Consumption Dynamics and Inequality of Opportunity with an application to Uganda *

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Abstract

This paper proposes the adoption of an opportunity egalitarian perspective to assess and compare growth processes and their distributional implications. To this aim a set of graphical tools are introduced, which allow to evaluate the role of growth and recessions in the evolution of individuals' opportunities over time. These tools satisfy the ex-post principle of equality of opportunity and represent an extension of the Opportunity Growth Incidence Curve, a framework recently introduced in the literature to evaluate growth according to the ex-ante principle of equality of opportunity. This measurement framework is applied to evaluate the recent economic dynamic in Uganda. The results show that despite a reduction in the real value of household consumption and a surge in outcome inequality between 2009 and 2011, its effects appear to be less dramatic when the (ex-post) equality of opportunity perspective is invoked.

Keywords: Economic growth, consumption inequality, equality of opportunity, Uganda.
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1 Introduction

In this paper we argue that a better understanding of the distributional dynamics that take place in an economy can be obtained by complementing the standard micro-approach, based on income and consumption, with an analysis of the distributive effects of growth in terms of opportunities.

The relevance of opportunities for the analysis of distributional phenomena has been defended by a recent but well-established branch of the literature, the equality of opportunity literature: see Ferreira and Peragine (2016), Fleurbaey (2008), Ramos and Van de gaer (2015), Roemer and Trannoy (2016) for recent surveys of the opportunity egalitarian approach. For a specific discussion of the opportunity perspective for the analysis of developing countries see World Bank (2006). This literature revolves around the idea that it is useful to distinguish between the outcome inequalities, which can be attributed to exogenous circumstances, i.e., factors that lie outside the sphere of individual responsibility, and the residual inequalities attributable to individual effort. Different models are proposed in which the opportunities open to individuals are deduced from basic assumptions on the functional relations between individual achievements, circumstances, and individual effort.

We endorse this view and, in this paper, we propose an extension of the theoretical framework introduced by Peragine et al. (2014) to investigate the distributional impact of growth. In their paper, the opportunity redistributive impact of growth is measured by estimating the individual Opportunity Growth Incidence Curve (individual OGIC) and the type Opportunity Growth Incidence Curve (type OGIC). The individual OGIC enables to assess the pure distributional effect of growth in terms of increasing or reducing aggregate inequality of opportunity (IOp). Whereas, the type OGIC allows to track the evolution of specific groups of the population in the growth process to detect the existence of possible inequality traps.[1]

As it is the case for any analytical tool aimed at evaluating inequality of opportunity, the construction of the OGIC requires the explicit endorsement of an exact definition of equality of opportunity (EOp), among all possible declinations offered by the literature. The ex-ante approach is at the base of the OGIC framework. It postulates that there is EOp if the value of the opportunity set of all types is the same, hence inequality of opportunity can be measured as inequality between individual opportunity sets. In practice, every individual's actual outcome is replaced by some evaluation of her opportunity set and inequality between these values is identified as inequality of opportunity. However, the ex-post principle of EOp is also widely used in the literature. It postulates that there is equality of opportunity if individuals exerting the same degree of effort are given the same outcome (Roemer, 1998), hence inequality of opportunity can be measured as inequality within the group of individuals with same endogenous characteristics (the tranches). Although apparently similar in spirit, ex ante and ex-post EOp principles have been shown to be

[1] These curves are extensions of the Growth Incidence Curve (GIC), originally proposed by Ravallion and Chen (2003). The GIC plots the mean income growth of each percentile in the distribution and allows to compare the incidence of growth (or contraction) in poorer segments of the population with respect to that of richer segments.

incompatible (Fleurbaey and Peragine, 2013). In particular, it has been shown that an ex-ante measure of IOp is inconsistent with the compensation principle at the base of the ex-post approach. This has, of course, implications when the evaluation of growth under the light of EOp becomes the focus of the analysis: the OGIC framework introduced by Peragine et al. (2014), based on the ex-ante approach, results to be not fully consistent with the ex-post approach.

In order to deal with this issue, in this paper we propose a new framework for the evaluation of consumption dynamics from an opportunity egalitarian perspective, which arises to be coherent with the ex-post principle of EOp. This framework consists of two curves: the ex-post individual Opportunity Growth Incidence Curve (ex-post individual OGIC) and the class Opportunity Growth Incidence Curve (class OGIC). The former plots the rate of growth of the individuals in the same position in two outcome distributions neutralized for the effect of effort on inequality. The latter plots the rate of income growth for each sub-group of the population, where the sub-groups are defined in terms of individuals that share the poorest outcome for each given level of effort. These curves integrate the set of existing tools for the evaluation of growth according to an EOp perspective and can be used to complement the standard outcome-based analysis of growth.

We apply these frameworks to analyze the distributional impact of the recent growth episode in Uganda - the one that took place between the 2009-2010 and the 2010-2011, using two waves of the Uganda National Panel Survey (UNPS). This period was characterized by a growth in both GDP and nominal consumption, following prolonged trend of the peace and security that begun after the end of the civil war and a series of structural reforms introduced since the late 1980s, including trade and financial liberalization.[2] In fact, in 2013 the Ugandan Government announced that Uganda had achieved the first target of the Millennium Development Goals: the poverty headcount ratio declined from above 56 percent in 1992 to 24.5 percent in 2010 (The Republic of Uganda, 2013).

However, as shown by Ssewanyan et al. (2004), changes in poverty were almost entirely due to growth rather than redistribution. The poorer regions lagged behind the richer and the inequality between regions tripled from 1992-1993 to 2009-2010 (World Bank, 2012). Thus, although poverty headcount has decreased significantly since the early 1990s, regional disparities remain, with rural poverty being more than three times higher than that in urban areas (see Benin et al., 2008; Ellis and Freeman, 2004). The rate of inequality increase accelerated in more recent years. According to the Uganda Bureau of Statistics the Gini index rose from 0.372 in 2009-2010 to 0.411 in 2010-2011 (Uganda Bureau of Statistics, 2013).

Using our framework, we show that the recent Ugandan consumption dynamic had similar regressive effects on inequality of outcome and inequality of opportunity. However, while growth contributed to worsen markedly outcome inequality, as witnessed by the steadily upward slope of the standard GIC, the consequent increase in opportunity inequality was less severe according to both

[2]Moreover, improved access to markets and a progressive diversification of household activities away from subsistence farming triggered a process of development, which has led Uganda to be one of the World's fastest growing economies in the last decade (World Bank, 2012).

the ex-ante and ex-post approach, as witnessed respectively by the ex-ante individual OGIC with no dominating slope, and the the ex-post individual OGIC with a more pronounced upward trend. The trend interaction between outcome inequality and inequality of opportunity resulted in a decrease of the share of overall inequality that is explained by inequality of opportunity. The estimation of the type and class OGICs further widen our knowledge about the distributional implications of the recent Ugandan consumption dynamic. In fact, despite the surge in outcome inequality and the slight increase in inequality of opportunity, types with initially poorer opportunities do not seem to grow less than type with initially richer opportunities. Most importantly, when we allow for effort to play a role this even results an a progressive evaluation of the impact of growth between initial classes.

It deserves to be noted that, to the best of our knowledge, this is the first attempt to evaluate a growth episode in Uganda using micro-data and according to both the inequality of outcome and the inequality of opportunity perspective.[3]

Hence, this paper makes two main contributions to the literature. The first and most important is methodological as we propose the ex-post individual OGIC and the class OGIC, two graphical tools that can be used to complement the standard analysis on the distributional implications of growth. The second contribution is empirical as we provide an analysis of the recent economic dynamic in Uganda, both using a standard outcome perspective as well as an opportunity egalitarian perspective.

