

Inequality convergence

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Abstract

Evidence is found that within-country income inequalities have been slowly converging since the 1980s; inequality is tending to fall (rise) in countries with initially high (low) inequality. Correcting for classical measurement error in the initial inequality measures has little affect on the speed of convergence.

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1. Introduction

It is known that the neoclassical growth model can yield convergence of the whole distribution, not just its mean (Bénabou, 1996). Countries with the same fundamentals will tend to evolve toward a common distribution, with falling inequality in high inequality countries, and rising inequality in low inequality countries.

Could we also expect to find *unconditional* inequality convergence? The period since around 1990 has seen a remarkable policy and institutional convergence in economic fundamentals relevant to inequality. Socialist control economies have become more market-oriented, and non-socialist economies have adopted market-friendly reforms. To see how this process might generate inequality convergence, suppose that reforming countries fall into two categories: those in which pre-reform controls on the economy were used to benefit the rich, keeping inequality artificially high, and those in which the controls had the opposite effect, keeping inequality low. Then liberalizing economic policy reforms can entail sizable redistribution between the poor and the rich, but in opposite directions in the two groups of countries.

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Are we seeing any signs of such inequality convergence? Bénabou (1996) found supportive evidence. This paper revisits Bénabou's findings using new and better data and taking account of likely measurement errors in inequality data. The following section outlines the test for inequality convergence. The results are found in Section 3, while Section 4 concludes.

2. Testing for inequality convergence

The simplest test for inequality convergence is to regress the observed changes over time in a measure of inequality on the measure's initial values across countries, analogous to standard tests for convergence in average incomes. Let G_{it} denote the observed Gini index (or some other measure of inequality) in country i observed at both date $t=0$ and $t=D$. A test equation for inequality convergence is then:

$$G_{iD} - G_{i0} = a + bG_{i0} + e_i \quad (i = 1, \dots, N) \quad (1)$$

where a and b are parameters to be estimated and e is a zero mean error term. If the 'convergence parameter' b is negative (positive) then there is inequality convergence (divergence). This is the method of testing for inequality convergence used by Bénabou (1996).

Measurement error in the initial inequality measure will bias this test in the direction of suggesting convergence. Under (over) estimating the initial level of inequality would lead to over (under) estimation of the subsequent trend. When inequality measures are observed between dates 0 and D one would also like to use these observations rather than throw the data away.

To construct a test that can deal with these concerns, let the true value of the Gini index be G_{it}^* . (These are date specific, since the fundamental determinants of inequality can change.) Each country is assumed to have an underlying trend, T_i , in inequality, such that the change in the true level of inequality between date 1 and any date t is:

$$G_{it}^* - G_{i1}^* = T_i(t-1) + \nu_{it} \quad (i = 1, \dots, N; t = 2, \dots, D) \quad (2)$$

where ν_{it} is a zero-mean innovation error term. (Measured inequality at date 0 is now retained for use as an instrumental variable.) The observed measure of inequality is assumed to be:

$$G_{it} = G_{it}^* + \varepsilon_{it} \quad (3)$$

where ε_{it} is a zero-mean and serially independent measurement error. The working paper version tests the more general model, $G_{it} = \phi G_{it-1} + (1-\phi)G_{it}^* + \varepsilon_{it}$, where ϕ is a common autoregression coefficient ($-1 < \phi < 1$) (Ravallion, 2001). This complicates things given the uneven spacing. However, the test results could not reject the null hypothesis that $\phi = 0$, so I use the simpler specification in this paper.

The hypothesis to be tested is that the trend in inequality depends on its initial level. I assume a linear relationship of the form:

$$T_i = \alpha + \beta G_{i1}^* + \mu_i \quad (4)$$

where α and β are parameters to be estimated and μ_i is a zero-mean innovation error term.

Combining Eqs. (2)–(4), the estimable test equation can be written in the form:

$$G_{it} - G_{i1} = (\alpha + \beta G_{i1})(t - 1) + e_{it} \quad (i = 1, \dots, N; t = 2, \dots, D) \quad (5)$$

where the composite (heteroskedastic) error term is:

$$e_{it} \equiv v_{it} + \varepsilon_{it} - \varepsilon_{i1} + (t - 1)(\mu_i - \beta \varepsilon_{i1}). \quad (6)$$

Notice that ε_{i1} jointly influences G_{i1} and e_{it} . So it cannot be assumed that $\text{cov}(G_{i1}, e_{it}) = 0$. However, G_{i0} is a valid instrument for G_{i1} . The key assumption for this to hold is that the errors in measuring inequality are serially independent.

