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Convergence in income distributions: Evidence from a panel of countries☆

Dustin Chambers [a], Shatakshee Dhongde [b,*]

[a] Department of Economics and Finance, Salisbury University, United States
[b] School of Economics, Georgia Institute of Technology, United States

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ABSTRACT

There is growing evidence that countries' income distributions have changed significantly since globalization accelerated in the early 1990s. Using a large panel of Gini indices covering 81 countries between 1990 and 2010, we find strong evidence that inequality declined in nations that were initially highly unequal, while inequality increased in nations with initially low inequality. This pattern holds for both developed and developing countries, but developed countries' relative income distributions have converged at a more rapid pace. These findings are robust to the method of estimation, level of economic development, time horizon, data source or measure of inequality. Our results suggest that income distributions in countries are becoming increasingly unequal yet more similar to each other. Consequently, countries are beginning to coordinate their strategies to jointly reduce inequality through initiatives such as the United Nations' Sustainable Development Goals.
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1. Introduction

Rising income inequality consistently ranks as one of the most important political issues around the globe. The World Economic Forum's 2015 report stated that there is no bigger policy challenge preoccupying leaders around the world than reducing rising inequality and making growth more inclusive.[1] The Pew Research Center reported that 60% of respondents worldwide described the gap between the rich and the poor as a major challenge.[2] In 2015, the G20 listed income inequality as a threat to global security, and urged member nations to raise tax rates and coordinate tax collection efforts.[3] President Obama has called widening income inequality the "defining challenge" and Pope Francis has spoken out against the "economy of exclusion."[4] Persistently high inequality can lead to political turmoil and instability. High inequality levels not only undermine the effectiveness of economic growth but impact a range of social outcomes, such as trust, crime, social mobility, health and educational achievement (Wilkinson and Pickett, 2007).

The rise in inequality within countries in the last few decades has often been linked to policies broadly referred to as globalization. For instance, a UNDP (2013) report on inequality stated that globalization, and to a certain extent skills-based technical change, were important exogenous drivers of inequality (also see IMF, 2007). Galbraith (2010) argued that in a world of globalized financial and commodity markets, the upward movement of inequality within-countries exhibited a strong common pattern across countries. Dreher and Gaston (2008) found evidence that globalization, on average, increased income inequality in OECD countries from 1970 through 2000. Inequality increased within developed countries since the 1990s, according to Morelli et al. (2015). With globalization, these countries faced similar economic conditions: rising imports from emerging markets, slowing

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* Corresponding author at: 221 Bobby Dodd Way, Atlanta, GA 30332, United States.
E-mail address: Shatakshee.Dhongde@econ.gatech.edu (S. Dhongde).
1 See: https://www.weforum.org/reports?page=4.
2 See: http://www.pewresearch.org/fact-tank/2015/01/21/inequality-is-at-top-of-the-agenda-as-global-elites-gather-in-davos/.
3 See: http://www.consilium.europa.eu/en/meetings/international-summit/2015/11/G20-Antalya-Leaders-Summit-Communique-_pdf/.
4 See: http://www.cbsnews.com/news/obama-income-inequality-the-defining-challenge-of-our-time/ and https://berkleycenter.georgetown.edu/quotes/pope-francis-on-rejecting-an-economy-of-exclusion.

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economic growth, and outsourcing of service jobs. Jayadev (2007) demonstrated that under globalization, openness of capital account invariably led to a decline in labor's share in the national income. Bergh and Nilsson (2010) observed that inequality increased most sharply in high income countries in response to greater freedom to trade internationally. Reddy (2005) argued that in middle income countries, where wage determination involved rent sharing, increased competition due to international trade led to a lowering of bargained wages and an overall rise in inequality. [5] Whereas inequality within-countries increased, simultaneously there was also a decline in between-country inequality (Moatsos et al., 2014). Income shares of different segments of society became more similar across countries. Chambers and Dhongde (2016) showed that the decile income shares exhibited a statistically significant decline in dispersion between countries. Alvaredo and Gasparini (2015) found that the standard deviation of the Gini coefficients between countries decreased substantially over time. It is likely that policies, broadly referred to as globalization, shaped the income distributions within countries in a similar fashion. Are income distributions within countries converging? In this paper we seek an answer to this question.

We compile data on as many as 81 countries over a period of two decades (1990 to 2010) and test for convergence in income distributions. We focus on the conventional notion of beta convergence, which predicts that countries with low inequality will experience a rise in inequality levels whereas more unequal countries will witness a decline in inequality. In the last few decades, traditionally more equal nations such as India and China experienced a surge in their inequality levels. After the fall of communism, inequality levels also increased in low inequality countries in Eastern Europe and Central Asia. On the other hand, inequality decreased in highly unequal nations. Latin American countries (with initially higher than median inequality levels) registered a significant decline in inequality in the early 2000s, in part because several of these countries adopted pro-equality policies such as increases in minimum wages and cash transfers targeted at lower income households (UNDP, 2013). Thus, anecdotal evidence supports the notion of convergence in relative income distributions.

Convergence of income distributions is also implied by the Kuznet's hypothesis (Kuznets, 1955) because 1) developing nations, with low initial inequality, will experience a rise in inequality, 2) developed nations near the threshold will have high initial inequality but will subsequently experience a prolonged decline in inequality, and 3) inequality is predicted to decline in all nations in the long-run. Empirical evidence on Kuznet's Curve is ambiguous. In recent years, Huang et al. (2007) showed that an inverted-U shaped relationship between inequality and per capita GDP prevails in countries with mild inequality, but not in countries with very high or very low inequality. Barro (2008) and Agnello et al. (2012), on the other hand, found strong evidence in favor of the Kuznet's hypothesis. Galbraith (2010) and Bhattacharya (2011) observed that there is a tendency for the Gini coefficient to rise and then decline; however inequality may rise again. Since the Kuznet's hypothesis is implicitly consistent with convergence in income distributions, testing such convergence will shed more light on the veracity on Kuznet's theory.

Furthermore, convergence in income distributions is implied in other ways in the literature. Per capita income is only the first moment of a country's income distribution. Once augmented with idiosyncratic shocks, most versions of the neoclassical growth model imply convergence in distribution: countries with the same fundamentals should tend towards the same invariant distribution of wealth and pretax income (Benabou, 1996). Tselios (2009) argued that when capital flows from high-income (low-inequality) countries where it is abundant to low-income (high inequality) countries where it is scarce, spatial disparities decline and both income per capita and inequality converge. Similarly, when individuals migrate for better jobs, they move to high-wage regions with low inequality, resulting in convergence in income distribution. Gallup (2012) predicted convergence in distributions through a different channel. As income levels increase democratic participation also increases. Greater political activism by low income groups will likely change the income distribution through government tax rates and transfers, increased public funding for education and health, and so on. Such redistributive policies increase the rate of convergence in highly unequal nations.

