.9	8.2	37.8	16.13	4.6	5.1	-0.9	Swe	
Uki	0.0200	1.9	75.3	7.71	75.2	63.6	6.1	32.7	16.35	3.2	6.3	-1.2	Uki	
Nor	0.0235	4.4	73.3	8.17	85.3	73.7	3.1	13.9	39.99	4.4	4.1	-0.3	Nor	
Average	0.0160	8.7	63.0	0.00	68.1	55.5	8.8	44.7	0.00	4.6	9.7	1.4	Average	
Std	0.0059	6.5	9.2	8.10	8.1	9.6	3.4	12.6	16.47	3.5	7.8	3.7	Std	

Table 1B. Descriptive statistics for the independent variables (Cont.)

Education indicators		Expenditure in Social protection and taxes											
Education attained (at least secondary upper, level 4) 1998	Education attained (at least secondary upper, level 4) 1998	Education PC 1998	Tertiary education - levels 5-6	Total expenditure in Social protection benefits	Health care/Sickness	Disability	Child care	Social exclusion	Unemployment benefits	Old age	Tax VAT	Tax imports and welfare	Tax income and welfare
Eurostat (ISCED 1997)	Eurostat (ISCED 1997)	---	Eurostat (ISCED 1997)	Eurostat (Living conditions and welfare)	Eurostat (Living conditions and welfare)	Eurostat (Living conditions and welfare)	Eurostat (Living conditions and welfare)	Eurostat (Living conditions and welfare)	Eurostat (Living conditions and welfare)	Eurostat (Living conditions and welfare)	Eurostat (Living conditions and welfare)	Eurostat (Living conditions and welfare)	Eurostat (Living conditions and welfare)
% population : % female pop. % people 18-2	% population : % female pop. % people 18-2	---	% population : % female pop. % people 18-2	% GDP	% GDP	% GDP	% GDP	% GDP	% GDP	% GDP	% GDP	% GDP	% GDP
56.7	56.2	-11.56	5.6	25.6	6.1	2.2	2.3	0.4	3.2	8.6	6.8	0.7	19.7
85.6	80.3	26.93	2.9	17.9	6.0	1.4	1.6	0.3	0.5	7.0	6.1	1.8	9.0
78.5	75.8	17.74	5.5	29.2	5.6	3.4	3.8	1.1	3.4	11.2	9.8	0.2	31.8
80.0	74.8	16.98	4.0	27.9	8.1	1.8	3.0	0.2	2.3	9.6	6.6	0.8	13.5
83.9	85.2	26.82	4.9	14.0	4.5	0.9	1.5	0.3	0.2	6.0	8.1	3.6	11.0
52.0	17.0	-16.33	6.0	14.5	5.5	0.7	1.9	0.3	1.8	2.8	7.1	1.7	14.8
47.7	45.6	-26.67	7.2	20.9	5.1	1.0	1.7	0.2	1.0	10.6	6.7	0.2	9.2
34.5	33.0	-46.76	6.8	19.7	5.7	1.6	0.5	0.1	2.6	8.3	5.6	0.2	11.7
59.9	56.8	-9.11	5.5	28.5	8.1	1.7	2.8	0.4	2.2	10.8	7.6	0.1	16.1
41.5	40.5	-36.62	5.1	23.7	5.6	1.5	0.9	0.0	0.6	12.6	6.1	0.1	18.5
82.6	84.1	22.31	4.6	15.8	2.6	1.3	1.6	0.1	0.5	9.0	8.0	0.5	10.2
83.2	82.9	23.47	4.3	14.8	4.8	1.1	1.3	0.5	0.2	6.3	8.1	1.1	9.6
67.3	61.1	-1.50	3.8	20.0	5.7	2.0	2.8	0.2	1.0	7.9	7.9	1.6	9.4
64.4	59.4	-4.49	4.5	26.1	7.3	3.1	1.2	1.5	1.9	9.3	6.8	1.7	13.1
74.1	66.6	8.41	5.9	27.6	7.2	2.7	2.7	0.4	1.5	10.6	8.2	0.2	17.0
77.8	75.6	17.40	4.7	20.0	4.0	2.8	1.0	0.1	1.0	9.0	7.1	1.4	12.2
17.8	18.7	-72.84	5.4	18.3	5.9	2.3	1.0	0.2	0.9	6.7	7.5	0.4	9.6
72.5	67.7	8.53	5.1	24.0	7.4	2.0	2.0	0.4	1.3	10.4	6.2	1.6	8.7
80.0	74.5	18.80	3.2	19.2	6.9	1.3	2.1	0.9	1.0	6.8	7.5	2.5	9.8
70.1	72.1	10.13	7.6	26.1	5.9	3.8	3.4	0.6	3.1	8.0	8.3	0.1	19.2
75.5	77.9	18.03	5.4	30.9	7.5	3.7	2.9	0.8	2.9	11.6	8.8	0.2	25.5
58.0	51.0	-15.84	5.4	25.2	6.4	2.6	2.2	0.3	0.8	10.4	6.4	0.2	18.2
83.5	82.6	26.20	6.8	26.3	8.6	4.3	3.5	0.7	0.8	7.9	9.7	0.2	16.5
66.4	64.2	0.0	5.2	22.4	6.1	2.1	2.1	0.4	1.5	8.8	7.4	0.9	14.5
18.0	17.7	26.4	1.2	5.1	1.4	1.0	0.9	0.4	1.0	2.2	1.1	0.9	5.8

APPENDIX C

The residuals of model (9) Vs the residuals of model (10) for total inequality and IO.

