THINGS YOU SHOULD KNOW ABOUT THE GINI INDEX

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1. Introduction

The Gini index (Gini, 1914) is the most famous and widely used inequality measure. It is an important measure for forecasting the wealth of a country and is available for almost every country in the world from various international organizations' datasets (Decancq and Lugo, 2012).

Its importance has been immediately made clear. Since its first proposal, the Gini index has been the subject of numerous publications, both theoretical and applicative. Some of the reasons for its success and longevity are simplicity, fulfilment of general properties, interesting interpretations, useful decomposition, links with the Lorenz curve (Lorenz, 1905) and the mean difference (Gini, 1912) (see Giorgi, 1990, 1992, 1993, 1999, 2005, 2011a; Giorgi and Gubbiotti, 2017 for more details). Moreover, its use is not only restricted to economics and, every year, many applications in different and unthinkable fields continue to pop up (Giorgi, 2019). The present paper aims to retrace some lines of research related to the Gini index, pointing out the most important results and the reference works, as well as some errors several times published and re-published in the immense literature on the Gini index.

The paper is organized as follows. In Section 2, the definition of the Gini index is recalled. In Section 3, some aspects related to its origin are clarified. In Section 4, the Gini index decomposition is tackled, while its inferential aspects are treated in Section 5. Finally, in Section 6, brief conclusions are outlined.

2. The Gini index

The Gini index is a measure of the degree of inequality in the distribution of a non-negative variable X, most of the time income[1]. It is defined between 0 and 1. Where 0 marks equidistribution (or minimum concentration) of income, that is when all the recipients earn the same amount of income. Instead, it is equal to 1 when all the individuals except one have 0 income, while one earns the total amount of the income. In this case, we refer to maximum concentration. There are several equivalent ways of writing the Gini index[2]. Some of these, which will be useful in the following of the paper, are:

$$R = \frac{2\sum_{i=1}^{N} x_i(i-1)}{(N-1)\,t_X} - 1 = \tag{1}$$

$$= \frac{2\sum_{i=1}^{N} i\,x_i}{(N-1)\,t_X} - \frac{N+1}{N-1} \tag{2}$$

where N is the population size, x_i is the income earned by the i-th recipient which occupies the i-th position in the ranking of incomes arranged in a non-decreasing way, and $t_X = \sum_{i=1}^{N} x_i$ is the total income in the whole population.

Another expression for R, equivalent to (1) and (2), has been derived as a function of the covariance, $cov()$, by De Vergottini (1950) and Piesch (1975)[3]:

$$R = cov\left(\frac{i}{N}, \frac{x_i}{N}\right). \tag{3}$$

Furthermore, the Gini index can be obtained also through the Lorenz diagram (Gini, 1914). In particular, R is twice the area between the Lorenz curve and the egalitarian line (for more details see Nygård and Sandström, 1981).

3. The origin of the Gini index

Despite the fame of the Gini index, sometimes there is still confusion about the year of its first appearance in literature. It is not uncommon to find papers that place it in 1912. But indeed, Corrado Gini (1884-1965) proposed R in 1914 (Gini, 1914) as the final result of a series of studies on the measurement of the concentration of wealth and income he started in the early twentieth century.

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[1] Besides income, the Gini index can be computed also on other variables, such as wealth, expenditure, revenue, etc. However, for the sake of comodity, in the following, we will assume that it is applied to the income.

[2] See Yitzhaki (1998) for the continuous case, Giorgi and Gigliarano (2017) for the discrete case and Giorgi (1992) for a more general discussion.

[3] The corresponding expression in the continuous case has been proposed by Lerman and Yitzhaki (1984).

The main reason for this mistake is that in his 1914 paper, Gini showed, as a corollary, that R can be written also as a function of the mean difference, Δ, introduced by himself in 1912. Then, several scholars wrongly thought that R and Δ were the same index, so they started to quote the paper of 1912 as a reference for the Gini index. In reality, R and Δ are different measures with different aims useful in different contexts. The former is a concentration measure, while the latter is a variability measure. Of course, the two concepts although related are different.

