Inequality of opportunity and growth in Italy

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Abstract

Recently, many studies look at the decomposition of inequality index into inequality of opportunity (IO) and inequality of returns to effort (IE) in US and Europe. The decomposition of inequality index in two components allows not only to analyze the prevalence of fair or unfair income inequality in a country, but also to find a clearer relation between inequality and growth. In fact, it is still missing an analysis of the relation between inequality of opportunity and economic growth in Italy. This paper aims at filling in that gap, by using Italian data from Bank of Italys Survey on Income and Wealth from 1998 to 2014. We choose the coefficient of variation to measure inequality of opportunity at the regional level and, then, we studied its relation with economic growth using Dynamic Panel Data models estimated through System-GMM. Finally, in order to check if the coefficient of variation could be a measure as good as the Entropy's index, I will compare the results of the estimated panel models with the two different inequality of opportunity indeces. We evaluate the effect of inequality of opportunity on different economic growth period, going from a short run growth (2 years) to a very long run growth (10 years). Our results shows that, in Italy, inequality of opportunity is negative for growth in the short period, but it does not have any effect on long run growth.

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1 Introduction

Income inequality and economic growth have been the subject of many economic studies for decades, in particular, the main question concerned the sign of the relation between this two socio-economic phenomena.

Conversely, literature on the measurement of inequality of opportunity (IO) has only recently emerged in the 1970s and 1980s. The distinction between inequality of opportunity and inequality of effort is graded on Rousseau concepts of natural and social inequalities (Rousseau, 1755, On the sources of inequality). The concept of equality of opportunity was born in the political philophy field thanks to the contribution of John Rawls (1971), who introduced the concept of distributive justice as a principle that depends not only on individuals free will, but also on equality of options for all. Starting from this political and philosophical debate the theory on equality of opportunity acquire great relevance in Western liberal societies, expecting that all individuals should get the chances to achieve the same outcome and any exogenous circumstances should not prevent them from it (Arneson, 1989 and Cohen, 1989). Following this approach one society could be defined equal not when there is equality in final achievements (such as equal richness, level of education and health), but when everyone has guaranteed equal ex ante opportunity to attain outcomes they care about. In the 1990s, formal economic theories of the evaluation of social states began to include the concept of equal opportunity when studying the optimal allocation rule (see e.g. Roemer, 1993, 1998 and Fleurbaey, 1995, 2008).

During last years, most of the economic papers on inequality of opportunity focused on three main questions, namely: (i) finding a more precise index of opportunity inequality, in order to overcome the limitation of a downward measure; (ii) comparing results from the ex ante and ex post approach; (iii) using IO results to define appropriate public policies. The peculiar starting point of this literature is the distinction between the determinants of different outcomes (called circumstances) and the factors that depends on individual responsibility (called effort). This distinction gives rise to the two components of income inequality, namely unfair inequality, which are due to circumstances and are ethically unacceptable, and fair inequality due to individual effort and not offensive in a just society. This approach considers equal a distribution where efforts are rewarded and the effect of circumstances are compensated. In this case, the individual level of effort, that is also freely chosen, determines all the disparities described above. In recent years, a number of empirical studies attempts to determine the degree of inequality of opportunity in different countries (Bourguignon et al. in Brazil, 2007, Lefranc et al. in some western countries, 2009, Pistolesi in the US, 2009, Ferreira and Gignoux in Latin America, 2011, Checchi and Peragine and in Italy and EU, 2010, 2016), but only one looked at the effect of IO on economic growth (Marrero and Rodriguez, 2013).

The main goal in analysing the relation between inequality of opportunity and economic growth consists in the clarification of the ambiguous relationship between total income inequality and aggregate economic growth (Marrero and Rodriguez, 2013). Indeed, the World Bank in its World Development Report of 2006 argued that income inequality due to exogenous conditions might lead to suboptimal accumulation of human capital slowing down economic growth. In contrast, income inequality caused by the individual choice of effort may encourage individuals to invest in human capital.

This work aims to contribute to this research question through an empirical analysis which looks at the relation between growth and inequality of opportunity in Italy. We follow the pioneer work of Marrero and Rodriguez, which combines the empirical growth literature from macroeconomics and the inequality of opportunity literature from microeconomics. However, our analysis contributes in two ways:

1. A different choice of the inequality index to measure the two sources of inequality. We use the coefficient of variation [1] instead of the usual Theil 0 index (corresponding to the Mean Log Deviation) [2].

2. The analysis of the effect of inequality of opportunity and its counterpart, namely, inequality due to effort, on different length of the growth rate period considered, starting from a short term to a very long term economic growth period. Moreover, we considered more than one inequality of opportunity indeces on the basis of the choice of different combination of exogenous circumstances.

Still today there are only two italian databases, which contain necessary information on exogenous circumstances, such as family background, in order to measure inequality of opportunity. On one side, the Italian Survey on Income and Living Conditions (IT-SILC) conducted by the Italian National Statical Office, where the available data consists in two cross-sectional waves (2005 and 2011). On the other side, the Italian Survey on Income and Wealth (SHIW) conducted by the Bank of Italy every two years, starting from 60s

[1] **In a previous work, we showed that it is a good measure of inequality of opportunity, because it could be statistically tested and the measure of IO does not differ too much from Checchi and Peragine's (2010) analysis on Italian data and other studies on European data such as Marrero and Rodriguez (2012).**

[2] However, we report the estimated results also considering this most common alternative inequality decomposable index.

and containing a panel component. For this reason, we decided to compute inequality of opportunity using SHIW data.

The remainder of the paper is organized as follows. Section 2 reports a brief literature review on the relation between inequality, growth and the link with the inequality of opportunity concept. Then, it follows a presentaion of the simple canonical model of inequality of opportunity. Section 3 explains the methods chosen to measure IO and the estimation techniques for the regression models. Section 4 presents a description of the data used to conduct this analysis and some descriptive statistics on the relative measure of IO in Italy. Finally, in section 5 we discuss the most important results and section 6 concludes the paper.

