WPS6599

Policy Research Working Paper 6599

Economic Growth and Equality of Opportunity

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The World Bank
Development Economics Vice Presidency
Partnerships, Capacity Building Unit
September 2013

Abstract

The paper proposes an approach to understand the relationship between inequality and economic growth obtained by shifting the analysis from the space of final achievements to the space of opportunities. To this end, it introduces a formal framework based on the concept of the Opportunity Growth Incidence Curve. This framework can be used to evaluate the income dynamics of specific groups of the population and to infer the role of growth in the evolution of inequality of opportunity over time. The paper shows the relevance of the introduced framework by providing two empirical analyses, one for Italy and the other for Brazil. These analyses show the distributional impact of the recent growth experienced by Brazil and the recent crisis suffered by Italy from both the income inequality and opportunity inequality perspectives.

This paper is a product of the Partnerships, Capacity Building Unit, Development Economics Vice Presidency. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org.
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Economic Growth and Equality of Opportunity*

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September 9, 2013

JEL Classification codes: D63, E24, O15, O40.

Keywords: social development (SDV); income inequality; inequality of opportunity; economic growth.

*The authors are grateful to Francisco Ferreira, Dirk Van de Gaer, and to the editors and three anonymous referees for helpful comments on earlier drafts. The authors also wish to thank Jean-Yves Duclos, Michael Lokshin, and Laura Serlenga. Insightful comments were received at conferences or seminars at the World Bank ABCDE Conference, the University of Rome Tor Vergata, VI Academia Belgica-Francqui Foundation Rome Conference and GRASS workshop, and the College d'Etudes Mondiale, Paris. The authors also thank Francisco Ferreira and Maria Ana Lugo for kindly providing them with access to data.

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INTRODUCTION

In recent years, a central topic in the economic development literature has been the measurement of the distributive impact of growth (see Ferreira 2010). This literature has provided analytical tools to identify and quantify the effect of growth on distributional phenomena such as income poverty and income inequality. Indices for measuring the pro-poorness of growth have been proposed,[1] and the Growth Incidence Curve (GIC), measuring the quantile-specific rate of economic growth in a given period of time (Ravallion and Chen 2003; Son 2004), has become a standard tool in evaluating growth from a distributional viewpoint. The interplay among growth, inequality, and poverty reduction has also been investigated (Bourguignon 2004). All of these tools are now used extensively in the field of development economics to evaluate and compare different growth processes in terms of social desirability and social welfare (see Atkinson and Brandolini 2010; Datt and Ravallion 2011).

A common feature of this literature is the focus on individual achievements, such as (equivalent) income or consumption, as the proper "space" of distributional assessments.

In contrast, recent literature in the field of normative economics has argued that equity judgments should be based on opportunities rather than on observed outcomes (see Dworkin 1981a,b; Cohen 1989; Arneson 1989; Roemer 1998; Fleurbaey 2008). The equal-opportunity framework stresses the link between the opportunities available to an agent and the initial conditions that are inherited or beyond the control of this agent. Proponents of equality of opportunity (EOp) accept the inequality of outcomes that arises from individual choices and effort, but they do not accept the inequality of outcomes caused by circumstances beyond individual control. This literature has motivated a rapidly growing number of empirical applications interested in measuring the degree of inequality of opportunity (IOp) in a distribution and evaluating public policies in terms of equality of opportunity (see, among others, Aaberge et al. 2011; Bourguignon et al. 2007; Checchi and Peragine 2010; LeFranc et al. 2009; Roemer et al. 2003). Book-length collections of empirical analyses of EOp in developing countries can be found in World Bank (2006) and de Barros et al.

[1] See Essama-Nssah and Lambert (2009) for a comprehensive survey.

(2009).

The growing interest in EOp, in addition to the intrinsic normative justifications, is motivated by instrumental reasons: it has been convincingly argued (see World Bank 2006, among others) that the degree of opportunity inequality in an economy may be related to the potential for future growth. The idea is that when exogenous circumstances such as gender, race, or parental background play a strong role in determining individual income and occupation prospects, there is a suboptimal allocation of resources and lower potential for growth. The existence of *inequality traps*, which systematically exclude some groups of the population from participation in economic activity, is harmful to growth.

We share this view, and we believe that a better understanding of the relationship between inequality and growth can be obtained by shifting the analysis from the space of final achievements to the space of opportunities. If two growth processes have, say, the same impact in terms of poverty and inequality reduction, but in the first case, all members of a certain ethnic minority - or all people whose parents are illiterate - experience the lowest growth rate whereas poverty reduction in another case is uncorrelated with differences in race or family background, our current arsenal of measures does not readily allow us to distinguish them. Moreover, although a set of tools has been proposed to explain changes in outcome inequality as the result of differences in growth for individuals with different initial outcomes, to the best of our knowledge, the relationship between the change in IOp and growth has never been investigated.

Our aim is to address this measurement problem[2] by proposing a framework and a set of simple tools that can be used to investigate the distributional effects of growth from an opportunity egalitarian viewpoint. In particular, with reference to a given growth episode, we address the following questions: is growth reducing or increasing the degree of IOp? Are some socio-economic groups systematically excluded from growth?

To answer these questions, we depart from the concept of the GIC provided by Ravallion and Chen (2003) and further developed by Son (2004) and Essama-Nssah (2005), and we extend it to

[2]Hence, we investigate the relationship between growth and inequality of opportunity using a "micro approach"; an alternative "macro approach" would also be possible by investigating the relationship between growth and IOp from a cross-country or longitudinal perspective (see Marrero and Rodriguez 2010).

the space of opportunities. Hence, we introduce the concept of the Opportunity Growth Incidence Curve (OGIC), which is intended to capture the effect of growth from the EOp perspective. We distinguish between an *individual OGIC* and a *type OGIC*: the former plots the rate of growth of the (value of the) opportunity set given to individuals in the same position in the distributions of opportunities. The latter plots the rate of income growth for each sub-group of the population, where the sub-groups are defined in terms of initial exogenous circumstances. As shown in the paper, these tools capture distinct phenomena: the individual OGIC enables us to assess the pure distributional effect of growth in terms of increasing or reducing aggregate IOp; the type OGIC, in contrast, allows us to track the evolution of specific groups of the population in the growth process to detect the existence of possible inequality traps. For each of the two, we also provide summary measures of growth.

These tools can be used as complements to the standard analysis of the pro-poorness of growth and may provide interesting insights for the design of public policies. In particular, they may help target specific groups of the population and/or identify priorities in redistributive and social policies. Moreover, these tools can be used for the evaluation of public policies in terms of equality of opportunity. In fact, the two-period framework could easily be adapted for the comparison of pre- and post-public intervention distributions–for instance, if one is interested in evaluating the distributive impact of a certain fiscal reform in the space of opportunities.

In this paper, we adopt this theoretical framework to analyze the distributional impact of growth in two different countries, Italy and Brazil, in recent years. These two countries experienced very different patterns of growth in the last decade. On the one hand, Italy experienced a period of very limited growth. According to the Bank of Italy, in the 2002–04 and 2004–06 periods, the average household income increased by 2% and 2.6%, respectively, whereas the equivalent disposable income of Italian households was characterized by a long spell of negative growth during the recent economic crisis: it decreased by 2.6% in the 2006–10 period and by 0.6% between 2008 and 2010 (Banca d'Italia 2008, 2012). Inequality in the same period increased, but only slightly. On the other hand, Brazil faced a period of sustained growth (with an average 5% GDP yearly growth in the last decade), and this growth, as shown in the literature, was markedly progressive. In fact, the

Gini index for the entire distribution decreased during the period considered from 60.01 in 2001 to 54.7 in 2009 (see contributions by Ferreira et al. 2008, World Bank 2012).

Therefore, it is interesting to examine how the perspective of opportunity inequality can add elements of knowledge to the analysis of two markedly different distributional dynamics.

We use the Bank of Italy's "Survey on Household Income and Wealth" (SHIW) to assess the distributional impact of growth in Italy. In particular, we consider four of the most recent available waves to compare the 2002–06 growth episode with the 2006–10 episode. We use the "Pesquisa Nacional por Amostra de Domicílios" (PNAD), provided by the Istituto Brazilero de Geograpia e Estatistica, to analyze growth in Brazil, and we focus on the 2002–05 growth episode against the 2005–08 episode.

As far as Italy is concerned, when we focus on each single growth episode, some relevant insights arise. For instance, when the 2002–06 growth period is considered, the standard GIC shows a clear progressive pattern, but this pattern is reversed when the individual OGIC is adopted. When the 2006–10 period is considered, the regressive pattern shown by both the individual OGIC and the type OGIC demonstrates that the burden of the economic crisis has been borne by the weak groups in the population. Important information can be gained when we compare the two periods. The first period dominates the second according to the GIC and the individual OGIC, but this dominance does not hold when the type OGIC is adopted. We suggest that these results may be interpreted as the consequence of differences in per capita income growth between regions and some structural changes introduced in the Italian labor market in the recent past.

With respect to Brazil, it is interesting to note that although the growth experienced by the individual outcome in 2002–05 appears considerable for the whole distribution (with the exception of the top 15%), the growth experienced in terms of opportunities is less prominent. Indeed, most of the types suffer a reduction in the value of the opportunity during the growth process.[3] In contrast, the 2005–08 growth episode appears to be beneficial for the whole population regardless of the focus of the analysis (whether outcome or opportunity). Our analysis shows that the 2005–08 growth process is not only generally progressive but that it also leads to a reduction in the IOp (progressive

[3]To obtain this conflict between type OGIC and GIC, it is necessary that rich individuals experiencing losses are spread across the majority of socioeconomic groups.

individual OGIC). Furthermore, the initially disadvantaged groups of the population seem to benefit more from growth than those that were initially advantaged (decreasing type OGIC). When the two processes are compared, the dominance of the 2002–05 growth episode over the 2005–08 episode is evident for every perspective adopted.

Hence, we contribute to the literature by showing how it is possible to extend the existing frameworks proposed for the distributional assessment of growth to make them consistent with the EOp approach. The empirical analyses conducted in the paper show that the evaluation of growth may differ if the opportunity inequality perspective is adopted instead of the standard income inequality perspective.

The rest of this paper is organized as follows. Section I introduces the models used in the literature on the distributional effect of growth and in the EOp literature. It then proposes the opportunity growth incidence curves and summary indexes to assess the distributional impact of growth in terms of opportunity. Section II provides the empirical analyses based on Italian and Brazilian data. Section III concludes.

I. THE INCIDENCE OF GROWTH IN THE SPACE OF OPPORTUNITIES

A well-developed body of literature has proposed a number of tools that can be used to evaluate the distributive impact of growth[4] in the space of final achievements. After a brief survey of these tools, this section will propose a set of formal tools that can be used to evaluate the impact of growth in the space of opportunities.

Growth and Income Inequality

Let $F(y_t)$ be the cumulative distribution function of income at time t, with mean income $\mu(y_t)$, and let $y_t(p)$ be the quantile function of $F(y_t)$, representing the income corresponding to quantile

[4]In what follows, we focus, in particular, on those tools that will be extended to the EOp model in the next section. For a detailed survey of other existing measures of growth, see Essama-Nsaah and Lambert (2009) and Ferreira (2010).

p in $F(y_t)$. To evaluate the growth taking place from t to $t+1$, Ravallion and Chen (2003) define the Growth Incidence Curve (GIC) as follows[5]:

$$g(p) = \frac{y_{t+1}(p)}{y_t(p)} - 1 = \frac{L'_{t+1}(p)}{L'_t(p)}(\gamma + 1) - 1, \text{ for all } p \in [0,1], \tag{1}$$

where $L'(p)$ is the first derivative of the Lorenz curve at percentile p and $\gamma = \mu(y_{t+1})/\mu(y_t) - 1$ is the overall mean income growth rate. The GIC plots the percentile-specific rate of income growth in a given period of time. Clearly, $g(p) \geq 0$ ($g(p) < 0$) indicates positive (negative) growth at p. A downward-sloping GIC indicates that growth contributes to equalize the distribution of income (i.e., $g(p)$ decreases as p increases), whereas an upward-sloping GIC indicates non-equalizing growth (i.e., $g(p)$ increases as p increases). When the GIC is a horizontal line, inequality does not change over time, and the rate of growth experienced by each quantile is equal to the rate of growth in the overall mean income.

