

Chapter 4. Inequality of opportunity



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This chapter discusses what is meant by inequality of opportunity (i.e. “ex-ante inequality”), in the sense of how different circumstances involuntarily inherited or faced by individuals could affect their economic achievements later in life. This concept is also taken to include how fair the procedures are. The chapter presents the theoretical principles that can be used for measuring inequality of opportunity. Practical issues of measurement are illustrated through examples and stylised facts from the applied literature on inequality of opportunity and, in particular, on intergenerational economic mobility. The chapter summarises the nature of the data needed to monitor the observable dimensions of inequality of opportunity and makes recommendations on the statistics that should be regularly produced for effectively monitoring them.

4.1. Introduction

Conceptually, economic inequality can be considered from two different angles. The *ex-post* view looks at differences in individual economic results or “outcomes”, like economic well-being, living standards, earnings, income, etc. The *ex-ante* view looks at how different the circumstances involuntarily inherited or faced by individuals and affecting their economic achievements are; this is also taken to include the procedural aspect of inequality – how fair the procedures are. The *ex-post* view is referred to as inequality of outcome, with income inequality probably the most common example. The *ex-ante* view is referred to as inequality of opportunity. Both types of inequality are clearly linked but in an asymmetric way. An increase in *ex-ante* inequality will, all things being equal, increase *ex-post* inequality. In the same way, inequality of outcome at a point of time or within a generation may affect inequality of opportunity in the future or in the next generation. However, a higher level of *ex-post* inequality can also result from changes in people’s economic behaviour, independently of circumstances, and in how the economic system transforms given individual circumstances into economic results.

A marathon where runners don’t start from the same line provides a useful analogy. *Ex-post* inequality would essentially be the distribution of the finishing times. *Ex-ante* inequality would refer to the distance competitors have to run to reach the finish line. *Ex-post* and *ex-ante* inequality are not the same because competitors may not have expended the same effort during the race. The winner might well be the one who had the least distance to cover. But it may also be the one who had the most to run but had the strongest will to win and suffered the fewest setbacks.

Focusing on one type of inequality or another may depend on the value judgment made on inequality. The most common value judgment behind concentrating on *ex-post* inequality is “egalitarianism”; the one behind *ex-ante* and procedural inequality is “fairness”. In the marathon race, egalitarian observers would simply like to minimise the gap between the performance of the winner and that of the loser, irrespective of the starting position of the runners. More liberalistic observers would insist on fairness and try to make the runners run the same distance, irrespective of the distribution of performances. Of course, doing so would most likely also reduce the differences between finishing times, so that in practice the two approaches to inequality are not necessarily opposed to each other.

Another aspect of inequality of opportunity is that it may reduce the aggregate efficiency of an economy, or the average outcome, by weakening incentives. This effect, which has been emphasised and debated in the recent economic literature, is easily understood. In the unequal race, the contestants who have the longest distance to run have little incentive to run fast, as they will likely be among the last over the finish line. But the same holds for people running the shortest distances, who know they will be among the first to finish even without making much effort. In other words, *ex-ante* inequality has two important consequences: on the one hand, it generates more *ex-post* inequality; on the other hand, it may reduce the aggregate performance of society. Thus, correcting inequality of opportunity may strengthen incentives – whereas correcting the inequality of outcomes is often held to do the opposite.

Another difference between the two concepts of inequality is their measurement. Considerable knowledge has accumulated over the last 40 years or so on how to measure the inequality of scalar outcomes like earnings, income, or standard of living, and the value judgments behind these measures. Things are much less advanced for inequality of

opportunity. Whereas statements like “there is less inequality in country A than in country B” or “at time t than at time $t-1$ ” are easily understood and may be solidly grounded in data in the case of outcomes, they are difficult to substantiate in the case of inequality of opportunity.

Defining inequality of opportunity in the tradition of Dworkin (1981), Arneson (1989) or Roemer (1998) as inequality in “the circumstances beyond the control of individuals”, the view taken in this chapter is that it will never be possible to observe differences among individuals across all the circumstances that may shape their economic success independently of their will. (The fact that personal “will” may itself be a “circumstance”, thus introducing a circularity into the definition of the inequality of opportunity, is discussed below.) Besides, what is not under the control of individuals, i.e. circumstances, and what is often referred to as “efforts”, may be extremely ambiguous. It should also be mentioned that circumstances and efforts may interact in producing some outcomes, thus making the distinction between them still more ambiguous. It follows that it is not possible to measure inequality of opportunity in the most general sense as we measure inequality of outcomes like earnings or income and compare it across space or time. However, this does not mean that it is not possible to measure **some** observable dimensions of inequality of opportunity and, most importantly, their impact on inequality of outcomes. This is actually what the inequality of opportunity literature does without always saying so. It is in this restricted sense that the expression will most often be used throughout this chapter.

Analysing how a person’s income depends on the education or income of their parents when that person was a child, on where they grew up, on gender, race, migration status, etc. informs us as to the role of specific circumstances – family characteristics, region of birth, or how the labour market discriminates across gender or race – in shaping the distribution of income. It matters for policy to know whether this role has increased or not, or that more inequality in the income of the present generation is likely to generate more inequality in future generations. Yet such analysis is essentially partial. On the one hand, non-observed circumstances may counteract the effect of observed ones, so that concluding that there is more inequality of opportunity based on intergenerational earnings mobility may be misleading. On the other hand, measuring the influence of a given circumstance on outcomes does not say much about the channels through which this effect takes place and on the policies to correct it. Deeper analysis is needed for some specific policy to be recommended.

The ambition of this chapter is essentially practical. It is not to contribute to the normative debate on the definition of inequality of opportunity in some absolute sense, or to the positive debate on its potential efficiency cost. It is rather concerned with the evaluation of the inequality specific to a given individual characteristic, duly considered as a circumstance; and, more importantly, to measure its contribution to the inequality of outcomes. The latter objective also applies to the case where several circumstances are considered simultaneously, as there are various ways of mapping the inequality of specific circumstances onto the inequality of given outcomes. In short, the chapter is rather brief on purely conceptual issues, on whether such and such a type of inequality is socially fair or unfair. The emphasis is on measurement issues and the practical use to be made of available measures.

The chapter is organised into three sections. A first section addresses a few conceptual issues, in particular what is meant by inequality of opportunity, and discusses the theoretical principles that can be used for measuring it. Practical issues of measurement

are taken up in the second section and illustrated through several examples and stylised facts from the burgeoning applied literature on inequality of opportunity and in particular on intergenerational economic mobility. The final section summarises the nature of the data needed to monitor the observable dimensions of inequality of opportunity and makes recommendations on the statistics that should be regularly produced for effectively monitoring them.

4.2. Conceptual issues in defining and measuring inequality of opportunity

This section first addresses the definition of opportunity as distinct from other factors that may contribute to the inequality of outcomes. It then discusses a few theoretical principles that may guide the measurement of the inequality of opportunity.

4.2.1. Opportunities and economic outcomes: normative and positive issues

Figure 4.1 below summarises the debate about the definition of inequality of opportunity as opposed to inequality of outcomes. The box on the left hand side of the figure refers to factors beyond the control of an individual, called “circumstances”, and likely to affect how she or he will manage and perform in the economic sphere. Some of them are observable, like personal traits – gender, ethnicity, disabilities, place of birth – or parental background. Others, like genetic traits, parents’ social capital, or cultural values, generally are not. Together they form the basis for inequality of opportunity.

The circle beneath the circumstance box stands for individual preferences, supposed to be independent from circumstances, thus with some genetic origin or resulting from all sorts of life experiences with no relationship with parental background. This assumption of course is quite debatable and will be discussed further below.

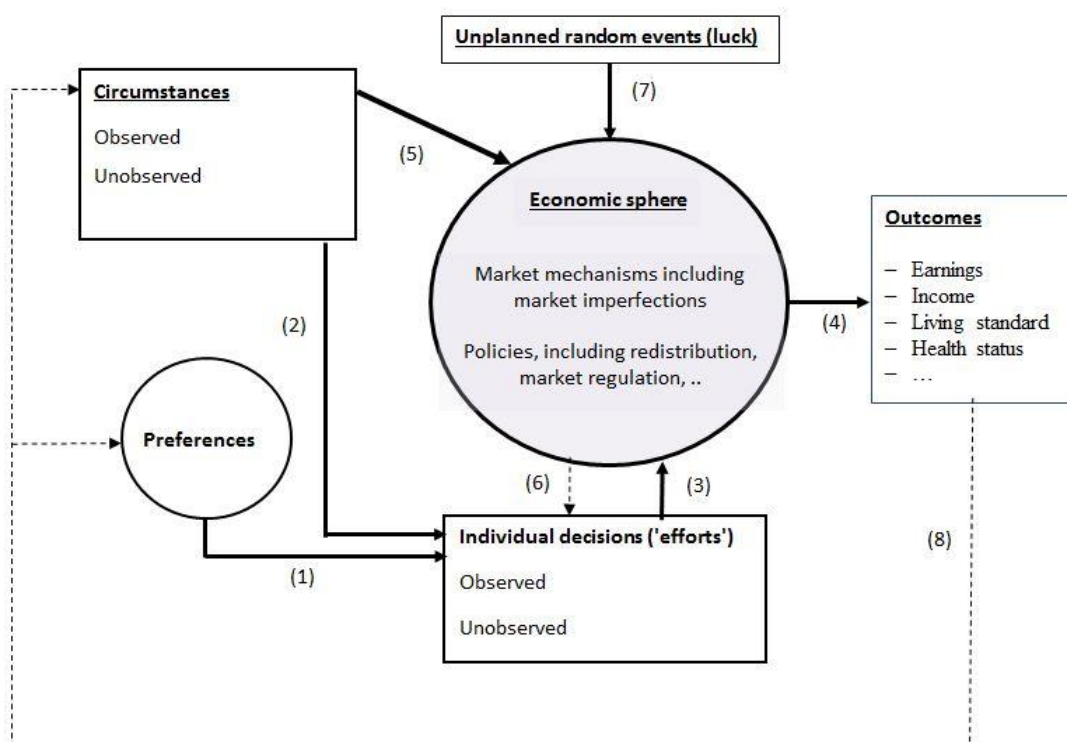
Circumstances, preferences and some key parameters from the economic sphere, like prices and wages, determine individual economic decisions in the box at the bottom of the figure – arrows (1), (2) and (6). To the extent these decisions determine the contribution of the individual to the economic system, they are called “efforts”. A good example of this is the supply of labour, which may depend on the wealth of an individual, i.e. **circumstances**, the wage rate, taxes on labour income and, of course, preferences.

Given the market mechanisms and the policies implemented in the economic sphere, and some randomness in those mechanisms, the individual contribution to the economic sphere results – arrows (3) and (4) – in some individual economic outcomes, be they earnings, income, consumption expenditures, etc. The key point, however, is that circumstances may also determine outcomes, together with individual decisions, through the economic sphere. This is the case for instance if some personal traits affect labour market rewards, as where there is discrimination according to gender, migrant status, ethnicity, or social origin. This direct influence of circumstances on outcomes through the economic sphere is represented by arrow (5), going from the circumstance box to the economic sphere. The corresponding inequality in outcomes has to do with what is often termed “procedural” inequality. Circumstances may also indirectly affect individual decisions by modifying the prices and wages faced by an individual – through arrow (6).

Within this representation of the determinants of economic outcomes, the latter thus result *directly* from individual economic decisions, which result themselves from personal preferences and economic conditions, and *indirectly* from the way personal traits and parental influence may affect the rewards for a given effort in the economic sphere.

In this framework, inequality of opportunity corresponds to the diversity of individual circumstances and the way it maps onto unequal outcomes. However, in a dynamic setting, unequal outcomes may themselves map onto unequal individual circumstance. For instance, the thin dotted line (8) in Figure 4.1 may stand for the intergenerational transmission of inequality: successful people in the current generation provide better circumstances to their children in the next. Within a generation, that link may also stand for a random event at some point of life, which, given individual preferences (in particular with respect to risk), affects future earning potential, as in the case of poverty trap phenomena.

Figure 4.1. The relationship between individual circumstances, opportunities and outcomes



In the economic inequality literature, a key distinction is made between defining inequality in the space of circumstances and in the space of outcomes. This distinction clearly matters from the point of view of moral philosophy and normative economics.² For some authors, only the inequality of individual circumstances should matter as they are, to some extent, forced upon individuals, and people are not morally responsible for them. Social justice thus requires these sources of inequality to be compensated in the outcome space, for instance through cash transfers. In contrast, the outcome inequality that arises from individual decisions or efforts should not be a matter of social concern as it essentially results from individuals' free will, or preferences, so that individuals can be taken as morally responsible for them.³ The opposite stream of the literature rejects this distinction between circumstances and efforts on the basis of preferences being themselves partly transmitted to individuals by their families or the social group they belong to. If so, most outcome determinants may be understood as circumstances, and the correction of inequality should entirely focus on the distribution of final outcomes.

At this stage, incentives must be taken into account. In the case where all determinants of outcome, including the taste for hard work, are considered as circumstances, compensating for all of them would lead to equalising outcomes irrespective of individual actions and initiatives, thus eliminating work, entrepreneurship or innovation incentives. In the case where only some income determinants are taken to be circumstances, compensating for differences in circumstances and leaving uncorrected the inequality arising from individual decisions may not always be possible or efficient. In the case of labour market discrimination, for instance, we may know that women or children of immigrants are discriminated against on average, but it would be difficult, and certainly controversial, to establish this discrimination at the individual level. Even if it were possible, compensating through lump-sum payments those who are discriminated against would reinforce the market distortion created by discrimination, as people would get the same wage as before but would possibly expend less effort due to the lump-sum transfer. This is a clear case where inequality of opportunity is responsible for both inefficiency and inequality of outcomes, and where the only efficient corrective policy is to eliminate the market imperfection responsible for the inequality of opportunity in the first place.