Compared to the extensive literature on convergence in per capita incomes across countries, empirical literature on convergence in income distribution is relatively sparse. Until recently, most evidence of inequality convergence was based on country-specific case studies, not cross-country investigations. In a series of papers, Lin and Huang (2011, 2012a, 2012b), found that income inequality across U.S. states has converged over time. Within-country convergence in income inequality has been reported by Goerlich and Mas (2004) for Spanish provinces, Marina (2000) in Argentine provinces, and Gomes (2007) in Brazilian municipalities. Benabou (1996) was the first to undertake a cross-country analysis of inequality convergence using data for about 30 countries. Overall, his findings are ambiguous, with evidence of convergence between 1970 and 1980, and separately between 1980 and 1990, but no evidence of convergence over the combined time period of 1970 to 1990. Ravallion (2003) found a negative correlation between the initial Gini index and the subsequent change in the Gini index among developing countries in the 1990s, though the effect was less statistically significant when one allowed for measurement error. Bleaney and Nishiyama (2003) showed that income distribution among OECD countries converged significantly faster compared to developing countries. Both Ezcurra and Pascual (2005) and Tselios (2009) found convergence in income inequality among European Union countries. More recently, Alvaredo and Gasparini (2015) found evidence supporting convergence in the Gini coefficients among developing countries between 1981 and 2010.

We contribute to this nascent but slowly emerging literature in the following ways. The biggest obstacle to testing cross-country inequality convergence has been the lack of reliable data. Our first contribution is to compile a notably larger panel of Gini indices compared to the previous literature. Our panel covers Gini indices in 81 countries over two decades (1990 and 2010). Cross-country data on inequality indices is often less compatible, and of poor quality. Typically, a researcher faces a tradeoff between the extensive coverage of a dataset versus the reliability of its estimated inequality measures. In an attempt to strike a balance, we choose two datasets, both published by the World Bank. We use the All the Ginis dataset to compile highly consistent values on the Gini indices for developed countries and use the Povcal dataset which is more extensive but less consistent for Gini indices in developing countries. We find that the relative income distributions of developed countries converged at a faster speed compared to developing countries. The result is consistently observed in the literature and can be attributed to the fact that developed countries are more homogeneous, possessing more similar institutions, and capital and labor endowments, compared to developing countries which experienced uneven economic development.

Our second contribution is that we test convergence in relative income distribution by using cross-section as well as panel data models. We use the Ordinary Least Squares (OLS) estimator in a cross-section setting and the Generalized Method of Moments (GMM) estimator for a dynamic panel model with country effects. However, in small-sized samples such as ours, the GMM estimates, though consistent, are often inefficient. Hence we also use a novel OLS estimator (Bao and Dhongde, 2009) which makes use of a greater number of observations

[5] Note that there is some ambiguity regarding the impact of certain policies, implemented during globalization, on income distributions; the impact may differ depending on countries/years included in the analysis. For instance, Asteriou et al. (2014) found that financial globalization has been the driving force of inequality in the EU-27 nations. On the other hand, Ang (2010), and Agnello et al. (2012) demonstrated that financial reforms such as the elimination of subsidized directed credit, the reduction of excessively high reserve requirements, and improvements in securities market policies, helped promote a more equal distribution of income within countries.

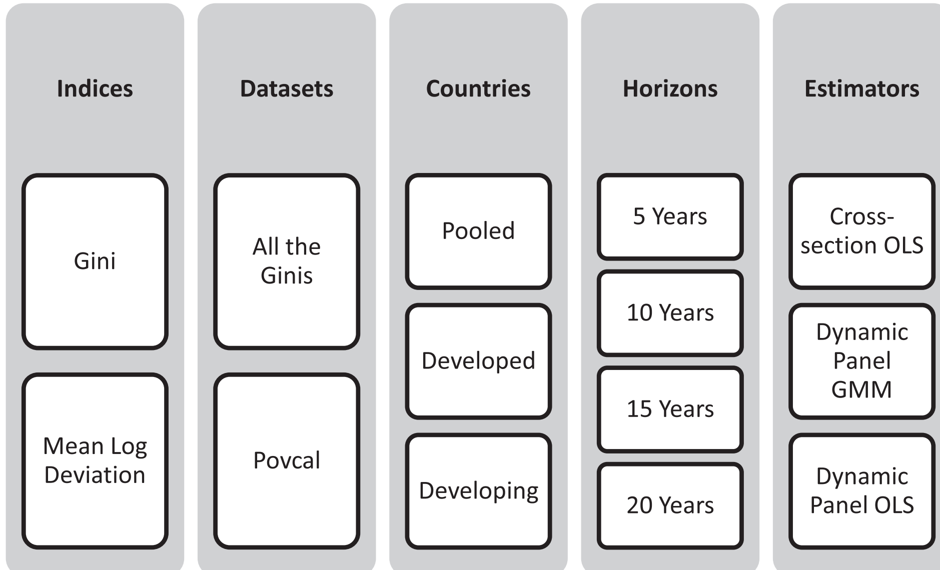

Fig. 1. Evidence on convergence in inequality is robust across different dimensions.

over time and provides more reliable inference when cross-section sample size is small. Finally, we test the robustness of our analysis by using 1) multiple measures of inequality (both the mean log deviation of income and the Gini index), 2) multiple country groups (developed and developing nations) and 3) multiple time horizons (5, 10, 15, and 20 years). Fig. 1 summarizes the multiple dimensions along which we test the robustness of our results. Overall, we find strong evidence supporting convergence in inequality across countries – inequality tends to decline in highly unequal countries and increase in those with low inequality, irrespective of the measure of inequality employed, time horizon considered, or nations' level of economic development.

The remainder of the paper is structured as follows: Section 2 describes the data, Section 3 describes the empirical models and resulting estimates, Section 4 consists of robustness tests, and Section 5 concludes.

