Measures of Relative and Absolute Convergence and Pro-poor Growth with an Illustration based on China in the 2010s

Elena Bárcena-Martin, Jacques Silber, Yuan Zhang[*]

Abstract

Income mobility is a key issue for understanding the process of economic growth and distributional change. Some economists have used the concept of "pro-poor growth" to examine, with individual-level panel data, whether the poor benefit more than the rich from economic growth by tracking the extent of income mobility among different population subgroups. There is also literature in macroeconomics on the measurement of convergence. This paper introduces population-weighted relative and absolute indices of mobility, convergence, and pro-poor growth; it also distinguishes between anonymous and nonanonymous approaches to these issues. The empirical analysis is based on Chinese panel data for the period 2010–2018. In both absolute and relative terms, income growth in China was greater for individuals with an initially lower income but only for lower income deciles in relative terms. There was also an overall increase in individual welfare from anonymous and nonanonymous perspectives, which was higher among younger individuals. The welfare of the poor did not increase more than that of the nonpoor. These results shed light on the evolution of income distribution in China during the past decade's rapid economic growth.

Keywords: anonymous and nonanonymous approach, convergence, exchange and structural mobility, pro-poor growth

JEL codes: D31, I32, O15

I. Introduction

[*]Elena Bárcena-Martin, Professor, Facultad de Ciencias Económicas y Empresariales, Universidad de Málaga, Spain. Email: barcenae@uma.es; Jacques Silber, Professor, Department of Economics, Bar-Ilan University, Israel. Email: jsilber_2000@yahoo.com; Yuan Zhang (corresponding author), Professor, China Center for Economic Studies, Fudan University, China. Email: zhangyuanfd@fudan.edu.cn. A previous version of this paper was presented by Jacques Silber at the Western Economic Association International (WEAI) 15th International Conference, which took place on March 21–24, 2019, at Keio University, Tokyo, Japan. Jacques Silber is grateful to the participants in his session, in particular to Peter Phelps, for their very useful comments. He is also grateful for the comments he received at seminars that he gave at the Asian Growth Research Institute in Kitakyushu and at Kyoto University, and at the Encuentro de Economia Publica (Barcelona, January 23–24, 2020). Elena Bárcena-Martín acknowledges financial aid from Grant PID2020-115429GB-I00 funded by MCIN/AEI/ 10.13039/501100011033; Yuan Zhang acknowledges financial aid from the Natural Science Foundation of China (No. 72173026).

Many studies have investigated the relationship between economic growth and inequality (e.g., Barro, 2000; Forbes, 2000; Easterly, 2007; Halter et al., 2014; Aiyar and Ebeke, 2020). The availability of individual-level panel data has increased recently, allowing economists to track the extent of income mobility among certain population subgroups, and they have used the concept of "pro-poor growth" to examine whether the poor benefit more than the rich from economic growth (e.g., White and Anderson, 2001; Dollar and Kraay, 2002; Ravallion and Chen, 2003; Son, 2004; Kakwani and Son, 2008). A large body of literature also exists on the measurement of convergence (e.g., Sala-i-Martin, 1990, 1996; Barro and Sala-i-Martin, 1992; Islam, 1995, 2003). Although there has been much research on the link between economic growth and inequality, as well as on pro-poor growth and the measurement of economic convergence, the question arises as to whether these three strands of literature may be linked. This paper therefore seeks to develop a unified framework for analyzing inequality change, pro-poor growth, mobility, convergence, and distributional change more generally. To this end, we propose a set of population-weighted measures of mobility, convergence, and pro-poor growth to understand better the type of distributional change that accompanies economic growth, and to improve policy assessment, including redistribution policies that target specific subgroups in the population.

This approach is particularly relevant for China. Despite the country's considerable income growth, there is evidence of rapid increases in income inequality in comparison with its past and with other countries with similar levels of economic development (Xie et al., 2015). By analyzing national accounts, surveys, and tax data, Piketty et al. (2019) corrected China's underreported inequality index for the period 1978–2015 and found that inequality levels in 2015 approached the levels found in the US. Recognizing that increased inequality could hinder sustainable, long-term growth, the Chinese government emphasized the target of "leaving no one behind," invested resources in underdeveloped areas, and improved the country's social protection network to avoid marginalizing the poor during periods of economic growth. For example, China introduced the Minimum Wage Regulation in 2004 to protect the legal rights of low-skilled workers; in 2008, China promulgated the new *Labor Contract Law* to enforce the minimum wage regulation of 2004 more strictly, and both of these laws aimed to reduce income inequality. While economists often possess cross-sectional information about income levels and distribution in China, the extent of income mobility within different cohorts remains unclear (i.e., the reshuffling of populations with different income levels). This paper, therefore, uses population-weighted measures to attempt to estimate the extent of mobility, convergence, and pro-poor growth in China during the period 2010–2018.

The contributions of this paper are threefold. First, the method proposed here introduces population-weighted indices of mobility, convergence, and pro-poor growth. These measures can be applied to panel data in both developing and developed countries, which allows the investigation of the distributional changes that occur in the process of economic growth and the formulation of related policies. Second, it uses both relative and absolute indices to examine inequality, mobility, convergence, and pro-poor growth. As Clark et al. (2008) argued, relative indices are more important in rich countries because the absolute level of personal consumption plays an increasingly marginal role, whereas status is a luxury good. This paper further analyzes what has happened to welfare over time. Third, regarding empirical investigation, this paper's analysis of data for individuals in China for the period 2010–2018 elucidates the role of changes in individual income during periods of macroeconomic growth. Most important, the empirical analysis demonstrates the importance of distinguishing between anonymous (cross-sectional comparisons) and nonanonymous (panel data) approaches to pro-poor growth. More specifically, it shows how the proposed indices can be used to determine whether income growth in China during the period 2010–2018 favored specific subgroups in the population. Considering the latest changes in China's economic structure and the introduction of new policy tools, the analysis of income growth and distribution provides relevant information about changes in income, individual income mobility, and the way in which income distribution is influenced by the effects of economic and policy changes. It thus aims to answer the following research questions: Has growth promoted convergence? What kind of convergence? Who has benefited more from growth – the poor or the rich, the educated or the uneducated, and the old or the young?

The remainder of this paper is organized as follows: Section II reviews the literature on distributional patterns of economic growth. Section III reviews distributional changes that have taken place in China in recent years. Sections IV, V, and VI describe the methodology for the relative, absolute, and welfare approaches, respectively, while Section VII analyzes data for China. Section VIII concludes.

II. Review of the literature on distributional change

To derive measures of distributional change, Cowell (1985) first examined the meaning of distributional change. In the context of mobility, distributional change merely estimates the amount of movement taking place when a vector, $\boldsymbol{x}$, of individual incomes becomes a vector, $\boldsymbol{y}$, of the same population size. Such changes generally involve a re-ranking of individuals. For example, using household panel data from China and Vietnam, Wagstaff (2009) compared inequality decomposition results that do and do not allow re-ranking. He found that pro-poorness under re-ranking was stronger than without re-ranking. There may have been some amount of distributional change, even without re-ranking if there is a change in the inequality of the distribution. Distributional change may, however, refer to another issue – horizontal inequity – when a given distribution (e.g., post-tax income) is compared to a reference distribution (e.g., pretax income). Here, re-ranking may also be required. However, even without re-ranking, it may be useful to examine the distance between pre- and post-tax incomes.

In a follow-up to a previous paper (Cowell, 1980), Cowell (1985) proposed a measure of distributional change related to the concept of generalized entropy. Both of these studies employed a relative approach to distributional change, whereas Berrebi and Silber (1983), borrowing ideas from Kolm (1976), proposed an absolute measure of distributional change. Using kernel density methods, DiNardo et al. (1996) presented a semiparametric procedure to analyze the effects of institutional and labor market factors on changes in the distribution of wages in the US. Silber (1995) introduced a Gini-related index of distributional change, which Jenkins and van Kerm (2006) extended using the concept of a generalized Gini. Their study provides an analytical framework in which changes in income inequality over time are related to the re-ranking of individuals during the study period, in addition to the income growth pattern across income ranges. In fact, Jenkins and van Kerm's approach links the concept of distributional change with that of pro-poor growth. Another valuable contribution is that of Shorrocks and Wan (2009), who proposed an improved method for calculating distributional indicators such as inequality values and poverty rates from grouped distribution data. Their proposed algorithm allows a sample of "income" observations to be reconstructed from any valid set of Lorenz coordinates and then used to compute inequality and poverty statistics.

Since 2000, there have been an increasing number of studies on the concept of pro-poor growth (for a short review, see Deutsch and Silber, 2011). A distinction is generally made between an approach that labels growth as pro-poor if the incomes of the poor grow and one that assumes that growth is pro-poor if the incomes show greater increases in proportion to the average income (e.g., Dollar and Kraay, 2002; Kakwani et al., 2004; Ravallion, 2004). This literature also distinguishes between anonymous approaches, where two or more cross sections of income are compared, and nonanonymous approaches based on panel data (e.g., Fields et al., 2003; Grimm, 2007; Nissanov and Silber, 2009).

Nissanov and Silber (2009) highlighted the similarity between pro-poor growth and convergence analyses. While the literature on pro-poor growth has mainly focused on individual or household data, the literature on convergence emphasizes macroeconomic data because such research has a solid theoretical foundation in growth theory. Following previous work on convergence (e.g., Baumol, 1986; Barro and Sala-i-Martin, 1992; Mankiw et al., 1992), Sala-i-Martin (1996) introduced the concepts of

σ- and β-convergence and noted that "There is absolute β-convergence if poor economies tend to grow faster than rich ones" (p. 1020), while "a group of economies are converging in the sense of σ if the dispersion of their real per capita GDP levels tends to decrease over time" (p. 1020).[1] O'Neill and van Kerm (2008) later revealed the link between the measurement of β-convergence and that of tax progressivity. They measured σ-convergence as the change over time in the Gini coefficient and decomposed this change into two components: one corresponding to β-convergence and the other to the concept of leapfrogging.[2] The component reflecting β-convergence measures the extent to which poor economies grow faster than rich ones. As O'Neill and van Kerm (2008) emphasized, this term is parallel to the notion of vertical equity in the tax literature (e.g., Kakwani, 1977; Reynolds and Smolensky, 1977), whereas leapfrogging corresponds to re-ranking.

A unified analysis framework such as that of O'Neill and van Kerm (2008) also appears in Dhongde and Silber (2016), who defined a set of income-weighted measures of mobility, convergence, and pro-poor growth for both nonanonymous and anonymous cases. The nonanonymous case evidently assumes the presence of panel data where it is possible to track changes in the incomes of specific individuals over time. However, this is impossible when the only available data are surveys that do not necessarily cover the same individuals over time, in which case we can only ascertain what happens over time to the incomes of the various centiles. This paper proposes a population-weighted measure of distributional change. More generally, it introduces a set of population-weighted mobility, convergence, and pro-poor growth measures for nonanonymous and anonymous cases using relative and absolute indices for distributional change.[3] It also examines the change in welfare over time.

[1]These concepts were introduced in a PhD dissertation by Sala-i-Martin (1990).
[2]The notion of leapfrogging can be found, for example, in Brezis et al. (1993).

[3]Population weights may be more appropriate than income-weighted indices. Regarding inequality indices, Portnov and Felsenstein (2010) showed that population-weighted inequality measures are more reliable when applied to countries with a small number of regions and with varying population sizes.