The rest of the paper is organized as follows. Section 2 describes the methodological framework that is used to evaluate inequality and growth consistently with the EOp model and introduces the new tools. Section 3 presents the results of the analysis on the recent consumption dynamic in Uganda. Section 4 concludes.

2 The methodological framework: ex-ante and ex-post equality of opportunity

Consider a population in which each individual $p \in \{1, ..., N\}$ obtains an outcome at a given time $t \in \{1, ..., T\}$, $y_{p,t}$, as function of his circumstances $\mathbf{c}_p \in \Omega$, fixed over time, and effort $e_{p,t} \in \Theta$, $g : \Omega \times \Theta \to \mathbb{R}_+$:

$$y_{p,t} = g(\mathbf{c}_p, e_{p,t}) \tag{1}$$

The population can be partitioned into n types, where a type $i = 1, ..., n$ includes all individuals with circumstances i, and into m tranches, where a tranche $j = 1, ...m$ includes all individuals

[3]The analysis of inequality of opportunity in Uganda is also very limited. The only contribution we are aware of is the one by Cogneau and Mesplé -Somps (2008) and Brunori et al. (2016).

exerting effort j.

On the basis of the model reported in eq.(1) the literature has explored two main approaches to measuring (in)equality of opportunity (see, in particular, for recent surveys Ferreira and Peragine, 2015; Ramos and Van de gaer, 2012): these are the so called ex-ante and ex-post approaches.

The ex-ante EOp principle states that there is EOp if the value of the opportunity set is the same for all individuals. To make this principle operational, we need a measure of the value of an individual's opportunity set. Given the partition above, the literature suggests to interpret the type outcome distribution as the set of opportunities open to each individual belonging to that type. Hence, individuals in the same type have different outcomes but the same opportunity set. Thus, from the ex-ante perspective, inequality of opportunity is outcome inequality between types. Moreover, most of the literature evaluates the type outcome distribution by using a single statistics, its mean (of course other solutions are possible).

In particular, following Checchi and Peragine (2010), ex-ante IOp can be evaluated by using the following procedure: starting with an outcome distribution Y^t partitioned into types, first types are ordered on the basis of the value of their opportunity set, measured by their mean outcome, $\mu_i(y_t)$, that is: $\mu_1(y_t) \leq \mu_2(y_t) \leq, ..., \leq \mu_n(y_t)$. Then, a smoothing transformation is applied, by replacing each individual outcome with the mean outcome of the type she belongs to, obtaining the smoothed distribution $Y_S^t = (\mu_1^t, ..., \mu_k^t, ..., \mu_N^t)$. Given an outcome distributions $Y^t \in \mathbb{R}_+^N$ and an inequality measure $I : \mathbb{R}_+^N \to \mathbb{R}_+$, ex-ante IOp is given by $I(Y_S^t)$, where I can either be an absolute or a relative measure of inequality and satisfies the standard properties of anonymity and Pigou-Dalton transfer. Ex-ante IOp is often estimated relatively to total inequality, that is, dividing $I(Y_S^t)$ by the inequality of the original outcome distribution, $I(Y^t)$.

The ex-ante principle is by far the most adopted approach to evaluate IOp;[4] however, a second approach has been widely used in theoretical and empirical analyses aimed at evaluating IOp: the ex-post approach. The ex-post approach to compensation (associated with Roemer, 1998) proposes that inequalities should be eliminated among individuals who exert the same degree of effort. Under this approach there is no need to evaluate opportunity sets but, on the other hand, one must observe (or agree on a measure of) effort. Roemer's specific proposal for the identification of effort, which has been widely used in empirical applications, measures the degree of individual effort by the rank of the individual in the relevant type outcome distributions. Two individuals belonging to different types who sit at the same rank of their relevant distribution are declared to have exerted the same effort, despite having different outcomes.

Hence, the ex-post approach focuses on inequality within tranches. This requires to construct a standardized distribution, by proportionally scaling each tranche distribution until it has the same mean as the overall distribution. This distribution removes all the between-tranch inequality while it does not alter within-tranche inequality.

[4] In a meta analysis Brunori et al. (2013) reported ex-ante IOp estimates for 42 countries.

Following again Checchi and Peragine (2010), for any outcome distributions $Y^t \in \mathbb{R}^N_+$, the outcome of a generic individual of type i and exerting effort j is rescaled as follows: $y^t_{i,j} \to \hat{y}^t_{i,j} = \frac{y^t_{i,j}}{\hat{\mu}^t_j}\mu^t$, where $\hat{\mu}^t_j$ is the average outcome of tranche j. This standardizing process eliminates all the inequality between the tranches, interpreted as inequality due to effort. Given an inequality measure $I : \mathbb{R}^N_+ \to \mathbb{R}_+$, ex-post IOp is obtained by applying I to the standardized distribution $Y^t_B = (\hat{y}^t_1, ..., \hat{y}^t_k, ..., \hat{y}^t_N)$. A relative measure of ex-post IOp is again obtained dividing $I(Y^t_B)$ by overall inequality, $I(Y^t)$.

Although similar in spirit and empirically strongly correlated, ex-ante and ex-post IOp have been shown to be incompatible in general (Fleurbaey and Peragine, 2013).

2.1 Ex-ante opportunity growth incidence curves

There are two natural ways to look at the distributive effects of growth in terms of ex-ante opportunities. The first is to ask how growth affects the distribution of opportunities: is growth opportunity-progressive (IOp is lower at time $t+1$ than at time t) or opportunity-regressive (IOp is lower at time t than at time $t+1$)? The second possible way is to investigate whether different circumstances beyond individual control are associated with different levels of growth, therefore investigating whether or not opportunity sets grow disproportionately between types.

Consider for example a population made of two types based on one circumstance, namely, the employment status of parents: having blue collar parents or having white collar parents. Their outcomes at time t and $t+1$ are reported in the two tables:

Time t

blue	4	3	6
white	2	8	9

Time $t+1$

blue	3	6	11
white	2	3	7

Total inequality, measured by the mean logarithmic deviation, increased overtime: from 0.133 to 0.170. However, to evaluate whether growth has been opportunity-progressive one should first replace individual outcomes with types' average, then rank them in ascending order, finally calculate the difference between the two distributions. On the other hand, if one is interested in knowing whether offspring of white collar and blue collar experienced different level of growth, one should simply calculate the rate of growth in the average outcome of each type. Because to construct the OGIC one has to rank in ascending order both distributions, whenever there is re-ranking of types and changes in types' population size, the two methods are not equivalent, as in the example above.

This explains why Peragine et al. (2014) introduce two versions of the OGIC: ex-ante individual OGIC and type OGIC, which respectively furnish an answer to the first and the second question above. They, in fact, show that the two curves can lead to different judgments in very general cases.

The ex-ante individual OGIC plots the rate of growth of the (value of the) opportunity set given to individuals in the same position in the distribution of opportunities. Given an initial distribution of outcome Y^t and the corresponding smoothed distribution Y_S^t introduced in the previous section, the ex ante individual OGIC can simply be obtained applying the GIC proposed by Ravallion and Chen (2003) to Y_S^t and Y_S^{t+1}. Hence the ex-ante individual OGIC can be defined as:

$$g^o_{Y_S}\left(\frac{k}{N}\right) = \frac{\mu_k^{t+1}}{\mu_k^t} - 1, \forall k \in \{1, ..., N\} \tag{2}$$

Where $g^o_{Y^S}\left(\frac{k}{N}\right)$ measures the proportionate change in the value of opportunities of the individuals ranked $\frac{k}{N}$ in the smoothed distributions. Obviously, $g^o_{Y_S}\left(\frac{k}{N}\right) \geq 0$ ($g^o_{Y_S}\left(\frac{k}{N}\right) < 0$) means that there has been a positive (negative) growth in the value of the opportunity set given to the individuals ranked $\frac{k}{N}$ respectively in Y_S^t and in Y_S^{t+1}. Note that, given the assumption of anonymity implicit in this framework, the individuals ranked $\frac{k}{N}$ in t can be different from those ranked $\frac{k}{N}$ in $t+1$. A flat individual OGIC signals that growth does not have any impact on the level of IOp. On the contrary, when growth is progressive (regressive) in terms of opportunity, growth acts by reducing (worsening) IOp and the individual OGIC will be a decreasing (increasing) curve.