3. Results

The convergence tests were done on two data sets. The first is the [Chen and Ravallion \(2001\)](#) data set, which was not available at the time [Bénabou's \(1996\)](#) paper was written. In common with other data sets on inequality, the welfare indicators are a mixture of consumption expenditures and income surveys. One difference with other data sets is that all the Gini indices in the Chen–Ravallion data have been estimated from the primary data (micro data or consistent tabulations of points on the distribution) by consistent methods; no secondary sources have been used. Another difference is that all measures in the Chen–Ravallion data set are based on per capita distributions and are household-size weighted. About 80% of the surveys are in the 1990s. However, for many countries there may be only one or two observations; the working paper version gives summary data on the time periods and number of surveys for each country ([Ravallion, 2001](#)). For 66 countries there are two or more observations; this drops to only 21 countries if one wants four or more observations. For the main analysis I focused on the countries with four or more surveys, giving 86 ‘spells’ for these 21 countries (though I consider other samples). The simple mean Gini index for this sample is 41.4% (a median of 40.2%) and the standard deviation is 10.5%. The second data set is that used by [Li et al. \(1998\)](#), drawing on [Deininger and Squire \(1996\)](#).

[Table 1](#) gives both OLS and IVE estimates of Eq. (5) using the Chen–Ravallion data set. These are regressions of the change in the Gini index between each date and the second survey year on the Gini index for the latter. (Results are also given for the log of the Gini index.) Notice that 21 observations

Table 1
Tests for convergence in Gini indices

		Intercept (α)	Slope (β)	N	R^2
Gini index	OLS	1.1527 (0.2852)	-0.0284 (0.0070)	65	0.1571
	IVE	1.1791 (0.3552)	-0.0291 (0.0089)	65	0.1570
Log Gini index	OLS	0.1012 (0.0372)	-0.0274 (0.0094)	65	0.1647
	IVE	0.1076 (0.0383)	-0.0290 (0.0103)	65	0.1391

Standard errors in parentheses; the heteroskedasticity-consistent covariance matrix estimator is used (HC1). IVE columns use the initial value as the instrument for the inequality measure in the second survey.

have to be dropped to form the instrument. For comparison purposes, the OLS estimate is for the same sample as the IVE estimate. I tried adding two dummy variables to the regressions, one for when the survey switched from income to expenditure (relative to the initial survey) and one when it switched from expenditure to income. However, there were only a few cases of such switches, and the extra dummy variables made negligible difference to the convergence results (coefficients and standard errors), so I dropped them.

There is a strong indication of convergence for both the linear and log specifications, and this is robust to allowing for measurement error, using initial inequality as the instrument for the second observation in the series. (The first stage regressions were significant at better than the 0.1% levels.) Indeed, the IVE and OLS estimates are very close, suggesting only a small bias due to measurement error.

The intercepts are low enough to generate convergence toward medium inequality. Consider two countries, one with a Gini index of 30%, one 60%. Taking the instrumental variables estimates for the (linear) Gini index to be preferred, the expected trend will be 0.31 percentage points per year in the first case and -0.57 in the second. In 15 years, the two countries would expect to reach Gini indices of 35% and 51%. The log specification gives a similar result. The implied steady-state level of the Gini index is in the range 40–41% in all specifications, close to the mean (and median) of the data set.

There is little sign of bias in the OLS estimates in [Table 1](#), and by not instrumenting for the first inequality observation one gains 21 observations. So I now switch to OLS on the larger samples. [Table 2](#) gives results for various sample choices. The results are quite similar if one excludes the countries in Eastern Europe and the former Soviet Union. The table also gives the results of the convergence test if one uses the full sample in the Chen–Ravallion data set, i.e. including countries with fewer than four surveys (but at least two). This increases the sample size considerably, with 155 observations for 66 countries (mean Gini index is then 40.5% with a median of 39.8% and a standard deviation of 10.3%). Again the convergence parameter is negative and very significant. This is again robust to dropping Eastern Europe.