III. Distributional changes and pro-poor growth in China

China has experienced three decades of rapid economic growth accompanied by marked reductions in poverty since the early 1980s. This has attracted the attention of researchers, who began investigating the features of what appeared to be pro-poor growth. Zhang and Wan (2006), for example, decomposed the change over time in the Sen–Shorrocks–Thon poverty index into two components: one measuring the progressivity of income growth among those who were originally poor and the other estimating the extent of downward mobility experienced by those currently poor. Applying this framework to longitudinal household samples in China between 1988 and 1996, they found that income growth was always progressive for rural samples but regressive for urban samples. Sun et al. (2014) found that income mobility was stable and relatively high and that the poor and nonpoor converge, based on a decomposition of the Gini index by income source and an examination of the income transition matrix among rural households in 23 provinces from 2003 to 2006. Luo (2011) used urban samples from the 1988, 1995, and 2002 China Household Income Project surveys and showed that the poor benefited from economic growth but proportionally less so than the nonpoor.

Although marked income growth and poverty reduction exist in China, there is evidence of rapid increases in income inequality (Xie et al., 2015). The official Gini index reported by the National Bureau of Statistics of China (NBS) showed a downturn in 2008 (0.479 in 2003, 0.491 in 2008, and 0.465 in 2019, respectively). This has attracted considerable attention, with the World Bank (2007) warning that high inequality could pull China into a middle-income trap. Some economists, however, remained concerned about whether this was a long-term turning point, given that high-income groups were potentially undersampled. As a result, few economists have attempted to explain the driving force behind the improvement in income inequality in China since 2008.

Bai et al. (2020) were among the first to explain the perceived decline of inequality in China after 2008, and they attributed it to the government's CNY 4 trillion stimulus policy, in which loose monetary policy made credit readily available to firms that mainly employed unskilled labor. As financing costs lowered, these firms increased their investment, created job opportunities, and absorbed more unskilled laborers, thus helping to reduce income inequality. Kanbur et al. (2021) investigated the evolution of inequality in China via the decomposition of inequality by income source. They found that wage income was the largest contributor to total inequality, with a range of 66–79 percent. They also observed that declining inequality in wage income and transfer incomes were the main determinants of the decline in total income inequality in China. Using longitudinal data from the China Family Panel Studies (CFPS) to investigate income inequality in China from 2010 to 2014, Xie et al. (2015) showed that inequality declined between 2010 and 2012 and that the urban–rural gap narrowed. They also emphasized that income growth was greater for middle-income families than for high- or low-income families. More important, poverty decreased between 2010 and 2012: two-thirds of the families that were poor in 2010 were no longer poor in 2012. A more recent study by Foltz et al. (2020) indicated that the lineage networks of peasants could reduce income inequality in rural China by improving migration from rural to urban areas where these workers could earn much higher wages. In 2012, the Chinese government modified the 2008 Labor Contract Law and enforced equal pay for equal work. This may have helped further to reduce the income gap between domestic and migrant workers (Cheng et al., 2015; Gallagher et al., 2015; Li and Freeman, 2015), thus playing an active role in reducing inequality in urban labor markets.

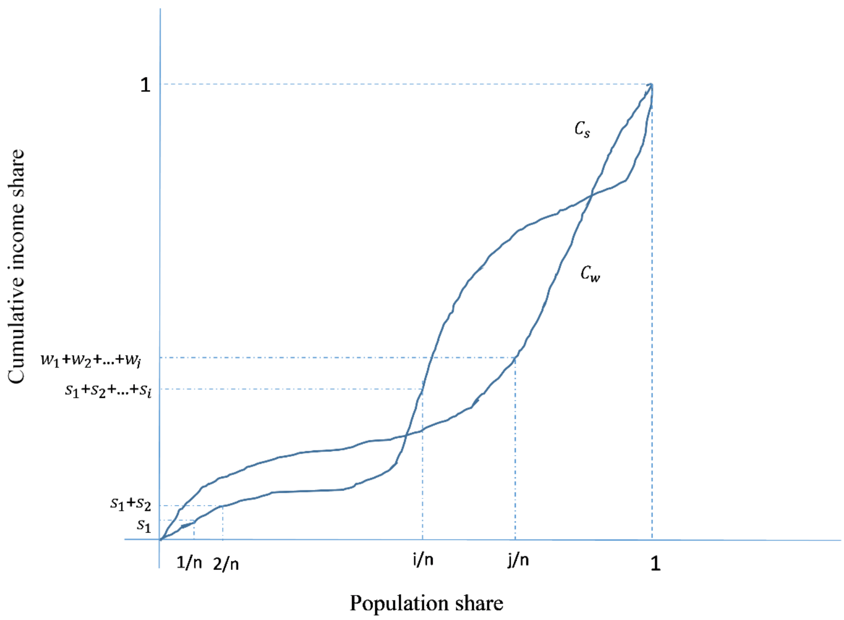
However, there have been few studies employing panel data to reveal the microstructural changes that might have occurred in China during the recent period of economic growth. Considering these economic changes in the country, it is important to understand distributional patterns and identify who benefited more from economic growth. This paper therefore attempts to estimate the extent of mobility, convergence, and pro-poor growth in China from 2010 to 2018. Our methodological framework and empirical analysis shed light on the relationship between inequality and growth and the issue of pro-poor growth.

IV. Population-weighted relative approaches to measuring distributional change, convergence, and pro-poor growth

1. Distributional change

Assuming that *n* refers to the number of individuals, let us plot in a one-by-one square the cumulative values of the population shares $\frac{1}{n}, \frac{2}{n}, \ldots \frac{i}{n}, \ldots, \frac{n-1}{n}, 1$ on the horizontal axis, and the corresponding cumulative values of the income shares s_i at time 0 and w_i at time 1 on the vertical axis, where these shares are ranked according to a given criterion (e.g., the level of education). This yields two curves: the first, C_s, is obtained by plotting (on the vertical axis) the cumulative values of the income shares at time 0 versus the corresponding population shares on the horizontal axis. For the second curve, C_w, the same procedure is performed for the cumulative values of the income shares at time 1. These two so-called concentration curves are increasing, starting at point (0, 0) and ending at point (1, 1). They may, of course, cross the diagonal more than one time.

Figure 1. Concentration curves at time 0 and time 1



Source: Authors’ calculations.

Let A_s and A_w be the areas below curves C_s and C_w, respectively. In Appendix A.1 we provide the exact formulation for these two areas and define the relative distributional change (*RDC*) as twice the difference between area A_w and area A_s. If *RDC* is positive, the curve C_w will tend to lie more above than below curve C_s such that area A_w will be greater than the area A_s. In other words, *RDC* is positive when what we defined as the equivalent growth rate in Appendix A.1. is higher than the average growth rate. This signals that growth is greater for lower incomes, i.e., that poorer individuals did better on average than richer ones.

2. Two relative approaches to measuring convergence

When measuring convergence, it is important to distinguish between anonymous and nonanonymous approaches. In the anonymous approach, two or more cross sections of incomes are compared, while the nonanonymous approach is based on panel data and the same element (e.g., individual, region) is followed over time. In the nonanonymous approach, we track income changes for individuals rather than income changes for income groups (e.g., the bottom quintile). Note that the composition of the group forming the bottom quintile changes over time because some individuals remain in this quintile, some escape from it, and some enter it. In contrast, the anonymous approach, which analyzes income distribution trends using cross-sectional data, ignores the reshuffling of individuals in the income distribution over time.

(1) Relative convergence in the anonymous case

Here, we ignore the identity of the individuals by assumption. We thus simply look at the income growth rates of the different centiles. If we assume that the income shares s_i and w_i are ranked by nondecreasing value, C_s and C_w will, in fact, be traditional Lorenz curves. If what is defined as the equivalent growth rate is higher than the average growth rate, Figure 1 would show that curve C_w, as a whole, is closer to the diagonal than curve C_s. We could then conclude that there is anonymous convergence.

(2) Relative convergence in the nonanonymous case

Here, a relative measure of distributional change can be used to observe greater growth rates for poorer individuals. Incomes may still diverge because initially poorer individuals may overtake richer ones, thus changing the ranking of individuals. That is, our measure of distributional change may not presume anything about dispersion across individuals but this dispersion information can be obtained by adopting a nonanonymous approach and decomposing distributional change into two components: the income-weighted average of individuals' income growth and leapfrogging.

Assume, as before, that income shares s_i at time 0 are ranked by nondecreasing values. Then, let v_i represent the income shares at time 1, which are also ranked by nondecreasing values. Finally, let w_i refer to the income shares at time 1 ranked by nondecreasing values of the income shares of individuals at time 0. Call C_s, C_v, and C_w the curves obtained by cumulating shares s_i, v_i, and w_i on the vertical axis. By construction, C_s and C_v are Lorenz curves at times 0 and 1, while C_w is called a concentration curve and may lie below or above curve C_s or even cross the diagonal once or several times. Thus, the *RDC* measure may be expressed as:[4]

$$RDC^{Nonanonymous} = SM + EM, \tag{1}$$

where structural mobility (*SM*) can be expressed as:

$$SM = \left(\frac{1+\eta_E^{s\to v}}{1+\bar{\eta}} - 1\right)\sum_{i=1}^{n}\left(\frac{2n+1-2i}{n}\right)s_i, \tag{2}$$

and where $\bar{\eta}$ is the average growth rate. The equivalent growth rate, $\eta_E^{s\to v}$, is obtained when the change taking place is the change observed when moving from the vector of income shares $\boldsymbol{s_i}$ to the vector of income shares $\boldsymbol{v_i}$. We may also define exchange mobility (*EM*) as:

$$EM = \sum_{i=1}^{n}\left(\frac{2n+1-2i}{n}\right)v_i\,\eta_E^{v\to w}, \tag{3}$$

[4]The derivation can be seen in detail in Appendix A.2.

where $\eta_E^{v \to w}$ is the equivalent growth rate obtained when the change that takes place is the change observed when moving from the vector of income shares $\boldsymbol{v_i}$ to the vector of income shares $\boldsymbol{w_i}$. In Appendix A.2, we provide the exact formulation and decomposition of *RDC* in the nonanonymous case, which is, in fact, a population-weighted measure of income mobility. In Appendix A.3 we show, like Jenkins and van Kerm (2006), how the generalized Gini index may also be used to derive generalized measures of convergence and pro-poor growth.

3. Two relative approaches to measuring pro-poor growth

(1) Relative pro-poor growth in the anonymous case

The literature on pro-poor growth (e.g., Kakwani and Pernia, 2000) initially adopted an anonymous approach to the topic, which is quite relevant when comparing two cross sections. Let us therefore assume that a poverty line *z* has been defined and that the proportion of the poor in the population is $\frac{q}{n}$. Now compute the equivalent growth rate η_E^{poor} among the centile groups that were poor at time 0. Suppose this equivalent growth rate is higher than the average growth rate in the population. In that case, we can conclude that growth has been pro-poor in the anonymous sense because the originally "poor" centile groups experienced a higher growth rate than the average growth rate in the population.