The ex-ante individual OGIC does not track the evolution of the opportunity set of each type during a growth episode: 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 on the change of both type specific mean outcome and type specific population share, but it is neutral with respect to a possible re-ranking of types that may occur during a growth process. Now, while these features are desirable when one is interested in studying the evolution of IOp over time, the same characteristics make the individual OGIC unable to detect if there are groups of the population which are systematically excluded from growth.

To address this specific issue and to investigate the relationship between overall economic growth and type specific growth, Peragine et al. (2014) introduce the type OGIC. Given this analytical framework, the focus is on the outcome prospects of individuals of the same type, represented by the type-specific outcome distribution $F_i(y_t)$; we. This distribution is interpreted as the set of opportunities open to each individual in a type i. In other words, the observable actual outcome of all individuals in a given type is used to proxy the unobservable ex-ante opportunities of all individuals in that type. We let $Y_\mu^t = (\mu_1(y_t), ..., \mu_n(y_t))$ be the distribution of types' mean outcome at time t, where types are ordered increasingly according to their mean, and $Y_{\tilde{\mu}}^{t+1} = (\tilde{\mu}_1(y_{t+1}), ..., \tilde{\mu}_n(y_{t+1}))$ the distribution of types' mean outcome at time $t+1$, where types are ordered according to their position at time t. Hence, $\mu_i(y_t)$ is the opportunity set at time t of a type whose mean outcome

ranked i in the initial distribution of types' mean outcome and $\tilde{\mu}_i(y_{t+1})$ is the opportunity set at time $t+1$ of the type whose mean outcome ranked i in the initial distribution of types' mean outcome, independently of its rank in the final distribution. This implies that $\mu_i(y_t)$ and $\tilde{\mu}_i(y_{t+1})$ are the opportunity sets, respectively in the initial and final period, open to individuals defined by the same set of circumstances.

We define the type OGIC as:[5]

$$g^o_{Y_\mu}\left(\frac{i}{n}\right) = \frac{\tilde{\mu}_i(y_{t+1})}{\tilde{\mu}_i(y_t)} - 1, \ \forall i \in \{1, ..., n\} \tag{3}$$

The type OGIC plots, against each type, the variation of the opportunity set of that type. It can be interpreted as the rate of economic development of each social group in the population, where these groups are defined on the base of exogenous factors that can affect the individual outcome. $g^o_{Y_\mu}\left(\frac{i}{n}\right)$ is horizontal if each type benefits (looses) 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.

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 outcome - usually, income or consumption - 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 information on the temporal evolution of type-specific opportunity sets.

To understand the need of employing both type and individual OGIC to evaluate the same growth process, consider again the pre- and post-distribution of individual outcome, reported in the tables below. Now we assume that individuals can exert three possible degrees of effort: low, medium, high.

It can be easily checked that ex-ante IOp - measured using, for instance, the mean logarithmic deviation - is 0.0178 at time t and 0.0319 at time $t+1$. Therefore we expect an upward slopping ex-ante OGIC, meaning that growth has been regressive in terms of opportunity:

$$\textit{ex-ante OGIC} : (-0.0769, -0.0769, -0.0769, 0.0526, 0.0526, 0.0526)$$

However, if types are tracked, growth appears to have been progressive: individuals with low

[5]Note that the type OGIC tracks the same types but not necessarily the same individuals. Indeed, what matters for our tool is the comparison of the opportunity set of a given type in t with the opportunity set of the same type in $t+1$. That is, we compare the opportunity set in t of a group of individuals, for instance, born in rural area by low educated parents, with the opportunity set in $t+1$ of the group of individuals characterized by the same circumstances. By assuming that these individuals might not be necessarily the same, we allow our framework to be easily applied from an empirical point of view, given that by construction many surveys do not have any longitudinal component, hence preventing to track the same individual over time.

Time t

	l	m	h
blue	4	3	6
white	2	8	9

Time $t+1$

	l	m	h
blue	3	6	11
white	2	3	7

socioeconomic background increased their outcomes, while outcome is decreasing for all the others:

$$type\ OGIC : (0.5385, 0.5385, 0.5385, -0.3684, -0.3684, -0.3684)$$

Since the individual OGIC considers anonymous types and the type OGIC, instead, traces types over time, the re-ranking taking place from time t to time $t+1$ causes the two curves to have an opposite slope.[6] This conflict is not a contradiction: a downward sloping type OGIC does not imply a reduction of IOp over time.

Another intriguing feature of the example proposed above is that, contrarily to the ex-ante IOp trend, ex-post IOp is reducing over time: from 0.0629 to 0.0343 in terms of MLD.[7] The use of the OGIC described before would then lead to misleading conclusions on the impact of growth on inequality of opportunity in an ex-post perspective.

For this reason, in this paper we introduce a dual version of the ex-ante OGIC framework described above that results to be consistent with the ex-post principle of IOp. This dual version is composed of two curves, namely the ex-post individual OGIC and the class OGIC.

2.2 Ex-post opportunity growth incidence curves

Given an initial distribution of outcome Y^t and the corresponding standardized distribution Y_B^t, assuming that individual standardized outcomes are sorted non-decreasingly, that is $Y_B^t = (\hat{y}_1^t \leq ... \leq \hat{y}_k^t \leq ... \leq \hat{y}_N^t)$, the individual OGIC can simply be defined as the GIC applied to the ex-post standardized distributions Y_B^t and Y_B^{t+1}. Hence, the ex-post individual OGIC is expressed as follows:

[6] In the example, at time $t+1$ individuals with a low socioeconomic background become richer than individuals with a high socioeconomic background.

[7] As shown by Fleurbaey (2008) and Fleurbaey and Peragine (2013), the conflict stems from the partial incompatibility between the two principles at the base of the idea of equal opportunity: the principle of compensation and the principle of reward.

$$g^{o}_{Y_B}\left(\frac{k}{N}\right) = \frac{\hat{y}^{t+1}_{k}}{\hat{y}^{t}_{k}} - 1, \forall k = 1, ..., N \tag{4}$$

It plots the percentage outcome change of individuals ranked $\frac{k}{N}$ in the standardized distributions Y^t_B and Y^{t+1}_B. As in the ex-ante version, $g^{o}_{Y_B}\left(\frac{k}{N}\right) \geq 0$ ($g^{o}_{Y_B}\left(\frac{k}{N}\right) < 0$) means that there has been a positive (negative) growth for those individuals ranked $\frac{k}{N}$ in Y^t_B. Furthermore, a decreasing curve implies that growth has been ex-post opportunity equalizing, whereas an increasing curve implies that growth has been regressive in terms of ex-post IOp. This interpretation is straightforward if we recall that at the bottom of the distribution we find individuals suffering most the negative effect of bad circumstances. When growth does not alter inequality of opportunity, the curve will just be an horizontal line. Hence, the ex post individual OGIC captures the impact of growth on ex post inequality of opportunity.

Considering again our example, the individual ex-post OGIC will be obtained by first dividing, for each point in time, individual outcomes by the average of the three columns: l, m, h. Then, computing the GIC between these two distributions.

