The Measurement of Economic Inequality*

Stephen P. Jenkins

Institute for Social and Economic Research
University of Essex, Colchester CO4 3SQ, United Kingdom
Email: stephenj@essex.ac.uk

Philippe Van Kerm

CEPS/INSTEAD
B.P. 48, L-4501 Differdange, Luxembourg
Email: philippe.vankerm@ceps.lu

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1 Introduction

This chapter provides an introduction to methods for the measurement of economic inequality. We provide a reference point for the other chapters of the book, and a self-contained review for applied researchers more generally.[1] The focus on inequality measurement and space constraints mean that much is omitted from our review. For example, methods for the measurement of poverty are not considered.[2] Also not considered are multidimensional inequality measurement,[3] or issues of statistical inference,[4] measurement error and robustness.[5]

To set the scene, consider Figure 1, which shows for four OECD countries inequality trends over 20 years according to two inequality indices. Clearly, the pattern of inequality across countries, and inequality trends within countries depends on the index chosen. But is the Gini coefficient a better index than the P90:P10 ratio? Are there other indices which might tell a different story, and which are better in some sense? This chapter provides a review of the inequality measures that economists have developed, and explains how one might choose between indices or check whether conclusions about inequality difference can be derived without choosing any specific index. Pictures like Figure 1 provide snapshots of the income distribution at particular points in time for a country, but they do not tell us whether those individuals who were poor in one year were also poor in the next year, or whether the rich stay rich. This is the subject of mobility measurement, and we review it too. Figure 1 also raises more fundamental questions about how the distributions of economic interest are defined. We begin with this topic.

2 Essential Preliminaries

There are three aspects to consider: the economic variable of interest for the inequality assessment, and the demographic unit and time period to which the variable refers. The methods discussed in subsequent sections are compromised if these definitions are not right. We summarize the key issues.[6] Aspects of these topics are taken up in more detail in Chapters 4, 14, 18, and 24.

[1]For a technical review of inequality measurement, see Cowell (2000). Jenkins and Jäntti (2005) discuss special issues arising in the measurement of wealth inequality (the subject of Chapter 6). For software, see Duclos and Araar (2006) and Jenkins (2006).

[2]Poverty measurement methods are surveyed by Zheng (1997). See also Chapters 11 and 13.

[3]See Maasoumi (1986).

[4]See inter alia Biewen (2002), Biewen and Jenkins (2006), Binder and Kovačević (1995), Davidson and Duclos (2000), Davidson and Flachaire (2007).

[5]See Cowell and Flachaire (2007), Cowell and Victoria-Feser (1996, 2002), van Praag *et al.* (1983), Van Kerm (2007).

[6]For longer reviews, see Expert Group on Household Income Statistics (2001) and Atkinson *et al.* (2002, especially Chapter 5). On the measurement of consumption expenditure using household surveys, see Browning *et al.* (2003).

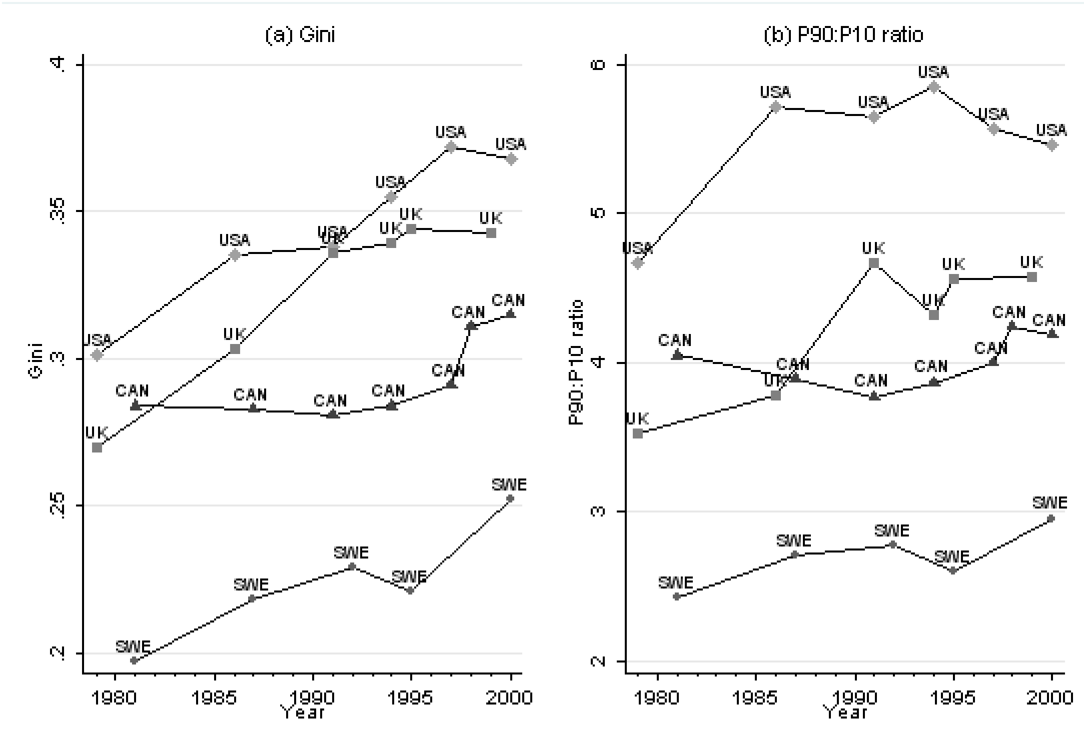

Fig. 1. Inequality in Canada, Sweden, the USA, and the UK, by year. Source: LIS Key Figures, accessed from `http://www.lisproject.org/figures.htm` on 6 December 2007.

The Variable of Interest

The two variables most commonly studied are household income and household consumption expenditure ('consumption' for short). Gross household income in a given year is the sum, across all household members, of labour market earnings from employment or self-employment, income from savings and investments, incoming private transfers such as receipts of gifts or alimony, and public transfers such as social insurance or social assistance benefits. Deducting from this total outgoing private transfers (e.g. gifts to private individuals or child support payments), and income taxes and social insurance contributions yields net (or disposable) household income. Consumption is net income minus accrued savings.

The conventional welfarist approach to measuring economic well-being suggests that consumption is a more appropriate measure for distributional analysis than income because it is consumption that enters an individual's utility function. The welfarist view is not universally accepted, however. Economic inequality is often considered to be about differences in access or control over economic resources rather the actual exercise of that power, in which case income is the measure preferred to consumption: a miserly millionaire is considered rich rather than poor.