Furthermore, to complicate matters even more and to contribute to the propagating of the mistake in literature it is the fact that both the papers (Gini1912, 1914) – as well as most of the literature produced by the Italian school of statistics in those years – were written in Italian, so not easily understandable by non-Italian speakers and, moreover, not even easily available. However, after a careful reading of the two papers, it looks clear that the Gini index had been unequivocally proposed for the first time in 1914. Furthermore, any possibility of doubt about this issue is eliminated by Gini himself who stated "… in 1914 I proposed the concentration ratio showing contemporarily the relations between this index and the Lorenz curve and the mean difference" (Gini, 1931 p. 305). Moreover, from the quotation, it is curious to notice that Gini refers to R as the concentration ratio. The other names by which the index is actually known in literature, that explicitly refer to the namesake author, such as Gini index, Gini ratio and Gini coefficient, have only been used later and by Italian scholars to pay homage to Corrado Gini.

4. The Gini index decomposition

The decomposition is a common and recurring practice in the study of inequality measures. According to the structure of the data and the research objectives, it is mainly possible to distinguish decomposition by sources and by population subgroups (for a comprehensive survey on the subject see, e.g., Giorgi 2011b).

The general aim is to determine how much of the inequality is due to each income source or population subgroup. Then, the results of the decomposition are very useful to better understand the inequality and bring out where it lurks.

4.1. Decomposition by sources

When data enables us to decompose the total income by different income sources (for instance, wages, salaries, capital incomes, etc.), it is possible to decompose inequality measures and, of course, the Gini index by the contribution of each income source to the inequality.

The Gini index is additively decomposable by income sources, that is, the overall inequality can be broken up into the contribution of each income source (Rao, 1969):

$$R = \sum_{j=1}^{k} F_j = \sum_{j=1}^{k} q_j R_j \, E_j.$$

The contribution of each income source ($j = 1, \dots, k$), F_j, is given by the product of three factors:

- q_j, the ratio between the mean income of the source j and the population mean;
- R_j, the Gini index computed only on the incomes of the source j;
- E_j ($-1 \leq E_j \leq 1$), the ratio between the inequality index calculated with (3) for the source j in accordance with the ranking established on the basis of the total income and the Gini index calculated for the source j in accordance with its own internal ranking, R_j. It is equal to 1 only when the ranking within source j coincides with the total income one. E_j plays a crucial role and occurs in several studies on the decomposition by income sources of the Gini index. It provides a measure of the "disequalizing effect" induced by the source j in the income distribution. It has been independently obtained by several scholars, such as Fields (1979a, 1979b) that proposed the Factor Inequality Weights (FIW) and named it "relative coefficient of variation" and by Lerman and Yitzhaki (1985) and Schechtman and Yitzhaki (1987) who named it "Gini correlation". Furthermore, since q_j and R_j are not negative, E_j provides the sign of the contribution of the source j. When it is negative, the source j reduces the total inequality. On the contrary, when it is positive it contributes to increase the total inequality.

4.2. Decomposition by sub-population

When income data are gathered together with individuals characteristics such as age, sex, level of education, geographical area, etc., it is possible to explore the contribution of each population subgroup – identified by these features – to total inequality (see for more details, Deutsch and Silber 1999; Mussard *et al.* 2006).

Bhattacharya and Mahalanobis (1967) were the first to try decomposing R by population subgroups. They attempted to decompose the Gini index as in the ANalysis Of VAriance (ANOVA), that is, into the sum of within (w) and between (b) components. However, they discovered that R cannot be additively decomposed in this way. This overshadowed the Gini index with respect to other indices that instead are additively decomposable in terms of the analysis of variance, such as the Theil index and the entropy index, at least till Mehran (1975) showed that R can also be decomposed additively. In order to do so, it is necessary to take into account the within component (w) and the across component (a) defined as $a = b + i$, where i is the interaction,

$R = w + b + i.$

The interaction component is “a measure of the extent of income domination of one group over the other apart from the differences between their mean incomes” (Mehran, 1975, p.148).