This way of looking at growth and IOp is similar to the ex-ante individual OGIC: it is consistent with the measurement of ex-post IOp, but does not track individuals or types. However, in the ex-ante individual OGIC, the sign of the $i-th$ coordinate can be directly interpreted as an improvement/worsening of the value of the opportunity set of those people sitting at the $i-th$ quantile of the distribution of opportunities. Whereas, in the ex-post individual OGIC, the sign of the $i-th$ coordinate can be interpreted as an improvement/worsening of the unfair advantage/penalty, in terms of outcome due to circumstances beyond individual control.

As expected the ex-post version of the individual OGIC, applied to the example above, is downward slopping, signaling a progressive redistribution in terms of opportunity between time t and $t+1$:

$$\textit{ex-post individual OGIC} : (0.2768, 0.5669, 0.3849, 0.1079, 0.0446, 0.1970)$$

The ex-post individual OGIC reported in eq.(4) is clearly related to the variation of ex-post IOp over time, as the ex-ante individual OGIC in eq.(2) is related to the variation of ex-ante IOp over time. A natural question here is whether it is also possible to construct an ex-post version of the type OGIC. Recall that the type OGIC is a tool aimed at evaluating the dynamic of each type-specific opportunity set. The ex-post approach is more demanding as it focuses on the outcome dynamic, not only considering the type of origin but also the effort exerted. This makes a difference in all the cases in which the advantage of belonging to a type is not the same across tranches. In this case, focusing on types is unsatisfactory because belonging to a type produces different outcomes, depending on the effort exerted. Take the distribution at time $t+1$ in the *ad hoc* example above:

being the daughter of a blue collar implies being worse off if the effort exerted is low; by contrast it implies being better off if the effort exerted is high. Therefore, in an ex post perspective, tracking the outcome of different groups means tracing the group of individuals sitting in the same position of the within-tranche distribution. The theoretical foundations of this procedure are provided in an IOp measurement model recently introduced by Fleurbaey et al. (2017).

To illustrate, consider the following matrix

$$Y^t = \begin{array}{c|ccc} & \mathbf{e}_1 & \mathbf{e}_j & \mathbf{e}_m \\ \mathbf{c}_1 & y_{11} & y_{1j} & y_{1m} \\ ... & ... & ... & ... \\ \mathbf{c}_i & y_{i1} & y_{ij} & y_{im} \\ ... & ... & ... & ... \\ \mathbf{c}_n & y_{n1} & y_{nj} & y_{nm} \end{array}$$

Starting with Y^t, we construct a new distribution, Y_C^t, by permuting the elements within each column such that they are ordered increasingly within each column. We call the rows of this new distribution Y_C^t "classes".[8] This implies that class means are sorted non-decreasingly such that $\breve{\mu}_1^t \leq ... \leq \breve{\mu}_j^t \leq ... \leq \breve{\mu}_n^t$. Now, ordering class means in $t+1$ on the base of their rank in the initial period t, independently of their rank in $t+1$, the class OGIC can be defined as follows:

$$g^o_{Y_{\breve{\mu}}}\left(\frac{i}{n}\right) = \frac{\breve{\mu}_i^{t+1}}{\breve{\mu}_i^t} - 1, \ \forall i \in \{1, ..., n\} \tag{5}$$

It plots, for each class, the variation in the set of final outcome open to individuals in the same class. It can be interpreted as the rate of economic development of each class in the population. $g^o_{Y_{\breve{\mu}}}\left(\frac{i}{n}\right)$ is horizontal if each class benefits (looses) in the same measure from growth.[9] It is negatively (positively) sloped if the initially disadvantaged classes get higher (lower) benefit from growth than those initially advantaged. Type OGIC and class OGIC are indeed equivalent if no re-ranking of types takes place in any tranche. In our numerical example we get two modified distributions Y_C^t and Y_C^{t+1}:

The class OGIC is only slightly decreasing signaling that the rate of growth in the lower class has been a little higher than in the upper class:

[8] Note that calculating ex-post IOp in this new distribution, as suggested in Section 2.1, is exactly equivalent to using the original distribution Y^t.

[9] Note that tracking classes across time does not imply tracking individual outcomes: individuals remain in the same class only if, given their effort, the rank of their type in terms of outcome is the same at time t and $t+1$.

Time t

	l	m	h
class 1	2	3	6
class 2	4	8	9

Time $t+1$

	l	m	h
class 1	2	3	7
class 2	3	6	11

$$\textit{class OGIC} : (0.0909, 0.0909, 0.0909, -0.0476, -0.0476, -0.0476).$$

Note that our approach is a generalization of Roemer's (1993) approach, which only looks at $\breve{\mu}_1^t$. Moreover, it is also a generalization of the lexicographic extension of the Roemer's rule found in Ooghe et al (2007), which looks at the all $\breve{\mu}_j^t$ in lexicographic order.[10]

A remark is in order here. The class OGIC allows to account for the interplay between circumstances and effort that is, instead, ignored in the type OGIC. Individuals in a given class have the same relative position in their respective tranche distributions, therefore they face a similar impact of circumstances, if this impact is evaluated by their rank in their tranche. This is not the case for individuals in a given type. Individuals in the same class have exerted different degrees of responsibility; however, because of the impact of circumstances, they have same rank in their respective tranche distribution. Thus, this rank represents an interpersonally comparable measure of the impact of circumstances.

To sum up, the class OGIC allows to investigate whether growth has been more or less beneficial on the outcome of individuals more disadvantaged by the interplay between circumstances and effort with respect to those less disadvantaged. Whereas the type OGIC allows to investigate whether growth has had differential impacts on the different opportunity sets open to individuals, independently of the interplay between circumstances and effort.

Table 1 summarizes the four OGICs formula and properties.

Finally, when implementing our approach on survey data it is necessary to consider important empirical aspects. For example, survey data typically do not contain exhaustive information on individual circumstances. As far as the measurement of inequality of opportunity is concerned, this issue has been discussed by a number of contributions (Roemer, 1998; Ferreira and Gignoux, 2011; Luongo, 2011). The prevailing view is that with partial observability of circumstances estimates are a lower-bound of the real level inequality of opportunity. The implications of partial

[10] See also Fleurbaey et al. (2017)

Table 1: OGICs properties

OGIC	Formula	Anonymous	Interpretation
Individual ex-ante	$g^o_{Y_S}\left(\frac{k}{N}\right) = \frac{\mu_k^{t+1}}{\mu_k^t} - 1, \forall$ individual	yes	if increasing/decreasing signals positive/negative Δ ex-ante IOp
Type	$g^o_{Y_\mu}\left(\frac{i}{n}\right) = \frac{\tilde{\mu}_i(y_{t+1})}{\tilde{\mu}_i(y_t)} - 1, \forall$ type	no	shows heterogeneity of growth of different types
Individual ex-post	$g^o_{Y_B}\left(\frac{k}{N}\right) = \frac{\check{y}_k^{t+1}}{\check{y}_k^t} - 1, \forall$ individual	yes	if increasing/decreasing signals positive/negative Δ ex-post IOp
Class	$g^o_{Y_{\check{\mu}}}\left(\frac{i}{n}\right) = \frac{\check{\mu}_i^{t+1}}{\check{\mu}_i^t} - 1, \forall$ class	no	shows heterogeneity of growth of different classes

observability are less straightforward for our approach. Ex-ante and ex-post individual OGICs show how the counterfactual distribution of opportunity has changed over time. As these counterfactual distributions reflect only a part of the total variability due to opportunity, it is possible to obtain a regressive OGIC when the real level of inequality of opportunity has instead declined, or *vice versa*. However, individual OGICs will always be consistent with changes in the lower bound estimates of inequality of opportunity based on observable circumstances. That is to say, if one considers acceptable to estimate inequality of opportunity when circumstances are only partially observable, then individual OGICs are valuable tools to go beyond a description of the change in a summary index. Nevertheless, empirical implementations should always be assessed considering the possibility that unobservable circumstances may have modified the distribution in a different direction. Similarly, class OGIC can lead to misleading interpretation when some of the relevant exogenous characteristics are not observable. If individuals are incorrectly assigned to types their degree of effort will also be incorrectly identified. The partial observability of circumstances indeed represents a threat for our approach and, more in general, is a serious limitation of the empirical literature on inequality of opportunity. Hence, in empirical implementation it is essential to clearly state on what observable circumstances the analysis is based.