2. Data

The Gini index measures the extent to which an income distribution deviates from a perfectly equal distribution. A Gini index equal to 0 implies perfect equality (all individuals have equal income) and a value equal to 100% implies extreme inequality (one individual possesses all the income). Our analysis uses the Gini index because 1) it has been most often used by previous studies testing convergence, 2) it relates more directly to the models which predict inequality convergence, and most importantly, 3) it is the *only* inequality measure on which data for multiple countries and years are available in most datasets. In addition to the Gini index, we also use another inequality measure, namely the mean log deviation of income, to test the robustness of our results in Section 4.

Data on Gini indices in developed nations is compiled from All the Ginis (ATG) database.[6] The ATG is a large collection of Gini values compiled from multiple sources such as the Luxembourg Income Study, World Income Distribution, and PovcalNet. An important feature of the dataset is that it provides quality filters allowing the choice of Gini indices based on consistent notions of income. We use this feature to select *only* those countries in which the Gini index for each year is measured using household net per capita income. Consequently, the data on the 23 developed countries listed in Table 1, albeit small, are highly consistent and of good quality.[7] For developing nations, the Gini indices compiled from the World Bank's Povcal dataset are more extensive but less consistent. Gini indices in Povcal are based on data from more than 850 household surveys representing almost 90% of the developing world's population. The values are less consistent because Gini indices in most Latin American countries are based on household income surveys, whereas in most Asian and African countries

Table 1
Country list with Gini data: 1990 to 2010 notes.

23 developed countries	58 developing countries		
Austria	Albania[a]	Indonesia	Senegal
Belgium	Argentina[b]	Jordan	South Africa
Czech Republic	Armenia[a]	Kyrgyz Republic[b]	Sri Lanka
Denmark	Azerbaijan[a]	Lao	Tanzania
Estonia[b]	Bangladesh	Lesotho	Thailand
Finland[b]	Bolivia	Madagascar	Tunisia
France	Brazil[b]	Malawi[a]	Turkey
Germany[b]	Bulgaria[b]	Malaysia	Uganda
Hungary[b]	Burkina Faso[a]	Mali[a]	Ukraine[ab]
Israel	China[b]	Mauritania	Venezuela[b]
Italy	Colombia[b]	Mexico	Vietnam
Latvia[b]	Costa Rica[b]	Moldova	Zambia
Luxembourg	Cote d'Ivoire	Mongolia[a]	
Netherlands	Dominican Republic	Morocco	
Norway	Ecuador	Mozambique[a]	
Poland[b]	Egypt	Nicaragua	
Russia[b]	El Salvador[b]	Niger	
Slovak Republic[b]	Ethiopia[a]	Nigeria	
Slovenia[b]	Georgia[a]	Pakistan	
Spain	Guatemala	Panama	
Sweden	Guinea	Paraguay	
Taiwan, China	Honduras[b]	Peru[b]	
United Kingdom[b]	India	Philippines	

[a] Denotes countries with data beginning in 1995.
[b] Countries included in the OLS estimation of the dynamic panel model.

[6] Developed nations are high income countries with a GNI per capita of $12,746 or more, while developing nations are middle and low income countries with a GNI per capita of $12,745 or less, based on 2014 World Bank country classification. See Smeeding and Latner (2015) for an excellent review of existing data sets on inequality measures.

[7] Even after choosing household net per capita income as the basis to measure the Gini index, the Gini values may be still incompatible. First, even if the observable characteristics are coded the same, there could still be some differences, for example, in the way benefits from owner-occupied housing or home-consumption are imputed. Second, the Ginis may be calculated from micro or grouped data; they may be calculated using slightly different formulas or using geometrical approximations to the Lorenz curve.

they are based on household consumption surveys. However, this poses less of a problem in our analysis, since we model the change in a country's inequality as a function of its initial inequality level. Therefore, we ensure that all Gini indices in a country belong to the *same survey type* (income or consumption) and remove countries such as Belarus, Hungary, and Romania, which report Gini indices constructed from income surveys in some years and consumption surveys in others. [8]

We have a nearly balanced panel of Gini indices from 81 countries (23 developed and 58 developing nations; see Table 1 for a list) spanning 5-year periods beginning in 1990 (t = 1) and ending in 2010 (t = 5). In the first time period (1990), our panel is missing observations for 11 developing nations, which are identified in Table 1. The panel is balanced in all the remaining time periods (i.e. 2 through 5). The countries on which data is compiled represent 46% of the population in developed nations and 84% of the population in developing nations.

Table 2 contains Gini summary statistics across countries. As expected, inequality is higher in developing countries compared to developed countries. The average Gini index in developing countries is 43, compared to 30 in developed countries. Trends in average Gini values are illustrated in Fig. 2. In developed countries, the Gini index increased from 27 to 31 between 1990 and 2010; it was roughly constant at 43 in developing countries. It is apparent from the standard deviations of the Gini index, that inequality varied significantly among developing nations and less so among developed nations, which reflects in part the consistent income concept used to measure the Gini indices in developed nations. Interestingly, in both country groups, the standard deviation decreased over time, suggesting convergence in inequality.

3. Convergence tests

Beta convergence is evident when nations with high initial inequality experience smaller increases (or larger declines) in inequality, while those nations with low initial inequality experience a greater increase (or smaller decrease) in inequality. Fig. 3 is a scatter plot of initial inequality (Gini index in 1995) against the percent change in inequality between 1995 and 2010. There is clearly a negative correlation ($\rho = -0.53$) between initial inequality and subsequent changes in inequality. Consistent with convergence, the rise in inequality is greater in countries with low initial inequality (e.g. Bulgaria and Slovakia) and smaller in countries with relatively high initial inequality (e.g. South Africa and Venezuela). Conversely, in countries where inequality decreased, the decline is smaller in countries with low initial inequality (e.g. Bangladesh) and greater in countries with high initial inequality (e.g. Bolivia and Russia). Of course there are some exceptions such as Norway (small rise in inequality and low initial inequality), and Columbia (small decline in inequality and high initial inequality), but overall, the scatter in Fig. 3 suggests beta convergence across countries. Below, we formally test for convergence by using cross-section and panel data models.

3.1. Cross-section OLS regression

Let $Gini_{iT}$ denote the Gini index of country i ($i = 1, 2, \ldots, N$) at time T. Eq. (1) models the subsequent average annual growth rate of the Gini index as a function of the Gini index in the initial year. The convergence parameter is denoted by β, and u_i is a mean zero error term. Ordinary Least Squares (OLS) estimates of Eq. (1) are used to test for beta convergence over varying time horizons ($\tau = 5, 10, \ldots, 25$), in order to reduce the impact of possible measurement errors in any particular initial or final year. For example, when the initial Gini index ($Gini_{i,T-\tau}$) is set equal to the value from 1990, we estimate convergence over $\tau =$ 5 years (1990–1995), 10 years (1990–2000), 15 years (1990–2005) and 20 years (1990–2010).

