Inequality of opportunity: some challenges for the existing literature

Daniele Checchi
University of Milano
daniele.checchi@unimi.it

Vito Peragine
University of Bari
vitorocco.peragine@uniba.it

Abstract

This chapter provides a discussion of recent literature on the measurement of inequality of opportunity. After introducing the canonical model and the main definitions of EOp used in the literature, it focuses on some of the recent challenges faced by such approach: dynamics, multidimensionality, heterogeneity and drivers of IOp.

1. Introduction

The notion of "equal opportunities" has been of long-standing relevance in public debates and is increasingly proposed as a principle of social justice by politicians of different orientations. However, the meaning of equality of opportunity remains often vague in the public discourse, and this may partly explain its popularity. Though multiple definitions exist, the essence of the concept is that equality of opportunity is obtained when everyone exerting the same degree of effort (or responsibility) attains the same level of advantage (or well-being), regardless of any predetermined circumstances beyond their control (Roemer, 1998). Outcome inequalities are therefore consistent with equal opportunities only to the extent that they derive from differences in factors individuals can be held responsible for.

There are different reasons for embracing the opportunity perspective. The first is that most of those who worry about inequality do so because they think that it is unjust, or at least partially unjust. In addition, existing surveys show that most people judge income inequalities arising from different levels of effort as less objectionable than those due to exogenous circumstances as gender, race, family origin, etc. The implicit idea is that what matters for a just society is the distribution of opportunities, rather than the distribution of outcomes. Hence, it is interesting to measure that portion of outcome inequality that can be attributed to exogenous circumstances and that, thus, reflects unequal opportunities.

Along the same lines, prominent political philosophers propose a distinction between fair (justifiable) and unfair (unjustifiable) inequalities (Arneson, 1989; Cohen, 1989; Dworkin, 1981a, 1981b). According to these theories, inequality arising from factors over which the individual does not have any control — such as race, sex, ethnicity, religion, birthplace, and family background — should be of primary concern from an ethical standpoint and should therefore be considered as unfair. On the other hand, inequality resulting from factors for which one can arguably be held responsible are regarded as fair.

In addition to normative reasons, the analysis of opportunity inequality can have an instrumental value. First, social attitudes towards redistributive policies may be affected by the knowledge, or the perception, of the origin of income inequalities (Alesina and La Ferrara, 2006 and Cappelen and Tungodden, 2017). By recognising that a small (large) amount of existing inequalities is due to unequal opportunities, one may decrease (increase) the support for redistributive policies. Second, opportunity inequality, rather than income inequality, can be related to aggregate economic performance: it has been suggested (Bourguignon et al., 2007 and World Bank, 2006) that the existence of strong and persistent inequalities in the initial opportunities open to individuals can generate true inequality traps that represent severe constraints to perspectives of future growth of an economy, by preventing entire groups from participation into economic and social life.[1]

Finally, the analysis of opportunity inequality may help the understanding of the generation of income inequality since it constitutes the hardest layer to remove through public intervention. The knowledge of the factors determining opportunity inequality can help to identify the more deprived groups in a society, thereby revealing new points of emphasis in social and redistributive policies.

[1] For an empirical analysis of the relationship between inequality of opportunity and growth in a sample of US states see Marrero and Rodríguez (2013); they decompose total inequality into inequality of opportunity and inequality of effort, showing that GDP per capita growth rate is negatively correlated with the former and positively with the latter. A similar line of research has been followed by Ferreira et al. (2018), with a cross-country analysis involving a sample of 84 countries.

Mainly inspired by the philosophical debate on responsibility-sensitive egalitarian justice, Roemer (1993, 1998), Van de Gaer (1993) and Fleurbaey (1994 and 2008) have proposed formal economic models in which inequality of opportunity (IOp) is defined as the part of overall inequality that is generated by factors beyond an individual's control. Following these seminal contributions, a rich literature has flourished in the past two decades, proposing different approaches and methodologies to measure the degree of inequality of opportunity in different dimensions of well-being, time periods, and countries (see reviews in Ferreira and Peragine 2016, Roemer and Trannoy 2016, and Ramos and Van de Gaer 2016). The diversity in methodological approaches has offered a variety of empirical evidence.

This chapter aims at proposing a critical discussion of this literature, focusing on some of the most recent challenges faced by it: dynamics, multidimensionality, heterogeneity and drivers of IOp. The chapter is articulated as follows. Section 2 introduces the canonical theoretical model of equality of opportunity (section 2.1) and an empirical model which has been extensively used in the literature (section 2.2). Section 3 discusses some papers dealing with intertemporal evaluation of inequality of opportunity. Section 4 presents a recent model for the analysis of IOp in a context in which the individual outcome is multidimensional. Section 5 discuss whether the IOp approach admits the introduction of heterogeneity, while Section 6 reviews what the literature identifies as potential drivers for such inequality. Section 7 concludes.

2. The equality of opportunity approach

2.1 The theoretical model

Following Ferreira and Peragine (2016), we present in this section the canonical model of EOp used in most of the literature and based on the seminal contributions by Bossert (1995), Fleurbaey (1994), Roemer (1993) and Van de Gaer (1993). Consider a distribution of outcome x in a given population. Suppose that all determinants of x including the different forms of luck can be classified into either a set of <u>circumstances C</u> that lie beyond individual control, or as responsibility characteristics, summarized by a variable[2] e, denoting <u>effort</u>, belonging to the set Θ. Circumstances belong to a finite set Ω. For example, suppose that the only circumstance variables are the following: race taking values in the set {black, white} and parental education restricted to values in the set {college education, high school education}. In this case the set Ω would be the following: Ω = ({black, parents with high school education}, {black, parents with college education}, {white, parents with high school education}, {white, parents with college education}).

The outcome of interest is generated by a function $g\colon \Omega \times \Theta \to R$ such that:

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

This is a reduced-form model in which outcomes are exclusively determined by circumstances and effort, such that all individuals having the same circumstances and the same effort obtain the same outcome. Neither opportunities themselves, nor the process by which some outcomes are chosen, are explicitly modelled in this framework. The idea is to infer the opportunities available to individuals by observing joint distributions of circumstances, effort, and outcomes. Roughly speaking, the source of unfairness in this model is given by the effect that circumstance variables (which lie beyond individual responsibility) have on individual outcomes.

Thus, there is a population of individuals, each of whom is fully characterised by the triple (x, C, e). For simplicity, treat effort e, as well as each element of the vector of circumstances, C, as

[2] Effort could also be treated as a vector. However, following the literature, it is treated as a scalar in this chapter.

discrete variables. Then this population can be partitioned in two ways: into types T_i, within which all individuals share the same circumstances, and into tranches T_j within which everyone shares the same degree of effort. Denote by x_{ij} the outcome generated by circumstances C_i and effort e_j. Suppose, in addition, that there are n types, indexed by $i = 1, \dots, n$, and m tranches, indexed by $j = 1, \dots, m$. In this setting, the population can be represented by a matrix $[\mathbf{X}_{ij}]$ with n rows, corresponding to types, and m columns, corresponding to tranches:

Table 1. Distribution of outcomes according to circumstances and effort

	e_1	e_2	e_3	$\cdots$	e_m
C_1	x_{11}	x_{12}	x_{13}	$\cdots$	x_{1m}
C_2	x_{21}	x_{22}	x_{23}	$\cdots$	x_{2m}
C_3	x_{31}	x_{32}	x_{33}	$\cdots$	x_{3m}
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
C_n	x_{n1}	x_{n2}	x_{n3}	$\cdots$	x_{nm}

To the $n \times m$ dimensional matrix $[\mathbf{X}_{ij}]$ in Table 1, there is an associated $n \times m$ dimensional matrix $[\mathbf{P}_{ij}]$ where each element p_{ij} represents the proportion of total population with circumstances C_i and effort e_j.

Given this model, the measurement of inequality of opportunity can be thought of as a two-step procedure: first, the actual distribution $[\mathbf{X}_{ij}]$ is transformed into a counterfactual distribution $[\widetilde{\mathbf{X}}_{ij}]$ $[\widetilde{\mathbf{X}}_{ij}]$ that reflects only and fully the unfair inequality in $[\mathbf{X}_{ij}]$, while all the fair inequality is removed. In the second step, a measure of inequality is applied to $[\widetilde{\mathbf{X}}_{ij}]$. The construction of the counterfactual distribution $[\widetilde{\mathbf{X}}_{ij}]$ should reflect the principle of equality of opportunity.