Growth incidence curves are used to detect how a given growth spell affects the different parts of the distribution. In addition, they are used as criteria to rank different growth episodes. Ravallion and Chen (2003) apply first-order dominance criteria based on the GIC: first-order dominance implies that the GIC of a growth spell is everywhere above the GIC of another growth spell. Son (2004) elaborates on this concept by proposing weaker second-order dominance conditions, requiring that the mean growth rate up to the p poorest percentile in a growth episode - or the "cumulative GIC" - be everywhere larger than in another. In this case, the cumulative GIC is given by $G(p) = \int_0^p g(q)\, y_t(q)\, dq / \int_0^p y_t(q)\, dq$ for all $p \in [0,1]$.

Building on the concept of the GIC, the literature has provided a variety of aggregate measures of growth. We recall, among these, the rate of pro-poor growth proposed[6] by Essama-Nssah (2005): $RPPG_{EN} = \int_0^1 v(p)\, g(p)\, dp$, where $v(p) > 0$, and $v'(p) \leq 0$ is a normalized social weight, decreasing with the rank in the income distribution. Hence, $RPPG_{EN}$ represents a rank-dependent aggregation of each point of the GIC and measures the overall extent of growth, giving more im-

[5]For a longitudinal perspective on the evaluation of growth, see Bourguignon (2011) and Jenkins and Van Kerm (2011).

[6]In the original paper, RPPG$_{EN}$ is applied to discrete distributions. Here, we use a continuous version of the same index to be consistent with our notation.

portance to the growth experienced by the income of the poorest individuals.[7] We enrich this framework by looking at the literature on EOp measurement.

From Income to Opportunity Inequality

In the EOp model (see Roemer 1998, Van de Gaer 1993, Peragine 2002), the individual income at a given time, $t \in \{1, ..., T\}$, y_t, is assumed to be a function of two sets of characteristics: the circumstances, $\mathbf{c}$, belonging to a finite set Ω and the level of effort, $e_t \in \Theta \subseteq \mathbb{R}_+$. The individual cannot be held responsible for $\mathbf{c}$, which is fixed over time; he is, instead, responsible for the effort e_t that he autonomously decides to exert in every period of time. Income is generated by a production function $g : \Omega \times \Theta \to \mathbb{R}_+$:

$$y_t = g(c, e_t). \tag{2}$$

This is a reduced form model in which circumstances and effort are assumed to be orthogonal, and the function g is assumed to be monotonic in both arguments. Although the monotonicity of g is a fairly reasonable assumption, the orthogonality assumption rests on the theoretical argument that it would be hardly sustainable to hold people accountable for factor e_t if it were dependent on exogenous circumstances.

In line with this model, a partition of the total population is now introduced. Each group in this partition is called a *type* and includes all individuals sharing the same circumstances. For example, if the only two circumstances were gender (male or female) and race (black or white), then there would be four types in the population: white men, black men, white women, and black women. Hence, considering n types, for all $i = 1, ..., n$, the outcome distribution of type i at time t is represented by a cdf $F_i(y_t)$, with population size m_{it} , population share q_{it}, and mean $\mu_i(y_t)$.

Given this analytical framework, the focus is on the income prospects of individuals of the same type, represented by the type-specific income distribution $F_i(y_t)$. This distribution is interpreted as the set of opportunities open to each individual in type i. In other words, the observable actual incomes of all individuals in a given type is used to proxy the unobservable *ex ante* opportunities

[7] Ravallion and Chen (2003) also propose the $RPPG_{RC} = \int_0^{H_t} g(p)\, dp / H_t$ where H_t is the initial poverty headcount ratio. $RPPG_{RC}$ measures the proportionate income change of the poorest individuals.

of all individuals in that type.

Let us underline here a dual interpretation of the types in the EOp model: on the one hand, the type is a component of a model that, starting from a multivariate distribution of income and circumstances, allows us to obtain a distribution of (the value of) opportunity sets enjoyed by each individual in the population. On the other hand, given the nature of the circumstances typically observed and used in empirical application, the partition in types may be of interest *per se:* they can often identify well-defined socio-economic groups that may deserve special attention by the policy makers. As we will see, this dual interpretation of the types will be exploited in the analysis of the impact of growth on EOp.

A specific version of the EOp model, which is called "utilitarian", further assumes that the value of the opportunity set $F_i(y_t)$ can be summarized by the mean $\mu_i(y_t)$. This is clearly a strong assumption because it implies neutrality with respect to the inequality within types. Assuming within-type neutrality, the next step consists of constructing an artificial distribution in which each individual income is substituted with the value of the opportunity set of that individual, that is, the mean income of the type to which the individual belongs. More formally, by ordering the types on the basis of their mean such that $\mu_1(y_t) \leq ... \leq \mu_j(y_t) \leq ... \leq \mu_n(y_t)$, the *smoothed distribution* corresponding to $F(y_t)$ is defined as $Y_t^s = \left(\mu_1^t, ..., \mu_j^t, ..., \mu_N^t\right)$. N is the total size of the population, and μ_j^t is the smoothed income, interpreted as the value of the opportunity set, of the individual ranked $\frac{j}{N}$ in Y_t^s. Hence, in this model, measuring opportunity inequality simply amounts to measuring inequality in the smoothed distribution Y_t^s.

Some authors have questioned this "utilitarian" approach (see Fleurbaey 2008 for a discussion of the issue). For instance, some authors argue that in addition to circumstances and effort, an additional factor, luck, plays a role in determining the individual outcome (see, inter alia, Van de Gaer 1993; LeFranc et al. 2008, 2009). Therefore, they argue, only part of within-type heterogeneity can be directly attributable to differences in effort. In particular, the unequal outcomes resulting from "brute" luck should be compensated for.[8] Furthermore, these authors argue, individuals may

[8]The literature distinguishes between *brute luck,* which is unrelated to individual choices and hence deserves compensation, and *option luck*, which is a risk that individuals deliberately assume and does not call for compensation. See Ramos and Van de Gaer (2012), Fleurbaey (2008), and LeFranc et al. (2009) for a detailed discussion of the different meanings of luck.

be risk averse; hence, the within-type inequality may have a cost for them. Following this line of reasoning, alternative models of EOp that consider within-type heterogeneity have been proposed in the literature.[9]

The model adopted in this paper, based on the assumption of within-type inequality neutrality and the use of the mean income conditional on each type as the value of the opportunity set, is well grounded on normative reasons and, in particular, is consistent with a strong version of the reward principle; see Fleurbaey (2008) and Fleurbaey and Peragine (2013) for a discussion. However, it is also motivated by practical reasons; accounting for within-type heterogeneity is very demanding in terms of data. It is often the case that the small size of the samples used makes it difficult to obtain easily comparable within-type distributions. This approach makes our empirical analysis fully consistent with most of the analyses performed in the existing literature.[10] Nevertheless, although our theoretical model is built on the assumption of within-type neutrality, we explore the issue of within-type heterogeneity in the empirical section by looking at growth within each type. It is shown that the dynamic of inequality within types can be a source of divergence between the standard approach based on income inequality and the opportunity egalitarian approach.

A final methodological consideration is in order here and concerns the issue of omitted circumstance variables. We use a pure deterministic model where, given a set of selected circumstances, any residual variation in individual income is attributed to personal effort. This amounts to saying that once the vector of circumstances has been defined, on the basis of normative grounds and observability constraints, all other factors are implicitly classified as within the sphere of individual responsibility. However, the vector $\mathbf{c}$ observed in any particular dataset is likely to be a sub-vector of the theoretical vector of all possible circumstances that determine a person's outcome. Whenever the dimension of the observed vector $\mathbf{c}$ is less than the dimension of the "true" vector, then we

[9] For example, LeFranc et al. (2008) and Peragine and Serlenga (2008) use stochastic dominance conditions to compare the different type distributions. Moreover, LeFranc et al. (2008) measure the opportunity set as (twice) the surface under the generalized Lorenz curve of the income distribution of the individual's type, that is $\mu_i (1 - G_i)$, where the type mean income μ_i and $(1 - G_i)$ represent, respectively, the return component and the risk component, with G_i denoting the Gini inequality index within type i. See also O'Neill et al. (2000) and Nilsson (2005) for empirical analyses that attempt to provide alternative evaluations of opportunity sets using parametric estimates.

[10] As discussed in Brunori et al. (2013), the (ex ante) utilitarian approach has been by now adopted by several authors to assess IOp in about 41 different countries, making an international comparison of inequality of opportunity estimates across the world possible.

obtain lower-bound estimators of true inequality of opportunity; that is, the inequality that would be captured by observing the full vector of circumstances. The implication is that the empirical estimates obtained using this model should be interpreted as lower-bound estimates of IOp.[11] Similarly, it is worth underlining that whenever circumstances are partially unobservable, the change in IOp due to growth should be interpreted as the change in the lower bound IOp conditioned to the observable circumstances. An evaluation of change in IOp based on a different set of variables could lead to different conclusions.

The Opportunity Growth Incidence Curve

In this section, we introduce the *two versions of* the Opportunity Growth Incidence Curve (OGIC), which can be considered complementary tools to the GIC, to improve the understanding of the distributional features of growth when an opportunity egalitarian perspective is adopted. *The two versions, the individual OGIC and the type OGIC,* capture two different intuitions about the relationship between growth and EOp. The first focuses on the impact of growth on the distribution of opportunities. The second focuses on the relationship between overall economic growth and type-specific growth.

Given an initial distribution of income Y_t and the corresponding smoothed distribution Y_t^s introduced in the previous section, the individual OGIC can simply be obtained by applying the GIC proposed by Ravallion and Chen (2003) to the smoothed distribution. Hence, the *individual OGIC* can be defined as follows:

$$g^o_{Y^s}\left(\frac{j}{N}\right) = \frac{\mu_j^{t+1}}{\mu_j^t} - 1, \forall j \in \{1, ..., N\}. \tag{3}$$

$g^o_{Y^s}\left(\frac{j}{N}\right)$ measures the proportionate change in the value of opportunities of the individuals ranked $\frac{j}{N}$ in the smoothed distributions. Obviously, $g^o_{Y^s}\left(\frac{j}{N}\right) \geq 0$ ($g^o_{Y^s}\left(\frac{j}{N}\right) < 0$) means that there has been positive (negative) growth in the value of the opportunity set given to the individuals ranked

[11] For a discussion of this issue with reference to a non deterministic, parametric model of EOp, see Ferreira and Gignoux (2011) and Luongo (2011).

$\frac{j}{N}$ respectively in Y_t^s and in[12] Y_{t+1}^s.

The individual OGIC provides information on the impact of growth on IOp. Consider the Lorenz curve of Y_t^s:

$$L_{Y_t^s}\left(\frac{j}{N}\right) = \frac{\sum_{k=1}^{j} \mu_k^t}{\sum_{k=1}^{N} \mu_k^t}, \forall k \in \{1, ..., N\}, \forall t \in \{1, ..., T\}. \tag{4}$$

The individual OGIC defined in eq. (3) can be decomposed in such a way that it becomes a function of the Lorenz curve defined in eq. (4), as follows:

$$g_{Y^s}^o\left(\frac{j}{N}\right) = \frac{\Delta L_{Y_{t+1}^s}\left(\frac{j}{N}\right)}{\Delta L_{Y_t^s}\left(\frac{j}{N}\right)}(\gamma + 1) - 1, \forall j \in \{1, ..., N\}, \tag{5}$$

where $\Delta L_{Y_t^s}\left(\frac{j}{N}\right) = \frac{\mu_j^t}{\mu(y_t)}$ is the first derivative of $L_{Y_t^s}\left(\frac{j}{N}\right)$ with respect to $\frac{j}{N}$, and $\gamma = \frac{\mu(y_{t+1})}{\mu(y_t)} - 1$ is the overall mean income growth rate.