From that moment on, different methods for additively decomposing the Gini index have been proposed. Frick *et al.* (2006) exploiting the results by Mehran (1975) and by Yitzhaki (1994), proposed the ANalysis Of the Gini Index (ANOGI). according to which the Gini index is decomposed by between (b), within (w), overlapping between (ob) and overlapping within (ow) components:

$R = w + ow + b + ob$

The two additional elements, ow and ob[4], are functions of the overlapping, a measure and a concept introduced in the literature on the Gini index by Yitzhaki and Lerman (1991). The overlapping represents the extent by which one subgroup is overlapped by the other. When there is no overlapping, a population is stratified, that is, there is a kind of “segregation” between the subgroups with respect to the income distribution. Therefore, this measure has very important and practical economic implications. In fact, a stratified society, in which the membership of a group automatically precludes certain incomes to its members, can bear less inequality and takes more the risk of instability. Stratification is both the cause and the consequence of inequality. Furthermore, this type of information cannot be captured by the inequality measures that are additively decomposable. In the end, what initially looked like a drawback for the Gini index is one of its strengths. However, to be precise and exhaustive, the concept of overlapping is close to the concept of “transvariation” already grasped by Gini (1916) (see also Pittau and Zelli, 2017).

It is possible to obtain an interesting decomposition of the Gini index also applying the concept of Shapley value in cooperative game theory (Shapley, 1953). The Shapley value provides the marginal impacts of some components, suitably chosen, which play in determining a profit function. Deutsch and Silber (2007) in their work put down the Gini index as the profit function and consider the components within (w), between (b), ranking (r) and the relative size in each population subgroup (n) (see also Shorrocks, 1999). So, they additively decompose R as:

$R = w + b + r + n.$

Finally, another interesting result, that goes by the name of Balance Of Inequality (BOI) decomposition, has been proposed by Di Maio and Landoni (2015). The

[4] In general, ob is negative because the overlapping reduces the differences between subgroups.

interest in this work is twofold. First, they demonstrate that R in (2) coincides with the normalized barycenter of the income distribution, the BOI. This provides, if additional proof were needed, the extraordinariness of the Gini index which also has a physical interpretation. Then, they propose a decomposition that, besides the components within (w) and between (b), consider the asymmetry ($asym$) and irregularity[5] (irr). Therefore,

$$R = BOI = w + b + asym + irr.$$

5. Inference

The study of the sampling properties of the Gini index is a very interesting and prolific research field that has remained uncharted for a long period, at least by Italian statisticians. In fact, Gini was very critical of statistical inference and the attitude of such recognized authority like him, who had a great impact on the Italian school of statistics, which for many years neglected almost completely this topic and, therefore, the study of the inferential aspects of the Gini index (Piccinato, 2011). Then, the first attempts of studying the sampling properties of R were by non-Italian scholars. Furthermore, inference on the Gini index is a tricky problem and this generated a large number of publications and a large number of mistakes, often even re-published in the literature. For the sake of brevity, parametric inference and finite population inference are here considered.

5.1. Parametric inference

Parametric inference aims to express the Gini index as a function of parameters in theoretical distributions. This is useful for facing inferential problems but also the problem of missing data, especially at the top of the distribution, and, then, for imputing the data and improving the estimates.

The expression of the Gini index has been already determined under several continuous theoretical distributions, such as Pareto (Michetti and Dall'Aglio, 1957; Girone, 1968), exponential (Cicchitelli 1968), lognormal (Langel and Tillé, 2012). Giorgi and Nadarajah (2010), in a very extensive work, determined the expression of R under thirty-five continuous distributions.

Under discrete distributions, Conti and Giorgi (2001) suggested using a kernel estimation for filling the gap between observations. They proposed a two steps procedure: in the first step, the unknown population distribution is estimated via a kernel method; in the second step, the kernel estimate of the density is used to produce an estimate of the Gini index.