Within this framework, the construction of the counterfactual distribution, which is the main normative moment of the measurement exercise, is driven by the opportunity egalitarian theory, which in turn can be decomposed into two distinct and independent sub-principles: *the Reward Principle*, which is concerned with the apportion of outcome to effort and, in some of its formulations, requires to respect the outcome inequalities due to effort; and *the Compensation Principle*, according to which all outcome inequalities due to circumstances are unfair and should be compensated by society. Any satisfactory measure of opportunity inequality should respect both the compensation and the reward principles.

The existing literature has developed two main versions of the compensation principle and two consequent approaches to the measurement of opportunity inequality, namely the ex-ante and the ex-post approach.

According to the ex-ante approach, there is equality of opportunity if the set of opportunities is the same for all individuals, regardless of their circumstances. Hence in the ex-ante version, the compensation principle is formulated with respect to individual opportunity sets: it requires reducing the inequality between opportunity sets (*ex-ante compensation*). In the model introduced above, a given row i, that is the outcome distribution of a given type, is interpreted as the opportunity set of all individuals with circumstances C_i. Hence the focus is on the rows of the matrix above: the counterfactual distribution should reflect the inequality between the rows.

On the other side, according to the ex-post approach, there is equality of opportunity if and only if all those who exert the same effort end up with the same outcome. The compensation principle, in the ex-post version, is thus defined with respect to individuals with the same effort but different outcomes: it requires reducing outcome inequality among the individuals with the same effort (*ex-post compensation*). This means that opportunity inequality within this approach is measured as inequality within the columns of the matrix. Hence, the corresponding counterfactual distribution should reflect the inequality within the columns.

As far as the *reward* principle is concerned, different versions of the principle have been proposed by the literature, expressing different attitudes with respect to the outcome inequality observed among individuals endowed with the same circumstances: from utilitarian reward (Van de Gaer 1993, Fleurbaey 2008) which expresses perfect neutrality, to inequality averse reward (Ramos and Van de Gaer, 2016) which expresses aversion to inequality, to intermediate and agnostic positions (Peragine, 2002 and Fleurbaey and Peragine 2013).

Different measures, which are either consistent with the ex-ante or the ex-post approaches, and with different versions of reward, have been proposed in the literature (see Ferreira and Peragine 2016, Ramos and Van de Gaer 2016): they express different and sometimes conflicting views on equality of opportunity and in fact the rankings they generate may be different.[3] In addition, their informational requirements are quite different: while for the ex-ante approach one needs to observe the individual outcome and the set of circumstances, for the ex-post approach a measure of individual effort is required. Therefore, in addition to normative considerations, the choice of the methodology to adopt should also reflect the data availability. As often the database does not contain a satisfactory measure of effort, most of empirical applications focus on the ex-ante approach.

A measure extensively used in the literature, based on ex-ante compensation and utilitarian reward, is *Between-Types* inequality proposed in its non-parametric version by Peragine (2002) and Checchi and Peragine (2010). It relies on a counterfactual distribution $[\tilde{\mathbf{X}}_{BT}]$ that is obtained by replacing each individual outcome x_{ij} by the average outcome of the type she belongs to (μ_i). This smoothing transformation is intended to remove all inequality within types. Formally:

Between-types counterfactual distribution $[\tilde{\mathbf{X}}_{BT}]$:

$$For\ all\ j \in \{1, \dots, m\}\ and\ for\ all\ i \in \{1, \dots, n\}, \tilde{x}_{ij} = \mu_i = \frac{\sum_{j=1}^{m} p_{ij} x_{ij}}{\sum_{j=1}^{m} p_{ij}}$$

It is immediate to notice that between-types inequality is consistent with the principle of utilitarian reward: the types of $\tilde{X}_{BT}$ are made up of replications of the same outcome, the mean, and therefore the artificial distribution does not reflect any inequality within types – the kind of inequality which is fair according to the reward principle, and thus should be cleansed in $[\tilde{\boldsymbol{X}}_{ij}]$. It is also consistent with ex-ante compensation, as the inequality between types (evaluated as the inequality between the means of each type) is preserved. Once the smoothed distribution $[\tilde{X}_{BT}]$ is obtained, any inequality measure I applied to such distribution $I(\tilde{X}_{BT})$ is to be interpreted as a measure of inequality of opportunity.

An alternative, ex-post measure, inspired by Roemer's (1993) and implemented by Checchi and Peragine (2010) and Aaberge et al (2011), is based on the *Within-Tranches* counterfactual distribution ($\tilde{X}_{WTR}$). It is obtained by replacing each individual outcome x_{ij} in a given tranche with the ratio between such outcome and the average outcome of that tranche: $\nu_j = \sum_{i=1}^{n} p_{ij} x_{ij}$. This normalization

[3] See Fleurbaey and Peragine (2013) for a discussion of the clash between ex-ante and ex-post equality of opportunity.

procedure is intended to remove all inequalities between tranches and to leave unchanged the inequality within tranches. Formally:

Within tranches *counterfactual distribution* ($\widetilde{X}_{WTR}$):

$$For\ all\ j\ \in\ \{1,\ldots,m\}\ and\ for\ all\ i\ \in\ \{1,\ldots,n\},\ \tilde{x}_{ij} = g(c_i, e_j)/\nu_j$$

It is easy to see that within-tranches is consistent with ex-post compensation: each tranche is obtained simply by rescaling original outcomes by a constant $(1/\nu_j)$. Therefore $\tilde{X}_{WTR}$ accounts for all the original (relative) inequality within tranches. On the other hand, compliance with the reward principle is not guaranteed, since Table 1 does in general contain inequality within types: for at least one i and a couple j, h, $\tilde{x}_{ij} = g(c_i, e_j)/\nu^j \neq g(c_i, e)/\nu = \tilde{x}_i$.

Once the counterfactual distribution has been obtained, either in the ex-ante or in the ex-post versions, the specific inequality index $I(.)$ to be applied to such distribution does vary across different authors.

2.2 The empirical model

The ex-ante between-types measure $I(\tilde{x}_{BT})$ has been extensively implemented in empirical analyses of inequality of opportunity by a number of authors.

All these papers use a measure of economic well-being – mostly household per capita income, household per capita consumption, or individual labour earnings – as the advantage indicator. For this reason, Brunori et al. (2013) refer to the between-types measure of IOp in these studies as an index of Inequality of Economic Opportunity (IEO). Two closely related versions of the index are often reported: the absolute or level estimate of inequality of opportunity (IEO_L), given simply by the inequality measure computed over $[\widetilde{\mathbf{X}}_{BT}]$, i.e. by $I(\tilde{x}_{BT})$. The ratio of IEO_L to overall inequality in the relevant advantage variable (e.g. household per capita income), which yields the relative measure, IEO_R

$$IEO_R = \frac{I(\tilde{x}_{BT})}{I(x)} \tag{2}$$

The partition of types varies across studies (see Brunori et al. 2013). Because in some cases the data sets are not large enough to yield precise estimates of μ_i for all types, some authors compute IEO_L using a parametric approximation. After estimating the reduced-form regression of income on circumstances:

$$y = C\beta + \epsilon \tag{3}$$

and obtaining coefficient estimates $\hat{\beta}$, these authors use predicted incomes as a parametric approximation to the smoothed distribution:

$$I(\hat{x}_{BT}),\ \text{where}\ \hat{x}_i = C_i\hat{\beta} \tag{4}$$

Parametric estimates are also presented either as levels (IEO_L) or ratios (IEO_R), analogously. This approach follows Ferreira and Gignoux (2008), which in turn draws on Bourguignon et al. (2007). This method is particularly useful when the number of circumstances to be included in the analysis (which usually depends on data availability) gets larger. Under this condition, the non-parametric approach would be based on partition of the population into types containing a small number of individuals, and hence would face the risk of higher estimation bias.

3. Dynamics

In the literature addressing the problem of evaluating income distributions according to equality of opportunity (EOp), typically snapshots of income form the basis of EOp analyses. That is, the analysis is static and does not pay attention to the evolution and the dynamics of the phenomenon.

