Bootstrapping the LIS: Statistical Inference with the Gini Index and Patterns of Inequality in the Global North*

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Abstract: The problem of statistical inference in empirical inequality research has persisted despite the solutions long suggested by asymptotic theory. Within the last five years, however, significant developments have occurred in both the theory and practice of conducting formal statistical inference with common measures of inequality such as the Gini index. These new techniques involve the use of Monte Carlo, bootstrap resampling plans that seek to recover the standard error and sampling distribution of inequality estimates directly through the empirical distribution of the sample data. Using the income survey of the Luxembourg Income Study (LIS) project, this paper provides an analytical evaluation of the bootstrap procedure in the context of comparative inequality research, and uncovers patterns of distributional change in the global North over the last two decades. While it is now generally accepted that inequality has increased in the United States and United Kingdom during this period, the extent to which other wealthy nations have been able to avoid this trend (or not) has generated some debate. The paper presents new evidence to address this discussion, demonstrating along the way how the ability to conduct formal statistical inference with the Gini index provides an effective and important new evaluative tool.

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Bootstrapping the LIS: Statistical Inference with the Gini Index and Patterns of Inequality in the Global North

The absence of statistical significance has been a glaring shortcoming in comparative research more broadly and in inequality evaluations in particular. Practitioners seeking to quantify inequality have traditionally relied on descriptive devices such as the Lorenz curve, quintile income shares, and various summary indices. In the absence of well established and practically useful analytical error theories for these measures, practitioners are left making evaluations—often between relatively minor differences in measurements—informally based on little more than visual or absolute-numerical comparisons. As Rossi, et al. (2001:905) explain, “[p]oint estimates unaccompanied by any precision measure are the rule rather than the exception, so that tracking the changes of personal distribution through time rests to a large extent on scholars’ *a priori* beliefs.” As a result, error or random variation in the samples can produce discrepant portraits of distributional change within countries even as scholars build models attempting to explain such changes cross-nationally. Moreover, minor changes in Gini coefficients might not warrant directional conclusions at all, perhaps signaling instead that “no change” in inequality has occurred (a description rarely used by scholars looking for trends). In short, the conclusions we tend to draw in empirical inequality research are “far more tentative than has often been realized” (Mills and Zandvakili 1997:140).

Within the last few years, however, significant developments have occurred in both the theory and practice of conducting formal statistical inference using methods that seek to nonparametrically estimate (at least an approximation of) the sampling distribution of inequality measures such as the Gini index. Pioneered by Efron (1979), these methods employ Monte Carlo, bootstrap resampling plans to recover the standard error and sampling distribution numerically (as opposed to theoretically) via repeated random samples drawn with replacement from the observed sample distribution, thus allowing the construction of confidence intervals and
hypothesis tests on inequality and poverty indicators that lack generally useful analytical error theories, yet are important normative measures in quantitative cross-national research.

Using the surveys of the Luxembourg Income Study database (LIS), this paper presents a systematic application of bootstrap methodology in the context of cross-national comparisons of inequality. The paper is divided into two sections. The first section examines the theoretical and practical aspects of conducting statistical inference via the new bootstrap procedures, both in the context of inequality analysis generally, and with regard to the specific needs and constraints of the LIS database more specifically. The second section presents and discusses the substantive findings of the project. While it is now generally accepted that inequality has substantially increased in the United States and United Kingdom during this period, the extent to which other wealthy nations have been able to avoid this trend (or not) has generated some debate. The paper presents new evidence to address this discussion, demonstrating along the way how the ability to conduct formal statistical inference with the Gini index provides an effective and important new evaluative tool.

I. Bootstrap Resampling Methods for Statistical Inference

Until recently, attempts at conducting formal statistical inference in the context of inequality data were limited to theories of asymptotic normality, where mathematical theory is used to analytically derive the limiting behaviors of parameter estimators (as the sample size tends to infinity).\(^1\) While in practice the sample size cannot increase indefinitely, the asymptotic normal approximation is taken as a guide for the “true” behavior of an estimate as sample sizes get reasonably large.\(^2\) Inference making via asymptotic theory has a long tradition in the statistical sciences, even as applied to inequality measurement (see for example Hoeffding 1948; Glasser 1962; Gastwirth 1974), yet scholars have long sought alternatives primarily because asymptotic theory often yields poor approximations to the distribution of test statistics in the
context of finite samples. As discussed more fully below, and as Mills and Zandvakili (1997:134) argue, asymptotically derived confidence intervals for inequality measures constructed from fixed samples simply “may not be accurate.” Secondarily, while asymptotic inference is now understood for most inequality measures, it is problematic for the most popular measure – the Gini index. This is because the Gini index is not estimable by the method of moments (i.e., it is not an index that can be expressed as some differentiable function of the weighted moments of the distribution). Although some have used what are called $U$-statistics (Lee 1990) to justify the asymptotic properties of the Gini index, the variance estimates are difficult to compute, and corrections for its finite-sample properties introduce bias into the index estimators (Xu 2000).

