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Abstract
Neoclassical models imply convergence of the entire distribution, not just the mean income levels. In this paper, we test for convergence in income inequality across countries. We compile extensive data on gini indices over a period of 25 years. Convergence in inequality is tested separately for developed and developing countries, using cross-section and panel data. We estimate a dynamic panel model using the GMM estimator and as well as an efficient OLS estimator for a smaller sample. Our results indicate that during 1980 and 2005 inequality converged across countries. The speed of convergence in gini indices is faster than the conventional 2% per year speed of convergence in per capita income. Developed countries appear to have converged faster than developing countries. The result of convergence in inequality is robust across different time horizons, data sources and estimation methods.

Keywords: Convergemce, Countries, Dynamic Panles, Gini, Inequality

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1. Introduction

The idea of convergence of per capita income was proposed by Solow (1956) and Swan (1956) as part of the neoclassical growth models. The neoclassical models, due to diminishing returns to factors of production, predict that per capita income in poor countries will eventually converge with that in rich countries. Per capita growth rate tends to be inversely related to the starting level of output or income per person; hence if countries are similar in respect to preferences and technology, then poorer countries will grow faster than rich ones. The convergence prediction sparked enormous interest and led to extensive literature testing convergence in average incomes both within and across countries. Benabou (1996) noted, however, that neoclassical growth models can yield convergence of the entire distribution of income, not just the first moment, the mean. The question- whether countries with different degrees of inequality tend to converge towards median inequality- has received much less attention in the literature. Extending the notion of convergence to other moments of the distribution implies that countries with similar fundamentals will eventually converge toward the same distribution of income. Inequality levels will tend to fall in countries with high inequality and they will rise in countries with low inequality. This paper contributes to the sparse literature on inequality convergence by empirically testing convergence across countries.

"*Ideally, one would apply to an international panel of inequality measures the same tests which are now standard in the literature on the convergence of first moments.......The binding constraint, however, is data: no such panel exists over a long enough period……Hopefully, future studies with more sophisticated econometrics and better data will help resolve the issue*" Benabou (pg.51, 1996). We partially overcome the data constraint by compiling data on gini values from more than 50 developed and developing countries. The data includes gini values over 25 years -during 1980 and 2005- from the latest and most extensive datasets available. In order to make sure that our results are not data dependent, we do not rely on a single data source. Instead we compile data from two of the latest and most extensive datasets on gini indices namely the PovcalNet by the World Bank (Povcal) and the United Nations's World Income Inequality Database (WIID v. 2.0c). We estimate separate sets of regression models using each dataset and compare convergence estimates across datasets. We test for convergence in: 1) a sample of 32 developing countries from Povcal, 2) a sample of the same 32 developing countries from WIID, 3) a sample of 23 developed countries from WIID and 4) a combined sample of 55 developing and developed countries from WIID.

Convergence in income inequality is tested over varying time horizons ranging from 5, 10, 15, 20 and 25 years and by using an array of regression models including cross-section as well as panel data models. We use the ordinary least squares method (OLS) in the cross-section setting. The cross-section model does not control for country specific effects and the estimates are not consistent. Hence we also estimate a dynamic panel model which treats the country effects explicitly. The dynamic panel model is estimated by using both one-step and two-step Generalized Method of Moments (GMM) estimator developed by Arellano and Bond, (1991). However the asymptotics of the GMM estimator is not valid, especially in our case since the cross-section sample size is small (55 countries). The GMM estimates and their associated test statistics are imprecise in small sized-samples. We test the robustness of our results by estimating an alternate OLS estimator proposed by Bao and Dhongde (2009). The proposed OLS estimator in panel setting uses the sample information more efficiently and gives more reliable inference especially in small samples.

We find strong evidence on convergence in income inequality across countries. A quick look at the data (figure 1) shows that by 2005, inequality had declined in countries which were highly unequal at the start in 1980. On the other hand, inequality in 2005 had increased significantly in many countries with low inequality in 1980. Thus countries were converging towards a medium inequality level and our various regression models support the finding. We regress changes in inequality on initial inequality levels and find that in most cross-section as well as panel data models, the beta coefficient of convergence is significant and negative. Additionally, we find that the impact of initial gini level on change in inequality diminishes over longer time horizons. The speed of convergence in inequality is much higher than the speed of convergence in per capita incomes. Developed countries converged at a higher speed than developing countries.

The remainder of the paper is structured as follows. Section 2 reviews relevant literature and Section 3 describes the data. The multiple regression models and the results are presented in Section 4. Section 5 concludes. An Appendix to the paper includes tables with estimates of cross-section regression models adjusted to outlier values.

2. Literature Review

There is an extensive body of literature testing empirically convergence in income using cross-country data.[1] Beta convergence is the most commonly tested notion of convergence and refers to the presence of a negative relationship between the growth of per capita income and the initial level of income. Compared to the literature testing convergence in income levels, the literature testing beta convergence in income inequality is relatively sparse. Most of the studies use data on the gini index of income inequality and test for the presence of a negative relationship between the change in the gini index and its initial value.

2.1. Inequality Convergence within Countries

Marina (2000) uses gini values of 25 provinces in Argentina between 1984 and 1998; Gomes (2007) uses gini data on more than 5000 municipalities in Brazil between 1991 and 2000. Both find evidence on beta convergence in gini values within Argentina and Brazil respectively. Panizza (2001)

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[1] For instance, see Barro (1991), Barro and Sala-i-Martin (1991), Baumol (1986), Jones (1997), Mankiw, Romer and Weil (1992) and Pritchett (1997) among others.

finds evidence in support of the convergence hypothesis among the states in the U.S. between 1940 and 1980. Using both cross-section and panel type of data, he finds that initial inequality accounts for more than 80 percent of the variance of the changes in the Gini index over time. Goerlich and Mas (2004) find strong evidence of beta convergence in gini indices among Spanish provinces during 1973-1991. Ezcurra and Pascual (2005, 2009) do not test beta convergence but instead adopt Quah's (1996) non-parametric approach and estimate a stochastic kernel distribution. They analyze the spatial distribution of income inequality and find convergence in inequality among countries in the European Union (2005) as well as among states in the U.S. (2009). Tselios (2009) also finds unconditional convergence in income inequality in the regions of the European Union. Lin and Huang (2011) investigate convergence in the U.S. over 80 years, using data on top income shares in addition to the gini index from 1916-2005. They find strong evidence on convergence which is robust to other measures of inequality, different regional divisions and alternate time periods.

2.2 Inequality Convergence between Countries

There seems to be a general consensus that convergence within regions/states of a country was evidenced in most countries studied. However there is no consensus that inequality levels converged across countries. Few studies test cross country convergence due to data limitations. Table 1 contains summary information of empirical studies testing cross country beta convergence. Benabou (1996) is the first to empirically test cross-country convergence in income inequality. He uses data on gini indices from about 30 countries and finds evidence on convergence during 1970-1980, 1980 -1990 but finds no evidence on convergence during 1970-1990. Gottschalk and Smeeding (2000) analyze trends in gini indices and do not find a clear relation between the trend in the 1980s and the overall level of inequality at the start of the period. Ravallion (2003) uses gini values solely based on household survey data and finds that developing countries converged towards medium inequality in the 1990s. Bleaney and

Nishiyama (2003) calculate an income equality index by subtracting the Gini index (on a 100 point-scale) from 100. They use WIID data on gini indices in 1965 and 1990 and find that compared to developing countries; income distribution among OECD countries converged significantly faster and to a more equal distribution. Lopez (2004) compares convergence in income levels with convergence in inequality and finds that between 1960 and 2000, inequality within countries converged much faster than their average incomes.

