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The redistributive impact of growth on opportunities in Uganda

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Abstract

We propose a set of analytical tools to explore the link between economic growth and inequality of opportunity. Although we do not assume any causal relationship between income dynamic and inequality of opportunity, our approach studies the link in a growth-to-inequality direction. We adopt the proposed approach to evaluate the effect of economic growth on inequality of opportunity in Uganda between 2009 and 2010. We show how despite a surge in inequality, in that period, inequality of opportunity declined.

1 Introduction

In the last decade there has been a renewed interest among economists and policy makers on the study of the relationship between economic inequality and growth. While this complex relationship has been originally investigated by a macroeconomic-oriented literature that has focussed on the effect of inequality on growth (see Voitchovsky, 2009 for a recent review), a microeconomic-oriented approach has recently flourished. This approach inverts the causal relationship and aims at evaluating the impact of income dynamics on poverty and inequality. A standard practice, in the micro-oriented literature is to compare the pre-growth and post-growth distribution of individual outcomes such as income or consumption in order to understand the distributional impact of growth. The main instrument used here is 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 that of richer segments. As discussed by Ferreira (2011) for a large number of inequality indices *"changes in inequality are ultimately just different ways of aggregating the information contained in the growth incidence curve."* p. 14..

Today the GIC is probably the most popular tool among economists and policy makers to evaluate distributive effect of growth on outcomes such as individual consumption or income. However, a recent branch of the literature, the Equality of Opportunity (EOp) literature, considers the

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individual "opportunity" as the most appropriate variable for equity judgements (Roemer, 1998; Fleurbaey, 2008). The EOp theory basically distinguishes between unfair and fair inequality. The former, is inequality between opportunity sets and should be eliminated, because it is determined by factors beyond the individual control. The latter is inequality within opportunity sets and should not be eliminated, because generated by individual choices and effort.

Sharing this view, in a recent paper (Peragine, et al., 2013), we argued that a better understanding of the distributional effect of growth can be obtained complementing the standard micro-approach with an analysis of the distributive effect of growth in terms of opportunities. To this end we adopted a theoretical framework standard in the EOp literature in which individuals obtain an outcome of interested (income for example) as a result of a variable of choice (effort) and the effect of circumstances beyond their control. We then modified the standard GIC approach introducing the concept of *Opportunity Growth Incidence Curve* (OGIC): an analytical tool able to capture the distributive effect of growth in terms of opportunities.

To construct the OGIC we were compelled to endorse an exact definition of EOp. Now, the literature provides a wide range of approaches to decline the very general definition of EOp, from which we opted for the so called *ex ante* approach to measure inequality of opportunity (IOp). According to this approach, IOp 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 IOp.

The main shortfall of this approach is its inconsistency with the so called ex post principle of EOp. The ex post EOp principle states that "there is equality of opportunity if individuals exerting the same degree of effort are given the same outcome" (Roemer, 1998). The ex post approach is therefore based on a principle of compensation that call for compensation of unfair inequality when individuals with the same variable of choice end up with a different outcome. Although apparently similar in spirit ex ante and ex post EOp principles have been shown to be incompatible (Fleurbaey, 2008; Fleurbaey and Peragine, 2012). In particular an ex ante measure of IOp has been shown to be inconsistent with the compensation principle at the base of the ex post approach.

In what follows we widen the set of tools to evaluate the effect of growth on IOp proposing two growth incidence curves consistent with the compensation principle: the *ex post Opportunity Growth Incidence Curve* (ex-post OGIC) and the *class Opportunity Growth Incidence Curve* (class OGIC). We then adopt this theoretical framework to analyze the distributional impact of the income dynamics in Uganda in recent years. We use two waves of the Uganda National Panel Survey (UNPS). This survey was done as part of the Living Standards Measurement Study - Integrated Surveys on Agriculture project established by 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 main regional levels Both waves contain information about individual circumstances beyond individual control - namely ethnicity and rural/urban area of birth - to allow an estimation of changes in the degree of IOp between 2009/10 and 2010/11.

The rest of the paper is organized as follows. Section 2 describes the building-blocks of the EOp model and reviews the two most popular methods used to evaluate IOp and to evaluate growth consistently with this model. Section 3 introduces the ex post OGIC and class OGIC. Section 4 presents the empirical implementation of the tools to the growth dynamic in Uganda. Section 5 concludes.

2 EOp Framework

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

$$y_t = g(c, e_t) \tag{1}$$

Assume that it is possible to partition the population 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 exerting effort j.