4.2.2. Ambiguity and observability issues in defining opportunities

The framework shown in Figure 4.1, and the idea that inequality of opportunity could be compensated by transfers in the outcome space, has three fundamental weaknesses for practical application, in addition to the preceding inefficiency argument. First, there is a fundamental ambiguity about what can be defined as circumstances and individual decisions resulting from preferences supposedly independent of circumstances. Second, even if the distinction between circumstances and efforts were unambiguous, there is a problem with the fact that many circumstances and many efforts are not observable. Third, the relationship between opportunities and outcomes is actually two-way. If, at a point of time, inequality of opportunity is affecting inequality of outcomes when Figure 4.1 is read from left to right, the dotted array (8) in Figure 4.1 stands for the fact that inequality of outcome, possibly due to the free decisions of economic agents, may dynamically affect future inequality of opportunity. Taken together, these weaknesses justify focusing on the inequality of outcomes, while at the same time taking into account the sources of the inequality related to specific observable circumstances. These points are developed below.

The first critique of the distinction between circumstances outside individual control and individual decisions reflecting independent personal preferences is precisely that it is difficult to hold that preferences are under individual control, as if they were freely chosen by people. An in-depth critique of that assumption has been made by Arneson (1989). Somebody's taste for work, for thrift or for entrepreneurship must come from somewhere, possibly from family background.⁴ If so, the distinction between the inequality in outcomes due to circumstances and due to individual decisions becomes fuzzy and practically non-operational.

The fact that many circumstances are not observed is another reason why the distinction between circumstances and efforts may have limited empirical relevance, at least as long as one is not ready to make several restrictive assumptions. Many circumstances that shape people's professional and family trajectory are not observable. Yet they may affect individual decisions as well as outcomes. For instance, parents may transmit to their children values or talents that will make them decide to go to graduate school and at the same time will help them in their career. If those values and talents are not observed, however, how could we disentangle in observed outcomes what is actually due to

observed efforts – i.e. graduate school – and what is due to unobserved circumstances? It is only when it can be assumed that efforts do not depend on unobserved circumstances that also affect outcomes that such identification is possible. If this is not the case, the contribution of efforts to outcomes cannot be properly identified, which makes again the distinction between circumstances and efforts somewhat artificial.⁵

Another weakness of the distinction between inequality of opportunity and inequality of outcomes illustrated by Figure 4.1 is that, if outcomes are determined by circumstances and individual decisions, then outcomes at one point of time may determine future circumstances. As a matter of fact, the whole framework is set in static terms, when it should actually be dynamic. Outcomes of one generation or at one point of time are likely to affect circumstances in the next generation or at a future point of time, for instance through accumulating or running down wealth or human capital, taken as a circumstance. Under these conditions, ignoring that part of the inequality of outcomes that comes from individual decisions implies ignoring a future source of inequality in the space of circumstances. It may also be noted that, in such a dynamic framework, the measurement of the inequality of outcomes raises some issues. If the unit of time is a generation, how should outcomes be defined? Certainly not by their value at a point of time. Within a dynamic intra-generational analysis, isn't it the case that many 'individual decisions' quickly become circumstances, so that again the distinction between circumstances and efforts yields limited insights?

Summing up, the focus put by some moral philosophers and normative economists on inequality of opportunity rather than on inequality of outcomes may be perfectly justified in theory. Practically, however, the distinction that has to be made between factors that are under individual responsibility (efforts) and those that are not (circumstances) is most often blurred, in part because of observability issues. Even when relying only on observed circumstances and efforts, disentangling what part of inequality of outcome is due to one or the other is difficult once it is admitted that observed and unobserved circumstances may affect both outcomes and efforts. Actually, the only solid empirical evidence that can be relied upon is the way outcomes depend on observed circumstances, i.e. essentially some personal traits and family-related characteristics.

4.2.3. Measuring inequality of observed opportunities

Data on specific outcomes, some circumstances and, possibly, some types of efforts are available in household surveys or from administrative sources. Based on them, it is possible to estimate the relationship between specific outcomes, circumstances and efforts.

Before getting into the measurement of inequality of opportunity, or rather some dimensions of it, within these databases it is worth formalising that relationship and the arguments in the preceding section. Assume that a survey sample of the population is available with information on individual or household economic characteristics and background. Denote by y_i the outcome of interest for an individual i in the sample; his/her observed circumstances by C_i ; and his/her efforts by E_i . We can represent the way in which circumstances and efforts determine outcome by the relationship:

$$y_i = f(C_i, E_i) + u_i$$

where $f()$ is some function to be specified below and u_i stands for the role of unobserved circumstances and efforts as well as temporary shocks or measurement errors on the observed outcome. In empirical work, that relationship is often assumed to be log-linear:

$$\text{Log } y_i = a.C_i + b.E_i + u_i \quad (1)$$

where a and b are vectors of parameters. Such a specification of the function $f(,)$ is very restrictive, as one would expect some interaction between circumstances and efforts in determining outcome. Yet, it is simple and quite sufficient for our purpose.

The argument in the preceding section and in the Annex 4.A suggests that E_i is correlated to the observed circumstances C_i and the unobserved circumstances in u_i . Because of the latter, it is thus not possible to get unbiased estimates of a and b . Under these conditions, the only empirical relationship that can be reliably estimated is a reduced form model where the outcome depends only on observed circumstances:

$$\text{Log } y_i = \alpha.C_i + v_i \quad (2)^6$$

where α is a set of coefficients that describe the effect of observed circumstances on the outcome directly or indirectly through their correlation with efforts (observed or not observed), and v_i stands for all outcome determinants different from observed circumstances. It should be noted, however, that for α to be estimated without bias, it is necessary to assume that all these unobserved outcome determinants are independent of the observed circumstances, C_i . Otherwise, the estimated α coefficients will also include the effects of all unobserved outcome determinants that are correlated in one way or another with C_i .

Estimating models of type (2) through ordinary least square (OLS) is a trivial exercise that has been performed under a variety of specifications for the outcome variable, y_i , and the explanatory variables, C_i . Perhaps the most familiar specification is the famous Mincer equation that includes the earnings rate of employed people as the outcome variable, and schooling⁷ and personal traits as explanatory variables.

There is a burgeoning literature on the measurement of inequality of opportunity based on models of type (1) or (2). Using model (1), it essentially consists of comparing the actual inequality in outcomes to the inequality that would be observed if all individuals in the data sample were facing the same circumstances, or were all expending a given level of effort. This literature is exhaustively summarised in Ramos and Van de Gaer (2012) and Brunori (2016). We take here a simpler approach based on the fact that efforts are either not observed or endogenous – i.e. correlated with unobserved outcome determinants – so that model (2) is the only solid basis to measure the inequality of opportunities described by the variables in C_i .

It can be noted that, in some cases, it is possible to measure the inequality of single components of C irrespectively of outcomes and model (2). For instance, parental income or cognitive ability may be components of C , inequality of which can be observed in some databases.⁸ The higher the inequality component of C , the more unequal the distribution of outcomes, provided that the corresponding coefficient in α is strictly positive.

The inequality of the distribution of C may also be expressed in terms of the inequality of outcomes. When the latter is measured by the variance of logarithms and when there is a single component in C , model (2) implies that:

$$\text{Var}(\text{Log } y) = \alpha^2.\text{Var}(C) + \text{Var}(v)$$

Thus, the inequality of that single component of C can also be expressed as what could be the inequality of outcomes if other determinants of outcomes were neutralised, i.e. in the case where they were the same for all individuals. If the inequality of outcomes is

measured by the variance of logarithms (*VL*), the inequality of *C*, $I_{VL}(C)$, could in that case be written as:

$$I_{VL}(C) = \alpha^2 \cdot Var(C) \quad (3)$$

$$\text{and } I_{VL}(C) = \alpha' \cdot Covar(C). \alpha$$

when there is more than one component in *C*.

This definition can be generalised to any measure of outcome inequality $M\{ \}$ – i.e. Gini, Theil, mean logarithmic deviation – and to any number of components in *C* in two ways.

First, define the “virtual” outcome, $y^\circ(C_i, v^e)$, for every individual *i*, as what would be the outcome of that individual if all the outcome determinants other than the opportunities in *C* were equal to some exogenous value, v^e , common to all, i.e.:

$$\text{Log } y^\circ(C_i, v^e) = \alpha C_i + v^e \quad (4)$$

Then compute the measure of inequality $M\{ \}$ on the distribution of $y^\circ(C_i, v^e)$ in the whole sample. An absolute measure of the inequality of opportunities in *C* is then given by $M\{ y^\circ(C, v^e) \}$, where $y^\circ(C, v^e)$ stands for the whole distribution of $y^\circ(C_i, v^e)$ in the sample. Fleurbaey and Schokkaert (2009) labelled this measure the “direct unfairness” (*du*) of the inequality of opportunity associated with *C*:

$$I_M^{du}(C) = M\{ y^\circ(C, v^e) \} \quad (5)$$

Thus, $I_M^{du}(C)$ measures the inequality of opportunities in *C* by considering their impact on the inequality of outcome, irrespective of all other outcome determinants. Of course, a measure of inequality of opportunities in *C* can be defined for each measure $M\{ \}$ of outcome inequality. As most outcome inequality measures $M\{ \}$ are scale invariant, the arbitrary value of v^e does not actually matter.⁹

Second, one may use the “dual” of the preceding definition of inequality of opportunities in the following sense. Instead of equalising the outcome determinants other than *C*, one may define a virtual income resulting from the equalisation of the opportunities in *C* across all individuals in the sample. Let C^e be the common value of opportunities and $y^*(C^e, v_i)$ the corresponding virtual income:

$$\text{Log } y^*(C^e, v_i) = \alpha C^e + v_i \quad (6)$$

Then another absolute measure of inequality of opportunities in *C* may be defined for any outcome inequality measure $M\{ \}$ as the difference between the actual inequality of outcome and that which would result from equalising circumstances among all individuals in the sample. Fleurbaey and Schokkaert (2009) proposed to label this the “fairness gap” (*fg*) measure of inequality of opportunity associated with *C*:

$$I_M^{fg}(C) = M\{ y \} - M\{ y^*(C^e, v) \} \quad (7)$$

As before, this measure is independent of the arbitrary value, C^e , taken for opportunities when the outcome inequality measure is scale invariant.

Both measures of inequality of opportunities may also be defined in “relative” terms by expressing them as a proportion of the actual inequality of the outcome being studied, $M\{ y \}$. They will be denoted respectively $\tilde{I}_M^{du}(C)$ and $\tilde{I}_M^{fg}(C)$.

The preceding notations may seem a bit complicated. Their interpretation is extremely simple and intuitive when applied to actual data, as illustrated by the few remarks below.

1. Consider equation (2) as a standard regression equation of outcomes on a set of observed opportunities with the unobserved outcome determinants, v , as the residuals of the regression. Then, if the inequality measure of outcome $M\{ \}$ is the variance of logarithms, then both the direct unfairness (5) and the fairness gap measures (7) are equal to *the variance of the logarithm of outcome explained by the opportunities C*, and the corresponding relative measure is simply the familiar R^2 statistic associated with regression (2).
2. Consider now the individual “types” defined by combinations of the variables in C with a minimum number of observations. For instance with only gender in C , there would be two types. With gender and two possible values for the education of the parents, there would be four types: men from low education parents, women from high education parents, etc. It turns out then that the direct unfairness inequality of opportunity (5) is very close to the familiar *between group* inequality of outcomes *when groups are defined by types*, except that the inequality is defined on the mean of the logarithm of outcomes rather than on the outcome means.¹⁰
3. The preceding expressions to evaluate the inequality of observed of opportunities refer to the linear case, where the opportunities being considered have independent effects on the outcome of interest. Of course, it is also possible to take into account interactions between opportunities, as for instance, between gender and education in explaining the inequality of earnings.
4. When considering types, the above formulae seem to leave little room for the inequality of outcomes within types. This is not completely true since the outcome inequality between types corresponding to (5) is not the same as the inequality between the types’ mean outcomes, the difference depending on the distribution of outcomes within types. An approach that takes more explicitly into account outcome inequality within types is the inequality of opportunity measure that can be derived from the principles set in Roemer (1998).

$$I^R = \frac{1}{\bar{y}} \int_0^1 [\bar{q}(\pi) - \text{Min}_t\{q_t(\pi)\}] d\pi \quad (8)$$

where $q_t(\pi)$ is the outcome of the quantile of order π in the outcome distribution for type t , $\bar{q}(\pi)$ is the (weighted) mean of those quantiles across types, and \bar{y} is the overall mean outcome. In other words, inequality of the opportunities defined by types is the mean across quantiles of a Rawlsian type of inequality measure across types for each quantile.¹¹

The preceding inequality measure corresponds to the case where the residual term, v , in (2) is heteroskedastic with a distribution, and hence a variance, that depends on the observed circumstance variables, C , or differs across types. This is perfectly consistent with the usual assumptions that the residual term v has zero expected value and is orthogonal to C . With heteroskedasticity, however, defining the inequality of opportunity through (5) or (7) is not possible anymore. The definition of the virtual income in (4) ignores the dependency of the residual term on C and the equalising of circumstances in (6) should require modifying the v_i term, so that its distribution does not depend on C anymore or, equivalently, is the same across types.