Thus, when growth is proportional, it does not have any impact on the level of IOp: $\frac{\Delta L_{Y_{t+1}^s}\left(\frac{j}{N}\right)}{\Delta L_{Y_t^s}\left(\frac{i}{N}\right)} = 1$, and $g_{Y^s}^o\left(\frac{j}{N}\right)$ will just be an horizontal line, with $g_{Y^s}^o\left(\frac{j}{N}\right) = \gamma$ for all j. On the contrary, when growth is progressive (regressive) in terms of opportunity, growth acts by reducing (worsening) IOp: $\frac{\Delta L_{Y_{t+1}^s}\left(\frac{j}{N}\right)}{\Delta L_{Y_t^s}\left(\frac{i}{N}\right)} \neq 1$, and $g_{Y^s}^o\left(\frac{j}{N}\right)$ will be a decreasing (increasing) curve.

The main aspect that distinguishes the individual OGIC from the standard GIC is represented by the distributions used to construct that curve. This variation allows us to establish a link between growth and IOp. Note that the smoothed distribution at the base of the individual OGIC is the same used by Checchi and Peragine (2010) and Ferreira and Gignoux (2011) to measure ex ante IOp. Therefore, our evaluation of growth based on the individual OGIC is, by construction, consistent with the IOp index they proposed; other things being equal, an individual OGIC curve that is downward sloping in all of its domain implies a reduction in IOp.

However, the individual OGIC is unable to track the evolution of each type during the growth process. In the smoothed distribution, types are ranked according to the value of their opportunity set at each point in time. Thus, the shape of the curve depends not only on the change in the

[12] Note that, given the assumption of anonymity implicit in this framework, the individuals ranked $\frac{j}{N}$ in t can be different from those ranked $\frac{j}{N}$ in $t+1$.

type-specific mean income but also on the type-specific population share and the reranking of types taking place during the growth process. Now, although these features are desirable when one is interested in studying the evolution of IOp over time, the same characteristics make it impossible to detect the individual OGIC if there are groups of the population that are systematically excluded from growth. However, this can provide valuable information for analysts and policy makers. For example, consider a very small type that suffers a deterioration of its condition over time. This information could be irrelevant for the evolution of the overall opportunity inequality, but it would be extremely important for the design of tailored policy interventions toward that group.

To address this specific issue and to investigate the relationship between overall economic growth and type-specific growth, we introduce a second version of the OGIC, which we label the *type OGIC*.

Letting $Y_{\mu t} = (\mu_1(y_t), ..., \mu_n(y_t))$ be the distribution of type mean income at time t, where types are ordered increasingly according to their mean, i.e., $\mu_1(y_t) \leq ... \leq \mu_n(y_t)$, and $\tilde{Y}_{\mu t+1} = (\tilde{\mu}_1(y_{t+1}), ..., \tilde{\mu}_n(y_{t+1}))$is the distribution of type mean income at time $t+1$, where types are ordered according to their position at time[13] t, we define the *type OGIC* as follows:

$$\tilde{g}^o\left(\frac{i}{n}\right) = \frac{\tilde{\mu}_i(y_{t+1}) - \mu_i(y_t)}{\mu_i(y_t)}, \ \forall i \in \{1, ..., n\}. \tag{6}$$

The type OGIC plots, against each type, the variation of the opportunity set of that type. This can be interpreted as the rate of economic development of each social group in the population, where these groups are defined on the basis of initial circumstances. $\tilde{g}^o\left(\frac{i}{n}\right)$ is horizontal if each type benefits (loses) in the same measure from growth. It is negatively (positively) sloped if the initially disadvantaged types get higher (lower) benefit from growth than those initially advantaged.[14]

The type OGIC differs from the standard GIC in two aspects. The first is represented by the distribution used to plot the curve: the GIC is based on the income distribution, whereas the OGIC is based on the distribution of opportunity sets. The second is represented by the weakening of the anonymity assumption for types. Thus, the type OGIC, tracking the same type over time, provides

[13]Note that we track the same type but do not track the same individuals.

[14]Note that the type OGIC is a generalization of the idea underlying the first component of Roemer's (2011) index of development, that is, "how well the most disadvantaged type is doing".

information on the temporal evolution of the opportunity set.

The OGIC, in both the individual and the type versions, can be used to rank different growth episodes. Analogously with the literature on the standard GIC, we can apply first-order dominance criteria based on the OGIC.[15] First-order dominance implies that the OGIC of a growth spell is everywhere above that of another.

However, the two approaches (individual and type OGIC) are generally not equivalent, and they can generate a different ranking of growth processes. In fact, beyond their interpretation and the fact that they can be used to investigate different aspects of the relationship between economic growth and EOp, the differences between the individual and the type OGIC are mainly due to demographic and reranking issues. The following remark makes this point clear.

Remark 1. *Let Y_t^A and Y_t^B be two initial distributions of income, and let G^A and G^B be two different growth processes taking place, respectively, on Y_t^A and Y_t^B and generating, respectively, two final distributions of income, Y_{t+1}^A and Y_{t+1}^B. Moreover, let n_A and n_B be the number of types, respectively, in Y_t^A and Y_t^B and m_{Ai} and m_{Bi} be the number of individuals in each type $i = 1, ..., n$, respectively, in Y_t^A and Y_t^B. If (i) $n_{At} = n_{Bt}, \forall t = 1, ..., T$, (ii) $m_{Ait} = m_{Bit}$ $\forall i \in \{1, ..., n\}, \forall t = 1, ..., T$, (iii) no reranking of types, then $\tilde{g}^{Ao}\left(\frac{i}{n}\right) \succeq \tilde{g}^{Bo}\left(\frac{i}{n}\right)$ $\forall i \in \{1, ..., n\}$ if and only if $g_{Y^s}^{Ao}\left(\frac{j}{N}\right) \succeq g_{Y^s}^{Bo}\left(\frac{j}{N}\right)$ $\forall j \in \{1, ..., N\}$.*

Proof. See appendix.

This remark establishes that when the two distributions have, at each point in time (i), the same number of types and (ii) the same type-specific population size, and when (iii) types keep their relative position in the type mean income distribution over time, ranking income distributions according to the individual OGIC is equivalent to ranking income distributions according the type OGIC. Because conditions (i) and (ii) basically impose restrictions on the types' demography and condition (iii) imposes restrictions on the rank of the types, it is clear that possible differences in the ordering provided by the two OGICs are determined by variations in the type's population shares, between the two distributions and the two periods compared, and by the reranking of types over time.

[15] For a normative justification of these dominance conditions based on a rank-dependent social welfare function, see the working paper version of the paper: Peragine et al. (2011).

Although the conditions in Remark 1 may seem demanding, an interesting case in which they are met is the comparison of growth processes taking place on the same initial distribution. This is the standard case in the literature on microsimulation analyses[16] and, in general, in the case of an evaluation of policy interventions.

The Cumulative OGIC

So far, we have focused on first-order OGIC dominance, which is a strong condition that is rarely verified with real data. A weaker condition is obtained by second-order dominance. This order of dominance builds on the definition of the cumulative[17] OGIC.

To obtain the cumulative OGIC, one should look at the proportionate difference between the generalized Lorenz curves applied to the smoothed distribution at time t and $t+1$, which, after rearranging, gives the following expression for the individual version:

$$G^o_{Y^s}\left(\frac{j}{N}\right) = \frac{\sum\limits_{k=1}^{j} g^o_{Y^s}\left(\frac{k}{N}\right)\mu^t_k}{\sum\limits_{k=1}^{j}\mu^t_k} = \left(\frac{L_{Y^s_{t+1}}\left(\frac{j}{N}\right)}{L_{Y^s_t}\left(\frac{j}{N}\right)}(\gamma+1)\right) - 1, \forall j \in \{1, ..., N\}. \tag{7}$$

The cumulative individual OGIC plots the mean income growth rate up to the jth poorest individual in Y^s. It can be downward or upward sloping depending on the pattern of growth among smoothed incomes. Clearly, at $\frac{j}{N} = 1$, $G^o_{Y^s}\left(\frac{j}{N}\right)$ equals the overall mean income growth rate, γ.

The above decomposition allows to express the cumulative OGIC as depending on two components: the overall mean income change and the variation in the level of the IOp. In case of proportional growth, the Lorenz curves do not change, and the cumulative OGIC is equal to overall mean income growth rate.

[16] See, *inter alia*, Sutherland et al. (1999).

[17] Similar to the OGIC, the derivation of its cumulative version closely follows the methodology proposed by Son (2004), adequately adapted to be consistent with the EOp theory.

On the other hand, the cumulative type OGIC is defined as follows[18]:

$$\tilde{G}^{o}_{Y_{\mu}}\left(\frac{i}{n}\right)=\frac{\sum\limits_{j=1}^{i}\tilde{g}^{o}\left(\frac{j}{n}\right)\mu_{j}\left(y_{t}\right)}{\sum\limits_{j=1}^{i}\mu_{j}\left(y_{t}\right)},\forall i\in\{1,...,n\} \tag{8}$$

The cumulative type OGIC plots the mean income growth rate up to the type ranked i in the initial type mean distribution against each type in the population. It can be downward or upward sloping, depending on the pattern of growth among types. At $i=n$, $\tilde{G}^{o}_{Y_{\mu}}\left(\frac{i}{n}\right)$ equals the overall mean growth rate of Y_{μ}.

OGIC Indexes

To avoid inconclusive results because of the partiality of the dominance conditions based on the curves presented so far, we propose aggregate measures of growth that incorporate some basic EOp principles.

From the individual perspective, adopting a rank-dependent approach to the evaluation of growth, an aggregate measure of growth consistent with the EOp theory can be expressed as follows:[19]

$$G_{Y^{S}}=\frac{1}{N}\frac{\sum\limits_{j=1}^{N}v\left(\frac{j}{N}\right)g^{o}_{Y^{S}}\left(\frac{j}{N}\right)}{\sum\limits_{j=1}^{N}v\left(\frac{j}{N}\right)}. \tag{9}$$

Given the assumption of anonymity of the individual OGIC, the weight $v\left(\frac{j}{N}\right)$ depends on the relative position of individuals in the smoothed distribution, respectively, in t and $t+1$. Thus, the same weight is given to the value of the opportunity set of individuals ranked the same in the smoothed distribution of the two periods[20]. $v\left(\frac{j}{N}\right)$ represents the social evaluation of the growth in the opportunity enjoyed by individuals in the same position in t and $t+1$.

[18]Similar to the cumulative inividual OGIC, the cumulative type OGIC is obtained by rearranging the difference between the Generalized Lorenz curves applied to the type mean distributions $Y\mu_{t}$ and $\tilde{Y}_{\mu_{t+1}}$.

[19]The approach is close in spirit to Essama-Nssah (2005), reviewed in a previous section. For a normative justification of the rank-dependent approach to IOp analyses, see Peragine (2002), Aaberge et al. (2011), and Palmisano (2011)

[20]See endnote12.

