Chapter 3:

The Gini Index: A Modern Measure of Inequality

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Synopsis

The Gini index is the most widely accepted inequality measure across the Globe, with almost all governmental and international agencies using it to summarise income or wealth inequality in a nation or the world. Although originally developed to be a standardised measure of statistical dispersion intended to understand income distribution, the Gini index has evolved into quantifying inequity in all kinds of distributions of wealth, gender parity, access to education and health services, and environmental policies, among others. In this work, we present the original Gini index, as well as some of the various existent alternative Gini formulations, while also exploring various traditional and modern applications of the index in different settings, at national and international levels. We further discuss the implications of the traditional Gini index for international diplomacy and policymaking and conclude with some future directions on the topic.

Keywords: Gini index, inequality, wealth, income distribution, policymaking.

1. Introduction

Inequality among people has always been a problem but has become more salient in recent years. Indeed, data and research show that the degree of inequality has increased in most countries around the world, which in turn, has generated concerns both from the perspective of the sustainability of economic growth, as well as from the perspective of social cohesion and well-being.

In economics, the Gini index or coefficient (also known as the Gini ratio), is a measure of statistical dispersion intended to denote the income inequality or the wealth inequality within a nation or a social group. Figure 1 shows the world map of the Gini indices by country, as of 2021, with higher values indicating greater inequality.

To be noted that income distribution can vary greatly from wealth distribution in a given country; by all accounts, in practice, income and wealth are two distinct concepts. For example, the income originating from the black-market economic activity, a subject of current economic research, is not included.
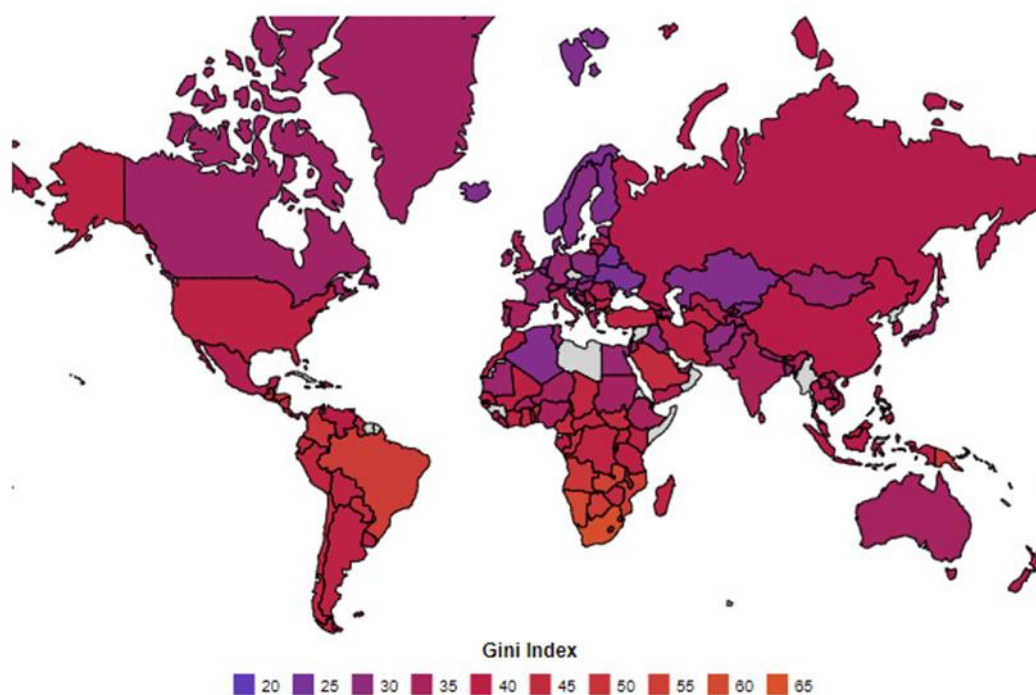
Figure 1. Gini indices by country 2021. Source:
https://worldpopulationreview.com/country-rankings/gini-coefficient-by-country

The Gini index has been most widely used in the field of economics. However, fields as diverse as sociology, health science, ecology, engineering, and agriculture have also benefited from the same (Sadras & Bongiovanni, 2004). The existing literature demonstrates the breadth of applications of the Gini index. As with any other index, the Gini index has been used by a range of actors, from governments to national and international organisations and businesses alike, to monitor income inequality within a given country or across countries.

For policymakers, the Gini index plays a vital role, as it can assist in determining where resources and support are most needed. For example, the Pan American Health Organization (PAHO) uses a Sustainable Health Index (SHI), which contains the Gini index as one of its components, in order to allocate its budget among its member states. It is worth mentioning that this budget policy formula is composed by a floor component (core staff and general operating expenses), a needs-based component (SHI), a resource mobilisation component (ability to raise resources by a country), and a variable component (to address emergent situations that may not be reflected in the needs-based calculation, for example, natural disasters, epidemics, and so on) (PAHO, 2019).

In view of the above, the Gini index is more relevant today than ever before, being a powerful inequality measure and the most popular of all to help understand the economic diversity of an area, especially when used along with additional data on income, education, and poverty, among others. In this work, our aim is to present the original Gini index, as well as some of the various existent alternative Gini formulations, while also exploring various traditional and modern applications of the index in different settings, at national and international levels. We further discuss the implications of the traditional Gini index for international diplomacy and policymaking and conclude with some future directions on the topic.

2. History of the GINI Index

The Gini index is a commonly used objective measure of inequality (Wu & Chang, 2019), which was first introduced by the Italian statistician Corrado Gini (Gini, 1912, cited in Luebker, 2010). It can theoretically take any value between zero (perfect equality, *i.e.*, everybody has the same income) and one (perfect inequality, *i.e.*, all income goes to a single person) (Luebker, 2010, p. 1). In other words, the Gini index measures the degree of wealth concentration among citizens on a 0-1 scale, wherein a Gini index of 1 indicates the most unequal situation, in which all income is owned by a single person and all others have nothing (Wu & Chang, 2019, p. 1479).

2.1. Uses and Purposes of the Gini Index

It is widely acknowledged that both growth and equity play a role in poverty reduction. Since economic and financial crises have undermined development prospects over time, many policymakers have revived their focus on greater equity as a means out of poverty (Luebker, 2010, p. 6). As a result, the Gini index becomes even more vital and relevant.

Ceriani and Verme (2015) defined the Gini index as the sum of individual contributions where individual contributions are interpreted as the degree of diversity of each individual from all other members of society (p. 637). As the authors further elegantly highlighted, "one cannot talk of individual inequality but one can talk of individual diversity and it can be reasonably argued that the sum of individual income diversities in a given population is one possible measure of societal income inequality" (p. 638).

The Gini index (just like the Bonferroni index and the De Vergotinni index) can be interpreted as a measure of social deprivation, as well as a measure of social satisfaction. The absolute Gini index is a measure of mean social deprivation or mean social satisfaction when an individual (a) considers the whole distribution when he compares his/her income with each and all of the incomes of others and (b) he/she does not identify

with any group (Imedio-Olmedo *et al*., 2012, pp. 479, 484). Imedio-Olmedo *et al*. (2012) argued that "the social deprivation and social satisfaction measures are the expected value of the functions that assign deprivation or satisfaction to each income level. However, when aggregating these two concepts along the income distribution, a policymaker may want to discriminate between different parts of the distribution by attaching different weights. This can be done by computing the mean social deprivation or the mean social satisfaction as weighted means using different weighting profiles" (p. 485). Because of the relationship between deprivation, satisfaction, and inequality, inequality indices in general can be thought of as aggregate measures of the feelings of people who perceive themselves to be disadvantaged or advantaged in terms of income (Temkin, 1986, 1993).