The definitions of income and consumption given above leave many issues of practical application unresolved, and there are conflicting principles to take into account. On the one hand, one wants as comprehensive a measure as possible for, if one neglects to take into account particular types of income or expenditure, then one will get biased measures of economic inequality, with the magnitude of the problem depending on the importance of the source on average and how its inequality compares and correlates with other sources. On the other hand, there are issues of data quality, availability, and comparability over time or countries and regions. The more comprehensive a measure is, the greater the risk of incorporating components that are potentially measured with error, or for which valuation methods are difficult or controversial, or that are inordinately costly to collect data about.

The treatment of non-monetary (non-cash) sources of income illustrates some of these problems. These can be major sources of economic resources and substitute for money income; without them, households could have maintained consumption levels only by spending money income. Examples include subsistence agriculture and home production, publicly-provided access to education and health care, and non-cash fringe benefits in employee remuneration. The importance of such sources differs across countries. For example, much effort has been given to measurement and valuation of subsistence agriculture in low-income countries but not in high-income countries. However, the issue is increasingly pertinent in the expanded EU, which now includes a large number of middle-income countries where home production plays a substantial role. Construction of the new EU Statistics on Living Conditions (EU-SILC) needs to address this issue in order to ensure cross-national comparability (see Eurostat (2006) and the Council and European Parliament regulation 1177/2003).

Derivation of accurate measures of income from self-employment and income from financial assets such as bank deposits, bonds, stocks and shares etc. is also a tricky issue. So, too, is the measurement of income taxes and social insurance contributions. Concerns regarding accuracy of respondent recall, respondent burden and constraints on questionnaire length mean that many surveys do not attempt to collect this information directly from respondents, and simulation models are used to impute income tax and social insurance contributions to households. Similar issues constrain the collection of comprehensive household consumption expenditure data. Detailed diary methods are commonly used in specialist expenditure surveys but, in general purpose surveys, information about only a small number of expenditure components is typically collected, e.g. food, utilities, housing, and total household expenditure may need to be imputed: see Browning *et al.* (2003).

The Time Period

The choice of the time period over which income is measured matters because, other things equal, lengthening the reference period will reduce measured inequality. Transitory fluctuations are smoothed out, arguably producing a more representative picture of household circumstances. In practice, however, a person's ability to smooth income over time depends on her income or assets. For example, if poor people are less able to borrow or save than rich people, then variations in their income on a week to week or month to month basis may provide a more accurate reflection of their access to resources than an annual income measure would.

Another consideration, less commonly cited, arises from the common requirement to analyze income or consumption expenditure with reference to the characteristics of the individuals or household to which the measure refers. With a short-period measure, the reference period and the members of the income or spending unit are closely matched. The longer the reference period prior to the interview, the more likely it is that household itself may have changed composition. It is difficult to collect information about individuals who were present at some time during the reference period but who had left by the date of data collection.

The Expert Group on Household Income Statistics (2001) recommended that a year be used as the reference period on the basis that this was the natural accounting period for a number of income sources, e.g. profit and loss accounts for self-employed people, or employment earnings derived from administrative sources. However the Group were also careful to note that different periods may be relevant in different contexts, especially when data is collected using household surveys. For example, if sources such as wages and salary income, or social security benefits, are paid on a regular weekly or fortnightly basis, then respondent burden may be lower and reporting accuracy higher if the shorter reference period were used.

Many of the same issues also arise in the measurement of consumption. For example, spending over a shorter period may not measure consumption, because consumption may also be based on accumulated stocks. Spending may also reflect purchase of consumer durables that do not directly contribute to consumption.

The Income Unit and Related Issues

In principle, income or consumption might refer to a household, a family or an individual. However, it is widely accepted that it is the income or consumption of a population of individuals that is of key interest. The analytical issue is how to measure this distribution given the data typically available.

For employment earnings, there is a one-to-one link between the income earner and the income recipient. However this is no longer true when one moves to the household level. Some individuals may not receive any income at all in their own name, and yet they benefit from income and consumption sharing within the household. The problem is that the final within-household distribution is unobserved.

The standard practice is to assume that income and consumption within households are equally shared among each household member; equivalently, each individual within the same household has the same amount, which is almost certainly wrong in most cases. Some useful progress has been initiated on this issue using economic models of the family decision-making (see e.g. Bourguignon and Chiappori, 1992), but no allocation method has yet been widely acknowledged to be sufficiently accurate and reliable to implement routinely.

There are also issues of how to compare incomes (or expenditures) across recipient units of different household composition in different time periods, and located in different geographical regions within countries or between countries. Equivalence scales adjust for differences in household size and composition: $5000 per month is of greater benefit to a single person than a family of four. Comparisons based on income per capita ignore the fact that adults and children have different needs, and that larger-sized units can benefit from economies of scale. Equivalence scales deflate household income (or expenditure) by a household-specific factor that is less than one for each extra household member, and often differentiate between adults and children.

There is a large literature concerning the appropriate relativities. Derivation methods are surveyed by Coulter *et al.* (1992a) who emphasize the essentially normative content of equivalence scales: a 'correct' scale cannot be determined from observational data alone.

This has led to a stream of theoretical and empirical research investigating the sensitivity of distributional analyses to the choice of equivalence scale (see *inter alia* Buhmann *et al.*, 1988, Coulter *et al.*, 1992b, Jenkins and Cowell, 1994b).

For comparisons of income or expenditure for households at different dates, one requires a suitable index of inflation so that the purchasing powers of nominal amounts at different times are equivalized. The most commonly-used approach is simply to deflate incomes or expenditures by a inflation index that is common to all households, i.e. ignoring the fact that different inflation rates may be relevant to households of different types.

The choice of price deflators for comparisons of households across geographical regions within a country or across countries has received greater emphasis. For example, in low-income countries, there are often substantial differences in prices between urban and rural areas (see e.g. Deaton, 1997). For cross-national comparisons of income and expenditure distributions, exchange rates can provide misleading pictures of true relative purchasing power of different currencies and be unduly influenced by foreign exchange market dealing. More appropriate are Purchasing Power Parities (PPPs). For further discussion of the issues, see e.g. Gottschalk and Smeeding (2000) and Chapters 4 and 24.

Summary

The best measure of household income or consumption expenditure is likely to be a compromise between desired principles and necessary pragmatism, and to vary with the purpose for which the statistics are to be employed, and the context. However, substantial progress has been made in the last decade in producing harmonized data incorporating a high degree of comparability.

An example of high quality data for studying income distribution trends over time within a given country is Britain's official income distribution statistics, the so-called Households Below Average Income series (Department for Work and Pensions, 2006). The ability to make reliable cross-national comparisons of income has been substantially advanced by the Luxembourg Income Study (`http://www.lisproject.org`). LIS produces harmonized data for a large number of countries. Atkinson *et al.* (1995) is an influential study based on it. For developing countries, the World Bank has sponsored Living Standards Measurement Surveys (LSMS) in over 40 countries since 1980, promoting a high quality research-orientated methodology (see Deaton, 1997, Chapter 1). There have also been initiatives providing cross-nationally harmonized panel data such as the Cross National Equivalent File (Frick *et al.*, 2007).