Thus, eq. (9) represents a rank-dependent aggregation of the information provided by each single point of the individual OGIC. In particular, imposing *monotonicity*, $v\left(\frac{j}{N}\right) \geq 0$, $\forall j \in \{1, ..., N\}$, and *opportunity inequality aversion,* $v\left(\frac{j}{N}\right) \geq v\left(\frac{j+1}{N}\right)$, $\forall j \in \{1, ..., N-1\}$, we obtain a measure of opportunity-sensitive growth. This measure is increasing in each individual opportunity growth and is more sensitive to the growth in the opportunity experienced by those individuals with the lowest opportunities. Using the specification $v\left(\frac{j}{N}\right) = 2\left(1 - \frac{j}{N}\right)$, we obtain a Gini-type measure of opportunity-sensitive growth.

If, instead, one is interested in assessing the pure progressivity of growth without concern for the aggregate growth, then the following index can be adopted:

$$OG_{Y^S} = G_{Y^S} - \overline{G}_{Y^S}, \tag{10}$$

where $\overline{G}_{Y^S} = \frac{1}{N}\sum_{j=1}^{N} g^o_{Y^S}\left(\frac{j}{N}\right)$. $OG_{Y^S} = 0$ if growth is proportional; it is positive (negative) if growth is progressive (regressive).

An alternative expression can be obtained by using a weighted average of the growth experienced by each type, with weights incorporating a concern for the initial condition of the types:

$$G_{Y_\mu} = \frac{1}{n}\frac{\sum_{i=1}^{n} w\left(\frac{i}{n}\right)\tilde{g}^o\left(\frac{i}{n}\right)}{\sum_{i=1}^{n} w\left(\frac{i}{n}\right)}. \tag{11}$$

The function $w\left(\frac{i}{n}\right)$ is the social weight associated to type i and depends on the rank of the type in the initial distribution of income. As before, this index satisfies *monotonicity*: $w\left(\frac{i}{n}\right) \geq 0$, $i \in \{1, ..., n\}$ (that is, aggregate growth is not decreasing in each type growth) and *opportunity inequality aversion*: $w\left(\frac{i}{n}\right) \geq w\left(\frac{i+1}{n}\right)$, $i \in \{1, ..., n-1\}$ (that is, more weight is given to the income growth experienced by the most disadvantaged types).

Following Aaberge et al. (2011) and choosing $w\left(\frac{i}{n}\right) = 1 - \sum_{j=1}^{i} q_{jt}$, a Gini-type index of opportunity-sensitive growth results.

II. THE EMPIRICAL ANALYSES

This section investigates the distributional changes that occurred in Italy and Brazil in the last decade. These analyses pursue two additional aims: (i) assessing the main consequences of the actual economic crisis on the Italian distribution of income according to the EOp perspective and (ii) assessing the distributional implications of the most recent economic development experienced by Brazil in terms of EOp.

For both applications, we first provide an assessment of growth according to the equality of outcome perspective. We then move to the analysis of growth according to the EOp perspective.[21]

Opportunity and Growth in Italy: The Data

Italy is the first country considered in this section. This analysis is developed using the Bank of Italy's "Survey on Household Income and Wealth" (SHIW), a representative sample of the Italian resident population interviewed every two years. Three waves of the survey are considered: 2002, 2006, and 2010 (the latest available).

The unit of observation is the household, defined as all persons sharing the same dwelling. The individual outcome is, then, measured as the household equivalent income in 2010 euro.[22] Income includes all household earnings, transfers, pensions, and capital incomes, net taxes, and social security contributions. The richest and poorest 1% of the households in each wave are dropped to avoid the effect of outliers. To identify the types, the distribution is partitioned into 18 types using information about three characteristics of the head of the family: the highest educational

[21] We calculate confidence intervals for the difference between individual OGIC, type OGIC, and indexes in the two growth processes. The resampling procedure that we use is in line with the approach proposed by Lokshin (2008) for the GIC. We assume that the income distributions observed at the two points in time, y^t, y^{t+1}, are independent and identically distributed observations of the unknown probability distributions $F(y^t), F(y^{t+1})$. γ is the statistic of interest, and its standard error is $\sigma(F(y^t), F(y^{t+1})) = \sqrt{Var\hat{\gamma}(y^t, y^{t+1})}$. Our bootstrap estimate of the standard error is $\hat{\sigma} = \sigma\left(\hat{F}(y^t), \hat{F}(y^{t+1}\right)$, where $\hat{F}(y^t), \hat{F}(y^{t+1})$ are the empirical distributions observed. The 95% confidence interval is obtained by resampling $B = 1,000$ ordinary non parametric bootstrap replications of the two distributions y_t^*, y_{t+1}^*. The standard error of parameter $\hat{\gamma}$ is obtained using $\hat{\sigma}_B = \sqrt{\sum_{b=1}^{B}\{\hat{\gamma}^*(b) - \hat{\gamma}(.)\}^2/(B-1)}$, where $\hat{\gamma}(.) = \frac{\sum_{b=1}^{B}\gamma^*(b)}{B}$. We know that $\hat{\sigma}_B \to \hat{\sigma}$ when $B \to \infty$, and, under the assumption that γ is approximately normally distributed, we calculate confidence intervals: $\hat{\gamma} = \hat{\gamma} \pm z_{1-\alpha/2}\hat{\sigma}_B$. Our estimate quality relies on strong assumptions. However, as will be clear in the discussion of the results, dominances appear rather reliable for the illustrative purpose of the exercise.

[22] We use the OECD equivalence scale given by the square root of the household size.

attainment of her parents (three levels: up to elementary school, lower secondary, and higher), the highest occupational status of her parents (two levels: not in the labor force/blue collar and white collar) and the geographical area of birth (three areas: North, Centre, and South). Note, however, that those households for which the identification of the type is not possible because of missing information about one or more circumstances are excluded. The sample sizes of each wave considered are 6,428 in 2002, 6,354 in 2006, and 6,579 in 2010.

The list of types with their respective opportunity profiles[23] is reported in Table 1 for each wave. Types are ranked according to their average income. Rankings are clearly driven by the regional origin of the household head. In particular, although some reranking takes place for types of other regions, five of the six types from the South of Italy are the lowest-ranked at all times.

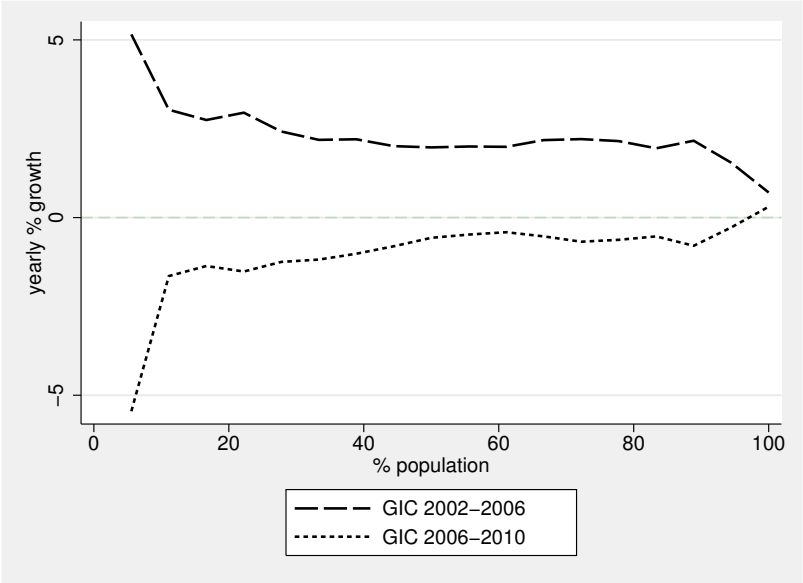
To analyze growth, we consider two four-year periods: 2002–06 and 2006–10. The exercise is appealing because it compares two periods during which Italy faced two different economic slowdowns. The former was characterized by the almost total absence of growth in 2002 and 2003. The latter, triggered by the 2008 financial crisis, was characterized by a deep fall in the GDP growth rate in 2008 and, after a slight respite between 2009 and 2010, is ongoing.

Opportunity and Growth in Italy: The Results

The GICs for the two periods are reported in Figure 1. These curves are obtained by partitioning the distribution into percentiles and by plotting against each percentile its specific growth rate, expressed in yearly percentage points.

[23] All standard errors are obtained using the sample weights according to the suggestion in Banca d'Italia (2012).

Figure 1: Italy 2002–2006–2010: Growth Incidence Curve



Source: Authors' calculation from SHIW (Bank of Italy)

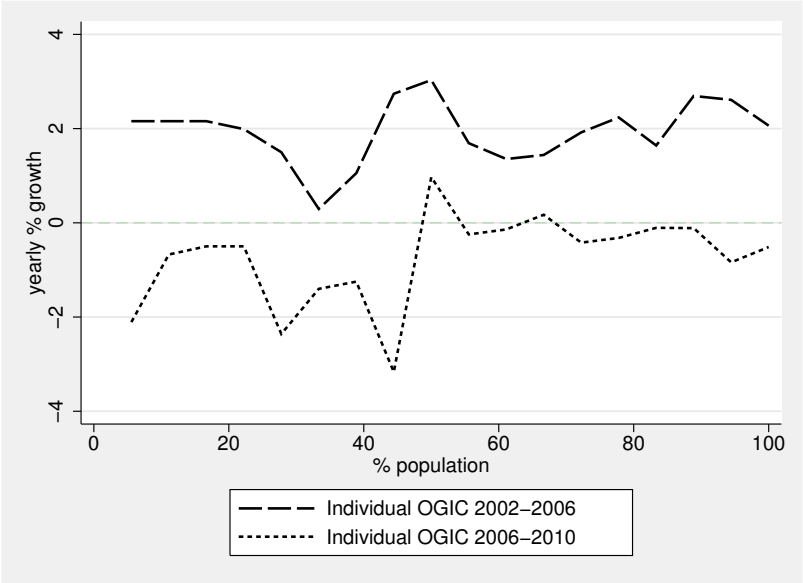
Table 1: Italy 2002-2006-2010: descriptive statistics and partition in types

Area	*Education*	*Occupation*	$rank^{02}$	$sample^{02}$	q_i^{02}	μ_i^{02}	$rank^{06}$	$sample^{06}$	q_i^{06}	μ_i^{06}	$rank^{10}$	$sample^{10}$	q_i^{10}	μ_i^{10}
South	No-edu/Elementary	Blue c./not in l.f.	1	1241	0.2174	14065.82	2	1273	0.2291	15279.71	3	1512	0.2385	14974.97
South	Lower secondary	Blue c./not in l.f.	2	110	0.0214	14386.26	4	124	0.0214	17783.99	1	198	0.0408	13593.33
South	Higher	Blue c./not in l.f.	3	137	0.0233	15673.90	1	104	0.0150	14800.64	2	126	0.0214	14749.59
South	No-edu/Elementary	White c.	4	682	0.1130	16949.30	3	604	0.1098	17149.07	4	594	0.0990	17021.24
South	Lower secondary	White c.	5	213	0.0324	17917.02	6	230	0.0421	20127.67	5	228	0.0372	17903.09
Centre	No-edu/Elementary	Blue c./not in l.f.	6	657	0.0822	19477.92	7	604	0.0755	21970.48	9	622	0.0729	23528.86
Centre	Lower secondary/Higher	Blue c./not in l.f.	7	51	0.0068	20106.76	12	49	0.0082	26077.04	13	60	0.0111	26010.30
North	Lower secondary	Blue c./not in l.f.	8	135	0.0237	20910.44	10	182	0.0301	24799.79	10	162	0.0294	23548.54
North	No-edu/Elementary	Blue c./not in l.f.	9	1137	0.1623	22095.60	8	1121	0.1591	23292.56	8	1022	0.1465	23063.41
Centre	No-edu/Elementary	White c.	10	316	0.0384	22579.76	9	287	0.0401	23873.59	14	260	0.0268	26348.91
South	Higher	White c.	11	270	0.0406	22828.57	13	239	0.0356	26290.72	11	295	0.0375	24052.45
North	No-edu/Elementary	White c.	12	594	0.0996	23922.43	11	543	0.0839	25240.80	12	474	0.0709	25209.78
Centre	Lower secondary	White c.	13	107	0.0187	24702.06	16	93	0.0128	30371.49	16	119	0.0202	28257.28
North	Higher	Blue c./not in l.f.	14	71	0.0094	25625.36	14	94	0.0140	27060.96	7	100	0.0160	22652.13
Centre	Higher	Blue c./not in l.f.	15	32	0.0039	25664.17	5	45	0.0059	20096.12	6	30	0.0034	21798.12
North	Lower secondary	White c.	16	253	0.0421	26890.26	15	250	0.0387	27748.28	15	247	0.0471	27114.15
North	Higher	White c.	17	296	0.0452	29955.46	17	363	0.0519	32143.62	18	343	0.0543	32106.09
Centre	Higher	White c.	18	126	0.0197	30786.71	18	149	0.0268	33395.35	17	187	0.0268	30670.72

Source: Authors' calculations on SHIW (Banca d'Italia).
Types are ranked in ascending order according to the average income at the beginning of each growth period.