2.1.1. Advantages of the Gini Index

Among the advantages of the Gini index are:

a.   The Gini index is a prominent measure of income or wealth inequality, with relevancy at an international level. The Gini index is used by almost all governmental and international bodies to summarise income inequality in a country or the world (Liu & Gastwirth, 2020, p. 61). It will not be an overstatement to say that the Gini index is the most widely accepted across the Globe.

b.   Although originally developed to be a standardised measure of statistical dispersion intended to understand income distribution, the Gini index has evolved to quantify inequity in all kinds of wealth distributions, gender parity, access to education and health services, and environmental regulations, among others (Mukhopadhyay & Sengupta, 2021).

c.   Also, it is worth noting that the appeal of the Gini index comes from its simplicity, as it condenses a country's total income distribution on a scale of 0 to 1; the higher the number, the higher the degree of inequality (Adeleye, 2018, cited in Osabohien *et al*., 2020, p. 581). It is, therefore, quite easy to interpret, helping in easily drawing conclusions.

d.   Its popularity also comes from the fact that as the amount and quality of inequality data have increased, the Gini index, in particular, has become a 'cross-over statistic', known and understood by non-specialists (Moran, 2003, p. 353).

e.   There are a variety of summary measures of inequality (please see Table 1 below, compiled by Kokko *et al*., 1999), each with its own set of assumptions and mathematical properties. Only two of these, however, the Gini index and Henri Theil's (1967 cited in Moran, 2003, p. 373) entropy measure, satisfy the five most sought-after features or properties. In order to satisfy these properties, an inequality indicator must be: (1) symmetrical, (2) income scale invariant, (3) invariant to absolute population levels, (4) defined by upper and lower bounds, and (5) able to satisfy the Pigou-Dalton Principle of Transfers, which states that any redistribution from richer to poorer reduces inequality and vice versa. To satisfy the transfer principle, inequality measures must reflect any income transfer, regardless of where it occurs in the distribution. None of the other summary metrics have all of these properties (Moran, 2003, pp. 355, 373).

Table 1
Measures of Inequality

Measure	Equation
Sample variance, s_y^2	$\frac{1}{n-1}\sum_{i=1}^{n}(y_i-\bar{y})^2$
Index of dispersion, I	$\frac{s_y^2}{\bar{y}}$
Coefficient of variation, CV	$\frac{s_y}{\bar{y}}$
Morisita coefficient, I_δ	$\frac{n}{(n\bar{y})^2-n\bar{y}}\sum_{i=1}^{n}y_i^2-n\bar{y}$
Standardized Morisita coefficient, I_p	See Krebs (1989) or Tsuji and Tsuji (1998) for adjustment procedure
Herfindahl index, H (or Simpson's index, S)	$\sum_{i=1}^{n}p_i^2$
Bradbury's bounded skew index, B (originally: H)	ns_p^2
Keller's weighted skew index, W	$\frac{n_0+n_+B_+}{n_0+n_+}$, where $B_+ = \begin{cases} n_+s_{p+}^2 & if\ n_+ > 1 \\ 1 & if\ n_+ = 1 \end{cases}$
Keller's corrected skew index, $\widetilde{W}$	$\frac{W-\mathrm{E}[W|H_0]}{1-\mathrm{E}[W|H_0]}$
Kokko's iterative skew, K_{med} (originally: λ)	Iterative solution of $y_i \sim \frac{K(1-K)^{i-1}}{1-(1-K)^n}$ such that resampled s_y^2 agrees with observed value
Hovi's mean error skew, M	$\frac{n}{2}\times\frac{1}{n-1}\sum_{i=1}^{n}|p_i-\bar{p}|$
Pamilo's linear skew, L (originally: S_3)	$\frac{1}{n-1}\left[n-\left(\sum_{i=1}^{n}p_i^2\right)^{-1}\right]$
Pietra ratio ("Robin Hood index"), P	$\max_{j=1,\dots,n}\left|\sum_{i=1}^{j}p_i - \frac{j}{n}\right|$
Alatalo's cumulative skew, C_t	$\sum_{i=1}^{\frac{nt}{100}}y_i$, where t is a threshold ($0 < t < 100$)
Poissonian deviance, δ	$s_y^2 - \bar{y}$
Index of monopolization, Q (Green's coefficient, F)	$\frac{s_y^2-y}{n\bar{y}^2-\bar{y}}$
Lloyd's mean crowding index, m^*	$\bar{y} + \frac{s_y^2}{\bar{y}} - 1$
Gini coefficient, G	$\frac{1}{2n^2\bar{y}}\sum_{i=1}^{n}\sum_{j=1}^{n}|y_i-y_j|$
Theil index, I_v	$\ln(n) + \sum_{i=1}^{n}p_i\ln(np_i)$
Moment skewness, g_1	$\frac{n}{s_y^3(n-1)(n-2)}\sum_{i=1}^{n}(y-\bar{y})^3$
L-moment skewness, g_L	$\frac{2w_2-\bar{y}}{6w_3-6w_2+\bar{y}}$, where $w_2 = \frac{1}{n(n-1)}\sum_{i=2}^{n}(i-1)y_i$ and $w_3 = \frac{1}{n(n-1)(n-2)}\sum_{i=3}^{n}(i-1)(i-2)y_i$ with y_i ordered: $y_1 \leq y_2 \leq \cdots \leq y_n$

Source: Kokko *et al.* (1999, pp. 362-363).

f.   The Gini index satisfies the following four essential conditions which are frequently imposed on any good poverty index: (1) Continuity (Gini values for closed distributions are similar); (2) Anonymity (the invariance of the Gini index to a

permutation of the income values); (3) Invariance when the income measure scale is changed; and as aforementioned (4) the Dalton-Pigou transfer principle. However, it is noteworthy that these four essential requirements are insufficient for choosing an acceptable poverty indicator (Stefanescu, 2011, pp. 256-257).

2.1.2. Disadvantages of the Gini Index

Among the disadvantages of the Gini index are:

a. The Gini index does not directly reflect people's views on income distribution (Wu & Chang, 2019, p. 1479). Specifically, Gimpelson and Treisman (2018, cited in Wu & Chang, 2019, p. 1479) found that the Gini index is not related to people's support for redistribution. Instead, as the perceived levels of inequality rise, so do the demands for redistribution (Wu & Chang, 2019, p. 1479).

b. Mathematically, the Gini index is most sensitive to income transfers towards the middle of the distribution, whereas Theil's index, for example, becomes progressively receptive to transfers near the lower end of the income scale (Allison, 1978, cited in Moran, 2003, p. 373).

c. The Gini ratios' absolute magnitudes are not consistent across surveys or in view of changes in measurement specifications within surveys (Moran, 2003, p. 364).

d. The Gini index has often been chastised for yielding results that are equal when calculated from two different distributions (p. 61). However, Liu and Gastwirth (2020) showed that expecting a single measure to completely describe the entire income distribution is unrealistic. As a result, researchers may benefit from combining the Gini index with another measure that emphasises the section of the underlying distribution that is most important to the research problem. For instance, Foster and Wolfson (2010, cited in Liu & Gastwirth, 2020, p. 68) combined the Gini index with the relative median deviation, *i.e.*, $(\mu_U - \mu_L)/\mu$, where μ_U is the mean of those above the median and μ_L is the mean of those below the median, to measure the polarisation of an income distribution.

e. Needless to say, on its own, the Gini index presents a narrow view of overall inequality prevailing in a society and does not measure the quality of life.