2.1 Ex ante and ex post IOp

The framework summarized in eq. (1) is at the base of a variety of definitions of equality of opportunity existing in the literature (for a recent review see Ramos and Van de Gaer 2013). In what follows we will refer in particular to two of these: the so called *ex ante* and *ex post* principles of EOp. The ex ante principle states that:

ex ante EOp: "There is EOp if the value of the opportunity set of all types is the same. Inequality of opportunity is outcome inequality between types."

Following Checchi and Peragine (2010), ex ante IOp can be evaluated by applying an index of inequality to a smoothed distribution in which all inequality due to effort has been eliminated. Such smoothing process is obtained, first, by ordering types on the base of the value of their opportunity set, which is usually summarized by their mean outcome, that is: $\mu_1(y_t) \leq \mu_2(y_t) \leq, ..., \leq \mu_n(y_t)$, and then 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 $I(Y_S^t)$. Due to its property of path independent additive decomposibility, the inequality measure generally used is the mean logarithmic deviation. Hence:

$$ex\ ante\ IOp = MLD\left(Y_S^t\right) = \frac{1}{N}\sum_{p=1}^{N} \ln \frac{\mu^t}{\mu_k^t} \tag{2}$$

where μ^t is the population grand mean.

Ex ante IOp is often estimated as share of total inequality due to opportunity obtained simply dividing eq. 2 by the mean logarithmic deviation of the original outcome distribution Y^t.

The ex ante IOp is by far the most adopted measure of IOp[1], however, a second approach to measure IOp has been widely adopted: the ex post approach. The ex post principle of EOp states that:

ex post EOp: "There is EOp if all those who exerted the same degree of effort have the same outcome. IOp is inequality within tranches of the distribution."

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

In this case inequality of opportunity is measured as inequality within tranches (we follow again Checchi and Peragine 2010). 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 between tranches inequality while does not alter inequality within tranches.

Hence, for any outcome distributions $Y^t \in \mathbb{R}_+^N$, the outcome of a generic individual of type i and exerting effort j is first substituted with the mean outcome of her cell (set of those in the same type and exerting the same effort): $\mu_{i,j}^t$ and then rescaled as follows: $\hat{y}_k^t = \frac{\mu_{i,j}^t}{\hat{\mu}_j^t}\mu^t$, where $\hat{\mu}_j^t$ is the mean income of tranche j. This smoothing process eliminates all the 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 $Y_B^t = (\hat{y}_1^t, ..., \hat{y}_k^t, ..., \hat{y}_N^t)$. Using the mean logarithmic deviation, ex post inequality opportunity is given by:

$$ex\ post\ IOp = MLD\left(Y_B^t\right) = \frac{1}{N}\sum_{k=1}^{N} \ln \frac{\mu^t}{\hat{y}_k^t} \tag{3}$$

Although similar in spirit and empirically strongly correlated ex ante and ex post IOp have been shown to be incompatible in all cases in which the function mapping circumstances and effort into outcome is not separable in its argument (Fleurbaey, 2008).

2.2 Opportunity Growth Incidence Curve

In Peragine et al. (2013) we propose a set of tools to evaluate the effect of growth on the distribution of opportunities which is consistent with the *ex ante* approach. There are two natural ways to look at the distributive effect 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 ($\text{IOp}^{t+1} > \text{IOp}^t$)? The second possible way is to investigate wether different circumstances beyond individual control are associated with different levels of growth. IOp in this case is inequality of average growth between types. Although inspired by the same ethical concern the two questions are not at all equivalent. This explains why we introduced 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 - and we showed that they can lead to different pictures in very general cases.

The *ex ante 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 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 OGIC can be defined as:

$$g_{Y_S}^o\left(\frac{k}{N}\right) = \frac{\mu_k^{t+1}}{\mu_k^t} - 1, \forall k \in \{1, ..., N\} \tag{4}$$

Where $g_{Y^S}^o\left(\frac{j}{N}\right)$ measures the proportionate change in the value of opportunities of the individuals ranked $\frac{k}{N}$ in the smoothed distributions. Obviously, $g_{Y_S}^o\left(\frac{j}{N}\right) \geq 0$ ($g_{Y_S}^o\left(\frac{k}{N}\right) < 0$) 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.

However, the ex ante 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 type specific mean outcome, but it also depends on the type specific population share and the possible re-ranking of types taking place during the 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, we introduce a second version of the OGIC. The *type OGIC* plots the rate of outcome growth for each sub-group of the population, where the sub-groups are types, defined in terms of circumstances beyond individual control.