Using Equations (21), (23), and (24) in Appendix A.1, we derive

$$\eta_{E,pro-poor}^{Anonymous} = \sum_{i=1}^{q} \varphi_i \eta_i, \quad (4)$$

$$\varphi_i = \frac{\tau_i}{\sum_{i=1}^{q} \tau_i},$$

$$\tau_i = \left(\frac{2q+1-2i}{q}\right) s_i',$$

$$s_i' = \frac{s_i}{\sum_{i=1}^{q} s_i},$$

where *i* refers to a given centile. If $\eta_{E,pro-poor}^{Anonymous} > \overline{\eta}$, growth has been pro-poor in the anonymous sense.

(2) Nonanonymous relative pro-poor growth

A measure of pro-poor growth can be defined in a similar way for the nonanonymous case. Here, the growth rates refer to specific individuals whose incomes are known at times 0 and 1 and who were poor at time 0. We can then compute the corresponding equivalent growth rate and conclude that, if it is higher than the average growth rate, this nonanonymous growth has been pro-poor.

We can define, in a similar way, a measure of nonanonymous pro-poor growth for the nonanonymous case and write that

$$\eta_{E,pro-poor}^{Nonanonymous} = \sum_{i=1}^{q} \varphi_i \eta_i. \quad (5)$$

In Equation (5), however, the subscript *i* does not refer, as in the anonymous case, to a given centile, but to a given individual whose income is known at times 0 and 1. If $\eta_{E,pro-poor}^{Nonanonymous} > \overline{\eta}$, nonanonymous growth has been pro-poor. As in the anonymous case, $\eta_{E,pro-poor}^{Nonanonymous}$ takes account of the inequality in growth rates among the poor because different weights are attached to the various individuals. The generalized population-weighted measures of *RDC*, convergence, and pro-poor growth are examined in Appendix A.3.

4. Measuring relative distributional change with another ranking criterion

The previous analysis assumed that the variable under discussion is also the ranking criterion in both the anonymous and nonanonymous cases. In fact, our approach may be used for any ranking criterion. Then, in computing the equivalent growth rate η_E, the weight given to an individual will depend on that individual's rank according to the variable that serves as the ranking criterion. For example, it may be interesting to ascertain whether educational growth has been more favorable to those who originally had a low income level. We can also do the inverse and check whether income growth favored those who originally had a low level of education or, for example, those who were young at time 0.

The focus hitherto was on a relative approach. For example, we saw in the anonymous case that convergence in relative terms would occur if relative inequality decreases. In contrast, there would be relative pro-poor growth if the relative increase in income among those who were poor at time 0 was higher than the relative increase in income among the whole population. We could, however, also consider an absolute approach. Going back to the two previously mentioned illustrations, we could say that there would be absolute convergence if absolute inequality decreased, or there would be absolute pro-poor growth if the increase (in terms of US$) in the income of those who were originally poor (at time 0) was higher than the average increase (in terms of US$) of the whole population. Section V therefore focuses on an absolute approach.

V. Population-weighted absolute approaches to measuring distributional change, convergence, and pro-poor growth

1. Absolute anonymous distributional change

Following Moyes (1987), the absolute Lorenz curve is defined as:

$$LA\left[\left(\frac{k}{n}\right); x\right] = \frac{1}{n}\sum_{i=1}^{k}(x_i - \bar{x}) \text{ for } k = 1, \dots, n, \tag{6}$$

where n is the size of the population, $\frac{k}{n}$ represents a certain percentage of the population, x_i is the income of individual i, and $\boldsymbol{x}$ is the vector of all incomes ranked by nondecreasing values. It is then easy to prove that the area B_x' between the absolute Lorenz curve and the horizontal axis at height 0 may be expressed (see Appendix A.4) as:

$$B'_x = \frac{1}{2}(\bar{x} - x_E), \tag{7}$$

where x_E is a weighted average of the incomes of the individuals which gives a greater weight to an individual, the lower his or her income, and is defined as:

$$x_E = \sum_{i=1}^{n} \left(\frac{2n-2i+1}{n^2}\right) x_i. \tag{8}$$

B'_x is assumed to refer to incomes at time 0, so we can similarly define an area B'_y where incomes y_i are those observed at time 1. In such a case, we would write:

$$B'_y = \frac{1}{2}(\bar{y} - y_E), \tag{9}$$

where $\bar{y}$ is the average income at time 1, and y_E is Atkinson's "equally distributed equivalent level of income" at time 1, assuming again that we use the social welfare function corresponding to the Gini index. We can then define the change between times 0 and 1 in the area under the absolute Lorenz curve as:

$$\Delta B'_x = B'_y - B'_x = \frac{1}{2}[(\bar{y} - y_E) - (\bar{x} - x_E)] = \frac{1}{2}[(\bar{y} - \bar{x}) - (y_E - x_E)]. \tag{10}$$

Assuming that $\Delta\bar{x} = (\bar{y} - \bar{x})$ and $\Delta x_E = (y_E - x_E)$, we can define Equation (10) as absolute distributional change (*ADC*), and write that:

$$ADC^{Anonymous} = \Delta B'_x = \frac{1}{2}(\Delta\bar{x} - \Delta x_E). \tag{11}$$

If $\Delta\bar{x} < \Delta x_E$, then $ADC < 0$, which suggests convergence in absolute incomes because the increase in average income is smaller than the increase in the equally distributed equivalent level of income (when we attach more weight to lower incomes). If the average income increased between times 0 and 1 ($\Delta x > 0$), the equally distributed equivalent level of income must therefore increase more ($\Delta x_E > \Delta x$). Conversely, if the average income decreased between times 0 and 1 ($\Delta\bar{x} < 0$), the equally distributed equivalent level of income must decrease less.

2. Absolute income convergence

As in the relative approach, we can distinguish between anonymous and nonanonymous approaches when measuring convergence.

The absolute convergence in the anonymous case is equivalent to the situation described in the previous section, in which the incomes at time 1 are ranked in nondecreasing order without considering the identity of the individual. We are thus examining the change in income of the different deciles.

Next, we discuss the nonanonymous case of absolute convergence – in other words, we do not consider the income changes of deciles but of individuals. Here, we compute the income change of individuals, who are compared at two points in time. Let us call $\boldsymbol{x}$ the vector of incomes x_i at time 0 ranked by nondecreasing values and $\boldsymbol{y}$ the vector of incomes y_i at time 1, also ranked by nondecreasing values. Let us further define a vector $\tilde{\boldsymbol{y}}$ of incomes $\tilde{y}_i$ where the set of $\tilde{y}_i$s are incomes y_i at time 1 ranked, this time, by nondecreasing values of the incomes the individuals had at time 0. We then define an income y_E as:

$$y_E = \sum_{i=1}^{n} \left(\frac{2n-2i+1}{n^2}\right) y_i. \tag{12}$$

We then derive

$$\Delta x_E = y_E - x_E = \sum_{i=1}^{n} \left(\frac{2n-2i+1}{n^2}\right) (y_i - x_i). \tag{13}$$

Let us now also define an income $\tilde{y}_E$ and a change $\Delta\tilde{x}_E$ as:

$$\tilde{y}_E = \sum_{i=1}^{n} \left(\frac{2n-2i+1}{n^2}\right) \tilde{y}_i, \tag{14}$$

$$\Delta\tilde{x}_E = (\tilde{y}_E - x_E). \tag{15}$$

The absolute distributional change in the nonanonymous case will then be defined as:

$$ADC^{Nonanonymous} = \frac{1}{2}(\Delta\bar{x} - \Delta\tilde{x}_E) = \frac{1}{2}[(\bar{y} - \bar{x}) - (\tilde{y}_E - x_E)]. \tag{16}$$

It can be shown that *ADC* can be decomposed into two components. The first is called absolute structural mobility (*ASM*), and the second is absolute exchange mobility (*AEM*). See Appendix B.1 for more details.

3. Using an absolute approach for pro-poor growth

We assume again that a poverty line, *z*, has been defined for periods 0 and 1 and that the proportion of the poor in the population at time 0 is $\frac{q}{n}$. We can then compute the average incomes $\bar{x}_{poor}$ and $\bar{y}_{poor}$ among the *q* poor individuals at times 0 and 1. We can similarly compute the equally distributed equivalent levels of income $x_{E,poor}$ and $y_{E,poor}$ among the poor at times 0 and 1. We can now extend the previous results concerning the necessary conditions to decrease absolute inequality. To compute absolute pro-poor growth, we restrict the analysis to individuals who were poor at time 0.

The generalized population-weighted measures of absolute distributional change, convergence, and pro-poor growth are similar and details can be found in Appendix B.2. We can further measure absolute distributional change with another ranking criterion. As in the case of *RDC*, we can examine the case in which the variable under discussion is not the one from which the ranking of the individuals is derived. For example, we may want to check whether absolute distributional income change favors those with a low level of education.

VI. Change in welfare and pro-low welfare change

1. The concept of the generalized Lorenz curve

This generalized Lorenz curve was introduced by Shorrocks (1983) and is an extension of the Lorenz curve. We still plot the cumulative values of the population shares on the horizontal axis while we plot the product of the cumulative values of the income shares by the average income in the population on the vertical axis. This generalized Lorenz curve therefore ends at a point *A*, whose horizontal coordinate is equal to 1, while its vertical coordinate is equal to the average income. Let us assume that point *O* refers to the origin of the axis. The area lying between the line *OA* and the generalized Lorenz curve is equal to the area under the absolute Lorenz curve (in absolute value) defined previously. Remember that the Gini index I_G may be written as

$$I_G = 1 - \frac{x_E}{\bar{x}}, \tag{17}$$

where x_E is Atkinson's (1970) equally distributed equivalent level of income when using the Gini-related social welfare function. Because the area between the Lorenz curve and the diagonal is equal to half the Gini index, we derive that the area below the Lorenz curve is equal to $\frac{1}{2}-(\frac{1}{2}-\frac{x_E}{2\bar{x}})=\frac{x_E}{2\bar{x}}$. The area under the generalized Lorenz curve will therefore be equal to $\frac{x_E}{2\bar{x}}$.

2. Distributional change in welfare

As in the absolute and relative approaches for measuring convergence, we can distinguish between anonymous and nonanonymous approaches when measuring distributional change in welfare.

For the anonymous distributional change in welfare, as before, let us call $\{y_1, \ldots, y_i, \ldots, y_n\}$ the distribution of incomes at time 1, $\bar{y}$ the average income at time 1, and y_E the equally distributed equivalent of income at time 1, again using the Gini social welfare function. The anonymous distributional change in welfare between times 0 and 1, $DC_W^{Anonymous}$, may then be expressed as

$$DC_W^{Anonymous}=\frac{1}{2}y_E-\frac{1}{2}x_E=\frac{1}{2}(y_E-x_E). \quad (18)$$

Clearly, if $DC_W^{Anonymous} > 0$, the distributional change between times 0 and 1 leads to an increase in social welfare because y_E and x_E may be considered measures of social welfare at times 0 and 1. The measurements of nonanonymous distributional change and welfare change are examined in Appendix B.3.

3. Measuring pro-low welfare change

For the anonymous case, if we limit the analysis to q individuals who are poor at time 0 (below the poverty line z), we can compute the equally distributed equivalent level of income $x_{E,\,poor}$ and $y_{E,\,poor}$ among the q poor individuals and then derive a measure $DC_{W,\,poor}$ of welfare change among the poor. If $DC_{W,\,poor} > 0$ and $DC_{W,\,poor} > DC_W$, we can conclude that the increase in the welfare of the lower deciles between times 0 and 1 was higher than that observed in the whole population.