2.2. Construction of the Gini Index to Measure Inequality

2.2.1. Data and variables used in the index system

Some authors utilise Gini indices that have been derived directly from a household survey to measure income distribution disparity, using household per capita income as a welfare indicator (Székely & Mendoza, 2015, p. 399).

It should be noted that the sensitivity of all inequality measures to the measurement choices on which they are based is one of the most important yet ignored elements of all inequality measures.

The choice of income-receiving unit (*e.g.*, households, person equivalents) is statistically as well as conceptually significant, yet it is a topic that is frequently disregarded in inequality studies. Adopting a larger unit should, on the surface, reduce the degree of assessed disparity because the incomes of the various members are essentially averaged (Moran, 2003, pp. 358-359).

Different aggregations of the same distribution will return conflicting Gini ratio estimations, similar to discrepancies in receiving units. Even if the poorest population quintile has the same number of households as the highest quintile (*e.g.*, both 20%), it may (and often does) contain fewer people of working age, and thus the quintile's low overall income can be attributed in part to having comparatively fewer income-receiving people (Moran, 2003, p. 360).

The next methodological concern is agreeing on a definition of 'income' after the receiving unit has been decided and the level of aggregation has been established. The more progressive and effective the national tax system is, the more crucial it is to quantify income in pre- or post-tax statistics for inequality measurements. Estimates of inequality based on gross income should, by definition, provide larger Gini indices than those based on income net of taxes, especially in developed countries with progressive tax systems. Significant discrepancies in inequality measurements could also be due to how non-monetary expenditures are accounted for (such as in-kind government transfers and benefits) (Moran, 2003, p. 360).

Although Gini indices are commonly employed to measure income disparity, some relate to market earnings (*i.e.*, income before taxes and transfers) and others refer to disposable incomes (*i.e.*, income after taxes and transfers). Calculating Gini indices for wages or earnings, while omitting income from other sources, can be useful at times. Furthermore, Gini indices can be calculated using consumption or expenditure data (rather than income), or taxable income can be calculated using tax records. They can also be computed for other types of distributions, such as wealth or land ownership (Luebker, 2010, p. 1).

Gini indices are reported exclusively by most major cross-national data aggregates, and they are regularly released by both national statistical agencies like the UK Government Office of National Statistics and the US Census Bureau, as well as international development organisations like the United Nations and the World Bank (Moran, 2003, p. 353).

The European Union's statistical office, EUROSTAT, calculates a standard Gini index, which measures how far a country's wealth distribution deviates from a fully equal wealth distribution, with 0 representing complete equality and 100 indicating complete inequality when expressed in percentages (Tammaru *et al.*, 2019, p. 6; EUROSTAT, 2021).

As a particular case, there are some differences and similarities between the Gini index published by the Organisation for Economic Co-operation and Development (OECD) and the one published by the National Institute of Statistics and Informatics (INEI, for its acronym in Spanish) in Peru, a developing country in Latin America. In this sense, although the Gini index published by INEI showed a decreasing trend from 2007 to 2017 (Castillo, 2020, p. 4), the level of inequality in Peru was higher than the levels of

inequality in countries from the European Union, members of OECD (Yamada *et al*., 2016, p. 4).

INEI measured inequality both for real household income and expenditure per capita using data from the National Household Survey of Peru (ENAHO, for its acronym in Spanish; Castillo, 2020, p. 3). Also, INEI (2018, cited in Castillo, 2020, p. 5) published the Gini estimates for real household income per capita at the regional level, using for its classification a geographical criterion. In Peru, there are three main geographical regions: the Coast, the Highlands, and the Jungle. According to INEI (2018, cited in Castillo, 2020, p. 5), the Coast appears to be the most equal, while there is no clear dominance between the Highlands and the Jungle.

The measurement of per-capita income used by INEI to calculate the Gini index was obtained after adding the following income components at the household level (A+B+C+D), dividing this addition by the number of the household members, and deflating the result in order to express it in terms of prices from the Lima Metropolitan area in 2014 (Yamada *et al*., 2016, pp. 6-7):

A. Income from Employment comprises salaries received from the main and secondary employment activities, including extra payments and commissions, whether the individual is an employee or involved in self-employment jobs. Also, it includes goods and services produced for own consumption (mainly, from agriculture), extraordinary payments (gratuities, bonuses, and termination pay), and payments made with free or subsidised goods.

B. Property income includes interests from financial assets, royalties and income from properties, and payments received for the use of properties.

C. Private Monetary Transfers include transfers from resident and non-resident private agents (specifically, remittances), but none of them includes employment pensions.

D. Private Non-Monetary Transfers comprise transfers from private institutions including non-governmental organisations (NGOs).

Nevertheless, OECD defined income and its components based on the principle of disposable income. Therefore, OECD considered the following sources of income, which were not considered by INEI (Yamada *et al*., 2016, p. 7):

E. Public Monetary Transfers or Transfers received from Social Security refer to transfers delivered by the government in order to subsidise the population in poverty or the target population according to the type of programme.

F. Public Employment Pensions received by retired workers.

G. Workers' Contributions paid through pension schemes to which the individual is affiliated when accessing the employment market.

H. Direct Taxes paid proportionally to the individual income.

These differences and similarities regarding the sources of income considered by INEI and OECD are shown in Table 2 below (Yamada *et al*., 2016, p. 8).

Table 2. Composition of income per capita by methodology of measurement

	Sources of income	INEI	OECD
A.	+Income from employment	x	x
B.	+Property income	x	x
C.	+Private monetary transfers	x	x
D.	+Private non-monetary transfers	x	
E.	+Public monetary transfers		x
F.	+Public employment pensions received		x
G.	-Workers' contributions paid		x
H.	-Direct taxes paid		x

Source: Yamada *et al*. (2016, p. 8).

Furthermore, OECD used the following formula to calculate the disposable income adjusted per capita (Yamada *et al*., 2016, p. 8):

$$\frac{Y_i}{S_i^\epsilon},$$

where Y_i is the total disposable income in household i, S_i is the number of household members, and ϵ is defined as the equivalent elasticity.

2.2.2. Methods to compute the Gini index

The Gini index is conceptualised geometrically in terms of the quintile-quintile plot, often known as the Lorenz curve. The Gini index is defined as the ratio of the area between the Lorenz curve and the diagonal (area A) to the total area under the diagonal (area A + B), as shown in Figure 2. The Gini indices can range from 0 (complete equality, area A = 0 and the Lorenz curve follows the 45° diagonal, so that 20% of the population receives 20% of total income and so on) to 1 (total inequality, all of the area A + B). Greater differences between a given distribution and the criterion of complete equality are represented by higher Gini ratios (Moran, 2003, pp. 354-355).
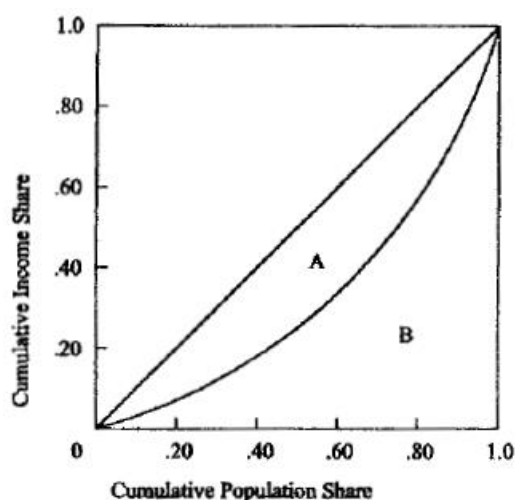

Figure 2. Lorenz curves.