Thus it seems that cross-country evidence on convergence varies according to the period covered, the countries included, and the type of data used. In this paper, we test convergence across different samples of countries (developing and developed), originating from different data sources (Povcal and WIID), over different time horizons (5, 10 15, 20, 25 years), using data types (cross-section and panel) and by using different regression models (OLS, GMM1, GMM2). We find robust evidence on convergence in cross-country inequality. In the next section, we briefly describe the data compiled on gini indices from more than 50 countries during 1980 and 2005.

3. Data

Countries publish data on income distributions in different forms, such as population quintile/decile share of income, or on summary measures of income inequality such as the gini index, the mean log deviation and the coefficient of variation. We choose the gini index since it is the most commonly available inequality measure on which data is available over time for many countries, and from multiple data sources. The gini index (Gini, 1912) measures the average difference between all possible pairs of incomes in the population expressed as a proportion of total income. It ranges from 0 indicating perfect equality, to 100 percent indicating perfect inequality.[2] We compile data on gini indices

[2] Like any other summary measure, the Gini index has its advantages and drawbacks. It satisfies desirable axioms of inequality such as anonymity, scale independence, and transfer sensitivity but violates the property of decomposability (see Cowell, 2011, for details).

from the two most frequently used datasets, namely, the Povcal data of the World Bank and the WIID published by the United Nations University. The latest version of each dataset is used to form a panel data on as many countries as possible. Table 2 lists the countries included in this study.

The Povcal dataset is available on PovcalNet—a global poverty monitoring website maintained by the World Bank. Povcal compiles data from more than 850 household surveys from 127 developing countries, representing 90 percent of the population of the developing world. Most of the surveys are conducted by national agencies which collect information on consumption expenditures or income levels. Survey data is converted using latest (2005 International Comparison Program) Purchasing Power Parity (PPP) exchange rates for cross-country compatibility. It is based on per capita distributions and is household size weighted. The gini indices published by Povcal are exclusively measured from primary sources; no secondary sources are used; hence cross-country data is consistent but suffers from lack of observations for many countries and years.

Compared to Povcal, data on gini values in WIID is significantly more abundant since it is compiled using primary as well as secondary sources. It is one of the most extensive datasets on inequality and poverty measures available for both developing and developed countries. However, the WIID is not integration, but a collection of all available datasets. We use the latest version WIID 2.0c (updated on May 2008) which includes unit record data from several datasets including Deininger and Squire's (2004) and the Luxembourg Income Study (LIS) dataset.[3] For many countries, several observations in a single year are listed, based on different sources. WIID2.0c reports two different Gini values; the first one is calculated by using methods developed by Shorrocks and Wan (2008), and the second one - called the "reported Gini" - is the one reported by the source or calculated by using parametric extrapolation. We choose gini values calculated by Shorrocks and Wan (2008) method which

[3] WIID also includes data on gini index from the Transmonee data by UNICEF/ICDC, Central Statistical Offices and other research studies on income distribution.

estimates the Gini index from decile data almost as accurately as if unit record data were used. Since cross-country data originate from different sources and refer to a variety of income and population concepts, sample sizes and statistical method, WIID ranks gini values by the quality of the income concept and the survey; rank 1 denoting the best quality and rank 4 the worst.[4] We exclude any observations with the poorest quality ranking of 4 (see Chambers and Krause, 2010) and choose nationally representative data over data on urban or rural areas only. We prefer gini values based on disposable income over those based on gross income and/or on consumption expenditure.

3.1 Summary Statistics

We compile data on gini index over a 5 year interval between 1980 and 2005. We compile data on 32 developing countries from Povcal and compare it with data on the same 32 developing countries from WIID. Tables 3 and 4 contain summary statistics on gini indices for developing countries from Povcal and WIID datasets respectively. In general, gini values from WIID are greater than those from Povcal, since the former are mostly calculated from income, whereas the latter are largely based on consumption expenditure. Between 1980 and 2005, average gini values in both datasets increased from about 38 to 43, whereas the standard deviation of gini indices decreased from about 13 to 7 percent. Thus in developing countries, inequality increased on average but its variance across countries decreased over a period of time. The highest recorded gini index reduced from 65 in 1980 to 57 in 2005, while the least gini index increased from 22 in 1980 to 28 in 2005; thus indicating a possibility of convergence in inequality levels.

Since Povcal has data only on developing countries, we use WIID database to compile gini indices in developed countries. When we compare the summary data in tables 4 and 5, both of which is

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[4] Rank 1 signifies sufficient quality of the income concept and the survey, rank 2 means quality of one of the two cannot be verified, rank 3 means quality of both the income concept and the survey is problematic and rank 4 is for observations derived from “unreliable” data (see the user guide included with WIID 2.0c for further details).

based on gini indices compiled from WIID, we find striking differences in inequality within developing and developed countries. In every year, average gini index in developed countries was considerably lower than that in developing countries. Furthermore average gini value in developed countries was equal to 30 and did not vary much; in developing countries, the average gini index increased from 37 to more than 43. Thus during 1980 to 2005, average inequality levels increased in developing countries compared to developed countries. Table 6 shows the summary statistics of data on all 55 countries from WIID. The two common trends, namely of an increase in average inequality, and a decline in cross-country variation over time are also seen in the pooled sample.

In figure 2, we plot the percent change in gini index between 1980 and 2005 against the initial gini index in 1980. The scatter plot shows a negative relation between the two variables and suggests inequality levels across countries converged over a period of time. In countries like China and U.K., with relatively low initial inequality (22 and 25 respectively) in 1980, inequality increased significantly in 2005 (47 and 34 respectively). Inequality also increased in other relatively equal countries in East Europe (Azerbaijan, Georgia, Hungary, Kyrgyz Republic, Latvia, Lithuania, Poland, Russia, and Uzbekistan) and in some Scandinavian countries (Estonia, Finland, and Norway). On the other hand, highly unequal countries in 1980 experienced a decline in inequality. For instance, countries such as Brazil, Gautemala, Jamaica, Peru and others such as Malaysia, Nigeria, Turkey, had high gini values (between 50 and 60) in 1980. In 2005, gini values in these countries declined and were between 20 and 30. Below we formally test for convergence by estimating regression models based on cross-section as well as panel data.