2 Theoretical Framework

2.1 The intersection between inequality, growth and inequality of opportunity

The analysis of the relation between inequality and growth was born at least two decades before the first theorization of opportunity equality, producing hundreds of theoretical and empirical paper on this topic [3]. This literature could be divided into two macro-group: the first one interested in the causation from growth to inequality and mainly based on inverted-U Kuznets hypothesis (1955) and augmented Kuznets hypothesis (Milanovic, 1994). Along this theoretical line the economic growth and its consequence on socio-economic and political developments should contribute to the reduction of income inequality. The second group, instead, simply studied the reverse-causation that means the effect of inequality on growth. The analysis, that is going to be estimated, refers to this last group, which reported results that are more controversial about this relation. In particular, the theoretical literature found several channels through which inequality could affect economic growth. The most important contributions entail credit market imperfections (Galor and Zeira, 1993), fiscal policy (Alesina and Rodrik, 1994; Persson and Tabellini, 1994; Perotti,1996), socio-political instability (Gupta, 1990; Alesina and Perotti, 1996; Keefer and Knack, 2002) and savings (Kaldor, 1956; Galor and Moav, 2004). Thus, the relationship between inequality and growth could be positive or negative, depending on the channels, which prevail. On the other side, the empirical literature did

[3]Recent survey on these studies can be found in Aghion et al. (2009), Ehrhart (2009), Clark et al.(2014) and Neves et al. (2015).

not find any of those channels with a significant role to explain the effect of inequality on growth. Therefore, the impact of inequality on growth is still ambiguous and without a causal relation between the two economic phenomena. The reason behind these inconclusive econometrics outcomes could be fallen into the unavailability of complete and correct data, the choice of inequality measurement or the econometric model and estimation techniques. Essentially, the empirical literature on inequality and growth produced two sets of models, models that predict a positive effect of inequality on growth and models that found only a negative relation. The main mechanism behind a positive sign of relation between inequality and growth can be synthetize in three macro sets. As first, the Kaldors hypothesis on the increasing marginal propensity to save of rich, when income inequality augments, induces a faster growth in more unequal economy (Stiglitz, 1969; Bourguignon, 1981). As second, the most important factor, that affects growth, concern investment. Indeed, when wealth is more concentrated, individuals are easily able to launch new entrepreneurial activity (Barro, 2000). As third, some political economy mechanism through, for instance, the median voter mechanism, which could promote higher or lower income taxes if they know that government expenditure will allocate it to consumption (Li and Zou, 1998). The political group, which has the power, represents another alternative; if the political power is reached by high income individuals they will promote pro-growth policies (Partridge, 1997). On the contrary, it seems that inequality and growth are, most of the time, negatively correlated because of redistributive policy, political instability, imperfect financial markets, and fertility-human capital mechanism. In the first channel, high inequality and low redistribution reduces the opportunity for individuals to invest and accumulate human capital, depressing economic growth (Perotti, 1993; Persson and Tabellini, 1994: Alesina and Rodrik, 1994; Clark, 1995). Then, high inequality is one of the cause of political instability that contribute to reduce investment and worse the economic performance (Alesina and Perotti, 1996).

In the second channel, the basic idea is that the restriction on the possibility to borrow, generates an under investment in physical and human capital and again in this system high inequality is seriously dangerous for growth (Galor and Zeira,1993; Banjeree and Newman,1993; Piketty,1997).

Furthermore, this channel represents the main reason for giving a role to inequality of opportunity in the economic growth. Indeed,an unequal distribution of parental wealth combined with unfavourable initial circumstances circumstances could prevent individuals from exploiting their full intellectual potential through formal education, because they face considerable barriers for accessing credit. As a consequence, if there is high inequality of opportunity, the investment in human capital will be subotimal and the return in terms of economic growth negative. In the literature, there are arguments supporting the role of inequality of opportunity coming from some particular circumstance such as parental education. In particular, Chiu(1998) shows that under liquidity constraints and decraesing marginal utility, a redistribution of wealth from rich to poor will bring talented children from poor families to college and disincentivate less talented children from richer families (see also Loury, 1981 and Benabou, 1996).As a consequence, aggregate human capital will increase and,therefore, so will economic growth.

Finally, the fertility-human capital channel has constituted one of the principal arguments to link inequality and economic growth. Indeed, following Kremer and Chen (2002), who found that there are empirical evidence showing that less equal countries reported higher fertility differentials between educated and uneducated individuals. Moreover, they found that fertility differentials affects negatively growth. Piketty (2011), instead, affirms that higher fertility contribute to reduce inequality, undermining the power of inheritance. Following the line of Castell and Domenech (2002) built a Gini index for human capital inequalities and after including it in a growth regression; they found that it is negatively related with growth. However, when income inequality is included in the regression, its sign is no more negative, so as they introduce geographical dummies the coefficient of income inequality became insignificant. Albeit, the presence of extensive literature on this argument has tried to explain the link between inequality and growth, there is only one valid outcome, that still emerges, and it stated the absence of a clear and conclusive results.

At this point, Marrero and Rodriguz (2013), following the second channel theories, formulated the first contribution to this literature substituting to the simple overall inequality the concept of inequality of opportunity and analyzing its relation with growth. They linked the Mirrless's theory regarding the positive sign of the relation coming from the incentives due to merits and effort and other theories where the realization of some circumstances depress human capital accumulation and, hence, growth by using the decomposition of overall inequality index. Indeed, they estimated a growth regression, including a measure of inequality of opportunity and inequality of effort, and they showed that higher inequality of opportunity tends to depress growth, instead inequality of effort positively affects economic performance. Referring to this approach, they demonstrated, which type of inequality is detrimental for growth, thus, the negative sign of inequality of opportunity defines the infective channels, as well as inequality of effort shows the positive influence of an healthy system of competition and meritocracy.

