Cross-Country Convergence in Income Inequality

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CROSS-COUNTRY CONVERGENCE IN INCOME INEQUALITY

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This thesis is dedicated to my parents.
For their endless support, care and encouragement

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SUMMARY

Neoclassical models imply convergence of the entire distribution, not just the mean income levels. In this paper, we analyze convergence in income inequality by using the considerably enlarged data bases from the world bank (povcal) and the world institute for development economic research (wider). Convergence in gini indices of inequality is tested across 55 countries. We consider three major sample subsets; one for the developing countries, second of the developed countries and third with all countries together. We test for convergence in gini indices over a period of 5, 10, 15, 20 and 25 years. Additionally we use cross-section (ols), panel (gmm) and novel ols estimation methods. Our results uniformly indicate that inequality levels among developing countries converged. Evidence of convergence is weaker among developed countries. Developing countries appear to converge faster than developed countries.

CHAPTER 1

INTRODUCTION

The neoclassical growth models (Solow 1956) suggest that an economy will converge towards a steady state rate of growth and the speed of convergence is inversely related to the difference between income and its steady state value. This hypothesis, known as conditional convergence, has sparked enormous interest to test convergence in average income (the first moment). However, as noted by Benabou (1996), the neoclassical models also imply convergence of the entire distribution. A pressing question that has received less attention in the literature is whether countries with different degrees of inequality tend to converge towards a common distribution. Do initially highly unequal countries exhibit a trend towards decreasing inequality over time? Similarly, do low inequality countries experience a rise in inequality?

We analyze convergence in income inequality by using the latest and considerably enlarged data bases, which are credited to the effort of the World Bank (Povcal) and the World Institute for Development Economic Research (WIDER). Convergence across countries during 1980-2005 is primarily examined based on four panel datasets: a sample of 32 developing countries from Povcal, a sample of the same 32 developing countries from the UNU-WIDER World Income Inequality Database (WIID), a sample of 23 developed countries from WIID and a combined sample of 55 developing and developed countries from WIID. Besides, an annual frequency dataset spanning the 1996-2005 period is also constructed for 21 countries from WIID in order to apply a novel OLS method proposed by Bao and Dhongde (2009).

Testing convergence in income inequality is highly significant according to

Benabou. First, the question itself is very intriguing. It is well known that East Asia is the most equal region in the world, while Latin America and Africa are the most unequal. Second, multiple steady states and path dependence can be examined and the joint mechanisms of credit market incompleteness and negative influence of inequality on social mobility can be tested. Third, income distribution can be regarded as the second moment of average per capita income.

The study significantly extends and complements the existing literature by adopting high-quality data and implementing advanced estimation models. In contrast to previous literature which tests for convergence in income distribution within a country or between a subset of countries, we examine inequality convergence across all countries on which data is available. Regarding methodology, we apply GMM method introduced by Arellano and Bond (1991) to mitigate the issue of small sample size in the unconditional test of convergence and a novel OLS method proposed by Bao and Dhongde (2009) to make more efficient use in data than GMM. The implementation of both methods is the first attempt for cross-country data.

CHAPTER 2

LITERATURE REVIEW

Convergence of income, first predicted by Solow (1956) in his neoclassical growth model, refers to the hypothesis that poor economies will eventually catch up with rich economies with regard to per capita income. The hypothesis hinges critically on the Solow's assumption of diminishing returns of capital, which allows poor economies to get higher marginal returns from additional investment than rich economies, thus providing a chance for the former to catch up the latter.

Starting with Baumol (1986), there is a vast body of literature testing convergence of income empirically. In his analysis of the income convergence, Baumol (1986) makes use of data available only for industrialized economies over the 1870-1979 period and gleans some evidence in support of convergence by showing some relative poor countries significantly reduce the per capital income gap with rich ones over the years. The finding is soon under criticism by studies pinpointing the problem of selection bias. And scholars began to steer attention to test the hypothesis in a wider pool of countries.