When discussing the nonanonymous case, using the previous notations, we can compute the nonanonymous distribution change, $DC_{W,poor}^{Nonanonymous}$, among those who were poor at time 0. We can thus conclude that the increase in welfare between times 0 and 1 of those who were poor at time 0 was higher than that observed in the whole population if $DC_{W,poor}^{Nonanonymous} > 0$ and $DC_{W,poor}^{Nonanonymous} > DC_{W}^{Nonanonymous}$.

We can further measure welfare change with another ranking criterion. For example, as in the case of *RDC* and *ADC*, we can examine the case where the variable under discussion is not the variable from which the ranking of the individuals is derived (e.g., we may want to determine whether welfare change favored those who had a low level of education).

VII. Results of the empirical investigation

This section analyzes absolute and relative income convergence and welfare convergence in China for the period 2010–2018. Data from the CFPS, which is funded by the 985 Program of Peking University and carried out by the Institute of Social Science Survey of Peking University, are used to conduct the analysis. The CFPS is the first nationally representative survey designed to characterize China's ongoing social transformation by collecting data at the community, family, and individual levels (Xie and Hu, 2014). First launched in 2010, the CFPS has since been conducted every 2 years. The survey uses a multistage, implicit stratification and a proportion-to-population size sampling method with a rural–urban integrated sampling frame. The CFPS sample is drawn from 25 provincial regions in China, excluding Hainan, Inner Mongolia, Ningxia, Qinghai, Xinjiang, Xizang, Chinese Hong Kong SAR, Macao SAR, and Taiwan province. The population of these 25 provincial regions in China (excluding Chinese Hong Kong SAR, Macao SAR, and Taiwan province) includes 95 percent of the total Chinese population, so the CFPS can be regarded as a nationally representative sample.[5]

[5] China Family Panel Studies data have also been used by Kanbur et al. (2021) and Piketty et al. (2019) as nationally representative data for investigating the evolution of inequality in China.

The CFPS contains a family questionnaire that poses a series of questions pertaining to family income, including labor and nonlabor income, expenditures in different categories, and the income-generating activities of all family members. The longitudinal design of the CFPS makes it possible to study trends in income inequality and individual income growth in contemporary China at the micro level. In this study, we analyze changes in incomes and welfare during the period 2010–2018. Regarding the use of sample weights, the CFPS data contain regional subsamples and thus require weighting to be nationally representative (Xie and Hu, 2014; Xie and Lu, 2015). Following Xie and Lu (2015), we use a restricted sample with panel weights that include families who were successfully interviewed in both 2010 and 2018.

The income variable used in this study is equivalent family net income (i.e., the total net income from all sources divided by the number of equivalent family members).[6] Income includes five major components: (i) wage income (the after-tax wages and salaries of individual family members employed in the agricultural or nonagricultural sector, including employer-provided bonuses and in-kind benefits); (ii) income from agricultural production and profits from family-run or owned businesses; (iii) property income (rents from land, housing units, and other assets); (iv) transfer income (sum of pensions, as well as various kinds of government aid and allowances); and (v) monetary compensation for government appropriation of land and residential relocation and all other income (private transfers and gifts).[7] In our analysis, we compare the 2010 and 2018 incomes using longitudinal data and, following the suggestion of Xie et al. (2017), for the longitudinal analysis, we use the income variables in 2018 that are comparable to those in 2010.[8] We adjust the value of the

[6]We used the equivalence scale of Buhmann et al. (1988) with the parameter equal to 2. We also repeated the analysis with per capita income and the conclusions remained the same for the relative case and almost the same for the other cases. Results for per capita income are available upon request from the authors. Given that some of the changes in income could be driven by family formation, we checked for robustness, and the results remained the same, even when the sample was restricted to cases where the number of family members did not change (around 35 percent of the sample). Results for households with no change in family size using the Buhmann et al. (1988) equivalence scale are also available upon request from the authors.
[7]For details about the income component adjustment of the CFPS, see Xie and Lu (2015).
[8]See Table 6 and Section VII.4 of Xie et al. (2017) for a detailed description of the incomes included.

income to account for inflation.[9] We then obtain an inflation-adjusted net family equivalent income for each member of the household and follow the individual across the years 2010 and 2018.

The annual samples have been symmetrically truncated with the elimination of 1 percent of the observations at each end of the income distribution. Such truncation is frequent in intertemporal comparisons due to the possible contamination of the data by anomalies in the extreme values (Cowell et al., 1999). A balanced panel of 19,900 records was therefore generated, which contained data on the same individuals for both years. Table 1 presents the summary statistics for the income distribution of the truncated sample for 2010 and 2018.[10]

Table 1. Descriptive statistics of equivalent family income in 2010 and 2018

Income	Mean	Standard deviation	Min.	Max.
2010	16,042.9400	15,166.1900	583.3300	95,840.1500
2018	30,869.0400	26,014.2000	0.5800	147,947.8000

Sources: Calculated by authors from CFPS 2010 and 2018 data.

1. A relative population-weighted measure of distributional change

We begin with the nonanonymous measurement of changes in relative income. Table 2 shows that the measure of *RDC* (Equations (20) or (26) in the Appendix) is equal to 0.2481 for the nonanonymous case. The equivalent growth rate η_E turns out to be equal to 1.7873, which is significantly higher than the average growth rate $\bar{\eta}$, which is 0.9242.[11] We can thus conclude that there was relative income convergence during the period – that is, individuals with lower incomes were generally those with higher income growth rates. We assume that parameter γ, which measures the degree of distribution sensitivity, is equal to 2 and decompose this change in relative income into

[9]We use the China Consumer Price index, with 2010 as the base year, provided by the NBS of China.
[10]We worked with comparable incomes in 2018 to match the income variables reported in 2010, as suggested in the CFPS manuals. We should therefore be cautious about the interpretation of the results; even so, the income definition is the same for both years, thus ensuring comparability.
[11]We use 95 percent confidence intervals based on the bootstrap procedure with 1,000 bootstrapped estimates for each point estimation.

two components: relative structural mobility and relative exchange mobility. Most of the change (0.2458) comes from exchange mobility – that is, from the re-ranking of individuals.

Table 2. Estimates of the relative convergence indices in China (2010–2018)

		η_E	$\bar{\eta}$	*RDC*	*RSM*	*REM*
$\gamma = 2$	Nonanonymous	1.7873	0.9242	0.2481	0.0023	0.2458
		(1.7801, 1.7940)	(0.9202, 0.9278)	(0.2470, 0.2492)	(0.00123, 0.0036)	(0.2440, 0.2474)
	Anonymous	0.9322		0.0023		
		(0.9317, 0.9328)		(0.0020, 0.0026)		

η_E: Sensitivity

	$\gamma = 3$	$\gamma = 4$	$\gamma = 5$	$\gamma = 10$
Nonanonymous	2.4490	3.0429	3.6054	6.2458
	(2.4388, 2.4622)	(3.0291, 3.0619)	(3.5843, 3.6302)	(6.1913, 6.3058)
Anonymous	0.8346	0.7346	0.6425	0.2980
	(0.8336, 0.8356)	(0.7334, 0.7359)	(0.6410, 0.6442)	(0.2957, 0.3004)

Sources: Calculated by authors from CFPS 2010 and 2018 data.

Notes: The numbers in parentheses are 95 percent confidence intervals based on the bootstrap procedure with 1,000 bootstrapped estimates for each point estimation. RDC, relative distributional change; REM, relative exchange mobility; RSM, relative structural mobility.

For the anonymous case, the equivalent growth rate appears to be 0.9322 and is also significantly, but only slightly, higher than the average growth rate. We can therefore conclude that income growth in China in the period 2010–2018 was slightly higher for the lower income deciles, leading to a slight anonymous convergence. At the same time, there was nonanonymous convergence because income growth was significantly higher among individuals who initially had a lower income.

Results for the case in which the sensitivity parameter takes different values are shown in the other columns (γ = 3, 4, 5, and 10) of Table 2. For higher values of γ, the equivalent growth rates are significantly higher in the nonanonymous case and smaller in the anonymous case, and they become lower than the average growth rate from $\gamma = 3$. This means that the higher the weight attached to lower income individuals, the greater the nonanonymous convergence and the greater the anonymous divergence.

In summary, during the period examined, income growth was higher for individuals at the lower end of the distribution, and the lower the rank, the higher the growth rate. At the same time, lower income quantiles experienced greater growth rates only when $\gamma = 2$; however, there is an anonymous divergence when we attach greater weight to the lowest part of the distribution.

(1) Checking for relative pro-poor growth

Now we focus on poor individuals. We use the World Bank's international per person per day poverty lines of US$1.90 and US$3.20 (both in 2011 PPP). In Table 3, we estimate the equivalent growth rates for the anonymous and nonanonymous cases among those considered poor.

Table 3. Relative equivalent growth rates for poor individuals in China (2010–2018)

		η_E		
		Poverty line = US$1.90	Poverty line = US$3.20	$\bar{\eta}$
$\gamma = 2$	Nonanonymous	22.4455	11.7407	0.9242
		(22.0646, 22.8681)	(11.6059, 11.8999)	(0.9202, 0.9278)
	Anonymous	−0.4304	−0.1753	
		(−0.2977, −0.2945)	(−0.0266, −0.0244)	
Sensitivity				
$\gamma = 3$	Nonanonymous	31.0938	15.9117	
		(30.9103, 31.2773)	(15.83869, 15.9848)	
	Anonymous	−0.5096	−0.2755	
		(−0.5113, −0.508)	(−0.2767, −0.2742)	
$\gamma = 4$	Nonanonymous	39.3587	20.0286	

		(39.1441, 39.5734)	(19.9415, 20.1156)
	Anonymous	−0.5620	−0.3501
		(−0.5641, −0.5599)	(−0.3515, −0.3486)
$\gamma = 5$	Nonanonymous	47.0501	24.1270
		(46.8032, 47.2971)	(24.0286, 24.2254)
	Anonymous	−0.5998	−0.4081
		(−0.6021, −0.5974)	(−0.4098, −0.4063)
$\gamma = 10$	Nonanonymous	73.3793	43.5523
		(72.9777, 73.7809)	(43.3979, 43.7067)
	Anonymous	−0.7045	−0.5707
		(−0.7080, −0.7010)	(−0.5733, −0.5682)

Sources: Calculated by authors from CFPS 2010 and 2018 data.

Note: The numbers in parentheses are 95 percent confidence intervals based on the bootstrap procedure with 1,000 bootstrapped estimates for each point estimation.

We obtained notable results that agree with the observations made previously. The nonanonymous equally distributed equivalent growth rate among those who were poor in 2010 is 22.4455 when using the US$1.90 poverty line (11.7407 using the US$3.20 poverty line), which is significantly higher than the average growth rate ($\bar{\eta} = 0.9242$). Nonanonymous growth was therefore clearly pro-poor. The anonymous equally distributed equivalent growth rate is equal to –0.4304 (–0.1753 when using the US$3.20 poverty line), thus indicating that anonymous income growth was clearly not pro-poor. The different conclusions of the anonymous and nonanonymous approaches are due to the fact that the position of the individuals was reshuffled in the nonanonymous approach, while we cannot reshuffle the individuals in the anonymous approach. We can even state that poorer quantiles experienced a decline in income. We assess this result under different sensitivity parameters in the other rows of Table 3 (γ = 3, 4, 5, and 10). For higher values of γ, the nonanonymous equivalent growth rates are higher than the average growth rate, and the anonymous equivalent growth rates are more negative. Thus, when using lower poverty lines, we can expect to reach similar conclusions (pro-poor nonanonymous growth and non-pro-poor anonymous growth).