2.2 The simple canonical model of Inequality of Opportunity

The theoretical model used in this paper is grounded on Roemer (1993), Fleurbaey (1994) and Van de Gaer's (1993) decomposition of inequality where each individual in the society is described by a list of traits, classified into two classes. The first class includes traits beyond the individual control and represented by a vector of circumstances C, such as gender, race, family background, place of birth etc. These set of circumstances constitute a finite set, say, $\Omega = c1, ..., cn$. Apart from these circumstances there are various alternative channels through which parents may affect the income generating capacity of their children. Moreover, literature highlights the importance of parental background on child's human capital accumulation. First, parents may influence the provision of social connections, which are important in the labour market. Secondly, they affect the formation of belief, preferences and skills of children, through family culture and investment. Finally, ability is considered as a native characteristic since it is transmitted genetically. This last channel is implicitly classified into the sphere of individual responsibility. The second class of traits refers to efforts, i.e. to factors for which the individual is fully responsible. Effort may be treated as either a continuous or a discrete variable belonging to the set . Income is generated by a function $g : \Omega \times \Theta \longrightarrow R_+$such that:

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

This is a pure deterministic model, where for any given existing circumstances any variation in individual income is attributed only to personal effort: all individuals with the same characteristics of circumstances and effort obtain the same income. The population of individuals is thus characterized by the triplet (x, C, e) related to income, circumstances and effort. Then, the population is partitioned into two ways: into types T_i, within which all individuals share the same circumstances, and into tranches T_j, within which everyone share the same degree of effort. Let us denote with x_{ij} the income generated by circumstances C_i and effort, e_j. Supposing that there are n types $(i = 1, .., n)$, and m tranches $(j = 1, ..m)$, the population can be represented by a matrix with n rows and m columns. Given this model, the measurement of inequality of opportunity can be thought of as a two-step procedure. In the first step, the actual distribution x_{ij}, is transformed into a counterfactual distribution that reflects only the unfair inequality in x_{ij}, and all the fair inequality is removed. In other words, supposing that everyone employs the same effort, this counterfactual matrix contains only the income (x_{ij}) for each type (T_i), which consists in the mean income ($\bar{x}_i$) for each $i = 1, ..., n$. In the second step, a measure of inequality is applied to this counterfactual matrix and it will only capture the inequality of opportunity defined as inequality between types.

This analysis refers to the ex-ante approach and, hence, it focuses on the row of the $n \times m$ matrix. A given row i is interpreted as the opportunity set of any individual with circumstances C_i. As a result, the counterfactual distribution may reflect the inequality between the rows. On the other side, the ex-post approach focuses on the columns of the $n \times m$ matrix. Given the effort level, the inequality within each column refers to inequality of opportunity. Hence, the corresponding counterfactual distribution assumes that each individual belongs to a tranche T_j, given by a quantile of the income distribution (x_{ij}), whatever difference in income within the tranche is due to the initial circumstances.

3 Methods

3.1 Measuring inequality of opportunity

An inequality index is a scalar representation of the interpersonal differences in income within a given population, in a way that all the different characterostics due to income inequality are considered into a single number (Cowell, 1995). This kind of indicators has the advantages of observing the variation of inequality, its distribution and the ranking of the individuals. The most conventional measures of the overall inequality in the literature are the Range, the Gini coefficient and general entropy index. Sen (1973) referred to those as objective or positive measures that make no explicit use of any of social welfare functions. This family of inequality indices includes the variance, the coefficient of variation (CV), the log variance and the relative mean deviation.

The first simple property concerns the scale invariance. The second property concerns the principle of population. The most important one regards the principle of transfers, which Cowell (1995) divides in two properties: weak and strong principle of transfers. The weak principle requires that after the transfer, inequality decrease without specifying the proportion of its variation. Whereas in a strong sense, the reduction of inequality depends only on the distance between the two individuals incomes, independently on their choice. The majority of the inequality index do not satisfy the strong principle of transfers, but are ordinally equivalent to measures satisfying it. Directly connected to this property is the sensitivity of the inequality index to the differences in income shares in different part of the distribution. The last property fits into the decomposability, strictly necessary to measure IO. A decomposable inequality measure may be written as a function of inequality within the constituent groups and inequality between the groups. Specifically, inequality of opportunity corresponds to the measure of inequality between groups, whereas inequality within groups represents the residual inequality, due to differences in effort and others not observable factors (such as luck, innate ability, creativity, loyalty). Some inequality measures are not decomposable and this is the case of the Gini coefficient, the Logarithmic variance, the Variance of logarithm and the Relative mean deviation. Any inequality measure that simultaneously satisfies the properties of the weak principle of transfers, decomposability, scale independence and population size must be expressible either in the form:

$$E_{\vartheta} = \frac{1}{\theta^2 - \theta}[\frac{1}{n}\sum_{i=1}^{n}[\frac{y_i}{\bar{y}}]^{\theta} - 1] \tag{2}$$

or as $J(E_\theta)$, an ordinally-equivalent transformation of E_θ, where θ is a real parameter that may be given any value, positive, zero or negative. This formulation refers to the generalized entropy measures, which are typically used in the IO literature to measure the two component of inequality following an ex ante or an ex post approach.

3.2 Decomposing inequality in IO and IE

In the present analysis, differently from the literature on IO, the selected measure for inequality of opportunity strictly depended on a previous work (Arbia, Pace 2016), where using the coefficient of variation, we could statistically test in a simple way (using ANOVA analysis) the validity of the circumstances as determinant of inequality between individuals. Given the goodness of that results and the consistency with previous findings on IO in Italy [4], we decided to keep on applying this decomposable index in the analysis of the relation of per capita GDP growth and IO in Italy.

On the other side, Marrero and Rodriguez (2013) applied to PSID data the Theil-0 index to decompose total inequality and find a measure of IO and IE to be included in the growth model. Thus, I also choose to calculate IO and IE through the decomposition of Mean Logarithm Deviation (MLD) index, in order to show that the empirical results, obtained using CV as IO measure, coincide with MLD.