3 Charting Distributions

In this section, we review the main ways to summarize distributions graphically, noting that there is no obvious best way of representing income distributions graphically; each uses the same data but provides a different perspective.

We assume that all essential preliminaries have received their due attention and, for convenience, the variable of interest will be referred to as 'income', the reference period as the 'year', and the economic unit as the 'individual'. We conceptualize income as a random variable Y with a distribution from which the income of each individual in a given society is drawn. The cumulative probability distribution function (CDF), $F(y) = \Pr[Y \leq y]$, shows the probability that Y is smaller or equal to some value y. The probability density function (PDF), $f(y)$, summarizes the concentration of individual incomes at exactly y, with $f(y) = dF(y)/dy$. The mean is denoted μ_Y. The quantile function is the inverse of the CDF, $Q(p) = F^{-1}(p)$, and shows the income value below which a fraction $0 \leq p \leq 1$ of individuals is found. The median is the income splitting the population ranked in income order into two equal-sized groups, $Q(0.5)$; the x^{th} percentile is $Q(x/100)$.

Histograms and Kernel Density Estimates

A histogram typically shows, for each of a series of income ranges ('bins'), the fraction of the population with an income in that range. This device is related to the CDF since the population proportion with income in some range $[a, b]$ is $(F(b) - F(a))$. If we were to make $[a, b]$ so small, so that b were only infinitesimally larger than a, then the height of the histogram between a and b (divided by $b - a$) would equal the density function at b, $f(b)$. This suggests that the PDF might be estimated using a histogram with very narrow bin widths. This is problematic, however, because the number of sample observations is finite and so, if histogram bin widths are narrowed then in practice, they either contain no or very few observations. Kernel density estimation avoids this problem by smoothing the histogram values over a number of overlapping income intervals (see e.g. Silverman, 1986). The idea is to take a 'window' of some chosen width, and to slide this along the income range, smoothing the histogram values as one goes, allocating a relatively high weight to observations close to the middle of the window (y) and a low (possibly zero) value to observations further away from y. The weighting function is known as a 'kernel', and there is a substantial literature about its functional form, and the appropriate width of the window.

PDFs are useful for identifying the income ranges with high concentration of incomes, the mode(s), and the overall location and spread of the distribution. Income PDFs are typically skewed to the right, with the mean above the median. This is illustrated in Figure 2 using data from two hypothetical countries A and B.[7] In A, the mean income is 33,897 and the median is 28,675; in B, the mean and median are 29,905 and 26,100. The 'bumps' in the PDFs may represent the aggregation of different-shaped distributions among subgroups of the population: see below.

Pen's Parade – the Quantile Function

The quantile function highlights the presence of very large incomes, and can be interpreted as follows. Suppose each individual in the population is represented by someone who has a height proportional to the individual's income. Now line these representatives up in order of height with the tallest at the front and have them all march past a certain spot in an hour. Heights increase slowly for a very long time: the person with median size walks by after half an hour, it is well over half an hour before the representative with mean income passes the finishing post, and the one with twice mean income only arrives

[7]For this and all subsequent graphs, we use the test data for the 'USA' (A) and 'Italy' (B), downloadable from `http://www.lisproject.org/dataccess/stata_samplefiles.htm`.

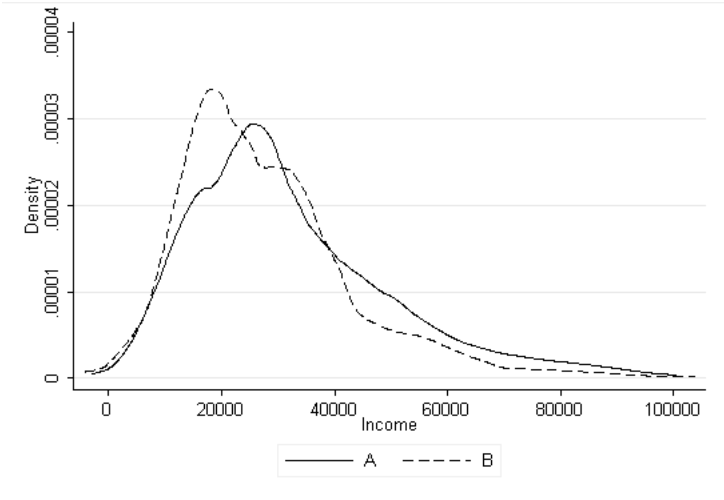

Fig. 2. Probability density functions for countries A and B (kernel density estimates)

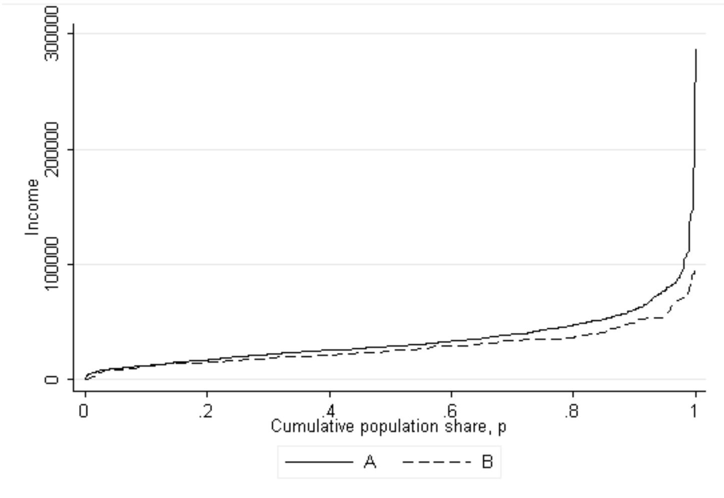

Fig. 3. Pen's Parades (quantile functions) for countries A and B

in the last five minutes. And there a dramatic increase in heights at the very end of the parade as the representatives of the very rich pass by. Hence Jan Pen's evocative reference to a Parade of Dwarfs and and a few Giants (Pen, 1971).[8]

Figure 3 illustrates the shapes of the income parades for countries A and B. There are no millionaires in these countries; if there were, the graphs would be well of the top of the page. Incomes are higher in A than in B at each point in the parade, a result that can be interpreted in terms of differences in social welfare in A and B (see below).

Lorenz Curves

Call upon the representatives in Pen's Parade again. This time we ask each individual to put her income into a communal pot as she passes by. The Lorenz curve summarizes the cumulative amount of income in the pot as people walk by, normalized by the to-

[8]See also Jenkins and Cowell (1994a).