Two features stand out. First, the GICs for the two periods lie in two different domains: positive for the first period and negative for the second period, with the exception of the last percentile. This feature is further captured by the mean income growth rate relative to each period, which is

Figure 2: Italy 2002–2006–2010: Individual Opportunity Growth Incidence Curve



Source: Authors' calculation from SHIW (Bank of Italy)

1.96% for 2002–06 and -0.66% for 2006–10. Second, the two growth processes show very different and symmetric patterns. The income dynamic is progressive between 2002 and 2006, but it becomes quite regressive between 2006 and 2010. Their symmetrical shape suggests that the two processes might have an equally opposed redistributional impact. The sign of the variation over time of their respective aggregate indexes of inequality confirms this supposition: income inequality decreases during the first period and increases during the second period[24] (see Table 2).

We proceed in our analysis with the assessment of the distributional effects of growth in the space of "opportunities". The individual OGIC for the periods considered are reported in Figure 2.

The individual OGIC of 2002–06 shows that growth acts by increasing the value of the opportunities for all quantiles of the smoothed distributions.[25] However, the growth rate is not stable across quantiles. In particular, the slightly increasing pattern of the individual OGIC over the

[24]The results for the second period are consistent with other empirical evidence on the effect of the last financial and economic crisis. See, for example, Jenkins et al. (2013).

[25]To make the individual OGIC and the type OGIC graphically comparable, we partitioned the smoothed distributions into 18 quantiles.

whole distribution demonstrates an opportunity-regressive impact of growth.

The peculiarities of this growth process are confirmed by the value of the synthetic measures of growth (see Table 2). The first index, measuring the extent of the opportunity-sensitive growth, is positive, as expected because the individual OGIC lies above 0. The second index, exclusively capturing the equal opportunity-enhancing effect of growth is negative, demonstrating that growth might have failed in its role as an instrument to reduce IOp. These results emphasize the relevance of extending standard analyses of growth to the space of "opportunity". For instance, the different shapes characterizing the GIC and the individual OGIC explain the diverging trends of inequality of outcome compared to the trend of IOp: inequality of outcome decreases, whereas IOp increases.

For the second period, the 2006–10 individual OGIC lies below zero for most of the distribution, suggesting that growth generates a reduction in the values of the opportunities enjoyed by individuals. In particular, it appears that the highest cost of the recession is borne by the individuals in the poorest quantiles of the smoothed distributions. Furthermore, similar to the previous period, the individual OGIC for 2006–10 shows an increasing trend, implying that growth might have acted by worsening opportunity inequality. The severe consequences of the recession are also captured by the two synthetic measures of growth, which both take a negative value.

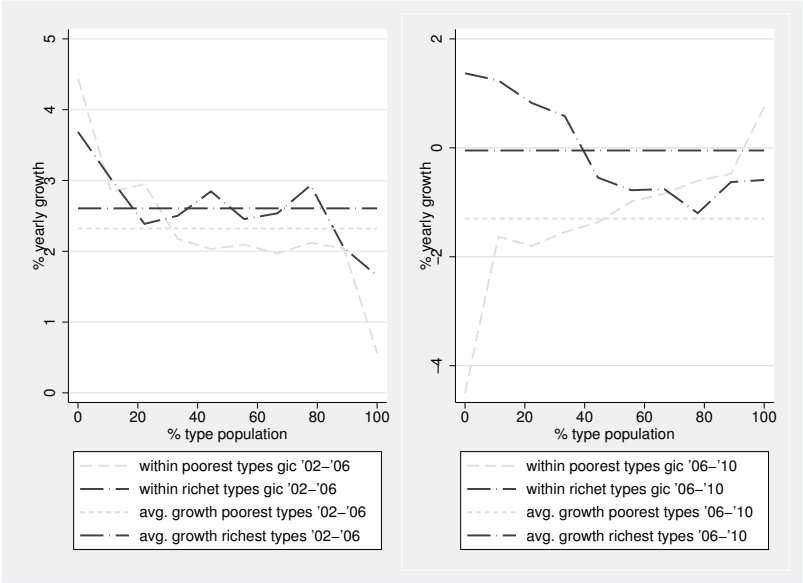
Turning now to the comparison of the two episodes, the results are clear. The individual OGIC of 2002–06 lies always above the individual OGIC of 2006–10, and the dominance is statistically significant at all points of the curves.[26].

Hence, the growth process in 2002–06 dominates the growth process in 2006–10 when both the extent of growth and progressivity components are considered. However, if we want to focus exclusively on their opportunity-redistributive impact (that is, on the extent to which these processes act by increasing or reducing IOp), the dominance is not clear because they both show a regressive pattern. It can be helpful, in this case, to compare the values of their respective opportunity-equalizing indexes, which show that 2002–06 is, with statistical significance, less regressive than 2006–10.

We can conclude that both of the income dynamics under scrutiny act by increasing IOp. However, whereas this trend is consistent with the change in outcome inequality in the second

[26]This dominance is confirmed by the comparison of their cumulative individual OGICs (figures and data available upon request)

Figure 3: Italy 2002–2006–2010: Within-Types Growth Incidence Curve



Source: Authors' calculation from SHIW (Bank of Italy)

period, in the first period, the variation of outcome inequality and the variation of opportunity inequality are in the opposite direction. This result reveals that a conflict may arise in the evaluation of growth when these two different perspectives are adopted for the assessment of the same growth process.

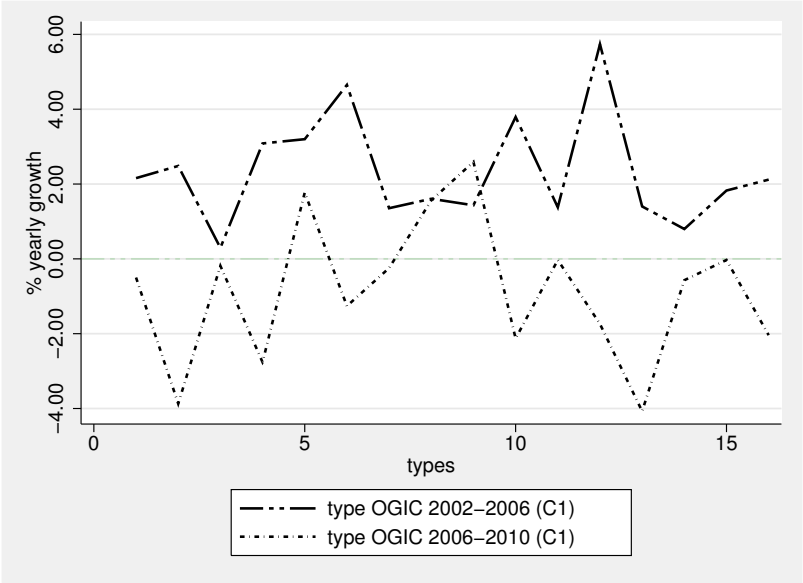
It is interesting to examine why such a conflict arises. If inequality between types increases while overall outcome inequality declines, the within-type share of total inequality must necessarily decline.[27] From this perspective, it may be helpful to look at Figure 3, which reports the GICs within types for the nine poorest and the nine richest types in each process. As expected, growth is progressive in both the poorest and richest types, with an higher average growth in the richest type.[28] This within-type dynamic explains the divergence between the income- and opportunity-based distributional assessments.

Turning the focus to the type-specific growth, the picture changes dramatically. The type

[27]Note that in these empirical applications, the inequality measure used is additively decomposable for within and between groups.

[28]We aggregate types to have sufficient observations in each quantile of the within-type GIC.

Figure 4: Italy 2002–2006–2010: Type Opportunity Growth Incidence Curve



Source: Authors' calculation from SHIW (Bank of Italy)

OGIC for 2002–06, reported in Figure 4, does not always lie above zero for the whole distribution; in particular, the types ranked 3 and 15 experience a loss. Most importantly, the shape of the type OGIC differs significantly from the shape of the individual OGIC. According to this perspective, growth can no longer be classified as regressive. For the Italian case, this is equivalent to saying that households whose heads were born in the South grow, on average, less than households with different geographical origins.[29]

[29] As reported in Table 1, the circumstance "head born in the South" appears in the five poorest types in 2002 and 2010 and in the four poorest types in 2006.

Table 2: Italy: 2002–2006–2010 dominance conditions

quantiles/types rank	GIC		type OGIC		cum. type OGIC		individual OGIC		cum. individual OGIC	
1	10.5691	***	2.6484	***	2.6180	***	3.9839	***	3.9744	***
2	4.6810	***	11.5799	***	7.3428	***	2.6985	***	3.3317	***
3	4.1114	***	-1.5181		4.3373	***	2.6562	***	3.1058	***
4	4.4694	***	0.5413		3.3125	***	2.5996	***	2.9757	***
5	3.6610	***	5.9404	***	3.9061	***	3.4201	***	3.0512	***
6	3.3625	***	1.3937		3.3944	***	1.6977	***	2.7881	***
7	3.2277	***	7.8721	**	4.0511	***	2.8942	***	2.8017	***
8	2.8174	***	6.0244	***	4.3561	***	5.4506	***	3.1885	***
9	2.5479	***	1.6141	**	3.9883	***	1.8843	***	2.9947	***
10	2.4750	***	-1.1908		3.3700	***	2.1158	***	2.8801	***
11	2.3956	***	5.7042	***	3.6263	***	1.5239	***	2.7224	***
12	2.7012	***	1.4691		3.3977	***	1.3037	***	2.5751	***
13	2.8946	***	7.2706	**	3.8027	***	2.6333	***	2.5808	***
14	2.7802	***	5.3008	**	3.9270	***	2.6164	***	2.5835	***
15	2.4743	***	-7.5717	**	3.0613	***	1.8334	***	2.5185	***
16	2.9552	***	1.4023		2.9156	***	2.6758	***	2.5292	***
17	1.8412	***	1.9006		2.8161	***	3.4850	***	2.6090	***
18	0.3548		4.2672	**	2.9169	***	2.5781	***	2.6063	***

Source: Authors' calculations on SHIW (Banca d'Italia).
*=90%, **=95%, ***=99% are significance levels for the difference between curves obtained from 1,000 bootstrap replications of the statistics.

Table 3: Italy: 2002–2006–2008 Complete rankings and inequality

	2002	2006	2010		
$\mu(y)$ eq.	20116.82 (4735.42)	21692.12 (5275.08)	21117.34 (5445.91)		
mld (all)	0.1422 (0.0026)	0.1301 (0.0021)	0.1437 (0.0027)		
mld (between)	0.0256 (0.0006)	0.0274 (0.0001)	0.0313 (0.0007)		
				'02-'06	'06-'10
G_{Ys}				1.821 (0.0145)	-0.9532 (0.0155)
OG_{Ys}				-0.0946 (0.0080)	-2.869 (0.0244)
$G_{Y\mu}$				-0.2340 (0.3707)	-1.2618 (0.0197)

Source: Authors' calculations on SHIW (Banca d'Italia).
mld = mean logarithmic deviation or generalized entropy index with parameter 0, G_{Ys} = EOp consistent aggregate measures of growth (eq. 9), OG_{Ys} = EOp consistent aggregate measures of growth progressivity (eq. 10), $G_{Y\mu}$ = Aggregate measure of between-type inequality of growth (eq. 11); 95% bootstrapped standard errors are reported in parenthesis.