Basically, the inequality of opportunity, both in absolute and relative terms, and inequality due to return to effort (IE) is computed for each Italian region [5], through the coefficient of variation and MLD. We determine two inequality of opportunity measures combining two circumstances together, which divide the sample in 8 and 16 types, respectively, and are defined as "IO 8-groups" and "IO 16-groups". However, an IO index for each singular circumstance is also computed and, then, included in the estimated growth model. In order to calculate the IO 8-group index, the sample is divided into four groups on the base of the level of father education and then, each one of this group is subdivided between male and female. Hence, we have eight different groups for each Italian Region, where we measure the income inequality between these groups. In other words, following the ex-ante approach, we built the conterfactual matrix with eight columns and we substitute in each column the mean income for that type. The same process is implemented for the case of IO 16-groups where the sample is divided into 16 groups, firstly based on father

[4] See Checchi and Peragine, 2010.

[5] The Region refers to the Region of residence.

education and, then, each level is partitioned on mother's educational level. Once this matrix is built, we compute IO using coefficient of variation (CV)[6] for each one of the Italian Regions, as follows:

$$IO_{CV_{it}} = \frac{\sigma(\bar{x}_i)}{\bar{X}_{Region}} \tag{3}$$

where IO_t is the inequality of opportunity measure in the year $1, ...T$ and $\sigma(\bar{x}_i)$ corresponds to the standard deviation between the mean income of each group relying on exogenous circumstances taken into considerations. Finally, the denominator is the overall sample mean income of each Italian Region. Then, this computation procedure is applied to all single factor determining IO, ending up with four simple index and two composite. After that, each one of these inequality of opportunity measure is calculated, we determine the residual part coming from the decomposition of a general inequality index, which, in this literature, is defined as the inequality due to return to effort (IE). It is calculated for each Italian Region by subtracting from the total income inequality [7] the different IO computed before and hence, the total inequality due to effort is given by:

$$IE_{CV_{it}} = \mu(CV_{Region} - IO_{CV_t}) \tag{4}$$

where CV_{Region} refers to the total income inequality measured in each Italian Region and IO_t stands for the different IO computed for single and group of exogenous circumstance using CV.

As already said before, we compare the results obtained using the between component of CV as IO measure with that one obtained through the most common Theil 0 (namely MLD) index. In this analysis, following Haughton and Khandker(2009) the decomposition of the MLD index can be represented as:

$$MLD = \sum_i (\frac{N_i}{N}) MLD(x_i) + \sum_i \frac{N_i}{N} ln(\frac{\bar{X}}{\bar{x}_i}) \tag{5}$$

where the first term on the right side represents the within group inequality (namely IE) and the second term the between group inequality, which is again defined as inequality of opportunity. Hence, as before, we applied to the conterfactual matrix the MLD determining IO for each one of the Italian Region as follows:

[6] For the CV decomposition into between and within component refers to the appendix of the first chapter (Arbia, Pace, 2016).

[7] Obviously, it is measured following the decomposable index chosen for IO.

$$IO_{MLD_{it}} = \mu(ln(\frac{\bar{X}_{Region}}{\bar{x}_i})) \quad (6)$$

Then, as in the case of CV, the IE measured with MLD corresponds to the mean of the subtraction of each single IO_{MLD} from the total inequality (MLD).
Finally, in Table 1, we will report the relative measure of inequality of opportunity (IOR) for each region and year, given by the following formulation (see Ferreira and Peragine,2015):

$$IOR = \frac{IO_{it}}{I(x_t)} \quad (7)$$

where $I(x)$ is the measure of overall inequality in a given distribution x_{ij} [8]

3.3 Empirical model and estimation technique

The empirical model follows the specification of Barro (1991, 2003, 2013), considering the growth rate of real per capita GDP a function:

$$\frac{d}{dt}(y) = F(y_{t-1}, h_t, X, \psi) \quad (8)$$

where y_{t-1} denotes initial GDP per capita, h_T is human capital endowment per person and X includes a set of control variables. This model correspond to the conditional covergence hypothesis, in which the relation between the initial level of GDP per capita and the growth rate must be examined after holding constant some crucial variables. These variables usual include state and enviroment determinants and capture country specific potential for economic growth. when holding constant the effects emanating from this variables, it is possible to study to what extent inequality ψ can contribute to explain empirical growth patterns. Then, in our case we have the advantage of dealing with regions instead of coutries and it means that the heterogeneity due to political process is almost null. Indeed,the political process is the same in the italian context. Moreover, the same happens for institutional, cultural and religious differences. Hence, there is no need a lot of variables for controlling for country specific enviroments reducing the estimation

[8] In this specific case, it is the overall regional income inequality.

issues due to omitting variables.In this way, we don't have to deal with Durlauf's statement (2005), for which there exist as many growth determinants in empirical literature as there are countries to be examined.Thus, the choice of Barro specification results the best one, given that it proves to explain empirical growth patterns accurately in a number of studies.

In our analysis, we use two variables to measure human capital: the percentage of the population between 25 and 65 years of age who have graduated from high school but not have a college degree [9] and the percentage of the population who have graduated. In the set of control variables, we includes the fertility rate, which has been proved to be an important trasmission channel from which inequality affects growth and the initial economic sector composition for each region [10].

Controlling for those variables, we will examine if income inequality and its decomposition in inequality of opportunity and inequality of effort affects the growth rate of GDP per capita in Italy. To this aim, the empirical model we want to estimate is the following basic dynamic OLS growth model with a set of inequality indices and growth determinats,which assume the following form:

$$Gy_{i(t-s,t)} = \alpha_i + \phi T_t + \beta_1 lny_{i,t-s} + \beta_2 Ineq_{i,t-s} + \beta_3 X_{i,t-s} + \epsilon_{it} \tag{9}$$

where $Gy_{i(t-s,t)} = \frac{lny_{it} - lny_{i,t-s}}{lny_{i,t-s}}$ is the logarithmic real growth rate of GDP per capita; α_i and T_i are the region and time specific effects,respectively; $lny_{i,t-s}$ is the logarithm real per capita lagged GDP; $Ineq_{i,t-s}$ represents the inequality indices (total income inequality, inequality of opportunity and inequality due to effort, depending on the case we are analyzing). Finally $X_{i,t-s}$ represents the set of control variables described above and ϵ_{it} is an i.i.d error term.