Barro and Sala-i-Martin's (1992) seminal paper distinguished two notions of convergence, namely, σ-convergence and β-convergence. β-convergence indicates a negative relationship between the growth of per capita income and the initial level of income across regions over a given time period. σ-convergence, however, signals a trend in which the dispersion of real mean income decreases over time. β-convergence is necessary, but not sufficient condition for σ-convergence. To briefly outline the idea, suppose a framework set within a simple log-linear model where the growth rate of real per capita income for an economy in period t is defined as:.

$$\log(\frac{y_{it}}{y_{i,t-1}}) = \alpha - \beta \log(y_{i,t-1}) + u_{it} \quad (1)$$

y_{it} denotes the level of real mean income. u_{it} : $i.i.d.(0, \sigma_t^2)$, where σ_t^2 is the variance of log per capita income. Then β-convergence suggests β to be greater than zero, hence a statistically significant negative correlation between growth and initial log per capita income. σ_t^2 can be expressed by the definition of variance in a sample as,

$$\sigma_t^2 = (\frac{1}{N-1})\sum_{i=1}^{N}(\log(y_{i,t}) - \mu_t)^2 \quad (2)$$

where N is the sample size and μ_t is the sample mean of log per capita income. Using equation (1) and (2), the relationship between beta and sigma can be determined,

$$\sigma_t^2 = (1-\beta)^2 \sigma_{t-1}^2 + \sigma_{u_t}^2 \quad (3)$$

If $0 < \beta < 1$, the evolution of σ_t is stable, which justifies our previous remark that β-convergence is a necessary condition for σ-convergence. Then the steady-state variance $(\sigma^2)^*$ can be calculated from (3) and the result is given below,

$$(\sigma^2)^* = \frac{\sigma_{ut}^2}{1-(1-\beta)^2} \quad (4)$$

It is not hard to see that the steady-state cross-section distribution rises with σ_u^2, but decreases with β.

The literature has largely focused on testing β-convergence. Friedman (1992) and Quah (1993) criticized the focus on β-convergence by pointing out its weakness like Galton's fallacy. Specifically, Quah(1993) points out that the common approach to run cross-section regressions accomplishes little toward explaining the dynamic trend of growth rates and the yielded negative coefficient on initial level of measures may indeed imply the absence of convergence. Using output per worker, the author shows that in the long run, economies either tend to be very rich or very poor with middle class vanishing, which disproves β-convergence.

Overall, convergence in income distribution has received less attention in the literature. Most of the studies test convergence in income inequality within countries, especially within the U.S. (Gomes and Paulo 2007, Lin and Huang 2012). Panizza (2001) finds overwhelming evidence in support of the hypothesis among the U.S states between 1940 and 1980. Using both cross-section and panel type of data, he shows that initial inequality accounts for more than 80 percent of the variance of the changes in the Gini index over time.

Lin and Huang (2011) expand the time dimension of the data and investigate convergence in the U.S. during 1916-2005. They test convergence in income inequality based on measures of top 1% and 10% income shares, and find the results to be robust to other measures of inequality, and different regional divisions and alternate time periods.

Based on the same data, but adopting a different approach, panel unit root test, Lin and Huang (2012) further strengthen their previous conclusion indicating uniform convergence. Given the 90-year span of time (1916-2005) of the data coverage, implementing the approach, as noted by the author, controls for the effect of structural changes incurred by economic shocks.

Ezcurra and Pascual (2009) explores the dynamics of spatial distribution of income inequality in the U.S. over the 1969-1999 period using a non-parametric methodology proposed by Quah (1993,1996) , which can capture the dynamics across economies and overcome some limitations involved in traditional approaches. Their findings reinforce the presence of a process of convergence in income inequality within the U.S and those states with most degree of inequality in 1969 experienced the greatest increase in income dispersion in the next three decades. Such trend however, tends not to be lasting infinitely.

Among a handful of studies testing inequality convergence within other countries, Gomes (2007) examines the issue covering over 5,000 municipalities in Brazil in the 1991-2000 period. It is worth mentioning that their data are very uniform because the inequality measures are all calculated based on the same definition and drawn from the same source. Their test supports the convergence hypothesis of income inequality after controlling for regional differences.

Though income distributions tend to converge within countries, evidence of convergence between countries is ambiguous. Benabou (1996) is the first to propose to test convergence in income inequality. Inspired by Barro and Sala-i-Martin's (1992) methodology, he regresses average changes in Gini coefficients over time on initial level of Gini coefficients across 30 or so countries and he interpolates missing data so as to take advantage of panel estimation.But he fails to provide uniform evidence corroborating the hypothesis by identifying convergence only between1970-1980, but not between 1970-1990.