The type population share and the anonymity implicit in the individual OGIC explain why a regressive individual OGIC is coupled with a non-regressive type OGIC. The smoothed distribution, constructed to evaluate distributional phenomena from an EOp perspective, ranks the types according to their average income at each point in time. Hence, growth is evaluated by comparing the average of different types whenever there is a reranking of types over time. In contrast, the type OGIC tracks types over time. Hence, types are ranked according to their average income

at the initial period of time. Whenever there is a reranking of types over time, some GIC-OGIC divergence may emerge.

For the second growth process, the 2006–10 type OGIC shows some similarity to the individual OGIC of the same period. In particular, most of the types experience a reduction in the value of their opportunity set, and this reduction is higher for the disadvantaged types. In sum, both the individual and the type OGIC confirm the negative impact of the crisis in terms of the extent of opportunity and the distribution of opportunity.

Interestingly, the only three types that demonstrate positive growth in this period share the circumstance of coming from central Italy. This finding is consistent with the reduction of between-region inequality in Italy due to their different rates of income decline during the recent economic recession. Whereas the North-South gap remained stable, the recession narrowed the gap between the North and the Centre. Among the reasons that may explain this trend is the negative performance of incomes in the North during the recent slowdown, which is generally attributed to the decline of the car industry and other manufacturing sectors, largely developed in Piedmont and Friuli-Venezia-Giulia (Istat, 2012). A severe crisis in the agricultural sector and a growing service industry (especially in the health care sector) may explain, at least in part, the diverging trend of the Southern and Central regions.

The comparison of the two growth episodes is less clear because they have a specular shape: types that benefit most from growth during the first process are those that lose more during the second. The two type OGICs intersect more than once; hence, it is not possible to establish a ranking between the two growth processes.[30] It is possible to obtain an unambiguous ordering by weakening the dominance conditions and comparing the cumulative type OGICs. We find that the first process dominates the second and that this dominance is always statistically significant. This result is also supported by the comparison of the synthetic measures of growth between the two periods. The index evaluating the extent of growth, with concern for the growth experienced by the initially disadvantaged types, is positive for the first period and negative for the second, and their difference is statistically significant (see Table 3).

[30] Although the first process is better than the second and the dominance is statistically significant for most of the types, for type 15, the second process is preferred to the first one with statistical significance.

It is not an easy task to understand the driving forces of these transformations. Given that, by definition, the rank of types and income are correlated, it is extremely difficult to disentangle the changes that may have affected, in opposite directions, the distribution of outcome and the distribution of opportunities.[31] However, the trend of the North-South divide and labor market reforms may be considered among the determinants of redistribution since 2002. First, the different reforms realized in the recent past to reduce the gap in the opportunities accessible to different individuals have not been able to fulfill the desired goal. In particular, as shown by Pavolini (2011), among others, different public services, particularly different measures and interventions of the welfare state, are still suffering from territorial divergences with consequences in terms of an increase in IOp over time, as witnessed by the lower growth rates experienced by the Southern types.

Second, the labor market reforms introduced in 1998 and extended in 2000 and 2003, which mainly aimed to reduce the labor protection legislation (particularly for temporary workers), have increased wage flexibility and job turnover, increasing the "instability" in the opportunity faced by individuals (Jappelli and Pistaferri, 2009). This instability may explain why growth appears more opportunity regressive in the second period, a period of crisis. Boeri and Garibaldi (2007) suggest that although job flexibility generates instability, it may provide more job opportunities during periods of positive growth. This is not the case during recessions because these workers, in all categories of atypical job contracts, are more likely to be fired and are often excluded from social security benefits. We suggest that such an effect has been stronger in the southern regions, thereby explaining the territorial gradient in the diverging trends of different types.

Opportunity and Growth in Brazil: The Data

Our theoretical framework may be of particular interest in the analysis of developing and emerging economies that experience lively growth processes with a dramatic impact on poverty and redistribution. For this reason, the second country considered in this paper is Brazil. To perform this analysis, the 2002, 2005, and 2008 waves of the Brazilian Pesquisa Nacional por Amostra de

[31] This may be a challenging question for future research.

Domicílios (PNAD), a representative survey of the Brazilian population, are used.

The unit of observation is the household, and the individual outcome is measured as the monthly household equivalent income, expressed in 2008 Brazilian real.[32] Household income is computed as the sum of all household members' individual incomes, including earnings from all jobs, and all other reported income, including income from assets, pensions, and transfers.

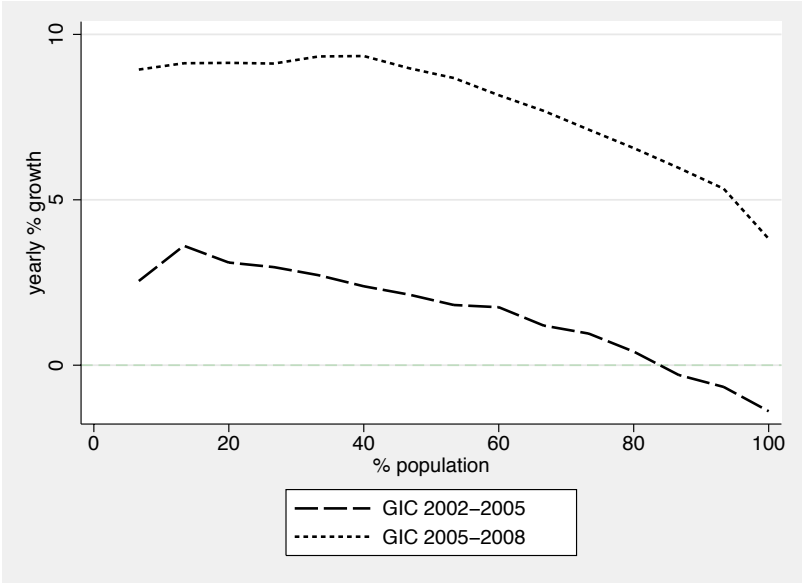
The population is partitioned into 15 types using the information on two circumstances: region of birth and race. Region of birth is coded in five categories (North, Northeast, Southeast, South, Center-west), and race is coded in three categories (white/east Asian, black/mixed race, and indigenous). Individuals who were born abroad and those classified as "other" for the variable race are excluded because the number of observations is too low to make appropriate inference. Hence, the sample sizes of each wave considered in this analysis are as follows: 366,388 households in 2002, 390,046 in 2005, and 372,581 in 2008.[33].

The full opportunity profiles for the three waves are reported in Table 4 in the appendix.[34] In this table, it is clear that race is the main determinant of the disparity in opportunities. Consistent with a number of contributions on socio-economic inequality in Brazil, racial relationships appear to be the major source of outcome and opportunity inequality in Brazil (Telles 2004; Bourguignon et al. 2007; among others).

To analyze the distributional impact of growth in Brazil according to the EOp perspective, two three-year period growth processes are considered: 2002–05 and 2005–08. The choice of these particular periods is driven by the observation that during these years, Brazil experienced quite diverging economic trends. The former was a period of economic slowdown; the PNAD data record an increase in the overall mean income of only 0.26%. In contrast, the latter period was a period of pronounced growth, with an overall mean income growth of approximately 6.36%.

[32]Equivalent income is obtained by dividing total income by the square root of the household size.
[33]Again, the richest and poorest 1% of the household distribution in each wave are dropped.
[34]All estimates are based on the sample weights according to Silva et al. (2002).

Figure 5: Brazil: 2002–2005–2008 Growth Incidence Curve



Authors' calculation from PNAD (Instituto Brasileiro de Geografia e Estatística)

Opportunity and Growth in Brazil: The Results

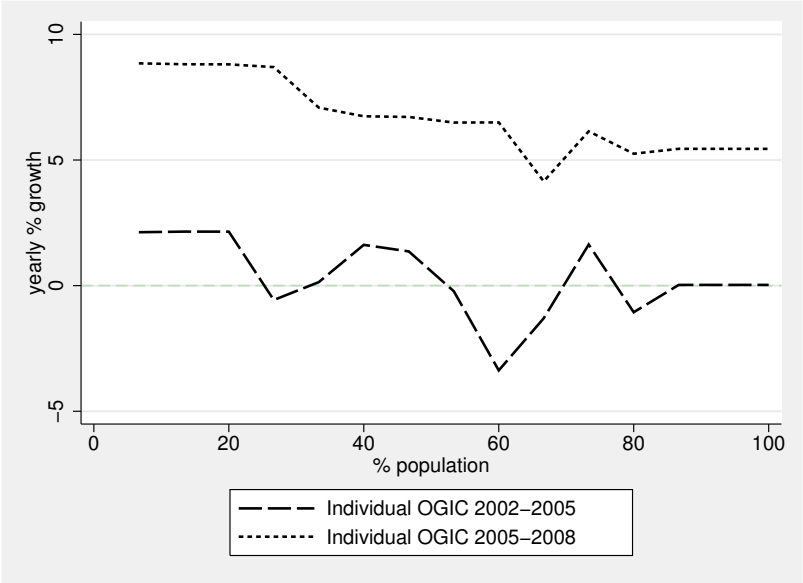
Table 4: Brazil: 2002–2005–2008 descriptive statistics and partition in types

Region	*Race*	$rank^{02}$	$sample^{02}$	q_i^{02}	μ_i^{02}	$rank^{05}$	$sample^{05}$	q_i^{05}	μ_i^{05}	$rank^{08}$	$sample^{08}$	q_i^{08}	μ_i^{08}
Northeast	black-mixed	1	91118	0.2227	516.73	2	97846	0.2229	550.09	1	93547	0.2272	695.64
Northeast	indigenous	2	299	0.0007	576.47	6	309	0.0006	702.42	2	398	0.0010	715.49
North	black-mixed	3	25874	0.0381	631.47	3	35053	0.0542	604.64	3	33200	0.0556	769.59
South	black-mixed	4	10121	0.0270	683.06	7	11549	0.0292	748.19	6	12006	0.0319	937.98
Southeast	black-mixed	5	42007	0.1448	768.61	9	48800	0.1606	806.90	8	47725	0.1633	969.41
Center-west	black-mixed	6	16052	0.0300	777.33	8	17223	0.0306	799.66	10	17472	0.0321	1006.28
Center-west	indigenous	7	154	0.0003	806.05	1	136	0.0002	444.41	4	175	0.0003	859.83
Northeast	white-east asian	8	42720	0.1094	821.07	10	42911	0.1017	823.36	9	40880	0.1018	975.68
South	indigenous	9	119	0.0002	866.19	5	128	0.0003	628.87	7	183	0.0005	940.65
North	indigenous	10	98	0.0002	879.60	4	206	0.0002	622.59	5	236	0.0003	861.65
North	white-east asian	11	9916	0.0146	970.79	11	11088	0.0167	903.47	11	9942	0.0164	1102.10
Southeast	indigenous	12	117	0.0004	1082.98	12	105	0.0004	1011.33	12	153	0.0005	1192.87
South	white-east asian	13	49021	0.1311	1169.46	14	49133	0.1244	1229.42	14	44957	0.1198	1456.16
Center-west	white-east asian	14	12717	0.0244	1179.96	13	13147	0.0238	1176.54	13	12642	0.0236	1433.06
Southeast	white-east asian	15	66055	0.2561	1385.93	15	62412	0.2341	1387.16	15	59065	0.2255	1613.84

Source: Authors' calculations on PNAD (Instituto Brasileiro de Geografia e Estatística).
Types are ranked in ascending order according to the average income at the beginning of each growth period.