Following Durlauf, Johnson and Temple (2005), the vast majority of the first panel data growth studies used a fixed-effect estimator rather than a random effect. Indeed, standard random effect estimators require that the individual effects α_i are distributed independently of the explanatory variables, and this requirement is violated in our model, given

[9] Marrero and Rodriguez(2013) refers to the percentage of the population over 24 years of age. However, the only available data containing this information from ISTAT human capital section refers to the age class starting from 15 years old. Hence, we prefer to use the age interval, which represents the age of the sample we used to compute inequality indexes.

[10] These data come from the Italian National Statistics Office (ISTAT).

the dependence of both the lagged income and the inequality indexes on α_i. The main advantage of the fixed effect method consists in the ability to address one form of unobserved heterogeneity: any omitted variable that are constant overtime will not bias the estimates, even if the omitted variables are correlated with the explanatory variables. Moreover, Fixed Effect estimator is preferred when individual unit are "one of a kind", for instance OECD countries or American States (Baltagi,1995). In our case, we consider Italian regions and, hence, the fixed effect estimator is a more properly panel model specification. As proof of this statement, each kind of model specification, both reduced and complete model, are re-estimated using random-effect estimator [11] and the results are always worse than fixed effect estimations. It means that it could not be a random results and fixed effect shows consistent results. However, Nickell(1981) showed that within-groups estimates of a dynamic panel data model can be badly biased for small T, even as N goes to infinity. Furthermore, another potential issue in this model concerns the simultaneous determination of inequality and growth. Hence, both inequality indexes and the set of control variables in equation (2) are considerd at the beginning of each decade.

To deal with this issue, the literature focused on a specific GMM estimation techniques, namely, the system-GMM estimator. It represents the Blundell and Bond's (1998) improvement in the properties of the first-difference GMM estimator, developed by Arellano and Bond (1991). Basically the first-diffrence GMM estimator eliminates the fixed effect term α_i by differencing equation (10) and then, it employs lagged values of y and X as instruments [12]. However, Blundell and Bond found, through some simulation studies, that when the autoregressive parameter is moderately large and the number of time series is moderately small, the first-difference GMM estimatorlarge finite sample bias and poor precision. In this case, they stated that lagged levels of the series povide weak instruments for first-differences (Blundell and Bond, 1998). For this reason, in this empirical analysis we use, firstly, the system-GMM and then we check the results through the fixed effect estimator, following Marrero and Rodriguez who mainly carried out a similar analysis using the system GMM estimator. Moreover, Soto(2009) analyses through a Monte Carlo Simulations the performance of several standard panel estimators if N is small ($N = 100, 50, 35$). The study concludes that the System-GMM estimator leads to the results with the lowest bias, declaring it as the most appropriate method to investigate empirical growth patterns in the class of the standard dynamic panel model data estima-

[11] The random effect estimation are completely not significant at all, but available on request.

[12] The instruments are valid only if the error term is not serially correlated

tors.
The system GMM estimator consists in adding a set of equation in levels to the first-difference model, where the instruments of the levels are suitable lags of their own first differences, such as Δlny_{it-s}, $\Delta Ineq_{it-s}$ and ΔX_{it-s} and on the other side, lagged levels variables constitute a good instrument for the first-difference equation. This approach have to satisfy three moment conditions, where the last two are focused on the case where T=3:

1. $$E(y_{i,t-s}\Delta v_{it}) = 0 \tag{10}$$

   where $\Delta v_{it} = v_{it} - v_{i,t-1}$. This condition depends exclusively on the assumed absence of serial correlation in the time-varying disturbances v_{it}.

2. $$E(u_{it}\Delta y_{i,t-1}) = 0 \tag{11}$$

   for $t = 4, 5, ..., T$.

3. Given that Δy_{i2} is observed, Blundell and Bond found an additional restriction:

   $$E(u_{i3}\Delta y_{i2}) = 0 \tag{12}$$

The last two moment conditions remain valid under heteroskedasticity (Blundell and Bond, 1998). Thus, the combination of moment restrictios for differences and levels results in the following estimator called GMM-system-estimator:

$$\hat{\gamma}^{GMM-SYS} = (XW\hat{V}^{-1}W'X)^{-1}X'W\hat{V}^{-1}W'y \tag{13}$$

where $\gamma = (\rho, \beta)$, W represents the matrix of instruments in first-difference and lagged levels, differently from the first-difference GMM where W just contains lagged levels variables as instruments and, V is the covariance matrix taking into account first order autocorrelation into the error term in differences.
When applying this kind of instrumental variable estimation, there is always a great risk to overfit the endogenous variable, and the System-GMM can easily create a proliferation of lagged and first-difference variables as instruments, beacause of the quadratic count of the instruments in the time dimension of the panel. Hence, the Hansen's-J test of overidentifying restrictions is the test most commonly used to verify these conditions

and avoiding instruments proliferations. IN particular, the null hypothesis considers the absence of correlation between the instruments and the regression residuals, in other words it checks the joint validity of the set of instruments. Furthermore, the possibility to have valid internal instruments lagged two or more period requires the absence of the autocorrelation in the disturbance term ϵ_{it} in equation (10). This autocorrelation in the error term is tested through the Arellano-Bond's test which examine the first, the second and higher order correlation of the residuals in first differences (Roodman, 2009). Finally, the System-GMM estimators have one and two-step procedure. Albeit, one step procedure reports standard errors that are asymptotically robust to heteroskedasticity and more consistent for finite sample inference. For this reason we adopted the one-step system GMM estimator, following the formula reported above and considering the necessary testing procedure (Blundell and Bond, 1998; Bond et al. 2001).