To minimize the effect of wide disparities in country-level inequality measures and make cross-national data more comparable, Gottschal and Smeeding (1997) adopt the Luxembourg Income Study database and study a small sample of industrialized countries in the 1980s. The paper does not find convergence to a single mean; instead they find a "twin-peak" style of convergence. Specifically, their paper suggests that some countries such as the United States experience an increasing level of inequality, while others including Italy and France are progressing towards lower levels of inequality.

Ravallion (2003) directs focus on two samples of developing countries and tests for unconditional convergence incorporating both OLS and IVE procedures. Estimates based on Gini index and log of the Gini index uniformly report evidence of inequality convergence in developing countries. However he notes that the effect of convergence is not statistically significant if measurement error is considered.

The paper by Bleany and Nishiyama (2003), confirms convergence among OECD countries and developing countries during 1965 to 1990. Lopez (2004) too verifies a trend of convergence in inequality across countries. Using survey data, Ezcurra and Pascual (2005) estimate density functions for the regional distributions of the Gini index in the European Union between1993-1998 and corroborate inequality convergence.

CHAPTER 3

DATA

The standard measure of income inequality across countries is the Gini coefficient, named after its developer, Corrado Gini (1912). Its value ranges from 0 indicating perfect equality, to 1 indicating perfect inequality. The Gini index is related to the Lorenz curve of income inequality which shows a graphical representation of cumulative percentages of total earned income against the cumulative number of recipients (figure 1).

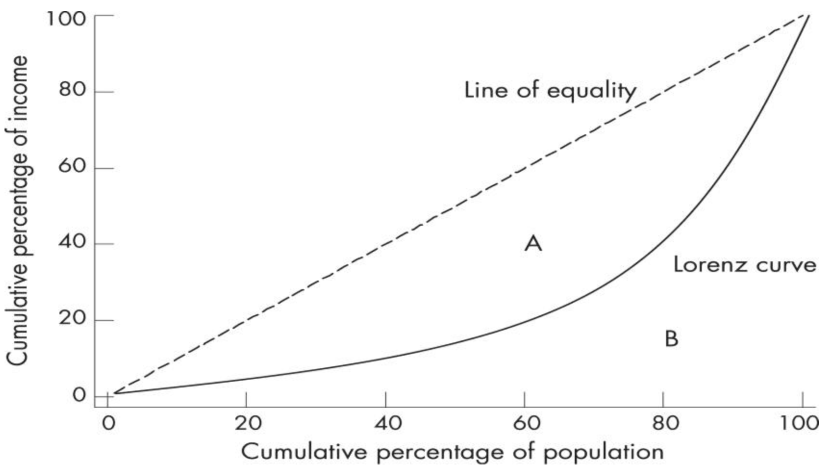

Figure 1 Gini index

Suppose the Lorenz curve is defined as a function $Y = L(X)$ then the Gini index can be formulated as,

$$G = 1 - 2\int_0^1 L(X)dX \quad (5)$$

a measure of the area A between the Lorenz curve and a hypothetical line of absolute equality. The Gini index has obvious advantages over other indices of inequality being scale independent, anonymous towards individuals and transfer sensitive.

Deininger and Squire (1996) significantly improved the quality and quantity of distributional data. Their dataset includes 682 high quality observations for 108 countries, of which 65 percent are drawn from primary sources, constituting almost 10 times as many observations and 3 times as many countries as the second largest data set at that time. As a first application, Bénabou (1996) uses this dataset to test for inequality convergence.

The Chen and Ravallion (2001) dataset is available on PovcalNet—a global poverty monitoring data website maintained by the World Bank. The PovcalNet dataset uses Purchasing Power Parity (PPP) exchange rates for household consumption from the 2005 International Comparison Program and data from more than 850 household surveys from 127 developing countries. The most distinguished feature of the dataset is that its data are exclusively measured from primary sources and grounded upon per capita distributions (Chen and Ravallion 2001). But for a majority of countries, only one or two observations are available and most data is available for the 1990s.