As in the first illustration, we begin this analysis with the assessment of growth according to the equality of outcome perspective. The GICs for the two periods considered are reported in Figure 5.

Figure 6: Brazil: 2002–2005–2008 Individual Opportunity Growth Incidence Curve



Authors' calculation from PNAD (Instituto Brasileiro de Geografia e Estatística)

Although both curves lie almost always above zero, growth is outstanding in the second period. In fact, it is possible to unambiguously order the two growth processes because the difference between the GIC coordinates in the two periods is always statistically significant (see Table 5). The redistributive impact of the two processes is very similar. The respective curves are both neatly decreasing, demonstrating that growth acts by alleviating outcome inequality.

We now proceed in the evaluation of the Brazilian growth by endorsing an opportunity-egalitarian perspective. The individual OGICs for the two growth episodes are reported in Figure 6.

One feature stands out. For the 2002–05 growth episode, although the GIC lies almost always above zero, the individual OGIC is positive only for half of the smoothed distribution. This conflict indicates that although the majority of households experience positive growth, the extent of the losses borne by the richest 15% is substantial in determining the change in the value of the opportunity sets. This effect is plausible whenever the richest households are not concentrated only in the richest type; that is, income quantiles and types are not perfectly correlated, as for the case of Brazil during 2002–05.

This does not happen during 2005–08, when the individual OGIC lies above zero, implying that growth plays a positive role in determining an improvement of the opportunities faced by the entire population. As a result, the second process also dominates the first when an opportunity-egalitarian perspective is adopted, and the dominance is statistically significant (see Table 5). The sign of the dominance is also confirmed by the plot of the cumulative individual OGIC. The progressivity of the two growth episodes is clarified by the decreasing shape of the two curves. These results are further supported by the estimation of the synthetic measures of growth. The index capturing the opportunity-sensitive extent of growth is positive for both the 2002–05 and 2005–08 processes, but it is higher for 2005–08. In the same way, the value of the index capturing the progressivity of growth, in terms of equality of opportunity, is positive for both processes. This means that during the two periods, growth acts by alleviating the disparities in opportunities, but this effect is stronger for the 2005–08 process (see Table 6).

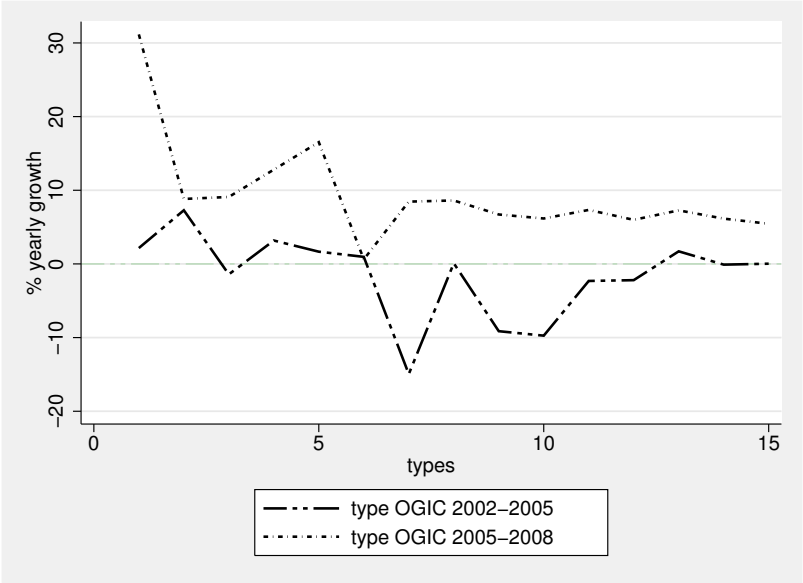
Similar features characterize the assessment of growth when the focus is on the type-specific growth. Figure 7 reports the type OGICs for the 2002–05 and 2005–08 periods.

Regarding the first period, it is possible to observe that, consistent with the individual OGIC, most of the types experience a reduction in the value of their opportunity set. These types particularly include households with an indigenous head.[35] However, the curve does not appear to show a clear pattern; it is progressive for the lowest part of the distribution up to type 7 and then takes a clear regressive shape. The unstable trend is confirmed by the negative value of the opportunity-sensitive growth measure. It can thus be inferred that the negative growth experienced by certain types more than compensates for the positive growth experienced by the poorest types.

For the second period, the positive distributional implications of the growth process are again confirmed by the type-specific OGIC. All types experience an increase in the values of their opportunity set with a quite progressive trend. These results are supported by the positive value of the index measuring the extent of opportunity-sensitive growth (see Table 6). Thus, we can conclude that this growth process is beneficial in terms of opportunity when both size and distributional aspects are considered.

[35] However, recall that this curve does not take into account the relative size of types. In this specific case, in fact, the types that experience an increase in the value of their opportunity set represent over 90% of the population.

Figure 7: Brazil: 2002–2005–2008 Type Opportunity Growth Incidence Curve

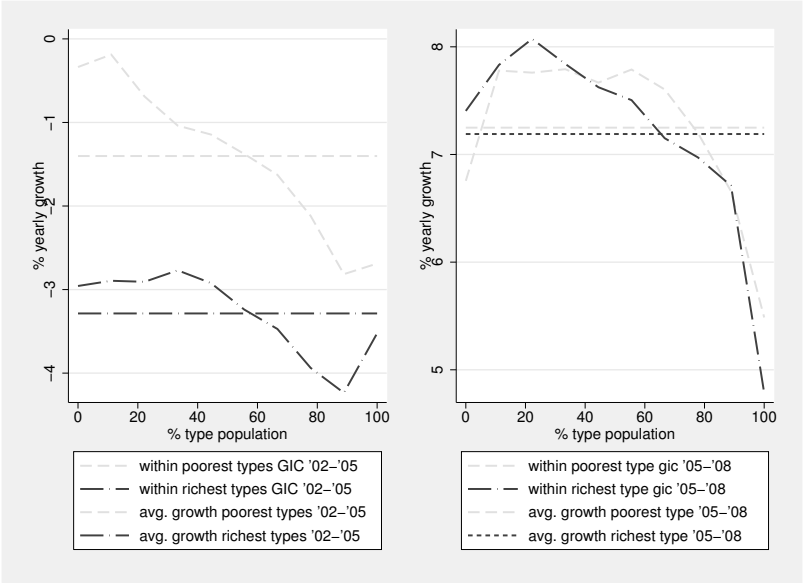


Authors' calculation from PNAD (Instituto Brasileiro de Geografia e Estatística)

As is reasonable to expect, the comparison of the two processes highlights an unambiguous dominance of the second period growth over the first. The difference in the OGIC coordinates is statistically significant for almost all types, as shown in Table 5 in the appendix. For robustness purposes, we also test the difference of the respective cumulative type OGICs coordinates, which is clearly statistically significant for all types, and the difference, which is again significant, of their aggregate index of growth (see Table 6).

Finally, Figure 8, reporting the within-type GICs, explains how the progressive growth of Brazil between 2002 and 2005 is the joint effect of a reduction of between- and-within type inequality. The four within-type GICs are downward sloping, and the average growth rate in the poorest seven types is higher in both cases than the same rate in the eight richest types.

Figure 8: Brazil: 2002–2005–2008 Within-Types Growth Incidence Curve



Authors' calculation from PNAD (Instituto Brasileiro de Geografia e Estatística)

Table 5: Brazil: 2002–2005–2008 dominance conditions

quantiles/types rank	GIC		type OGIC		cum. type OGIC		individual OGIC		cum. individual OGIC	
1	5.9040	***	29.4150	***	29.4150	***	9.7517	***	9.7517	***
2	6.3070	***	0.9296		13.9522	***	5.3240	***	7.3602	***
3	6.5042	***	10.7992	***	12.6996	***	5.4259	***	6.6773	***
4	6.6490	***	8.7660	**	11.5471	***	6.5167	***	6.6375	***
5	6.7888	***	18.3645	***	12.9442	***	8.3194	***	7.0596	***
6	6.9937	***	-1.1505		10.0393	***	6.6153	***	6.9932	***
7	6.6517	***	23.7151	***	12.5330	***	6.6142	***	6.9419	***
8	6.6463	***	9.3222	***	12.0397	***	6.6130	***	6.9018	***
9	6.6600	***	16.2690	***	12.5658	***	6.6119	***	6.8700	***
10	6.3123	***	15.8542	***	12.9423	***	6.8518	***	6.8707	***
11	6.2099	***	8.8956	***	12.4650	***	6.6791	***	6.8519	***
12	6.0596	***	5.1427		11.5463	***	5.3881	***	6.7002	***
13	6.0661	***	5.6651	***	10.8799	***	5.3695	***	6.5675	***
14	6.2796	***	6.6171	***	10.4224	***	5.2087	***	6.4396	***
15	5.7342	***	5.4429	***	9.8781	***	5.2070	***	6.3336	***

Source: Authors' calculations on PNAD (Instituto Brasileiro de Geografia e Estatística).
*=90%, **=95%, ***=99% are significance levels for the difference between curves obtained by 1,000 bootstrap replications of the statistics.

Table 6: Brazil: 2002–2005–2008 complete rankings and inequality

	2002	2005	2008		
N	366,388	390,046	372,581		
$\mu(y)$ eq.	934.66 (333.55)	937.057 (324.13)	1113.48 (355.26)		
mld (all)	0.4738 (0.0014)	0.4327 (0.00131)	0.3922 (0.0010)		
mld (between)	0 0.0672 (0.0004)	0.0618 (0.0004)	0.0512 (0.0003)		
				'02-'05	'05-'08
avg. growth.				0.26%	6.36%
G_{Ys}				0.7547 (0.0910)	7.4937 (0.1169)
OG_{Ys}				0.4384 (0.0559)	0.7891 (0.0566)
G_Y				-1.0213 (0.6120)	9.5304 (1.0758)

Source: Authors' calculations on PNAD (Instituto Brasileiro de Geografia e Estatística).
mld = mean logarithmic deviation or generalized entropy index with parameter 0, G_{Ys} = EOp consistent aggregate measures of growth (eq. 9), OG_{Ys} = EOp consistent aggregate measures of growth progressivity (eq. 10), $G_{Y\mu}$ = Aggregate measure of between type inequality of growth (eq. 11), 95% bootstrapped standard errors are reported in parenthesis.

This considerable change in the overall inequality for the time span considered is well known in the literature. Ferreira et al. (2008) suggest a number of determinants of this change: the decline in inequality between educational subgroups, a reduction in the urban-rural gap, a reduction of inequalities between racial groups, a dramatic increase in the minimum wage, and improvements in social protection programs. Clearly, these variables have a direct impact on inequality of outcome and on the distribution of opportunities. Moreover, our analysis shows that these growth processes have been beneficial in terms of improving opportunities and that Brazil has experienced an impressive increase in the degree of EOp, particularly during the 2002–05 period. Our conclusions complement the findings of Molinas et al. (2011), who look at the development of IOp in Brazil with a specific focus on the opportunities of children.

III. CONCLUSIONS

In this paper, we have argued that a better understanding of the relationship between inequality and growth can be obtained by shifting the analysis from final achievements to opportunities.

To this end, we have introduced the individual OGIC and the type OGIC. The former can be used to infer the role of growth in the evolution of IOp over time. The latter can be used to evaluate

the income dynamics of specific groups of the population. For both versions of the OGIC, we have also proposed aggregate indices that can be used to measure the distributional impact of growth from the EOp perspective when it is not possible to rank growth episodes through the use of curves. We have shown that possible divergences in the rankings obtained through the use of the individual OGIC and the type OGIC are mostly due to demographic issues.