The Gini index (G) is determined mathematically as the average of the absolute value of the relative mean difference in incomes between all possible pairs of individuals, as shown in the equation below (Osberg, 2017, p. 575):

$$G = \frac{1}{2\bar{y}.n.(n-1)} \sum_{i \neq j}^{n} \sum_{j}^{n} |y_i - y_j|$$

where $y_i, y_j = income\ of\ individuals\ i\ and\ j$, $n = total\ population\ size$, and $\bar{y} = average\ income\ of\ all\ individuals$.

Alternatively, if we let y_i designate a random distribution such as income, let $\pi = F(y_i)$ indicate the distribution for y_i, and let $\eta = F_1(y_i)$ represent the corresponding first moment distribution function, then the relation between η and π, defined for $0 \leq y_i < \infty$, is the Lorenz curve, and the relation can be denoted by $\eta = L(\pi)$. Thus, the Gini index can be defined accordingly (Liao, 2006, pp. 203-204):

$$G = 1 - 2 \int_0^1 L(\pi) d\pi$$

Outside of the economics field, the Gini index is significantly less well-known, and even within economics, different indices of inequality are frequently used to substitute the Gini index. The critiques regarding the Gini index's computability are one explanation for this (Furman *et al.*, 2019, p. 1). In their note, Furman *et al.* (2019) proposed an alternate expression and interpretation of the Gini index based on the concept of a size-biased distribution (p. 1). The authors demonstrated that the Gini index, as opposed to the distribution of the actual wealth (random variable X), measures the size-bias hidden in the random sample distribution (random variable Y*). The closer the Gini index value is to zero, the more accurate the sampling technique (in terms of size bias) is (p. 2).

Since its inception, the Gini index has been reformulated in a variety of ways that can be stated as sums of individual observations throughout the population and that reflect various individual functions. These formulations are listed in Table 3, considering a population of N individuals, $i = 1, 2, ..., n, n \in \mathbb{N}, n \geq 3$, and an income distribution $Y = (y_1, y_2, ..., y_i, ..., y_n)$, where $Y \in \mathbb{R}_{++}^n$, $y_1 \leq y_2 \leq \cdots \leq y_n$, μ_Y and y_M are, respectively, the arithmetic mean and the median of distribution Y, and M is the rank of the individual with the median income (Ceriani & Verme, 2015, pp. 639-640):

Table 3
Alternative Gini Formulations

Gini index	Individual diversity	Alleged original proponent	Form
$G^I = \frac{1}{n^2 \mu_Y} \sum_{i=1}^{n} \frac{(n+1-2i)(y_{n-i+1}-y_i)}{2}$	$g_i^I = \frac{(n+1-2i)(y_{n-i+1}-y_i)}{2}$	Gini (1912, 1914)	Original
$G^{II} = \frac{1}{n^2 \mu_Y} \sum_{i=1}^{n} 2(i-M)(y_i-y_M)$	$g_i^{II} = 2(i - M)(y_i - y_M)$	Gini (1912)	In terms of distances from the median

$G^{III} = \frac{1}{n^2\mu_Y}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{|y_i - y_j|}{2}$	$g_i^{III} = \sum_{j=1}^{n}\frac{|y_i - y_j|}{2}$	Kendall and Stuart (1958)	Adjusted Gini
$G^{IV} = \frac{1}{n^2\mu_Y}\sum_{i=1}^{n}(n+1)\mu_Y - 2(n+1-i)y_i$	$g_i^{IV} = \mu_Y - 2(n+1-i)y_i$	Sen (1973)	Geometric
$G^{V} = \frac{1}{n^2\mu_Y}\sum_{i=1}^{n}\sum_{j>i}(y_j - y_i)$	$g_i^{V} = \sum_{j>i}(y_j - y_i)$	Yitzhaki (1979)	Deprivation
$G^{VI} = \frac{1}{n^2\mu_Y}\sum_{i=1}^{n}2iy_i - (n+1)\mu_y$	$g_i^{VI} = 2iy_i - (n+1)\mu_Y$	Anand (1983)	Covariance
$G^{VII} = \frac{1}{n^2\mu_Y}\sum_{i=1}^{n}(2i-n-1)y_i$	$g_i^{VII} = (2i-n-1)y_i$	Silber (1989)	Matrix
$G^{VIII} = \frac{1}{n^2\mu_Y}\sum_{i=1}^{n}2i(y_i - \mu_y)$	$g_i^{VIII} = 2i(y_i - \mu_Y)$	Shorrocks (2013)	In terms of distances from the mean

Source: Ceriani and Verme (2015, p. 640).

Ceriani and Verme (2015) proved that, among these eight possible formulations of the Gini index, only the index of individual diversity g_i^{III} satisfies the desirable properties that a measure of individual diversity should have, which are the following: Continuity, Additivity, Linear homogeneity, Translation invariance, Symmetry, and Anonymity (pp. 642-643). The definition of individual contribution to inequality proposed in the paper allows for a distinct type of additive Gini index decomposition by population subgroups. Individual contributions to the Gini index are seen as a measure of individual variety. We can simply sum up the individual values by group to get the Gini value when we aggregate these individual degrees of diversity across groups such as males and females. When we divide Gini's share by group, we get an exact subgroup decomposition (p. 644).

It is worth pointing out that there exists a long-standing stream of literature discussing how to decompose the Gini index, although such treatment is outside the scope of the present manuscript. For example, more recently, Sarntisart (2020) proposed a novel method that divides the Gini index into *within-subgroup* and *across-subgroup* components, which was then applied to the case of Thailand during the years 2009–2017.

2.2.3. Limitations and difficulties related to the construction and interpretation of the Gini Index

A relevant question that gets asked and over which there is still debate going on among specialists is: when is the Gini index big enough to represent a 'high' level of inequality? "Because summary measures of inequality are not associated mathematically with probability functions, or theoretically with sampling distributions, their magnitude and change can only be interpreted using subjectively defined criteria. Once we are satisfied that differences in Gini ratios can not be attributed to methodological choices, we are left with no objective, scientific method to assess whether these differences in measured inequality are 'statistically significant' – large enough to rule out measurement error, sampling error, or random chance – or whether they are 'substantively meaningful' – large enough to signal a material shift in the way society distributes income" (Moran, 2003, p. 365).

Moran (2003) goes on to state that "like other statistics involving subjective interpretation, the magnitude of inequality represented by Gini can only be assessed in relation to the Gini ratio of other units, and even in these situations, we can only imprecisely conclude which Gini ratios fall toward the 'high' or 'low' end historically. In

the presence of intersecting Lorenz curves, even this comparison can at times be problematic" (p. 365).

3. Traditional Views and Applications of the Gini Index

As previously stated, inequality measures have been used in the economics field ever since the seminal study conducted by Gini (1912), which proposed an income inequality index. A substantial part of the literature, therefore, is dedicated to what can be called the "traditional Gini index". Below, we explore some of the most recent literature in this regard, across countries.

For example, Chauhan *et al*. (2016) aimed to provide a comparable estimate of poverty and inequality in the regions of India over the past two decades. The unit data from three quinquennial rounds of consumption expenditure survey, *i.e.*, 1993–1994, 2004–2005, and 2011–2012, were used in the analysis. Thus, the authors estimated the extent of money metric poverty and inequality in the regions of India, based on these three quinquennial rounds. The Gini index, rich–poor ratio, and regression analyses were used in the process to understand the extent of economic inequality in the regions of India (pp. 1249, 1253). The comparable estimates were provided for 81 regions of India to the extent possible for rural and urban areas as well otherwise for overall areas (p. 1253). Results indicated that although the extent of poverty declined, economic inequality increased in the regions of India. By contrast to poverty estimates, the Gini index decreased in 20 regions and increased in 61 regions. Based on these findings, the authors suggested that the regions with persistently high poverty be accorded priority in the poverty alleviation programme, while also exploring the factors leading to increasing economic inequality (pp. 1249-1250).