4. Convergence Tests

4.1 OLS-Cross-Section Regression

Convergence in inequality is tested by finding whether there is a negative relation between the change in inequality and the initial inequality level. Let $Gini_{iT}$ denote the Gini coefficient of country *i* *where i=1, . . .,N* at time *T=1985, 1990,…2005*. Equation (1) tests for convergence over τ-period ($\tau = 5, 10, 15, 20, 25$) by modeling annual average growth rate in gini index as a function of gini index in the initial year. $\beta$is the convergence parameter to be estimated and u_i is a zero mean error term.

$$\frac{1}{\tau}\ln\left(\frac{Gini_{i,T}}{Gini_{i,T-\tau}}\right) = \alpha + \beta ln\left(Gini_{i,T-\tau}\right) + u_i \qquad (1)$$

Tables 7 to 10 summarize the regression estimates over different time intervals. For instance, for gini index initially set in 1990 we estimate convergence over $\tau = 5$ years (1990-1995), 10 years (1990-2000) and 15 years (1990-2005).

Regression estimates for developing countries are given in tables 7 (Povcal data) and 8 (WIID data). Estimates of β coefficient in most cases are significant and vary between -0.02 to -0.09. It is evident that the gini measure of inequality among developing countries converges regardless of the data source. Table 9 shows convergence estimates for developed countries and table 10 summarizes estimates for the pooled sample comprising of all developing and developed countries from WIID data. Overall, the estimates show evidence on convergence in inequality. The estimated coefficients lie well within the range of values estimated in the literature (see Table 1).

The value of the estimated beta coefficient varies inversely with τ, the time horizon over which convergence is measured. In tables 7 through 10 the estimated (absolute) value of β for $\tau = 5$ is greater than the estimated value for $\tau = 20\ or\ 25$. As τ gets larger, the impact of initial gini level on average growth in inequality diminishes. Lin and Huang (2011 pp. 201) who find a similar effect note that since inequality is the second moment of income distribution, the speed of convergence in inequality declines over time for the same reason as the speed of convergence in mean income declines overtime—the rate of return on capital diminishes overtime. The "iron law of convergence" states that countries converge to their steady-state level of per-capita income at a rate of approximately 2% per year.[5] We find that the speed of convergence $\left(\rho = \frac{1}{\tau}\ln(1+\beta\tau)\right)$ in gini values is about 4% per year implying that countries are converging towards similar inequality levels at almost double the speed of countries converging towards similar per capita income levels.

We test whether results in tables 7 to 10 are subject to effects of outlier values (see Panizza, 2001). Observations whose Cook's distance is greater than 1 are dropped and all the regressions are re-estimated by weighing Gini values using Huber and Tukey weights. Estimates of the robustness tests in the Appendix are qualitatively similar. Reweighing the sample results in smaller coefficient values but does not impact the sign and the level of statistical significance.

4.2 GMM-Panel Regression

Caselli et. al. (1996) argue that the cross-section regression estimates in equation (1) are not consistent and are susceptible to omitted variable bias since the cross-section model does not control for country specific effects representing differences in technology or tastes. Instead the following dynamic panel model with fixed effects is estimated.

$$\frac{1}{\tau}\ln\left(\frac{Gini_{i,t}}{Gini_{i,t-\tau}}\right) = \beta ln\left(Gini_{i,t-\tau}\right) + \acute{\eta}_{\iota} + \acute{\xi}_t + u'_{\iota,t} \tag{2}$$

In equation (2), *i=1, . . .,N* and *t* =0, . . .,*T*., and $\acute{\eta}_{\iota}$ denotes the unobserved country specific effects, $\acute{\xi}_t$ denotes time specific effects and $u'_{\iota,t}$ is an error term with zero mean and serially uncorrelated across countries. A negative significant estimate of β indicates convergence over τ –periods. Rearranging the terms in equation (2) we get:

$$\ln G_{it} = \alpha ln\left(Gini_{i,t-\tau}\right) + \eta_i + \xi_t + u_{it} \tag{3}$$

[5] See Barro (1991), and Barro and Lee (1994)

In equation (3), $\alpha = \beta\tau + 1$, $\eta_i = \tau\acute{\eta}_\imath$and $\xi_t = \tau\acute{\xi}_t$. In order to eliminate ξ_t, the time-specific constant, we take deviations from period means for all variables in equation (3).

$$g_{it} = \alpha g_{it-\tau} + \eta_i + u_{it} \tag{4}$$

In equation (4), g_{it} denotes the deviation of $\ln(G_{it})$ from its period mean. Equation (4) is a dynamic panel model with a lagged dependent variable and hence the least squares dummy variable or within-group estimator is not consistent; in large samples it is often biased downward, see Nickell (1981). In fact in most convergence studies where N is large but T is finite, the standard OLS estimate of equation (4) is also not consistent and is typically biased upwards. In order to remove the country-specific effect η_i, Caselli et al. (1996) take the following τ-order difference transformation of equation (4).

$$g_{it} - g_{it-\tau} = \alpha(g_{it-\tau} - g_{it-2\tau}) + u_{it} - u_{it-\tau} \tag{5}$$

In equation (5), $(g_{it-\tau} - g_{it-2\tau})$is correlated with$(u_{it} - u_{it-\tau})$, the OLS estimate of α is biased. Hence, Caselli et al. (1996) propose a GMM estimator instead by assuming that there is no τ –order serial correlation, $E(u_{it}, u_{it-\tau}) = 0$. Then all lagged values of the gini index, $g_{i0}, g_{i\tau}, \ldots\ldots g_{it-2\tau}$ are uncorrelated with $(u_{it} - u_{it-\tau})$ and are valid instruments. The validity of instruments is checked by a Sargan (1958)-Hansen (1982) test of over-identifying restrictions.

We estimate equation (5) by using both one-step (GMM1) and two-step (GMM2) estimation methods developed by Arellano and Bond, (1991).[6] Results based on the panel data are presented in Tables 11 to 14. Comparing the cross section estimates to GMM estimates it is seen that the latter are larger in magnitude than those based on cross-sectional data, consistent with Panizza (2001). Thus support for the convergence hypothesis is unambiguous and much stronger in panel data compared to cross-sectional data.

[6] GMM1 makes further assumptions on the weighting matrix while GMM2 uses GMM1 residuals to build the weighting matrix. Panizza (2001) notes that GMM2 tends to produce low-power t statistics.

The tables show both—the coefficient of initial inequality (α) and the implied β values, based on the relation$(\alpha = \beta\tau + 1)$. All β values are negative and significant at 1% level implying convergence of inequality. For the sake of comparison, we also report FE (within-group) estimates along with the GMM estimates. The FE estimates of (α) in large samples are biased downwards and are smaller in magnitude than GMM1 and GMM2 estimates (tables 11 to 14). Convergence in income inequality was faster in developed countries compared to developing countries (tables 12 and 13). Our findings are consistent with those by Bleaney and Nishiyama (2003) who also find that the speed of convergence is faster among OECD countries compared to developing countries. The implied speed of convergence in the all country sample (Table 14) is between 9 to 13 percent. The speed of convergence based on GMM estimates using panel data is much higher than the one implied by OLS estimates of the cross-section data. However this is not surprising. In one application, Caselli et. al. (1996) find that per capita incomes converge to their steady state levels at a rate of approximately 10 percent per year—in contrast to the consensus convergence rate at 2%.