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

We find that the convergence parameter β in Eq. (1) is negative *for all country groups and time horizons*, confirming both short and long-run beta convergence in inequality levels.

Table 3A shows the regression estimates for all 81 countries (i.e. the pooled sample of developed and developing nations). Regardless of the initial year or the length of the time horizon, the convergence parameter (β) is negative and statistically significant. Moreover, for a given initial year, the absolute value of β declines as the time horizon lengthens. In other words, the speed of convergence is greatest in the short-run, and steadily slows with the passage of time. The long-run coefficient estimates of β (i.e. the 20-year horizon model with initial inequality anchored in 1990) are consistent with a steady state Gini index of 38; the predicted value is almost exactly equal to the average Gini value in 2010 (38.4).[9] As we state in the Introduction section, the neoclassical growth models imply convergence in distribution of income. Our finding of convergence in inequality is supported by evidence of convergence in per capita income. Li et al. (2016) find that there was unconditional

Table 2
Summary statistics of Gini indices.

	1990	1995	2000	2005	2010
All countries					
Min.	17.8	20.0	23.7	16.6	24.8
Max.	60.5	63.2	63.0	67.4	65.0
Mean	38.1	39.3	40.0	39.3	38.4
St. dev.	11.7	10.4	9.7	9.4	8.8
Developed countries					
Min.	17.8	20.0	23.7	24.8	25.3
Max.	47.2	45.2	42.0	41.7	42.8
Mean	27.2	29.8	31.3	31.9	30.8
St. dev.	6.9	6.0	4.7	4.7	4.6
Developing countries					
Min.	23.4	24.3	29.0	16.6	24.8
Max.	60.5	63.2	63.0	67.4	65.0
Mean	43.4	43.1	43.4	42.3	41.4
St. dev.	9.8	9.3	9.0	9.2	8.3

Notes: 1) Values of Gini indices are given as percentages.

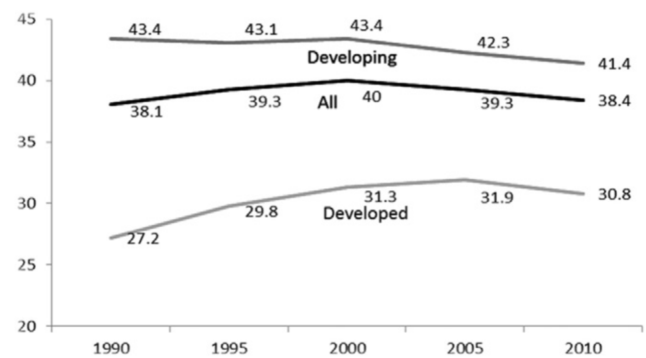

Fig. 2. Trends in average inequality as measured by the Gini index. Shows average Gini indices shown in Table 2.

[8] We make no adjustments to the reported values in either dataset. If a value is not available for a benchmark year, we choose a value available within two years of the benchmark year. At the time of writing, the latest version of All the Ginis (2014) is used and is available at: http://go.worldbank.org/9VCQW66LA0.
Likewise, the latest version of PovcalNet was downloaded (January 2015) and is available at: http://iresearch.worldbank.org/PovcalNet/.

[9] Using Eq. (1), the steady state Gini index equals $e^{-\frac{\alpha}{\beta}}$.

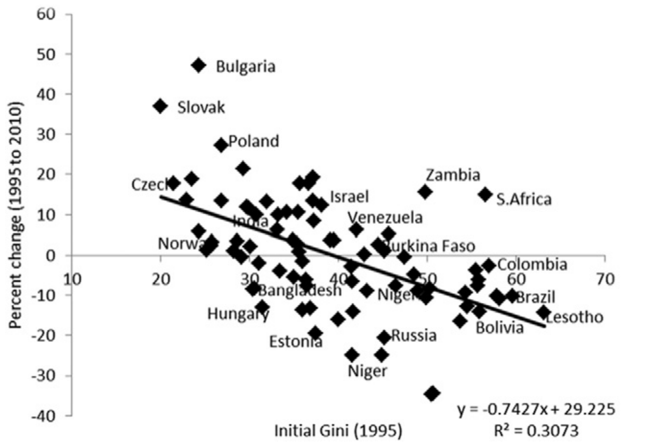

Fig. 3. Percent change in inequality vs. initial inequality levels. Scatter plot shows Gini indices from our combined sample of 81 countries. Although 1990 is the initial time period, 1995 is the earliest time period containing observations for all 81 countries. We have labeled some data points for the sake of illustration.

convergence in real per capita GDP among 120 world economies between 1980 and 2010.

Table 3B reports the regression estimates for developed countries. The estimated β values are negative and statistically significant at all time horizons when initial inequality is anchored in 1995 or earlier. Recall that the Gini index among all developed nations is measured using household net per capita income. Consequently, our estimates predict that inequality as measured by the Gini index in post-tax/transfer disposable incomes among the 23 developed countries will converge to a steady state level of 31.9. In 2010, the latest year in our data, average Gini index based on household net per capita income was equal to 30.8. Furthermore, convergence in income inequality is consistent with similar evidence in other studies on developed nations. Especially in EU nations, Van Kerm and Alperin (2013) find evidence on convergence in mean incomes and Beyer and Stemmer (2016) find convergence in unemployment rates.

Table 3C summarizes the results for developing countries. Again, all but one of the estimated β values are statistically significant, and all are negative and range in value from −0.018 to −0.062, which is consistent with the literature.[10] The implied long-run steady state Gini index is 44.7, which is slightly greater than the average value of 41.4 in 2010. As in the pooled sample, the speed of convergence in developed as well as developing nations is most rapid in the short-run, declining with longer time horizons. Lin and Huang (2011) also find this difference in the speed of convergence in their sample of developing countries.

Table 3A
OLS estimator using cross-section data in all countries.