While there are theoretical problems with asymptotic theory, more limiting are the practical issues in applying these methods. For one, no generally accepted asymptotic procedure exists for conducting hypothesis tests for differences in inequality estimates between units or over time, a major shortcoming in applied settings. For another, the mathematical complexity of asymptotic theory and the computational demand involved in the formulae to derive asymptotic properties are difficult to manage even in relatively straightforward settings. The econometric refinements necessary to modify a test statistic analytically so that it approaches its asymptotic distribution (i.e., so that it is more accurate with finite samples) requires algebraic derivations that are “far from trivial” and in many cases do not seem feasible (Davidson and MacKinnon 1999b:361). These formulae are cumbersome even to the most experienced econometricians, too inaccessible and too inflexible for most practitioners to employ.

In response, scholars have recently proposed bootstrap resampling methods as both statistically more accurate and practically more advantageous solutions to statistical inference. Pioneered by Efron (1979), the bootstrap is a versatile member of a general group of resampling procedures that employ simulation methods to evaluate a parameter estimate at reweighted versions of the empirical probability distribution found in the sample data (for general
discussions of the bootstrap, see Chernick 1999; Efron 1982; Efron and Tibshirani 1993). While the mathematical justifications can be quite sophisticated (for more rigorous treatments see Hall 1992, and Shao and Tu 1995), the bootstrap method requires no theoretical calculations, applies the same to any inequality measure currently in use, and is available no matter how mathematically complicated the parameter estimate or its asymptotic standard error may be.

The bootstrap method is conceptually based on the “plug-in principle,” where known sample values are taken as simple estimates of the entire population. Say an empirical distribution \( \hat{F} \sim \{x_1, x_2, \ldots, x_n\} \) is a known, random i.i.d (independent and identically distributed) sample taken to estimate the entire population distribution \( F = \{X_1, X_2, \ldots, X_N\} \). Similarly, let \( \hat{\theta} \) represent the pont estimate of an unknown population parameter of interest \( \theta \), computed from \( \hat{F} \). The general idea behind the plug-in principle is to recover the variance of \( \hat{\theta} \) through the known distribution \( \hat{F} \). This is obviously a straightforward affair when dealing with the mean, yet for most other statistical estimators it is difficult to evaluate the variance of \( \hat{\theta} \) theoretically though \( \hat{F} \) (see Shao and Tu (1995:10) for an elaboration of this point). The bootstrap solution is to employ an old technique known as the Monte Carlo method to establish a numerical approximation of the variance through repeated simulations – in other words evaluate variance of \( \hat{\theta} \) empirically through \( \hat{F} \). The nonparametric, one-sample approximation works as follows.\(^4\)

First, randomly draw an independent data set \( \{x_1^*, x_2^*, \ldots, x_n^*\} \sim \hat{F} \) of size \( n \) with replacement from the sample distribution, so that each \( x_i^* \) represents a bootstrap version of \( x_i \) and has probability \( \frac{1}{n} \) of being selected. Replacement here refers to each draw not each sample, thus
some observations can be counted more than once, some not all in any given resample. Next, evaluate $\hat{\theta}^*_b$, a bootstrap replication of $\hat{\theta}$ computed from the $b^{th}$ bootstrap resample.

Independently repeat this procedure a large number of $B$ times, each time obtaining bootstrap replications $\hat{\theta}^*_1, \hat{\theta}^*_2, \ldots, \hat{\theta}^*_B$. The bootstrap standard error of $\hat{\theta}$ can then be estimated as:

$$\hat{se}_{\text{boot}} = \left\{ \frac{1}{B-1} \sum_{b=1}^{B} \left[ \hat{\theta}^*_b - \bar{\theta}^* \right]^2 \right\}^{1/2}$$  \hspace{1cm} (1.0)

where $\bar{\theta}^* = \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}^*_b$ is the mean of the parameter estimates obtained in the $B$ resamples. Based on the law of large numbers, as the number of $B$ replications approaches infinity the bootstrap standard error (1.0) converges to the estimate of the standard error found in the sample $\hat{F}$.  