[5] The income distribution is regular if the distance between two adjacent recipients in the population or in the subgroup is constant.

5.2. Finite population inference

Finite population inference deals with the sample surveys commonly carried out for collecting income data on which the Gini index is usually computed.

The Gini index is a non-linear statistic, since it is based on rank statistics, therefore its variance is not straightforward, especially under complex sampling designs. Three main lines of research can be distinguished in the finite population framework: (i) asymptotic theory, (ii) linearization methods, (iii) resampling methods.

In the asymptotic theory, the properties of an estimator are studied for n that going to infinity. The first attempt of studying the inferential properties of the Gini index is framed within this framework and traced back to Hoeffding (1948). There were also prior attempts in the same framework, but they had focused on the numerator of the Gini index, the mean difference (such as Nair, 1936). Instead, Hoeffding showed, as part of an application of his general results, that the Gini index is a ratio of two U-statistics and that under certain conditions, it is asymptotically normal. The same result has been obtained with different procedures by other scholars (see Giorgi and Gigliarano 2017 for further details).

Linearization methods include a range of techniques (such as Taylor series expansions, estimating equations, influence function, indicator variables). The basic idea of these techniques is to approximate the variance of a non-linear statistic, like R, through the variance of the total of a linear function of the observations, i.e., a linearized variable. All the linearization techniques have been applied to the Gini index, but with mixed success (see Langel and Tillé, 2013). The method, currently used by Eurostat in the estimation procedure for computing the sampling error of the Gini index on Eu-Silc[6] income data, has been developed by Osier (2009). This method uses the influence function, already known in the field of robust statistics, as artificial variables for approximating the variance of non-linear statistics (Deville, 1999) and, therefore, also of the Gini index. However, the linearized expression of R obtained with the influence function and used by Osier (2009) was not new and was initially determined by Monti (1991). Vallée and Tillé (2019), used the method proposed by Graf (2011) based on the Taylor series expansion with respect to indicator variables, for dealing with the cases in which the Gini index is computed in the presence of non-response and re-weighting procedures, such as calibration. Also, resampling methods have been applied in the last fifty years for estimating the variances of the Gini index. Manfredi (1974) was the first to use the jackknife method followed by, among others, Yithzaki (1991) who proposes an estimator

[6] European Union Survey on Income and Living Conditions. For further details, please see the material on this link <https://ec.europa.eu/eurostat/web/microdata/european-union-statistics-on-income-and-living-conditions>.

based on the influence function. Moreover, Dixon *et al.* (1987) were the first to use bootstrap. Most recently, Antal and Tillé (2011) derive a time-efficient bootstrap method useful under classical sampling designs.

6. Conclusions

The Gini index is the most famous and widely used inequality measure. Since its first proposal, it has been subject of numerous publications. Nowadays, after more than one century, it is still a matter of great interest. Hence, it is important to keep track of the oceanic quantity of papers already written and, moreover, be able to navigate among them.The present paper represents an attempt to clarify and resume some aspects related to the origin, the decomposition and the inferential aspects of the Gini index. Of course, the topics and the literature covered represent only the tip of the iceberg. Several interesting topics have been overlooked just for reasons of space. Anyway, this paper hopefully could be a useful starting point for scholars approaching this topic.

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This paper is an attempt to resume in few pages some of the main knowledge, notions and curiosities on the Gini index that Prof. Giovanni Maria Giorgi attempted to convey to me from 2010 until the day before his departure. So, this paper is a simple way to thank him for all the teachings I received and simply a first attempt to not waste his immense knowledge on this topic.

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SUMMARY

The present paper retraces a few of the main lines of research related to the Gini index, pointing out the most important results and the reference works, as well as some errors, several times published and re-published in the literature. It can be seen as a short compendium, based on the works, teachings and discussions of Prof. Giovanni Maria Giorgi.

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