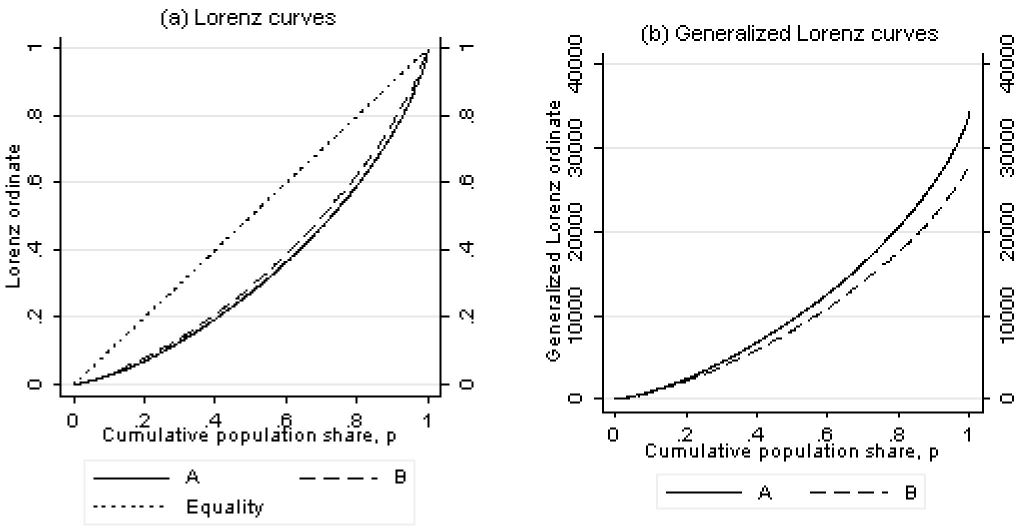

Fig. 4. Lorenz and generalized Lorenz curves for countries A and B

tal amount of income in the pot at the end of the parade. By contrast, the generalized Lorenz curve also summarizes cumulative incomes, but the normalization is instead by the total population size. Put another way, the Lorenz curve is the graph of cumulative income shares against cumulative population shares, and the generalized Lorenz curve is the Lorenz curve scaled up by mean income.

The curvature of the Lorenz curve summarizes inequality: if everyone had the same income (the perfect equality case), the Lorenz curve would lie along a $45°$ ray from the origin and, if all income were held by just one person (complete inequality), the curve would lie along the horizontal axis. The generalized Lorenz curve has the same general shape, but ranges from 0 to μ_Y rather than from 0 to 1. Whereas a Lorenz curve conveys information about inequality – how income shares are distributed – the generalized Lorenz curve also shows information about income levels: distributions with higher mean will finish higher on the right axis than distributions with lower mean, regardless of inequality.

Figure 4(a) shows the Lorenz curves for countries A and B. Although the Lorenz curve for A lies everywhere on or below that for B, A's generalized Lorenz curve is everywhere above that for B – it is pulled upwards by a mean that is larger than B's: see Figure 4(b). We interpret these results further below.

4 Inequality Indices

Many indices have been used to summarize inequality in terms of a single number. We first describe the most commonly-used ones and then discuss their properties in order to identify differences in the concept of inequality encapsulated in them. We also introduce the Lorenz ordering, a concept that refers to whole classes of indices.

Commonly-used Indices of Inequality

In statistics, the variance (or its square root, the standard deviation) is often used to summarize dispersion. One problem with the variance for inequality measurement is that, if every income is increased equiproportionately, inequality increases: the variance is not 'scale invariant'. Scale invariance is usually considered desirable: inequality should be the same for a given country regardless of whether income is expressed in Euros, Dollars, or Yen.[9] A scale invariant counterpart to the variance is the coefficient of variation (CV), which is the standard deviation divided by the mean. A different way of imposing scale invariance would be to take a logarithmic transformation of every income before computing the variance, thus generating the 'variance of the logs' inequality index.

Other commonly-used scale invariant indices include those based on percentile ratios, such as the ratio of the 90th percentile to the 10th percentile ('P90:P10 ratio') or, to compare dispersion at the top of the distribution with dispersion at the bottom, the P90:P50 and P50:P10 ratios. One oft-cited advantage of the P90:P10 ratio is that it avoids problems of 'top-coding' in survey data.[10] However, by their very nature, percentile ratio measures ignore information about incomes other than the percentiles selected.

Inequality indices can also be derived directly from the Lorenz curve. Because the Lorenz curve plots income shares, it is scale invariant, and so measures derived from the Lorenz curve inherit this property. One index is the Pietra ratio, also known as the Ricci-Schutz index, the Robin Hood index, or half the relative mean deviation. It is defined as the largest difference between the Lorenz curve and the perfect equality line, and is also equal to the proportion of total income that would have to be redistributed from those above the mean to those below the mean in order to achieve perfect equality.

Perhaps the most commonly-used inequality index is the Gini coefficient, which ranges from 0 (perfect equality) to 1 (perfect inequality). It is the ratio of the area enclosed by the Lorenz curve and the perfect equality line to the total area below that line:[11]

$$G(Y) = 1 - 2\int_0^1 \mathrm{L}(p;Y)dp$$

A generalization of the Gini coefficient is the 'generalized Gini' (or S-Gini) class of indices (Donaldson and Weymark, 1980, Yitzhaki, 1983):

$$S_\upsilon(Y) = 1 - \int_0^1 W(p;\upsilon)\mathrm{L}(p;Y)dp$$

where $\upsilon > 1$ and weighting function $W(p;\upsilon) = \upsilon(\upsilon-1)(1-p)^{\upsilon-2}$. The standard

[9] The variance is unchanged by equal absolute additions to each income ('translation invariant'). See Cowell (2000) and references therein for discussion of this property and absolute, intermediate, and relative inequality indices.

[10] Top-coding arises when data producers, to maximize confidentiality and minimize disclosure risk, replace all incomes above a particular value with that value (the 'top code'). See Burkhauser *et al.* (2007) and Chapters 4, 6, and 7.

[11] There are many alternative formulae: see Yitzhaki (1998).

Gini coefficient arises if $\upsilon = 2$. Higher values of υ mean that a given income difference among bottom-ranked individuals counts more towards overall inequality than the same difference among top-ranked ones.

A family of inequality indices originating from quite different considerations (Cowell and Kuga, 1981), is the Generalized Entropy class, E_α, of which prominent members are the Theil index,

$$\mathrm{E}_1(Y) = \int \frac{y}{\mu_Y} \log\left(\frac{y}{\mu_Y}\right) f(y)dy,$$

the Mean Logarithmic Deviation,

$$\mathrm{E}_0(Y) = \mathrm{E}_0(Y) = \int \log\left(\frac{\mu_Y}{y}\right) f(y)dy,$$

and half the squared coefficient of variation,

$$\mathrm{E}_2(Y) = \mathrm{CV}^2/2.$$

The general formula for Generalized Entropy indices is

$$\mathrm{E}_\alpha(Y) = \frac{1}{\alpha^2 - \alpha} \int \left(\left(\frac{y}{\mu_Y}\right)^\alpha - 1\right) f(y)dy$$

for $\alpha \neq 0, 1$. Different values of α correspond to differences in the sensitivity of the inequality index to differences in income shares in different parts of the income distribution. The more negative that α is, the more sensitive is the index to differences in income shares among the poorest incomes; the more positive that α is, the more sensitive is the index to differences in income shares among the rich. A useful feature of the Generalized Entropy class is that every member is additively decomposable by population subgroup: see Section 6.