4 Data and Descriptive Statistics

4.1 Sample design

The empirical analysis starts using the Survey on Income and Wealth of Italians Households (SHIW) from waves 1998 to 2014. This survey is conducted every two years by the Bank of Italy and for each wave, they interview approximately eight thousands of households corresponding to twenty thousands of individuals. For this analysis we preferred the Bank of Italy survey, because, contrarily to IT-SILC data, it contains a panel component, which, for the last 16 years, includes one-third of the interviewed. Hence, we built a panel for the analyzed period, containing all the relevant information for the measurement of inequality of opportunity. In particular, we need individuals income, parents education, area of birth and region of residence [13] and individuals characteristics such as gender.Accordingly to Marrero and Rodriguez (2013), we redefine the sample to estimate the inequality of opportunity following three step:

1. We keep only the household heads, identified in the sample as the major wage earner in the family. Then, we computed the gross income as the sum of the households labor and capital income divided by the number of adults in the family.

2. The second step involved the reduction of the composition effect due to the fact that individuals with different ages are in different phases of the wage-earning time series. To overcome this issue, the literature on inequality of opportunity suggests to consider only household heads in a defined age group, for instance, 25 to 50 years old. In our analysis, this rule allowed to have a sample of 5845 individuals, which means approximately six hundred individuals each wave, which is considered a normal sample for a panel with T=9.

3. Finally, we selected a set of exogenous circumstances, that are the standards in this literature, such as family background, area of birth, gender and, with respect to these usual factors, we add the size of the family. Family background includes father and mother education, treated as two separated circumstances. Each one divides the sample in four types, where the first group includes individuals with illiterate father or mother. On the other side, the last group is composed by individuals with high-educated parents. Furthermore, we combine two of the most

[13] The questionnaire collects information also on provinces and municipalities of birth and residence, but this information is not freely distributed. When we asked to get these data, the Bank of Italy explained us that this information is hidden and not available for privacy reasons.

relevant circumstances [14]: firstly, we calculated the so called inequality of opportunity 8-groups [15], given that the sample is partitioned in eight types (4×2 matrix), where the father education detrmines the first four types and the gender the other two types. Secondly, the combination of father and mother education gives rise to inequality of opportunity 16-groups, because they generate sixteen different types (4×4 matrix).

4.2 Final Panel Dataset

In the last stage, the panel data containing the computed inequality of opportunity and inequality of effort index for the 20 Italian regions and for each year, is matched with the data on GDP per capita for the Italian regions from 1998 to 2014 available at regional level on the National Account section of the National Italian Statistical Institute (ISTAT). In order to compare the effect of inequality of opportunity and inequality due to effort on different length of the economic growth period, we consider five different period of GDP's growth rate:

- short term economic growth: it is a two-years GDP per capita growth rate, which conduces to a panel with T=8.
- medium term economic growth: it corresponds to four-years GDP per capita growth rate, which brings to a panel with T=7.
- medium-long term economic growth: it means six-years GDP growth rate, that produces a panel with T=6.
- long term economic growth: it is an eight-years GDP growth rate, restricting the panel to T=5.
- very long term economic growth: it represents ten-years growth rate and it builds a panel with T=4.

As a consequence, for each period of growth rate considered, we have a panel with N=20 and various length for T, going from four to eight. Then,to each one of the growth rate, as

[14]This statement come from the result of our previous work, Testing inequality of opportunity within the ANOVA framework: the case of Italy(2016), in which we found that the father education and gender are the main factors which determine inequality of opportunity in Italy. However, we also found that the mother education has increased its relevance in the last years.

[15]G.A.Marrero and J.G. Rodriguez did the same using fathers education and race.

far as computed, we have the inequality indeces (IO and IE) measured at the begining of each period considered. Further variables available at the regional level on ISTAT website were added to those panel. In particular, there are the common human capital proxies corresponding to the percentage of population with a certain level of education attained, the fertility rate, which is really low on average in Italy, the percentage of old population, the percentage of total employers for some NACE 2 sectors.

5 Results

In this section, we report the most important results of this empirical analysis. As stated before, we refer to the classical benchmark model of conditional convergence for panel data adding the two inequality indices, namely IO and IE, estimated on the indivduals SHIW data. In statistical term, Barro's beta-convergence model for panel differs from the cross-sectional, because of the interpretation of coefficient on the lagged income (originally β) become 1+ β. Following Panizza(2002) and Marrero and Rodriguez(2013), we estimated two models:

1. a *base* form, in which we estimate a dynamic panel growth model including inequality of opportunity and inequality due to return to effort as independent variables [16]. The lagged income varibale is always included, because there is a great risk of misspecifciation of the model, if it is excluded (Marrero and Rodriguez, 2013). In particular, we estimated five models, based on the length of the growth rate considered as dependent variable. Hence, we analyzed the effect of inequality of opportunity on economic growth in Italy from the very short period (2 years growth rate) to a very long period of growth (10 years growth rate). The following models are maily estimated using the System-GMM estimator (Blundell and Bond, 1998) and referring to the composite IO index 8-groups. However, some robustness check are present using IO 16-groups and, then, Fixed Effect estimator [17].

2. a *complete* model, where we add the common control variables tipically included in inequality and economic growth models. Indeed, as highlighted in Panizza(2002), it could be that the coefficients attached to inequality may reflect the effects of other variables correlated with both inequality and growth. In this case, we found that the inclusion of these controls variables does not improve the base models results. Furthermore, most of these control variables became insignificant when thetwo form of inequality are in the economic growth model [18] Indeed, in our analysis, the complete form model fundamentally represents just another check of the base form estimated results and it confirms that the two indices of inequality are sufficient to explain or not GDP per capita growth in Italy [19].

[16] Alternativily, the same model is estimated including total inequality instead of IE. The results are basically the same with respect to sign and significance and they are available on requests.

[17] From this robustness we report only some results, even in this case the others are available on requests.

[18] These set of controls is usually highly significant in the literature when included in the growth model.