Letting $Y_\mu^t = (\mu_1(y_t), ..., \mu_n(y_t))$ be the distribution of type 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 type mean outcome at time $t+1$, where types are ordered according to their position at time t, we define the *type OGIC* as:[2]

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

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 initial circumstances. $g^o_{Y_\mu}\left(\frac{i}{n}\right)$ 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.

To summarize consider the tables below. Each reports the distribution of outcome of individuals at a given time exerting three possible degrees of effort (low, medium, high) and belonging to two groups based on their socioeconomic background (blue collar parents, white collar parents).

We can easily verify that ex ante IOp is 0.0178 at time t and is 0.0319 at time $t+1$. Therefore we expect an upward slopping ex ante OGIC:

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

However, if we track types we notice that growth was progressive: individuals with low socioeconomic background increased their outcomes, while outcome is decreasing for all the others:

$$\textit{type OGIC}: (0.5385, 0.5385, 0.5385, -0.3684, -0.3684, -0.3684)$$

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

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

Because the individual OGIC approach considers anonymous types, and the type OGIC instead traces types' outcome across time, the re-ranking tanking place from time t to time $t+1$ causes the two curves to have opposite slope.[3] This conflict is not a contradiction: a downward sloping type OGIC does not imply a reduction of IOp over time.

However, a more intriguing characteristic of the example above is the change in IOp in terms of ex post IOp, which signals a reduction in IOp, from 0.0629 to 0.0343. This conflict appears much more worrisome because ex ante and ex post IOp are two approaches that measure the same thing: inequality of chances. The clash between ex ante - ex post EOp principles has been analyzed in depth (Fleubaey, 2008; Fleurbaey and Peragine, 2010). 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. It is therefore impossible to construct an OGIC consistent both with the ex ante and the ex post approach to measure IOp. However, as we show in the next section, it is possible to construct ex post versions of the two OGICs introduced above, that we will call: *ex post individual OGIC* and *class OGIC*.

3 Compensation consistent OGIC

3.1 Ex post individual OGIC

In this section we introduce the *ex post (individual) Opportunity Growth Incidence Curve*. The ex post OGIC captures the impact of growth on the distribution of opportunities, according to the ex post approach.

Given an initial distribution of outcome Y^t and the corresponding smoothed distribution Y_B^t, assuming that individual smoothed 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 smoothed distributions Y_B^t and Y_B^{t+1}. Hence the *ex post individual OGIC* can be defined as:

$$g^o_{Y_B}\left(\frac{k}{N}\right) = \frac{\hat{\mu}_k^{t+1}}{\hat{\mu}_k^t} - 1, \forall k = 1, ..., N \tag{6}$$

The individual ex post OGIC plots the percentage outcome change of individuals ranked $\frac{k}{N}$ in the smoothed distributions Y_B^t and Y_B^{t+1}. A decreasing curve means that growth has been

[3] In the example at time $t+1$ individual with poor socioeconomic background become richer than individuals with rich socioeconomic background.

opportunity equalizing, an increasing curve means that growth has been regressive in terms of IOp. This interpretation is straightforward if we recall that at the bottom of the smoothed distribution are individuals suffering the most the negative effect of poor circumstances.

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

To see the relationship between *ex post individual OGIC* and ex post IOp, consider the Lorenz curve of Y_B^t:

$$L_{Y_B^t}\left(\frac{k}{N}\right)=\frac{\sum_{j=1}^{k}\hat{\mu}_j^t}{\sum_{j=1}^{N}\hat{\mu}_j^t},\forall k\in\{1,...,N\},\forall t\in\{1,...,T\} \tag{7}$$

The ex post OGIC defined in eq. (6) can be decomposed in such a way that it becomes a function of the Lorenz curve defined in eq. (7), as follows:

$$g^o_{Y_B}\left(\frac{k}{N}\right)=\frac{\Delta L_{Y_B^{t+1}}\left(\frac{k}{N}\right)}{\Delta L_{Y_B^t}\left(\frac{k}{N}\right)}(\gamma+1)-1,\forall k\in\{1,...,N\} \tag{8}$$

where $\Delta L_{Y_B^t}\left(\frac{k}{N}\right)=\frac{\hat{\mu}_k^t}{\mu^t}$ is the first derivative of $L_{Y_B^t}\left(\frac{k}{N}\right)$ with respect to $\frac{k}{N}$ and $\gamma=\frac{\mu^{t+1}-\mu^t}{\mu^t}$ is the mean outcome growth rate. Thus, when growth is proportional, it does not have any impact on the level of IOp: $\frac{\Delta L_{Y_B^{t+1}}\left(\frac{k}{N}\right)}{\Delta L_{Y_B^t}\left(\frac{k}{N}\right)}=1$ and $g^o_{Y_B}\left(\frac{k}{N}\right)$ will just be an horizontal line, with $g^o_{Y_B}\left(\frac{k}{N}\right)=\gamma$ for all k. On the contrary, when growth is progressive (regressive) in terms of opportunity, growth acts by reducing (worsening) IOp: $\frac{\Delta L_{Y_B^{t+1}}\left(\frac{k}{N}\right)}{\Delta L_{Y_B^t}\left(\frac{k}{N}\right)}\neq 1$, and $g^o_{Y_B}\left(\frac{k}{N}\right)$ will be a decreasing (increasing) curve.