4.3 OLS-Panel Regression

In the case of persistent data and for a small number of time series observations, the lagged dependent variables can be weak instruments and the GMM estimator can be biased. The finite sample properties of the GMM estimates and their associated test statistics are imprecise. In our case, the cross-section sample is equal to 55 countries, and for each country, the GMM estimator uses observations only at multiples of τ $(\tau = 5)$and effectively has $(T/\tau) - 1$ i.e. only four observations per country over time. Hence to test the robustness of our prediction of convergence, we estimate the panel model in equation (4) by using an OLS estimator proposed by Bao and Dhongde (2009). In a dynamic panel set-up, the OLS estimator provides more reliable inference especially in small cross-section samples and proves to be an improvement over the GMM estimator.

Recall that in order to remove the country-specific effect η_i, Caselli et al. (1996) take τ-order difference transformation of equation (4) to arrive at equation (5). Bao and Dhongde (2009), instead, take the first difference of equation (4).

$$g_{it} - g_{it-1} = \alpha(g_{it-\tau} - g_{it-\tau-1}) + u_{it} - u_{it-1} \quad (6)$$

Assuming there is no $\tau, (\tau-1)$and $(\tau+1)$-order serial correlation, i.e. $E(u_{it}, u_{it-\tau}) = E(u_{it}, u_{it-\tau+1}) = E(u_{it}, u_{it-\tau-1}) = 0$, the explanatory variable in equation (6) $(g_{it-\tau} - g_{it-\tau-1})$ is uncorrelated with the error term $(u_{it} - u_{it-1})$. Thus the standard OLS procedure is consistent and we do not need to use instrumental variables estimator.

The OLS estimates are based on $(T-\tau) = 20$ period observations instead of $(T/\tau) - 1 = 4$ period observations per country. In order to employ the OLS method, we need data on gini indices is available at a higher frequency than $\tau = 5$. Few countries in either Povcal or WIID data bases have annually recorded gini values. From our previous total of 55 countries from WIID, we compile a panel of 20 countries; with annual gini values during 1980 and 2005 (see Table 1 for country names).[7] Thus the OLS estimator, reported in Table 15, is based on 400 country-period observations. It is seen that the OLS estimate of the convergence coefficient is negative and significant—confirming our earlier finding. For the sake of comparison, we again report both, estimates based on OLS, GMM1 and GMM2. We find that GMM estimates of α are biased upwards as suggested by the Monte Carlo evidence in Bao and Dhongde (2009). The validity of the OLS method rests on the key assumption that is no $\tau, (\tau-1)$and $(\tau+1)$-order serial correlation. Bao and Dhongde (2009) construct m-test statistic which is asymptotically normally distributed. The OLS estimator is valid if the m-statistic is equal to zero. As seen in Table 15, the m statistic equals - 0.04, and is statistically insignificant from 0, justifying the use of the OLS method.

[7] We choose countries with less than three consequent missing values and impute the missing gini values using values in the immediate vicinity.

5. Conclusions

Although neo-classical growth models imply convergence in the entire distribution of income, the literature has largely focused on testing convergence in average income levels. Of the few empirical studies testing convergence in income inequality, most test regional convergence within a particular country, because of poor data availability across countries. The paper contributes to the literature by comprehensively testing cross-country convergence in income inequality.

We found strong evidence showing inequality levels across countries converged during 1980 and 2005. Convergence was evident in developed and developing countries based on data from Povcal as well as WIID. The result was robust to different regression models based alternately on cross-section and panel data. The speed of convergence in inequality was higher than the speed of convergence in per capita income found in the literature. Over time we found that inequality decreased in highly unequal countries but it increased in highly equal countries. In short, countries across the world are becoming equally unequal.

We understand that we test convergence in income distributions by using gini index which is after all a summary measure of inequality. Different distributions may have the same gini value. As more data becomes available, the next step would be to use more disaggregated measures of income distribution such as the decile shares of income and to perform additional convergence tests like sigma convergence. On the theoretical side, one can perhaps look beyond the implications of the neo-classical models to explain how current globalization and the integration of the world economy have contributed to the convergence phenomenon.

References

Arellano, M. and Bond, S. (1991). ‘Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations’, Review of Economic Studies, Vol. 58, pp. 277-297.

Bao, Y. and Dhongde, S. (2009). ‘Testing convergence in income distribution’, Oxford Bulletin of Economics and Statistics, Department of Economics, University of Oxford, Vol. 71(2), pp.295-302, 04.

Barro, R. (1991). ‘Economic growth in a cross section of countries’, Quarterly Journal of Economics, Vol. 106(2), pp. 407-443.

Barro, R. and Lee, J. (1994). ‘Losers and Winners in Economic Growth’, Proceedings of the World Bank Annual Conference on Development Economics, The World Bank, pp. 267-297.

Barro, R. and Sala-i-Martin, X. (1991). ‘Convergence across states and regions’, Brookings Pap. Econ. Act. 1, pp. 107-158.

Bénabou, R. (1996). ‘Inequality and growth’, in Bernanke B. S. and Rotemberg J. J. (eds), NBER Macroeconomics Annual, Vol. 11, MIT Press, Cambridge, pp. 11–73.

Bleaney, M. and Nishiyama, A. (2003). ‘Convergence in income inequality: differences between advanced and developing countries’, Economics Bulletin, Vol.4 (22), pp. 1-10

Baumol, W. J. (1986). ‘Productivity growth, convergence, and welfare: what the long-run data show’, The American Economic Review, pp.1072-1085.

Caselli, F., Esquivel, G. and Lefort, F. (1996). ‘Reopening the convergence debate: a new look at cross-country growth empirics’, Journal of Economic Growth, Vol. 1, pp. 363–389.

Chambers, D. and Krause, A. (2010). ‘Is the relationship between inequality and growth affected by physical and human capital accumulation?’, Journal of Economic Inequality, Vol. 8(2), pp.153-172.

Chen, S., Ravallion, M., (2001). ‘How did the world’s poorest fare in the 1990s,’ Policy Research Working Paper.World Bank, Washington DC.

Cowell, F. (2011). ‘Measuring inequality’, Oxford University Press, Oxford.

Deininger, K. and Squire, L. (2004). Unpublished data provided by World Bank based on unit record data.

Ezcurra, R. and Pascual, P. (2005). ‘Is there convergence in income inequality levels among the European regions?’ Applied Economic Letters, Vol. 12(12), pp. 763-767(5).

Ezcurra, R. and Pascual, P. (2009). ‘Convergence in income inequality in the United States: a nonparametric analysis’, Applied Economic Letters, Vol. 16(13), pp. 1365-1368.

Goerlich, F. and Mas, M. (2004). ‘Three (marginal?) questions regarding convergence’, Journal of Economic Studies, Vol. 31, pp. 25–38.

Gomes, F. A. R. (2007). ‘Convergence in income inequality, the case of Brazilian municipalities’, Economics Bulletin, Vol.15(15), pp.1-9.