[19] For this reason, the complete form model's results are not present in the paper, but available on requests

Table 1 shows the results of five base form model estimated through the System-GMM and using the coefficient of variation as inequality index. The first column reports the estimated coefficients for the lagged income, IO 8-groups and the inequality due to return to effort in the short term period. In the short term, the inequality of opportunity is negatatively related to economic growth and significant, instead the inequality due to effort is positive and significant, as we expected. Meaning that in the short period the "unfair" income inequality is dangerous for economic growth, while inequality dependent on individual responsability affects positively the economic growth. Hence, looking at a possible interpretation of the coefficient we can imagine a policy that will reduce the standard deviation of the types means of an amount equal to the gross regional mean, it will increase GDP per capita of 7,7 % [20].

From the second to the fifth column, we consider longer term growth rate, when we pass from the short term to the medium, the results have already changed. Indeed, both the coefficient of the two inequality indeces are no more significant, instead the lagged income is still highly significant, showing that the model is correctly specified and instrumented. At the end of each column, we show some relevant test and necessary information when dealing with System-GMM estimator. In particular, the Hansen-J test is an overidentification test on the validity of the System-GMM instruments choice and given the easily proliferation of instruments [21] when using System-GMM, Roodman(2009) suggested to keep it in the following interval: $0.1 < H < 0.25$. Our models specification reports an Hansen test always inside this interval, confirming the validity of the instruments system. Another relevant information concerns the number of instruments, which should not overcome the number of observtions. Even in that case, the number of instruments is always reasonable and it decreases with the time length, as expected. The last two rows refers to Arellano-Bond autocorrelation test on the residual in difference, which allows to know if some lag are invalidate as instruments. The first row, AR(1), tests the first-order serial correlation in difference [22], which is usually expected, so evidence of it is uninformative. Hence, we are more interested in the results of the second-order serial correlation, AR(2), which we would not be serially correlated, in order to make use of first order lag in levels. Table 2 is specular to 2, but in this case the inquality of opportunity and due to effort

[20] The interpretation of the coefficient is not so straightforward, given that we are dealing with an index, but this seems a reasonable one.

[21] Instruments proliferation can overfit endogenous variables and fail to expunge their endogenous components (Roodman, 2009)

[22] The autocorrelation test is on residuals in differences, because in this way it evaluate residual aside from the fixed effects (Roodman, 2009).

is computed through the Theil-0 (MLD).The previous findings are confirmed when using the Mean Log Deviation as IO and IE measure, it goes in the direction of confirming the coefficient of variation as a valid inequality decomposable index with the advantageous of being statistically testable [23]. The interpretation of the significant IO coefficient for the short term is again a bit tricky, thus if thanks to a public policy, the types mean decreases of an amount equal to the gross regional mean (supposing that this last is fixed), then for a $\Delta MLD = e = 2,71$, the growth rate will increase of about 11%. Moreover, all the check on the instruments reported in the last rows respects the requests for a right specification of the System-GMM model estimation.
In a more global perspective, we can interpret these results by supposing that inequality of opportunity is a way to measure social mobility in the short run, indeed a reduction in inequality of opportunity in the short term will bring to an hgher social mobility in the long run. This could be a possible reason for the finding of a significan effect of IO and IE in the short term and not in the mdeium and long term.

5.1 Robustness checks

In order to emphasis the results obtained and presented before, we conducted some robustness analysis on the estimation method and the inequality of opportunity choice. Indeed, as stated in the section on method, panel data growth model has been largely estimated with the Fixed Effect estimator, hence we estimated the same base form model using Fixed Effect. Table 3 and 4 report these robustness results, only for the short, medium and very long period for both inequality indeces chosen, the period selection was done to show the correspondence on the three main different growth rate term [24]. In particular, in Table 3, the estimation of the base form model as a Static Panel using Fixed Effect confirm the previous findings on the negative effect of inequality of opportunity and the positive one of ineuqality due to effort on economic growth in the short period, while the effect for both kind of inequalities on the medium and long term growth rate is null again. Another important robustness check consists in substituting inequality of opportunity based on 8-groups types with the 16-groups types [25] In this case, the base model is

[23] As shown in Arbia, Pace (2016).

[24] Clearly, we developed the same robustness analysis for each one of the five period growth rate and the results of the System-GMM are always confirmed.

[25] It is somehow possible to combine more than two circumstances together, but it goes in the direction of reducing the number of individuals in each group and, thus, it ends up in calculating inequality in income based on the differences between few individuals. The choice of the circumstances combined to compute the two IO indeces depended on previous ANOVA analysis (see Arbia and Pace, 2016).

specified in the form of a dynamic panel model, as before, and estimated again with System-GMM. Table 4 shows the results of these robustness check for both the inequality indeces used before, they validate previous outcome enhancing the only short term effect of IO and IE on GDP per capita growth. However, there is one interesting results concerning the effect of IE, measured with CV, on the very long run economic growth, which is negative and significant. Indeed, if we carefully look at the Table 4, when using Fixed Effect, the same inverse sign of the relation and a significance level of 0.1 for the two inequalities indeces measured through CV is found. Even if it would be a great findings, this is not confirmed when IO and IE are measured with MLD, thus further analysis should be developed to check for this peculiar and interesting result.

Table 1: Growth, IO and IE: Reduced form with System-GMM (CV)

	(1) Short Period	(2) Medium Period	(3) Medium-Long Period	(4) Long Period	(5) Very-Long Period
lagged income	-0.0316***	-0.0843**	-0.107***	-0.102***	-0.114***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
IO 8-groups	-0.0770*	-0.129	-0.107	0.139	0.127
	(0.016)	(0.221)	(0.647)	(0.341)	(0.158)
IE	0.0650**	-0.191	-0.174	-0.396	-0.370
	(0.009)	(0.233)	(0.384)	(0.501)	(0.208)
Constant	0.319***	0.875**	1.099***	1.065***	1.176***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Observations	157	138	119	100	80
Number of instruments	10	9	5	7	7
F (p-value)	0.000	0.000	0.000	0.000	0.000
Hansen test (p-value)	0.166	0.187	0.158	0.187	0.142
AR (1) (p-value)	0.0107	0.819	0.714	0.391	0.209
AR (2) (p-value)	0.650	0.150	0.532	0.751	0.627

p-values in parentheses

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

Table 2: Growth, IO and IE: Reduced form with System-GMM (MLD)