(2) Conditional convergence

In this part of the empirical analysis, we checked whether the relative income growth was more favorable for individuals with a higher educational level or for older people. We therefore applied the previously defined conditional measures of distributional change, and we worked with two conditioning variables: the educational level and age of individuals in 2010.[12]

For education, the following categories were considered: (i) illiterate or semi-literate, (ii) primary school, (iii) junior high school, (iv) senior high school, (v) 2-year or 3-year college, (vi) 4-year college or bachelor's degree, and (vii) master's degree. We ranked the individuals according to their level of education and checked whether those with a higher educational level experienced more favorable income growth. Similarly, we ranked the individuals by their age and checked whether income growth was higher for younger or older people. Table 4 reports the summary statistics for education and age.

Table 4. Descriptive statistics for the level of education and age in 2010

Level of education	Proportion (%)
Illiterate or semiliterate	23.1900
Primary school	20.8400
Junior high school	33.3800
Senior high school	15.1300
3-year college	5.0700
4-year college or bachelor's degree	2.2600
Master's degree	0.1000

	Mean	Standard deviation	Min.	Max.	Q1	Q2	Q3
Age	42.1000	15.3800	16	92	30	41	54

Source: Calculated by authors from CFPS 2010 data.

[12]The respondents' educational level could change during the period under study, which might affect the results of conditional convergence. We checked the robustness of the results with the fraction of the sample that did not move from one education category to another over time (83 percent of observations) and reached the same conclusions. These results are available upon request.

Note: Q1, Q2, and Q3 are the first, second, and third quartiles, respectively.

Table 5 shows the equally distributed equivalent growth rate for the anonymous and nonanonymous cases for the two conditional variables.

Table 5. Relative equivalent growth rates conditional on education and age in China (2010–2018)

	Conditional on education	Conditional on age
Nonanonymous	1.0431	1.0113
	(1.0375, 1.0481)	(1.0065, 1.0164)
Anonymous	0.9423	0.9020
	(0.9416, 0.9430)	(0.9007, 0.9033)

Sources: Calculated by authors from CFPS 2010 and 2018 data.

Given that the nonanonymous equally distributed equivalent growth rate for individuals ranked according to their educational level (1.0431) is greater than the average growth rate (0.9242), we conclude that relative income growth has favored individuals with lower levels of education. This conclusion also holds for the anonymous case.

Regarding age, the same conclusion was reached for the nonanonymous case, given that the equally distributed equivalent growth rate for individuals ranked according to their age (1.0113) is higher than the average growth rate (0.9242). Thus, income growth appears to have favored younger individuals, while the anonymous equally distributed equivalent growth rate for individuals ranked according to their age (0.9020) is lower than the average growth rate. Hence, income growth seems to have favored older deciles.

Important driving forces behind our results may have been the Lewis turning point (LTP) potentially being reached, together with the previously introduced minimum wage regulations.[13] For example, Zhang et al. (2018) applied the method Minami

[13]The LTP occurs in economic development when there is no more surplus rural labor.

(1968) used to identify the LTP in Japan to a nationally representative rural household sample from the NBS of China and provided evidence suggesting that the Chinese economy reached the LTP around 2010. Consequently, we expect that the incomes of low-skilled workers or younger workers would have increased faster than the incomes of highly educated workers or older workers. Indeed, the previous empirical investigation indicates that the relative income growth in China during the period 2010–2018 favored older individuals and those with lower educational levels, thus confirming the first hypothesis but refuting the second one.

2. An absolute population-weighted measure of distributional change

In this section, we focus on absolute measures of distributional change. This approach should give us a complementary assessment of the changes that occurred in the distribution of incomes in China between 2010 and 2018. In Table 6, the nonanonymous measurement of *ADC* is negative (–369.5900), which indicates that the equivalent increase in income is greater than the average increase in income. We can therefore conclude that there was absolute income convergence during the period 2010–2018: individuals with lower incomes had, in general, greater absolute increments in income. The decomposition of this change in absolute income into two components reveals that the change was driven by *AEM* (–4,004.7200) because *ASM* (3,635.1200) was positive. In other words, while the change in absolute inequality did not favor lower incomes at time 0, the re-ranking of individuals between 2010 and 2018 had an offsetting role and was stronger in absolute value than the change in absolute inequality. Thus, the net effect was an absolute convergence in incomes. This result is evidently confirmed by the results of the anonymous approach because the *ADC* is identical to the structural mobility observed in the nonanonymous approach. Note that when repeating the computations with different values of γ ($\gamma = 3, 4, 5,$ and 10), as in Table 6, a convergence in absolute incomes for all values of the parameter can be observed in the nonanonymous case, while in the anonymous approach, the higher the value of γ, the stronger the divergence in absolute incomes.

To summarize, and similar to the observations made when using a relative approach, during the period 2010–2018 in China, the absolute increase in income was higher for individuals who were poor in 2010 than it was for the whole population. At the same time, higher income quantiles generally experienced greater absolute increases in income. The reshuffling of the ranking of the individuals (which is not taken into account in an anonymous approach) explains why different conclusions are drawn in the anonymous and nonanonymous cases.

Table 6. Estimates of the absolute convergence indices in China (2010–2018)

		ADC	*ASM*	*AEM*
$\gamma = 2$	Nonanonymous	−369.5900	3,635.1200	−4,004.7200
		(−397.3624, −340.9647)	(3,584.8060, 3,687.6250)	(−3,954.4880, −4,056.4900)
	Anonymous	3,635.1200		
		(3,584.8060, 3,687.6250)		

ADC: Sensitivity

	$\gamma = 3$	$\gamma = 4$	$\gamma = 5$	$\gamma = 10$
Nonanonymous	−260.0400	−214.5200	−224.0500	−543.9400
	(−303.6230, −218.6048)	(−263.9988, −164.9552)	(−283.4271, −160.8720)	(−643.8998, −450.3795)
Anonymous	5,314.3900	6,296.7200	6,952.6100	8,524.2300
	(5,265.2610, 5,364.9730)	(6,246.3620, 6,344.5980)	(6,904.4470, 7,002.0410)	(8,472.3490, 8,569.3340)

Sources: Calculated by authors from CFPS 2010 and 2018 data.

Notes: The numbers in parentheses are 95 percent confidence intervals based on the bootstrap procedure with 1,000 bootstrapped estimates for each point estimation. ADC, absolute distributional change; AEM, absolute exchange mobility; ASM, absolute structural mobility.

(1) Checking for absolute pro-poor income change

Focusing on poor individuals (Table 7), in the anonymous and nonanonymous cases (using the US$1.90 and US$3.20 poverty lines), we observe that the *ADC* (169.3200 and 9,127.9900 for the nonanonymous and anonymous cases, respectively) is higher than that observed for the overall distribution (−369.5900 and 3,635.1200 for the nonanonymous and anonymous cases, respectively). This implies that the absolute income change among those who were poor in 2010 was smaller than that observed in the whole population. Absolute income growth was therefore not pro-poor.

Table 7 also shows that, in the nonanonymous and anonymous cases for both poverty lines, the absolute income change observed in the period 2010–2018 among the poor was frequently positive (except for the nonanonymous case for the US$1.90 poverty line and γ greater than 3 and the US$3.20 poverty line and $\gamma = 2$); it was also, in any case, higher than that observed in the whole population for all parameter values. This clearly indicates that the absolute income change was not pro-poor.

Table 7. Absolute income changes for poor individuals in China (2010–2018)

		Poverty line = US$1.90	Poverty line = US$3.20
$\gamma = 2$	Nonanonymous	169.3200	−108.7800
		(45.1777, 308.7917)	(199.5236, −9.5457)
	Anonymous	9,127.9900	11,815.0500
		(8,922.9020, 9,340.7010)	(11,618.5700, 11,984.4900)
		Sensitivity	
$\gamma = 3$	Nonanonymous	40.4300	173.4700
		(−135.8171, 219.1022)	(38.4356, 298.2309)
	Anonymous	9,101.8600	11,930.5300
		(8,905.1350, 9309.7530)	(11,741.2000, 12107.2600)
$\gamma = 4$	Nonanonymous	−64.7600	761.2900
		(−278.1867, 150.4997)	(600.5400, 914.1420)
	Anonymous	9,082.0100	11,984.6900
		(8,886.5610, 9,302.5320)	(11,794.6000, 12,170.8700)
$\gamma = 5$	Nonanonymous	−155.1000	1,338.5200
		(−421.7596, 115.4943)	(1,148.985, 1,509.6520)
	Anonymous	9,067.3900	12,011.0800
		(8,855.8930, 9,268.3310)	(11,825.0600, 12,195.1000)
$\gamma = 10$	Nonanonymous	−141.6000	2,660.3900
		(−506.6187, 185.0076)	(2,385.2530, 2,938.7540)

Anonymous	9035.0800	12,021.3200
	(8,830.7620, 9,251.8540)	(11,849.9100, 12,214.4000)

Sources: Calculated by authors from CFPS 2010 and 2018 data.

Note: The numbers in parentheses are 95 percent confidence intervals based on the bootstrap procedure with 1,000 bootstrapped estimates for each point estimation.

(2) Conditional convergence

The results of this investigation are shown in Table 8. For both the anonymous and the nonanonymous cases, absolute income increases appear to have favored individuals with higher levels of education. Regarding age, absolute income increases seem to have been higher among younger individuals than the whole population.

Table 8. Absolute income changes conditional on education and age in China (2010–2018)

	Conditional on education	Conditional on age
Nonanonymous	1,332.7600	−763.1200
	(1,309.2490, 1,359.2610)	(−790.3212, −735.5918)
Anonymous	2,048.9400	−170.0200
	(1,994.6530, 2,100.9760)	(−225.3281, −116.1491)

Sources: Calculated by authors from CFPS 2010 and 2018 data.

Note: The numbers in parentheses are 95 percent confidence intervals based on the bootstrap procedure with 1,000 bootstrapped estimates for each point estimation.

3. A population-weighted measure of the distributional change in welfare

Regarding welfare, Table 9 shows that, in the nonanonymous and anonymous cases, the welfare distribution changes are positive, which indicates that the distribution change between 2010 and 2018 led to an increase in welfare. In the nonanonymous case, this increase is driven slightly more by structural than exchange mobility. Moreover, as a greater weight is attached to the lower part of the distribution, the increase in welfare becomes greater in the nonanonymous case, whereas the opposite is true in the anonymous case.

Table 9. Estimates of the distributional change in welfare indices in China (2010–2018)

		WDC	*WSM*	*WEM*
$\gamma = 2$	Nonanonymous	7,877.3500	4,099.8300	3,777.5200

		(7,850.4700, 7,903.7600)	(4,090.2100, 4,110.2220)	(3,749.0340, 3,804.4200)
	Anonymous	4,099.8300		
		(4,090.2100, 4,110.2220)		
WDC: Sensitivity				
	$\gamma = 3$	$\gamma = 4$	$\gamma = 5$	$\gamma = 10$
Nonanonymous	8,020.2500	8,175.9500	8,347.5600	9,270.9000
	(7,988.0630, 8,052.1230)	(8,138.2920, 8,211.9920)	(8,303.4540, 8,395.3420)	(9,193.9830, 9,344.3490)
Anonymous	2,724.1900	1,965.3300	1,479.6900	436.3300
	(2,715.2060, 2,733.0520)	(1,957.0250, 1,973.4320)	(1,472.1100, 1,487.6280)	(431.7301, 441.5249)

Sources: Calculated by authors from CFPS 2010 and 2018 data.