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

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

3.2 Class OGIC

In the previous section we have proposed an ex post version of the *individual OGIC*. The *ex post individual OGIC* is a tool to evaluate growth consistently with the ex post EOp theory. In particular the OGIC introduced here in eq. (4) is clearly related to the variation of ex post EOp over time. A natural question here is to ask wether it is also possible to construct an ex post version of the type OGIC. Recall that the ex ante version of the type OGIC was a tool meant to evaluate inequality between types in terms of average growth. 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 effort tranches. In this cases to focus on types is unsatisfactory because to belong to a type has a different meaning depending on the effort exerted. Take the distribution at time $t+1$ in the *ad hoc* example above: to be the daughter of a blu collar means to be worse off if she exerts effort low, but has the opposite meaning if she exerts higher degree of effort. In an ex post perspective to track the outcome of different groups means to trace the group of individuals sitting in the same position of the within tranche distribution. This can be done using the reference framework recently introduced by Fleurbaey and Peragine (2014).

Given the following matrix

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

it is possible to construct a new distribution, call it Y_C^t, by permuting each columns such that the rows dominate each other. We call the rows of this new distribution "classes".[4]

The next step consists in constructing a class OGIC that can be interpreted as the ex post counterpart of the type OGIC of eq. (3). We first order class means in ascending order $\breve{\mu}_1^t \leq ... \leq \breve{\mu}_j^t \leq ... \leq \breve{\mu}_n^t$ and then obtain the *class OGIC* with the formula:

$$g^o_{Y_{\hat{\mu}}}\left(\frac{i}{n}\right) = \frac{\breve{\mu}_i^{t+1}}{\breve{\mu}_i^t} - 1, \ \forall i \in \{1, ..., n\} \tag{9}$$

The class OGIC plots, against each class, the variation of the opportunity set of that class. It can be interpreted as the rate of economic development of each class in the population. $g^o_{Y_{\hat{\mu}}}\left(\frac{i}{n}\right)$ is horizontal if each class benefits (looses) in the same measure from growth.[5] 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, 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 higher class:

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

[4]Note that calculating ex post IOp in this new distribution as suggested in section 2.1 is exactly equivalent than using the original distribution Y^t.

[5]Note that to track classes across time does not imply to track 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

4 Growth and inequality of opportunity in Uganda

We apply the four curves proposed to show how growth affected the degree of IOp in Uganda between 2009/10 and 2010/11. We exploit two waves of the Uganda National Panel Survey (UNPS). The 2010/11 UNPS survey contains information about households and community conditions in 80 districts in Uganda. Out of the 7,400 households interviewed during the Uganda National Household Survey (UNHS) 2005/06, 3,200 households were selected for the UNPS and the same sample was maintained in both 2009/10 and 2010/11 panel surveys. In order to evaluate the impact of growth on the distribution of opportunities we had to choose an outcome variable able to summarize individual opportunity and a set of circumstances beyond individual control to identify types. The sample considered includes only household heads and their spouse. The outcome considered is per capita yearly consumption obtained dividing the total household consumption by the number of its components and expressed in 2010 Ugandan Shilling. An ideal partition in types would include all possible characteristics beyond individual control of household members such as sex, socioeconomic origin, ethnicity, area of birth. However, to obtain reliable estimate of IOp we are forced to limit the number of circumstances considered. This issue is common to all empirical applications that estimates IOp. Because of the lack of information or due to the size of the sample only a subsample of the real circumstances is considered. As discussed among other by Ferreira and Gignoux (2011) IOp estimates obtained limiting the number of circumstances to a subsample of the real 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.

In the case of Uganda UNPS contains a large set of circumstances: parental education, parental occupation, area of birth, ethnicity. However, the large number of missing information about parental socioeconomic background of adult household members, forced us to restrict the analysis to only two circumstances: ethnicity and urban/rural area of birth. We obtained a partition of 26 types whose members share the same origin in terms of rural/urban area and ethnicity. Although 26 is clearly a subset of the real number of types in which Uganda could be partitioned it represents an improvement if compared with the only available estimate of IOp in the country which is based on only three types (Cogneau and Mesplé-Somps, 2008).