4.3. Practical issues and some stylised facts in measuring the inequality of opportunity

The discussion in the preceding section has focused on conceptual issues in the definition and measurement of inequality of opportunities. We now turn to the way these principles and approaches to measurement are handled in the empirical literature and present stylised facts about some specific dimensions of inequality of opportunity.

The focus will first be on single dimensions of inequality of opportunities, without necessarily making reference to specific outcomes. More direct applications of the measurement tools discussed above will then be considered with various combinations of outcomes (income, earning rates) and sets of opportunities. Special emphasis will be put on the measurement of intergenerational transmission of inequality, which has attracted much attention among social scientists, and which may be considered as a particular case of the measurement principles set out above. Emphasis will also be put on labour market discrimination, which raises some interesting questions when studied from the perspective of inequality of opportunity.

4.3.1. Direct measures of some particular dimensions of the inequality of opportunity

The measurement of specific dimensions of inequality of opportunities can be undertaken in an autonomous way, without explicit reference to economic outcomes. This direct approach simply consists of analysing the distribution of particular circumstances, *C*. Many individual characteristics could be analysed in this way, provided they are described by some quantitative index. Given its huge importance in the literature on inequality of opportunity, this section focuses on cognitive ability and then briefly considers the difficulty of handling directly other single dimensions of inequality of opportunity.

Cognitive ability as an opportunity and as an outcome

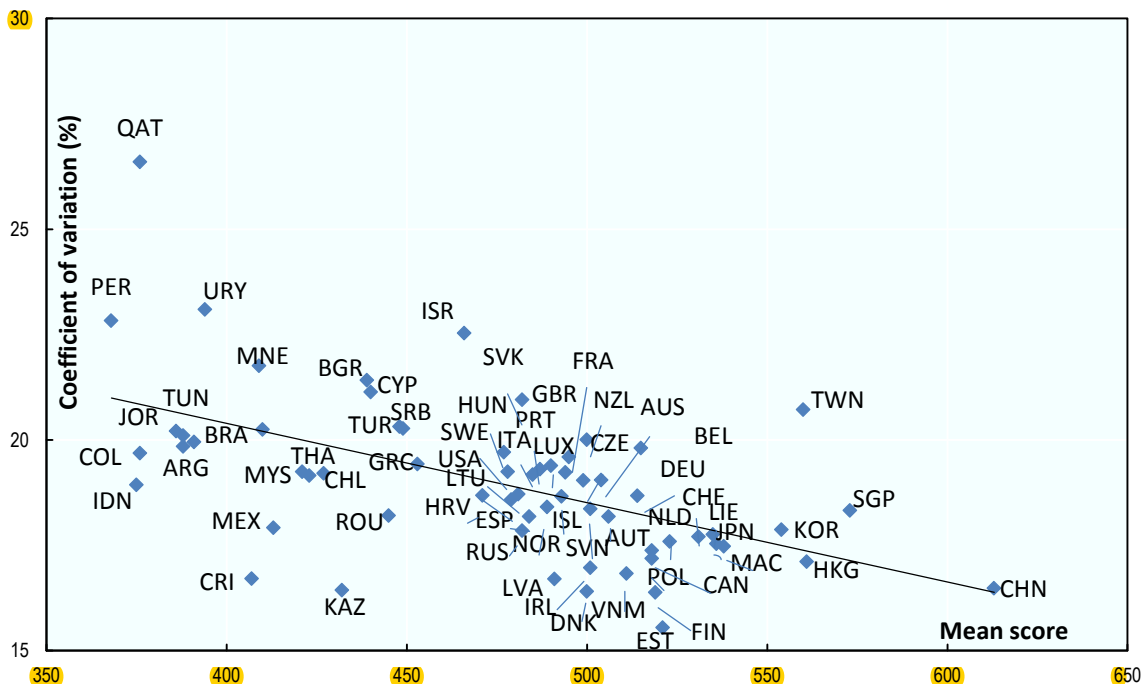
The PISA initiative by the OECD provides first hand data to measure inequality in one of the most important dimension of individual circumstances: cognitive ability. It now gathers the scores of samples of 15-year old school children in more than 70 advanced and emerging economies in three tests: one on reading, i.e. answering questions about a short text; one on mathematics; and the third on science. This instrument has been fielded at 3-year time intervals since 2000. In addition to students' answers to these assessment tests, the database also reports information on their family background and on the characteristics of their schools.

Considering PISA scores as circumstances implicitly supposes looking at cognitive ability at 15 as one of the important determinants of future individual economic outcomes, earnings in particular, and acknowledging that it essentially depends on genetic factors and the family context. Adults cannot be held responsible for that part of their life, so that the inequality of PISA scores among 15 year-olds today will be responsible for some of the inequality of opportunity they will face later in their lifetime. But PISA scores may also be seen at the outcome of the educational process and, as such, dependent on family circumstances, the efforts of the children, and the educational system itself.¹² Hence the debate on how schools may correct for the inequality of opportunity arising from family background. It is however the former perspective, i.e. cognitive scores as a circumstance, that is discussed in what follows.

Much publicity is given at each new edition of PISA to mean scores by country, to the ranking of countries and how rankings change over time. From the viewpoint of measuring inequality of opportunities, however, what matters most is the statistical distribution of these scores, or their disparities across students.

Figure 4.2 plots the inequality of PISA scores in mathematics, as measured by the coefficient of variation, against the mean score in the 2012 exercise for OECD countries. Interestingly, there is a clear negative relationship between the inequality and the mean of scores (putting aside the three emerging economies, Chile, Mexico and Turkey where the coverage of the PISA survey is much lower than in advanced countries, essentially because a non-negligible proportion of 15 year-olds have already dropped out of school).¹³ This is presumably because better mean scores are logically obtained by improving more the lower than the upper tail of the distribution. Yet what may be more important is the substantial difference in the inequality of scores for countries in the same range of average scores. For instance, inequality is 30% higher in Belgium than in Finland or Estonia, in the upper part of the scale of mean scores; the same holds true for France compared to Denmark in the middle.

Figure 4.2. Mean and coefficient of variation of PISA mathematics scores in OECD countries, 2012



Source: OECD (2014), *PISA 2012 Results: What Students Know And Can Do*, <http://dx.doi.org/10.1787/9789264208780-en>.

Cognitive ability can be considered as a dimension of economic opportunity only insofar as it is a significant determinant of an outcome like earnings or the standard of living of an individual. In this respect, it is important to stress that test scores in surveys like PISA, the OECD's Survey of Adult Skills (PIAAC) or its predecessor (the International Adult Literacy Survey, IALS) only explain a limited part of earnings. Murnane et al. (2000) and Levin (2012) make this point on the basis of US data. According to the former, a 1%

increase in high school test scores entails a 2% increase in earnings when students are 31 years old, which is substantial.¹⁴ However, the variance of adults' (log) earnings explained by high school test scores is small, slightly less than 5% for men (Murnane et al. (2000, p. 556). Family background is a more powerful determinant of earnings, all the more so when considering that test scores are very much dependent on the education and income of parents.

Instead of cross country comparisons as in Figure 4.2, it would be interesting to see how inequality, or more exactly the whole distribution of scores, changes over time in a given country. Data reported by the OECD in 2012 include the 90/10 inter-decile and 75/25 inter-quartile ratios for the four exercises since 2003. These measures are remarkably constant except for emerging economies where inequality goes down at the same time as mean scores go up. France is one of the few advanced countries where the 90/10 inter-decile ratio increased significantly over time. As France's mean score did not change much, this would suggest that good performers do better and bad ones do worse, possibly a clear sign of an increase in the inequality of that specific component of opportunities. A careful study of the evolution of the whole distribution of test scores country by country might reveal other interesting features and it is surprising that so much emphasis is being put on the evolution of the means without considering distributional features.

The same kind of analysis, based on quite different tests, is being performed at younger ages by a number of organisations, for instance the Progress in International Reading Literacy Study, led by the International Association for the Evaluation of Educational Achievement. However, the results have not received as much publicity, even though they are equally, if not more, relevant in the analysis of inequality of opportunity, as numerous studies have shown that differences in individual cognitive abilities appear very early in life. Pre-school tests already show high variability among children depending on their family background, and several studies have shown that these differences might have long-lasting effects, as school systems would at best compensate only part of them. Experiments with preschool programmes aimed at levelling the playing field like the Perry programme or the Abecedarian programme in United States have provided evidence of this – see for instance Kautz et al. (2015). As shown in recent work by Heckman,¹⁵ the origins of these preschool inequalities are due in large part both to “parenting”, i.e. the care the parents devote to their young children, and to health factors.

Other single dimensions of the inequality of opportunity

Initial inequality in non-cognitive skills is also important throughout lifetime, and may be considered as another dimension of the inequality of opportunity, even though no synthetic measure is actually available, which makes comparing societies over space or over time difficult.

Health status is another dimension of childhood circumstances related to family background, and another component of human capital. In the same way that cognitive skills at 15 influence future earnings and are heterogeneous across young people, health status at earlier ages is known to potentially influence the whole career of people and to be heterogeneous too.¹⁶ The difficulty here is to monitor inequality in health status. There is an important literature for instance on birth weights as a predictor of health status, future education achievements and adult earning levels (e.g. Currie, 2009). The same may be true of anthropometric indices at early ages, although most indices are strongly influenced by weight at birth. It is somewhat surprising that more attention is not given to

the evolution of inequality in these indices and, as for educational test scores, their dependency on parental characteristics.

Another single dimension of the inequality of opportunity, different from human capital, is inherited financial capital. It is certainly possible to measure the inequality of inheritance flows during a given period. Wolff (2015) does so for the United States using data from the University of Michigan's Panel Study of Income Dynamics (PSID) and provides Gini coefficients of inheritance flows both for the whole population and among recipients. However, this is not very informative because of the heterogeneity in the age of inheritors. The extent to which inheriting the wealth of one's parents at the age of 55, something frequent these days, may be considered as a component of inequality of opportunity is not totally clear, except if, somehow, one has been able to borrow, effectively or virtually, much earlier in life against this future wealth flow. As the credit market is highly imperfect, and the inheritance date or the amount to be inherited highly uncertain, it is not even sure it would make much sense to try to estimate something like the inequality in discounted expected inheritance flows of all 25 year-old individuals. Further, donations as well as inheritances would have to be taken into account.

Inheritance is a dimension of the inequality of opportunity whose inequality is difficult to evaluate as such, even though it is a key factor shaping inequality in economic outcomes like income or standard of living when considering cohorts beyond a certain age.

4.3.2. Outcome-based measures of inequality of opportunities

Rather than considering the inequality of various dimensions of opportunities in an isolated way, it is possible to measure it indirectly through their overall effect on the inequality of the outcomes under study, using a relationship of type (2) above. It was seen that, in various ways, this relationship provides an indirect scalar metric of inequality of opportunity. Various illustrations of this approach are shown below, while also reporting stylised facts on some key components of inequality of opportunities.

Intergenerational mobility of earnings

Much work has been devoted to the estimation of models of type (2) where the outcome y_i is the (full-time) earnings of an observed individual, i , and C_i is the (log) (full-time) earnings of their parents, most often their father, observed roughly at the same age. Denoting the latter by $y_{-1,i}$, the basic specification of the model is thus:

$$\text{Log } y_i = \gamma \text{Log } y_{-1,i} + a + v_i \quad (9)^{17}$$

where a is a constant and v_i is a zero mean random term, standing for all unobserved earnings determinants independent of fathers' earnings. The coefficient γ summarizes all the channels through which fathers' earnings, and their own determinants like education, may affect sons' earnings.

This model, reminiscent of the famous Galton (1886) analysis of the correlation of height across generations, is generally presented as belonging to the literature on intergenerational mobility, with the least square estimate $\hat{\gamma}$ being interpreted as the intergenerational elasticity (IGE), or the degree of immobility across generation. Equivalently, in a Galtonian spirit, the coefficient $1 - \hat{\gamma}$ is interpreted as the speed of the regression towards the mean.

This approach to intergenerational mobility is based on a parametric specification and the estimation of a specific parameter. Non-parametric specifications come under the form of

mobility matrices showing the probabilities p_{ij} for the earnings of sons whose father's earnings is in income bracket i to be in bracket j . We consider these two approaches in turn.

Parametric representation of intergenerational mobility

To see more clearly the relationship between IGE and inequality of opportunity, one may consider applying directly the alternative definition of inequality of opportunities provided in the preceding section of this chapter. Applying (4)-(7) to model (9) and assuming that the inequality measure $M\{\cdot\}$ is scale invariant, it can be shown easily that:

$$I_M^{du}(y_{-1.}) = M\{y_{-1.}^{\hat{y}}\} \quad \text{and} \quad I_M^{fg}(y_{-1.}) = M\{y\} - M\{\exp(\hat{v})\}$$

where the notation $\hat{\cdot}$ refers to least square estimates. In the particular case where $M\{\cdot\}$ is the variance of logarithms, VL , it turns out that the two measures in absolute terms are identical because of the additivity property of the variance:

$$I_M^{du}(y_{-1.}) = I_M^{fg}(y_{-1.}) = \hat{y}^2 VL\{y_{-1.}\}$$

while in relative terms:

$$\tilde{I}_M^{du}(y_{-1.}) = \tilde{I}_M^{fg}(y_{-1.}) = \frac{\hat{y}^2 VL\{y_{-1.}\}}{VL\{y\}} = R^2 \quad (10)$$

where R^2 is the measure of the explanatory power of the independent variables in regression (9) or, in the present case, the square of the correlation coefficient between the (log) earnings of parents and children.