Finally, there is the Atkinson family of inequality measures (Atkinson, 1970):

$$A_\epsilon(Y) = 1 - \left(\int \left(\frac{y}{\mu_Y}\right)^{1-\epsilon} f(y)dy\right)^{\frac{1}{1-\epsilon}}$$

where $\epsilon > 0$, and $\epsilon \neq 1$, and

$$A_1(Y) = 1 - \exp\left(\int \ln\left(\frac{y}{\mu_Y}\right) f(y)dy\right).$$

$\epsilon > 0$ is an inequality-aversion parameter that we discuss later. The Atkinson and Generalized Entropy measures are closely related. For each value of ϵ, there is a Generalized Entropy index E_α with $\alpha = 1 - \epsilon$ that ranks a pair of distributions in the same way as A_ϵ.

Properties of Inequality Measures

One way to choose between the large number of inequality indices available is to evaluate them in terms of their properties. We have already encountered the scale invariance property. Another property is 'replication invariance': it holds if a simple replication of the population of individuals and their incomes does not change aggregate inequality. The symmetry (or anonymity) axiom says that the index depends only on the income values used to construct it and not additional information such as who the person is with a particular income. This property underlines the importance of equivalization: if incomes were not adjusted to take account for differences in household size and composition, then these characteristics would be relevant for inequality assessments.

A fourth and fundamental property is the Principle of Transfers. Consider some distribution A from which a person (labelled i) is arbitrarily chosen. Now form a new distribution B by transferring a small amount of income from person i to a poorer person j, though keeping i richer overall. This is a Pigou-Dalton transfer, also called a progressive transfer. Most people would agree that inequality falls in going from A to B, though they may disagree about how much. An inequality measure I satisfying $I(A) > I(B)$ is said to satisfy the Principle of Transfers.

For infinitesimal transfers of the type described, the Principle of Transfers reduces to the condition $dI < 0$, where

$$dI = \left(\frac{\partial I}{\partial y_j}\right) dy_j + \left(\frac{\partial I}{\partial y_i}\right) dy_i = dy \left[\frac{\partial I}{\partial y_j} - \frac{\partial I}{\partial y_i}\right],$$

and the change in inequality, dI, is the total differential of I and, by construction, the transfer $dy_i = -dy_j$.[12] Views about the precise size of the inequality reduction from the transfer dy are likely to depend on the income level of the recipient. Taking two pairs of individuals the same income distance apart, where one pair is relatively rich and the other relatively poor, many would argue that a given transfer from richer to poorer should reduce inequality more for the second pair than the first. Inequality measures satisfying this property are known as 'transfer sensitive' (Shorrocks and Foster, 1987).

It can be shown that the Principle of Transfers is satisfied by the Gini, Generalized Entropy and Atkinson indices, but not by percentile ratio indices, the variance of logs, or the Pietra ratio. All Atkinson indices are transfer-sensitive but the CV, for instance, is not. Nor are Generalized Gini indices because of their dependence on ranks rather than income.

The Lorenz Ordering

Lorenz curves have a useful role to play other than as descriptive devices. A key result is that if the Lorenz curves of two distributions do not cross, i.e. $\mathrm{L}(p; A) \leq \mathrm{L}(p; B)$ for any cumulative population share p (and the two Lorenz curves are not identical), then one can conclude unambiguously that inequality is higher in distribution A than in distribution B according to any inequality index that respects the properties of scale invariance, replication invariance, symmetry, and the Principle of Transfers (Foster, 1985). Distribution B is said to Lorenz-dominate distribution A. With non-intersecting Lorenz curves, it does not matter whether one chooses Generalized Entropy measures, Atkinson indices, or generalized Gini coefficients to compare inequality in A and B: in every case, inequality would be higher for distribution A. This what we saw in Figure 4(a).

The Lorenz curve ordering is only partial. Unambiguous conclusions cannot be drawn

[12] Jenkins (1991) evaluates the expressions for various indices and provides more extensive discussion.

when Lorenz curves intersect unless further restrictions are placed on the inequality measure. For example, if two Lorenz curves cross only once, and if (i) the Lorenz curve for A crosses the Lorenz curve for B from above and (ii) $\mathrm{CV}(A) \leq \mathrm{CV}(B)$, then inequality is lower in A for any transfer sensitive inequality measure (Dardanoni and Lambert, 1988, Davies and Hoy, 1995, Shorrocks and Foster, 1987). Thus comparisons of CVs may result in unambiguous inequality orderings according to a broad class of inequality indices.

5 Social Welfare and Inequality

It is standard practice to evaluate policy outcomes with reference to their effects on social welfare where this is evaluated using a social welfare function (SWF) that aggregates information about the income distribution into a single number. Inequality indices aggregate incomes and so are a form of SWF. This suggests that another systematic approach to inequality measurement could be to start with a SWF known to incorporate specific ethical principles, and then to derive an inequality index from this, knowing that it must reflect these same properties.

Properties of Social Welfare Functions

The following properties are commonly imposed on the SWF. First, the SWF is individualistic and satisfies the Pareto principle, i.e. if the income of one person increases and the income of no other person decreases, then the SWF must record an improvement in social welfare or at least leave it unchanged. Second, the SWF satisfies symmetry, as for inequality indices. Third, the SWF is usually assumed to be additive in individual utilities, where utility for person i is a function of her income only, $U(y_i)$. Social welfare is then the average of the individual utilities:

$$W(Y) = \int U(y)f(y)dy.$$

Fourth, it is typically assumed that U is concave. In other words, the social marginal utility of income for each income not only increases with income but increases at a decreasing rate ($\partial U^2(y)/\partial y^2 \leq 0$). This is fundamental because it implies social preference for equality, guarenteeing that a Pigou-Dalton transfer increases aggregate social welfare.

Two routes can be taken from here. First, as for the Lorenz ordering, one may look for criteria that lead to unambiguous orderings of distributions using only these properties. Clearcut conclusions derived using this approach are robust in the sense that they rely on relatively few assumptions. However there is no guarantee that one will be able to order any two distributions. A second route is to select a particular functional form for the SWF, and to compare scalar values for estimated SWFs. We discuss these two strategies next.

Stochastic Dominance and the SWF Ordering

A powerful result links social welfare orderings with configurations of generalized Lorenz curves: if the generalized Lorenz curve for distribution A lies nowhere below that for distribution B, then social welfare is higher in distribution A than in B according to any individualistic, symmetric, increasing, and concave SWF (Shorrocks, 1983). This was the configuration shown in Figure 4(b) and, for countries A and B, the social welfare ordering is the reverse of the inequality ordering.