	5 years	10 years	15 years	20 years
Initial Gini 2005				
Constant	0.138*			
	(0.078)			
Initial Gini	−0.039*			
	(0.021)			
R-sq.	0.15			
N. obs.	81			
Initial Gini 2000				
Constant	0.076***	0.055***		
	(0.027)	(0.016)		
Initial Gini	−0.022***	−0.016***		
	(0.007)	(0.004)		
R-sq.	0.05	0.12		
N. obs.	81	81		
Initial Gini 1995				
Constant	0.136***	0.092***	0.074***	
	(0.030)	(0.016)	(0.012)	
Initial Gini	−0.036***	−0.025***	−0.021***	
	(0.008)	(0.004)	(0.003)	
R-sq.	0.21	0.20	0.30	
N. obs.	81	81	81	
Initial Gini 1990				
Constant	0.214***	0.149***	0.111***	0.080***
	(0.055)	(0.022)	(0.014)	(0.010)
Initial Gini	−0.057***	−0.039***	−0.029***	−0.022***
	(0.015)	(0.006)	(0.004)	(0.003)
R-sq.	0.26	0.42	0.49	0.51
N. obs.	70	70	70	70
Average β	−0.039	−0.027	−0.025	−0.022

Notes:
1) White's Heteroskedasticity-consistent standard errors are given in parentheses.
2) Two-sided significance levels at: *10%, **5%, and ***1%.

Table 3B
OLS estimator using cross-section data in developed countries.

	5 years	10 years	15 years	20 years
Initial Gini 2005				
Constant	0.071			
	(0.061)			
Initial Gini	−0.022			
	(0.018)			
R-sq.	0.06			
N. obs.	23			
Initial Gini 2000				
Constant	0.059	0.063		
	(0.044)	(0.040)		
Initial Gini	−0.016	−0.019		
	(0.013)	(0.012)		
R-sq.	0.06	0.12		
N. obs.	23	23		
Initial Gini 1995				
Constant	0.255***	0.147***	0.109***	
	(0.053)	(0.028)	(0.023)	
Initial Gini	−0.072***	−0.041***	−0.032***	
	(0.015)	(0.008)	(0.007)	
R-sq.	0.47	0.49	0.48	
N. obs.	23	23	23	
Initial Gini 1990				
Constant	0.495***	0.322***	0.205***	0.142***
	(0.130)	(0.049)	(0.031)	(0.024)
Initial Gini	−0.145***	−0.093***	−0.059***	−0.041***
	(0.038)	(0.015)	(0.009)	(0.007)
R-sq.	0.46	0.70	0.69	0.68
N. obs.	23	23	23	23
Average β	−0.064	−0.051	−0.046	−0.041

Notes:
1) White's Heteroskedasticity-consistent standard errors are given in parentheses.
2) Two-sided significance levels at: *10%, **5%, and ***1%.

3.2. Panel regression model

The cross-sectional model in Eq. (1) assumes that countries within a sample converge to the same steady state level of inequality in the long run. However countries that are not structurally similar will likely converge to different steady states. Therefore, we estimate the following dynamic panel model with fixed effects:

$$\frac{1}{\tau}\ln\left(\frac{Gini_{i,t}}{Gini_{i,t-\tau}}\right)=\beta\ln\left(Gini_{i,t-\tau}\right)+\eta_i+\xi_t+u_{i,t}. \quad (2)$$

In Eq. (2), nations are indexed by i ($i = 1,\ldots,N$), time periods by t ($t = 1995, 2000, 2005$, and 2010) and the time horizon is fixed at five years ($\tau = 5$). Let η_i denote the unobserved country specific effects, including differences in preferences and technology between countries, ξ_t

[10] See Table 1 in Dhongde and Miao (2013) for a concise summary of estimated beta convergence values in developing countries.

Table 3C
OLS estimator using cross-section data in developing countries.

	5 years	10 years	15 years	20 years
Initial Gini 2005				
Constant	0.227**			
	(0.106)			
Initial Gini	−0.062**			
	(0.028)			
R-sq.	0.26			
N. obs.	58			
Initial Gini 2000				
Constant	0.062	0.071***		
	(0.058)	(0.027)		
Initial Gini	−0.018	−0.020		
	(0.015)	(0.007)***		
R-sq.	0.02	0.13		
N. obs.	58	58		
Initial Gini 1995				
Constant	0.121**	0.067**	0.080***	
	(0.049)	(0.029)	(0.020)	
Initial Gini	−0.032**	−0.019**	−0.022***	
	(0.013)	(0.008)	(0.005)	
R-sq.	0.11	0.07	0.22	
N. obs.	58	58	58	
Initial Gini 1990				
Constant	0.147***	0.115***	0.095***	0.076***
	(0.052)	(0.024)	(0.017)	(0.014)
Initial Gini	−0.039***	−0.030***	−0.025***	−0.020***
	(0.014)	(0.006)	(0.005)	(0.004)
R-sq.	0.13	0.27	0.34	0.39
N. obs.	47	47	47	47
Average β	−0.038	−0.023	−0.024	−0.020

Notes:
1) White's Heteroskedasticity-consistent standard errors are given in parentheses.
2) Two-sided significance levels at: *10%, **5%, and ***1%.

denote time specific effects, and $u_{i,t}$ is a mean zero error term that is serially uncorrelated across countries. Rearranging the terms in Eq. (2) we obtain:

$$g_{it} = \alpha g_{it-\tau} + \eta_i + \xi_t + u_{it}. \tag{3}$$

In Eq. (3), g_{it} denotes $\ln(Gini_{it})$, $\alpha = \beta\tau + 1$, $\eta_i = \tau\eta_i$ and $\xi_t = \tau\xi_t$.

3.3. Dynamic panel GMM regression

Eq. (3) is a dynamic panel model with a lagged dependent variable, therefore the least squares fixed-effect dummy variable and within-group estimators are not consistent (Nickell, 1981). We undertake the following τ-order (5-year) difference transformation of Eq. (3):

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

where $\Delta g_{it} = g_{it} - g_{it-\tau}$, $\Delta\xi_t = \xi_t - \xi_{t-\tau}$, and $\Delta u_{it} = u_{it} - u_{it-\tau}$. In Eq. (4) the OLS estimate of α is biased since the lagged dependent variable (Δg_{it}) is correlated with the differenced error term (Δu_{it}). Following Caselli et al. (1996), we use the GMM estimator of Arellano and Bond (1991) which assumes that there is no τ-order serial correlation, i.e. $E(u_{it}, u_{it-\tau}) = 0$. If that assumption holds, then all the lagged values of the Gini index $g_{i0}, g_{i\tau}, \ldots g_{it-2\tau}$ are uncorrelated with Δu_{it}, and are valid instruments. Following Arellano and Bond (1991), we test the assumption of no τ-order serial correlation by way of a Sargan (1958) test of over-identifying restrictions, which tests the validity of the instruments. The Sargan test fails to reject the null hypothesis of valid instruments, thereby confirming the validity of the instruments and the use of the GMM estimator.[11]

[11] When time period effects are omitted from Eq. (4), the Sargan Test rejects the validity of the instruments.