It can be seen that there is a difference between the intergenerational mobility of earnings (IGE) and inequality of opportunity linked to father's earnings. The former is proportional to the latter with a coefficient equal to the ratio of the inequality of children's earnings to that of their fathers.¹⁸ In other words, it is only in a world where the inequality of earnings does not change across generations that both the inequality of opportunity, based on the variance of logarithm, and the IGE coincide.

In their study of geographical differences in intergenerational mobility in the United States, Chetty et al. (2014a) use the ranks of parents and children in the earnings distribution as a relative measure of mobility. Based on the 'copula' of the joint distribution of the (log) earnings of the two generations, i.e. the joint distribution of father/children ranks in their respective earnings distribution, this measure is independent of the marginal distributions of log earnings. It turns out that the rank-rank correlation is not very different from the log-earnings correlation for reasonable small values of the latter. Through (10), it is thus possible to recover the IGE from the rank-rank correlation.

Non-parametric representation: mobility matrices

Another way of representing the intergenerational mobility of earnings is through a transition matrix representing the way a two-generation dynasty transitions from a given earnings level for fathers to another (or the same earnings) level for sons. Let there be N earning brackets denoted Y_k and denote p_{ij} the probability that the sons of fathers in bracket Y_i find themselves in bracket Y_j . The distribution of earnings is given by the total rows and columns of the matrix $P=\{p_{ij}\}$, but it is also possible to break free from these distributions by defining the income brackets as the quantiles (deciles, vintiles...) of the distribution of the earnings for fathers, on the one hand, and for sons, on the other.¹⁹

Table 4.1. Intergenerational transition matrix for earnings

Fathers \ Sons	Y ₁	Y ₂	Y ₃	...	Y _N	Total
Y ₁	P ₁₁	P ₁₂	P ₁₃		P _{1N}	P _{1.}
Y ₂	P ₂₁	P ₂₂	P ₂₃		P _{2N}	P _{2.}
Y ₃	P ₃₁	P ₃₂	P ₃₃		P _{3N}	P _{3.}
...
Y _N	P _{N1}	P _{N2}	P _{N3}		P _{NN}	P _{N.}
Total	P _{.1}	P _{.2}	P _{.3}	...	P _{.N}	1

Whether the transition or ‘mobility’ matrix is defined in terms of income brackets or quantiles is not without implications for the interpretation that may be given to the comparison of two matrices. When referring to income brackets, the matrix shows ‘absolute’ mobility, i.e. the probability that children’s earnings could be higher, or lower, than their parents’, a concern of many parents today. Conversely, defining the matrix in terms of quantiles permits to analyse the ‘relative’ mobility, irrespectively of earnings levels. The difference between the two approaches lies essentially in the fact that the latter does not take into account the change in the distribution of earnings across generations.²⁰

There is a huge literature on how to draw mobility indicators from such a representation of the influence of parents’ earnings on children’s earnings – see Fields and Ok (1999) or the survey by Jäntti and Jenkins (2015). For instance, mobility is often measured by one minus the trace of the mobility matrix. Shorrocks (1978) suggested a “Normalised Trace” measure given by $[N - \text{trace}(A)] / (N - 1)$, where A is the matrix P with rows normalised to 1 – i.e. the N probabilities p_{ij} are divided by the row sum $p_{i.$. These measures are based on the expected number of jumps from one bracket, or decile, to another.

Rather than comparing transition matrices on the basis of mobility indices, some dominance criteria have also been developed, which may lead to incomplete ordering and, thus, to cases of non-comparability between two matrices. For instance, the diagonal criterion says there is less mobility in a transition matrix than in another if *all* diagonal elements, rather than their sum, are smaller in the former than in the latter. Shorrocks (1978) proposed a stronger criterion, the “strong diagonal view” according to which there is more mobility in matrix A than in B if $a_{ij} \geq b_{ij}$ for all $i \neq j$.

Although related, this kind of measure based on the transition probabilities has only an indirect link with measures of inequality of opportunity in the sense that it is not expressed in terms of the distribution of outcomes, which logically should be here the distribution of children’s earnings. There are various ways such a link may be established:

- The Roemer inequality of opportunity formula (8) would be one way, although apparently seldom used, mostly because the transition matrix consistent with it would be conceptually different from P above. Indeed, the children’s earnings brackets should be row dependent so as to correspond to the deciles – or other quantiles – of the distribution of earnings among children from parents in a given earnings bracket or quantile.

- An alternative would consist of associating to each row of the matrix a scalar depending on the mean earnings and its distribution within the row. In a more general context, van de Gaer (1993) suggested measuring the inequality of opportunity by the inequality of the mean earnings across “types”, i.e. fathers’ earnings here, which is actually a measure of type I^{du} as defined in (4). Lefranc et al. (2009) argued in favour of combining the mean with some inequality measure within type. More generally, one could consider the observed distribution of children’s earnings with the same father’s earnings, as being that of the ex-ante random earnings of the typical child in that type. Then one would associate to each row of the transition matrix the certainty equivalent of the distribution of earnings in that row for a given level of risk aversion. This would be equivalent to associating to each row of the matrix the equivalently distributed earnings (EDE) for that row, in the sense of Atkinson (1970) and then defining inequality of opportunity as the inequality of these EDEs across rows.²¹
- A social welfare approach to the measurement of intergenerational mobility has been proposed by Atkinson (1981) and Atkinson and Bourguignon (1982), which differs somewhat from the inequality of opportunity analytical framework presented here. It consists of defining social welfare on father-son pairs, so that each cell of the transition matrix is given a utility $U(Y_i, Y_j)$ and the social welfare of society is defined by the mean value of this utility, weighted by the transition probabilities, p_{ij} . The simplest case is when $U(\cdot)$ is additive in the earnings of parents and children. Atkinson and Bourguignon (1982) derived dominance criteria to compare transition matrices on that basis, depending on the properties of the function $U(\cdot)$.
- A similar line of thought has been pursued by Kanbur and Stiglitz (2015) who extend the preceding approach by considering a steady state of an economy consisting of infinitely lived dynasties under the assumption of constant transition matrix and earnings distribution across generations. Within that framework, they identify a social welfare based dominance criterion of one matrix over another or, in other words, of one stationary state of an economy with some intergenerational mobility feature over another stationary state with a different mobility matrix.

In the perspective of inequality of opportunity, there are problems with the last two approaches. On the one hand, the assumption of a fully stationary economy and a social welfare dominance comparison based on dynasties with an infinite number of generations seems extreme, even though the stationarity assumption is often implicit in statements about intergenerational earnings mobility. On the other hand, it is a problem that the very nature of circumstances is used to make comparisons of outcomes across groups of individuals with identical circumstances. In other words, the mobility of children with rich parents may matter less than that of poor parents. What should matter from the point of view of inequality of opportunity is how different the distribution of earnings is across parents’ earnings levels, with no particular importance being given to those levels.

In summary, there is some ambiguity about the way in which inequality of opportunity corresponding to non-parametric specifications of the intergenerational mobility of earnings can be measured. There are various ways mobility can be evaluated or transition matrices compared based on social welfare criteria. But the link with measures of inequality of opportunity of the kind that can be derived from simple parametric models of type (9) – at least under the assumption of homoscedasticity of the residual term, v – is unclear. For this reason, the rest of this section looks at the parametric case.

Data requirements

A priori, the data requirement to estimate the IGE or the parents-children earnings transition matrix seems extremely demanding. One should observe the earnings of parents, generally the father, and that of the children, generally the sons, at more or less the same age or during the same period of the lifecycle in both cases. Long panel data bases extending over 20 years and more would allow this to be done. For instance, the PSID (Panel Study of Income Dynamics) in the United States has been collecting data on the same families and their descendants for almost 50 years. The British and the German household panels also extend over 25 years and more. In some countries, register data, most often tax data, allow researchers to follow people throughout their lifetime and from one generation to the next, but only a few countries have open and anonymized register data at this stage.

However, panel data are not really necessary to estimate model (9). The availability of repeated cross-sections over long periods is sufficient. Moreover, they permit the IGE to be estimated in a consistent – i.e. asymptotically unbiased – manner, something which is not certain with panel data.

To see this, it must be noted that the observation of $\text{Log } y_{-1}$ is most likely to include measurement errors or, at least, transitory components of fathers' earnings which are unlikely to have had any effect on their sons' earnings. Estimating γ in (9) with OLS and without precaution for measurement error will thus lead to the so-called attenuation bias, a bias that has been shown to be quite substantial in intergenerational mobility studies.²² The solution is to “instrument” $\text{Log } y_{-1}$ by regressing that variable on some fathers' or parents' characteristics, Z , at the same date, say t_{-1} , and to use the predicted rather than the observed value when estimating (9) with OLS. Thus, if the parents' characteristics Z are observed at time t in the same database as children's earnings, and if an earlier cross-section is available at time t_{-1} , this allows us to estimate the log earnings of adults with characteristics Z . Running OLS on (9) using the predicted earnings of the parents at time t_{-1} will yield an asymptotically unbiased estimator of the IGE. Through this so-called two-sample instrumental variable (TSIV) estimation strategy (Björklund and Jäntti, 1997) repeated cross-sections with information on respondents' parents and covering a period long enough are sufficient to estimate the IGE.²³

There are two important caveats to the preceding method. First, the instrumental variable approach just sketched is valid only to the extent that the instrument Z may be assumed to be orthogonal to the income of the children. It must be recognised, however, that this is unlikely to be the case, as most observable parents' characteristics, like education, occupation, wealth, etc., may be thought of as influencing the economic achievements of children. Second, even if the TSIV strategy did allow the IGE to be estimated consistently with repeated cross-sections rather than with panel data, it would not permit the corresponding inequality of opportunity to be estimated as defined by (10). This is because the variance of the instrumented earnings of parents is not the same as the variance of their true earnings.

Measurement errors are also likely to affect the estimation of mobility measures, social welfare dominance tests and inequality of opportunity through the transition probability matrix methods mentioned above. In that case, both the error on fathers and sons matter. The former may be responsible for misclassifying fathers in the income scale, whereas the latter introduces noise in the transition probabilities.

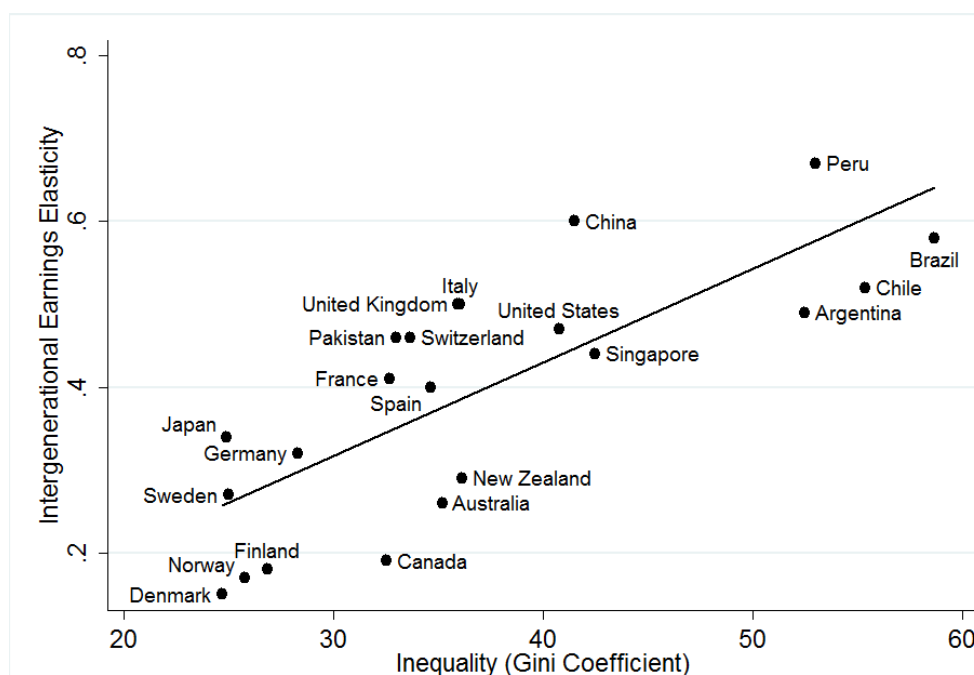
Stylised facts

The best illustration of this literature on the measurement of intergenerational mobility is the well-known “Great Gatsby” curve, due to Miles Corak and popularised by Alan Krueger. It plots estimates of IGE against the level of inequality – in the contemporaneous generation – for a set of developed and developing countries. This curve is shown in Figure 4.3 below.

Along the vertical scale of the chart, one observes a rather wide dispersion of the estimated IGE, from 0.2 for Nordic countries – Sweden being a little above that level – to 0.5 in the United States and 0.6 in Latin American countries. If it is assumed that the inequality of earnings is similar among parents and children, then (10) suggests that a consistent measure of inequality of opportunity is the square of the IGE, or the R^2 of the regression of the log of sons’ earnings over the log of fathers’. Then it can be seen that inequality of opportunity corresponding to the fathers’ earnings alone is extremely low in Nordic countries, amounting to less than 4% of the variance of log earnings, while it is more substantial in the United States, amounting to 25% of sons’ earnings inequality. Yet, this would still leave considerable room for mobility if it were the case that no other circumstance, orthogonal to parents’ earnings, constrained children’s earnings, which seems unlikely.