Gottschalk, P. and Smeeding, T. (2000). ‘Empirical evidence on income inequality in industrialized countries,’ Handbook of Income Distribution, in: A.B. Atkinson & F. Bourguignon (ed.), Handbook of Income Distribution, edition 1, Vol. 1, chapter 5, pp. 261-307 Elsevier.

Hansen, L. (1982). ‘Large Sample Properties of Generalised Method of Moments Estimators’, Econometrica Vol. 50, pp. 1029-1054.

Jones, C. I. (1997). ‘Convergence revisited’, *Journal of economic Growth*, Vol. 2(2), pp. 131-153.

Lin, P. and Huang, H. (2011). ‘Inequality convergence in a panel of states’, Journal of Economic Inequality, Springer, Vol. 9(2), pp. 195-206, June.

Lopez, H. (2004). ‘Pro-growth, pro-poor: is there a trade-off?’, World Bank Policy Research Working Paper 3378, The World Bank.

Mankiw, N. G., Romer, D. and Weil, D. N. (1992). ‘A contribution to the empirics of economic growth’, The Quarterly Journal of Economics, Vol. 107(2), pp. 407-437.

Marina, A. (2000). ‘Economic convergence of the first and second moment in provinces of Argentina’, Estudios de Economía, Vol.27, pp.259-77.

Nickell, S. (1981). ‘Biases in dynamic models with fixed effects’, Econometrica: Journal of the Econometric Society, pp. 1417-1426.

Panizza, U. (2001). ‘Convergence in income inequality’, Journal of Income Distribution, Vol. 10, pp. 5–12.

PovcalNet Online Database by the World Bank: http://iresearch.worldbank.org/PovcalNet/index.htm (accessed March 2013)

Pritchett, L. (1997). ‘Divergence, big time. *The Journal of Economic Perspectives’*, Vol. *11*(3), pp. 3-17.

Quah, D. (1996). ‘Empirics for economic growth and convergence’, European Economic Review, Vol. 40, pp. 1353–75.

Ravallion, M. (2003). ‘Inequality convergence’, Economics Letters, Vol. 80, pp. 351–356.

Sargan, J. (1958). ‘The Estimation of Economic Relationships Using Instrumental Variables’, Econometrica, Vol. 26, pp. 393-415.

Shorrocks, A. and Wan, G. (2008). ‘Ungrouping income distributions: synthesizing samples for inequality and poverty analysis’, United Nations University World Institute for Development Economic Research (UNU-WIDER) Paper No. 16. Helsinki, Finland.

Solow, R. (1956). ‘A contribution to the theory of economic growth’, The Quarterly Journal of Economics, Vol. 70, pp. 65-94.

Swan, T. (1956). ‘Economic growth and capital accumulation’, Economic Record, Vol. 32, pp. 344-361.

Tselios, V. (2009). ‘Growth and convergence in income per capita and income inequality in the regions of the EU’, Spatial Economic Analysis, Vol. 4, pp. 343–370

World Income Inequality Database by the United Nations University: http://www.wider.unu.edu/research/Database/ (accessed March 2013)

Table 1 Summary of Studies Testing Beta Convergence in Income Inequality across Countries

	Data Source	Countries	Years	Equation	Beta Coefficient
Benabou (1996)	Deninger and Squire (1995)	25	1970-1990	$\frac{1}{T}(Gini_{iT} - Gini_{i0}) = \alpha + \beta Gini_{i0} + u_i$	-0.039
Ravallion (2003)	Chen and Ravallion (2001)	21	1990s	$(Gini_{iT} - Gini_{i1}) = (\alpha + \beta Gini_{i1})(T-1) + u_{it}{}^{+}$	-0.0284
Bleaney and Nishiyama (2003)	WIID 1.0	79	1965-1990	$\frac{1}{T}(Gini^{\sim}{}_{iT} - Gini^{\sim}{}_{i0}) = \alpha + \beta Gini^{\sim}{}_{i0} + u_i$	-0.0125
Lopez (2004)	Dollar and Kraay (2002)	-	1960-2000		-0.0312
Dhongde and Miao (2013)	WIID 2.0	55	1980-2005	$\frac{1}{T}\left(\log\left(Gini_{i,T}\right) - log\left(Gini_{i,0}\right)\right) = \alpha + \beta log\left(Gini_{i,0}\right) + u_i$	-0.024

+u_{it} is a composite heteroskedastic term; $Gini^{\sim}{}_{it} = 1 - Gini_{it}$.

Table 2 List of Countries

32 Developing Countries			
Argentina*	Dominican Republic	Malaysia	Uzbekistan
Azerbaijan	Georgia	Mexico	Venezuela*
Bangladesh	Guatemala	Moldova	
Belarus	India	Nigeria	
Brazil*	Indonesia	Pakistan	
Bulgaria*	Jamaica	Peru	
Chile*	Kazakhstan	Russia	
China*	Kyrgyz Republic	Turkey	
Colombia	Latvia	Ukraine	
Costa Rica*	Lithuania	Uruguay*	
23 Developed Countries			
Australia*	Hungary*	Taiwan*	
Austria	Ireland	United Kingdom*	
Bahamas	Italy	United States*	
Belgium	Korea		
Denmark*	Netherlands*		
Estonia	New Zealand*		
Finland	Norway*		
France	Poland*		
Germany*	Spain		
Greece	Sweden*		

* indicates 20 countries included in the OLS estimation in the dynamic panel setting in Section 4.3.

Table 3 Developing Countries: Povcal

Gini Index: Summary Statistics						
	1980	1985	1990	1995	2000	2005
Min.	22.9	22.48	22.18	28.65	28.96	27.92
Max.	65.5	58.26	61.04	60.24	59.96	57.42
Mean	38.78	36.28	38.66	41.66	41.85	41.23
St. Dev.	13.90	12.08	10.83	8.82	8.94	8.59
No. obs.	32	32	32	32	32	32

Table 4 Developing Countries: WIID

Gini Index: Summary Statistics						
	1980	1985	1990	1995	2000	2005
Min.	22.3	22.4	23.7	29	26.8	28.2
Max.	65.5	59.3	60.5	60.3	61.2	56.4
Mean	37.83	36.81	39.78	42.92	43.39	43.46
St. Dev.	13.43	11.58	10.91	8.50	9.72	7.36
No. obs.	32	32	32	32	32	32

Table 5 Developed Countries: WIID

Gini Index: Summary Statistics						
	1980	1985	1990	1995	2000	2005
Min.	21.2	20.1	20.3	20	22	23
Max.	43.6	47.2	45	44.8	57.5	46.4
Mean	30.9	29.65	29.91	31.31	32.01	31.37
St. Dev.	6.75	6.64	6.39	6.08	7.56	5.50
No. obs.	23	23	23	23	23	23

Table 6 All Countries: WIID

Gini Index: Summary Statistics						
	1980	1985	1990	1995	2000	2005
Min.	21.2	20.1	20.3	20	22	23
Max.	65.5	59.3	60.5	60.3	61.2	56.4
Mean	34.93	33.82	35.65	38.07	38.63	38.40
St. Dev.	11.57	10.37	10.44	9.48	10.47	8.93
No. obs.	55	55	55	55	55	55