The work by Osabohien *et al*. (2020) measured inequality using the Gini index and examined how social protection policies and programmes can help in poverty and inequality reduction in Africa (p. 575). The study covered 38 African countries and engaged the fixed and random effects models utilising data sourced from the World Development Indicators, International Country Risk Guide, and the Country Policy and Institutional Assessment, for the period 2005–2017 (pp. 575, 581, 585). Results showed that a 1% increase in the provision of social protection would decrease poverty and inequality by 58% and 26%, respectively. The authors also showed that the type of social protection policies may need to differ from one region to the other (p. 575).

Zaborskis *et al*. (2019) aimed to compare socioeconomic inequality in adolescent life satisfaction across countries employing different measures, as well as to determine the correlations between outcomes of tested measures and country level socioeconomic indices (*e.g*., Gross National Income, Gini index, and so on; p. 1058). The paper introduced several methods for measuring family affluence inequality in adolescent life satisfaction and assessed its relationship with macro-level indices (p. 1055). The Gini index served as an indicator of country-level economic inequality. The data were collected in 2013/2014 in 39 European countries, Canada, and Israel, and were obtained from the Health Behavior in School-aged Children study, a cross-national survey with support from the World Health Organization (pp. 1055-1056, 1058). The 11-, 13-, and 15-year olds were surveyed by means of self-report anonymous questionnaires. Fifteen methods controlling for confounders (family structure, gender, and age were regarded as confounders) were tested to measure social inequality in adolescent life satisfaction (pp.

1056, 1072). The study found that gender, age, and family structure all played a role in defining inequities in adolescent life satisfaction, though to a lesser extent than family affluence (p. 1072). All metrics in each country showed that adolescents from more affluent homes were happier with their lives than those from less affluent families.

According to Poisson regression estimates, adolescents in Malta have the lowest level of life satisfaction inequality, whereas adolescents in Hungary have the highest level of life happiness disparity (p. 1056). The ratio between the mean values of the life satisfaction score at the extremes of family affluence (Relative Index of Inequality) derived from regression-based models is notable for its positive correlation with the Gini index and negative correlation with Gross National Income, Human Development Index, and the mean Overall Life Satisfaction score. From a cross-national viewpoint, the measure permitted the in-depth examination of the interplay between individual and macro-socioeconomic determinants affecting adolescent well-being (p. 1056).

In their paper, Panzera and Postigione (2020) introduced a new measure that facilitates the assessment of the relative contribution of spatial patterns to overall inequality. The proposed index is based on the Gini correlation measure, accounts for both inequality and spatial autocorrelation, and introduces regional importance weighting in the analysis, which distinguishes the regional contributions to overall inequality (p. 379). In the approach of this paper, the spatial Gini is based upon the correlation between the value that is observed for the reference unit and the values that are observed for the neighbouring regions (p. 384). The Gini correlation is a measure of association between two random variables, which is based on the covariance between one variable and its cumulative distribution function (p. 384). The Gini correlation between two variables is expressed as the ratio of two covariances. The covariance in the numerator is computed between one variable and the cumulative distribution function of the other, and it corresponds to the Gini covariance between the variables. The covariance in the denominator is computed between the variable and its cumulative distribution function and represents a measure of variability (p. 385). The paper introduces a measure that is defined as the Gini correlation between the variable Y and its spatial lag WY, where Y denotes the regional GDP per capita and W is a row-standardised spatial weight matrix that summarises the proximity relationship between regional units. The spatially lagged variable expresses a weighted average of the values of Y that are observed for neighbouring regions (p. 386). When the ranking of WY is identical to the original ranking of Y, the overall inequality is completely explained by the given pattern of spatial dependence. As the ranking of the regional GDPs (*i.e.*, Y) becomes more dissimilar to the ranking of average GDPs in neighbour regions (*i.e.*, WY), the spatial component of inequality decreases. When Y and WY are uncorrelated, the overall inequality is completely explained by its non-spatial component (p. 388). The proposed measure is demonstrated through empirical research of income inequality in Italian provinces that correspond to the NUTS 3 level of the official EU classification. The authors looked at regional GDP per capita data from the EUROSTAT database from 2000 to 2015 (p. 388). The spatial component of the Gini index is slightly greater than the non-spatial component for any specifications of the spatial weight matrix. This means that both of these factors account for nearly the same amount of global inequality in Italian provinces (p. 389).

Moreover, these findings show that a positive spatial autocorrelation increases inequality by forming clusters of similar incomes (p. 390). The ability to determine the role of the spatial dependence relationship in generating income inequality at fine geographical

scales is critical for providing meaningful information for location-based policies targeted at lowering income inequality (Márquez *et al*., 2019, cited in Panzera & Postiglione, 2020, p. 393).

The above are certainly not the only examples, and interested readers may wish to explore other studies.

4.   Modern Views and Applications of the Gini Index

Originally defined as a standardised measure of statistical dispersion intended to understand income distribution, it comes as no surprise that the Gini index has been most widely used in the field of economics. Interestingly enough, however, in time, the Gini index has evolved into quantifying inequity in all kinds of distributions of wealth, energies, masses, temperatures, city sizes, and pollution levels, gender parity, access to education and health services, environmental policies, and so on (Mukhopadhyay & Sengupta, 2021). This is because while the Gini index was devised in order to measure socioeconomic inequality, it is actually a "measure of *statistical variability* that is applicable to *size distributions* at large" (Eliazar, 2016, p. 67). As mentioned previously, fields as diverse as sociology, health science, ecology, engineering, and agriculture have thus also benefited from Gini's work (Sadras & Bongiovanni, 2004). This has given birth to a plethora of modern views and applications of the Gini Index, some of which we explore below.

For example, in engineering, the Gini index has been used to assess the fairness achieved by Internet routers in scheduling packet transmissions from different flows of traffic (Shi & Sethu, 2003). In health, the Gini index has been employed as a measure of health-related quality of life inequality in a population (Asada, 2005). Using race as an example, the study dissected the overall Gini index into the between-group, within-group, and overlap Gini indices to reflect health inequality by group. In addition to the absolute mean differences across groups, the researchers looked at how much the overlap Gini index contributed to the overall Gini index. In chemistry, it has been used to describe the selectivity of protein kinase inhibitors against a panel of kinases (Graczyk, 2007). In education, it has been used as a measure of the inequality of universities (Halffman & Leydesdorff, 2010). The Gini index has even been applied to examine inequality on dating apps (worst-online-dater, 2015; Kopf, 2017).

In ecology, it has been used as a measure of biodiversity, where the cumulative proportion of species is plotted against cumulative proportion of individuals (Wittebolle *et al*., 2009). In this sense, linear models have been used to evaluate the impacts of stress, the Gini index, the relative abundance of the dominant species, and that of their interactions on the ecosystem functionality.