The plot also shows a strong correlation between earnings immobility, i.e. IGE or inequality of opportunity, and the degree of inequality, as measured by the Gini coefficient of household disposable income, at a point in time. Several explanations have been given for the negative correlation shown in Figure 4.3. The most frequent one relies on some **kind of non-convexity in the way parents invest** in the human capital of their children, or possibly some unequal access to quality schooling depending on parents’ income. If rich parents invest a higher proportion of their own income in the education of their children, or if only the children of parents above some level of income have access to good quality schools, then more income inequality among parents should generate less intergenerational mobility.

Figure 4.3. The Great Gatsby curve



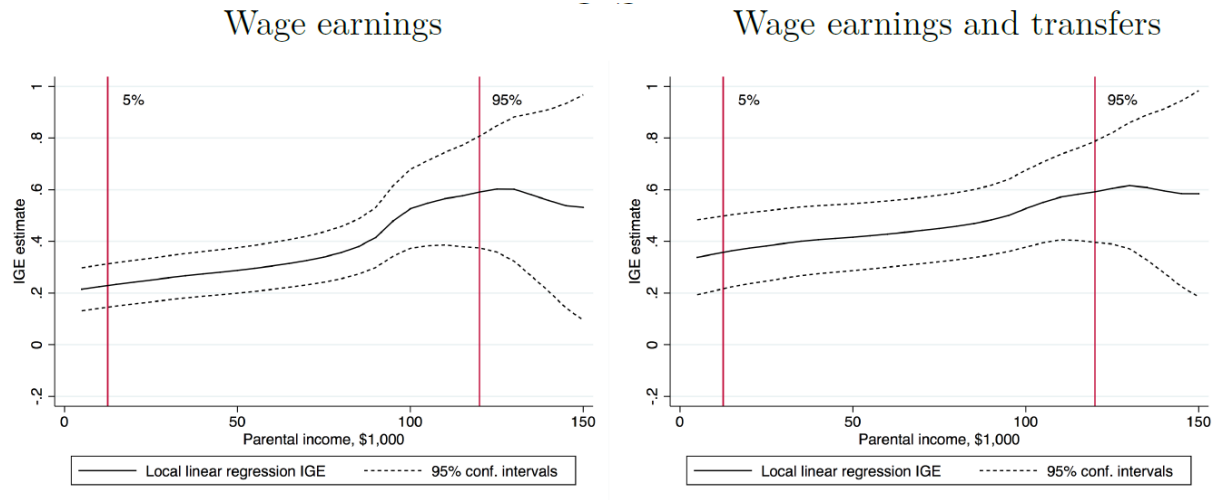
Source: Corak (2012).

The preceding argument is equivalent to assuming some non-linearity in the basic model (9) or, more exactly, that the IGE may depend on the level of income. If the IGE increases with income, as just suggested, then the linear approximation (9) would indeed yield an OLS estimate of the IGE that increases with the degree of income inequality.²⁴

That the IGE may vary with the level of income is shown in the case of the United States by Landersø and Heckman (2016), p. 22, as can be seen in Figure 4.4 below.²⁵

Figure 4.4. Non-linear IGE in the United States

Parents observed in 1987 and children 36-38 in 2011



Another, more mechanical, explanation of the negative slope of the Great Gatsby curve is based on (10) above. If one compares two countries where income inequality was the same in the older generation, then it is the case that with the same correlation coefficient (R^2) between the earnings of the two generations, the IGE will be higher in the country with the highest inequality today. For instance, Landersø and Heckman (2016, p.17) show that the IGE in Denmark would be much bigger than what it is if the distribution of children's earnings was identical to the US distribution. This again illustrates the difference between the concept of immobility as described by IGE and inequality of opportunity related to parents' earnings. Yet it is unlikely that Figure 4.3 would be fundamentally different if the IGE were replaced by the inequality of opportunity as defined in (10).²⁶

Other explanations of the upward sloping Gatsby curve are available that go from mobility to inequality rather than the opposite. For instance, Berman (2016) stresses that if the distribution of the residual term, v , is constant, model (9) leads to a steady-state distribution of earnings whose inequality is given by: $VL(y) = \frac{Var(v)}{1-\gamma^2}$. Thus, the inequality of income increases with IGE. As a matter of fact, it should be noted that this property does not hold only at a steady state. Among two societies with the same distribution of earnings in one generation, inequality will be higher, all things being equal, in the society where parents transmit more of their earning capacity to their children. Formally, (9) implies that:

$$VL(y) = \gamma^2 VL(y_{-1}) + Var(v)$$

which is increasing in γ .

One might ask whether this positive relationship between inequality and intergenerational immobility may also hold inter-temporally. Interestingly enough, Aaronsson and Mazumder (2008) show that trends in wage inequality between 1940 and 2000 in the United States coincide with trends in IGE, with a compression in the first part of the

period and increasing disparities in the later part.²⁷ However not enough data are available to test that hypothesis on a cross-country basis.

The same type of analysis may be undertaken with other economic outcomes. However to keep with the spirit of model (9) it is important to make sure that the same variable can be observed for both parents and children. For instance, having parents' earnings on the right hand side of the equation and income per capita (or per adult equivalent) on the left hand side is interesting, but the interpretation is not anymore in terms of intergenerational transmission of earning potential, as income per capita also depends on family size, marriage, and labour supply. There is also an issue with the period of observation of the right-hand variable. Presumably, one would expect parents' income to influence the lifetime earnings of children. This may not be reflected when observing children during a short period at some stage of their life.

Chetty et al. (2014a) address this issue when analysing the spatial heterogeneity of intergenerational income mobility in the United States, as they indeed use lifetime pre-tax family income as income variables in both generations as drawn from administrative tax data. They find considerable spatial variation of income mobility across "commuting zones": "the probability that a child reaches the top quintile of the national income distribution starting from a family in the bottom quintile is 4.4% in Charlotte (North Carolina) but 12.9% in San Jose (California)".

Taking advantage of the length of register data, Chetty et al. (2014b) also study the time evolution of intergenerational mobility, in effect the rank correlation between fathers' and sons' earnings. They find no significant change across birth cohorts born between 1971 and 1982. This is line with the results found earlier by Lee and Solon (2007) for the US using the PSID panel dataset for cohorts born between 1952 and 1975. Both results diverge somewhat from Aaronsson and Mazumder (2008). Non-consensual results are also found in other countries, as shown by the critiques by Goldthorpe (2012) to the finding by Blanden et al. (2008) that mobility would have fallen in the UK.

Another interesting concept, closer to the sociological view on mobility, has recently studied by Chetty et al. (2017). 'Absolute mobility', is defined as the proportion of 30-year old children whose real income is higher than their parents' when they were 30. Combining register data since 1970 with assumptions on rank correlation together with cross-sectional data for the period before, absolute mobility has declined continuously from the 1940 to the 1965 birth cohort – i.e. the baby boomers. It then stabilized but fell again soon because of the financial crisis – i.e. for cohorts born in the late 1970s.

Somewhat surprisingly, much less work has been done on the intergenerational transmission of wealth inequality and on the key role of inheritance in the inequality of opportunity. This is in part due to the availability of data. Typical household surveys generally do not include data on wealth. When they do, they do not necessarily include data on parents, or they are not repeated over a period long enough to apply the TSIV methodology. As for panel data, some waves of PSID do include wealth questionnaires. They have been used by Charles and Hust (2003) to estimate an IGE for wealth. Unfortunately, no information is available that would allow to correct for measurement error bias. The British and German household panels do include data on wealth but the number of observations is too small to estimate IGE for wealth at mid-life, an age at which the wealth concept becomes relevant for both parents and children. One could also think of using estate statistics, but these actually lack relevance as their link to inequality of opportunity is through the heirs, whose wealth is not observed.

In Nordic countries, several recent studies of intergenerational wealth dynamics have relied on administrative data. Boserup et al. (2014) provide estimates of the wealth IGE at mid-life in Denmark, and Adermon et al. (2015) do the same for Sweden. Both studies cover more than two generations. In both countries, the wealth IGE estimates are comparable and of limited size (around 0.3), a value comparable to the earnings IGE in Sweden but twice as large in Denmark.

Generalised intergenerational mobility analysis and inequality of observed opportunities

Parental income is only one of the circumstances affecting the economic outcome of an individual, even though it may be correlated with other circumstances. To provide a more complete picture, fathers' earnings, y_{-1} in equation (9) can be replaced or complemented by a vector of variables referring to the parental characteristics of an individual in the current generation. Labour force or household surveys often give information on the parents of respondents (education, occupation, residence, age when respondent was 10). Rather than using the TSIV approach to estimate parental earnings or income based on these characteristics, one may simply measure the related inequality of opportunity by the share of the inequality of income or earnings in the current generation that is accounted for by parents' earnings.

Formally, model (9) is replaced by:

$$\text{Log } y_i = \beta Z_i + v_i \quad (11)$$

where y_i is a particular economic outcome; Z_i a vector of variables that include all observed parental characteristics and some other characteristics beyond individual control, like gender; and v_i all the unobserved determinants of the economic outcome that are orthogonal to Z_i . In agreement with the definition (7), the R^2 statistics of that regression may be interpreted as the inequality of opportunities associated with individual characteristics in Z_i when measuring the inequality of outcomes with the variance of logarithms. Some authors prefer using other measures of inequality.²⁸

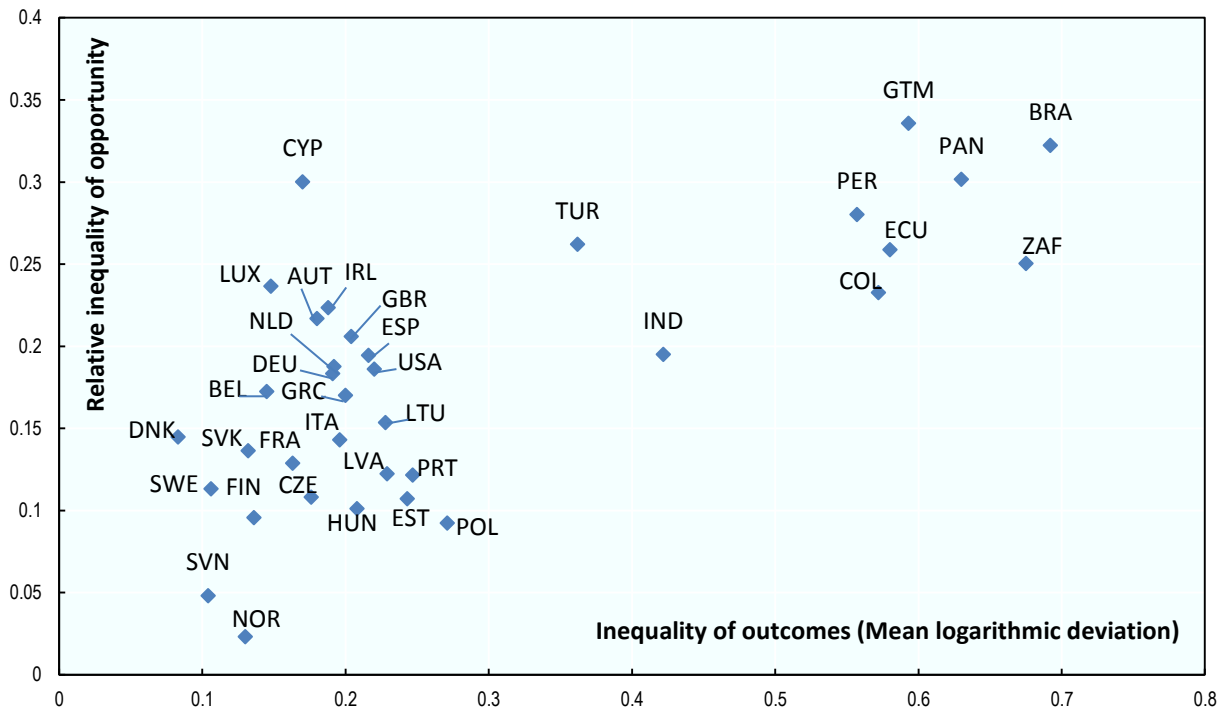
In comparison with model (9), model (11) may be considered as a model of “generalised” mobility in the sense that more parental characteristics are taken into account that do not necessarily include the outcome being explained in the current generation. It can also be noted that this model is identical to the model used in the intergenerational mobility analysis of earnings when instrumenting the earnings of the parent by a set of characteristics available in the data base – i.e. the TSIV approach. Model (11) would then correspond to the “reduced” form of the earnings mobility model, necessarily less restrictive than the structural form (9).

Figure 4.5 illustrates this approach to inequality of opportunity, drawing on a paper by Brunori et al. (2013) that puts together estimates of some observed dimensions of inequality of opportunity in selected countries as reported in several papers, including Checchi et al. (2010) and Ferreira and Gignoux (2011b). The inequality of opportunities measure used in these papers is the one defined in (5), with the mean logarithmic deviation as a measure of inequality.²⁹ The figure shows the relative inequality of observed opportunities (vertical axis) against the total inequality of outcomes (horizontal axis).

Figure 4.5 is in some sense the equivalent of the Great Gatsby curve, with the IGE being replaced by the inequality of observed opportunities.³⁰ This generalisation of the Great

Gatsby curve, which consists of replacing parental earnings by observed parents' characteristics and individual traits, leads to a relationship between inequality of observed opportunities and inequality of outcomes that is still positive. However that relationship disappears when restricting the sample to advanced countries, unlike what observed in Figure 4.3.