Notes: The numbers in parentheses are 95 percent confidence intervals based on the bootstrap procedure with 1,000 bootstrapped estimates for each point estimation. WDC, welfare distributional changes; WEM, welfare exchange mobility; WSM, welfare structural mobility.

(1) Checking for pro-poor welfare change

When we focus on the lower part of the distribution (Table 10), several interesting conclusions may be drawn. In the nonanonymous case, there is a welfare increase regardless of whether the US$1.90 or the US$3.20 poverty line is used. This welfare increase is higher than the overall welfare increase. In the anonymous case, there is a welfare decrease and therefore no pro-poor welfare increase, regardless of the selected poverty line. Note that when we attach a higher weight to lower incomes, the welfare increase in the nonanonymous case is higher. In the anonymous case, however, there is always a welfare decrease, regardless of the weight attached to lower incomes.

Table 10. Estimates of the distributional change in welfare for poor individuals in China (2010–2018)

		Poverty line = US$1.90	Poverty line = US$3.20
$\gamma = 2$	Nonanonymous	13,593.6900	10,568.9000

		(13390.1700, 13,799.2600)	(10,457.2300, 10,673.9500)
	Anonymous	−263.2600	−161.6300
		(−263.4963, −262.2509)	(−162.4465, −160.26100)
		Sensitivity	
$\gamma = 3$	Nonanonymous	16,331.5200	12,040.5800
		(16,070.4500, 16,598.5600)	(11,893.6800, 12,191.8800)
	Anonymous	−269.9100	−211.6700
		(−269.8209, −268.7132)	(−212.3305, −210.4799)
$\gamma = 4$	Nonanonymous	18,658.6400	13,388.9200
		(18,321.2700, 18,988.2900)	(13,198.9800, 13,564.9500)
	Anonymous	−268.4400	−236.8700
		(−268.2463, −267.1552)	(−237.3245, −235.7574)
$\gamma = 5$	Nonanonymous	20,647.7800	14,663.5900
		(20294.2600, 20,998.0100)	(14,429.7500 14,881.2500)
	Anonymous	−265.0600	−250.6000
		(−264.7987, −263.6492)	(−250.7940, −249.3926)
$\gamma = 10$	Nonanonymous	26,457.3900	19,991.8100
		(25,963.7400, 26,954.4200)	(19,652.1100, 20,317.3700)
	Anonymous	−255.5300	−263.9300
		(−254.4369, −253.1989)	(−263.6863, −262.5687)

Sources: Calculated by authors from CFPS 2010 and 2018 data.

Note: The numbers in parentheses are from 95 percent confidence intervals based on the bootstrap procedure with 1,000 bootstrapped estimates for each point estimation.

(2)Conditional convergence

In the nonanonymous case, as shown in Table 11, the welfare increase conditional on education is lower than that observed during the same period in the whole population, whereas the opposite occurs for age. We can therefore conclude that the welfare increase seems to have favored individuals with higher levels of education and younger individuals. Even so, the welfare increase seems to have favored lower levels of education and younger deciles in the anonymous case.

Table 11. Distributional change in welfare conditional on education and age in China (2010–2018)

	Conditional on education	Conditional on age
Nonanonymous	6,086.2500	8,444.4800
	(6,060.2200, 6,111.0980)	(8,413.7350, 8,475.4350)
Anonymous	5,495.5900	7,528.5800
	(5,483.1880, 5,507.8700)	(7,514.8440, 7,541.9570)

Sources: Calculated by authors from CFPS 2010 and 2018 data.

VIII. Conclusions

Following previous work on parallelisms between the study of income convergence in the growth literature and that of vertical and horizontal equity in the tax literature, as well as work on the similarity between the notions of convergence and pro-poor growth, this paper first took a relative approach to distributional change. It employed population-weighted measures of structural and exchange mobility, conditional and unconditional anonymous and nonanonymous convergence, and anonymous and nonanonymous pro-poor growth. Based on Chinese panel data, the analysis showed that income growth during 2010–2018 was higher for individuals with an initially lower income and higher the greater the weight attached to lower incomes. Simultaneously, income growth was greater for lower income deciles, leading to some nonsignificant anonymous relative income convergence, but only when $\gamma = 2$. As we attached more weight to lower deciles, anonymous convergence turned into anonymous divergence. Nonanonymous growth turned out to be pro-poor, while anonymous income growth was not pro-poor; this result was robust to a wide range of sensitivity parameter values. Finally, we concluded that relative income growth seemed to have favored individuals with lower levels of education, regardless of whether an anonymous or nonanonymous approach was taken. Income growth also seemed to favor younger individuals when using a nonanonymous approach, but the opposite was the case under the anonymous approach, where income growth seemed to favor older deciles.

The paper then measured distributional change in absolute terms, the latter being estimated in US$. Our empirical analysis revealed that, when taking a nonanonymous approach, the absolute increase in income was higher among individuals with lower incomes (in 2010) than in the whole population. However, when taking an anonymous approach, it appeared that higher income quantiles experienced higher increases in absolute income. The re-ranking of the individuals between 2010 and 2018 explains this difference between the findings obtained using an anonymous and a nonanonymous approach. When taking the nonanonymous and anonymous approaches, we also observed that the absolute income change among those who were poor in 2010 was smaller than that observed in the whole population. Absolute income growth was therefore not pro-poor. Finally, we also observed that changes in absolute incomes seem to favor individuals and deciles with a higher level of education and younger individuals.

The last section of this paper analyzed the distributional change in welfare. Using both an anonymous and nonanonymous approach, we found that there was an increase in individual welfare between 2010 and 2018. Moreover, as greater weight was attached to the lower part of the distribution, the increase in welfare became greater in the nonanonymous case, whereas the opposite was true in the anonymous case. We also compared the change in welfare among those who were poor in 2010 and the overall change in individual welfare. In the nonanonymous case, the increase in welfare was higher among the poor than among the whole population. When taking an anonymous approach, no matter which poverty line was selected, there was a decrease in welfare and thus no pro-poor increase in welfare. Finally, we observed that, with the nonanonymous approach, the increase in welfare seemed to favor younger individuals and individuals with higher levels of education. In the anonymous case, however, the welfare increase seemed to favor lower levels of education and younger deciles. The reshuffling of the positions of the individuals, which was not considered in the anonymous approach, is the cause of the divergent findings of both approaches.

The approach introduced in this paper has clear policy implications. When the analysis is limited to the anonymous case due to data constraints, it is still possible to draw conclusions about changes in inequality over time and to determine whether the government's policies have been pro-poor, assuming – as most studies on this topic do – that the focus is on what happens to the lower deciles. A nonanonymous approach seems to make it possible to draw additional policy implications concerning the extent of mobility, convergence, and nonanonymous pro-poor growth. China implemented an individual-targeted anti-poverty strategy in 2014 that put greater emphasis on fighting multidimensional poverty among the elderly, disabled, seriously ill, and unemployed individuals, and all absolute poverty was successfully eliminated in China by the end of 2020. Nonetheless, China needs to keep fighting absolute poverty, which means that it should pay attention to the vulnerable groups that may fall into poverty. For this reason, it is important that policymakers adopt a nonanonymous approach to track which group benefits less from economic growth and then use precisely targeted policies to help them. After this milestone, China is now turning to another development goal – reducing relative poverty and promoting shared prosperity. In other words, the goal is to select an economic growth pattern that improves the income mobility of individuals belonging to the lower deciles and to induce economic convergence. We believe that applying the methodology proposed in this paper to rotating household panel data collected by the NBS can result in fruitful policy implications and guarantee shared prosperity in the country.

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Appendices

Appendix A: More details on the relative approach to distributional change

A1. Deriving the concept of "equivalent growth rate"

Let x_i and y_i refer to the absolute income of the ith observation and $\bar{x}$ and $\bar{y}$ to the average incomes at times 0 and 1 in a population of n individuals, respectively.[14] Define the changes in incomes, Δx_i and $\Delta\bar{x}$, as $\Delta x_i = (y_i - x_i)$ and $\Delta\bar{x} = \bar{y} - \bar{x}$. Let $s_i = (x_i/n\bar{x})$ and $w_i = (y_i/n\bar{y}) = (x_i + \Delta x_i)/n(\bar{x} + \Delta\bar{x})$ refer to the income shares at times 0 and 1. The incomes x_i at time 0 are ranked by nondecreasing values. The ranking of the incomes y_i at time 1 depends on the case which is examined.

[14]For the ease of exposition, we refer to i as an individual here. However, i may also represent a population centile, a region, or a country, depending on the application.

Upon simplification, the difference ($w_i - s_i$) may be expressed as:

$$w_i - s_i = \frac{1}{n\bar{x}} \frac{\bar{x}\Delta x_i - x_i \Delta\bar{x}}{\bar{x} + \Delta\bar{x}},$$

which can be simplified as:

$$w_i - s_i = s_i \left(\frac{\eta_i - \bar{\eta}}{1+\bar{\eta}}\right), \qquad (19)$$

where $\eta_i = (\Delta x_i)/x_i$ denotes the growth in income of observation i and $\bar{\eta} = (\Delta \bar{x}/ \bar{x})$, denotes the growth in average income.

Let us first compute the area A_S situated below the curve C_S. Assuming n observations, it is identical to the sum of a triangle and of $(n - 1)$ trapezoids. It is easy to check that this area may be expressed as

$$A_s = \frac{1}{2n} s_1 + \frac{1}{2n}\left[\sum_{i=2}^{n}(s_i + 2\sum_{j=1}^{i-1} s_j)\right].$$

Similarly the area A_w situated below the curve C_w will be expressed as:

$$A_w = \frac{1}{2n} w_1 + \frac{1}{2n}\left[\sum_{i=2}^{n}(w_i + 2\sum_{j=1}^{i-1} w_j)\right].$$

The difference between these two areas will then be written as:

$$A_w - A_s = \frac{1}{2n}(w_1 - s_1) + \frac{1}{2n}\left[\sum_{i=2}^{n}\left[(w_i - s_i) + 2\sum_{j=1}^{i-1}(w_j - s_j)\right]\right].$$

We then derive

$$A_w - A_s = \frac{1}{2n}\frac{1}{1+\bar{\eta}}\sum_{i=1}^{n}\left[s_i(\eta_i - \bar{\eta}) + \sum_{j=1}^{i-1}\left[2s_j\left(\eta_j - \bar{\eta}\right)\right]\right]$$

$$= \frac{1}{2n}\frac{1}{1+\bar{\eta}}\sum_{i=1}^{n}(\eta_i - \bar{\eta}) s_i (2n + 1 - 2i).$$

Call RDC the measure of relative distributional change. RDC is equal to twice the difference ($A_w - A_s$), so we conclude that

$$RDC = \sum_{i=1}^{n} \tau_i \frac{\eta_i - \bar{\eta}}{1+\bar{\eta}} = \sum_{i=1}^{n} \tau_i \frac{(1+\eta_i)-(1+\bar{\eta})}{(1+\bar{\eta})} = \sum_{i=1}^{n} \tau_i \left(\frac{1+\eta_i}{1+\bar{\eta}} - 1\right), \qquad (20)$$

$$\tau_i = \left(\frac{2n+1-2i}{n}\right) s_i. \quad (21)$$

Equation (20) may also be written as:

$$RDC = \frac{\sum_{i=1}^{n} \tau_i (1+\eta_i)}{(1+\bar{\eta})} - \sum_{i=1}^{n} \tau_i = \frac{\sum_{i=1}^{n} \tau_i + \sum_{i=1}^{n} \tau_i \eta_i}{(1+\bar{\eta})} - \sum_{i=1}^{n} \tau_i,$$

$$= \sum_{i=1}^{n} \tau_i \left[\frac{(1+\sum_{i=1}^{n} \varphi_i \eta_i)}{(1+\bar{\eta})} - 1\right] = \sum_{i=1}^{n} \tau_i \left[\frac{(1+\eta_E)}{(1+\bar{\eta})} - 1\right], \quad (22)$$

$$\varphi_i = \frac{\tau_i}{\sum_{i=1}^{n} \tau_i}, \quad (23)$$

$$\eta_E = \sum_{i=1}^{n} \varphi_i \eta_i, \quad (24)$$

where η_E is the equivalent growth rate.