The choice of the two characteristics is guided by the Ugandan recent history in which ethnic origins and urban/rural divide have played an important role. Ugandans can be classified into several ethnic groups, none constitutes a majority. Before the colonial period some inter-ethnic conflicts occurred in Uganda though not on a large scale. However, after independence ethnicity

played 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, secondly different groups traditionally relied on different economic activities: pastoralism in the West and North, and agriculture in the lakes region. Finally different groups maintained different relationships with the central government both during the British colonial period and after independence.

The rural-urban development gap is instead a consequence of the industrialization effort promoted by the central governments in the first two decades after independence characterized by a urban bias (Mukwaya et al., 2012). Notwithstanding the government focus on rural development in recent years, the majority of rural areas, especially in the North, are still lagging behind in both income and access to services (World Bank, 2012).

Table 1 summarizes the partition in types based on rural/urban area of origin and into ethnic groups (divided into: Baganda, Bagisu, Bakiga, Banyakole, Basoga, Iteso, Langi, Lugbara, Acholi, Alur, Banyoro, Batoro, other). Table 1 ranks types according to the average per capita consumption at the initial time (2009/10), it 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. Interestingly the Uganda opportunity profile is clearly dominated by the circumstance rural-urban area of origin: the 12 poorest types are characterized by rural origin and only Baganda from rural areas have an average per capita consumption higher than some urban types.

4.1 Growth and Inequality in Uganda

In 2013 the Ugandan Government announced that Uganda had achieved the first target of Millennium Development Goal - halving the proportion of people below the national poverty line well ahead of the 2015 deadline: the poverty headcount ration declined from above 56% in 1992 to 24.5% in 2010 (The Republic of Uganda, 2013). This impressive reduction in the incidence of poverty was mainly due to the high rate of growth, which resulted in a growth of per capita consumption of about three percent per annum in the same period. The Uganda economic performance has been linked to a prolonged period of peace and security after the end of the civi war and a series of structural reforms introduced since the late '80s including trade and financial liberalization. Moreover, improved access to markets and a progressive diversification of households activity away from subsistence farming triggered a process of development which has led Uganda to be one of the World fastest growing economy in the last decade[6] (World Bank, 2012).

However, as shown by Ssewanyan et al. 2004, changes in poverty was almost wholly due to growth rather than redistribution. The poorer regions lagged behind the richer and between regions inequality tripled from 1992/3 to 2009/10 (World Bank, 2012). Inequality increases also within regions. Appleton (2001) estimated that with zero economic growth in the '90s poverty in Uganda would have increased by a three percentage points. The rate of inequality increase accelerated in the more recent years. According to the Uganda Bureau of Statistics inequality the Gini index rose from 0.372 in 2009/10 to 0.411 in 2010/11 (UBS, 2013), the World Bank reports a less dramatic but similar trend with an increase of two percent points between 2006 and 2009. The recent increase in inequality is witnessed by the GIC reported in figure 1 based on the UNPS waves 2009/10 and 2010/11. The GIC reports the quantile specific percent growth rate in per capita consumption in the period covered by our sample. The GIC shows an increasing pattern: only few of the poorest quantiles experienced a negative growth while richer quantiles experience a growth in equivalent

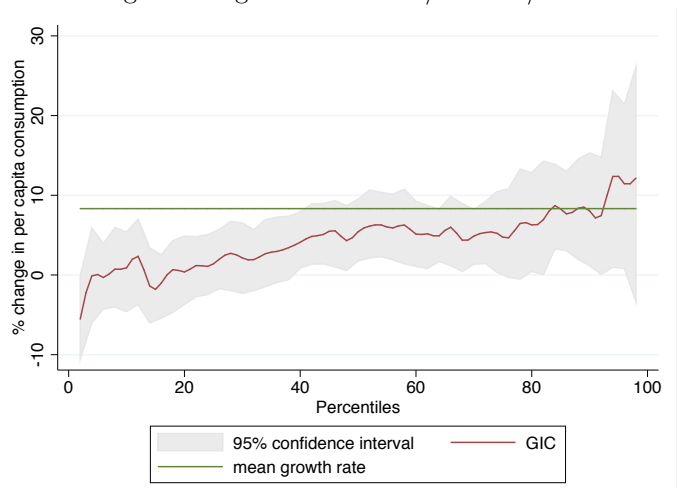
[6]Since 2003 Ugandan GDP has grown by 7.4% per year.