It is also possible to compare distributions without using the concavity assumption. If the quantile function for A lies above that for B, then social welfare is higher in society A according to any individualistic, symmetric, and increasing SWF (cf. Figure 3). Quantile function dominance implies generalized Lorenz dominance.

An equivalent set of conditions is stochastic dominance (Hadar and Russell, 1969, Saposnik, 1981). First-order stochastic dominance involves comparisons of CDFs. If the CDF of distribution A lies below the CDF of B then social welfare is higher in A according to any individualistic, anonymous, and increasing SWF. This result is unsurprising because comparisons of CDFs are equivalent to comparisons of quantile functions. Second-order stochastic dominance involves comparisons of cumulations of CDFs. Dominance of A over B at the second order is equivalent to generalized Lorenz dominance – social welfare is higher in A for any individualistic, symmetric, increasing, and concave SWF. Higher-order dominance can be checked by continuing the sequence and comparing cumulations of the curves obtained at the lower order. Increasing the order imposes stricter restrictions on higher order derivatives of the $U(\cdot)$ function, e.g. third-order dominance corresponds to an ordering of distributions according to SWFs that are transfer sensitive.

SWF-based Inequality Indices

Dominance checks may not yield clear cut orderings and, in any case, one may wish to estimate the magnitude of a difference in social welfare. For this purpose, one needs to specify a particular functional form for the SWF. The standard assumption made, in addition to the four properties stated above, is that individual utility functions have constant elasticity. Equiproportionate changes in each individual's income change total social welfare by the same proportion. The constant elasticity assumption leads to a specification for $U_\epsilon(y)$ of the form

$$U_\epsilon(y) = y^{1-\epsilon}/(1-\epsilon), \epsilon \neq 1,$$

with $\epsilon > 0$ to ensure concavity, and with $U_1(y) = \ln(y)$ as the limiting case when $\epsilon = 1$.

This can also serve as a basis for developing SWF-based inequality measures. Consider the income that, if it were received by every individual in a hypothetical, inequality-free society, would generate the same social welfare as observed in Y. This income is the equally distributed equivalent income, ξ, satisfying $W(\xi(Y;W)) = W(Y)$, and with a social preference for equality, $\xi \leq \mu_Y$. The welfare loss from inequality is an inequality index:

$$I(Y) = 1 - (\xi/\mu_Y).$$

In the constant elasticity case, this formula characterizes the Atkinson class of inequality indices with ϵ being the constant elasticity parameter. Larger values of ϵ correspond to a greater concern for inequality differences towards the bottom of the distribution (greater 'inequality aversion').[13]

[13] Generalized Gini inequality indices can be similarly motivated: set $U(y) = \upsilon(1-F(y))^{\upsilon-1}y$, $\upsilon > 1$.

6 Explaining Inequality: Decomposition and Regression Methods

Having summarized inequality, one might now ask how income differences within particular groups of a society combine to shape the overall level of inequality, or how overall inequality is related to the different types of income comprising an individual's total income. Breaking down inequality into its components helps one to explain the aggregate. Two main types of decomposition approach can be distinguished: non-regression based approaches and multivariate regression based approaches.

Decompositions by Factor Components and by Population Subgroups

Household income is the sum of income from different sources, e.g. labour income, capital income, transfers, etc.: $y_i = \sum_k^K y_i^k$. Decompositions by factor components identify the contribution of each factor source, k, to total inequality. Shorrocks (1982) proved that, given a set of 'reasonable' assumptions, the share of total inequality that is accounted for factor k is:

$$s_k = \frac{\mathrm{Cov}(Y^k, Y)}{\sigma^2(Y)} = \rho(Y^k, Y) \times \frac{\mu_Y^k}{\mu_Y} \times \frac{\mathrm{CV}(Y^k)}{\mathrm{CV}(Y)}$$

for all standard inequality indices. Observe that s_k does not depend on which inequality index is decomposed: the decomposition rule is independent on the inequality measure. The equation shows that the factor inequality shares depend on the correlation between the factor and total income ($\rho(Y^k, Y)$), the share of the factor in total income, and inequality of the source relative to the inequality of total income, where inequality is summarized using the CV. Factors may have equalizing effects on inequality of total incomes, when $\rho(Y^k, Y)$ and therefore s_k is negative, whereas other factors may be disequalizing as when $\rho(Y^k, Y)$ and s_k are positive. For example, we expect social security transfers to be inequality-reducing while labor and capital income tend to be inequality increasing.[14]

Decompositions by population subgroups begin with a partition of the population into M distinct non-overlapping groups of individuals, defined by characteristics such as e.g. age, sex, workforce attachment, etc. Decompositions by population subgroup allow to disaggregate overall inequality into the contribution arising from the inequality within each of the groups and the contribution from inequality between the groups.[15] E.g. does overall wage inequality largely reflect wage differences within skill groups, or wage differences between skill groups?

Generalized Entropy inequality indices have played a special role because they are decomposable by population subgroup.[16] In particular, we can write total inequality as the sum of the inequality between groups and the inequality within groups, where the latter is the weighted sum of the inequalities within each subgroup:

$$\mathrm{E}_\alpha(Y) = \mathrm{E}_\alpha^B(Y) + \mathrm{E}_\alpha^W(Y)$$

[14] For non-axiomatic approaches, see e.g. Fei *et al.* (1978) and Lerman and Yitzhaki (1985).

[15] See Shorrocks (1984) for a formal characterization of subgroup-decomposable inequality indices.

[16] For an application combining decompositions by population subgroup and factor components, see Jenkins (1995).

with

$$\mathrm{E}^W_\alpha(Y) = \sum_{m=1}^{M} \nu_m^\alpha \omega_m^{1-\alpha} \mathrm{E}_\alpha(Y^{(m)})$$

where ν_m is subgroup m's share of total income, ω_m is m's population share, and $\mathrm{E}_\alpha(Y^{(m)})$ is the inequality within m. Between-group inequality, E^B_α, is the inequality obtained by imputing to each person the mean income of the subgroup to which she belongs. Other inequality measures cannot be so conveniently expressed.[17]

Graphical tools can also be used to undertake decompositions by population subgroup because a PDF for a population can be expressed as the population share-weighted sum of the PDFs for each subgroup. If the number of groups is small, it is easy to visualize changes in subgroup relative incomes (between-group inequality), the shapes of each subgroup distribution, and the relative sizes of the groups (Jenkins and Van Kerm, 2005). A development of this idea is discussed further below.

Regression-based Methods

Decomposition methods are useful for describing the structure of income distributions, but differ in nature from the multivariate regression tools that economists instinctively use to explain incomes and their distribution. We now consider some regression-based approaches to explaining distributions. See Lemieux (2002) for a detailed discussion of alternative approaches.