Table 7 Cross-section evidence on convergence in developing countries: Povcal

	5 years	10 years	15 years	20 years	25 years
	Starting 2000				
Constant	0.068				
	(1.40)				
Initial Gini	-0.019				
	(-1.51)				
R2	0.05				
No. Obs	32				
	Starting 1995				
Constant	0.118**	0.063**			
	(2.54)	(2.57)			
Initial Gini	-0.032**	-0.017**			
	(-2.48)	(-2.61)			
R2	0.08	0.09			
No. Obs	32	32			
	Starting 1990				
Constant	0.264***	0.132***	0.086***		
	(6.29)	(6.22)	(7.09)		
Initial Gini	-0.068***	-0.034***	-0.022***		
	(-6.15)	(-5.98)	(-6.78)		
R2	0.48	0.49	0.52		
No. Obs	32	32	32		
	Starting 1985				
Constant	0.176***	0.199***	0.118***	0.092***	
	(3.51)	(7.84)	(9.38)	(8.62)	
Initial Gini	-0.045***	-0.051***	-0.030***	-0.024***	
	(-3.35)	(-7.55)	(-8.73)	(-8.15)	
R2	0.25	0.59	0.64	0.63	
No. Obs	32	32	32	32	
	Starting 1980				
Constant	0.107**	0.127***	0.148***	0.105***	0.084***
	(2.42)	(4.29)	(7.90)	(9.98)	(9.56)
Initial Gini	-0.033**	-0.035***	-0.039***	-0.028***	-0.022***
	(-2.55)	(-4.29)	(-7.63)	(-9.43)	(-9.24)
R2	0.18	0.39	0.66	0.68	0.69
No. Obs	32	32	32	32	32

Heteroskedasticity-consistent t-statistics in parentheses. *Significant at 10%, **5%, ***1%

Table 8 Cross-section evidence on convergence in developing countries: WIID

	5 years	10 years	15 years	20 years	25 years
			Starting 2000		
Constant	0.289***				
	(4.02)				
Initial Gini	-0.077***				
	(-4.12)				
R2	0.41				
N. Obs	32				
			Starting 1995		
Constant	0.049	0.162***			
	(0.51)	(3.41)			
Initial Gini	-0.013	-0.043***			
	(-0.52)	(-3.40)			
R2	0.01	0.29			
N. Obs	32	32			
			Starting 1990		
Constant	0.351***	0.166***	0.138***		
	(4.78)	(4.27)	(7.49)		
Initial Gini	-0.091***	-0.043***	-0.036***		
	(-4.73)	(-4.20)	(-7.35)		
R2	0.49	0.35	0.61		
N. Obs	32	32	32		
			Starting 1985		
Constant	0.201***	0.196***	0.146***	0.132***	
	(3.10)	(8.36)	(5.98)	(9.49)	
Initial Gini	-0.052***	-0.050***	-0.037***	-0.034***	
	(-3.02)	(-7.95)	(-5.68)	(-9.15)	
R2	0.20	0.59	0.47	0.67	
N. Obs	32	32	32	32	
			Starting 1980		
Constant	0.147**	0.140***	0.153***	0.124***	0.112***
	(2.60)	(4.33)	(8.60)	(6.87)	(11.73)
Initial Gini	-0.042**	-0.037***	-0.040***	-0.032***	-0.029***
	(-2.48)	(-4.19)	(-8.00)	(-6.52)	(-11.43)
R2	0.27	0.39	0.70	0.59	0.76
N. Obs	32	32	32	32	32

Heteroskedasticity-consistent t-statistics in parentheses. *Significant at 10%, **5%, ***1%

Table 9 Cross-section evidence on convergence in developed countries: WIID

	5 years	10 years	15 years	20 years	25 years
		Starting 2000			
Constant	0.206***				
	(3.29)				
Initial Gini	-0.060***				
	(-3.29)				
R2	0.38				
N. Obs	23				
		Starting 1995			
Constant	0.044	0.073**			
	(0.43)	(2.42)			
Initial Gini	-0.012	-0.021**			
	(-0.39)	(-2.41)			
R2	0.01	0.27			
N. Obs	23	23			
		Starting 1990			
Constant	0.307***	0.137*	0.126***		
	(3.06)	(1.97)	(3.23)		
Initial Gini	-0.088***	-0.038*	-0.036***		
	(-2.96)	(-1.84)	(-3.14)		
R2	0.27	0.20	0.41		
N. Obs	23	23	23		
		Starting 1985			
Constant	0.184	0.119***	0.067*	0.092***	
	(1.50)	(3.10)	(1.82)	(4.35)	
Initial Gini	-0.054	-0.033***	-0.018	-0.026***	
	(-1.52)	(-3.00)	(-1.65)	(-4.12)	
R2	0.14	0.22	0.15	0.41	
N. Obs	23	23	23	23	
		Starting 1980			
Constant	0.109	0.109**	0.096***	0.070**	0.087***
	(1.53)	(2.09)	(3.04)	(2.28)	(4.59)
Initial Gini	-0.034	-0.033**	-0.028***	-0.020**	-0.025***
	(-1.61)	(-2.17)	(-3.06)	(-2.19)	(-4.50)
R2	0.11	0.19	0.29	0.23	0.48
N. Obs	23	23	23	23	23

Heteroskedasticity-consistent t-statistics in parentheses. *Significant at 10%, **5%, ***1%

Table 10 Cross-section evidence on convergence in all countries: WIID

	5 years	10 years	15 years	20 years	25 years
			Starting 2000		
Constant	0.156***				
	(4.03)				
Initial Gini	-0.043***				
	(-4.13)				
R2	0.21				
N. Obs	55				
			Starting 1995		
Constant	0.040	0.072***			
	(1.02)	(3.30)			
Initial Gini	-0.011	-0.020***			
	(-0.97)	(-3.25)			
R2	0.01	0.14			
N. Obs	55	55			
			Starting 1990		
Constant	0.238***	0.113***	0.094***		
	(4.70)	(4.67)	(6.31)		
Initial Gini	-0.063***	-0.030***	-0.025***		
	(-4.66)	(-4.51)	(-6.19)		
R2	0.24	0.19	0.32		
N. Obs	55	55	55		
			Starting 1985		
Constant	0.141**	0.130***	0.096***	0.094***	
	(2.62)	(5.58)	(4.92)	(7.03)	
Initial Gini	-0.037**	-0.034***	-0.025***	-0.025***	
	(-2.55)	(-5.29)	(-4.59)	(-6.79)	
R2	0.10	0.26	0.23	0.37	
N. Obs	55	55	55	55	
			Starting 1980		
Constant	0.119**	0.107***	0.114***	0.093***	0.089***
	(2.47)	(3.75)	(6.05)	(5.66)	(8.31)
Initial Gini	-0.035**	-0.030***	-0.031***	-0.025***	-0.024***
	(-2.46)	(-3.72)	(-5.83)	(-5.41)	(-8.18)
R2	0.18	0.22	0.39	0.35	0.48
N. Obs	55	55	55	55	55