Table 1: Opportunity profiles

ethnicity	urban-rural area of birth	sample 2009-10	sample 2010-11	consumption 2009-10	consumption 20-2011
Langi	rural	369	391	430.0651	586.7095
Bagisu	rural	210	219	470.9875	488.6648
Alur	rural	135	126	505.0965	590.1815
Acholi	rural	60	39	518.938	616.4105
Bakiga	rural	268	235	530.1306	581.9967
Iteso	rural	278	283	558.95	605.054
other	rural	731	670	601.4477	737.6265
Batoro	rural	83	66	605.3352	849.8109
Basoga	rural	252	273	688.8183	768.6586
Lugbara	rural	183	187	727.6544	762.1089
Banyakole	rural	360	344	739.7861	734.6293
Banyoro	rural	82	68	758.285	950.3998
Alur	urban	44	37	776.1195	621.2897
Acholi	urban	49	66	996.4117	1179.854
Langi	urban	42	56	1032.615	1297.808
Bagisu	urban	43	47	1238.503	1526.846
Basoga	urban	83	74	1306.341	1615.649
Baganda	rural	463	474	1307.65	1433.052
Banyakole	urban	79	56	1436.758	1968.298
other	urban	133	94	1561.487	1697.711
Batoro	urban	41	30	1661.222	2432.966
Baganda	urban	363	275	1678.427	2131.403
Banyoro	urban	45	31	1782.319	1576.877
Bakiga	urban	58	31	1791.318	1368.553
Iteso	urban	31	29	1926.95	2008.48
Lugbara	urban	36	33	2604.324	1918.748

source: UNPS 2009/10-2010/11.
Consumption is expressed in yearly per capita thousands Ugandan shillings (2010).

Figure 1: Uganda GIC 2009/10-2010/11



source: authors' elaboration based on UNPS 2009/10-2010/11.
Standard errors are obtained through 2,000 bootstrap replications.

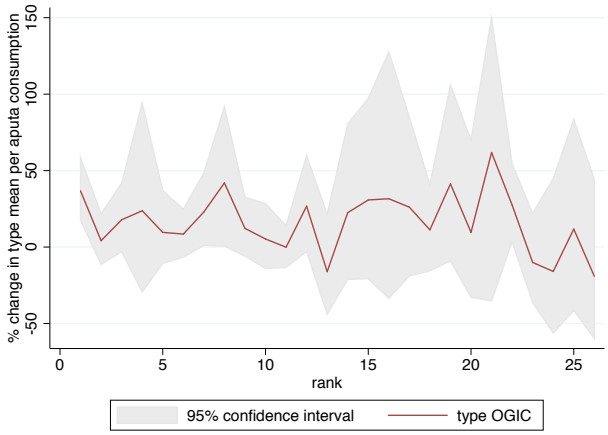
consumption far above the average growth rate. The consequence was an increase of inequality, in our sample the mean logarithmic deviation of per capita consumption rose from 0.41 in 2009/10 to 0.45 in 2010/11. Among the main drivers of this inequality increase there is a widening gap between the rural and urban area pace development, inequality in human capital investment and growing return to education, and the limited employment created by the most dynamic sectors of the economy (Ssewanyan et al. 2004; Mukwaya et al., 2012).

4.2 Consumption dynamic and Inequality of opportunity

In this context it appears of interest to understand wether increasing inequality affected all socioeconomic groups in the same way and if the amount of inequality due to differences in opportunities also increased. To answer these two questions we estimate two couples of curves: type and class OGIC, which track the outcome of individuals belonging to more or less advantaged groups; ex ante and ex post OGIC which disaggregate IOp change over time showing how progressive/regressive has been the consumption dynamic.

To estimate the type OGIC means to calculate the type specific growth rate. As explained before this curve has not a direct interpretation in terms of inequality of opportunity change, however, it shows how types with relatively poor opportunity have increased the value of their opportunity set in comparison to richer types. In the case of Uganda 2009/10-2010/11 the curve does not show a clear pattern. Among best performing types we find group with very poor initial condition such as member of Langi born in rural areas (36% increase in per capita consumption) and groups with relatively good initial condition such as Batoro born in urban areas (46% increase in per capita consumption). Similarly among the worst performing groups there are both rich and poor types but with a prevalence of rich such as Lugbara and Bakiga born in urban areas (-26% and -23%

Figure 2: Uganda type OGIC 2009/10-2010/11



source: authors' elaboration based on UNPS 2009/10-2010/11.
Standard errors are obtained through 2,000 bootstrap replications.

respectively).

The interpretation of class OGIC is even more complex because each class contains individual belonging to different types depending on the tranche considered. To draw the class OGIC we further partition the distribution of types in five quantiles for each type, we then permute each column such that the rows dominate each other. We then track the class exactly as we have done to obtain the type OGIC.