	(1) Short Period	(2) Medium Period	(3) Medium-Long Period	(4) Long Period	(5) Very-Long Period
lagged income	-0.0349***	-0.0721***	-0.0870**	-0.137***	-0.109***
(0.000)	(0.000)	(0.000)	(0.004)		(0.000)
IO 8-groups	-0.117*	0.0678	-0.311	-0.492	0.0257
	(0.018)	(0.601)	(0.684)	(0.552)	(0.902)
IE	0.176*	-0.310	0.595	0.678	-0.258
	(0.045)	(0.185)	(0.656)	(0.638)	(0.495)
Constant	0.353***	0.734***	0.877**	1.383***	1.101***
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)
Observations	157	138	119	100	80
Number of instruments	9	7	7	10	7
F(p-value)	0.000	0.000	0.000	0.000	0.000
Hansen (p-value)	0.204	0.213	0.205	0.141	0.196
AR(1) (p-value)	0.00709	0.278	0.326	0.822	0.142
AR (2) (p-value)	0.382	0.276	0.444	0.663	0.288

p-values in parentheses

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

Table 3: Growth, IO and IE: Base form model with Fixed Effect

	Short Period		Medium period		Very long term period	
	CV	MLD	CV	MLD	CV	MLD
lagged income	-0.0328***	-0.0338***	-0.0624***	-0.0625***	-0.121***	-0.121***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IO 8-groups	-0.0158**	-0.0288**	-0.00796	-0.00237	0.0106	0.0241
	(0.002)	(0.007)	(0.194)	(0.894)	(0.099)	(0.367)
IE	0.0209*	0.0418*	0.0114	0.00241	-0.0399	-0.0456
	(0.030)	(0.016)	(0.457)	(0.934)	(0.098)	(0.323)
Constant	0.332***	0.343***	0.632***	0.634***	1.223***	1.226***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	157	157	138	138	80	80
Adjusted R^2	0.669	0.660	0.817	0.815	0.966	0.964
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000

p-values in parentheses

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

Table 4: Growth, IO and IE: Base form using IO 16-groups (System-GMM)

	Short Period		Medium Period		Very Long period	
	CV	MLD	CV	MLD	CV	MLD
lagged income	-0.0324***	-0.0285***	-0.0767**	-0.0655**	-0.107***	-0.104***
	(0.000)	(0.000)	(0.016)	(0.001)	(0.000)	(0.001)
IO 16-groups	-0.041**	-0.0732**	-0.250	0.0900	0.038	0.00905
	(0.009)	(0.001)	(0.210)	(0.516)	(0.232)	(0.966)
IE	0.053**	0.122**	-0.310	-0.337	-0.281*	-0.221
	(0.017)	(0.001)	(0.160)	(0.167)	(0.046)	(0.560)
Constant	0.327***	0.289***	0.816**	0.668***	1.107***	1.060***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Observations	157	141	138	124	80	72
Number of instruments	10	13	9	7	7	7
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
Hansen test (p-value)	0.127	0.207	0.165	0.200	0.164	0.253
AR(1)	0.007	0.00503	0.308	0.392	0.051	0.127
AR(2)	0.769	0.291	0.124	0.289	0.456	0.275

p-values in parentheses

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

The small sample correction is applied and hence, we report the F test instead of Wald χ^2 test for overall fit.

Robust clustered standard errors.

6 Preliminary Conclusion

Despite the incredible quantity of economic literature addressing the relation between inequality and growth, the sign of this relationship is still an open question. This work tried to solve this question by decomposing inequality into two sources: inequality of opportunity and inequality due to return of personal effort. This decomposition should allow to better define this sign, expecting a negative sign of the effect of IO on growth and a positive sign when it turns to inequality due to effort.

Differently from the pioneer work of Marrero and Rodriguez (2013), we analyzed diffrent length of the growth rate periods for a total of sixteen years period in Italy and we choose to measure inequality of opportunity mainly using the coeffcent of variation.However,the results are checked for the most common Theil 0 index, or Mean Log Deviation. Using a panel data of Italian regions built on the SHIW database from the Bank of Italy and the regional GDP per capita from the Italian National Statistical Institute (ISTAT) for the period 1998-2014, we estimate a base and a complete form model, on the base of the inclusion in the growth regression equation of the typical set of control variables. We estimated these models applying two different estimators: System-GMM on the Dynamic panel model, in order to overcome endogeneity and reverse causality issues.

The base models' results show a negative and significant coeffiecient for IO and a positive a significant coefficient for inequality due to effort in the base form model considering as dependent variable the short run growth rate, considering a 2 years growth rate. These coefficents then turns to be no more significan when we look at longer period of economic growth, starting from a 4 years growth rate to a 10 years one. In other words, the main findings of this work state that in Italian regions there is a negative effect of inequality of opportunity only in the short run GDP per capita growth, while this effect disappear when we analyse longer period of economic growth. Instead, we decide to not report the complete models' results because adding the set of control variables does not improve the previous findings and all the controls variables are most of time not significant. Furthermore, these base models' outcomes are supported by the good results in the Hansen-J tests on the validity of instruments set and on the number of instruments used, which are always quite lower than the number of observation [26]. Furthermore, we reported a set of robustness analysis considering a different estimator, such as the Fixed Effect, quite common in panel growth models, and another combination of circumstances for the inequality of opportunity index, such father and mother's educational levels. These ro-

[26] Following, the rule of thumb on instruments number suggested by Roodman (2009)

bustness checks confirms in both cases the initial findings on the negative and significant effect of IO and a positive one for IE in the short run growth. Finally, there are some future possible and interesting developments of this analysis: the possibility to study the same relationship using Spatial Panel models, which have been spreadly used in the last fifteen years to estimate the typical Barro's conditional conrvegence growth model; the application of an ex-post approach to compute inequality of opportunity and the extension to the effect of IO on a more broad economic performance measure.

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