On the other hand, over the last decades, increasing discontent has been expressed with distributional analysis based on observations of income for a single year. The reason is twofold: (i) the existence of transitory income components, and (ii) the life-cycle variation in income. On the one hand, inequality in annual income is expected to overestimate the extent of long-term income inequality, since idiosyncratic shocks to income average out over time. On the other hand, measuring income early (late) in individuals' working lifespan is expected to understate (overstate) long-term income inequality, as individuals with high permanent income tend to be those with high income growth. This has led to a spur of research on inequality and social welfare in long-term or permanent income according to the Equality of Outcome (EO) principle.[4]

Only a few contributions have tried to bridge these two strands of the literature by introducing and applying different frameworks for evaluating long-term income distributions according to the EOp principle. Aaberge et al. (2011) propose a model that can be used to measure short-term or long-term EOp, depending on whether snapshots of income or permanent income form the basis of analysis. Measuring long-term EOp requires aggregation in two steps. The first step consists of aggregating the income stream of each individual into an interpersonal comparable measure of permanent income. To this end, they follow Aaberge and Mogstad (2009) in using a measure of permanent income which incorporates the costs of and constraints on making inter-period income transfers. The second step consists of aggregating individuals' permanent incomes into EOp measures of social welfare and inequality. Specifically, they employ an axiomatic approach to justify the introduction of a generalized family of rank-dependent measures of ex-post as well as ex-ante opportunity inequality and social welfare. When measuring short term EOp, the measures of opportunity and social welfare are simply applied to the distributions of annual income. Hence, their framework allows for both an ex-ante and an ex-post approach to EOp: there is long-term ex-post inequality of opportunity if individuals who exert the same effort have different permanent incomes; on the other hand, the ex-ante approach focuses on the expected permanent income for groups of individuals with identical circumstances. Hence, the ex-ante approach pays attention to inequalities in expected permanent income between different types of individuals.

The gain in studying long-run EOp is twofold. First of all, by focusing on the distribution of permanent income, Aaberge et al. (2011) eliminate life-cycle bias in opportunity inequality. In particular, they overcome the problem of separating out how much of the life-cycle variation in annual income that is due to circumstances, and how much that is due to effort. Secondly, by letting permanent income form the basis for the EOp analysis, they eliminate opportunity inequality due to

[4] See e.g. Aaberge and Mogstad (2015) and Corneo (2015).

idiosyncratic shocks to income. This can be important since such transitory income components average out over time, and therefore do not call for compensation according to the Compensation Principle. The long-term perspective on EOp can also be important from a policy perspective, by highlighting that inequality opportunities may accumulate over time, if (dis)advantages beget (dis)advantages. Moreover, it allows for the possibility that groups viewed as (dis)advantaged based on snapshots of income may change positions over time. In such cases, policies that minimize snapshots of opportunity inequality may deviate from those optimizing equality of opportunity in long-term income.

To demonstrate the empirical relevance of their EOp framework, Aaberge et al. (2011) exploit a unique panel data set from Norway on individuals' incomes over their working lifespan. The insights from their empirical results may be summarized as follows: (i) First, EOp measures of inequality are less than one third of the corresponding EO measures, suggesting that a large fraction of inequality of outcomes is attributable to initial circumstances. This is true both when permanent income and snapshots of income form the basis for the analysis (ii) Second, snapshots of income overstate inequality compared to analysis based on permanent income, suggesting substantial income mobility. However, their results indicate that snapshots of inequality based on income early in the working lifespan may provide a reasonable approximation of inequality in permanent income; (iii) Third, they find some differences between ex-ante and ex-post EOp measures of inequality and social welfare. Considering that the ex-ante measures are focused on the inequality between social types, while the ex-post measures capture in a finer way the individual income gaps, their results indicate that the distance between social groups, as defined by the circumstances, become increasingly important, relatively to the individual differences, in the last part of the working lifespan.

In a pioneering paper, Bourguignon et al. (2007) propose an alternative approach for measuring long-term EOp, which is in line with an ex-ante perspective. In their approach, first individuals are divided into types who are homogeneous with respect to exogenous circumstances at a given point in time, where the income distributions represent the opportunity set of individuals belonging to specific type in a given period. Second, for each type the opportunity sets are aggregated across time periods to obtain the long-tern opportunity sets. Finally, the distribution of long-term opportunity sets across types is evaluated. Then, Bourguignon et al. (2007) discuss two different methods to evaluate distributions of long-term opportunity sets across types.

As a first methodology, Bourguignon et al. (2007, p. 243) define EOp as follow: there is EOp if, in each period, there is no dominance between types. Hence, in each period of time, there should be equality or, as a weaker definition, non-dominance of opportunity sets. This can be seen as the natural extension of the approach used by Lefranc et al (2006) and Peragine and Serlenga (2008) to a long-term perspective. As second methodology, Bourguignon et al. (2007) propose a long-term extension of the utilitarian version of EOp, according to which there is EOp if the long-term expected value of all types are equal. They first use a utilitarian evaluation function which evaluates the opportunity set of each type at a given period t by its mean μ_{it}. Next, they introduce a *time aggregator* (either a standard discounting factor or a weigh in a social welfare function) in order to obtain an expression of the long-term value of the opportunity set. Hence, the order of aggregation is inverted with respect to Aaberge et al. (2011). In fact, in Aaberge et al (2011) the aggregation over time is performed for each individual, and this allows them to be specific with respect to the underlying model of intertemporal choice that underlies the construction of the distribution of long-term income. Moreover, their approach is also more general in the sense that it allows both an ex ante and an ex post approach to long-term EOp and allows for different attitudes towards inequality aversion.

In a recent contribution, Moramarco et al. (2020) propose a different approach for the analysis of intertemporal inequality of opportunity, which includes the possibility that both circumstances and effort change over time. They adopt the norm-based approach (Cowell, 1985; Magdalou and Nock, 2011), according to which a measure of inequality is derived by looking at the distance between the actual distribution and a benchmark (or norm) distribution. Specifically, they propose two different benchmark distributions, which refer respectively to the ex-ante and the ex-post versions of equality of opportunity. Moreover, they adopt an axiomatic methodology for the characterization of their social rankings. Once a norm distribution is defined, their strategy follows a two-step procedure. In the first step they derive a measure of intertemporal inequality of opportunity at the individual level, where the individual inequality of opportunity in each period is defined as a function of the divergence between the observed and the norm individual incomes. Then, for each individual, they aggregate this measure across time. In the second step, the individual evaluations are aggregated and a measure of intertemporal inequality of opportunity at a societal level is derived, which turns out to be equivalent to the average of a concave transformation of the individual intertemporal measure. They also show that, under particular conditions, the characterized measure corresponds to (the negative equivalent of) the average across time of the mean logarithmic deviation of the time specific distributions. In addition to characterizing families of intertemporal indexes, Moramarco et al. (2020) also propose an intertemporal opportunity version of the generalized Lorenz partial ordering, which provides suitable dominance conditions that can be used for robust social comparisons. They also provide an empirical application of the measurement tools characterized in the paper by analysing the Korean distribution of incomes from an intertemporal and opportunity egalitarian perspective. They use the KLIPS (Korean Labor and Income Panel Study), from 2001 to 2014, a rich but still very unexplored dataset, and show that, although South Korea is known as one of the most growing and progressive countries, it still suffers from some degree of unfairness. However, the country seems to be on the right path for improving equality of opportunity over time. The intense South Korea's GDP growth results to have been opportunity inequality improving for the new generations which receive a fairer remuneration of effort. They also find evidence of a territorial divide: individuals living in the two most important metropolitan cities (namely, Seoul and Busan) benefit, on average, of an opportunity premium compared to those living in other areas of South Korea.

A different set of tools has been proposed by Peragine et al. (2014) and Brunori et al. (2018) to evaluate the dynamics of growth from an opportunity egalitarian perspective: inspired by the Growth Incidence Curve (GIC) proposed by Ravallion and Chen (2003), they propose the Opportunity Growth Incidence Curves (OGIC), which is intended to capture the effect of growth from the EOp perspective. It plots the rate of growth of the (value of the) opportunity set given to individuals in the same position in the distributions of opportunities. Their ex-ante version[5] of the OGIC, the so-called "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 basis of exogenous factors that can affect the individual outcome. The "type OGIC", tracking the same types over time, provides information on the temporal evolution of type-specific opportunity sets. Hence the "type OGIC" answers the question: do different circumstances are associated with different levels of growth? Is there a differential in the economic development of

[5] Peragine et al. (2014) also propose an ex-post version of the OGIC.

different socio-economic groups in the population? The OGIC approach generalizes Roemer's methodology to measure economic development (Roemer 2013), which consists of a bidimensional indicator, where the first dimension is the average income level of those in the society with the most disadvantaged circumstances, i.e. the type with the lowest level of mean outcome, while the second dimension is the degree to which total income inequality is due to differential effort, as opposed to differential circumstances.

4. Inequality of opportunity in a multidimensional setting

In both the theoretical and the empirical literature on EOp (briefly reviewed in the previous sections), the outcome of interest is typically represented by a unidimensional variable: income, consumption, education, health. On the other hand, both the theory and the practice of inequality measurement have moved towards the multidimensional space: many researchers have advocated the inclusion of non-income dimensions in the evaluation of well-being (Kolm 1977, Maasoumi 1986, Atkinson and Bourguignon 1982) and several multidimensional measures of welfare and of inequality have been developed (Maasoumi 1986, Tsui 1995 and 1999): these are measures based on joint distributions that are sensitive to multidimensional generalizations of the Pigou-Dalton Transfer (PDT) principles such as uniform PDT or uniform majorization (Tsui 1999), and to transfers that change the dependence structure, namely, so called correlation-increasing switches (Tsui 1999). Thus it is widely acknowledged in the literature (and more so in practical decision making) that well-being is a multidimensional concept and cannot be reduced to a single proxy such as income.