Table 4
Gini panel: Alternative estimators.

	GMM2	3SLS
All countries		
α	0.500***	0.467***
	(0.118)	(0.110)
Implied β	−0.100***	−0.107***
	(0.024)	(0.022)
Countries	81	81
N. obs.	232	232
Instruments	6	6
Sargan test	1.92	3.02
p-Value	0.86	0.70
Developed countries		
α	0.219***	0.193*
	(0.057)	(0.103)
Implied β	−0.156***	−0.161***
	(0.011)	(0.021)
Countries	23	23
N. obs.	69	69
Instruments	6	6
Sargan test	8.02	6.85
p-Value	0.16	0.23
Developing countries		
α	0.527***	0.508**
	(0.152)	(0.156)
Implied β	−0.095***	−0.098***
	(0.030)	(0.031)
Countries	58	58
N. obs.	163	163
Instruments	6	6
Sargan test	2.86	3.44
p-Value	0.72	0.63

Notes:
1) Standard errors are given in parentheses below alpha point estimates. White's Period Heteroskedasticity-consistent standard errors are reported for GMM2 estimates. Period SUR weight (PCSE) standard errors are reported for 3SLS estimates.
2) Asymptotic standard errors for implied beta calculated via the delta method.
3) Two-sided significance levels at: *10%, **5%, and ***1%.
4) The p-values are given below the Sargan test statistic under the null hypothesis that the over-identifying restrictions of the instruments are valid.

We estimate Eq. (4) using the two-step (GMM2) estimation method of Arellano and Bond (1991).[12] Estimates for the dynamic panel model are summarized in Table 4, where we report both the coefficient of initial inequality (α) and the implied β values, based on the relation $\alpha = \beta\tau + 1$.[13] The implied β values are all negative and significant at the 5% level. Compared to the cross-section OLS model, there is stronger support for the convergence hypothesis in the dynamic GMM model. In all three samples (pooled, developed, and developing), we find that the absolute value of the implied beta coefficient from the dynamic model is approximately 2.6 times larger than that of the OLS estimate based on the same sample.[14] Although Caselli et al. (1996) test for convergence in mean per capita income and not income inequality, they too find that the implied speed of convergence in income is higher in a dynamic panel model (10%) compared to a cross section OLS model (2%). These consistently larger β estimates in the dynamic model suggest that

[12] GMM1 makes further assumptions on the weighting matrix while GMM2 uses GMM1 residuals to build a weighting matrix.

[13] Following standard practice, we do not difference-transform the time period effects when estimating Eq. (4). For developing countries, we also estimate Eq. (4) with a dummy variable for the underlying survey type (i.e. income or consumption) and find the variable to be statistically insignificant.

[14] For dynamic models, the average of the implied beta coefficient estimates from the GMM1 and GMM2 models equals −0.1035 (pooled sample), −0.1635 (developed countries), and −0.097 (developing countries). Taking the ratio of these values to the average 5-year time horizon beta estimates from Tables 3A to 3C yields: 2.72 (pooled sample: −0.1035/−0.038), 2.55 (developed countries: −0.1635/−0.064), and 2.55 (developing countries: −0.097/−0.038). The average of these three ratios is 2.61.

omission of the individual effects in the cross-section model induces a downward bias in the estimate of the corresponding convergence coefficient.

Furthermore, we find that developed countries converged at a faster speed compared to developing countries. [15] Specifically, the average rate of convergence in developed countries is 34% compared to 13% in developing nations.[16] This finding is consistent with the evidence found in the literature. Benabou (1996) finds that evidence of convergence is stronger in terms of both magnitude and stability in a smaller subsample of OECD countries compared to evidence on all countries combined. Bleaney and Nishiyama (2003) also find that the speed of convergence is faster among OECD countries compared to developing countries. The different rates of convergence between these two country groups provide evidence contrary to the "iron law of convergence" and more consistent with the conditional convergence hypothesis, which predicts that the steady state is determined by structural variables such as population growth, rate of investment, and human capital.

3.4. Cross section dependence

In this section, we test for cross section dependence in the panel errors. Global and regional crises, natural disasters, changes in globally traded commodities, and overall economic and financial integration may result in correlated shocks to nations' relative income distributions, which violates the assumption that $Cov(u_{it}, u_{jt}) = 0$ for all t and $i \neq j$. Untreated cross section dependence can result in misleading hypothesis test results, as the statistical significance of coefficient estimates is based on incorrect standard errors. Furthermore, estimators that ignore this covariance structure in the residuals are less efficient. To test for cross section dependence in our panel of Gini indexes, we employ the popular CD test of Pesaran (2004), which under the null hypothesis of no cross section dependence equals[17]:

$$CD = \sqrt{\frac{2\mathrm{T}}{\mathrm{N}(\mathrm{N}-1)}}\left(\sum_{i=1}^{\mathrm{N}}\sum_{j=i+1}^{\mathrm{N}-1}\hat{\rho}_{ij}\right) \rightarrow^{d} \mathrm{N}(0,1) \; as \; \mathrm{N}\rightarrow\infty \tag{5}$$

where $\hat{\rho}_{ij}$ is the correlation coefficient between the residuals of nations i and j. As demonstrated in Pesaran et al. (2008), the CD test is highly robust to a wide range of error distributions and underlying data generating processes, and performs very well in the context of dynamic panels. Constructing the largest balanced panel from our dataset (i.e. N = 70), we estimate Eq. (3), less the time period effect (ξ_t), for each nation (i) separately. This yields four residuals per OLS regression (T = 4). The resulting CD test statistic equals 10.60, which is statistically significant at any standard level of significance. We therefore conclude that our panel is cross sectionally dependent.