Figure 4.5. Inequality of outcomes and share due to observed dimensions of the inequality of opportunity, selected countries around 2005



Source: Based on Brunori et al. (2013).

This difference must be taken with very much precaution, though. On the one hand, countries are not the same. On the other hand, both the outcome variables and the observed circumstances Z in Brunori et al. (2013) may not be the same across countries. The economic outcome, y , refers to labour earnings for the EU countries and the United States³¹, household income per capita in Latin American countries, household earnings per capita in India, and household gross income per capita in South Africa. An important lesson to be drawn from these exercises is the need to use uniform definitions of variables. This is not always possible across countries, but is absolutely necessary for comparing the same country over time.

Another important caveat is that the inequality of observed opportunities reported in Figure 4.5 is estimated on the whole population rather than specific age cohorts as in studies of intergenerational earnings mobility. In other words, the implicit assumption is that this inequality is uniform across age groups, or cohorts, in national populations. This is far from granted. The way an economic outcome depends on individual and parental circumstances may change over the life cycle, and may change across cohorts. Cohorts are definitely the most relevant statistical reference. What policy makers and analysts are

interested in is whether younger cohorts are less dependent on their family background than older cohorts, presumably at the same age.³²

Improving and standardising generalised mobility analyses of the type described above – to make them comparable across countries, over time, and across cohorts – might be easier to implement than standardising intergenerational earnings mobility studies. It should permit key determinants of the inequality of outcomes to be monitored effectively, be it earnings, income or subjective well-being, and to identify forces behind the evolution of the inequality, or possibly behind its stability. Done in a systematic way, such analyses should be most helpful for policy making in the field of inequality.

It should also be noted that the same non-parametric matrix specification used for intergenerational mobility analysis can be used here. The matrix P in Table 4.1 would differ simply by the definition of the rows. Instead of referring to the earnings of parents, they would refer to types of individuals in the current generation, the types being defined by the most frequent combinations of individual characteristics, Z. This would not be a mobility matrix or a copula anymore but simply a matrix comparing the distribution of a given economic outcome across individuals with different social and family background or individual traits. The corresponding inequality of opportunity could be measured using the Roemer-like measure (8) above or some of the suggestions made when discussing the measure of intergenerational mobility.

Sibling studies

Other approaches have been used in the literature to identifying what part of the inequality of outcomes has its roots in family background in the strict sense, rather than in the mixed bag of characteristics, Z, that can be found in household surveys. In this context, the idea of using differences or similarities among siblings or twins is particularly attractive.

If the economic outcome being studied is labour earnings, the square of the correlation coefficient of earnings between siblings is a direct measure of the share of the inequality of outcomes that comes from a common family context. This requires some assumptions on the underlying earnings model.³³ If these assumptions are found to be reasonable, then this correlation coefficient logically account for all observed and unobserved family background characteristics as well as presumably for other circumstances which were common to siblings in their childhood or adolescence. Because of this, it is expected that the share of outcome inequality explained in this way be higher than with other estimations based on observed circumstances, even though siblings may not share all the family background factors susceptible to affect their earnings later in life. At first sight, however, orders of magnitude seem comparable to what is obtained in intergenerational earnings mobility studies – in the few countries where both estimates are available. For instance, the correlation coefficient between brothers' earnings is 0.23 in Denmark (Jäntti et al., 2002) and 0.49 in the United States (Mazumder, 2008). The former value is somewhat above what is shown in Figure 4.4, whereas the latter is roughly the same.

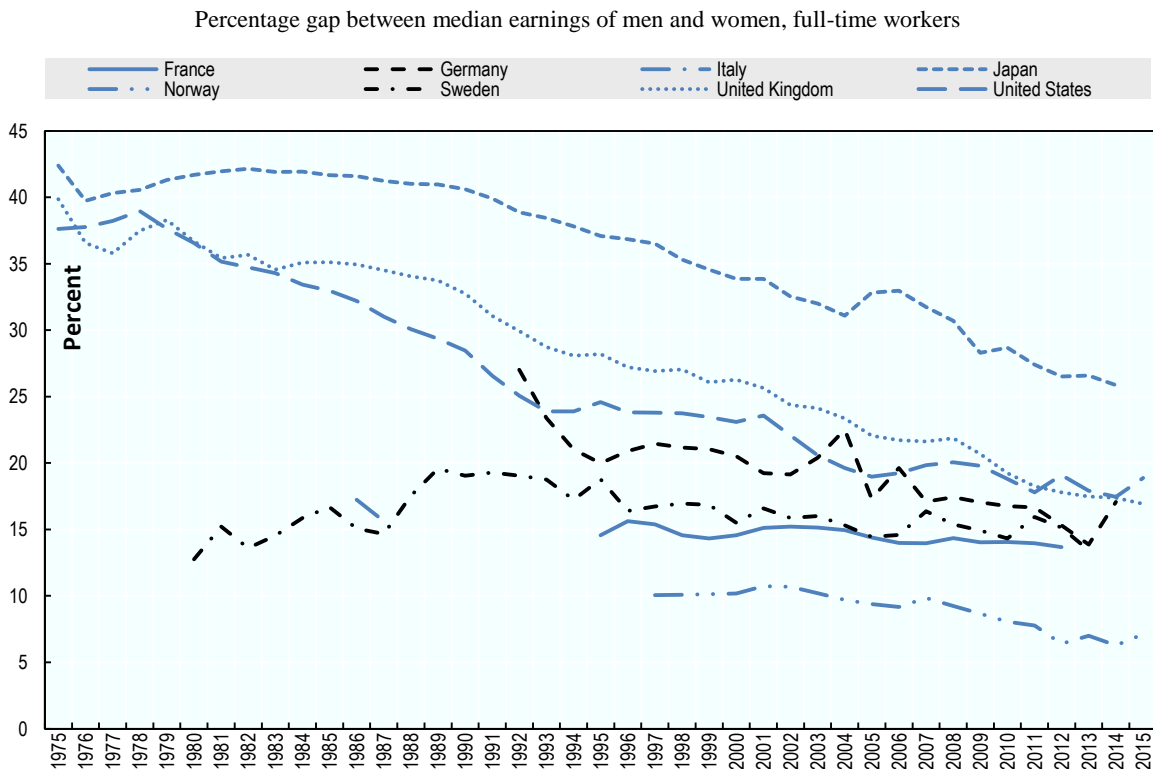
Sibling analysis of this type may well be able to capture a bigger part of the overall effect of family circumstances on outcome inequality but, contrary to the type of study described in the preceding subsection, it does not say much about the channels behind this effect. Also, this type of analysis cannot be performed on the basis of standard household surveys, which are the most commonly used source for measuring outcome inequality.

Outcome inequality related to gender or other personal traits

The characteristics Z considered in the generalised intergenerational mobility approach may be of different kinds. They may be personal traits like gender, ethnicity or migrant status, family background characteristics, or more generally the assets people may have received from their family, including schooling. The analysis of the inequality of observed opportunities discussed above did not make any distinction between these various components of Z . Yet the inequality associated with them may be subject to different value judgments and may have different policy implications in terms of the inequality of outcomes.

Gender is a case in point. If gender were the only component of the Z variables in the general model (11), then the associated decomposition of inequality would boil down to singling out the relative difference in the mean outcome across genders. This is the first step in the literature on gender earnings inequality, and more generally on “horizontal inequality”, i.e. inequality in the mean outcomes of people with different personal traits (for example race, migrant status or place of residence). Figure 4.6 on gender earnings inequality is typical of that literature. It shows how the male-female earnings differential fell substantially over the last decades in the OECD countries where it was the highest, but remains sizable, at around or above 15%, in a majority of countries.

Figure 4.6. Gender wage gap in selected OECD countries, 1975-2015



Source: OECD.

At the same time, this figure raises questions that are directly related to the distinction between circumstance and effort in the inequality of opportunity literature. To what extent is the observed earnings differential due to different occupational and career

choices made by male and female workers or to features completely outside their own control, like education or, most importantly, employer discrimination in the labour market? Also, to what extent do the differentials shown in Figure 4.6 reflect differences in labour force participation rates, themselves related to wage determinants like age or job experience? The answer to these questions is of great importance for policy, in particular to identify the role of labour market discrimination and the possible remedies to other sources of earnings inequality. For instance, concluding from Figure 4.6 that gender earnings discrimination has gone down by 15 to 20 percentage points in countries where it was around 45% 40 years ago would not be correct if the composition of the female (or male) labour force had changed over time or if the proportion of better paid women increased.

Part of the answer to the questions mentioned above is obtained by adding other personal traits and circumstances to gender as regressors in model (11). For instance, if schooling is introduced as an additional circumstance variable, the coefficient of the gender component would then reflect the male-female difference in earnings once the effect of male-female differences in schooling on the earnings differential had been accounted for. In a more general model, the gender coefficient would measure the gender earnings gap that comes in addition to gender differences in all observed earnings determinants. This coefficient is generally referred to as the ‘adjusted’ gender earnings gap.

It is possible to go further by making the model non-linear through interactions between the gender and the other components of Z , namely:

$$\text{Log } y_i = \beta Z_i + \delta Z_i * G_i + v_i \quad (12)$$

where G_i is a dummy variable that stands for the gender of person i and the δ coefficients measure the earnings differential associated with the individual characteristics in Z_i . Alternatively, model (12) can be estimated separately for male and female workers:

$$\text{Log } y_i^g = \beta_g Z_i^g + v_i^g, \quad g = M, F \quad (13)$$

Based on the estimates of the two sets of coefficients β_g , the gender earnings gap may be decomposed into gender differences in the earnings determinants and differences in the return to these determinants, i.e. between the estimated coefficients $\hat{\beta}_F$ and $\hat{\beta}_M$. For instance, women may be paid at a lower rate than men because they have less education, which was true for some time and still is for older cohorts, but they may also be paid less than men for any additional year of schooling, which might be considered as pure discrimination.

Formally, this so-called Blinder-Oaxaca decomposition is:

$$\text{Log } \bar{y}^F - \text{Log } \bar{y}^M = (n_F \hat{\beta}_F + n_M \hat{\beta}_M)(\bar{Z}^F - \bar{Z}^M) + (\hat{\beta}_F - \hat{\beta}_M) \cdot (n_F \bar{Z}^F + n_M \bar{Z}^M) \quad (14)^{34}$$

where the notation $\bar{}$ refers to means, and n_F and n_M are the weight of female and male workers respectively in the population sample. The first term corresponds to the contribution of differences in individual characteristics between men and women, i.e. the difference between the earnings gap and the adjusted earnings gap defined above. The second term stands for the true discrimination, i.e. the fact that the same characteristics are not rewarded in the same way among men and women. Actually, it is precisely the adjusted earnings gap defined earlier, the interest of (14) being that this adjusted gap can be decomposed into the contributions of the various components of Z . In the context of gender inequality, this adjusted gap may be considered as a measure of procedural

inequality, i.e. the way the same characteristics are not rewarded in the same way for two groups of individuals.

Figure 4.7 illustrates this decomposition and at the same time exhibits quite a remarkable stylised fact. The figure is drawn from a meta-analysis of gender wage discrimination and shows the mean gender earnings gap and the adjusted earnings gap in a set of 263 papers covering a large number of countries at different points of time. The figure reports the means of all studies reporting estimates for a given year, year by year. A remarkable pattern emerges. Over time, the mean gender wage gap has declined substantially, as shown in Figure 4.6 for selected countries. At the same time the mean adjusted gap, or the second term in the Oaxaca-Blinder equation above, remains more or less constant on average. In other words, on average across countries, the main reason why the gender earnings gap declined is because the gender differences in wage determinants like education or job experience have declined, not because the returns to these determinants have become less unequal. Assuming the studies in this meta-analysis are fully comparable, this would mean that the inequality of opportunity related to labour market discrimination has not changed in the average country.


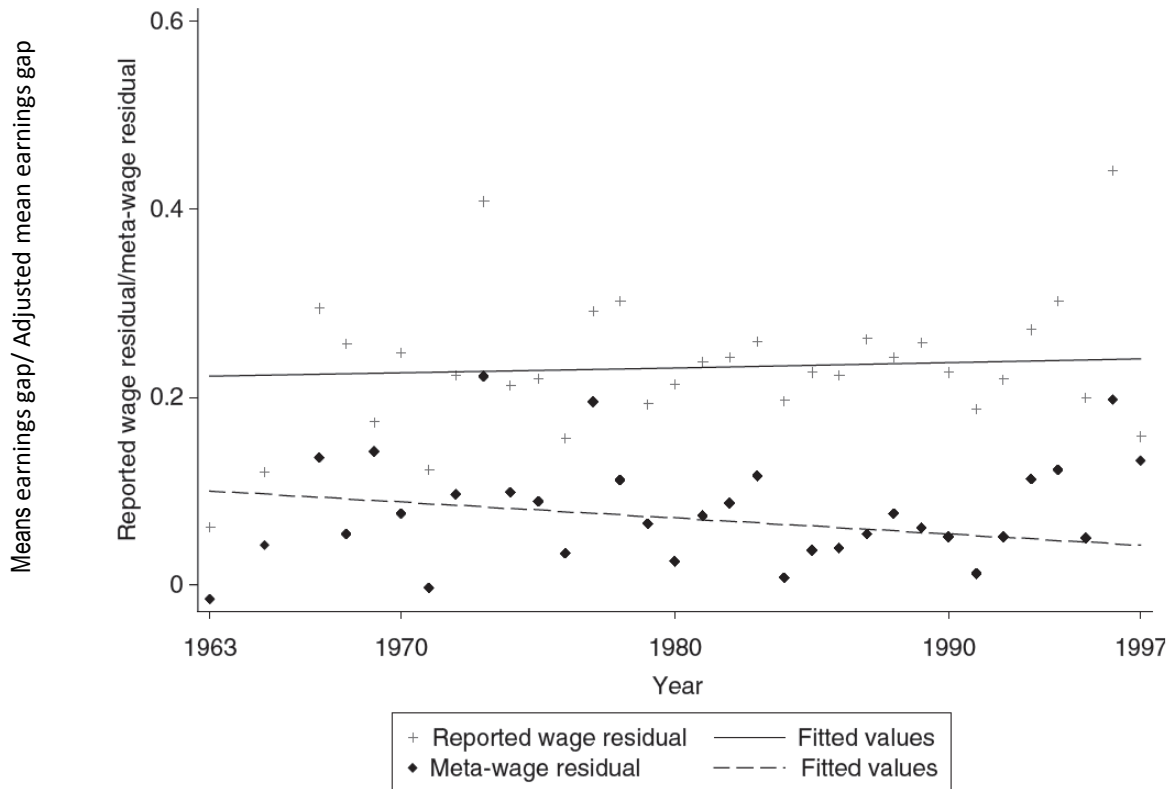
From a policy point of view, the Oaxaca-Blinder equation is of obvious interest since it shows the orientation to be chosen in order to reduce gender inequality, and therefore total earnings inequality. From a perspective of inequality of opportunity, however, it also raises an interesting issue, which is that focusing exclusively on circumstances as the source of inequality may not always be justified. The way efforts are rewarded by the economic system, depending on individual circumstances or personal traits, matters too. 