From the EOp view point, some empirical works jointly investigate the presence of unequal opportunities for multiple outcomes. Examples include Bourguignon et al. (2007) who analyse income and schooling outcomes in Brazil, Ferreira and Gignoux (2008) who focus on different income measures, or Peragine and Serlenga (2008) who analyse university graduation results and later life-income.

However, in such contributions the different dimensions are treated as separate identities: hence, these contributions are unable to account for a fundamental aspect of the multidimensional analysis, that is the correlation between the different dimensions of individual well-being.

As far as we know, the only paper which proposes a multidimensional analysis of inequality of opportunity is represented by Kobus et al. (2020), who proposes a IOp measure accounting for a vector of outcomes that are not necessarily correlated. They develop a normative approach to the measurement of inequality of opportunity when the outcome of interest is a multidimensional variable, focussing on the ex-ante approach. In their model, within each type, there is a multidimensional outcome distribution, but types differ not only dimension by dimension, but also with respect to the dependence structure between dimensions. In other words, in a multidimensional setting, the effect of circumstances may not only be that worse types have worse distributions of outcomes, but also that individuals corresponding to worse types are more likely to be jointly deprived in several outcomes than people corresponding to better types. The latter concerns dependence, which is a truly distinctive feature of multidimensionality. From a methodological point of view, Kobus et al. (2020) adopt an axiomatic approach.[6] They first characterize three classes of social welfare functions, all endorsing ex-ante compensation but each of them reflecting a specific reward principle: (1) utilitarian, (2) agnostic and (3) averse. These axioms use basic transformations that define the

[6] They impose the following axioms: Monotonicity, Additivity, Inequality neutrality/agnosticism/aversion within types, Inequality aversion between types.

concepts of inequality. In a multidimensional setting, the defining inequality transformations are transformations that reduce spread in many dimensions (i.e., Pigou-Dalton Transfer on each dimension with potentially different amounts of attributes transferred) and transformations that change the dependence between dimensions (i.e., correlation increasing or decreasing switches — see e.g. Tsui 1999). Different reward principles reflect different sensitivity to such transformations when they happen within a type: in particular, a welfare function which respects utilitarian reward does not change, since it does not pay attention to any inequality within type; a welfare function which is agnostic is silent and the one which respects averse reward goes up. Then they link these classes to implementable criteria (i.e., different versions of Lorenz Dominance). The first class is implemented via generalized Lorenz Dominance applied to each attribute separately. The agnostic and inequality averse classes are implemented by a welfarist Lorenz ordering, namely, of type-aggregate utilities. In the case of inequality-averse class, utility functions are submodular, hence capturing the dependence between attributes. Finally, they construct inequality of opportunity measures that are induced by these three classes via the so called AKS transformation (Atkinson, 1970; Kolm 1969; Sen, 1973).

Finally, Kobus et al. (2020) propose an empirical application based on the National Longitudinal Study of Adolescent to Adult Health (Add Health) in the US. They use self-reported personal earnings, years of education and BMI as outcomes and a set of circumstance variables. The results show how jointly considering the dimensions as opposed to considering them separately changes significantly the evaluation of IOp For example, univariate IOp for education and BMI are, respectively, 0.06 and 0.021, whereas for income it is 0.47. In such a case, IOp when outcomes are considered jointly is 0.2. This comes from the fact that joint evaluation takes into account that (i) some outcomes are distributed more equally than other, (ii) rankings by types with respect to mean outcomes values differ across outcomes (i.e. best income type is not necessarily best BMI type), (iii) within type, individuals occupy different positions on respective dimensions (i.e. highly educated individuals are not necessarily individuals with highest incomes). These are all factors that are missing when the focus is limited to a single well-being outcome such as income.

5. Heterogeneity in IOp

We now consider the issue of potential heterogeneity in IOp experienced by different population subgroups. In principle, heterogeneity in IOp within types may emerge if the list of circumstances is not exhaustive. Consider the following example, where types are defined according to races. If gender is not included among circumstances, one could end up computing different measures of IOp based on race when the population is partitioned by genders. The argument can be generalized by considering unobservable ability among the circumstances, which opens the door to evaluating the distributions of outcomes within each type.

We have explored the issue of heterogeneity across individuals in experiencing (in)equality of opportunity in the literature, finding quite few references. There are reasons for this result, both on theoretical and empirical grounds. From a theoretical point of view, if individuals are assumed heterogeneous in (observable) circumstances but homogenous in preferences, such that differences in effort and in luck become indistinguishable. Thus any heterogeneity corresponding to variables not explicitly included among the circumstances leads to an underestimate of the IOp.

However in principle we cannot exclude that circumstances operate in different ways across different individuals, a typical case being aging between men and women.[7] In such a case individuals would experience the same set of circumstances, but the coefficients associated to some of them would systematically differ (in a parametric approach) or the marginal distributions associated to types would exhibit some ordering (in a non-parametric approach).

From an econometric point of view, one strategy to cope with circumstances would be including interactions among different circumstances. If circumstances are measured by categorical or ordered variables (like parental education or ethnicity), interactions are implicitly taken into account when considering types, where types are defined by the cross product of the original variables. More difficult is interpreting the case of circumstances measured by continuous variables (like parental income), because in such a case individuals could differ by their endowments, by the gradient of their endowment or by both. In the parametric approach, the majority of the authors do not use interactions among circumstances, probably because of interpretability of the estimates. Let we consider a simple example

$$x_{it} = \alpha + \delta_i + \beta x_{it-1} + \gamma \delta_i x_{it-1} + \epsilon_{it} \tag{5}$$

where x_{it} is the income of child when adult, x_{it-1} is the parental income and δ_i is a dummy indicating a dichotomous condition (gender, race, citizenship, disability and the like). The societal IOp will be measured by $I(\hat{x}_{it}) = I(\hat{\alpha} + \hat{\delta}_i + \hat{\beta} x_{it-1} + \hat{\gamma}\hat{\delta}_i x_{it-1})$, but we may want to consider the IOp experienced by the two population subgroups

$$\begin{cases} I(\hat{x}_{it}|\delta = 0) = I\big(\hat{\alpha} + \hat{\beta} x_{it-1}\big) \\ I(\hat{x}_{it}|\delta = 1) = I((\hat{\alpha} + \hat{\delta}) + (\hat{\beta} + \hat{\gamma}\hat{\delta}) x_{it-1}) \end{cases} \tag{6}$$

A priori it is impossible to assess which group will experience the highest IOp, since this depends on the properties of the inequality index $I(\,)$ (whether scale or translation invariant), on the sign of $\hat{\gamma}$ as well as on the covariance between δ and x. In addition, if the index $I(\,)$ enjoys the decomposability property, one could appropriately aggregate the two subgroup measures computed in equation (6), in order to obtain the societal measure for IOp. A simpler alternative is splitting the sample into two groups and estimate $x_{it} = \alpha + \beta x_{it-1} + \epsilon_{it}$ separately in each sub-population. However the IOp measures would not be strictly comparable, since $\hat{\alpha}$ and $\hat{\beta}$ would differ in the two populations. Checchi and Peragine (2010) follow his strategy to investigate geographical differences between North and South Italy in terms of IOp.

Marrero and Rodrigues (2011) is the only paper that the summary table 1 of Mitnik et al (2020) cites as making use of interactions among circumstances in order to estimate IOp. The authors include the cross-effects between race and parental education on the argument that family background has a stronger impact for non-white in the US case. Following a parametric approach, they find that the joint combination of these two circumstances increases overtime, dominating the effect of each circumstance. Another interesting application of IOp to wealth inequality can be found in Salas-Rojo

[7] "From the investigation of the longitudinal changes of individual BAS [biological ages], it was suggested […] the rate of aging [of women] was slower than that of men, suggesting that these differences might present both disadvantages and advantages for women with regard to health and longevity." (Nakamura and Miyao 2008, p.936).

and Rodriguez (2020), where they consider received inheritances and parental education as circumstances, interacting the two variables in order to partition the first variable (which is rather asymmetrical) and using Shapley decomposition to account for their relative contributions.All these analysis could have been replicated by appropriate partitioning continuous variable, but the relative contribution of specific types (i.e. specific combination of circumstances) would have remain concealed.