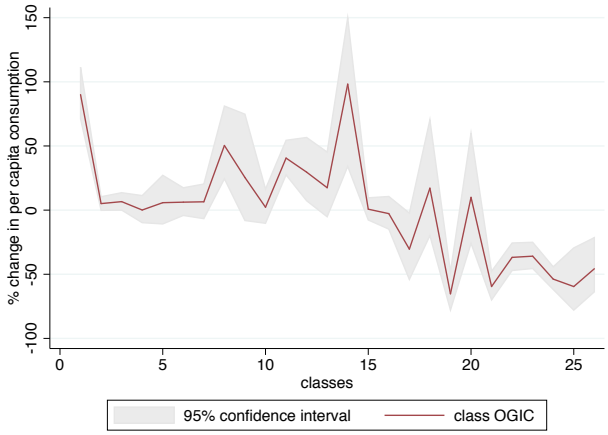
We first notice that the permutation takes place for the majority of the types: only for 8 classes the rank of types and class is the same, the remaining 18 classes are made by individuals belonging to different types. This suggest that the ex ante approach may be not sufficient to correctly understand how the distribution of opportunities evolves over time in Uganda. To be part of an ethnic group and to born in an urban/rural area seems to have a very different meaning depending of the quantile of the effort distribution one belongs to.

Moreover, the class OGIC in figure 3 shows a rather clear declining pattern suggesting that individuals in least advantaged classes gained more from the aggregated consumption dynamic than individuals belonging to richer classes. This means that if on average worst off types did not gain more from growth (the type OGIC is not decreasing), the worst off classes did.

The type and class OGIC show no evidence that increasing inequality was associated with growing IOp in Uganda. However, given that both type OGIC and class OGIC are non-anonymous their patterns cannot be directly interpreted in terms of IOp reduction/increase. To evaluate the impact of growth on the distribution of opportunity we must move to the ex ante and ex post OGIC which do have a direct interpretations in terms of IOp.

The ex ante and ex post OGIC are obtained calculating the coordinates of the GIC of the two smoothed distributions Y_S^t, Y_S^{t+1} and Y_B^t Y_B^{t+1} respectively. The ex ante OGIC reported in figure 4 is not monotonic but shows a declining trend: with the exception of the very rich types individuals

Figure 3: Uganda class OGIC 2009/10-2010/11



source: authors' elaboration based on UNPS 2009/10-2010/11.
Standard errors are obtained through 2,000 bootstrap replications.

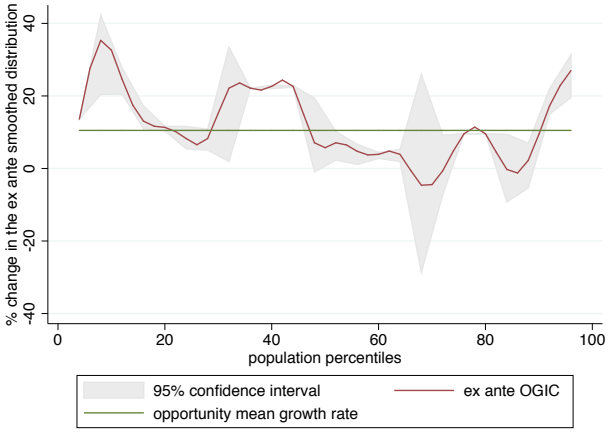
belonging to worst off types improved their set of opportunity more than individuals belonging to better off types. This pattern suggests a reduction of ex ante IOp which is witnessed by the change in the aggregated IOp measure which is 0.1204 in 2009/10 and declines to 0.1088 in 2010/11. In relative terms - the share of total inequality due to opportunity - the decline is larger, because of the increase in total inequality, relative IOp drops from 29.36% to 24.18%.

The ex post OGIC instead shows a less clear trend. The consumption dynamic was much less progressive in terms of ex post opportunity although individuals in worst of quantiles of the ex post smoothed distribution improved their position over time a large part of them worsen their position in the distribution of opportunities. This result is not a contradiction of what shown in figure 3 because the class OGIC is based on a non-anonymous definition of class while to measure IOp we rank individuals according to the value their opportunity sets at each point in time. The result is an ambiguous effect on the IOp in absolute term, this is witnessed by the aggregated index of ex post IOp which slightly increased during the period from 0.1031 in 2009/10 to 0.1099 in 2010/11 (a difference not statistically significant). However, when considering the share of total inequality due to opportunity IOp declines also considering the ex post approach (from 25.12% to 24.42%).