Figure 4.7. Gender earnings gap and adjusted earnings gap in a meta-analysis of the literature



Source: Weichselbaumer and Winter-Ebmer (2005).

As an example, consider the standard Mincer equation that explains the log of earnings or wages as a function of the number of years of schooling and job experience. A priori, it seems reasonable to consider years of schooling as a circumstance forced upon an individual by parents or family context, whereas job experience would more logically reflect decisions made by a person in adult life. But now, assume that the Oaxaca-Blinder decomposition shows that both education and job experience are rewarded differently for male and female workers. Then, the inequality of opportunity arising from labour market discrimination would actually depend on the inequality of circumstances – i.e. education – but also on efforts through the interaction between efforts and gender. In other words, the fact that a woman must make more effort to earn as much as a man with the same intrinsic productivity should be part of the inequality of observed opportunities.

Having said this, the issue remains of the fundamental ambiguity of the distinction between efforts and circumstances. Are interruptions to job, labour force participation and career caused by child rearing only the responsibility of women? Wasn't it society as a whole that constrained women's labour force participation and progressively relaxed that constraint under various economic and sociological pressures? These are difficult questions, which at the same time reveal the ambiguity of the very concept of gender-related inequality of opportunity and the measurement of it.³⁵ Under these conditions, it might be better to ignore the distinction between circumstances and effort and to make

sure that we measure correctly the effect on the overall inequality of earnings of different personal characteristics, including job experience or part-time work, across gender, as well as the effect of differentiated rewards to these characteristics by the economic system.

To conclude these remarks on the measurement of the inequality of opportunity related to gender, the fact that the earnings gap or adjusted earnings gap refers exclusively to averaging operations within the two samples of male and female workers must be stressed. The fact that the spread of earnings rates around the mean may be quite different in the two groups should also be taken into account. In relation to model (11), this is equivalent to allowing for a variance of the residual term, v , to depend itself on gender, i.e. heteroscedasticity. This is a good case for using the Roemer measure defined in (8), or to follow the suggestion made above to replace the mean earnings by some function of the mean and the variance.

4.4. Overview of practical issues

Measuring inequality of opportunity, seen as the inequality of outcome due to *all* factors completely outside individual control seems unrealistic. The best that can be done is to measure the contribution to inequality of outcomes of *some* factors that seem beyond individual responsibility. In that sense, it is only possible to measure some dimensions of the inequality of opportunity. Yet even that distinction between circumstances outside individual control and voluntary individual decisions in the determination of economic outcomes is often ambiguous. Indeed, some dimensions of inequality of opportunity depend on these individual decisions, as is the case with discrimination within the labour market.

It is possible to measure directly some dimensions of inequality of opportunity, independently of their impact on economic outcomes. This is true for instance of cognitive ability, in adolescence or pre-school, potentially of non-cognitive ability if some quantitative index is available³⁶, or of health status. Note also that these individual characteristics may be considered as circumstances contributing to the inequality of individual outcomes like earnings or standard of living, but also as an outcome whose inequality may be explained by family-related characteristics. Most often, however, measuring the observable dimensions of the inequality of opportunity goes through the measurement of their impact on the inequality of economic outcomes.

The most obvious example of the measure of single dimensions of inequality of opportunity is the sizable literature on the intergenerational mobility of earnings or other economic, or socio-economic outcomes. The observed dimension of inequality of opportunity is the earnings of parents and it is measured by its contribution to the inequality of children's earnings. This can be generalised to other observed family characteristics that may or may not include parental income or earnings, as well as personal traits like gender or ethnicity. Data requirements for this kind of analysis are much less demanding than what is needed for measuring the intergenerational mobility of earnings. Representative household surveys with recall information on the family background of respondents are the basic input. Of course monitoring the corresponding dimensions of the inequality of opportunity over time or making comparisons across countries requires some uniformity of the information available in these surveys.


When applied to single personal traits, the preceding type of analysis is equivalent to measuring what is called "horizontal inequality" in the inequality literature, typically

inequality of earnings or other income variable across gender, race, migrant status or other individual characteristics. Combined with other individual circumstances that may depend themselves on individual traits, the measurement of these dimensions of inequality of opportunity allows for a detailed analysis of the observed discrimination that society exerts on individuals through the traits being studied.

The empirical literature on inequality of opportunity relies on various types of measures. When focusing on single scalar dimensions of the inequality of opportunity, it is not clear that the various measures available for economic outcomes – which are implicitly based on value judgments – are relevant. For instance, is the Gini coefficient adequate to represent the inequality of health status or cognitive ability? The variance, the coefficient of variation or quantile ratios may be sufficient to describe the spread of the distribution. Things are different when the observed dimensions of inequality of opportunity are measured in the outcome space, or by their contribution to the inequality of outcomes. In that case, a distinction must be made between parametric and non-parametric approaches.

A parametric specification of the relationship between outcomes and individual characteristics allows us to figure out what the inequality would be if only outcome differences due to individual characteristics were taken into account; or, alternatively, what difference it would make with respect to the overall inequality of outcomes to ignore them. Then the resulting “virtual” outcome inequality can be evaluated by the usual measures of outcome inequality, including the Gini coefficient, the variance of logarithms, the Atkinson measures, etc. Based on the familiar log-linear relationship between economic outcomes and individual characteristics, this approach often leads to quite simple measures of the observed dimensions of the inequality of opportunity: the R^2 correlation coefficient when outcome inequality is measured with the variance of logarithms; the between-group component of decomposable inequality measures when the observed combinations of individual characteristics are used to define types of individuals; or the mean income gap in the case of a single individual trait like gender. Of course, as many measures of inequality of opportunity can be defined as there are measures of inequality of outcomes.

Things are different with non-parametric specifications that fully take into account the difference in the distribution of outcomes conditional on individual type. This includes the case where types correspond to the level of parental income as the dimension of the inequality of opportunity being studied, and where the intergenerational mobility of outcomes is described through a transition matrix; in these cases, comparing distributions requires comparing those matrices. Some interesting comparison criteria have been proposed which generally rely on strong assumptions about the way the social welfare of a society characterised by a given transition matrix is evaluated. At this stage, it cannot be said there is a consensus about these criteria.

The case where  quality of outcomes is shown to result from different outcome distributions across various types of people, defined by a set of characteristics assumed to be outside their control, is the most general and realistic specification on which to ground the measurement of the observed dimensions of inequality of opportunity. It is equivalent to the parametric specification when the distribution of the effects of unobserved determinants of outcomes depends on the individual characteristics under study, i.e. heteroscedasticity in the core specification. Most measures used in the literature ignore this aspect of the measurement problem. For instance, the adjusted gender earnings gap ignores the fact that not only the mean but also the distribution of earnings expressed as a

proportion of the mean differs across gender. The inequality measure drawn from Roemer (1998) would allow to remedy this.

4.5. Conclusions and key indicators for monitoring the observed dimensions of inequality of opportunity

Until now, concern about inequality focused mostly on inequality in key *outcomes* like earnings, gross or disposable income, standard of living or wealth. Monitoring inequality of outcomes, or inequality ex-post, is crucial to monitor social progress and redistribution instruments. Ideally, however, one would also want to monitor ex-ante inequality, or inequality of opportunity, as it is a key determinant of ex-post inequality. As argued throughout this chapter, however, there is something illusory in such an objective. The best that can be done is to monitor the observed dimensions of inequality of opportunity, or equivalently some determinants of inequality of outcomes that can be considered not to be the result of individual decisions or economic behaviours. Of course, such monitoring is of utmost importance for policy as it permits the sources of change in the distribution of the outcome considered to be identified and to adopt corrective policies if deemed necessary. These sources of change comprise the distribution in the population of individual characteristics like individual traits, family background including parental income or wealth, cognitive and non-cognitive abilities, and all assets people can rely on to generate economic outcomes. They also include the way in which the economic sphere rewards the efforts of people with different traits or background, i.e. procedural inequality.

While some observed dimensions of the inequality of opportunity have received much attention in the recent economic literature, it is fair to say that their measurement still belongs to the realm of research. Unlike the inequality of disposable income or earnings regularly monitored through Gini coefficients or other inequality measures, few statistics related inequality of opportunity are regularly produced by statistical institutes and publicly debated. For instance, we are ignorant in most countries about whether intergenerational mobility, one among many possible indicators of inequality of opportunity, has increased, remained the same or decreased in the last decades. Progress has been made in monitoring mean educational achievements in many countries, most notably under the PISA initiative, but no systematic reporting or discussion takes place on the evolution of their dispersion. If the mean earnings gap across gender is reported regularly in most advanced economies, the same cannot always be said of the adjusted earnings gap or the gap across ethnic groups or between natives and first- and second-generation migrants. Yet, in most countries, data to evaluate these indicators on a regular basis and several others either are available or could be made available at little cost.

Based on the analysis in this chapter, we list below the data required to improve the situation and monitor the observable dimensions of the inequality of opportunity in a systematic way rather than relying on the work done irregularly by researchers. We also list the statistics that should be published on a regular basis for a monitoring of inequality that would go beyond the Gini coefficient or other usual inequality measures of equalised disposable income or earnings.

4.5.1. Data requirements

Knowledge of the role that family background plays in determining inequality of earnings or income is essential for understanding the causes of inequality and possible changes in them. From that point of view, the ideal data are by far long-term panels such as the PSID

in the United States, which has been running since 1968, and covers 5 000 families and all their descendants. With such long panels, one may observe many of the circumstances that surrounded the childhood and the adolescence of the younger cohorts of the panel, including parental income and wealth. Other long panels include the British BHPS or the German Socio-Economic Panel. In Europe, the EU-SILC comprises longitudinal data but these are generally much shorter and do not follow descendants, so that family economic conditions during the youth of respondents are not observable.³⁷

An alternative to long panels is the linkage of administrative data. Matching the tax returns of parents 30 years ago to that of their 40-year old children today allows for the direct observation of income mobility. In some cases, it is even possible to link family characteristics other than income, thus allowing for more complete studies of the intergenerational sources of inequality. It was seen above that such data permitted detailed studies of the intergenerational transmission of wealth in Nordic countries and the spatial heterogeneity analysis of intergenerational mobility in the United States – as in Chetty et al. (2014). Unfortunately, data such as these are still extremely scarce, even though steps could be taken by administrations to make them more systematically available in the future.

It is not because long panels are not always available that it is impossible to monitor the role of family background in generating inequality in economic outcomes. Repeated standard cross-sectional household or labour force surveys with recall information on the family characteristics of the respondents already allow the impact of family background on the inequality of earnings, income or standard of living to be monitored. What is needed is to make sure that such information is available at regular time intervals and under the same, and possibly the most complete, format. It should not be too difficult to establish international norms in this area. Possible biases arising from the imperfect observation of top incomes in these data sources should not be ignored and measures to prevent such biases should be seriously considered.

Some of the studies reviewed in this chapter show the use that could be made of such information (see Figure 4.5). Note also that in a given cross-section, it is possible to conduct the analysis at the cohort level. The way the earnings of the 40-50 year-old depend at a given point of time on their family background is not the same as for the 30-40 or the 50-60 year-old. With repeated cross-sections, it would then become possible to distinguish the cohort and the age effect. Finally, note that if the repeated cross-sections cover a period long enough, which is now the case in many advanced countries, then it is possible to use family background variables as instruments to estimate the earnings or income of parents, thus allowing for some monitoring of intergenerational income mobility, as in the study by Aaronsson and Mazumder (2008) mentioned earlier.

In the field of the inequality of wealth, cross-sectional data are scarcer although several countries are now following the example of the Survey of Consumer Finance in the United States and its practice of oversampling the top of the distribution, where most wealth is concentrated. These surveys are extremely useful and one may only hope they will become more frequent. In particular, it would be interesting to investigate in more depth how it would be possible to monitor the role of bequests in generating wealth and income inequality, especially at a time where inheritance flows tend to grow faster than income, as suggested by Piketty (2014).