In China, the environmental Gini index is widely used for the allocation of regional water pollutant emissions and for the inequality analysis of urban water use. To build this environmental Gini index model, the cumulative proportion of various water pollutant emissions is generally used as the vertical axis and the cumulative proportion of the GDP or ecological capacity as the horizontal axis to establish the environmental Lorenz curve (Zhou *et al*., 2015, p. 1047). Specifically, Zhou *et al*. (2015, pp. 1049-1052, 1054) studied the application of an environmental Gini index optimisation model to the industrial wastewater chemical oxygen demand (COD) discharge in seven cities in the Taihu Lake

Basin, China, in order to improve the equality of water governance responsibility allocation and optimise water pollutant emissions and water governance inputs. The research found that three cities displayed inequality factors and were adjusted to reduce the water pollutant emissions and to increase the water governance inputs (Zhou *et al.*, 2015, p. 1047).

More recently, the Gini index has been used to measure the inequality in greenspace exposure of a city, with an application to 303 major Chinese cities; interestingly enough, the study leveraged multi-source geospatial big data and a modified urban greenspace exposure inequality assessment framework (Song *et al.*, 2021).

In credit risk management, the Gini index is sometimes used to assess the discriminating power of rating systems (Christodoulakis & Satchell, 2007). The applications of the Gini methodology to financial theory are relevant whenever one is interested in decision-making under risk (Yitzhaki & Schechtman, 2013, p. 365). Specifically, the Gini methodology has been applied to portfolio theory, which aims to find a combination of safe and risky assets that maximises the expected utility of the investor (Yitzhaki & Schechtman, 2013, p. 372). For instance, if we denote the absolute Lorenz curve (ALC) of a safe asset by LSA (the line of safe asset), then one can express same expected return) and its ALC: the farther the LSA from the ALC is, the greater the risk assumed by the portfolio. Thus, one possible measure of risk is the Gini mean difference of the portfolio which is obtained from the distance between the LSA and the ALC (Yitzhaki & Schechtman, 2013, p. 385).

In agriculture, Sadras and Bongiovanni (2004) explored the applicability of Lorenz curves and Gini indices to characterise the magnitude of the variation in grain yield. The agronomic relevance of the Gini index was summarised in an inverse relationship with yield. Lorenz curves seemed particularly apt to present crop heterogeneity in terms of inequality, and to highlight the relative contribution of low- and high-yielding sections of the field to total paddock yield. As assessed by the authors, the Lorenz curves and Gini indices provide a potentially useful extension tool, a complement to yield maps and other statistical indices of yield variation, and further contact points between site-specific management, economics, and ecology.

In business, Morais and Kakabadse (2014, pp. 393-394) considered that the Corporate Gini Index (CGI) is a valuable measure of corporate income inequality, urging regulators around the world to consider the CGI as a measure that should be disclosed in proxy statements, by introducing amendments to existing regulation. It is worth mentioning that Morais and Kakabadse (2014, p. 387) computed the CGI by collecting income distributions for six basic categories of pay for a company. These basic categories of pay were Executive Board, Top Management, Regional Directors/Deputy Directors, District Managers, Store Managers and Equivalent.

The Gini index has further been used in genetics for assessing the inequality of the contribution of different marked effects to genetic variability (Gianola, Perez-Enciso, & Toro, 2003), and in astronomy for providing a quantitative measure of the inequality with which a galaxy's light is distributed amongst its constituent pixels (Abraham, van den Bergh, & Nair, 2003).

Although, not exhaustive in nature, the above-mentioned studies demonstrate the breadth of applications of the Gini index, justifying its status as a modern measure of inequality. All in all, it is interesting to note how scientists and researchers across many fields have found occasions to apply the Gini index.

5. Implications for Economic Diplomacy and Future Research Directions

In this work, we have aimed to present the original Gini index, as well as the various existent alternative Gini formulations, while also exploring various traditional and modern applications of the index in different settings, at national and international levels. In this section, we briefly discuss the overall implications of the Gini index for international economic diplomacy and policymaking (therefore, taking the more traditional view of the index into account) and conclude with some future research directions.

Without a doubt, the problem of inequality among people has become more salient in recent years. Indeed, data and research show that the degree of inequality has increased in most countries around the world, which in turn, has generated concerns both from the perspective of the sustainability of economic growth, as well as from the perspective of social cohesion and well-being.

The Gini index is not without criticism. And some of it is justified, to some extent. For example, the fact that the Gini index, as a single statistical measure cannot capture the nature of inequality among people. Although nor should it be expected to do so in the first place. The Gini index is not a perfect measure and it is insufficient on its own, so much so that, if not properly understood in view of its limitations, it can turn out to be misleading. And that is exactly the point. One should never rely on a single summary statistic, be it the Gini index or any other index. To get a more comprehensive and accurate picture of any given socio-economic reality, any index needs to be complemented with insights obtained from other composite indices of well-being. In this sense, the Gini index remains a powerful inequality measure and the most popular of all to help understand the economic diversity of an area, especially when used along with additional data on income, education, and poverty, among others. For example, Pandey and Nathwani (1996) presented a new method for measuring the socio-economic inequality using a composite social indicator, Life-Quality Index, derived from two principal indicators of development, namely, the Real Gross Domestic Product per person and the life expectancy at birth. To account for the observed differences in life-quality of distinct quintiles of the population, income inequality and the accompanying life expectancy variations were combined into a quality adjusted income (QAI). The Gini coefficient of the distribution of QAI was introduced as a measure of socio-economic inequality (Pandey & Nathwani, 1996, p. 187).

Preventing and reducing inequality is a multi-stakeholder effort, requiring an efficient social and civil dialogue between various interested groups (Charles, Gherman, & Paliza, 2019), although it depends largely on the actions and reforms taken by the countries' governments. In this sense, then, the role and responsibility of the governments is to support policies and initiatives in the field of social inclusion and social protection by providing policy guidelines and budgetary support for reform implementation. Of course, policy responses will be dependent on the careful interpretation of the factors that determine inequality in each country, as well as in view of country-specific factors such

as unemployment rate, economic sectoral composition, labour market institutions, and the design of the social protection system (European Commission, 2017).

More recently, efforts have also been made to enhance the Gini index with insights from big data-driven approaches. Because the potential to exploit location to generate insights to understand relationships across different levels of geography is rising, geospatial analysis plays an essential role here. For example, Haithcoat *et al.* (2021) used big data geospatial analytics to examine ways that income inequality is associated with a range of health and health-related outcomes among individuals. In the authors' words, "the development of spatially enabled big data that integrates sociodemographic, environmental, cultural, economic, and infrastructural variables within a common framework has the potential to transform social research. Using geostatistical approaches to create new information from data captured through topology, intersection, and complex queries among data sets allows researchers to more fully explore context. Quantifying this "context" is fundamental to understanding disparity and inequality" (p. 547). In turn, this has important implications for international economic diplomacy and policymaking, as such insights "may be used to inform state-level relationships underpinning social and structural variables that may associate with the Gini coefficient itself" (p. 547).

The arrival of big data has indeed opened up new opportunities (Charles & Gherman, 2013; Charles, Emrouznejad, & Gherman, 2021; Charles, Tavana, & Gherman, 2015). And it remains an important direction for future research, which calls for more cross- and inter-disciplinary empirically grounded research, more specifically, for new research approaches to study people and practice in truly insightful and impactful ways [for an example, please see Charles and Gherman (2018); Gherman (2018)], which can then translate into the creation of better, more comprehensive composite indices, in general (Charles, Gherman, & Emrouznejad, 2022).

The Gini index can, thus, help governments in their efforts to track inequality and poverty levels, but this is not the only use for the index. Studies (e.g., Gurr, 1970) have shown that increased inequality increases the likelihood of violent conflict and violent social conflict. Therefore, another practical use of the Gini index is in policy support on conflict prevention by means of reducing economic inequality through various policy interventions. In other words, supporting socio-economic development through aid programmes and diplomacy. As Tadjoeddin *et al*. (2021) elegantly stated, "local governments at sub-national level must have a clear understanding of the taxonomy of collective violence (ethnic and routine) and inequality (vertical and horizontal), and more importantly, have an ability to closely monitor both variables and take necessary measures" (p. 566).