As x_i is the income of individual i at time 0 and $s_i = \frac{x_i}{n\bar{x}}$ we derive

$$\sum_{i=1}^{n} \tau_i = \sum_{i=1}^{n} \left(\frac{2n+1-2i}{n}\right) s_i = \sum_{i=1}^{n} \left(\frac{2n+1-2i}{n}\right)\left(\frac{x_i}{n\bar{x}}\right) = \sum_{i=1}^{n} \left(\frac{2n+1-2i}{n^2}\right)\left(\frac{x_i}{\bar{x}}\right). \quad (25)$$

However, $\sum_{i=1}^{n}(2n + 1-2i) = n^2$, so that $\sum_{i=1}^{n} \left(\frac{2n+1-2i}{n^2}\right) x_i = x_E$ in Equation (25) is a weighted average of the incomes at time 0. Note that the difference between the weights of two individuals who are adjacent in the ranking is always equal to $(1/n^2)$. It is easy to check that when the individuals are ranked by increasing income, x_E turns out to be Atkinson's "equally distributed equivalent level of income" at time 0, assuming we use Gini's social welfare function (Donaldson and Weymark, 1980).[15] $E_0 = (x_E / \bar{x})$ is then identical to Gini's measure of equality (the complement to 1 of Gini's famous inequality index) at time 0.

Combining Equations (22) and (25), we then end up with

$$RDC = E_0 \left(\frac{1+\eta_E}{1+\bar{\eta}} - 1\right). \quad (26)$$

A.2. Decomposing the population-weighted relative measure of distributional change in the nonanonymous case

[15]Donaldson and Weymark (1980) ranked the incomes by decreasing rather than increasing values, hence the difference in the formulations.

Following earlier work on an approach to the computation of the Gini index based on the use of the so-called *G*-matrix (Silber, 1989), Silber (1995) defined a population weighted measure J_{GP} of distributional change as:

$$J_{GP} = e'G(s - w), \qquad (27)$$

where e' is a 1 by n vector of the population shares $\frac{1}{n}$ whereas $\boldsymbol{s}$ and $\boldsymbol{w}$ are (n by 1) vectors of the income shares s_i and w_i, which were defined previously. In Equation (27), both sets of shares are ranked by decreasing values of the incomes x_i at time 0. Finally, G is a $n \times n$ square matrix, whose typical element is equal to 0 when $i = j$, –1 when $j > i$, and 1 when $i > j$. Silber (1995) has also shown that this index J_{GP} is actually equal to twice the area lying between the curves C_S and C_W previously defined. Note that, at the difference of what was assumed at the right hand side of Equation (27), in drawing these curves C_S and C_S, both sets of shares, s_i and w_i, were ranked by increasing values of the shares s_i at time 0. As the area between the diagonal and the curve C_S is equal to $e'Gs/2$, while the area between the diagonal and the curve C_w is equal to $e'Gw/2$, we derive

$$RDC = 2(A_w - A_s) = 2\left[\left(\frac{1}{2} - \frac{e'Gw}{2}\right) - \left(\frac{1}{2} - \frac{e'Gs}{2}\right)\right] = e'Gs - e'Gw = J_{GP}.$$

The properties of the index J_{GP} were derived and listed in Proposition 1 of Silber (1995). The main properties may be summarized as follows: the index J_{GP} is invariant to homothetic changes of the individual incomes. The effect on J_{GP} of an income swap is greater, the greater the difference between the swapped incomes and that between the ranks of the individuals who swap their incomes. Finally, if a sum Δ is transferred from individual j to individual f (assuming $s_j > s_f$ and no change in the ranking of the individuals), the value of the index J_{GP} will be an increasing function of Δ.

Note that the gap between the curves C_w and C_s, at a point corresponding to the i first observations, may be expressed as $GAP_i = \sum_{j \leq i}(w_j - s_j)$. If this gap is positive, it implies, using Equation (19), that

$$GAP_i = \sum_{j \leq i} s_j \left(\frac{\eta_j - \overline{\eta}}{1 + \overline{\eta}}\right) > 0 \Leftrightarrow (\frac{\sum_{j \leq i} s_j \eta_j}{\sum_{j \leq i} s_j} \frac{\sum_{j \leq i} s_j}{1+\overline{\eta}}) - \frac{\sum_{j \leq i} s_j}{1} \frac{\overline{\eta}}{1+\overline{\eta}} > 0, \quad (28)$$

$$\frac{\sum_{j \leq i} s_j \eta_j}{\sum_{j \leq i} s_j} = \frac{\sum_{j \leq i} x_j \eta_j}{\sum_{j \leq i} x_j} = \overline{\eta_i}, \quad (29)$$

where $\overline{\eta_i}$ is a weighted average of the growth rate of the i first observations. Combining Equations (28) and (29) we derive

$$GAP_i = \sum_{j \leq i} s_j \frac{\overline{\eta_i} - \overline{\eta}}{1+\overline{\eta}}.$$

We therefore conclude that the gap between the curves C_w and C_s, at a point corresponding to the i first observations, will be positive if the (weighted) average growth rate of the i first observations is higher than the average growth rate in the whole population – a result that seems intuitively convincing.

Silber (1995) has also proven that the index J_{GP} could be expressed as the sum of a component F_{GP} measuring the change in inequality (structural mobility) and another one, P_{GP} representing re-ranking (exchange mobility). Let us call **v** the vector of the income shares w_i at time 1 when these shares are ranked by their increasing values at time 1. In such a case we may express the measure *RDC* defined in Equation (26) as:

$$RDC = SM + EM,$$

where structural mobility, *SM*, is

$$SM = \sum_{i=1}^{n} \tau_i \left[\frac{(1+\eta_E^{s \to v})}{(1+\overline{\eta})} - 1\right]. \quad (30)$$

In Equation (30), τ_i is defined as previously because the starting vector is also the vector of the shares s_i. $\overline{\eta}$ is also defined as previously since the shares v_i and w_i are the same shares, just classified differently. The "equivalent growth rate" $\eta_E^{s\to v}$ is the one obtained when the change which takes place is the one observed when moving from vector ***s*** to vector ***v***.

We may also define exchange mobility, *EM*, as

$$EM = \sum_{i=1}^{n} \theta_i \left(\frac{1 + \eta_E^{v\to w}}{1 + \overline{\eta^{v\to w}}} - 1 \right),$$

where $\eta_E^{v\to w}$ is the one obtained when the change that takes place is the one observed when moving from vector ***v*** to vector ***w***. Note $\overline{\eta^{v\to w}} = 0$ since the shares v_i and w_i are the same shares, just ranked differently. Finally, θ_i is defined as:

$$\theta_i = \left(\frac{2n+1-2i}{n}\right) v_i,$$

where, as mentioned previously, the shares v_i are ranked by increasing values. We therefore end up with:

$$EM = \sum_{i=1}^{n} \left(\frac{2n+1-2i}{n}\right) v_i \, \eta_E^{v\to w}.$$

A.3. Generalized population-weighted relative measures of distributional change, convergence, and pro-poor growth

(1) The anonymous case

This is the case where we have two cross-sections and compare anonymous income distributions at time 0 (the set of incomes x_i) and 1 (the set of incomes y_i).

Using Atkinson's (1970) concept of "equally distributed equivalent level of income," Donaldson and Weymark (1980) have defined a generalized Gini index I_{GG} as:

$$I_{GG} = 1 - \left\{ \sum_{i=1}^{n} \left[\left(\frac{(n-i+1)}{n}\right)^{\gamma} - \left(\frac{n-i}{n}\right)^{\gamma} \right] \frac{x_i}{\bar{x}} \right\},$$

where x_i is the income of individual i (at time 0) with $x_1 \leq \cdots \leq x_i \leq \cdots \leq x_n$ where n is the number of individuals, γ is a parameter measuring the degree of distribution sensitivity ($\gamma > 1$, and the higher γ means the stronger this sensitivity) while $\bar{x}$ is the average income in the population at time 0. A similar expression may be computed at time 1.

It is then easy to derive that the population-weighted change in inequality between times 0 and 1 will be expressed as:

$$\Delta I_{GG} = \sum_{i=1}^{n} \left[\left(\frac{(n-i+1)}{n} \right)^{\gamma} - \left(\frac{n-i}{n} \right)^{\gamma} \right] \left(\frac{x_i}{\bar{x}} - \frac{y_i}{\bar{y}} \right). \quad (31)$$

When $\gamma = 2$, ΔI_{GG} will be expressed as:

$$\Delta I_{GG} = \sum_{i=1}^{n} \left(\frac{2n-2i+1}{n^2} \right) \left(\frac{x_i}{\bar{x}} - \frac{y_i}{\bar{y}} \right) = \frac{x_E}{\bar{x}} - \frac{y_E}{\bar{y}}, \quad (32)$$

where x_E and y_E are respectively Atkinson's "equally distributed equivalent levels of income" at time 0 and 1, assuming we use Gini's social welfare function. Note that from Equation (32) we derive

$$\Delta I_{GG}^{\gamma=2} = \left(1 - \frac{y_E}{\bar{y}}\right) - \left(1 - \frac{x_E}{\bar{y}}\right) = I_G^y - I_G^x,$$

which is the difference between the Gini indices at times 1 and 0.[16]

(2)The nonanonymous case

(i) Decomposing the distributional change index. Let the sets of incomes $\{y_i\}$ and $\{x_i\}$ now refer to the incomes at times 1 and 0, ranked by increasing values of the incomes at time 0. Let $\{v_i\}$ refer to the incomes at time 1, ranked by increasing incomes (at time 1).

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[16]Donaldson and Weymark (1980) have already shown that if $\gamma = 2$, the index I_{GG} becomes equal to the traditional Gini index of inequality.

Extending Equation (31) we may express the distributional change ΔI_{GG} between times 0 and 1 as:

$$\Delta I_{GG} = \sum_{i=1}^{n} \left[\left(\frac{(n-i+1)}{n} \right)^{\gamma} - \left(\frac{n-i}{n} \right)^{\gamma} \right] [(\frac{x_i}{x} - \frac{v_i}{v}) + (\frac{v_i}{\bar{v}} - \frac{y_i}{\bar{y}})]. \qquad (33)$$

The first expression on the right side of Equation (33) is evidently the difference between the value of the generalized Gini index at times 0 and 1; that is, the change in inequality between times 0 and 1. The second expression on the right side of Equation (33) measures the amount of re-ranking that took place between times 0 and 1, since the sets of incomes $\{y_i\}$ and $\{v_i\}$ refer to the same incomes, just ranked differently.