In panels with many time series observations relative to the number of cross-sectional units (i.e. T > N), generalized least squares (GLS) estimation via Zellner's (1962) cross-sectional seemingly unrelated regression equation (SURE) technique is ideal.[18] Unfortunately, in panels with large N and small T, like ours, FGLS estimation is not feasible (see Chudik and Pesaran, 2013). When estimating Kuznet's Curve models in a panel of Gini indices, Barro (2000) employs an alternative approach, correcting for common variations in nations' error variance (i.e. period heteroskedasticity) and serial correlation by using an estimate of the period covariance-weighting matrix via GLS estimation:

$$\Omega_T = E(e_i e_i\prime | X_i) = \begin{pmatrix} \sigma_{11} & \cdots & \sigma_{1T} \\ \vdots & \ddots & \vdots \\ \sigma_{T1} & \cdots & \sigma_{TT} \end{pmatrix} \tag{6}$$

where e_i is the T × 1 column vector of errors for nation i, and X_i is a stacked matrix containing all nation i explanatory variables. This form of error dependence assumes that common shocks impact the volatility of the Gini index across all nations in a similar way. The obvious drawback to this assumption is that it does not capture/model income distribution shocks that impact a subset of nations.

Following Barro (2000), we utilize the GLS period weighting matrix in Eq. (6) but instead employ Three Stage Least Squares (3SLS) in order to conduct instrumental variable estimation of Eq. (4).[19] Overall, the results (provided in the second column of Table 4) are very similar to the GMM2 results in the first column and are consistent with our earlier findings.[20]

To summarize, we find that there is strong evidence of convergence in relative income distributions across countries and among developed and developing countries. The cross-country model is used to test convergence over varying time horizons in order to reduce the impact of possible measurement errors in any particular initial or final year. The dynamic panel model is used to allow for country specific effects. Compared to the cross-country model, the predicted speed of convergence is much higher in the panel setting. Correcting the estimator to account for period heteroskedasticity does not alter these results.

4. Robustness tests

4.1. Panel regression using OLS estimators

In case of persistent data such as the Gini index and with 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 can be imprecise. In a dynamic panel, the OLS estimator proposed by Bao and Dhongde (2009) provides more reliable inference especially in small cross-section samples, and performs better than the GMM estimator. For this reason, Lin and Huang (2011) employ this estimator to test for inequality convergence in the U.S. Therefore, we test the robustness of our convergence prediction using this alternative estimator.

Recall that in Eq. (3), we eliminated ξ_t, the time-specific constant, by taking deviations from period means for all variables. For the GMM estimator in Eq. (4), we removed the country-specific effect η_i, by taking a τ-order difference transformation of Eq. (3). Instead, we now take the first difference:

$$g_{it} - g_{it-1} = \alpha(g_{it-\tau} - g_{it-\tau-1}) + u_{it} - u_{it-1}. \tag{7}$$

Assuming there is no τ, $(\tau-1)$,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 Eq. (7) $(g_{it-\tau} - g_{it-\tau-1})$ is uncorrelated with the error

[15] The speed of convergence is calculated as $(\rho = \frac{1}{\tau}\ln(1+\beta\tau))$.

[16] For the developed country sample, we average the implied beta estimates (−0.1635) across all GMM models, and this average beta is used to calculate the average rate of convergence (−0.340). For developing countries, we calculate the average beta (−0.097) and average rate of convergence (−0.133) in an analogous way.

[17] The Breusch and Pagan (1980) Lagrange multiplier (LM) test suffers from significant size distortion when T is small relative to N. Like most development panels, we have a large number of nations (N) but a small number of time periods (T), making the CD test the more appropriate.

[18] SURE assumes exogenous regressors. If instrumental variables are also employed, Three Stage Least Squares (3SLS) utilizing the estimated contemporaneous variance covariance matrix ($\hat{\Omega}_{\mathrm{N}} = \hat{E}(u_t u_t\prime)$) is used instead.

[19] We estimate Eq. (4) using the same instruments used by the Arellano and Bond (1991) GMM estimator.

[20] As a final check for cross section dependence, we conduct CD tests on the residuals from Eq. (5) estimated by way of GMM using Eq. (7) alternative weights for all three groups of countries (developed, developing, and the combined sample). In every case, the CD test statistics were statistically insignificant, suggesting that the period heteroskedasticity weighting has suitably addressed the cross section dependence problem.

Table 5
Robustness: Alternative Gini panel estimators.

	Bao and Dhongde (OLS)	Bao and Dhongde (GLS)	GMM2
Initial Gini (α)	−0.089*	−0.092**	0.293***
	(0.053)	(0.014)	(0.073)
Implied (β)	−0.218***	−0.216***	−0.141***
	(0.011)	(0.003)	(0.015)
Countries	22	22	22
N. obs.	330	330	66

Notes:
1) White's Period Heteroskedasticity-consistent standard errors are given in parentheses for the Bao and Dhongde (OLS) and GMM2 estimates. Period SUR weight (PCSE) standard errors are reported for the Bao and Dhongde (GLS) estimates.
2) Asymptotic standard errors for implied beta calculated via the delta method.
3) Two-sided significance levels at: *10%, **5%, and ***1%.
4) Estimates of time period effects not reported for the GMM2 estimator.

term $(u_{it} - u_{it-1})$. Thus the standard OLS estimate $\hat{\alpha} = \frac{\sum_{i=1}^{N}\sum_{t=\tau+1}^{T}(g_{it}-g_{it-1})(g_{it-\tau}-g_{it-\tau-1})}{\sum_{i=1}^{N}\sum_{t=\tau+1}^{T}(g_{it-\tau}-g_{it-\tau-1})^2}$ is consistent, eliminating the need for instrumental variable estimation. The variance of $\hat{\alpha}$ can be estimated by using the period heteroskedasticity consistent variance estimator of White (1980).[21] However, in order to use the OLS method, we need data at a higher frequency than $\tau = 5$ years. We are able to compile annual data (1990 to 2010) on Gini indices on a small subset of 22 countries (denoted in Table 1). The small sample size prevents us from separately estimating the OLS coefficient for developed and developing countries.

Estimation results based on Eq. (7) are reported in Table 5. The estimated α value equals −0.089 and is statistically significant at the 10% level. Therefore, the implied convergence coefficient (β) is equal to −0.217 and is consistent with convergence in inequality. For the sake of comparison, we also estimate GMM2 model on the same subset of 22 countries. The GMM model (Eq. 4) uses 3 period observations per country whereas the OLS model (Eq. (7)) uses 15 period observations per country. Thus the sample size increases substantially from 66 (for GMM2) to 330 (for OLS) observations. The GMM2 model estimates α at 0.293. This is consistent with Bao and Dhongde (2009) who provide Monte Carlo evidence to show that the GMM estimates of α are biased upwards.

As a further robustness check, we also re-estimate Eq. (7) using the Generalized Least Squares (GLS) weighting matrix in Eq. (6) to correct for any period heteroskedasticity in the sample. The GLS estimation results are reported in Table 5, and are remarkably similar to the OLS. Consistent with our earlier findings, correcting for period heterogeneity does not materially affect our estimation results or conclusions.