6.   Conclusions

The Gini index is a prominent measure of income or wealth inequality, with relevancy at both national and international level. For policymakers, the Gini index plays a vital role, as it can assist in determining where resources and support are most needed. All in all, the Gini index is more relevant today than ever before, being a powerful inequality measure and the most popular of all to help understand the economic diversity of an area, especially when used along with additional data on income, education, and poverty, among others.

Although originally developed to be a standardised measure of statistical dispersion intended to understand income distribution, mainly used in the field of economics, the Gini index has evolved in time into a means of quantifying inequity in all kinds of distributions of wealth, gender parity, access to education and health services, and environmental policies, among others. Fields as diverse as sociology, health science, ecology, engineering, and agriculture have also benefited from Gini's work, and the existing literature stands as evidence of the breadth of applications of the Gini index.

Today, growing complexities of markets and states, enterprises and governments alike, coupled with technological developments, call for improved Gini indices. In this sense, it is necessary not only to make methodological improvements, but also to nurture an extended network of experts who can engage in constructive dialogue, with greater collaboration among a broader range of stakeholders, including scholars, data scientists, regulators and politicians, business leaders, and representatives of civil society, just to name a few. We, therefore, join calls for more cross- and inter-disciplinary research that can translate into more comprehensive, impactful Gini indices.

References

Abraham, R., van den Bergh, S., & Nair, P. (2003). A new approach to galaxy morphology, I: Analysis of the Sloan digital sky survey early data release. *Astrophysical Journal, 588*, 218-229.

Adeleye, N. (2018). *Financial reforms, credit growth and income inequality in sub-Saharan Africa*. A Ph.D. Thesis Presented to the Department of Economics and Development Studies, Covenant University, Ota, Nigeria, May 2018.

Allison, P. D. (1978). Measures of inequality. *American Sociological Review*, *43*(6), 865-880.

Anand, S. (1983). *Inequality and poverty in Malaysia: Measurement and decomposition.* New York, NY: Oxford University Press.

Asada, Y. (2005). Assessment of the health of Americans: the average health-related quality of life and its inequality across individuals and groups. *Population Health Metrics*, *3*, Article 7.

Castillo, L. E. (2020). Regional Dynamics of Income Inequality in Peru. *Working Paper N° 2020-004*. Lima, Peru: Central Reserve Bank of Peru.

Ceriani, L., & Verme, P. (2015). Individual Diversity and the Gini Decomposition. *Social Indicators Research*, *121*(3), 637-646.

Charles, V., & Gherman, T. (2013). Achieving competitive advantage through big data. Strategic implications. *Middle-East Journal of Scientific Research, 16*(8), 1069-1074.

Charles, V., & Gherman, T. (2018). Big Data and Ethnography: Together for the Greater Good. In A. Emrouznejad & V. Charles (eds.), *Big Data for the Greater Good* (pp. 19-34). Cham: Springer.

Charles, V., Emrouznejad, A., & Gherman, T. (2021). Strategy Formulation and Service Operations in the Big Data Age: The Essentialness of Technology, People, and

Ethics. In A. Emrouznejad & V. Charles (eds.), *Big Data for Service Operations Management* (pp. 1-30), Springer's International Series in Studies in Big Data, Springer-Verlag, UK. (Forthcoming)

Charles, V., Gherman, T., & Emrouznejad, A. (2022). The role of composite indices in international economic diplomacy. In V. Charles & A. Emrouznejad (eds.), *Modern Indices for International Economic Diplomacy*. Springer-Palgrave Macmillan. (Forthcoming).

Charles, V., Gherman, T., & Paliza, J. C. (2019). Stakeholder involvement for public sector productivity enhancement: strategic considerations. *ICPE Public Enterprise Half-Yearly Journal, 24*(1), 77-86.

Charles, V., Tavana, M., & Gherman, T. (2015). The right to be forgotten – is privacy sold out in the big data age? *International Journal of Society Systems Science, 7*(4), 283-298.

Chauhan, R. K., Mohanty, S. K., Subramanian, S. V., Parida, J. K., & Padhi, B. (2016). Regional estimates of poverty and inequality in India, 1993–2012. *Social Indicators Research*, *127*(3), 1249-1296.

Eliazar, I. (2016). Visualizing inequality. *Physica A, 454*, 66-80.

European Union. (2017). *Addressing Inequalities*. European Semester Thematic Factsheet. Available at https://ec.europa.eu/info/sites/default/files/file_import/european-semester_thematic-factsheet_addressing-inequalities_en_0.pdf

EUROSTAT. (2021). *Gini coefficient of equivalised disposable income - EU-SILC survey'*. Luxembourg City, Luxembourg: EUROSTAT [cited on August 12th, 2021]. Retrieved from: https://ec.europa.eu/eurostat/web/products-datasets/-/ilc_di12

Foster, J. E., & Wolfson, M. C. (2010). Polarization and the decline of the middle class: Canada and the U.S. *The Journal of Economic Inequality*, *8*(2), 247-273.

Furman, E., Kye, Y., & Su, J. (2019). Computing the Gini index: A note. *Economics Letters*, *185* (December 2019), 108753.

Gherman, T. (2018). Machine Learning and Ethnography: A Marriage Made in Heaven. *Informs OR/MS Tomorrow*, Spring/Summer 2018 Issue, pp. 12-13.

Gianola, D., Perez-Enciso, M., & Toro, M. A. (2003). On marker-assisted prediction of genetic value: Beyond the ridge. *Genetics, 163,* 347-365.

Gimpelson, V., & Treisman, D. (2018). Misperceiving inequality. *Economics & Politics*, *30*(1), 27-54.

Gini, C. (1912). Variabilitá e mutabilitá: Contributo allo studio delle distribuzioni e delle relazioni statistiche. *Studi Economico-giuridici della Regia Facolt`a Giurisprudenza, 3*(2), 3-159.

Gini, C. (1914). Sulla Misura della Concentrazione e della Variabilit`a dei Caratteri. *Atti del Reale Istituto Veneto di Scienze, Lettere ed Arti, 73*(2), 1203-1248.

Graczyk, P. (2007). Gini Coefficient: A New Way To Express Selectivity of Kinase Inhibitors against a Family of Kinases. *Journal of Medicinal Chemistry, 50*(23), 5773-5779.

Gurr, T. R. (1970). *Why Men Rebel*. Princeton, NJ: Princeton University Press.

Haithcoat, T. L., Avery, E. E., Bowers, K. A., Hammer, R. D., Shyu, C.-R. (2021). Income Inequality and health: Expanding Our Understanding of State-Level Effects by Using a Geospatial Big Data Approach. *Social Science Computer Review, 39*(4), 543-561.

Halffman, W., & Leydesdorff, L. (2010). Is Inequality Among Universities Increasing? Gini Coefficients and the Elusive Rise of Elite Universities. *Minerva, 48*(1), 55-72.

Imedio-Olmedo, L. J., Parrado-Gallardo, E. M., & Bárcena-Martín, E. (2012). Income Inequality Indices Interpreted as Measures of Relative Deprivation/Satisfaction. *Social Indicators Research, 109*, 471-491.

INEI. (2018). Evolución de la Pobreza Monetaria, 2007–2017. *Informe Técnico*. Instituto Nacional de Estadística e Informática. Lima, Peru: INEI.