Suppose that each individual's income depends on her observed characteristics, the 'returns' to those characteristics, and unobserved characteristics. If the relationship is assumed to take the standard linear regression form – income is the sum of each characteristics times its return (regression coefficient) plus an 'error' term summarizing unobservable factors – then, it is straightforward to show that the difference in means of two distributions A and B can be expressed as an exact linear function of a term representing differences in observed characteristics plus a term representing differences in returns to those. This is the celebrated Oaxaca-Blinder method for decomposing differences between the means of two distributions (Blinder, 1973, Oaxaca, 1973).

This framework has two limitations: it only considers differences in mean outcomes, although distributions may vary in other important respects, such as their dispersion, and the decomposition relies heavily on the linear regression functional form. These issues have been addressed in a number of ways. Whereas the classic linear regression approach links the mean of a distribution to observed characteristics, the quantile regression approach expresses each of a number of quantiles (e.g. the median, upper and lower quartiles) to observed characteristics, and provides a more comprehensive picture of the whole conditional distribution and of the effect of covariates on the location and shape of the distribution.[18]

Other approaches include modeling the conditional distribution itself, rather than the

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[17] Decomposition of the Gini requires a third term if the subgroup income ranges overlap. The three-term decomposition has useful interpretations in particular contexts: see e.g. Aronson and Lambert (1994). On Atkinson index decomposition, see Blackorby *et al.* (1981).

[18] Koenker and Hallock (2001) review quantile regression methods. The methods are applied to wage inequality by Buchinsky (1994), Gosling *et al.* (2000), and Mata and Machado (2005).

quantiles. For example, one can assume that the income distribution is described by a parametric functional form and express each of the parameters as a regression function of observed characteristics. Thus e.g. Biewen and Jenkins (2005) employ the Singh-Maddala functional form and relate cross-national differences in income distribution to differences in characteristics and differences in returns to those characteristics. Semi-parametric approaches to modelling the whole distribution have also been proposed, of which a leading example is Donald *et al.* (2000).

Another strand of literature, initiated by DiNardo *et al.* (1996), has modelled the whole distribution (PDF) non-parametrically using a clever variation on the kernel density estimation methods reviewed earlier. Suppose we wish to relate changes in the distribution of income between Year 1 and Year 2 to changes in the income distribution for particular groups and to changes in the relative sizes of these groups. The difference in PDFs between the two years is:

$$\Delta f^{(1,2)}(y) \equiv f^{(2)}(y) - f^{(1)}(y).$$

Since the PDF is additively decomposable, it may be written as the weighted sum (integral) of the PDF for each subgroup of individuals that is implicitly defined by a particular combination of observed characteristics:

$$f^{(m)}(y) = \int f^{(m)}(y|X)g^{(m)}(X)dX.$$

The goal is to decompose the overall PDF change $\Delta f^{(1,2)}(y)$ into differences attributable to changes in the conditional distributions $f^{(m)}(y|X)$ and changes in group sizes as defined by changes in the configuration of covariates $g^{(m)}(X)$. The decomposition is unproblematic if the number of covariate combinations is small but, if it is large (the typical case), accurate estimation is difficult.

DiNardo *et al.* (1996) saw that this problem could be circumvented by using reweighting methods. A reweighting function is defined, and expressed using Bayes Rule, as

$$\psi^{(1,2)}(X) = \frac{g^{(1)}(X)}{g^{(2)}(X)} = \frac{\Pr[m=1|X]}{\Pr[m=2|X]} \times \frac{\Pr[m=2]}{\Pr[m=1]}.$$

$\Pr[m=i|X]$ is the probability that a randomly selected individual with characteristics X belongs to group i if individuals from both groups are pooled in a common population. $\Pr[m=i]$ is the probability that any randomly selected individual belongs to group i after pooling the groups. Whereas $g^{(m)}(X)$ is a multidimensional function difficult to estimate, the four probabilities in the expression above are relatively easy to compute from probit regression estimates, and can be used to derive weights. Thus explanation of overall distributional change is accomplished by a sophisticated 'what if' exercise. This simulates the effects of compositional changes using weighted kernel density estimation (with weights derived as discussed), and infers the effect of subgroup distributional change from the difference that remains after taking account of the effects of composition differences.[19]

[19] See Daly and Valletta (2006) and Hyslop and Maré (2005) for recent applications.

7 Income Mobility and Inequality

All the methods considered so far summarize an income distribution at a point in time or consider differences between distributions across time or space or groups. But this snapshot information does not tell us how income changes over time for each individual within the population. Income mobility analysis provides tools for summarizing this. Information about income mobility enables us to link inequality at a point in time to inequality over the longer term. High point-in-time inequality combined with high mobility can result in low long-term inequality. It is this instrumental role of mobility as an equalizer of long-term attainments that leads some to argue that more of it is desirable.

Assessments of mobility involves additional considerations, however (Gottschalk and Spolaore, 2002). First, high mobility involves considerable income fluctuation over time. Because individuals typically prefer income stability, other things being equal, fluctuations provide a potentially offsetting force to the welfare gains of lowering long-term inequality. Second, the unpredictability of fluctuations per se is a second potentially offsetting force. Greater uncertainty about future outcomes reduces the utility of risk-averse individuals. These multiple considerations mean that mobility analysis is inherently complex.[20]

Representing Mobility

Graphical representation of mobility patterns is complicated because of the multiple dimensions. When comparing mobility between two periods, two methods are a scatter plot of the (Year 1, Year 2) pairs of income for each individual, or a three-dimensional density plot of the two-period joint distribution (see Chapter 20). Unfortunately, both density plots and the related contour plots are hard to interpret and compare. Trede (1998) suggests plotting smoothed estimates of the distribution of Y_2 at each $Y_1 = y$ value using smoothed quantile regressions. Van Kerm (2006) proposes a visualization in which the conditional expectation of a summary measure of individual-level income change is plotted against individuals' ranks in the initial income distribution. This 'mobility profile' is straightforward to interpret and is directly related to a number of mobility indices. As soon as one considers mobility over more years than two, the representation problem becomes even more complex. Virtually all mobility indices have been developed for the two-period case.

Dominance criteria for unambiguous mobility comparisons are few, and rarely applied. The most well-known criterion is based on checks for bivariate stochastic dominance (Atkinson, 1983). See also Dardanoni (1993).

Properties of Mobility Indices

There is no consensus about the properties that mobility indices should respect. For example, although scale invariance is widely accepted as an axiom for inequality indices, invariance properties for mobility indices are not. So, there are many different indices,

[20] Income mobility, within and across generations, is itself the subject of two chapters (see chapters 20 and 21).

and they encapsulate different mobility concepts (Fields, 2000).[21] See the reviews by Maasoumi (1998) and Fields and Ok (1999a) and Chapter 21.