Another circumstance that is often difficult to control for is the neighbourhood effect. Living in wealthy/deprived areas, going round with good/bad peers, has an impact over lifetime income (see also the next chapter). But most datasets do not contain geographical identifier and/or sufficient observations to render this type of analysis possible. An attempt in this direction has been conducted by Marrero et al (2016) when they partition the population by deciles and show that IOp (computed by population decile, using race and gender as circumstances) exert heterogeneous impacts on income growth (also measured by deciles). Their main findings is that IOp is particularly detrimental for income growth of the poor. However the IOp effect tends to become statistically insignificant when considering its potential endogeneity and instrumenting it with its past values or local measures of segregation.[8] A similar result is confirmed in a cross-country perspective by Aiyar and Ebeke (2019), who however use the intergenerational persistence in income or education as their proxy for IOp. Similarly Bradbury and Triest (2016) find that local IOp (again proxied by intergenerational mobility in incomes, from Chetty et al. (2014)) at commuting zone level in the US harms local growth perspectives. The main problem in connecting IOp and income growth is the potential reverse.[10]

One dimension of heterogeneity that has been investigated by partitioning the population is gender; the gender contribution is estimated according to previous equation (5) and decomposed according to equation (6). In Hederos et al (2017) the authors study the role of gender in determining IOp in Sweden. Analysing men and women separately, they find that circumstances account for up to 31% of income inequality among men and up to 25% among women. But when they analyse men and women together, treating gender as a circumstance, at most 38% of income inequality is attributed to circumstances. This is consistent with the findings obtained by Bussolo et al (2020) who have considered two sources of heterogeneity for four countries (France, Germany, Italy and UK): gender and birth cohort.[11] They find that women are characterised by higher level of earnings inequality compared to men, as well as by higher level of absolute IOp. However, in relative terms, the IOp experienced by men is typically higher, even though the gender gap is shrinking (except that in the case of Germany).

The availability of repeated cross sections from the same population enables the possibility of distinguishing between an "age" effect and a "birth cohort" effect: in the first case the relevant question is when the impact of circumstances reaches its highest impact during the life course, while in the second case one can compare the experience of IOp of individuals born in the same country

[8] Spiganti (2020) proposes a theoretical model that rationalizes these findings, based on an endogenous growth model with heterogeneous agents; due to credit frictions, inequalities in wealth lead to misallocation of talent. A more unequal reward scheme incentivises innovation in any given period, but it leads to a more unequal distribution of opportunities that may exacerbate the misallocation of talent in the next period.

[10] This is analysed by Perez-Arce et al (2016) whose main point is "*There is empirical evidence regarding the extent to which economic inequality and inequality of opportunity move together across time and geographies. The results of a metaregression analysis […] show that, across countries, there is a correlation between income inequality and proxy measures of inequality of opportunity. However, across time within a country, increases in inequality are not always accompanied by increases in inequality of opportunity. Overall, the strong cross-country correlation, but weak or null within-country, cross-time correlation, suggests that there is no unequivocal connection between the two types of inequality.*" (p.11)

[11] The vector of permanent circumstances is given by citizenship, region of birth and parental education.

but in different periods. Bussolo et al (2020) find that in their samples IOp exhibits an inverted U-shaped over the life-cycle, with a peak around the age of 40; in terms of birth cohorts, IOp is steadily declining over time for Germany and UK, while it was highest among the cohorts born in the 1950's for Italy and France.

6. Drivers of inequality

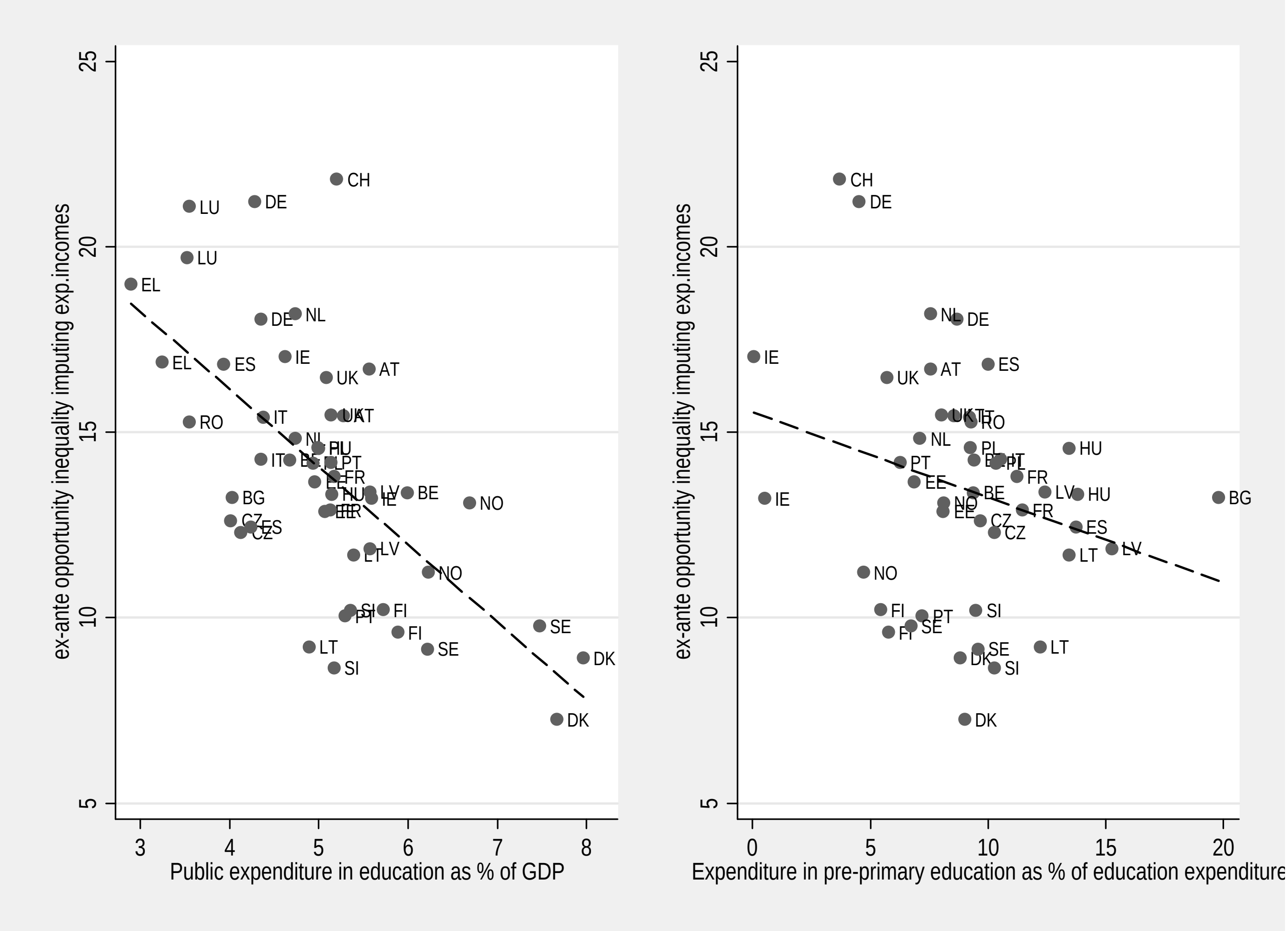
Despite the possible heterogeneity of inequality experienced by different segments of the population, there is limited research on the determinants of IOp The problem of identifying potential drivers for IOp is rather similar to the problem of identifying drivers for intergenerational mobility.[12] From a descriptive point of view, one can correlate country/year measures of IOp to domestic institutional measures, but the identification is rather weak and the results are exposed to the objection of spurious correlation.[13] For example in Checchi et al (2015) the ex-ante IOp is measured for the entire populations of 30 European countries for two sufficiently distant data points using SILC special modules containing information on parental background (2005 and 2011). Two observations available for most of the countries are then used to explore the relationship between many institutional dimensions and inequality of opportunity, finding evidence of negative correlation with educational expenditure (especially at the pre-primary level) and passive labour market policies, even when including country fixed effects. The IOp seems associated to institutional dimensions that operate before the entrance in the labour market and/or when (temporary) excluded by the same market (as in the case of recipients of unemployment benefits). In particular, the expenditure in education seems the most effective instrument available to governments, as highlighted by the following figure 1 (originally figure 5 in Checchi et al. (2015)). Obviously correlation does not mean causation, and two data points per country are clearly insufficient for excluding the possibility of spurious correlation and/or reverse causation, even when controlling for compositional effects. [14]

[12] Björklund and Jäntti 2020 discuss merits and limits of the two approaches, suggesting that the standard intergenerational elasticity in (log)incomes is a special case of IOp where circumstances coincide with parental income. On the contrary, Arenas and Hindriks 2020 propose a theoretical model where existing IOp (described by a differential probability in accessing better schools) generates intergenerational persistence in incomes (à la Becker et al 2018).