Heteroskedasticity-consistent t-statistics in parentheses. *Significant at 10%, **5%, ***1%

Table 11 Panel convergence tests for developing countries: Povcal

	1985-2005		
	FE-Within	GMM1	GMM2
Initial Gini (α)	0.117	0.577***	0.625***
	(0.077)	(0.096)	(0.073)
Implied (β)	-0.177***	-0.085***	-0.075***
	(0.015)	(0.019)	(0.015)
Countries	32	32	32
N. Obs.	128	128	128
Instruments		10	10
Sargan Test			12.97
			(0.164)

*Significant at 10%, **5%, ***1%. Standard errors are given in parentheses. p-value is given in the parentheses for Sargan Test

Table 12 Panel convergence tests for developing countries: WIID

	1985-2005		
	FE-Within	GMM1	GMM2
Initial Gini (α)	0.136	0.590***	0.697***
	(0.088)	(0.118)	(0.099)
Implied (β)	-0.173***	-0.082***	-0.061***
	(0.018)	(0.024)	(0.020)
Countries	32	32	32
N. Obs.	128	128	128
Instruments		10	10
Sargan Test			15.18
			(0.086)

*Significant at 10%, **5%, ***1%. Standard errors are given in parentheses. p-value is given in the parentheses for Sargan Test

Table 13 Panel convergence tests for developed countries: WIID

	1985-2005		
	FE-Within	GMM1	GMM2
Initial Gini (α)	-0.021	0.184	0.152***
	(0.112)	(0.169)	(0.055)
Implied (β)	-0.204***	-0.163***	-0.170***
	(0.022)	(0.034)	(0.011)
Countries	23	23	23
N. Obs.	92	92	92
Instruments		10	10
Sargan Test			15.78
			(0.072)

*Significant at 10%, **5%, ***1%. Standard errors are given in parentheses. p-value is given in the parentheses for Sargan Test

Table 14 Panel convergence tests for all countries: WIID

	1985-2005		
	FE-Within	GMM1	GMM2
Initial Gini (α)	0.098	0.525***	0.647***
	(0.068)	(0.121)	(0.097)
Implied (β)	-0.180***	-0.095***	-0.071***
	(0.014)	(0.024)	(0.019)
Countries	55	55	55
N. Obs.	220	220	220
Instruments		10	10
Sargan Test			12.46
			(0.189)

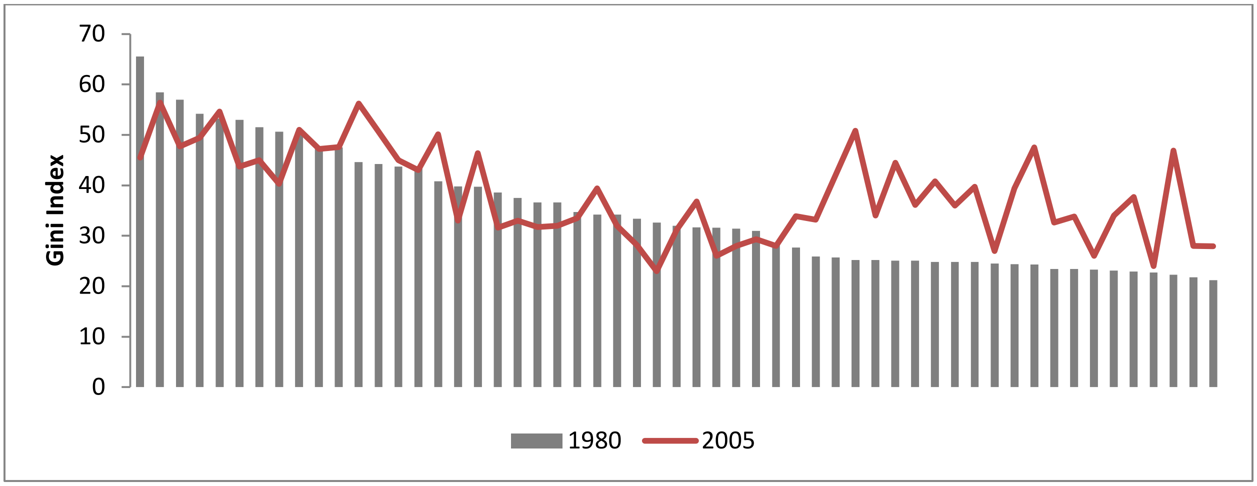
*Significant at 10%, **5%, ***1%. Standard errors are given in parentheses. p-value is given in the parentheses for Sargan Test

Table 15 OLS and GMM tests in panel setting

	1980-2005		
	OLS	GMM1	GMM2
Initial Gini (α)	0.093	0.451	0.433***
	(0.093)	(0.457)	(0.057)
Implied (β)	-0.181***	-0.110	-0.113***
	(0.019)	(0.091)	(0.011)
Countries	20	20	20
N. Obs.	400	80	80
Instruments		10	10
Sargan Test			6.59
			(0.68))
m statistic	-0.04		

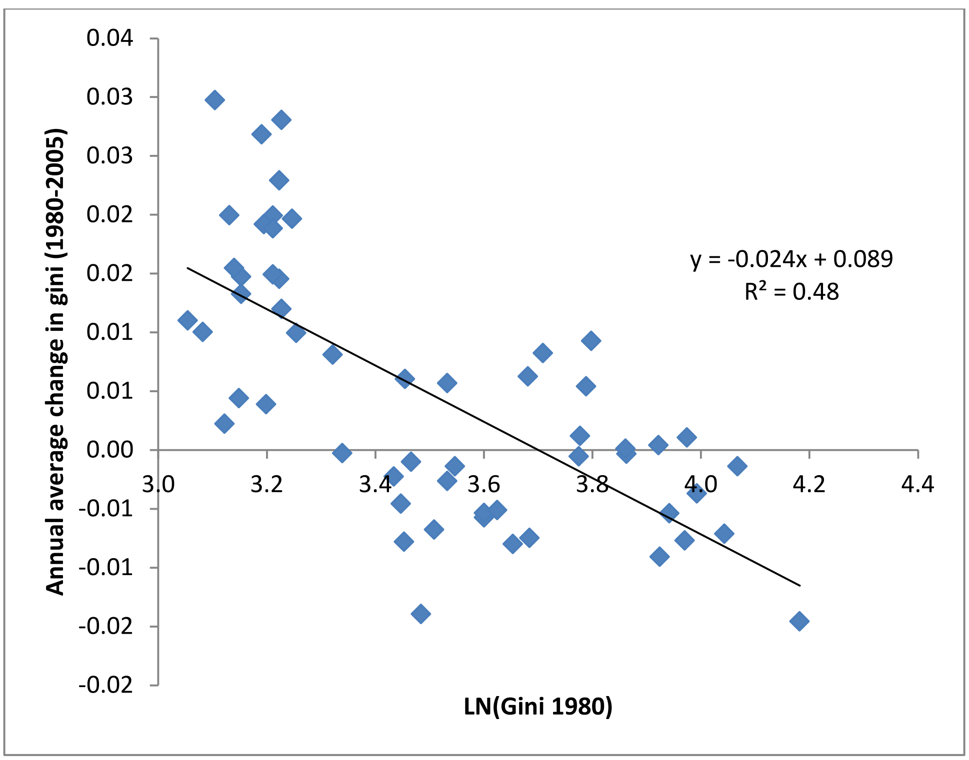
*Significant at 10%, **5%, ***1%. Standard error in parentheses. p-value in the parentheses for Sargan Test

Figure 1 Inequality levels across countries during 1980 and 2005



Data on gini indices in all 55 countries is taken from WIID 2.0C. Countries are arranged in descending order of gini values in 1980.