The data in WIID are significantly more abundant not only for developing economies, but also for developed economies. As part of the UNU/WIDER project “Global Trends in Inequality and Poverty”, WIID is not an integration, but rather a collection of available data from various primary and secondary sources, purporting to maintain integrity of data and use at scholar’s own discretion. Hence unavoidably, for many countries, several observations in a single year are listed based on different definitions or sources. Furthermore, two distinct categories of Gini coefficients are given: one calculated by WIDER from methods developed by Shorrocks and Wan (2008); the other reported by the source or calculated by Deininger and Squire for the old databases. The major distinction between the two is that Shorrocks and

Wan(2008)'s procedure applies decile data as an estimate of the Gini coefficients, yielding results nearly as accurately as if unit record data were used. Consequently, we select their data for analysis and for those countries with multiple observations in a year, a single one is picked via the following rules. To begin with, data with the poorest quality ranking, namely, the 4th ranking, are excluded from the datasets. Then, to be consistent, we always favor observations taken from the same primary and secondary sources based on a common income definition. Under this broad guidance, more trivialities are considered. Data covering only urban or rural areas are filtered out. Depending on the availability of data, the precedence is given to disposable income over gross income over expenditure based on Haig-Simons ideal measure of income. Accordingly, (1) a sample of 55 countries over the 1980-2005 period with 5-year interval is compiled from WIID. Following the World Bank's classification of countries, we then split the sample into another two subsamples: (2) one with 32 developing countries and (3) one incorporating 23 developed countries. For comparison purposes, we further generate a sample of (4) the same 32 developing countries over the same span of time from Povcal (FN: missing values are interpolated using WIID data).

Finally, we compile (5) an annual frequency dataset from WIID for 21 countries, which are a subset of 55 countries mentioned above. The data span a period of 1996-2005 and are of higher quality than the previous datasets. Though observations in all datasets are endeavored to be selected based on a single definition of income and from a single source, data in (1)–(4) sometimes have to be patched together to satisfy the 25-year time requirement. While for dataset (5), its observations are of shorter time span and thanks to the more frequent collections of Gini coefficients by countries and institutions in recent years, they are more homogenous in terms of data source and definition.

3.1 SUMMARY STATISTICS

Table 3.1 to 3.4 present summary statistics for the four datasets utilized in the study and two common trends are observed. Average inequality shows an increasing trend over time, but cross-country standard deviations have reduced in all datasets. In tables 3.1 and 3.2 where statistics for developing countries are summarized from Povcal and WIID datasets, average inequality increased from approximately 38 to about 43 over the 1980-2005 period, while the standard deviation of Gini indices dropped significantly from about 13 to 7 percent spanning the same period. Further, means of inequality measures from WIID are larger in value than those in Povcal (except for 1980), which can well be justified by the fact that data in the former are mostly calculated from income, generally larger than values from the latter mainly estimated on consumption or expenditure. Differences between inequality levels in developing and developed countries are also striking if tables 3.2 and 3.3 are compared. The average Gini coefficients of developing countries are, for most cases, considerably larger, reinforcing the general observation that income disparity is more of an issue to these countries. To get a quantitative perception of the gap in inequality, we subtract the mean Gini of developed countries from that of developing countries of each year, then add differences for all years together and divide the sum by five; we get a result of 9.8, the average difference of income inequality between developing and developed countries. The standard deviations declined more substantially in developing countries over the entire duration of time than in developed countries: from 13.4 to 7.4 in the former category and from 6.8 to 5.5 in the latter. Concerning all the 55 economies covering developing and developed countries, table 3.4 exhibits a trend where the mean Gini varies roughly from 35 to 38 and standard deviation diminishes from about 12 to 9 over the 1980-2005 period.

Table 3.5 presents annual inequality measures across 21 countries in the 1996-2005 period. The overall trend in mean, max, min and distribution over the decade still coincides with the one described above. But fluctuations are observable particularly for cross distribution of Gini coefficients.

Table 3.1 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 3.2 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 3.3 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 3.4 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 3.5 21 countries: WIID

Gini Index: Summary Statistics

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Min.	23.7	24.5	24.2	23.7	24.1	24.3	24.5	23.8	23	23
Max.	50.3	49.4	50.2	49.1	50.4	52.2	53.3	52.8	50.6	50.1
Mean	34.43	34.39	33.6	33.6	34.14	33.78	34.46	33.68	33.93	33.97
SD..	8.56	8.29	7.82	7.72	7.44	7.95	7.94	7.79	7.75	7.88
Obs.	21	21	21	21	21	21	21	21	21	21

To have a graphical view of the data, we plot the five compiled datasets using the Gaussian density functions for the starting year and the end year. It is apparent that in all figures, the standard deviation of the Gini index has significantly decreased.