**Bootstrap Hypothesis Testing**

Bootstrap inference can be undertaken either through confidence interval estimation, or by computing a bootstrap $p$-value, $p^*$, the proportion of bootstrap samples that yield a test statistic more extreme than the actual test statistic computed from the data. A one-tailed test that rejects above the test statistic can be approximated as:

$$p^* = \frac{\#\{ \hat{\theta}^*_b \geq \hat{\theta} \}}{B}$$  \hspace{1cm} (1.1)

In the two-sample context, when confidence intervals from two sample estimates (either between units or within them over time) do not overlap, we can unambiguously assess this difference to be statistically significant (at level $\alpha$). In the presence of overlap, however, it does
not immediately follow that the difference is not statistically significant. In this case, an hypothesis test is required that tests for the difference in parameter estimates.

Following the procedure outlined in Efron and Tibshirani (1993), say we have two i.i.d. samples \( x \) (size \( n \)) and \( y \) (size \( m \)) taken to represent populations \( X \) and \( Y \), and we want to test the null hypothesis \( H_0: X = Y \). The hypothesis test requires a test statistic \( t(s) \) which could be a parameter estimate \( \hat{\theta} \) but not necessarily. In the cross-national application presented in this paper, \( t(s) = \text{Gini}_x - \text{Gini}_y \), the difference between the inequality estimates say in two countries, or in one country in two time periods. As in conventional hypothesis testing using the mean, we attempt to find a one-sided \( p \)-value defined as the probability of finding at least that large of a difference when the null hypothesis is true.

\[
p - \text{value} = P_{H_0} \left\{ t(s^*) \geq t(s) \right\} \tag{1.2}
\]

where \( t(s) \) is fixed at its observed value and \( t(s^*) \) is distributed under the assumption that the null hypothesis is true. Since this distribution \( F_o \) is unknown, the bootstrap method derives a “plug-in” distribution \( F_o^* \) in the following manner.

Under the assumption that the two samples are randomly drawn and independent, first draw a bootstrap resample \( s_x^* \) of size \( n \) with replacement from \( x \) so that the probability for selection in \( s_x^* \) is \( 1/n \), and calculate the statistic of interest \( G_x^* \). Then draw a bootstrap resample \( s_y^* \) of size \( m \) in the same manner and again calculate the statistic of interest \( G_y^* \). Repeat the procedure a \( B \) number of times, each time evaluating the difference between the Gini coefficients

\[
t(s)^* = G_x^* - G_y^* \tag{1.3}
\]

Construct a bootstrap confidence interval of \( t(s)^* \), and the difference between \( G_x^* \) and \( G_y^* \) is then said to be statistically significant (at \( \alpha \)) if zero is not contained in the interval (\( p^* \) values can then be approximated by 1.1 above).
II. Bootstrap Inference in the Cross-National Context

In the analysis that follows, bootstrap inference techniques are systematically applied to the income surveys of the Luxembourg Income Study (LIS) database. The bootstrap procedures in this study employ resampling plans in the case of an independent and identically distributed (i.i.d) sample of fixed size \( n \) from an unknown population.\(^6\) Inequality is measured by the Gini index as specified according to the methodological recommendations of the LIS project as more fully outlined in Appendix A. The unit of analysis is the household, adjusted for size using an equivalence scale, and income is measured as net, disposable household income subjected to both top and bottom coding. Also based on LIS specifications, the bootstrap resampling procedures are weighted by “person weights” – the product of the household weight (the weights established by the procedure used in the original dataset, not by LIS) and the number of persons in the household.\(^7\)

\[ a. \text{ The Validity of the Bootstrap} \]

Soon after Efron’s pioneering work, Singh (1981) and Bickel and Freedman (1981) mathematically demonstrated the asymptotic validity of the bootstrap in a large number of situations. Recent work suggests that the procedure is not only valid, but that bootstrap tests will outperform tests based on asymptotic theory in finite samples in that they will commit errors that are of lower order in the sample size \( n \). Performance in this regard can be measured by evaluating the “size distortion,” or what Davidson and MacKinnon (1999b) term the “error in rejection probability” (ERP), of an inference test – the difference between the nominal level of a test and its actual rejection probability. The current consensus is that for a sample size \( n \), the ERP committed by tests based on the bootstrap is generally reduced by a factor of \( n^{-1/2} \) in one-tailed tests and \( n^{-1} \) or more in two-tailed tests. In theory, then, the bootstrap provides a higher-order, asymptotic approximation in that the difference between the test’s actual and nominal levels decrease more rapidly with increasing sample size than it would if the distribution of a test
statistic is obtained via asymptotic theory (Davidson and MacKinnon 1999b; Hall 1992; Horowitz 1994, 1997). In addition, several studies now provide evidence from Monte Carlo simulation experiments that the numerical performance of bootstrap tests improve asymptotic approximations (Davison and MacKinnon 1999a; Horowitz 1994, 1997; Shao and Tu 1995). The bootstrap, it is now generally regarded, almost always minimizes the ERP in fixed sample sizes that occur when critical values are obtained via asymptotic theory; and in cases when asymptotic and bootstrap critical values are very different, it is almost certain that the asymptotic values are inaccurate (Davidson and MacKinnon 2000). 8