We have provided two empirical applications, for Italy and for Brazil. These analyses show that the measurement framework we have introduced can be used to complement existing tools for the evaluation of the distributional implications of growth. Moreover, our tools appear to be potentially relevant for the understanding of the joint dynamic of income inequality and inequality of opportunity. Another field of application of our framework is the analysis of tax-benefit systems of reforms. Typically, the distributional aspects of these reforms are analyzed through microsimulation techniques and are evaluated in terms of income inequality reduction. Comparing reforms with the help of the tools developed in this paper, which allow the evaluation of the IOp reduction, seems a promising path for future research.

APPENDIX

Proof of Remark 1. *We start by showing the sufficiency that the individual OGIC implies the type OGIC dominance. Let the two type OGICs be defined as follows:* $\tilde{g}^{Ao}\left(\frac{i}{n_A}\right) = \frac{\tilde{\mu}_i^A(y_{t+1})}{\mu_i^A(y_t)} - 1$ $\forall i \in \{1, ..., n_A\}$ *and* $\tilde{g}^{Bo}\left(\frac{i}{n_B}\right) = \frac{\tilde{\mu}_i^B(y_{t+1})}{\mu_i^B(y_t)} - 1$ $\forall i \in \{1, ..., n_B\}$. *If* (i) *holds and there is type OGIC dominance between the two growth processes* G^A *and* G^B*, we will have the following:*

$$\tilde{g}^{Ao}\left(\frac{i}{n}\right) \geq \tilde{g}^{Bo}\left(\frac{i}{n}\right) \iff \frac{\tilde{\mu}_i^A(y_{t+1})}{\mu_i^A(y_t)} \geq \frac{\tilde{\mu}_i^B(y_{t+1})}{\mu_i^B(y_t)}, \forall i \in \{1, ..., n\}. \tag{12}$$

If (iii) *holds, the type OGIC dominance of the growth processes* G^A *over* G^B *will be*

$$\tilde{g}^{Ao}\left(\frac{i}{n}\right) \geq \tilde{g}^{Bo}\left(\frac{i}{n}\right) \iff \frac{\mu_i^A(y_{t+1})}{\mu_i^A(y_t)} \geq \frac{\mu_i^B(y_{t+1})}{\mu_i^B(y_t)}, \forall i \in \{1, ..., n\}, \tag{13}$$

where $\mu_i(y_{t+1})$ *is the mean income of the type ranked* i *in the final distribution of the types' mean income, which, under* (iii)*, corresponds to* $\tilde{\mu}_i(y_{t+1})$*. Now, let the two individual OGICs be defined as follows:* $g_{Y^s}^{Ao}\left(\frac{j}{N_A}\right) = \frac{\mu_j^{At+1}}{\mu_j^{At}} - 1$ $\forall j = 1, ..., N_A$ *and* $g_{Y^s}^{Bo}\left(\frac{j}{N_B}\right) = \frac{\mu_j^{Bt+1}}{\mu_j^{Bt}} - 1$ $\forall j = 1, ..., N_B$*.* (i) *and* (ii) *implies* $N_A = N_B$*. Hence, if there is individual OGIC dominance of the growth process* G^A *over* G^B*, we will have the following:*

$$g_{Y^s}^{Ao}\left(\frac{j}{N}\right) \geq g_{Y^s}^{Bo}\left(\frac{j}{N}\right) \iff \frac{\mu_j^{At+1}}{\mu_j^{At}} \geq \frac{\mu_j^{Bt+1}}{\mu_j^{Bt}} \forall j \in \{1, ..., N\}. \tag{14}$$

Now, for the individuals j *belonging to type* i*, given* (ii) *and because we use smoothed income, we can write eq. (13) in terms of (14):*

$$\tilde{g}^{Ao}\left(\frac{i}{n}\right) \geq \tilde{g}^{Bo}\left(\frac{i}{n}\right) \iff \sum_{j=1}^{m_{it+1}} \frac{\mu_j^{At+1}}{\mu_j^{At}} \geq \sum_{j=1}^{m_{it+1}} \frac{\mu_j^{Bt+1}}{\mu_j^{Bt}} \forall i \in \{1, ..., n\}. \tag{15}$$

If eq. (14) holds, than it must be the case that the dominance in their type aggregation holds, providing the dominance in eq. (15). Hence we have proved the sufficiency of the remark.

We now prove the necessary condition by contradiction.

Suppose that eq. (15) holds. Now, pick a type $i \in \{1, ..., n\}$*. Assume that for that type*

$\exists k \{1, ..., m_i\}$ *such that* $\frac{\mu_k^{At+1}}{\mu_k^{At}} < \frac{\mu_k^{Bt+1}}{\mu_k^{Bt}}$, *then because all individuals in the same type are given the same mean income,* $\sum_{j=1}^{m_i} \frac{\mu_j^{At+1}}{\mu_j^{At}} - \sum_{j=1}^{m_i} \frac{\mu_j^{Bt+1}}{\mu_j^{Bt}} < 0$ *for a given type* i*, contradicting eq. (15).* **QED**

Notes

[1]See Essama-Nssah and Lambert (2009) for a comprehensive survey.

[2]Hence, we investigate the relationship between growth and inequality of opportunity using a "micro approach"; an alternative "macro approach" would also be possible by investigating the relationship between growth and IOp from a cross-country or longitudinal perspective (see Marrero and Rodriguez 2010).

[3]To obtain this conflict between type OGIC and GIC, it is necessary that rich individuals experiencing losses are spread across the majority of socioeconomic groups.

[4]In what follows, we focus, in particular, on those tools that will be extended to the EOp model in the next section. For a detailed survey of other existing measures of growth, see Essama-Nsaah and Lambert (2009) and Ferreira (2010).

[5]For a longitudinal perspective on the evaluation of growth, see Bourguignon (2011) and Jenkins and Van Kerm (2011).

[6]In the original paper, RPPG_{EN} is applied to discrete distributions. Here, we use a continuous version of the same index to be consistent with our notation.

[7]Ravallion and Chen (2003) also propose the $RPPG_{RC} = \int_0^{H_t} g(p)\, dp / H_t$ where H_t is the initial poverty headcount ratio. $RPPG_{RC}$ measures the proportionate income change of the poorest individuals.

[8]The literature distinguishes between *brute luck*, which is unrelated to individual choices and hence deserves compensation, and *option luck*, which is a risk that individuals deliberately assume and does not call for compensation. See Ramos and Van de Gaer (2012), Fleurbaey (2008), and LeFranc et al. (2009) for a detailed discussion of the different meanings of luck.

[9]For example, LeFranc et al. (2008) and Peragine and Serlenga (2008) use stochastic dominance conditions to compare the different type distributions. Moreover, LeFranc et al. (2008) measure the opportunity set as (twice) the surface under the generalized Lorenz curve of the income distribution of the individual's type, that is $\mu_i (1 - G_i)$, where the type mean income μ_i and $(1 - G_i)$ represent, respectively, the return component and the risk component, with G_i denoting the Gini inequality

index within type i. See also O'Neill et al. (2000) and Nilsson (2005) for empirical analyses that attempt to provide alternative evaluations of opportunity sets using parametric estimates.

[10]As discussed in Brunori et al. (2013), the (ex ante) utilitarian approach has been by now adopted by several authors to assess IOp in about 41 different countries, making an international comparison of inequality of opportunity estimates across the world possible.

[11]For a discussion of this issue with reference to a non deterministic, parametric model of EOp, see Ferreira and Gignoux (2011) and Luongo (2011).

[12]Note that, given the assumption of anonymity implicit in this framework, the individuals ranked $\frac{j}{N}$ in t can be different from those ranked $\frac{j}{N}$ in $t+1$.

[13]Note that we track the same type but do not track the same individuals.

[14]Note that the type OGIC is a generalization of the idea underlying the first component of Roemer's (2011) index of development, that is, "how well the most disadvantaged type is doing".

[15]For a normative justification of these dominance conditions based on a rank-dependent social welfare function, see the working paper version of the paper: Peragine et al. (2011).

[16]See, *inter alia*, Sutherland et al. (1999).

[17]Similar to the OGIC, the derivation of its cumulative version closely follows the methodology proposed by Son (2004), adequately adapted to be consistent with the EOp theory.

[18]Similar to the cumulative inividual OGIC, the cumulative type OGIC is obtained by rearranging the difference between the Generalized Lorenz curves applied to the type mean distributions $Y\mu_t$ and $\tilde{Y}_{\mu_{t+1}}$.

[19]The approach is close in spirit to Essama-Nssah (2005), reviewed in a previous section. For a normative justification of the rank-dependent approach to IOp analyses, see Peragine (2002), Aaberge et al. (2011), and Palmisano (2011)

[20]See endnote12.

[21]We calculate confidence intervals for the difference between individual OGIC, type OGIC, and indexes in the two growth processes. The resampling procedure that we use is in line with the approach proposed by Lokshin (2008) for the GIC. We assume that the income distributions observed at the two points in time, y^t, y^{t+1}, are independent and identically distributed observations

of the unknown probability distributions $F(y^t), F(y^{t+1})$. γ is the statistic of interest, and its standard error is $\sigma(F(y^t), F(y^{t+1})) = \sqrt{Var\hat{\gamma}(y^t, y^{t+1})}$. Our bootstrap estimate of the standard error is $\hat{\sigma} = \sigma\left(\hat{F}(y^t), \hat{F}(y^{t+1}\right)$, where $\hat{F}(y^t), \hat{F}(y^{t+1})$ are the empirical distributions observed. The 95% confidence interval is obtained by resampling $B = 1,000$ ordinary non parametric bootstrap replications of the two distributions y_t^*, y_{t+1}^*. The standard error of parameter $\hat{\gamma}$ is obtained using $\hat{\sigma}_B = \sqrt{\sum_{b=1}^{B}\{\hat{\gamma}^*(b) - \hat{\gamma}(.)\}^2/(B-1)}$, where $\hat{\gamma}(.) = \frac{\sum_{b=1}^{B}\gamma^*(b)}{B}$. We know that $\hat{\sigma}_B \to \hat{\sigma}$ when $B \to \infty$, and, under the assumption that γ is approximately normally distributed, we calculate confidence intervals: $\hat{\gamma} = \hat{\gamma} \pm z_{1-\alpha/2}\hat{\sigma}_B$. Our estimate quality relies on strong assumptions. However, as will be clear in the discussion of the results, dominances appear rather reliable for the illustrative purpose of the exercise.

[22]We use the OECD equivalence scale given by the square root of the household size.

[23]All standard errors are obtained using the sample weights according to the suggestion in Banca d'Italia (2012).

[24]The results for the second period are consistent with other empirical evidence on the effect of the last financial and economic crisis. See, for example, Jenkins et al. (2013).

[25]To make the individual OGIC and the type OGIC graphically comparable, we partitioned the smoothed distributions into 18 quantiles.

[26]This dominance is confirmed by the comparison of their cumulative individual OGICs (figures and data available upon request)

[27]Note that in these empirical applications, the inequality measure used is additively decomposable for within and between groups.

[28]We aggregate types to have sufficient observations in each quantile of the within-type GIC.

[29]As reported in Table 1, the circumstance "head born in the South" appears in the five poorest types in 2002 and 2010 and in the four poorest types in 2006.

[30]Although the first process is better than the second and the dominance is statistically significant for most of the types, for type 15, the second process is preferred to the first one with statistical significance.

[31]This may be a challenging question for future research.

[32]Equivalent income is obtained by dividing total income by the square root of the household size.

[33]Again, the richest and poorest 1% of the household distribution in each wave are dropped.

[34]All estimates are based on the sample weights according to Silva et al. (2002).

[35]However, recall that this curve does not take into account the relative size of types. In this specific case, in fact, the types that experience an increase in the value of their opportunity set represent over 90% of the population.

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