(ii) Checking for convergence. From Equation (31) we derive

$$\Delta I_{GG} = n \sum_{i=1}^{n} \left[\left(\frac{(n-i+1)^{\gamma}}{n^{\gamma}} - \frac{(n-i)^{\gamma}}{n^{\gamma}} \right) \right] (s_i - w_i), \qquad (34)$$

where, as previously, $s_i = \frac{x_i}{n\bar{x}}$ and $w_i = \frac{y_i}{n\bar{y}}$.

Combining Equations (19) and (34) we obtain

$$\Delta I_{GG} = n \sum_{i=1}^{n} \left[\left(\frac{(n-i+1)^{\gamma}}{n^{\gamma}} - \frac{(n-i)^{\gamma}}{n^{\gamma}} \right) \right] \left(s_i \frac{(\eta_i - \bar{\eta})}{1+\bar{\eta}} \right) n \sum_{i=1}^{n} \psi_i \left[\frac{(1+\eta_i)-(1+\bar{\eta})}{1+\bar{\eta}} \right] = n \sum_{i=1}^{n} \psi_i \left[\frac{(1+\eta_i)}{(1+\bar{\eta})} - 1 \right], \qquad (35)$$

$$\psi_i = [\frac{(n-i+1)^{\gamma}}{n^{\gamma}} - \frac{(n-i)^{\gamma}}{n^{\gamma}}] s_i. \qquad (36)$$

Equation (35) may be also written as:

$$\Delta I_{GG} = n \left(\sum_{i=1}^{n} \psi_i \right) \left[\sum_{i=1}^{n} \frac{\psi_i}{\sum_{i=1}^{n} \psi_i} \frac{(1+\eta_i)}{(1+\bar{\eta})} - 1 \right] = n \left(\sum_{i=1}^{n} \xi_i \right) [\frac{\left(1+\eta_{E,GG}\right)}{(1+\bar{\eta})} - 1], \qquad (37)$$

$$\xi_i = \frac{\psi_i}{\sum_{i=1}^{n} \psi_i},$$

$$\eta_{E,GG} = \sum_{i=1}^{n} \xi_i \eta_i,$$

where $\eta_{E,GG}$ is clearly the "equivalent growth rate" derived from the generalization of the Gini index.

Finally note that, using Equation (36), $\sum_{i=1}^{n} \Psi_i$ may be also written as

$$\sum_{i=1}^{n} \psi_i = \sum_{i=1}^{n} [\frac{(n-i+1)^{\gamma}}{n^{\gamma}} - \frac{(n-i)^{\gamma}}{n^{\gamma}}] s_i = \sum_{i=1}^{n} [\frac{(n-i+1)^{\gamma}}{n^{\gamma}} - \frac{(n-i)^{\gamma}}{n^{\gamma}}] \frac{x_i}{n\bar{x}} = \frac{x_{E,GG}}{n\bar{x}},$$

where $x_{E,GG} = \sum_{i=1}^{n} [\frac{(n-i+1)^{\gamma}}{n^{\gamma}} - \frac{(n-i)^{\gamma}}{n^{\gamma}}] x_i$ is the "equally distributed equivalent level of income" at time 0 corresponding to the generalized Gini-related welfare function.

Combining Equations (36) and (37) we end up with

$$\Delta I_{GG} = \frac{x_E}{\bar{x}} [\frac{\left(1+\eta_{E,GG}\right)}{(1+\overline{\eta})} - 1]. \quad (38)$$

(iii) Checking for anonymous relative pro-poor growth. As in the case of the Gini index, we will say that there is pro-poor growth if

$$\eta_{E,GG,pro-poor}^{Anonymous} = \sum_{i=1}^{q} \delta_i \eta_i > \overline{\eta}, \quad (39)$$

$$\delta_i = \frac{[(q-i+1)^{\gamma} - (q-i)^{\gamma}] s_i'}{\sum_{j=1}^{q} s_j' [(q-j+1)^{\gamma} - (q-j)^{\gamma}]},$$

with s_i' defined in Equation (14); the subindex *i* refers to a given centile.

(iv) Checking for nonanonymous relative pro-poor growth. Here also we use Equations (38) and (39) but the subscript *i* refers now to a specific individual whose income is known at times 0 and 1.

A.4. Area below the generalized Lorenz curve

The area B_{x_i} between the absolute Lorenz curve and the horizontal axis at height 0 may be expressed as:

$$B_x = \sum_{i=1}^{n} \frac{1}{2n^2} (n - 2i + 1) x_i. \quad (40)$$

The Gini index G_{x_i} will be written as:

$$G_x = \sum_{i=1}^{n} \frac{2i-n-1}{n} \frac{x_i}{n\bar{x}},$$

with incomes arranged in nondecreasing order. The Gini index may be also expressed (Kendall and Stuart, 1969) as:

$$G_x = \frac{MD_{x_i}}{2\bar{x}},$$

where MD_x is the mean difference of the incomes x_i defined as

$$MD_x = 2\bar{x}G_x = \frac{2}{n^2}\sum_{i=1}^{n}(2i-n-1)x_i. \tag{41}$$

Combining Equations (40) and (41) we conclude that

$$B_x = -\frac{1}{4}MD_x.$$

The area B_x between the absolute Lorenz curve and the horizontal axis at height 0 is defined in Equation (40) as being negative. If we want to give a positive sign to this area, we will redefine Equation (40) as

$$B'_x = \frac{1}{2n^2}\sum_{i=1}^{n}(2i-n-1)x_i = \frac{1}{2}\left\{\left[\sum_{i=1}^{n}\frac{(2i-1)}{n^2}x_i\right] - \bar{x}\right\} = \frac{1}{2}(x_{FR} - \bar{x}), \tag{42}$$

where x_{FR} is, as stressed in Berrebi and Silber (1989), a weighted average of the incomes which gives a greater weight to an individual, the higher his income, because x_{FR} is defined as

$$x_{FR} = \sum_{i=1}^{n}\frac{(2i-1)}{n^2}x_i.$$

Berrebi and Silber (1989), however, have proven that

$$x_{FR} - \bar{x} = \bar{x} - x_E, \tag{43}$$

where x_E is a weighted average of the incomes of the individuals which gives a greater weight to an individual, the lower his income, and is defined as

$$x_E = \sum_{i=1}^{n}\left(\frac{2n-2i+1}{n^2}\right)x_i. \tag{44}$$

It is easy to observe that x_E refers to Atkinson's (1970) "equally distributed equivalent level of income" when the social welfare function corresponds to that lying behind the Gini index.

Combining Equations (42), (43), and (44) we conclude that

$$B'_x = \frac{1}{2}(\bar{x} - x_E).$$

Appendix B: More details on the absolute approach to distributional change

B.1. Decomposition of the absolute distributional change into absolute structural mobility and absolute exchange mobility

Recalling that the absolute distributional change (*ADC*) in the nonanonymous case is defined as

$$ADC^{Nonanonymous} = \frac{1}{2}(\Delta\bar{x} - \Delta\tilde{x}_E) = \frac{1}{2}[(\bar{y} - \bar{x}) - (\tilde{y}_E - x_E)], \quad (45)$$

it can be shown that *ADC* can be decomposed into two components. The first one is called absolute structural mobility (*ASM*) and the second one is absolute exchange mobility (*AEM*).

The *ASM* component assumes that there was no change in the ranking of the individuals between times 0 and 1. We can therefore define *ASM* as:

$$ASM = \frac{1}{2}(\Delta\bar{x} - \Delta x_E) = \frac{1}{2}[(\bar{y} - \bar{x}) - (y_E - x_E)].$$

ASM corresponds, as expected, to *ADC* in the anonymous case.

The second component, *AEM*, accounts for the fact that the ranking of individuals may vary between times 0 and 1. It therefore measures the absolute distributional change observed when moving from vector ***y*** to vector $\tilde{\boldsymbol{y}}$. *AEM* will therefore be expressed as:

$$AEM = \frac{1}{2}[(\bar{y} - \bar{y}) - (\tilde{y}_E - y_E)],$$

which is always nonpositive since $\tilde{y}_E \geq y_E$. The sum of *ASM* and *AEM* is then written as:

$$(ASM + AEM) = \frac{1}{2}\{[(\bar{y} - \bar{x}) - (y_E - x_E)] + [(\bar{y} - \bar{y}) - (\tilde{y}_E - y_E)]\} \leftrightarrow \quad (46)$$

$$(ASM + AEM) = \frac{1}{2}[(\bar{y} - \bar{x}) - (\tilde{y}_E - x_E)].$$

Comparing Equations (45) and (46) we conclude, as expected, that

$$ADC^{Nonanonymous} = ASM + AEM.$$

B.2. Generalized population-weighted measures of the absolute distributional change, convergence, and pro-poor growth

Again, following Donaldson and Weymark (1980), we may write x_E as:

$$x_E = \sum_{i=1}^{n}[\left(\frac{(n-i+1)}{n}\right)^{\gamma} - \left(\frac{n-i}{n}\right)^{\gamma}]x_i.$$

By varying the value of parameter γ ($\gamma \geq 2$), we can choose how much higher the weight given to poorer households will be. Corresponding formulations may then be obtained for distributional change, convergence, and pro-poor growth.

B.3. Nonanonymous distributional change and the measurement of nonanonymous welfare change

Let $(\tilde{y}_1, \dots, \tilde{y}_i, \dots, \tilde{y}_n)$ refer to incomes at time 1 ranked by nonincreasing values of the incomes the individuals had at time 0. We can then draw what we could call a "pseudo generalized Lorenz curve" at time 1. This curve, unlike the generalized Lorenz curve, would not necessarily have a nondecreasing slope along its length but would also end at point A, whose horizontal coordinate is 1 and whose vertical coordinate is $\bar{y}$. The area $D_{\tilde{y}_i}$ lying between this pseudo-generalized Lorenz curve and the horizontal axis (at height 0) is then expressed in the nonanonymous case as:

$$D_{\tilde{y}_i} = \frac{1}{2n^2}\sum_{i=1}^{n}(2n - 2i + 1)\tilde{y}_i.$$

Defining $\tilde{y}_E$ as in Equation (14) and $\Delta\tilde{x}_E$ as in Equation (15), we derive

$$\Delta\tilde{x}_E = \tilde{y}_E - x_E = (y_E - x_E) + (\tilde{y}_E - y_E).$$

The nonanonymous distributional change in welfare between times 0 and 1, $DC_W^{Nonanonymous}$, is therefore expressed as:

$$DC_W^{Nonanonymous} = \frac{1}{2}(\tilde{y}_E - x_E).$$

We can then decompose this nonanonymous distributional change in welfare into two components structural mobility in welfare (SM_w) and exchange mobility in welfare (EM_w) as:

$$SM_w = \frac{1}{2}(y_E - x_E\ ),$$
$$EM_w = \frac{1}{2}(\tilde{y}_E - y_E).$$

Note that EM_w is always non-negative because $\tilde{y}_E \geq y_E$. Thus, $DC_W^{Nonanonymous} = SM_w + EM_w$.