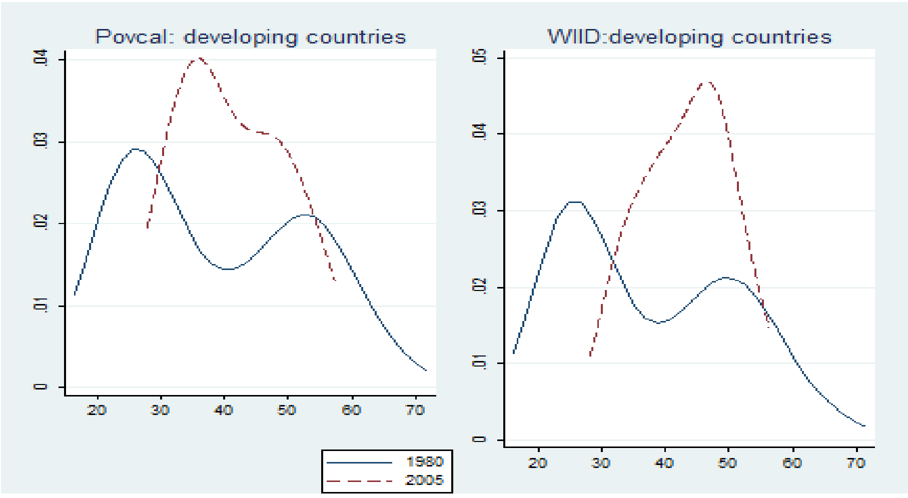

Figure 2 Developing countries: Povcal and WIID

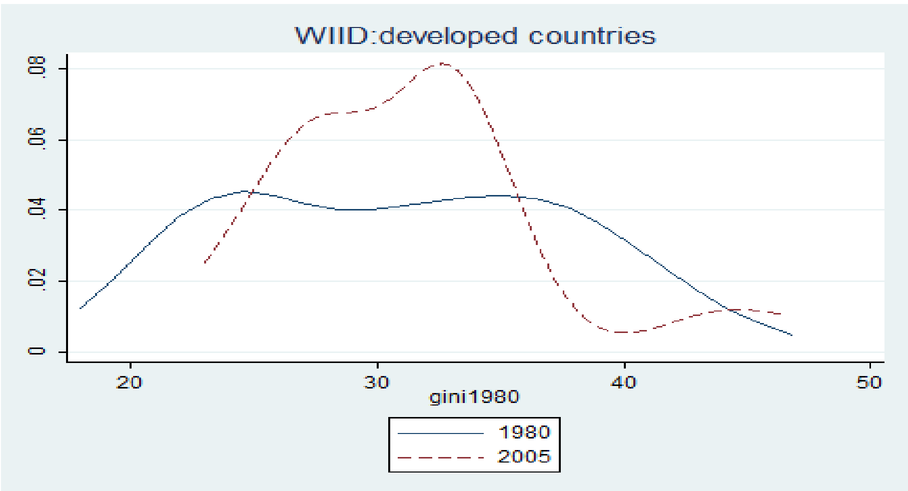

Figure 3 Developed countries: WIID

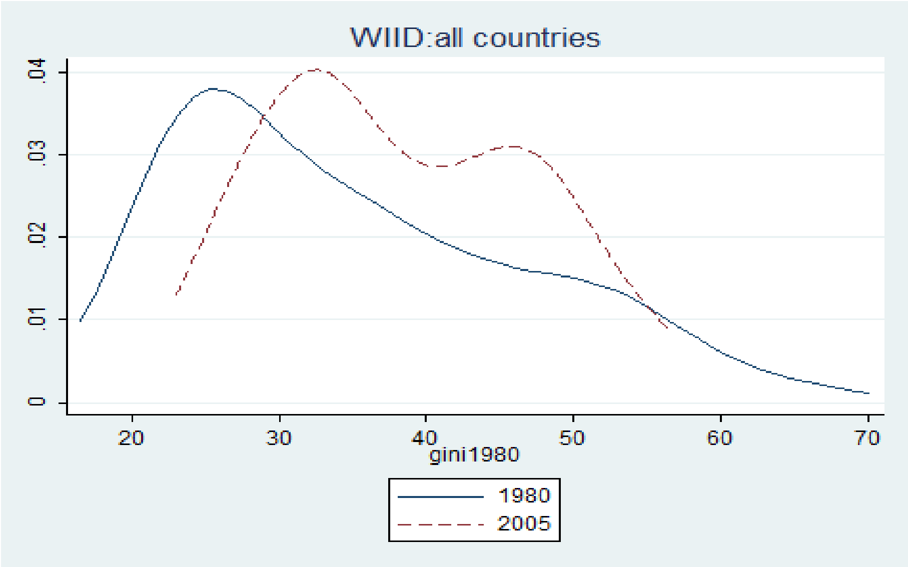

Figure 4 All countries: WIID

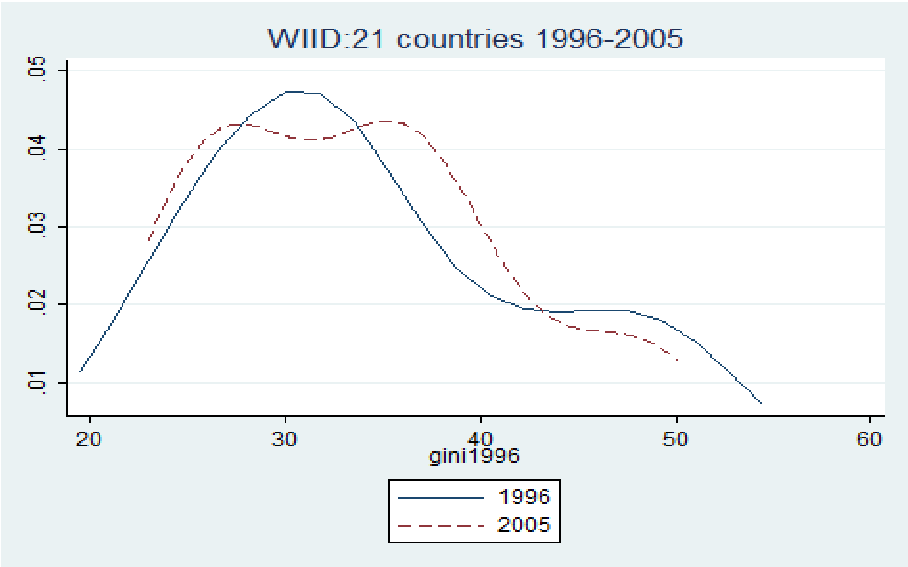

Figure 5 21 countries: WIID

CHAPTER 4

CONVERGENCE TESTS

4.1 CROSS-SECTION REGRESSION

We first examine unconditional convergence using the same equation used to test of convergence in average incomes (Barro and Sala-i-Martin, 1991). The method involves regressing annual average rate of change in a measure of inequality on the measure's initial values across countries.

$$\frac{1}{T}\log(\frac{Gini_{i,T}}{Gini_{i,0}}) = \alpha + \beta \log(Gini_{i,0}) + u_i \text{ (6)}$$

β is the convergence parameter to be estimated. u_i is an innovation error term with mean zero. T is the length of the observation interval. Since our observations start in 1980 and terminate in 2005, we are able to compute average changes in inequality over 5, 10, 15, 20 and 25 years. A statistically significant negative value of β can be regarded as evidence espousing the inequality convergence hypothesis.

Estimates obtained from Povcal and WIID data are presented in tables 4.1 through 4.4. Table 4.1 reveals that for developing countries collected from Povcal, coefficients of initial inequality vary between -0.07 and -0.02 and all are significant at 5% level which are primarily in accordance with the estimates of developing countries in table 4.2, where significant negative coefficients ranging from -0.09 to -0.01 are generated using WIID data. Evidently, inequality levels among developing countries seem to converge, though the speed of convergence is highly unstable. The most dramatic fluctuation of convergence speed occurs in the first column of table 4.1 and

4.2, differing between -0.068 and -0.019, -0.077 and -0.013 respectively, where annual average rate of change of Gini over the 5-year span is considered. Such capriciousness gradually declines as time dimension expands and our results, thus, progress towards precision. Estimates of the convergence speed over the 20-year lapse, for instance, differ only by 0.004 in table 4.1 and even smaller in table 4.2, 0.002.