3 An Empirical Illustration: Growth and inequality of opportunity in Uganda

In this section we apply our framework to investigate the distributive impact of the consumption dynamic that took place in Uganda between 2009-2010 and 2010-2011. This period is of particular interest for Uganda because between the second half of 2009 and the first of 2011 different indicators

of economic development moved in opposite direction. On the one hand, it is a period of sustained growth in terms of GDP, on the other the agriculture GDP declined, food prices surged, and inequality increased. It is therefore interesting to examine in depth the redistributive effect of growth in that particular period.

We first provide an assessment of this dynamic according to the equality of outcome perspective. We then move to the analysis of the consumption dynamic according to the EOp perspective, adopting the methodological tools introduced above. To this aim, we make use of two waves of the Uganda National Panel Survey (UNPS). This survey was realized as part of the Living Standards Measurement Study - the Integrated Surveys on Agriculture project established by the Bill and Melinda Gates Foundation and implemented by the Development Research Group at the World Bank and the Uganda Bureau of Statistics. The dataset is representative at the national and at the main regional levels. Out of the 7,400 households interviewed during the Uganda National Household Survey (UNHS) 2005-2006, 3,200 households were selected for the UNPS and the same sample was maintained in both 2009-2010 and 2010-2011 panel surveys. The sample considered includes only household heads and their spouses.

In order to evaluate the impact of growth on the distribution of opportunities we have to choose an outcome variable and a set of circumstances beyond the individual control. As regards the outcome variable, we choose per capita consumption, obtained by dividing total household consumption by the number of its components and expressed in 2010 Ugandan Shilling. As far as the second choice is concerned instead, an ideal partition in types would include all possible characteristics beyond the individual control of household members. However, because of the lack of information or due to the size of the sample, only a subsample of the real circumstances is considered; this issue is common to all empirical applications that estimate IOp. As discussed among others by Ferreira and Gignoux (2011), IOp estimates obtained using a subset of all possible circumstances should be interpreted as lower-bound estimates of the real IOp. The possible existence of unobserved circumstances guarantees that these estimates could only be higher if more circumstance variables were considered. The UNPS data allow us to use the information related to two circumstances: ethnicity and place of birth.[11]

Although the circumstances used are only two, these are fundamental. In the Ugandan recent history, ethnic conflicts and regional disparities have exerted an important role.[12] Ugandans can be classified into several ethnic groups, with none of them constituting a majority. Before the colonial period some inter-ethnic conflicts occurred in Uganda though not on a large scale. However, after independence, ethnicity has started to play a role in the civil conflicts and economic development. Today a first cleavage is between the Nilotic speakers in the North and Bantu speakers in the South.

[11] The UNPS also provides data on parental education and parental occupation. However, due to the large number of missing information, we cannot include them among circumstances.

[12] See, among others, Montalvo and Reynal-Querol (2005) and Rohner et al. (2013) on the relevance of ethnicity in distributional analysis.

Moreover, different groups have traditionally relied on different economic activities, for instance, pastoralism in the West and North, and agriculture in the lakes region, and have maintained different relationships with the central government, both during the British colonial period and after independence. The area is also characterized by regional disparities in access to opportunities, mostly related to the rural-urban development gap, a consequence of the industrialization effort, promoted by the central governments in the first two decades after independence, which has been suggested to be characterized by a urban bias (Mukwaya et al., 2012; Baland et al. 2007).[13] Hence, it appears natural to treat ethnicity and birthplace as circumstances in the context of our analysis.

We employ a non-parametric approach to obtain our estimates. Following Roemer (1998), the identification of the degree of effort exerted is based on the quantile type-specific outcome distribution. In order to provide meaningful non-parametric estimates of IOp, the circumstances observed need some additional treatment. In particular, they are aggregated so that, reducing the number of types and increasing their size, statistical reliability is allowed. In the original dataset, birthplace is categorized into 56 districts plus the capital city. This circumstance is recoded such that we can distinguish between four groups of districts according to their level of development as measured by the Human Development Index (UNDP, 2014), that is: districts with low development (with a HDI ranging from between 0.231 and 0.433), districts with lower intermediate development (with a HDI ranging from 0.434 to 0.470), districts with upper intermediate development (with a HDI ranging from 0.472 to 0.498), districts with high level of development (with a HDI above 0.500). The 44 ethnic groups present in the original data are also recoded to obtain six groups on the base of their linguistic origin, that is: ethnic groups whose language belongs to the Central Sudanic, ethnic groups whose language belongs to the Easter lacustrine Bantu, ethnic groups whose language belongs to the Western lacustrine Bantu, ethnic groups whose language belongs to the Eastern Nilotic, ethnic groups whose language belongs to the Western Nilotic, Ethnic Minorities.[14] We can then partition the population into 24 types, whose members are individuals born in districts with similar level of development as measured by the HDI and belonging to ethnic groups with similar linguistic origins. Although 24 is clearly a subset of the real number of types in which Uganda could be partitioned, it represents an improvement if compared to the only one available estimate of IOp in the country, which is based on three types (Cogneau and Mesplé-Somps, 2008). Finally, in each type three degrees of effort are identified with the corresponding quantiles of the empirical type specific outcome distribution function.

Table 1 summarizes the partition into types of the Ugandan population, where types are ranked

[13] See also Baland et al. (2007) and Shan and Stifel (2003) for the relevance of the regional divide in living standards in Africa, especially in terms of rural/urban divide.

[14] This subdivision is based on information reported by the Federal Research Division of the Library of Congress (2014), Wairama (2001).

according to the average per capita consumption at the initial time (2009-2010);[15] this table represents what Ferreira and Gignoux (2011) have named *opportunity profile*. Opportunity profiles are generally informative of which combinations of circumstances beyond individual control lead to the greatest opportunity deprivation in a given society. The most disadvantaged type is represented by individuals belonging to ethnic minorities and born in areas with a low HDI, whereas the most advantaged type is represented by Central Sudanic individuals born in areas with an high HDI. Interestingly, the Uganda opportunity profile seems to be more dominated by ethnicity than by area of birth. In general, people belonging to ethnic minorities or to Western Nilotic are those more disadvantaged while those belonging to Western or Eastern lacustrine Bantu are those placed in higher types (from 16 up to 21). However, it is also clear that a lot of re-ranking is taking place between the two periods analysed: only two types keep the same position in the two periods. Large re-ranking does not only concern types with a small sample size that are more likely to show large changes over time due to sampling variance (this is the case of the first type ranked 12th after one year). The re-rankings that takes place during this growth process implies a jump of more than two positions but involves local rerankings, that is, most of the types initially ranked in the first (second) half of the distribution are still ranked in that half of the distribution in the final period.

[15] Consumption is expressed in 2010 Ugandan Shellings applying and adjusting the value of consumption in 2009-10 according to prices.