4.2. Convergence in mean log deviation

Our analysis so far has relied on the Gini index primarily because it is the most widely available measure of income inequality. Cross-country data in the Povcal dataset are available for one other inequality measure, namely the mean log deviation of income (MLD). The mean log deviation gives the standard deviation of log of income. It belongs to the family of generalized entropy measures and unlike the Gini index, it is more sensitive to changes in the lower tail of the distribution. [22] We compile MLD data for the 58 developing countries at 5-year intervals from 1990 to 2010. Between 1990 and 2010, the average MLD declined from 37 to 32 (Table 6). The trend is similar to the declining trend observed in the Gini index. In fact the correlation between MLD and the Gini index was very high ($\rho = 0.9$). We re-estimate the dynamic panel model in Eq. (4) with this alternative measure of income inequality. The estimated value of α is highly significant and very similar in magnitude to the estimate obtained using the Gini index (see Table 7). In fact, the implied β convergence coefficient is −0.08 for MLD and −0.09 for the Gini index. This result confirms that convergence in relative income distributions is a robust empirical phenomenon not dependent on the measure of inequality employed in the analysis.

Table 6
Summary statistics of mean log deviation of income.

	1990	1995	2000	2005	2010
Minimum	9.0	13.8	14.2	4.5	10.0
Maximum	86.2	93.4	135.6	85.2	79.2
Mean	36.8	37.2	37.8	34.6	32.2
Standard deviation	19.7	19.4	22.7	17.5	14.8
Correlation coefficient	0.94	0.89	0.89	0.93	0.96

Notes:
1) Mean log deviation of income data on developing countries.
2) Correlation coefficient of mean with the Gini index.

Table 7
Robustness: Alternative measures of inequality.

	Gini index (GMM2)	Mean log deviation (GMM2)
α	0.527***	0.587***
	(0.152)	(0.198)
Implied β	−0.095***	−0.083**
	(0.030)	(0.038)
Countries	58	58
N. obs.	163	164
Instruments	6	6
Sargan test	2.86	6.85
p-Value	0.72	0.23

Notes:
1) White's Period Heteroskedasticity-consistent standard errors are given in parentheses below alpha point estimates.
2) Asymptotic standard errors for implied beta calculated via the delta method.
3) Two-sided significance levels at: *10%, **5%, and ***1%.
4) The p-values are given below the Sargan test statistic under the null hypothesis that the over-identifying restrictions of the instruments are valid.

5. Conclusion

At the outset, we sought to answer a fundamental question: do relative income distributions within countries tend to converge over time? Our results suggest that they do. Inequality tended to decline in highly unequal countries and increase in those with low inequality. Moreover, inequality converged at a faster speed among developed nations compared to developing nations, which likely reflects greater homogeneity in the economic fundamentals of developed nations. However, the impact of the initial Gini index on subsequent changes in inequality diminished over longer time horizons (i.e. the speed of convergence declines with time). Finally, convergence in inequality is robust to multiple inequality measures, datasets, and estimation methods. We acknowledge that the results are qualified by the availability of data, and the fact that Gini indices between nations are not strictly compatible. However there is no *a priori* reason to believe that the convergence estimates may be biased in any particular direction.

Whether income distributions converge or not is relevant to the accuracy of welfare measurement (Lin and Huang, 2012a, 2012b). Typically, a society's welfare is positively related to the average level of income and negatively related to the inequality in its distribution. However when income distributions vary significantly across countries, then average income is a poor indicator of welfare. Empirical evidence

[21] The validity of the OLS method rests on the key assumption of no τ,($\tau - 1$) and ($\tau + 1$)-order serial correlation. Using sample residuals of the regression, Bao and Dhongde (2009) construct an m-test statistic which is asymptotically normally distributed. The OLS estimator is valid if the m-test statistic is equal to zero. In our sample, the m-value is equal to 1.298 and is statistically insignificant, supporting the validity of the OLS method.

[22] See Kakwani (1980) for properties of the Gini index and the mean log deviation as inequality measures.

on convergence across countries is of practical significance and may be used to justify the use of average incomes of for cross-country welfare comparisons.

Testing convergence in relative income distributions is also important for policy purposes. Convergence in distributions across nations raises important questions especially in the light of the recent policy debate generated by Thomas Piketty's book, *Capital in the Twenty-First Century* (Piketty, 2014). The book analyzes income distributions in developed nations in Europe and the United States and finds a historical tendency in these nations toward rising wealth and income inequality. We find a similar rise in income inequality in our sample over the last two decades. We predict that inequality within developed nations will converge to a steady state Gini index of 31.9, which is close to the average Gini index in 2010 (30.8). Picketty's book has brought progressive tax reforms to the forefront among contemporary policy issues in many developed nations. Whether the current convergence in income distributions within developed nations will continue or whether it will reverse and diverge will depend upon how countries respond to policies such as progressive taxes. Despite evidence of convergence, the process will be far from smooth, since the dynamic responses of key macro variables to policy changes may vary from country to country (Kolasa, 2014).

Unconditional convergence in relative income distributions is symptomatic of underlying convergence in economic fundamentals. One probable explanation for convergence in inequality among developing nations is the widespread convergence of economic policy during the 1990s (Ravallion, 2003). With increasing globalization, many developing countries reduced trade barriers, promoted the migration of labor, liberalized the movement of capital, and encouraged the rapid transfer of technology (e.g. mobile phones). It is likely that these policies shaped income distributions within these nations in a similar fashion. Indeed, Alvaredo and Gasparini (2015) find that differences in income inequality among developing nations have become considerably smaller over the last three decades. Thus income distributions in developing countries are becoming increasingly unequal yet at the same time more similar to each other. Consequently, it would not be surprising to see nations joining forces and coordinating their strategies to jointly reduce inequality. A recent example is the United Nations adoption of the Sustainable Development Goals in 2015.[23] Among the numerous sustainable development goals, Goal 10 seeks to reduce inequality within and among countries. The description of the goal explicitly states that, while income inequality between countries may have reduced, inequality within countries has risen.

There is growing consensus that economic growth is not sufficient to reduce poverty if it is not inclusive. To reduce inequality, policies should be consistent across countries and focus on the needs of disadvantaged and marginalized populations. Thus, countries will have to work together in order to reduce income inequality.

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[23] See: http://www.undp.org/content/undp/en/home/sdgoverview/post-2015-development-agenda.html.