Table 4.1 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 4.2 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%

Apropos developed countries, some, but not overwhelming evidence of convergence is noticed, which may be attributed to the small sample size of the dataset. A simple comparison of the convergence parameters between table 4.2 and 4.3 suggests that for all time periods except for 1985-1990, developing countries appear to converge faster than or as fast as developed countries, where the biggest gap mounts to 0.022, occurring over the 1995-2005 period.

Table 4.3 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	0.183	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%

We now turn our attention to the estimates for the combined sample of developing and developed countries. It seems that convergence hypothesis is in general espoused for most periods (4.4) and the coefficients for initial Gini values are almost all significant at 1 percent level.

To sum up the cross-sectional analysis, we find that the regressions fit the data much better for longer periods in all samples. In particular, initial inequality explains as high as 69% (Povcal) and 76% (WIID) of the variance of the changes in the Gini coefficients of developing countries in the 1980-2005 periods against for instance, only 8% and 1% of the variances spanning the 1995-2000 period. With regard to developed countries, the regressions perform less satisfactorily in explaining the variances: the highest R-squared is only 0.48 over the 1980-2005 period, significantly less than the same period for the developing countries.

Table 4.4 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%

To check the robustness of aforementioned results, regressions are also implemented using Huber weights and Tukey biweights which drop observations whose Cook's distance is greater than 1. Results of the test are presented in table 4.5-4.8. Estimates of β-coefficient are always smaller than those from tables 4.1 to 4.4, but the statistical significance usually stays the same. Secondly, while all the observations are retained in tables 4.5, 4.6 and 4.8, an outlier is dropped for the sample of developed countries for the 1995-2000 period, turning the originally insignificant OLS convergence estimator of that period significant at 10% level.

Table 4.5 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 4.6 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 4.7 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 4.8 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%

4.2 PANEL REGRESSION

While the cross-section methodology sustains convergence across countries for nearly all time periods, it is highly susceptible to omitted variable bias and a significant downward trend in inequality estimates may be yielded. In addition, strong theoretical evidence puts forward that at least some explanatory variables are endogenous, which are rarely controlled, though recognized by most current literature. To mitigate these potential issues, we next employ an approach that takes advantage of panel data to control for country-invariant characteristics. The model is given in equation (7) where

$$\frac{1}{5}\log\left(\frac{Gini_{i,t+5}}{Gini_{i,t}}\right) = \beta\log(Gini_{i,t}) + \eta_i + \xi_t + \mu_{i,t} \quad (7)$$

η_i denotes a country fixed effect and ξ_t is a time fixed effect and $\mu_{i,t}$ is the error term. A regular OLS estimation of equation (8) does not provide consistent and unbiased estimators in that the regressor is actually a lagged dependent variable. To tackle this issue, we utilize the generalized method of moments (GMM) estimation for dynamic panel dataset proposed by Arellano and Bond (1991). As the first step, equation (7) is transformed to the following:

$$\log(Gini_{i,t+5}) = (5\beta+1)\log(Gini_{i,t}) + 5(\eta_i + \xi_t + \mu_{i,t}) \quad (8)$$

Then take the first difference of equation (9) to get rid of the country fixed effect and all the past information is used as instrumental variables. In consistent with Panizza (2001), we choose the set of instruments $(y_{i1,}...,(y_{i,T-2})$ for period T. If the error term is serially uncorrelated and homoskedastic, then the regressor is uncorrelated with unobserved fixed country effect and applying one-step GMM estimation is appropriate. In case of heteroskedastic error terms, two-step GMM should be used.

Yet, one problem associated with two-step GMM is that not all available moment conditions are exploited and less efficient estimators are generated. We, thus, estimate the coefficients using both one-step and two-step GMM procedures to balance their pros and cons.