Table 2: Opportunity profiles

		2009-2010					2010-2011				
ethnicity	*region of birth (HDI)*	rank 2009-2010	sample	population share	consumption p.c.	sd	rank 2010-2011	sample	population share	consumption p.c.	sd
Ethnic minorities	low	1	22	0.0053	517.04	327.58	12	9	0.0019	731.82	752.75
Western Nilotic	low	2	326	0.0528	567.88	597.68	3	290	0.0531	595.87	1,049.87
Western Nilotic	lower intermediate	3	459	0.0955	586.26	567.17	10	494	0.1231	674.00	787.74
Ethnic minorities	lower intermediate	4	42	0.0112	669.03	499.77	8	36	0.0096	666.50	1,393.91
Eastern Nilotic	low	5	202	0.0349	674.54	673.64	7	214	0.0454	664.25	972.56
Ethnic minorities	upper intermediate	6	177	0.0516	693.44	677.01	2	129	0.0425	540.53	588.08
Central Sudanic	upper intermediate	7	7	0.0014	695.20	542.06	1	5	0.0013	513.23	254.84
Western Nilotic	upper intermediate	8	30	0.0069	721.88	504.72	6	29	0.0070	659.07	453.99
Western lacustrine Bantu	lower intermediate	9	134	0.0378	765.29	815.99	15	115	0.0338	771.29	864.30
Central Sudanic	low	10	80	0.0125	799.96	531.48	11	81	0.0162	686.50	531.76
Ethnic minorities	high	11	236	0.0645	836.61	1,206.84	5	204	0.0599	649.37	772.70
Eastern Nilotic	high	12	37	0.0085	859.10	863.41	4	32	0.0079	609.18	904.63
Eastern Nilotic	lower intermediate	13	203	0.0434	868.63	734.35	14	200	0.0489	761.31	554.19
Eastern lacustrine Bantu	lower intermediate	14	230	0.0481	966.36	1,015.93	16	227	0.0552	802.66	2,510.22
Western Nilotic	high	15	15	0.0032	978.66	705.64	13	16	0.0035	748.40	1,386.86
Western lacustrine Bantu	upper intermediate	16	387	0.0912	1,041.32	884.89	21	345	0.0878	1,145.23	1,247.60
Western lacustrine Bantu	high	17	306	0.0711	1,066.37	1,180.65	17	266	0.0644	826.72	963.74
Western lacustrine Bantu	low	18	16	0.0045	1,099.72	550.43	23	15	0.0050	1,411.52	756.38
Central Sudanic	lower intermediate	19	165	0.0304	1,125.33	1,393.00	18	167	0.0358	848.43	763.95
Eastern lacustrine Bantu	low	20	26	0.0038	1,178.36	854.36	19	33	0.0065	856.06	853.58
Eastern lacustrine Bantu	upper intermediate	21	415	0.0936	1,229.25	1,052.49	20	443	0.1067	1,143.18	1,001.82
Eastern lacustrine Bantu	high	22	899	0.2235	1,386.56	1,482.31	22	809	0.1817	1,379.94	1,807.85
Eastern Nilotic	upper intermediate	23	10	0.0020	1,504.39	1,323.86	9	7	0.0011	671.75	455.83
Central Sudanic	high	24	10	0.0021	2,598.64	2,904.00	24	8	0.0017	2,086.62	1,486.51

Note: Consumption is expressed in yearly per capita thousands 2010-11 Ugandan shillings. Source: Authors' elaboration based on UNPS 2009-2010 and 2010-2011.

3.1 Growth and inequality in Uganda

In the last decades, episodes of sizable growth have characterized Uganda's economy. Its performances have also been above the average among the other Sub-Saharan African countries.[16] Economic growth has been led mainly by strong private consumption growth rates and great performance of the export sectors (Matovu et al., 2011). The period between the second half of 2009 and the first of 2011 represents somehow an exception: if on the one hand the GDP grew by more than six percent on average, on the other, the agriculture GDP declined by 2.4 percent in the same period. Moreover, increasing food prices drove a surge in the CPI.[17] The generalized rise in prices reduced the value of the average per capita consumption, which dramatically decreased in the period considered for every quantile of the distribution (see Figure 1). Moreover, Uganda has experienced a considerable increase in the level of inequality. This recent increase in inequality is witnessed by the shape of the GIC reported in Figure 1 and based on the UNPS waves 2009-2010 and 2010-2011, which plots, against each quantile, the quantile specific percent growth rate in per capita consumption in the period covered by our sample.[18] As expected, the GIC is negative in all its domain, meaning that each part of the distribution faces a reduction in per capita consumption. Most importantly, the curve is characterized by an increasing shape: poorest quantiles experience a negative and sizable growth while richer quantiles experience a lower reduction in per capita consumption, far above the average growth rate, finally resulting in a massive increase in inequality. In our sample, inequality of per capita consumption, measured through the mean logarithmic deviation, rose from 0.34 in 2009-2010 to 0.37 in 2010-2011.

3.2 Consumption dynamic and inequality of opportunity

In this context it appears of interest to understand if the same distributional dynamic brought about the same increase in inequality of opportunity and how it affected the growth of specific socio-economic groups. To answer the first question we estimate the ex-ante and ex-post individual OGIC, which show the possible IOp progressivity/regressivity of this consumption dynamic. To answer the second question we estimate the type and class OGIC, which track the outcome of individuals belonging to more or less advantaged groups of the population.

The ex-ante and ex-post individual OGIC are obtained calculating the coordinates of the GIC of the smoothed and standardized distributions Y_S^t, Y_S^{t+1} and Y_B^t, Y_B^{t+1} respectively.[19] In this respect

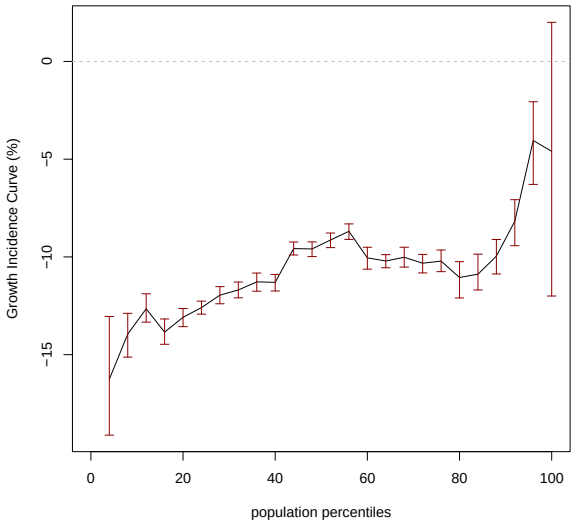
[16] See World Bank (2012).

[17] According to the Uganda Bureau of Statistics (2013), the composite CPI was 144.58 between September 2009 and August 2010 and averaged at 161.70 between October 2010 and September 2011.

[18] For all estimates in the empirical exercise, standard errors are obtained from the quantiles of the distribution of statistics obtained by 1,000 bootstrap resampling of the original dataset (Davison and Hinkley, 1997). The resampling procedure is constrained by imposing the structure of the partition in types to be reproduced at each step. That is, each replication of the sample contains the same number of types with the same sample size.

[19] Note that in order to obtain the counterfactual distribution Y_B, one needs first to substitute the outcome of a generic individual of type i and exerting effort j with the mean outcome of her cell (set of those in the same type and

Figure 1: GIC



Note: Standard errors are obtained through 1,000 bootstrap replications. Source: Authors' elaboration based on UNPS 2009-2010 and 2010-2011.

Uganda represents a peculiar case, in fact, these two curves are very different from each other and they do give additional information with respect to those obtained using the standard GIC, thus confirming the interest of applying an opportunity egalitarian perspective to the evaluation of growth, defined in both its ex-ante and ex-post principles. More in particular, differently from the GIC, the ex-ante individual OGIC reported in Figure 2 is not always negative and it is not monotonic, but shows a declining trend in the bottom part of the distribution, up to the 60th percentile, becoming upward sloping in the upper part of the distribution. Overall, this particular pattern results in a slight increase of ex-ante inequality of opportunity - measured through the mean logarithmic deviation - from 0.047 in 2009-2010 to 0.048 in 2010-2011.[20] However, given the massive increase in consumption inequality, ex-ante relative inequality of opportunity is indeed decreasing, from 13.7% to 12.9 %.

exerting the same effort). Only then the rescaling discussed in Section 2 can be applied. This is because, empirically, there is a certain amount of inequality among individuals of the same type and exerting the same effort. It depends on the specific tranche partition adopted: the higher the number of the tranches, the better is the approximation of the effort exercised, and the lower is the residual inequality. That is, this inequality is due to the coarseness of tranches and can thus be attributed to effort.