To assess the numerous measures, it is useful to compare them under four headings. First, measures differ about the pattern of mobility that is associated with the maximum possible. Some measures attain their maximum when there is a complete reversal of individuals' fortunes. By contrast, some mobility measures attain their maximum when Year 2 circumstances are independent of Year 1 circumstances. Independence from origin links mobility with concerns about equality of opportunity. And some measures do not have any maximum mobility reference.

Second, there is the question of whether a mobility index is sensitive to changes in the marginal distribution or only to churning of individuals within the distribution. Structural mobility is mobility due to changes in the distribution of income, which may be contrasted with exchange mobility which is due to changes in the relative ranks of individuals in the distribution (Markandya, 1984). Exchange mobility measures record zero mobility if everyone maintains the same rank in the income parade between any two time periods, and its value is unaffected by any monotonic transformation of incomes at any time period. By contrast, structural measures may register mobility even in the absence of reranking provided nominal incomes attached to ranks are changing. Exchange mobility measures are often seen as pure mobility indicators that are immune to undue influence of changes in marginal distributions. However, considerations of economic growth or redistribution of resources are discarded.

Third, there are scale invariance and translation invariance issues. Measures are strongly relative (intertemporal scale invariant) if equiproportionate income growth does not affect the mobility assessment. Measures are said to be weakly relative (or scale invariant) if the units in which income are measured are irrelevant but, by contrast with strongly relative measures, equiproportionate income growth may count as mobility. There are also translation invariance counterparts of these properties. Exchange mobility indices satisfy both intertemporal translation and scale invariance.

Fourth, there is the issue of directionality, which refers to the roles played by the base year and current year in mobility assessments. An index is directional if it matters whether a particular income change refers to a change from a base year to a current year or vice versa. This is relevant if one wishes to take the temporal ordering of changes into account.

A Selection of Mobility Indices

We now indicate the variety of mobility indices and their different properties. First we consider two-period distance-based mobility measures. These are all population averages of some function $\delta(y_1, y_2; H)$ that captures the degree of individual-level mobility associated with any income pair (y_1, y_2):

$$M\left((Y_1, Y_2)\right) = \int \delta(y_1, y_2; H) dH(y_1, y_2),$$

where H is the bivariate CDF.

[21] This is a matter of empirical relevance too, as different approaches have led to different conclusions (Cecchi and Dardanoni, 2003, Van Kerm, 2004).

Fields and Ok's (1996) index arises when $\delta(y_1, y_2; H) = |y_1 - y_2|$. It captures the magnitude of income movements non-directionally, placing no specific value on reranking or inequality, but directly assesses the magnitude of income change. There is no upper limit to mobility and the measure is only translation invariant. Fields and Ok's (1999b) index has $\delta(y_1, y_2; H) = |\log(y_1) - \log(y_2)|$, and so has similar properties except that it is scale invariant.

Hart's index is equal to $1 - r(\log(y_1), \log(y_2))$, where $r(\cdot)$ is Pearson's correlation coefficient of the logarithm of incomes (Hart, 1976).[22] The index is symmetric, scale invariant and translation invariant, and also intertemporally scale and translation invariant. Maximum mobility is achieved with a perfect negative correlation of incomes.

The average rank-jump index has $\delta(y_1, y_2; H) = |F_1(y_1) - F_2(y_2)|$. It focuses entirely on income ranks rather than income levels and is therefore a pure exchange mobility index. It is non-directional, and intertemporally scale and translation invariant. Maximum mobility is attained if income ranks are completely reversed.

Jenkins and Van Kerm (2006) proposed a distance-based mobility index based on changes in income ranks. Suppose we let

$$\delta(y_1, y_2; H) = [w(F_1(y_1); \upsilon) - w(F_2(y_2); \upsilon)]\, y_2/\mu(Y_2)$$

where $w(p; \upsilon) = \upsilon(1-p)^{\upsilon-1}$, $\upsilon > 1$, is a function that attaches greater weight to people with low rank in F_t the greater that υ is. This index provides a neat way to link changes in cross-sectional inequality over time with income mobility. Jenkins and Van Kerm (2006) show that change in the generalized Gini coefficient over time is equal to this reranking index minus a measure of the progressivity of income growth (the extent to which income growth is experienced by the poor rather than the rich, itself a type of income-movement mobility index). One implication of this identity is that, even if income growth is pro-poor, inequality may rise over time if reranking more than offsets pro-poor income growth.

A second group of measures includes those that summarize mobility in terms of the extent to which it reduces inequality over time. Shorrocks' index (Shorrocks, 1978) is the most popular index of this group. The idea is that, if one were to longitudinally average each person's income over a number of years, the inequality in these averaged incomes would be less than average annual inequality because each individual's income fluctuations would be smoothed out and no longer contribute to overall dispersion. Mobility is then defined as the proportionate reduction in inequality of aggregated incomes compared to the average of inequality in the marginal distributions. The index is non-directional and scale invariant, but not inter-temporal scale invariant. One feature of the Shorrocks mobility index which distinguishes it from all the others cited earlier is that is well-defined for any number of time periods, not just two. See Chapter 21 for more extensive discussion and empirical illustrations.

8 Conclusions and further research

What are the priorities for future research on the measurement of economic inequality? Perhaps heretically in the context of a chapter like ours, we suggest that substantial progress on analytical measurement methods has been made and that other developments

[22] Cecchi and Dardanoni (2003) give the expression for $\delta(y_1, y_2; H)$ in this case.

should receive greater priority, with the exception of further work on mobility measurement as that subject is much less mature. We would give higher priority to the following topics instead.

First, we have emphasized the importance of getting the essential preliminaries right. Choosing the correct PPP exchange rate for cross-national comparisons and global assessments is one example of this, as emphasised in Chapters 4, 23, and 24. Second, we suggest that work should also continue to be devoted to improvements in data quality broadly interpreted. This could include a range of activities, including e.g. improving survey population coverage and response rates, methods of imputation, or collecting more comprehensive but comparable measures of income or consumption expenditure. It is also likely to be valuable to explore further the role of administrative data vis-a-vis social surveys, whether used alone or linked. The former are typically much larger and measurement error may be less, but there are issues about coverage, the variables available and access by researchers. Third, alongside these improvements in data, we would support further development of methods to handle many of the issues that routinely arise with data, including sampling variation, measurement error, outliers and their implications for non-robustness.

Development of explanatory models of the income distribution, theoretical and empirical, is a fourth priority area. As one of us has said elsewhere, ‘Perhaps the greatest challenge is to develop more comprehensive models of the household income distribution, incorporating not only models of labour market earnings but also reflecting income from other sources including social benefits and investment income, and the demographic factors affecting whom lives with whom’ (Jenkins and Micklewright, 2007, p.19).

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