[13] Alternative measures of IOp regarding income or education are available at www.equalchances.org .

[14] The same dataset has been analysed by Marrero and Rodriguez 2012, but results are hard to compare for two reasons: the IOp has been estimated country by country, thus allowing for country heterogeneity in the relationship between circumstances and outcomes; in addition they have available only one data point (2005), thus opening their results to the objection of spurious correlation. They find correlation between IOp and lagged IOp indices, (lagged) GDP per capita growth rate, various measures of un/employment, early school leaving and public expenditure in social protection.

Figure 1 – Educational expenditure and inequality of opportunity



Some papers exploit cross-country and temporal variations to increase the statistical robustness of their claims. For example Marrero and Rodriguez (2013) estimate the ex-ante IOp in the United States between 1980 and 1990, showing that per-capita income growth is negatively correlated to IOp, while the inequality in the rates of return to effort (i.e. the acceptable component of inequality according to fairness) exhibits a positive correlation. They deal with the potential reverse causality issue by lagging the IOp measure at the beginning of the period of investigation.

The study of the association between institutions and/or policies and the distribution of outcomes (income, earnings, education, health) does not yet possess a “canonical” approach (García-Peñalosa 2018): some authors limit themselves to the first two moments of the distribution, while other consider variations along the distribution (DiNardo et al 1996). The same weakness is shared by the analysis of the impact of policies onto IOp. In a recent paper, Andreoli et al. (2019) define the role of policy as an exogenous variation capable of providing equalization of opportunities (in terms of stochastic dominance of the original distribution of opportunities). They then propose an empirical application of their approach by considering an expansion of childcare facilities introduced in Norway in 1975 (*Kindergarten Act*) and they examine to what extent the expansion of child care equalized children’s earnings distributions as adults, conditional on parental earnings deciles. They find that the policy was effective in raising the adult earnings in a differential effect: low and middle classes children experienced an earnings growth of 4.3% and 3%, respectively when compared to the untreated groups. In contrast, the value of the opportunity set of the upper class increased by only a modest 1%, which turns out to be statistically insignificant.

A different source of identification can be found by structurally modelling the aggregate relationships. Considering intergenerational income mobility as proxy for IOp, Solon (2004) presents a theoretical framework for interpreting the corresponding empirical evidence. The model shows that the steady-state intergenerational income elasticity increases with the heritability of income-related traits, the efficacy of human capital investment, and the earnings return to human capital, and it decreases with the progressivity of public investment in human capital. Cross-country differences in both intergenerational mobility and cross-sectional income inequality could arise from differences in any of these factors. In a similar vein, Bussolo et al. (2020) identifies three channels that are assumed to account for cross-country differences in temporal variations of IOp: a) changes in inequality of opportunity in education, or *intergenerational persistence in education achievements*, b) changes of the *returns to education*, c) additional *influence of parental background on the incomes of the offspring*. In their perspective, IOp declines whenever intergenerational persistence in education diminishes and/or the children return to education in the labour market lowers and/or the ability of parents in favouring the access of their children to better paid jobs (networking) declines. The temporal variations of these measures are reported in table 2 for the four countries under analysis. The table shows that inequality of opportunity shows a stable or declining pattern over the period considered in all four countries, due to enhancement of equality of educational opportunity (as captured by the intergenerational education persistence – see Italy and France), to a decline in the return to education (mostly affecting UK); these equalizing tendencies are counteracted by an increasing role of parental influence on labour market outcomes beyond educational achievement (notably in Italy).

Table 2 – Full period changes of coefficients of persistence of education, return to education, and networking

	Educational persistence			Return to education			Networking			IOp (st.dev.logs)		
Country	Start	End	Δ%	Start	End	Δ%	Start	End	Δ%	Start	End	Δ%
Italy 1993-2014	0.495	0.448	-9%	0.086	0.075	-12%	0.012	0.033	180%	0.481	0.471	-2%
Germany 1984-2013	0.669	0.696	4%	0.081	0.071	-13%	0.006	0.009	46%	0.537	0.402	-25%
France 1978-2005	4.801	3.767	-22%	0.054	0.047	-13%	0.173	0.136	-22%	0.457	0.370	-19%
Great Britain 1991-2014	0.139	0.138	-1%	0.177	0.118	-34%	0.015	0.028	92%	0.488	0.311	-36%

This decomposition is possible by the use of repeated cross-sectional surveys for the same country, which is not always easily available. However the future seems more and more associated to the use of administrative data, because they allow for more granular measurement as well as considering several heterogeneities. Björklund et al (2012) exploit a rich longitudinal dataset for Swedish males born between 1955 and 1967 (covering one third of the resident population), where they can partition circumstances over 1152 types (parental income, parental education, own IQ, own body mass, number of siblings and family structure). They find that even in a country with a rich welfare system, IOp accounts for almost one third of long-run income inequality, even accounting for indirect effect of circumstances on the distribution of effort. The IQ (measured at the entry of Armed Forces, thus incorporating most of the family effect) is the most significant circumstance for explaining income in Sweden. Similarly, Aaberge et al (2012) exploit administrative data for Norway to decompose IOp computed over long-run income and corresponding measures computed over short-run snapshots, showing that despite initial volatility of the latter, measures taken over individuals aged between 30 and 50 provide a reasonable approximation of measures obtained from permanent incomes. A more recent contribution compares US and Norway through the lens of administrative data (Mitnik et al 2020), showing that the share of IOp accounted by gender, family income, ethnicity and race is a larger fraction of long-run income inequality than usually expected (58% in the case of US). The view about the almost nil level of absolute IOp in Denmark in comparison to US is challenged by Heckman and Landersø (2021), using a larger set of outcomes (weight at birth, children achievements). They provide evidence that intergenerational educational mobility is about the same in both countries for the recent cohorts; similar pattern is also followed by skill transmission across generations, despite stark differences in income inequality and offered public services. They also use administrative data to reconstruct lifetime incomes of parents and children, showing that intergenerational elasticities of income (IGE) of lifetime well-being are much higher than those conventionally estimated using incomes measured over a small window of ages.[15] Finally they expand the analysis of family influence beyond the traditional analysis based on parental income and/or education, including choices of neighbourhood, peers, and schools as parental investments in their children. They provide evidence that sorting into better neighbourhood is associated to parental education, and typically occur at earlier stage of children life.[16] *In terms of IOp this implies that traditional circumstances based on family information (parental income, parental education, educational resources, number of sibling) represent a limited subset of potential influences that are out of control of a child who is growing up.* Omitting variables that drive the sorting of individuals in better neighbourhoods lead to biased estimates for the parental circumstances, thus yielding a biased prediction of counterfactual income distribution. Non-parametric methods are more robust against such a risk.

An impressive leap forward in the IOp analysis has been created by Raj Chetty and co-authors, who have matched large dataset from tax records and/or census in order to provide detailed description of circumstances, often based not only on parents but on neighbourhood information.[17] Chetty et al (2014a) mapped rank-rank correlation between parental and children incomes at commuting zone level, showing large variations across the United States. They also described the salient features of areas characterised by high intergenerational mobility: low residential segregation (by race and/or income), less income inequality, better primary schools, greater social capital (as measured by community involvement) and greater family stability (inversely proxied by the fraction of single mothers).[18]

In Chetty et al. (2017) they combine historical data from US Census and Current Population Surveys (CPS) cross-sections with longitudinal data for recent birth cohorts from tax records, obtaining a large panel linking parents and children. Their main result is that the fraction of children earning more than their father (known in the literature as "absolute income mobility") has declined from 90% in the cohort born in the 1940s to 50% in the cohort born in the 1980s. Their result corresponds to an increasing copula linking parent and children incomes, and it is suggestive of an

[15] This matches the results on long run IOp measures that are found in Aaberge et al 2011.

[16] The role of neighborhood has been analysed by Chetty and Hendren (2018) showing that the neighborhoods in which children grow up shape their earnings, college attendance rates, and fertility and marriage patterns. Their identification strategy (in order to estimate a causal impact) relies on studying families who move across commuting zones and counties in the United States, focusing on non-intended moves due to displacement shocks.

[17] Many research papers are collected in the website https://opportunityinsights.org/. Goux and Maurin (2007) had already pointed out that neighbourhood effects (at block level) were relevant for educational attainments.