A few simulation experiments have been performed in the context of income distribution data, and again all conclude that statistical inference based on bootstrap procedures outperform, often quite dramatically, asymptotic theory (Biewen 2002; Cowell and Flachaire 2002; Mills and Zandvakili 1997; Trede 2002). Given the newness of these methods in inequality applications, the precise accuracy of the bootstrap for the various indicators (or the extent of the improvement over asymptotic theory) is still an empirical matter. Early research in fact has illustrated an apparent contradiction between the theoretical expectations of using the bootstrap with inequality indicators and its numerical performance. For example, Beran (1988) shows that bootstrap inference is unproblematic when the indicator is asymptotically pivotal (i.e., its distribution does not depend on any unknown parameters) which is the case for every inequality measure except the Gini index. Yet Cowell and Flachaire (2002:15) conducted a number of simulation experiments in what to date is the only direct comparison of the different indicators, and concluded that among the most popular inequality measures, “the bootstrap does well only for the Gini.” In addition, all studies have found that confidence intervals around various inequality indices are too narrow (Biewen 2002; Cowell and Flachaire 2002; Davidson and Flachaire 2004).

In an effort to gauge the coverage accuracy of the confidence intervals established in this study, a Monte Carlo simulation experiment was performed on the Finland 2000 survey of the LIS. Following a similar procedure in Mooney (1996), the Gini index for this survey is taken a
priori to be the “true” population parameter. Drawing $B = 1000$ replications of a five percent subsample (521 households), a bootstrap “sample” Gini index and 95 percent confidence intervals are established. After 600 simulations, the accuracy of the intervals in capturing the “true” Gini index is evaluated via the ERP. Table 1 presents the results of this experiment, indicating that all three methods are very close, and that all three intervals are slightly too narrow, implying that inference tests based on them over-reject the null hypothesis. Said differently, the tests would result in more Type I errors than are nominally allowed. The bias-corrected method (.055) came the closest to yielding the exact nominal alpha level, followed by the normal approximation (.057), and the percentile (.063). Like other studies, then, the finding is that the intervals around the Gini index are close yet too narrow.

Table 1 about here

Davidson and Flachaire (2004) attribute the over-rejection primarily to the sensitivity of inequality measures to outliers in the upper-tail of the income distribution, which is usually described as being “heavy tailed” (i.e., as incomes get larger the tail decays slowly). Hall (1990) and Horowitz (2000) have shown that the bootstrap performs less well in these situations because a small number of extreme values can greatly influence the bootstrap distribution during resampling. The asymptotically pivotal indicators such as Theil and Atkinson are more sensitive to outliers in the upper tail than the Gini index which tends to be mid-range sensitive (see Cowell and Flachaire 2002 for a full discussion of this issue). While the coverage accuracy of the intervals is not perfect, at least the bias is known and is in a conservative direction. These methods, to paraphrase Chernick (1999:149), do not “get us something for nothing,” but instead should be better interpreted as “getting the most from the little that is available.”

In sum, the state of knowledge on using the bootstrap with inequality measures indicates that: a) The standard bootstrap is valid with all common indices, and preliminary tests suggest
that the Gini index numerically outperforms the others; b) ERP distortions are reduced for all measures when using the bootstrap, thus it now generally regarded as practical method for improving upon distributional approximations based on asymptotic theory; and c) Bootstrap critical values, although better, are still approximations, and the future direction of research in econometrics will explore ways to adjust the bootstrap to further reduce the ERP in income distribution data (see early attempts by Davidson and Flachaire 2004; Xu 2000).

b. Standard Errors in the LIS Database

To further assess the bootstrap in the cross-national context, ten recent LIS income surveys were selected on the basis of obtaining a group with varying sample sizes – from one of the smallest surveys (Luxembourg with 1,813 households) to one of the largest (United States with 49,351 households). Table 2 reports the bias and standard error of the Gini index, and the 95 percent confidence intervals under the standard normal, percentile, and bias-corrected procedures for the ten surveys. To assess the impact of the number of bootstrap replications \( B \), the intervals are calculated at 250, 500, and 1000 replications.