Kendall, M. G., & Stuart, A. (1958). *The advanced theory of statistics* (1st ed.). Vol. 1. New York, NY: Hafner Publishing Company.

Kokko, H., Mackenzie, A., Reynolds, J. D., Lindström, J., & Sutherland, W. J. (1999). Measures of Inequality are not Equal. *The American Naturalist, 154*(3), 358-382.

Kopf, D. (2017). These statistics show why it's so hard to be an average man on dating apps. *Quartz*. Retrieved on 28 April 2021 from https://qz.com/1051462/these-statistics-show-why-its-so-hard-to-be-an-average-man-on-dating-apps/

Krebs, C. J. (1989). *Ecological methodology*. New York, NY: Harper & Row.

Liao, T. F. (2006). Measuring and analyzing class inequality with the Gini index informed by model-based clustering. *Sociological Methodology, 36*(1), 201-224.

Liu, Y., & Gastwirth, J. L. (2020). On the capacity of the Gini index to represent income distributions. *METRON, 78*, 61-69.

Luebker, M. (2010). Inequality, income shares and poverty: The practical meaning of Gini coefficients. *TRAVAIL Policy Brief N° 3*. Geneva, Switzerland: International Labour Office.

Márquez, M. A., Lasarte-Navamuel, E., & Lufin, M. (2019). The role of neighborhood in the analysis of spatial economic inequality. *Social Indicators Research, 141*(1), 245-273.

Morais, F., & Kakabadse, N. K. (2014). The Corporate Gini Index (CGI) determinants and advantages: Lessons from a multinational retail company case study. *International Journal of Disclosure and Governance,* 11(4), 380-397.

Moran, T. P. (2003). On the Theoretical and Methodological Context of Cross-National Inequality Data. *International Sociology, 18*, 351-378.

Mukhopadhyay, N., & Sengupta, P. P. (2021). *Gini Inequality Index: Methods and Applications*. Routledge.

Osabohien, R., Matthew, O., Ohalete, P., & Osabuohien, E. (2020). Population-Poverty-Inequality Nexus and Social Protection in Africa. *Social Indicators Research, 151*, 575-598.

Osberg, L. (2017). On the Limitations of some Current Usages of the Gini Index. *Review of Income and Wealth, 63*(3), 574-584.

PAHO. (2019). *PAHO Budget Policy*. 57th Directing Council, 71st Session of the Regional Committee of WHO for the Americas. Pan American Health Organization, 30 September - 4 October 2019. Washington, D.C.: PAHO [cited on August 10th, 2021]. Available from:
https://www3.paho.org/hq/index.php?option=com_docman&view=download&alias=49746-cd57-5-e-budget-policy&category_slug=cd57-en&Itemid=270&lang=en

Pandey, M. D., & Nathwani, J. S. (1996). Measurement of socio-economic inequality using the Life-Quality Index. *Social Indicators Research, 39*, 187-202.

Panzera, D., & Postiglione, P. (2020). Measuring the Spatial Dimension of Regional Inequality: An Approach Based on the Gini Correlation Measure. *Social Indicators Research, 148*, 379-394.

Sadras, V. O., & Bongiovanni, R. (2004). Use of Lorenz curves and Gini coefficients to assess yield inequality within paddocks. *Field Crops Research, 90*(2-3), 303-310.

Sarntisart, I. (2020). Income inequality and conflicts: A Gini decomposition analysis. *The Economics of Peace & Security Journal, 15*(2).

Sen, A. K. (1973). *On economic inequality*. Oxford: Clarendon Press.

Shi, H., & Sethu, H. (2003). Greedy Fair Queueing: A Goal-Oriented Strategy for Fair Real-Time Packet Scheduling. Proceedings of the 24th IEEE Real-Time Systems Symposium. *IEEE Computer Society*. pp. 345-356. ISBN 978-0-7695-2044-5.

Shorrocks, A. F. (2013). Decomposition procedures for distributional analysis: A unified framework based on the Shapley value. *The Journal of Economic Inequality, 11*(1), 99-126.

Silber, J. (1989). Factor components, population subgroups and the computation of the Gini index of inequality. *Review of Economics and Statistics, 71*(1), 107-115.

Song, Y., *et al.* (2021). Observed inequality in urban greenspace exposure in China. *Environment International, 156*, 106778.

Stefanescu, S. (2011). About the Accuracy of Gini Index for Measuring the Poverty. *Romanian Journal of Economic Forecasting, 3*, 255-266.

Székely, M., & Mendoza, P. (2015). Is the Decline in Inequality in Latin America Here to Stay. *Journal of Human Development and Capabilities, 16*(3), 397-419.

Tadjoeddin, M. Z., Yumna, A., Gultom, S. E., Fajar Rakhmadi, M., & Suryahadi, A. (2021). Inequality and violent conflict: new evidence from selected provinces in Post-Soeharto Indonesia. *Journal of the Asia Pacific Economy, 26*(3), 552-573.

Tammaru, T., Marcinczak, S., Aunap, R., van Ham, M., & Janssen, H. (2020). Relationship between income inequality and residential segregation of socioeconomic groups. *Regional Studies, 54*(4), 450-461.

Temkin, L. S. (1986). Inequality. *Philosophy & Public Affairs, 15*, 99-121.

Temkin, L. S. (1993). *Inequality*. Oxford: Oxford University Press.

Theil, H. (1967). *Economics and Information Theory*. Chicago, IL: Rand McNally.

Tsuji, K., & Tsuji, N. (1998). Indices of reproductive skew depend on average reproductive success. *Evolutionary Ecology, 12*, 141-152.

Wittebolle, L., Marzorati, M., Clement, L., Balloi, A., Daffonchio, D., Heylen, K., De Vos, P., Verstraete, W., & Boon, N. (2009). Initial community evenness favours functionality under selective stress. *Nature, 458*, 623-626.

worst-online-dater. (25 March 2015). Tinder Experiments II: Guys, unless you are really hot you are probably better off not wasting your time on Tinder — a quantitative socio-economic study. *Medium*. Retrieved 10 October 2021 from https://medium.com/@worstonlinedater/tinder-experiments-ii-guys-unless-you-are-really-hot-you-are-probably-better-off-not-wasting-your-2ddf370a6e9a

Wu, W.-C., & Chang, Y.-T. (2019). Income inequality, distributive unfairness, and support for democracy: evidence from East Asia and Latin America. *Democratization, 26*(8), 1475-1492.

Yamada, G., Castro, J. F., & Oviedo, N. (2016). Revisitando el coeficiente de Gini en el Perú: El Rol de las Políticas Públicas en la Evolución de la Desigualdad. *Working Paper N° 16-06*; Lima, Peru: Centro de Investigación de la Universidad del Pacífico.

Yitzhaki, S. (1979). Relative deprivation and the Gini coefficient. *Quarterly Journal of Economics, 93*, 321-324.

Yitzhaki, S., & Schechtman, E. (2013). *The Gini Methodology. A Primer on a Statistical Methodology.* Springer Series in Statistics 272. New York, NY: Springer Science+Business Media.

Zaborskis, A., Grincaite, M., Lenzi, M., Tesler, R., Moreno-Maldonado, C., & Mazur, J. (2019). Social Inequality in Adolescent Life Satisfaction: Comparison of Measure Approaches and Correlation with Macro-level Indices in 41 Countries. *Social Indicators Research, 141*, 1055-1079.

Zhou, S., Du, A., & Bai, M. (2015). Application of the environmental Gini coefficient in allocating water governance responsibilities: a case study in Taihu Lake Basin, China. *Water Science & Technology, 71*(7), 1047-1055.