Horizontal inequality across gender and other personal traits can be followed through standard household or labour-force surveys. Here, the problem is not so much the availability of data as the use being made of them and the depth of the analysis

conducted. As shown above, there is much to be learned from going beyond pure differences in earnings means. At a time where migration has become such an important issue in so many countries, data for monitoring the differences that natives and migrants face in the labour market should also be made available.

Students' skills surveys at various stages in childhood and adolescence of the PISA type are extremely helpful for detecting changes in a dimension of inequality of opportunity that is likely to entail changes in the inequality of outcomes later in life. PISA is a mine of information, although it was suggested above that more emphasis should be put on the inequality of test scores – on top of their differences across family backgrounds. Also, developing PISA-type instruments to measure inequality in cognitive abilities at younger school-age and pre-school is essential. For primary school, the data seem to exist, and it is perhaps only a matter of analysing them in more detail, and certainly publicising them better.

Priority statistics

These data could and probably will generate many different types of statistics, related to various specific dimensions of the inequality of opportunity. It is important to define those that are likely to be the most useful in assessing social and economic progress, the most amenable to stimulating discussion between researchers, policy-makers, and civil society, and the most likely to be available in a timely manner in a reasonably large number of countries.

The lack of knowledge today in many countries of whether intergenerational mobility is increasing or decreasing is symptomatic of the data deficit and, until now, of the lack of interest by policy makers and statisticians in monitoring key sources of outcome inequality beyond inequality itself as measured by the usual inequality indices. Yet the social demand for such information is mounting.

Three basic statistics should receive priority attention and should be harmonised as much as possible across countries and over time within countries.

- *Inequality of economic outcomes* (earnings, income) arising from parental background and its share in total inequality of outcome. Variance of logarithms of outcomes among various types of individuals and the R^2 statistics of family background variables (at least, education, occupation and age of the parents at respondent's birth) in explaining outcomes are the simplest examples of such statistics. Statistical institutes could seek to publish these statistics at 5-year intervals, possibly distinguishing across 5-year cohorts. Reflection should start about the key family background variables that could be systematically included in the analysis so as to develop international and inter-temporal comparability.
- *Variance analysis of scores in PISA and analogous surveys at earlier ages*, including pre-school, and the share of it explained by parental/social background, or the gaps in scores between students from different families. The 3-year periodicity of PISA seems adequate.
- *Gender inequality in earnings, unadjusted and adjusted for differences in education, age, job experience, occupation, etc.* Mentioning gender differences explicitly in basic coefficients like the return to education or to job experience, or simply showing both the unadjusted and the adjusted gaps as in Figure 4.7 would be helpful. This could be done easily for gender, although this again requires defining standards to allow for comparability. Depending on the country, the

same type of analysis should also be performed for race, religion or migrant status.

Concerning the nature of the statistics to be released, the simplest would be to rely on the parametric approach emphasised in this chapter and on the measures it leads to, as they are easily understood. But extending them to the non-parametric case where the observed dimensions of the inequality of opportunity are represented in matrix form of individual types by outcome level would also be desirable.

Notes

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² This paragraph briefly summarises an important literature in economics and in moral philosophy, which started with Rawls (1971) and whose major contributions are from Dworkin (1981), Arneson (1989), Cohen (1989), Roemer (1998), Fleurbaey and Maniquet (2011).

³ This conclusion somewhat resembles Sen’s emphasis on the “equality of capabilities” rather than “equality of functionings”, at least when capabilities are defined as the set of functionings accessible to an individual (Sen, 1982, 1985). Interpreting functionings as a vector of outcomes, Sen’s “capability equality” concept, similar to the concept of “equality of access to advantage” in Cohen (1989), would consist of equalising the determinants of the set of accessible functionings, which are conceptually very similar to “circumstances” in the “equality of opportunity” framework. The only difference is that equalisation in that case would be through equalising those circumstances rather than compensation in the space of outcomes.

⁴ The debate in the sociological literature about the idea that people raised in a low socio-economic status environment may inherit low preferences for work effort illustrates that point. See a summary of that discussion in Piketty (1998).

⁵ A rigorous econometric analysis of this issue is provided in Annex 4.A to this chapter.

⁶ The notation used for this equation is different from the one used in the Annex 4.A.

⁷ Schooling being considered as a “circumstance”, mostly determined by parental background.

⁸ Both sources of inequality are analysed in detail below.

⁹ Thus, without loss of generality, v^e can be set to zero, its sample mean value when (2) is estimated by Ordinary Least Squares.

¹⁰ With enough observations for each type, the two means differ by a factor that depends on the inequality of unobserved outcome determinants within the type.

¹¹ Roemer justifies comparing outcomes across types for given quantiles by considering that individuals of different types (but in the same quantile of their own outcome distribution) expend the same efforts. The above formula does not appear in Roemer (1998) but it ensues logically from the specification of his objective function in the design of policies to minimise inequality of opportunities. Note also that $Min_t\{q_t(\pi)\}$ in (8) could be replaced by any standard outcome inequality measure across types.

¹² This dependency of PISA scores on family background has been studied in detail by the OECD (2015, vol. II) in an analysis where cognitive ability is precisely taken as an outcome rather than a circumstance.

¹³ Ferreira and Gignoux (2011a) analyse carefully this source of bias in a cross-country comparison.

¹⁴ The standard deviation in test scores being 7, this means that test scores at the end of high school may be easily responsible for earnings differentials of close to 30%.

¹⁵ See for instance the survey by Conti and Heckman (2012).

¹⁶ An interesting paper shows for instance the influence of in utero factors on adult earnings: see Almond et al. (2015)

¹⁷ Parameter notations differ from those used above or in the Annex 4.A.

¹⁸ Note that this is true only for the variance of logarithm as an inequality measure.

¹⁹ When brackets are deciles (or other quantiles) of the distribution of earnings of parents for rows and of sons for columns, the transition matrix is bi-stochastic with the sum of columns and rows being equal to 0.1 in the case of decile (and of 0.05 in the case of quintile, etc.). This mobility matrix is a representation of the copula of the joint distribution of father/children earnings defined above.

²⁰ Sociologists, who are used to work with socioeconomic classes rather than earnings or income, tend to emphasize ‘absolute’ mobility, i.e. moving from one rung of the social ladder to another. Economists traditionally tend to work with ‘relative’ mobility – although see the analysis of absolute earnings mobility in Chetty et al. (2017).

²¹ Note that this approach would also apply to the case where the parametric outcome model (2) is heteroskedastic, as discussed above.

²² See for instance Jäntti and Jenkins (2015, pp. 899-905) for examples drawn from the US literature.

²³ Björklund and Jäntti (1997) apply this technique to compare mobility in Sweden and in the United States, whereas Aaronson and Mazumder (2008) do so to compare earnings mobility in the United States over time.

²⁴ The argument is as follows. Let γ in (9) depend linearly on $y_{-1,i}$ for observation i , e.g. $\gamma_i = \gamma_0 + \gamma_1 y_{-1,i}$ with $\gamma_1 > 0$. Taking the means on both sides of (9), the average IGE for the whole population is then given by: $\bar{\gamma} = \gamma_0 + \gamma_1 \frac{1}{n} \sum_i y_{-1,i}^2 / \bar{y}_{-1}$ where n is the size of the sample and \bar{y}_{-1} the mean of parents’ income. For a given mean parent income, the mean IGE in the sample thus increases with the variance, or more generally with the inequality of parents’ income. Note however that the Gatsby curve refers to the inequality of household income at the time children’s earnings are observed.

²⁵ See also Chetty et al. (2014, Figure Ib).

²⁶ It is indeed unlikely that the change in inequality across generations could compensate for the differences in IGE.

²⁷ Aaronsson and Mazumder use the TSIV method sketched above with US census data.

²⁸ For instance, Bourguignon et al. (2007) use the relative version of (7) with the Gini coefficient for the inequality measure $M\{ \}$ and the mean of Z for the reference circumstance C^e in (6). Brunori et al. (2013) use the mean logarithmic deviation.

²⁹ The mean logarithmic deviation (MLD) in a sample of individuals with economic outcome y_i is simply the difference between the log of the mean of the y 's and the mean of the $\log y$'s. For some countries in Figure 4.5, a semi-parametric model is used, based on “types” of individuals, as defined by specific combinations of characteristics Z , rather than by these characteristics themselves.

³⁰ It is the case that the relative inequality of observed opportunities based on the mean logarithmic deviation is close to the R^2 of the regression of outcomes on observed opportunities. From (9), this implies that the square root of that measure is comparable to the IGE.

³¹ This uniformity in the European case comes from being based on a common data source, the EU-SILC which is roughly uniform across EU members. See Checchi et al. (2010).

³² Such an analysis by cohorts is performed in Bourguignon et al. (2007).

³³ Essentially, homoscedasticity in a model of type (11).

³⁴ Other expressions of the Oaxaca-Blinder decomposition use the β coefficients of one group in the first term and the mean characteristics of the other in the second rather than means over the two groups. The problem is that the decomposition then depends on what group is chosen for β . The formulation used here is path independent.

³⁵ Additional difficulties would appear if, instead of focusing on wages, gender inequality focused on income, or more exactly household income (per capita or equivalised), as labour supply, marriage, assortative mating, and fertility would become important issues, on top of the fact that the distribution of income within the household is not directly observed. (On these issues, see Meurs and Ponthieux, 2015).

³⁶ For instance through principal component analysis of answers to questions on non-cognitive ability in PISA.

³⁷ In connection with EU-SILC, it should be noted that shorter panels may still be helpful in analysing the inequality arising from involuntary shocks experienced by individuals in their recent past, which may be the main source of inequality of opportunity appearing during adult life. In particular, such data should help to evaluate the hysteresis of such events and the role of social policies in neutralising their long-run effects.

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Annex 4.A. The difficulty of empirically disentangling the role of opportunity and effort in the determination of earnings

Consider a database with information on individual earnings, circumstances and efforts and a linear model where (log) earnings of individual i , $\text{Log } y_i$, depends on the circumstances, C_i , and efforts, E_i , of the same person, both vectors being split into observed (C_{i1} , E_{i1}) and unobserved (C_{i2} , E_{i2}) components:

$$\text{Log } y_i = a + b_1 C_{i1} + b_2 C_{i2} + c_1 E_{i1} + c_2 E_{i2} + u_i \quad (1)$$

where u_i summarises all the other determinants of earnings, including luck and measurement error, and where a , b , and c are parameters, or vectors of parameters.

While a specification with interactions between circumstances and efforts would be more general, the points made below would be equally relevant with a more complete model – but a bit more intricate from a notational point of view.

Rearranging the terms in the preceding equation leads to:

$$\text{Log } y_i = a + b_1 C_{i1} + c_1 E_{i1} + \varepsilon_i \text{ with } \varepsilon_i = b_2 C_{i2} + c_2 E_{i2} + u_i \quad (2)$$

Where, without loss of generality, the residual terms, ε_i , may be assumed to have zero expected value for each observation in the sample.

The objective is to estimate the two sets of coefficients b_1 and c_1 so as to disentangle the role of observed circumstances and efforts in observed earnings. To do so with standard Ordinary Least Squares would require the residual, ε , to be independent of the explanatory variables C_i and E_i . This is problematic, however. Indeed, it is to be expected that the efforts expended by people to increase their earnings depend on the circumstances they face. This can be formalised as:

$$E_{i1} = \alpha_1 + \beta_{11} C_{i1} + \beta_{12} C_{i2} + \theta_{i1} \quad (3)$$

$$E_{i2} = \alpha_2 + \beta_{21} C_{i1} + \beta_{22} C_{i2} + \theta_{i2} \quad (4)$$

where θ_{i1} and θ_{i2} stand for other determinants of efforts, presumably independent of circumstances, but possibly mutually correlated. Substituting (3)-(4) into (2), it appears that ε_i is correlated to observed circumstances C_{i1} and observed efforts E_{i1} through unobserved circumstances and efforts, even when both are assumed to be orthogonal to their observed counterparts.

It follows that equation (2) cannot be estimated without a bias, and that disentangling the role of efforts and circumstances in the determination of earnings is generally impossible.*

This may not prevent estimating the *total effect* of observed circumstances on earnings. Substituting (3) and (4) in (2), gives:

$$\text{Log } y_i = \delta + \gamma \cdot C_{i1} + \omega_i \quad (5)$$

with:

$$\delta = a + c_1 \cdot \alpha_1 + c_2 \cdot \alpha_2; \gamma = (b_1 + c_1 \cdot \beta_{11} + c_2 \cdot \beta_{21}); \omega_i = (b_2 + c_1 \beta_{12}) \cdot C_{i2} + c_2 E_{i2} + u_i + c_1 \theta_{i1}$$

For the residual term, ω_i , in (5), to be independent of the observed circumstance variables in C_i it must be assumed that the unobserved circumstances and efforts E_2 and C_2 are orthogonal to observed circumstances. If this is not the case, this means that the coefficient γ in (5) accounts not only for the effects of observed circumstances, both directly and through efforts, but also for that part of unobserved circumstances and efforts correlated to observed circumstances.

Practically, parametric empirical analyses of the inequality of opportunity are based on a model of type (5). This lessens the relevance of some of the theoretical measures of inequality of opportunity proposed in the literature and justifies focusing on measures that can be derived from the reduced form (5) as done in the main text.

* Bourguignon et al. (2007, 2013) tried to find bounds on the b_1 and c_1 coefficients, but they proved to be too large to be of any use in identifying the inequality of opportunity conditional on efforts.