Table 2 about here

As seen in Table 2, the number of replications has little impact either on estimating the standard error of the Gini index or in establishing the confidence intervals (confidence interval boundaries established with 500 replications are never more than .001 off the intervals established with 1000 replications, which always translates into a less than 0.5 percent difference). Similarly, there is never more than a .001 difference across the interval methods, suggesting that the three methods are very close in terms of interval coverage. The close conformity across the methods is consistent with previous performance comparisons in the
literature. In every study using survey-based inequality data where different interval methods were constructed, the various intervals were virtually identical, differing by only a fraction of a percentage point (Biewen 2002; Mills and Zandvakili 1997; Trede 2002; Van Kerm 2002).

In contrast, however, larger sample sizes did lead to smaller standard errors as would be expected. Looking not only at Table 2 but at all 120 income surveys in the LIS database, we see that generally: sample sizes more than 10,000 lead to confidence intervals no bigger than one percentage point in the Gini index; samples between 10,000 and 5,000 lead to confidence intervals no bigger than two percentage points; and samples under 5,000 may be three percentage points wide. No confidence interval in the LIS database is wider than three percentage points in the Gini index.

While these findings provide an interesting guide for practitioners, there are exceptions and variations to this rule for samples of various sizes. For example, the width of the confidence intervals for Luxembourg and the Slovak Republic in Table 2 are roughly the same despite big differences in sample size. These variations in sampling error are caused by the differential ability of the bootstrap to consistently capture from sample to sample the full range of incomes, creating greater variation across the resamples. In part this reflects two interrelated characteristics of the underlying survey, features separate from the degree of inequality itself: 1) The shape of the population structure with regard to incomes, specifically the extent of income “clustering” and the importance of the upper tail of the distribution; and/or 2) The ability of the survey instrument to proportionately sample from the entire distribution. Thus we should expect higher standard errors in situations where income are less fluid, or when the when the upper tail is long (relatively higher incomes accrued to relatively fewer households), or if the survey instrument “creates” these characteristics through inadequate sampling. In these situations – in economies less fully monetized, perhaps, or where inequality is very high, or when administrative and other resource issues limit the survey’s effectiveness – greater variation will
exist from survey to survey in the population, and thus from resample to resample in the bootstrap.

II. Distributional Change in the Global North: 1980 – 2000

In the early 1980s researchers in the United States and the United Kingdom began to notice that, after a long period of relative stability, the distribution of income was becoming noticeably more unequal. The trend continued, and in 1988 the phenomenon was coined the “great U-turn” by Harrison and Bluestone in recognition that there was something historically unique about rising levels of inequality in wealthy, developed nations. Over time, this phenomenon has been extended, at least in theory, to the rest of the global North so that now academic and popular interpretations tend to discuss rising inequality as a nearly universal outcome of “globalization” processes in the 1980s and 1990s (Friedman 2000; Smeeding 2002a). As summarized by Ram (1997:577), “[t]he somewhat cheerless distributional position recently noted for the U.S. seems to characterize most of the postwar developed world.”

Recent debates, however, have begun to question the extent to which trends in the United States and United Kingdom were replicated throughout the global North. Observers of these contrasting outcomes argue that technological change has been less skill-based in parts of Europe than in the U.S. and U.K., and that returns to education and skill increased less sharply in these areas (because the supply of skilled workers increased faster), leading to “less of an increase, or even no change” in wage inequality in these countries (Acemoglu 2002:1). Another line of interpretation has emerged around the general idea that politics and political institutions matter. Some argue, for example, that European labor policies and wage-setting institutions mitigate the tendency toward increasing earnings inequality (Acemoglu 2002; Blau and Kahn 1996; Freeman and Katz 1995; Nickell and Bell 1996). In particular, many studies find that labor union density significantly reduces inequality (Alderson and Nielsen 2002; Freeman 1993; Gustafsson and
Johansson 1999), and that policy liberalism/leftist government strongly drives the redistribution process (Bradley, et al. 2003; Brady 2003; Kelly 2004).

Using the inference procedures outlines above, however, across the 17 nations examined here three distinct patterns of distributional change are evident over the period – a “Continental” pattern, an “Anglo” pattern, and a “Scandinavian” pattern. The three patterns, and the specific trends in inequality found in the constituent countries, are now described in turn. Historical trends in inequality for individual nations are presented in a series of figures (Figures 1a - 3) that chart the movement in the Gini index inclosed within the bootstrap 95 percent confidence interval. For various sub-periods within the 20-year period (marked by two vertical arrows), the magnitude of changes in the Gini index are evaluated using the following format:

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.008 ← Absolute change in the Gini coefficient
2.8 ← Percentage change in the Gini coefficient
.016 ← One-sided p-value of the null hypothesis test (if the intervals overlap)
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### a. The Continental Pattern – Steady States

Looking at the bootstrap results in Figures 1a through 1c, the prevailing trend in Continental Europe is one of little distributional change – or change that at least is not large enough to reach statistical significance. The Continental pattern is characterized by relatively moderate levels of inequality which remain essentially unchanged throughout the period, although in a few cases inequality actually declined.