[18] Chetty et al (2014b) extended the cross-sectional dimension to a temporal one using a birth cohort approach, showing that rank-rank correlation in incomes has not declined across US for the cohorts born between 1971 and 1993. Since income inequality increased over time in their sample "the consequences of the "birth lottery" – the parents to whom a child is born – are larger today than in the past" (pg.141). In terms of IOp this would imply a constant absolute IOp and a declining relative IOp.

increase in IOp as long as the copula has tightened among the youngest cohorts.[19] Since they focus on inequality in individual income growth rate, one could rephrase their results in terms of inequality in growth opportunities, conditional on parental status.

In Chetty et al (2018) the authors compile an atlas of children's outcomes in adulthood by Census tract in US, and for each tract they estimate children's rank in the earnings distributions by parental rank in their respective income distribution.[20] When they compare the predictive power of their environmental variables (which include gender and race segregation), they are de facto providing IOp indices for various population subgroups at any Census tract. What is impressive is that neighbourhood traits are persistent over time[21] and vary in terms of distance and exposure to a specific environment, which is defined by the aggregate values of parental variables in the same tract.[22] Even if we ignore how much these results are specific to the North America society, they raise challenges that the IOp literature cannot escape in the future. In other words, the main message stemming from this impressive series of paper boils down to the indication that circumstances should include neighbourhood where the child grew up. This would allow to better account for heterogeneous IOp experienced by individuals in their countries.

7. Conclusions

The equality of opportunity literature has made important advances in the last twenty five years, since the pioneering works of Roemer (1993), Van de Gaer (1993) and Fleurbaey (1994), which followed the debate among philosophers such as Rawls (1971), Sen (1973), Arneson (1989), Dworkin (1981) and Cohen (1989). Philosophical concepts have been translated into simple, coherent and powerful economic models by a number of economists since the 1990s, and a growing number of empirical applications particularly devoted to the measurement of inequality of opportunity have been proposed, with different methodologies and in different spheres of social life.

In this survey we have discussed the “canonical model” of EOp, some of the empirical models based on it and used extensively in empirical applications. We have then discussed some recent papers addressing the issue of dynamics of IOp. How to take into account the variable of time into a social assessment of equality of opportunity? The few papers addressing such issue offer some first methodologies to evaluate the dynamics of income distributions from and opportunity egalitarian perspective and to evaluate IOp by taking into account the individual income streams and the possibility of varying circumstances over time.

We have also documented that, while most of the EOp models consider a unidimensional individual outcome variable, and implicitly address the issue of multidimensionality by studying separately the extent of IOp in different spaces of evaluations (income, education, health), thereby

[19] Their results use copula stability (which corresponds to stable income relative mobility) as a benchmark against which contrast alternative calibrations of their model. This is consistent with other empirical evidence based on intergenerational elasticities of income and rank-rank correlations (Lee and Solon 2009).

[20] An interactive executive summary is available at https://opportunityinsights.org/wp-content/uploads/2018/10/atlas_summary.pdf.

[21] “*However, the power of tract-level outcomes in forecasting outcomes for future birth cohorts decays by only 10% over a decade. Moreover, historical outcome data are substantially better predictors of more recent outcomes than contemporaneous observables such as poverty rates. Our estimates are thus informative (albeit imperfect) predictors of economic opportunity even for children today*.” (Chetty et al 2018, p.4).

[22] “*In sum, neighborhood characteristics matter at a hyperlocal level. A child's immediate surroundings (within about half a mile) are responsible for almost all of the association between children's outcomes and neighborhood characteristics documented above*.” (Chetty et al 2018, p.4).

missing the fundamental dependence structure of the different dimensions, only very recently some papers have formulated a model for the rigorous analysis of multidimensional inequality of opportunity.

We have also discussed the issue of heterogeneity in IOp experienced by different population subgroups, finding little research in this respect, possibly due to the fact that in many circumstances group membership is a circumstance by itself. While gender and birth cohorts are considered by some authors, the novelty emerging from recent advancements in adjacent field of research is the heterogeneity introduced by considering neighborhood effects. In many dataset this information is not observable, but there is increasing evidence that the environment where individuals are born and grow up affect their future life course along several dimensions.

However the same literature lacks of convincing identification strategy to assess the contribution of aggregate drivers to IOp. Correlational analysis mostly exploits cross-country variability to claim associations between welfare state institutions (like education or social expenditure) and IOp. But very few papers exploit the individual exposure to institutional reforms to assess their impact onto the opportunities offered to the treated.

References

Aaberge, R. and M. Mogstad (2009): On the Measurement of Long-term Income Inequality and Income Mobility, Working Paper No. 09/2009, ICER, Torino, 2009.

Aaberge R. and Mogstad M., 2015. "Inequality in current and lifetime income," *Social Choice and Welfare*, vol. 44(2), pages 217-230.

Aaberge, R., Mogstad, M. and Peragine, V. (2011). Measuring long-term inequality of opportunity. *Journal of Public Economics*, *95*(3-4), 193-204.

Aiyar, Shekhar and Christian Ebeke. 2019. Inequality of Opportunity, Inequality of Income and Economic Growth. IMF working paper 19/34

Alesina, A. and La Ferrara, E. 2006. Who Trusts Others? *Journal of Public Economics* 85, 207–234

Andreoli, Francesco, Tarjei Havnes, and Arnaud Lefranc. (2019). Robust inequality of opportunity comparisons: theory and application to early childhood policy evaluation. *The Review of Economics and Statistics*, 101(2): 355–369

Arenas, Andreu and Jean Hindriks. 2020. Intergenerational Mobility and Unequal School Opportunity. *The Economic Journal*, Volume 131, Issue 635, Pp. 1027–1050

Arneson, R. J. (1989). Equality and equal opportunity for welfare. *Philosophical studies*, 56(1), 77-93.

Atkinson, A.B. (1970). 'On the Measurement of Inequality'. *Journal of Economic Theory*, 2(3): 244–63.

Atkinson, A.B., and F. Bourguignon (1982). The Comparison of Multi-Dimensioned Distributions of Economic Status. *Review of Economic Studies*, 49(2): 183–201.

Becker, G.S., Kominers, S.D., Murphy, K.M. and Spenkuch, J.L. 2018. A theory of intergenerational mobility. *Journal of Political Economy*, vol. 126(S1), pp. S7–25.

Björklund, Anders and Markus Jäntti. 2020. Intergenerational mobility, intergenerational effects, sibling correlations, and equality of opportunity: A comparison of four approaches. *Research in Social Stratification and Mobility* https://doi.org/10.1016/j.rssm.2019.100455

Björklund, Anders, Jäntti, Markus and Roemer, John E. (2012) Equality of opportunity and the distribution of long run income in Sweden. *Social Choice and Welfare* 39: 675-696

Bossert, W. (1995). Redistribution mechanisms based on individual characteristics. *Mathematical Social Sciences*, *29*(1), 1-17.

Bourguignon, F., Ferreira, F. H. and Walton, M. (2007). Equity, efficiency and inequality traps: A research agenda. *The Journal of Economic Inequality*, *5*(2), 235-256.

Bradbury, Katharine and Robert K. Triest. 2016. Inequality of Opportunity and Aggregate Economic Performance. *The Russell Sage Foundation Journal of the Social Sciences* , Vol.2 (2), pp. 178-201

Brunori, P., Palmisano, F. and Peragine, V. (2018). Consumption dynamics and inequality of opportunity with an application to Uganda. *Review of Development Economics*, *22*(2), 632-657.

Bussolo, M., Checchi, D. and V.Peragine. The long term evolution of inequality of opportunity" IZA Discussion Paper 13044/2020

Cappelen, A. W. and Tungodden, B. (2017). Fairness and the proportionality principle. *Social Choice and Welfare*, *49*(3), 709-719.

Checchi, D. and Peragine, V. (2010). Inequality of opportunity in Italy. *The Journal of Economic Inequality*, *8*(4), 429-450.

Checchi, D., L.Serlenga and V.Peragine. (2015). Inequality of Opportunity in Europe: is there a role for institutions ? in *Inequality: Causes and Consequences - Research in Labor Economics*, Volume 43/2015, 1-44

Chetty, R., J. N. Friedman, N. Hendren, M. R. Jones, and S. R. Porter. 2018. The opportunity atlas: Mapping the childhood roots of social mobility. Technical Report 25147, NBER Working Paper.

Chetty, Raj and N. Hendren. 2018. The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects. *The Quarterly Journal of Economics* 133 (3), 1107–1162.

Chetty, Raj, David Grusky, Maximilian Hell, Nathaniel Hendren, Robert Manduca, and Jimmy Narang. 2017. The Fading American Dream: Trends in Absolute Income Mobility Since 1940. *Science* 28 Apr 2017: Vol. 356, Issue 6336, pp. 398-406

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014a. Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States. *Quarterly Journal of Economics* 129 (4): 1553-1623.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, Emmanuel Saez, Nicholas Turner. 2014b. Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility. *American Economic Review* 104(5): 141-47.