Figure 2 Change in inequality in relation to initial inequality level



Data on gini indices in all 55 countries is taken from WIID 2.0C

Appendix: Regression Results Adjusted for Outlier Values

Table A1 Cross-section evidence on convergence in developing countries: Povcal

	5 years	10 years	15 years	20 years	25 years
			Starting 2000		
Constant	0.068				
	(1.39)				
Initial Gini	-0.019				
	(-1.41)				
N. Obs	32				
			Starting 1995		
Constant	0.096**	0.061			
	(2.19)	(1.69)			
Initial Gini	-0.024*	-0.016			
	(-2.00)	(-1.67)			
N. Obs	32	32			
			Starting 1990		
Constant	0.241***	0.130***	0.082***		
	(6.20)	(5.18)	(5.60)		
Initial Gini	-0.062***	-0.033***	-0.021***		
	(-5.76)	(-4.80)	(-5.24)		
N. Obs	32	32	32		
			Starting 1985		
Constant	0.163***	0.188***	0.118***	0.092***	
	(3.14)	(6.60)	(7.55)	(7.26)	
Initial Gini	-0.042***	-0.049***	-0.030***	-0.024***	
	(-2.87)	(-6.04)	(-6.81)	(-6.63)	
N. Obs	32	32	32	32	
			Starting 1980		
Constant	0.061	0.124***	0.141***	0.106***	0.084***
	(1.50)	(4.03)	(7.11)	(8.12)	(8.05)
Initial Gini	-0.018	-0.034***	-0.037***	-0.028***	-0.022***
	(-1.62)	(-3.98)	(-6.77)	(-7.68)	(-7.67)
N. Obs	32	32	32	32	32

Heteroskedasticity-consistent t-statistics in parentheses. *Significant at 10%, **5%, ***1%

Table A2 Cross-section evidence on convergence in developing countries: WIID

	5 years	10 years	15 years	20 years	25 years
			Starting 2000		
Constant	0.289***				
	(4.66)				
Initial Gini	-0.076***				
	(-4.61)				
N. Obs	32				
			Starting 1995		
Constant	0.016	0.111***			
	(0.18)	(3.45)			
Initial Gini	-0.004	-0.029***			
	(-0.17)	(-3.36)			
N. Obs	32	32			
			Starting 1990		
Constant	0.229***	0.150***	0.139***		
	(5.53)	(3.77)	(6.61)		
Initial Gini	-0.059***	-0.039***	-0.036***		
	(-5.19)	(-3.55)	(-6.25)		
N. Obs	32	32	32		
			Starting 1985		
Constant	0.191***	0.192***	0.143***	0.132***	
	(2.75)	(6.74)	(4.79)	(8.27)	
Initial Gini	-0.049**	-0.049***	-0.037***	-0.034***	
	(-2.51)	(-6.13)	(-4.39)	(-7.65)	
N. Obs	32	32	32	32	
			Starting 1980		
Constant	0.058***	0.134***	0.149***	0.122***	0.112***
	(3.05)	(4.21)	(8.20)	(6.40)	(10.16)
Initial Gini	-0.015***	-0.035***	-0.038***	-0.032***	-0.029***
	(-2.90)	(-3.99)	(-7.60)	(-5.97)	(-9.51)
N. Obs	32	32	32	32	32

Heteroskedasticity-consistent t-statistics in parentheses. *Significant at 10%, **5%, ***1%

Table A3 Cross-section evidence on convergence in developed countries: WIID

	5 years	10 years	15 years	20 years	25 years
			Starting 2000		
Constant	0.234***				
	(4.69)				
Initial Gini	-0.068***				
	(-4.71)				
N. Obs	23				
			Starting 1995		
Constant	0.142*	0.075**			
	(1.96)	(2.58)			
Initial Gini	-0.041*	-0.022**			
	(-1.95)	(-2.57)			
N. Obs	22	23			
			Starting 1990		
Constant	0.213***	0.148**	0.113***		
	(3.24)	(2.69)	(3.40)		
Initial Gini	-0.060***	-0.042**	-0.033***		
	(-3.08)	(-2.57)	(-3.31)		
N. Obs	23	23	23		
			Starting 1985		
Constant	0.048	0.112**	0.068*	0.091***	
	(0.58)	(2.44)	(1.99)	(3.82)	
Initial Gini	-0.014	-0.031**	-0.019*	-0.026***	
	(-0.57)	(-2.32)	(-1.84)	(-3.68)	
N. Obs	23	23	23	23	
			Starting 1980		
Constant	0.104	0.091	0.090***	0.092***	0.094***
	(1.37)	(1.64)	(3.03)	(3.52)	(4.34)
Initial Gini	-0.032	-0.028*	-0.026***	-0.027***	-0.028***
	(-1.45)	(-1.71)	(-3.01)	(-3.49)	(-4.33)
N. Obs	23	23	23	23	23

Heteroskedasticity-consistent t-statistics in parentheses. *Significant at 10%, **5%, ***1%

Table A4 Cross-section evidence on convergence in all countries: WIID

	5 years	10 years	15 years	20 years	25 years
			Starting 2000		
Constant	0.119***				
	(3.82)				
Initial Gini	-0.033***				
	(-3.84)				
N. Obs	55				
			Starting 1995		
Constant	0.032	0.048**			
	(0.68)	(2.55)			
Initial Gini	-0.009	-0.013**			
	(-0.65)	(-2.48)			
N. Obs	55	55			
			Starting 1990		
Constant	0.147***	0.097***	0.090***		
	(4.34)	(3.49)	(4.83)		
Initial Gini	-0.039***	-0.025***	-0.024***		
	(-4.02)	(-3.23)	(-4.54)		
N. Obs	55	55	55		
			Starting 1985		
Constant	0.030	0.125***	0.086***	0.088***	
	(0.72)	(4.43)	(3.87)	(5.42)	
Initial Gini	-0.007	-0.032***	-0.022***	-0.023***	
	(-0.62)	(-3.99)	(-3.49)	(-5.01)	
N. Obs	55	55	55	55	
			Starting 1980		
Constant	0.050**	0.097***	0.112***	0.088***	0.087***
	(2.32)	(3.42)	(5.75)	(5.11)	(6.84)
Initial Gini	-0.014**	-0.027***	-0.030***	-0.023***	-0.023***
	(-2.24)	(-3.33)	(-5.40)	(-4.81)	(-6.49)
N. Obs	55	55	55	55	55

Heteroskedasticity-consistent t-statistics in parentheses. *Significant at 10%, **5%, ***1%