[20]We use the mean logarithmic deviation applied to the smoothed distribution Y_S^t and Y_S^{t+1} because it is the inequality measure generally used in inequality of opportunity empirical literature. Although other measures such as the Gini coefficient can be used, the mean logarithmic deviation has been traditionally adopted because of its unique property of path independent perfect decomposability (Foster and Shneyerov, 2000).

Figure 2: Ex-ante individual OGIC

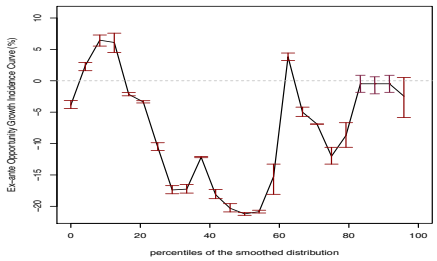
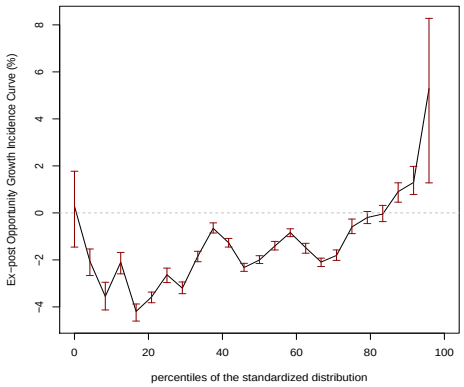


Figure 3: Ex-post individual OGIC



Note: Standard errors are obtained through 1,000 bootstrap replications.
Source: Authors' elaboration based on UNPS 2009-2010 and 2010-2011.

The ex-post individual OGIC reported in Figure 3, instead, shows similar features to the GIC, in that it is characterised by a neat increasing shape. However, its coordinates are negative for the first four quintiles of the distributions, they then become positive for the richest quintile. Differently from the ex-ante OGIC, the ex-post OGIC appears to be clearly regressive, although to a lesser extent than the standard GIC. The final implication is, in fact, an increase in ex-post inequality of opportunity, from 0.041 in 2009-2010 to 0.042 in 2010-2011;[21] whereas, ex-post relative inequality of opportunity decreases from 11.87 % to 11.25 % over the period considered (see Table 3).

Two main implications stem from this analysis: the effect of growth on each part of the distri-

[21] Here again we use the mean logarithmic deviation applied to the standardised distribution Y_B^t and Y_B^{t+1}.

bution differs depending on the EOp approach used, whether an ex-ante or an ex-post one, which makes meaningful the use of both the ex-ante and ex-post individual OGICs for an assessment of growth from an opportunity egalitarian perspective. When taking an ex-ante perspective, that is ignoring within-type inequality, the worst consequences of the recession appear to be suffered by the middle percentile of the distribution of opportunity. On the contrary, from the ex-post perspective, that is taking into account the effort exerted, worst performing individuals belong to the bottom of the opportunity distribution. The intuition is that if we limit the analysis to the ex-ante approach we do not fully recognize how regressive growth has been in terms of opportunity. Overall the results are robust in terms of inequality of opportunity variation over time, which slightly increases from 2009-2010 to 2010-2011 when measured in absolute terms. However, because of the dramatic increase in outcome inequality, the share of both ex-ante and ex-post inequality of opportunity on overall inequality decreases, which makes meaningful the adoption of an opportunity egalitarian perspective to complement the standard outcome oriented approach for the analysis of the distributional implications of growth.

Shifting the focus on the opportunity performance of each socio-economic group of the population during the same consumption dynamic, thus endorsing a non-anonymous approach to the evaluation of growth under an opportunity egalitarian perspective, provides us with additional information.

The type OGIC of Uganda is reported in Figure 4. It plots the growth rate of the opportunity set of each type with types sorted increasingly according to the value of their opportunity set in the initial period. The type OGIC thus shows how types with relatively poor opportunities in the initial period have increased the value of their opportunity set in comparison to richer types. The Ugandan type OGIC does not show a clear pattern: only 6 types benefit from an increase in their opportunity set, although this increase ends up to be statistically significant for only one type composed by individuals belonging to ethnic minorities and born in a district with an upper intermediate level of HDI. The type benefiting most from growth encompasses individuals of ethnic groups with Eastern lacustrine Bantu linguistic origins and born in highly developed areas. The remaining 18 types undergo a reduction of their opportunity set, which is statistically significant for 7 of them. In particular, the type experiencing the largest lost is represented by individuals belonging to ethnic groups with Eastern Nilotic linguistic origins and born in highly developed areas. As arisen in the discussion of the opportunity profiles, these results suggest that ethnic origins play a stronger role than birthplace does in determined the extent of opportunities of each group of the population and their dynamic over time.

The class OGIC, reported in Figure 5, is obtained by further partitioning the distribution of each type into three quantiles; it plots the consumption growth rate of each class, with classes sorted increasingly according to the level of their consumption in the first period.

A first interesting aspect has to do with the number of permutations we have to make in order

Figure 4: Type OGIC

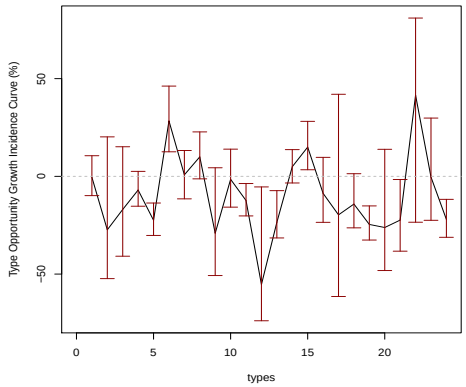
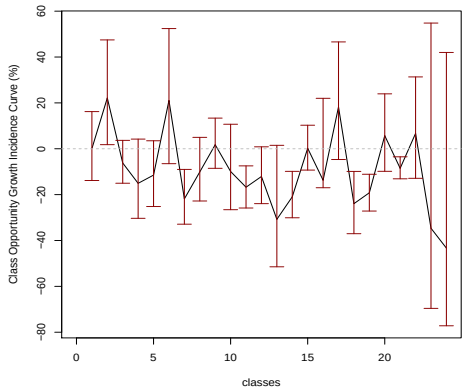


Figure 5: Class OGIC



Note: Standard errors are obtained through 1,000 bootstrap replications.
Source: Authors' elaboration based on UNPS 2009-2010 and 2010-2011.

to create classes. Recall that to make classes one has to rank cells in each quantile according to their average outcome. Doing so, cells belonging to different types can be re-ranked. In the case of Uganda, re-ranking takes place at least once for all types. That is, all classes are made by individuals coming from different types.

This suggests that the ex-ante approach may be not sufficient to correctly understand how the distribution of opportunities evolves over time in Uganda. To be part of an ethnic group and to be born in area with different levels of development, as measured by the HDI, has different implications depending on the effort exerted (or possibly depending on unobservable circumstances). Moreover, differently from the type OGIC, the class OGIC is characterised by a rather clear declining pattern,

suggesting that individuals in less advantaged classes gain more from the aggregated consumption dynamic under analysis than individuals belonging to richer classes. This implies that, if on average worst off types do not gain more from growth than better off types (the type OGIC is not decreasing, see Figure 4), the worst off classes do: there is some progressive redistribution taking place when we go beyond an analysis based on the types' average output, that is when we move from the ex-ante to the ex-post approach. Last, note that this result is not a contradiction of what shown in Figure 3: the class OGIC is based on a non-anonymous definition of class, while to measure IOp individuals are ranked according to the value of their opportunity set at each point in time.