- **Exemplars of the Continental Pattern:** Seven countries form what can be called the exemplar Continental group – experiencing essentially no change in (or declining) levels of inequality over the period. **France** shows statistically no change in inequality since 1979 (and significantly less
inequality than in 1984); **Germany** is just the opposite, showing significantly less (although substantively maybe the same) inequality than in 1973, with no change since 1984; the **Netherlands** shows no change since 1983; **Italy** and **Canada** illustrate the influence of beginning and end points in defining historical trends. Taking 1986 as the starting point for Italy, the trend shows significantly more inequality, but since 1987 Italy shows no change (and also no change since 1993). The last two data points for Canada (1998 and 2000) come from a different survey source than the rest, so the observed uptick in inequality may be attributed in part to survey inconsistencies. However, even using the 2000 figure, Canada shows significantly less inequality than in 1971, a span of some 30 years. Using the 1997 figure, Canada shows no change since 1975. **Switzerland** and **Spain** have only two data points, but show no change over the 1980s.

- **A Caveat Country**: **Ireland** represents a “hybrid” pattern where overall levels of inequality are more on par with the Anglo pattern (i.e., relatively high), but shows no change in inequality levels since 1987, as is the prevailing trend in the Continental pattern.

  Figures 1a - 1c about here

- **A Caveat Group**: Three countries form a caveat group within the Continental pattern. Each basically exhibit the overall pattern, but each also experience a significant increase in inequality over one survey in the 1990s. **Luxembourg** shows no change in inequality from 1985-1994, but an increase in inequality between the 1994 and 1997 surveys means inequality is significantly higher than in 1994. The same is true for neighboring **Belgium** which shows no change from 1985-1992, but a significant increase between the 1992 and 1997 surveys means inequality is significantly higher than in 1992. **Austria** shows a significant increase between the 1987 and 1994 surveys, but shows no change since 1994. Austria’s trend may also be partially attributed
to changes in survey sources, and in this case the two surveys have noticeably different sample sizes.

**Figure 1d about here**

**b. The Anglo Pattern – Divergence From the Continent**

As discussed in the introduction, the Anglo pattern is now a well known and much analyzed phenomena. Often overlooked, however, is the fact that at the start of the 1980s, levels of inequality are in line with those found in Continental Europe. Beginning sometime in the late-1970s/early-1980s inequality then begins to increase, rapidly in some instances, leading to the continuous separation of these countries from inequality levels found on the continent.

- **Exemplars of the Anglo Pattern:** Three counties in the LIS database illustrate the pattern (see Figure 2). For the **United Kingdom**, inequality levels remain constant until the 1980s, and at the start of the decade are lower than in France, Canada, Spain, and Switzerland. Inequality then begins to steadily increase beginning in 1979 and continues over the course of the period. Most evidence shows that inequality was also fairly stable in the **United States** prior to the 1980s, and at the start of the decade inequality in the U.S. is lower than Spain and Switzerland. Beginning in 1980, inequality begins to increase and also continues throughout the period (the down-turn seen in the last survey is not statistically significant). The LIS has less data for **Australia**, but here the pattern is also repeated – continuously rising inequality throughout the period.

**Figure 2 about here**
c. The Scandinavian Pattern – Convergence to the Continent

The Scandinavian pattern is characterized by relatively low levels of inequality at the start of the period that consistently increase throughout the 1980s and 1990s as they converge to levels of inequality seen on the Continent. This increase, however, still leaves these countries with perhaps the lowest levels of inequality in the world.

- Exemplars of the Scandinavian Pattern: Three Scandinavian countries illustrate the pattern (see Figure 3). In Norway, Sweden, and Finland, Gini coefficients at the start of the 1980s are as low as .197, then increase by 18 percent or more throughout the period. Although in Sweden, the Gini index in 2000 is still not higher than in 1967.