Cohen, G. A. (1989). On the currency of egalitarian justice. *Ethics*, *99*(4), 906-944.

Corak, M. (2013). Income Inequality, Equality of Opportunity, and Intergenerational Mobility. *Journal of Economic Perspectives*, Vol. 27, No. 3, pp. 79-102.

Corneo, G. (2015) Income inequality from a lifetime perspective. *Empirica* 42, 225–239.

Cowell, F. A. (1985). Measures of distributional change: An axiomatic approach. *The Review of Economic Studies*, *52*(1), 135-151.

DiNardo, John, Nicole M. Fortin and Thomas Lemieux. 1996. Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica* Vol. 64(5), 1001-1044

Dworkin, R. (1981a). *What is equality? Part 1: Equality of welfare*, Philosophy & Public Affairs, X(3), 185-246.

Dworkin, R. (1981b). *What is equality? Part 2: Equality of resources*, Philosophy & Public Affairs, X(4), 283-345.

Ferreira, F. H. and Gignoux, J. (2008). *The measurement of inequality of opportunity: Theory and an application to Latin America*. The World Bank.

Ferreira, F. H. and Peragine, V. (2016). Individual responsibility and equality of opportunity. In *The Oxford handbook of well-being and public policy*.

Ferreira, F. H., Lakner, C., Lugo, M. A. and Özler, B. (2018). Inequality of opportunity and economic growth: how much can cross-country regressions really tell us? *Review of Income and Wealth*, 64(4), 800-827.

Fleurbaey, M. (1994). On fair compensation. *Theory and decision*, *36*(3), 277-307.

Fleurbaey, M. (2008). *Fairness, Responsibility and Welfare*, 1st Edition, Oxford University Press, Oxford.

Fleurbaey, M. and Peragine, V. (2013). Ex ante versus ex post equality of opportunity. *Economica*, *80*(317), 118-130.

García-Peñalosa, Cecilia. 2018. Inequality in Macroeconomic Models. *Revue de l'OFCE* 2018/3 (157) : 93-115

Goux, Dominique and Eric Maurin. 2007. Close Neighbours Matter: Neighbourhood Effects on Early Performance at School. *Economic Journal*, vol. 117(523), pages 1193-1215.

Heckman, James J. and Rasmus Landersø. 2021. Lessons from Denmark about Inequality and Social Mobility. NBER Working Paper No. 28543

Hederos, Karin, Markus Jäntti and Lena Lindahl. 2017. Gender and inequality of opportunity in Sweden. *Social Choice and Welfare* 49, pp.605–635

Kobus M., Kapera M. and Peragine V. (2020). "Measuring multidimensional inequality of opportunity," WIDER Working Paper Series wp-2020-19, World Institute for Development Economic Research (UNU-WIDER)

Kolm, S.-C. (1969). 'The Optimal Production of Social Justice'. In J. Margolis and H. Guitton (eds), *Public Economics*. New York: Macmillan.

Kolm, S. C. (1977). Multidimensional Egalitarianisms. *Quarterly Journal of Economics*, 91(1): 1–13.

Lee, Chul-In and Solon, Gary (2009). Trends in Intergenerational Income Mobility. *Review of Economics and Statistics* 91(4): 766-772.

Lefranc A., Pistolesi N. and A., Trannoy (2006): Inequality of opportunity vs inequality of outcomes: are western societies all alike?, *Review of Income and Wealth*, vol. 54;

Maasoumi, E. (1986). The Measurement and Decomposition of Multi-Dimensional Inequality. *Econometrica*, 54(4): 991–97.

Magdalou, B. and Nock, R. (2011). Income distributions and decomposable divergence measures. *Journal of Economic Theory*, *146*(6), 2440-2454.

Marrero, G.A. and Rodríguez, J.G. (2011). Inequality of Opportunity in the United States: Trends and Decomposition. chapter 9 in Gabriel Rodríguez, J. (Ed.) *Inequality of Opportunity: Theory and Measurement* (Research on Economic Inequality, Vol. 19), pp. 217-246.

Marrero, G.A. and J.G.Rodríguez. (2012). Inequality of opportunity in Europe. *Review of Income and Wealth* 58 (4), 597-621

Marrero, G. A. and Rodríguez, J. G. (2013). Inequality of opportunity and growth. *Journal of Development Economics*, *104*, 107-122.

Marrero, Gustavo A. and Rodriguez, Juan Gabriel and van der Weide, Roy. (2016), Unequal Opportunity, Unequal Growth (October 11, 2016). World Bank Policy Research Working Paper No. 7853

Mitnik, Pablo, Anne-Line Helsø and Victoria L. Bryant. 2020. Inequality of Opportunity for Income in Denmark and the United States: A Comparison Based on Administrative Data. NBER Working Paper 27835 (forthcoming in *Measuring Distribution and Mobility of Income and Wealth*, edited by Raj Chetty, John N. Friedman, Janet C. Gornick, Barry Johnson, and Arthur Kennickell. NBER Book Series Studies in Income and Wealth. Chicago: University of Chicago Press.)

Moramarco, D., Palmisano, F. and Peragine, V. (2020). Inter-temporal Inequality of Opportunity. *Available at SSRN 3654123*.

Nakamura, E. and K.Miyao. 2008. Sex Differences in Human Biological Aging. *The Journals of Gerontology*: Series A, Volume 63 (9), pp. 936–944,

Peragine, V. (2002). Opportunity egalitarianism and income inequality. *Mathematical Social Sciences*, *44*(1), 45-64.

Peragine, V., Palmisano, F., and Brunori, P. (2014). Economic growth and equality of opportunity. *The World Bank economic review*, *28*(2), 247-281.

Peragine V and L. Serlenga (2008): Higher education and equality of opportunity in Italy, in J. Bishop and B. Zheng (eds.) *Research in Economic Inequality*, vol XIV

Perez-Arce, Francisco, Ernesto F. L. Amaral, Haijing Huang and Carter C. Price. 2016. Inequality and Opportunity. The Relationship Between Income Inequality and Intergenerational Transmission of Income. Rand Corporation

Ramos, Xavier and Dirk Van de gaer. 2015. Approaches to inequality of opportunity: principles, measures and evidence. *Journal of Economic Surveys* 30(5), pp.855-883.

Ravallion, M. and Chen, S. (2003). Measuring pro-poor growth. *Economics letters, 78*(1), 93-99.

Rawls, J. (1971). *A theory of justice*, Harvard University Press, Cambridge, MA.

Roemer, J. E. (1993). A pragmatic theory of responsibility for the egalitarian planner. *Philosophy & Public Affairs*, 146-166.

Roemer, J. E. (1998). *Equality of Opportunity*, Harvard University Press, Cambridge, MA.

Roemer, J. E. (2013). Economic development as opportunity equalization. *The World Bank Economic Review*, *28*(2), 189-209.

Roemer, J. E. and Trannoy, A. (2016). Equality of opportunity: Theory and measurement. *Journal of Economic Literature*, *54*(4), 1288-1332.

Salas-Rojo, Pedro and Juan Gabriel Rodriguez. 2020. Inheritances and Wealth Inequality: a Machine Learning Approach. LWS working paper n.32

Sen, A.K. (1973). '*On Economic Inequality'*. Oxford: Clarendon Press.

Sen, A. (1980). *Equality of what?,* in S. McMurrin (ed.), *Tanner Lectures on Human Values, Cambridge University Press. Rep. in Choice, Welfare and Measurement*, Basil, Blackwell, Oxford.

Solon, G. (2004). A Model of Intergenerational Mobility Variation over Time and Place. Chapter 2 in Miles Corak (ed.), *Generational Income Mobility in North America and Europe* Cambridge, UK: Cambridge University Press.

Spiganti, Alessandro. 2020. Inequality of Opportunity, Inequality of Effort, and Innovation. EUI Working Paper MWP 2020/02

Tsui, K.-Y. (1995). Multidimensional Generalizations of the Relative and Absolute Inequality Indices: The Atkinson–Kolm–Sen Approach. *Journal of Economic Theory*, 67(1): 251–65.

Tsui, K.-Y. (1999). Multidimensional Inequality and Multidimensional Generalized Entropy Measures: An Axiomatic Derivation. *Social Choice and Welfare*, 16(1): 145–57.

Van De Gaer, D. (1993). Equality of opportunity and investment in human capital, PhD dissertation, Katholieke Universiteit Leuven.

World Bank (2006). *World Development Report: Equity and Development*, World Bank, Washington, DC.