Table 3: Descriptive Statistics

	2009-2010	2010-2011
Average consumption	948.57 (1,081.80)	902.23 (1,290.74)
Per capita consumption inequality	0.342555 (0.0165)	0.374519 (0.0196)
ex-ante IOp	0.046761 (0.0005)	0.048317 (0.0008)
relative ex-ante IOp	13.65 %	12.90 %
ex-post IOp	0.040650 (0.0007)	0.042147 (0.0006)
relative ex-post IOp	11.87 %	11.25 %

Note: Standard errors are obtained through 1,000 bootstrap.
Source: Authors' elaboration based on UNPS 2009-2010 and 2010-2011.

In the choice of which results of EOp sensitive growth (ex-post or ex-ante) should be considered from a pure policy perspective, one must bear in mind that this choice depends on which principle is more relevant in our context. As we have already discussed, there are two different declinations of the equity principle. In particular, there are two different interpretations of the compensation principle, which constitutes the egalitarian component in the EOp theory. Ex-post compensation requires equal outcome for equal effort, while ex-ante compensation requires equal set of opportunities for all individuals: they may give different ranking and policy prescriptions (see Fleurbaey and Peragine 2013). While most of theoretical literature endorses the ex-post perspective (see in particular Roemer 1998 and Fleurbaey 2008), most of the applied literature uses, instead, the ex-ante approach because of its computational simplicity. Our contribution is inspired by the most theoretically compelling approach. To conclude, they are different tools that capture different principles and the choice of one instead of the other should be inspired by the normative principle endorsed by the analyst.

4 Conclusions

In this paper we have proposed a set of analytical tools to describe the redistributive effect of a growth process from an opportunity egalitarian perspective. In particular, we have proposed an extension to the ex-post dimension of EOp of the OGIC framework introduced by Peragine et al.

(2014), generally valid when the ex-ante perspective to EOp is endorsed. Our framework consists of the so-called ex-post individual OGIC - plotting the rate of growth of the individuals in the same position in two outcome distributions neutralized for the effect of effort on inequality - and class OGIC - plotting the rate of income growth for each sub-group of the population, where the sub-groups are defined in terms of individuals that share the poorest outcome for each given level of effort.

We have adopted these analytic tools to evaluate the recent consumption dynamic that has characterized the Ugandan economy, under the perspective of equality of opportunity. The analysis has been carried on applying the Opportunity Growth Incidence Curve framework to two waves of the Uganda National Panel Survey (UNPS) - the 2009-2010 and 2010-2011. We have shown that, according to the standard outcome perspective, this dynamic was heavily regressive, thus bringing about to a consistent increase of outcome inequality, confirming what has been found by previous contributions. However, as soon as opportunities become the space of evaluation, the growth's impact become smoothed. While the ex-post OGIC revealed a regressive impact of growth on IOp, but less severe than the one revealed by the standard GIC, the ex-ante OGIC did not show any clear feature. In aggregated terms this implied a slight rise of ex-post and ex-ante inequality of opportunity over the period considered, but it also implied a reduction of their share in terms of total inequality. Last, the focus on specific socio-economic groups of the population has even acted by reverting this conclusion through a type OGIC that did not show any clear pattern, and a class OGIC that instead revealed a progressive impact of growth among initial classes.

As soon as new data will be available, it will be possible to understand whether the outcome-opportunity relationship follows a specific trend over time and to study the mechanism through which this relationship is generated.

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Appendix

Table 4: Linguistic origin by ethnic group.

ethnicity	*ethnic group*	*sample*
Baganda	Eastern lacustrine Bantu	3085
Bagisu	Eastern lacustrine Bantu	776
Bagwe	Eastern lacustrine Bantu	17
Bagwere	Eastern lacustrine Bantu	202
Banyole	Eastern lacustrine Bantu	130
Basamia	Eastern lacustrine Bantu	262
Basoga	Eastern lacustrine Bantu	1262
Baamba	Western lacustrine Bantu	23
Babwisi	Western lacustrine Bantu	44
Bafumbira	Western lacustrine Bantu	196
Bahororo	Western lacustrine Bantu	22
Banyakole	Western lacustrine Bantu	1522
Banyarwanda	Western lacustrine Bantu	228
Banyoro	Western lacustrine Bantu	448
Batagwenda	Western lacustrine Bantu	11
Batoro	Western lacustrine Bantu	424
Ik (Teuso)	Eastern Nilotic	5
Iteso	Eastern Nilotic	1187
Kakwa	Eastern Nilotic	117
Karimojong	Eastern Nilotic	290
Kumam	Eastern Nilotic	114
Sabiny	Eastern Nilotic	90
Acholi	Western Nilotic	411
Alur	Western Nilotic	531
Chope	Western Nilotic	9
Dodoth	Western Nilotic	181
Japadhola	Western Nilotic	201
Jie	Western Nilotic	122
Jonam	Western Nilotic	34
Kebu	Western Nilotic	7
Langi	Western Nilotic	1467
Lugbara	Central Sudanic	752
Madi	Central Sudanic	163
Bangungu	Ethnic minorities	18
Bahehe	Ethnic minorities	1
Bakenyi	Ethnic minorities	25
Bakiga	Ethnic minorities	1055
Bakhonzo	Ethnic minorities	340
Banyara	Ethnic minorities	12
Basongora	Ethnic minorities	1
Baruli	Ethnic minorities	57
Nubi	Ethnic minorities	28
Nyangia	Ethnic minorities	1
Pokot	Ethnic minorities	41

Source: Byrnes, 1992; Asiimwe et al., 2012.

Table 5: HDI by district.

district	*HDI*	*HDI class*
Kotido	0.231	low
Nakapiripirit	0.240	low
Moroto	0.271	low
Yumbe	0.387	low
Katakwi	0.390	low
Adjumani	0.396	low
Moyo	0.396	low
Nebbi	0.399	low
Bundibugyo	0.417	low
Kumi	0.423	low
Mayuge	0.425	low
Gulu	0.428	low
Bugiri	0.432	low
Kitgum	0.433	low
Tororo	0.434	lower intermediate
Kyenjojo	0.438	lower intermediate
Pallisa	0.438	lower intermediate
Arua	0.441	lower intermediate
Kamwenge	0.442	lower intermediate
Lira	0.444	lower intermediate
Soroti	0.447	lower intermediate
Kisoro	0.451	lower intermediate
Kaberamaido	0.456	lower intermediate
Busia	0.458	lower intermediate
Apac	0.466	lower intermediate
Kamuli	0.468	lower intermediate
Nakasongola	0.469	lower intermediate
Pader	0.470	lower intermediate
Masindi	0.472	upper intermediate
Kanungu	0.478	upper intermediate
Iganga	0.480	upper intermediate
Sironko	0.481	upper intermediate
Kiboga	0.482	upper intermediate
Kayunga	0.482	upper intermediate
Kabarole	0.486	upper intermediate
Mbarara	0.489	upper intermediate
Rakai	0.489	upper intermediate
Mubende	0.496	upper intermediate
Kibaale	0.496	upper intermediate
Sembabule	0.496	upper intermediate
Kasese	0.497	upper intermediate
Hoima	0.498	upper intermediate
Kabale	0.502	high
Ntungamo	0.506	high
Bushenyi	0.510	high
Mbale	0.514	high
Mukono	0.515	high
Rukungiri	0.519	high
Mpigi	0.520	high
Luwero	0.520	high
Kalangala	0.529	high
Masaka	0.532	high
Jinja	0.533	high
Kapchorwa	0.543	high
Wakiso	0.601	high
Kampala	0.615	high

Source: UNDP (2014).