   Figure 3 about here

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As evidenced here, there are large differences in inequality trajectories for rich nations, and it seems that the tripartite typology of welfare-state regimes famously argued by Esping-Anderson (1990) still has descriptive power today. As Bradley et al. (2003) recently found, the different institutional configurations and political traditions underling Social-Democratic, Christian-Democratic, and Liberal welfare states play a decisive role in determining distributional outcomes. Given that these countries face a common set of socio-economic phenomena – continued de-industrialization, aging populations, immigration from the global South – and experience them from the same advantaged locations within the global hierarchy, the fact that distributional outcomes vary suggests that “globalization” has not usurped the importance of national policy or led to the insignificance of the state; world-economic processes do not compel any single national trajectory. This finding is consistent with recent literature, discussed at the outset, that emphasizes the importance of national political processes in counteracting market driven inequality. Strong leftist government (Bradley, et al. 2003; Brady 2003; Kelly 2004), high levels of democratic participation (Mueller and Stratman 2003), and low public tolerance for inequality (Lambert, Millimet, and Slottje 2003) are all associated with more equal income distributions. As summarized by Smeeding (2002a:28), “[t]he overall distribution of income in a country depends on the domestic political, institutional, and economic choices made by those individual countries.”

III. Conclusions

This project applied bootstrap resampling techniques to the income surveys of the LIS database in an effort to interpret patterns of distributional change in the global North over the last 20 years. The bootstrap allows us to perform conventional statistical inference and compare alternative distributions using measures that were previously only descriptive devices. These techniques provide analytically powerful methods to estimate the statistical accuracy of parameter estimates
regardless of whether an analytical formula for its standard error is known. The bootstrap does not require assumptions about the underlying form of the data, alleviates the need to work with complex mathematical derivations, and in other cases provides answers when analytical solutions either do not exist or are inappropriate.

The utility of this evaluative tool for comparative research was evident, illustrating in particular that for a sizable number of countries, representing a “Continental” pattern of distributional change, inequality levels at the end of the period were not statistically distinguishable from levels at the start. Where previously even small changes in the Gini index, such as those observed here, would lead scholars to make normative determinations of inequality trends, statistical inference provides new grounds to substantiate conclusions that “no change” in inequality has occurred. It also suggests why others, evaluating inequality estimates in absolute terms, simultaneously argue that inequality has increased universally across the global North. These findings provide empirical support to recent arguments emphasizing the impact of political contexts and collective social forces on distributional outcomes, and in particular that such contexts have mitigated the tendency for rising inequality in Continental Europe.

In the end, the ability to conduct formal statistical inference improves the quality of our empirical descriptions, which in turn helps focus theoretical explanations of distributional variation across countries and over time. The descriptions presented here, for example, can be useful in reorienting future studies of inequality in the global North from specifying the general relationship between globalization and inequality, to uncovering the processes by which specific institutional configurations and power arrangements can a) modify the extent to which different sectors within a population are included/excluded from global-economic processes; and b) shape the distribution of the gains and losses that result from such economic change.
Appendix A

Estimating the Gini Index

Gini coefficients estimated in this study are based on the following methodological recommendations of the LIS.

Definition of Income – The unit of analysis is the household, and income is measured as net disposable household income:
  gross income - direct taxes - employee social security contributions

Weights – Used to make adjustments in the relative influence of households in the survey to account for biases in the characteristics of the groups of non-respondents. The LIS does not carry out the weighting procedure, they are constructed by the survey sources themselves, so the exact impact of the weight variable varies throughout the database. The bootstrap procedure in this study resamples using person weights – the household weight multiplied by household size – standardized so that the weighted sample size equals the number of households instead of the population. The LIS standardizes person weights to handle deleted observations that nonetheless have non-zero weights (if one wishes to drop certain observations, for example, than the remaining weights will be adjusted accordingly). This procedure in no way effects the bootstrap results, which are identical with or without weight normalization.

Equivalence Scale – Used to adjust for economies of scale in households with different numbers of people (i.e., because a household’s economic needs are related in part to its size). The equivalence scale used in this study is the square root of household size.

Top and Bottom Coding – Used to correct for possible measurement errors in the database. Incomes at the top of the distribution are capped at ten times non-equivalized median income. Incomes at the bottom are limited to one percent equivalized mean income. For comparable cross-national evaluations, bottom and top codes can not be set differently across the countries, the lowest top code and highest bottom code must be applied to all. These particular limits represent the lowest top code (Canada) and highest bottom code (Australia) of all the countries in the landmark LIS study (Atkinson, Rainwater, and Smeeding 1995), and have been applied to all LIS datasets since.
Endnotes


2. These techniques are said to be “distribution free” in that the asymptotic sampling distributions are theoretically derived – i.e, without knowledge (or specification) of the underlying population distributions from which the sample data are drawn. Said differently, (asymptotically) the distributions of the test statistics do not depend on the stochastic process generating the data, thus a parametric specification of the income distribution function is not required.