Convergence is also evident throughout the Lorenz curve. [Table 3](#) gives the test results by fractile

Table 2
Tests for various samples

	Intercept		Slope		N	R ²
	Coefficient	S.E.	Coefficient	S.E.		
Gini index						
21 country sample	1.1458	0.2246	-0.0329	0.0054	86	0.3449
minus Eastern Europe	1.3392	0.2349	-0.0304	0.0054	74	0.3042
66 country sample	2.0843	0.2511	-0.0460	0.0058	155	0.2827
minus Eastern Europe	1.3907	0.2312	-0.0311	0.0054	117	0.1715
Log Gini index						
21 country sample	0.1446	0.0209	-0.0382	0.0056	86	0.3963
minus Eastern Europe	0.1234	0.0204	-0.0326	0.0054	74	0.3339
66 country sample	0.2090	0.0238	-0.0551	0.0064	155	0.3505
minus Eastern Europe	0.1245	0.0185	-0.0329	0.0049	117	0.1800

The dependent variable is the change in the Gini index relative to the first survey (log Gini index in the lower panel). The heteroskedasticity-consistent covariance matrix estimator is used (HC1).

Table 3
Tests for Lorenz curve convergence

	Intercept		Slope		N	R ²
	Coefficient	S.E.	Coefficient	S.E.		
Share of poorest decile minus Eastern Europe	0.1288	0.0169	−0.0538	0.0072	155	0.2941
Share of decile 2 minus Eastern Europe	0.0766	0.0152	−0.0240	0.0056	117	0.0956
Share of middle (3–8) minus Eastern Europe	0.1720	0.0208	−0.0505	0.0061	155	0.3228
Share of decile 9 minus Eastern Europe	0.1115	0.0186	−0.0282	0.0049	117	0.1477
Share of middle (3–8) minus Eastern Europe	2.8299	0.3290	−0.0627	0.0070	155	0.3830
Share of decile 9 minus Eastern Europe	2.8137	0.3932	−0.0624	0.0086	117	0.3423
Share of decile 9 minus Eastern Europe	0.8544	0.1557	−0.0559	0.0101	155	0.2140
Share of decile 9 minus Eastern Europe	0.7164	0.2033	−0.0475	0.0130	117	0.1613
Share of richest decile minus Eastern Europe	2.1507	0.2303	−0.0638	0.0071	155	0.3902
Share of richest decile minus Eastern Europe	2.0204	0.2963	−0.0605	0.0088	117	0.3217

The dependent variable is the change in the Lorenz share relative to the first survey. The heteroskedasticity-consistent covariance matrix estimator is used (HC1).

for the full sample, and excluding Eastern Europe. The Lorenz curve is converging to one in which the poorest quintile hold 5.8% of income (2.4% for the poorest decile), while the richest decile hold 33.7%.

I also tested for inequality convergence in the [Deininger and Squire \(1996\)](#) data set which includes OECD countries. This data set also goes back further in time allowing an average of 12 surveys per country, though with expected costs in terms of data quality, particularly for developing countries. [Li et al. \(1998\)](#) report the trend coefficients and intercepts for 49 countries of a static regression of the Gini index on time estimated on the Deininger and Squire data set ([Li et al., 1998](#), Table 4). I chose the reference year to be 1965, the median of the country-specific start dates reported in [Li et al. \(1998](#), Table 2). On performing my convergence test on these data, the OLS estimate of β was -0.0113 with a White standard error of 0.0028; the estimate of α was 0.4242 with a standard error of 0.1065 (and $R^2 = 0.267$).

4. Conclusions

Evidence is found of inequality convergence, with a tendency for within-country inequality to fall (rise) in countries with initially high (low) inequality. There is a reasonably strong negative correlation between the initial Gini index and the subsequent change in the index. The effect is not as statistically significant when one allows for measurement error by comparing estimated trends with predicted initial levels. But the correlation is still there and the speed of convergence is similar whether or not one allows for measurement error.

The process of convergence toward medium inequality implied by these results is clearly not rapid, and it should not be forgotten that there are deviations from these trends, both over time and across countries. The shortage of comparable survey observations over time for many countries raises doubts about how well the trends have been estimated. This issue should be revisited when more data come

on stream. This would permit more precise identification of any trends and weaker identification assumptions, notably by allowing for serial dependence in measurement errors.

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