5 Conclusion

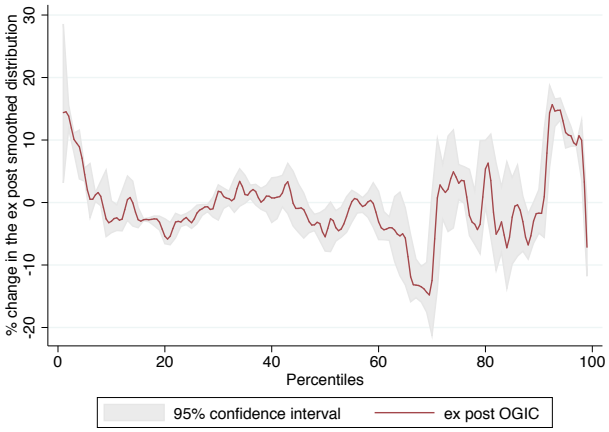
We have taken the growth-to-inequality direction to evaluate what are the effect of growth on the distribution of opportunities. Our starting point was the GIC by Ravaillon and Chen (2003). To adapt the GIC to the space of opportunity is not an innovation in the literature, two versions of the opportunity-GIC have been already proposed and estimated (Peragine et al., 2013). However, the main limitation of the proposed OGICs is that they are consistent only to a precise definition of inequality of opportunity, the so called ex ante IOp. The ex ante approach to equality of

Figure 4: Uganda ex ante OGIC 2009/10-2010/11



source: authors' elaboration based on UNPS 2009/10-2010/11.
Standard errors are obtained through 2,000 bootstrap replications.

Figure 5: Uganda ex post OGIC 2009/10-2010/11



source: authors' elaboration based on UNPS 2009/10-2010/11.
Standard errors are obtained through 2,000 bootstrap replications.

opportunity states that there is equality of opportunity whenever the value of the opportunity set of all individuals is the same. Despite its simplicity this principle conflicts with an other often adopted principle of equal opportunity, the ex post approach, which states that equality of opportunity is achieved whenever individuals exerting the same degree of effort obtain the same level of outcome. The type and individual OGIC proposed by Peragine et al. (2013) are two curves useful to evaluate the impact of growth on opportunities only when IOp is evaluated adopting an ex ante approach. As we have shown it is not difficult to define opportunity-OGIC consistent with the alternative approach to measure IOp: the ex post approach.

We have therefore proposed two curves that answer the two questions: 1) what is the effect of a period of economic growth/contraction on the value of opportunities of individuals which depending on their degree of effort had access to the poorest set of opportunity? What is the effect on the group with the second poorest se of opportunity? What the effect on the richest in terms of opportunity? 2) what is the effect of growth on the distribution of ex post opportunity? Did ex post IOp increased over time or declined?

The first question is answered estimating the class OGIC, a curve whose coordinates are the class specific growth rate ranked in ascending order according to their mean outcome at the initial time. This curve is not interpretable in terms of ex post IOp but shows how individuals in different initial advantage gained/lost during the growth period.

The second question is answered estimating the ex post OGIC, a curve obtained first estimating the distribution of ex post opportunity at the initial and final time and then estimating the GIC of these two distributions. This curve does have a clear interpretation in terms of ex post IOp change: an increasing curve signals that growth has been regressive in terms of opportunity (IOp increases) while a decreasing curve signals that growths has been progressive (IOp decreases).

We have applied these tools to a representative sample of the Uganda population. The case of Uganda is interesting because it represents an example of a dynamic economy that in recent years experienced, together with very high rates of growth, a dramatic increase in inequality. Our attempt was therefore to understand what was the impact of this growth dynamic on the distribution of opportunities.

To do so we exploit the information recorded in the first two waves of the UNPS (2009/10 and 2010/11). We first select a subsample of adult (household heads and their spouse) and then define the subset of circumstances beyond individual control to define types. We excluded parental socioeconomic background among circumstances because of the large number of missing observation and other variables (such as district of origin) to maintain a sufficiently large sample size in each type to allow inference. We end up partitioning the original sample into 26 types based on rural/urban area of birth and ethnicity.

Our estimates show a conflict between the inequality dynamic and the IOp dynamic. While the type OGIC and the ex post OGIC do not show a clear progressive/regressive impact of growth, the class OGIC and the ex ante OGIC do show a progressive impact of growth on the distribution of opportunities. In aggregated terms while inequality increased by 10% in one year, ex post IOp has remained stable and ex ante IOp has declined. In relative terms both the ex ante and ex post approach indicates that the share of total inequality due to opportunities has declined.

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