3. Technically speaking, the bootstrap and Monte Carlo methods are separate techniques with different traditions. But today this is more or less a semantical distinction. Efron’s pioneering contribution in fact was to recognize the benefits of marrying the two techniques, seeing that a “disparate, almost anecdotal” concept such as the bootstrap could be beneficent to all sorts of applications if Monte Carlo simulations were available via increasing computer power (Hall 1992:35). According to Hall (1992:35), the effect of combining these two ideas on statistical practice and theory “has been profound.”

4. This procedure is called the “nonparametric bootstrap” because the bootstrap approximation of the standard error is based on the sample distribution, which is taken to be a nonparametric estimate of the unknown population distribution.

5. The simulations can also be used to establish the bias of a functional statistic, approximated as:

\[ \hat{e} = \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_b^* - \hat{\theta} = \overline{\hat{\theta}}^* - \hat{\theta} \]

6. The goal of the LIS is to provide cross-national socio-economic data with as high a degree of comparability as possible, and this often comes with a trade-off in flexibility. Although relatively undeveloped in the statistical literature, some have advanced extensions of the iid bootstrap to data collected under complex sampling designs (Biewen 2002; Rao and Wu 1988; Jäntti 2003). Due to the constraints of working with cross-national aggregations of survey data, however, the LIS does not allow us to explore the usefulness of these extensions. The goal here is to obtain error estimates in contexts where currently none exist. To the extent that the iid resampling is successful, they are at least as good as those used throughout social science where complex sampling is rarely accounted for in inference testing procedures.

7. Adherence to the LIS guidelines was meant to assure maximum comparability of these findings to other quantitative analyses of the LIS database, and also in an effort to “test” the bootstrap procedures in the context of current LIS procedures.
8. In this sense, the bootstrap is a test of the reliability of asymptotic theory and thus should always be preferred. If the asymptotic and bootstrap critical values are similar in a given application, then one should use the bootstrap since it has already been computed. If the two are very different, than the bootstrap “provides an indication that asymptotic approximations are inaccurate” in that particular context (Horowitz 1997:202).

9. The computational requirements of other confidence interval methods, such as the bootstrap-t method, or more refined “bias-accelerated” methods, can not currently be accommodated through the remote access, batch machine system of the LIS project.

10. Efron and Tibshirani (1993:52) find that “very seldom are more than $B = 200$ replications needed for estimating a standard error” and “even a small number...say $B = 50$ is often good enough to give a good estimate...” To establish bootstrap confidence intervals, most acknowledge that $B$ must be much larger (as much as 1000 or more), however the literature offers little formal guidance on establishing $B$ for confidence interval estimation.

11. Results for other LIS member nations can be obtained by contacting the author.

12. While the bootstrap procedures are effective tools when one has access to the microdata, the findings presented here are potentially useful to researchers attempting to interpret differences and changes in Gini coefficients in situations where this access is limited or not possible. Specifically the hypothesis tests conducted here suggest the following guidelines when comparing two Gini coefficients over time:

   • less than 2.5 percent difference = conclude that the difference is not statistically significant
   • between 2.5 and 5.0 percent difference = conclusion is ambiguous and likely determined by size of the sampling error, hypothesis test probably required
   • more than 5.0 percent difference = conclude that the difference is statistically significant
References


Table 1. Simulation Analysis of CI Performance Using Finland 2000, 5% Subsample

Gini parameter = 0.2474; n = 521 households; B reps = 1,000; Monte Carlo trials = 600

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<th>Confidence Interval Method</th>
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<th>Median Upper-Bound</th>
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* Proportion of trials in which the interval fails to capture 0.2474.
** Difference between actual and nominal probabilities of rejection.
<table>
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<tr>
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<th>Sample Size</th>
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<th>Bias</th>
<th>Std. Error</th>
<th>Percentile LL</th>
<th>Percentile UL</th>
<th>Bias Corrected LL</th>
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Figure 1a. The Continental Pattern of Inequality

France

Germany

Netherlands
Figure 1b. The Continental Pattern of Inequality
Figure 1c. The Continental Pattern of Inequality

Spain


Gini Index, 95% Confidence Intervals

Ireland


Gini Index, 95% Confidence Intervals
Figure 1d. The Continental Pattern of Inequality

Luxembourg

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Belgium

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<td>1990</td>
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<td>-0.7, 0.025</td>
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Figure 2. The Anglo Pattern of Inequality

United Kingdom

United States

Australia
Figure 3. The Scandinavian Pattern of Inequality

Norway

Gini Index, 95% Confidence Intervals

Sweden

Gini Index, 95% Confidence Intervals

Finland

Gini Index, 95% Confidence Intervals
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Notes:
All Gini indices are based on net, disposable household income, see Appendix A
Reported confidence intervals are percentile method
*1994; ^1996
Figure 4. Patterns of Distributional Change in the Global North, 1980 - 2000