The results are presented in tables 4.9 to 4.12. Estimates of standard OLS fixed effects (LSDV) are also reported for contrasting purpose, in which the first column gives values using all available observations and estimates in the second column only employ observations from 1985-2005 so as to make LSDV and GMM estimators comparable. The convergence hypothesis is unanimously supported based on the finding that all the coefficients of initial inequality are significant at 5% significance level in all tables. LSDV estimators are mostly biased upwards except for the case of developed countries and are bigger in magnitude than GMM estimates. Surprisingly, we also notice that convergence in income inequality has been significantly slower in developing countries than developed countries spanning 1980-2005 period. In particular, the former are expected to converge at a rate ranging from 0.06 to 0.09 percentage points per year while for the latter, their annual expected rate of convergence is over 0.2 percentage points. Our conclusions are consistent with those by Bleany and Nishiyama (2003) who too find that the speed of convergence is faster among developing countries. The overall expected annual speed of convergence for developing and developed countries altogether is about 0.09 percentage points.

Table 4.9. Panel convergence tests for developing countries: Povcal

	1980-2005	1985-2005		
	LSDV	LSDV	GMM1	GMM2
Constant	0.501***	0.657***	0.339***	0.328**
	(9.33)	(10.30)	(3.75)	(2.55)
Initial Gini	-0.135***	-0.178***	-0.092***	-0.088**
	(-9.24)	(-10.28)	(-3.72)	(-2.53)
R2	0.54	0.64		
N. Obs	160	128	128	128

*Significant at 10%, **5%, ***1%. For LSDV, t-statistics in parentheses. For GMM1&GMM2, z-statistics in parentheses.

Table 4.10 Panel convergence tests for developing countries: WIID

	1980-2005	1985-2005		
	LSDV	LSDV	GMM1	GMM2
Constant	0.498***	0.652***	0.237***	0.217**
	(6.26)	(7.40)	(3.32)	(2.13)
Initial Gini	-0.133***	-0.173***	-0.063***	-0.057**
	(-6.17)	(-7.37)	(-3.22)	(-2.07)
R2	0.43	0.54		
N. Obs	160	128	128	128

*Significant at 10%, **5%, ***1%. For LSDV, t-statistics in parentheses. For GMM1&GMM2, z-statistics in parentheses.

Table 4.11 Panel convergence tests for developed countries: WIID

	1980-2005	1985-2005		
	LSDV	LSDV	GMM1	GMM2
Constant	0.598***	0.701***	0.686***	0.797***
	(6.48)	(7.15)	(5.42)	(6.84)
Initial Gini	-0.173***	-0.204***	-0.201***	-0.233***
	(-6.47)	(-7.09)	(-5.39)	(-6.86)
R2	0.49	0.56		
N. Obs	115	92	92	92

*Significant at 10%, **5%, ***1%. For LSDV, t-statistics in parentheses. For GMM1&GMM2, z-statistics in parentheses.

Table 4.12 Panel convergence tests for all countries: WIID

	1980-2005	1985-2005		
	LSDV	LSDV	GMM1	GMM2
Constant	0.483***	0.654***	0.319***	0.310**
	(7.91)	(9.84)	(3.92)	(2.40)
Initial Gini	-0.139***	-0.180***	-0.088***	-0.086**
	(-8.00)	(-9.79)	(-3.86)	(-2.38)
R2	0.43	0.54		
N. Obs	275	220	220	220

*Significant at 10%, **5%, ***1%. For LSDV, t-statistics in parentheses. For GMM1&GMM2, z-statistics in parentheses.

4.3 NOVEL OLS REGRESSION

GMM estimator, though consistent, is usually biased in finite samples. In this section, we provide a robust test to our previous estimates. The method is to perform the novel OLS method proposed by Bao and Dhongde (2009), which uses data more efficiently and the estimates are more reliable. To be specific, it makes use of $T-\tau$ observations for each economy, more than $(T/\tau-1)$ used by GMM procedure. However, there is one exception, when $\tau=1$, GMM and novel OLS estimates coincide.

Monte Carlo experiments in Bao and Dhongde (2009)'s paper suggest that GMM estimates are usually biased upward in magnitude than those yielded from novel OLS. The major assumption for this method is that there should be no τ, (τ -1), and (τ +1)-order serial correlation, which can be tested by the m-statistic (appendix A). Because of relative shorter span of data, we choose $\tau=3$. The method is given as follows:

We rewrite (7) by letting $\tau=3$

$$\frac{1}{3}[\log(Gini_{it})-\log(Gini_{i,t-3})]=\beta\log(Gini_{i,t-3})+\eta_i+\xi_t+\mu_{it} \quad (9)$$

To remove the time fixed effect, we subtract its period mean from each of $\log(Gini_{it})$, and denote the deviation g_{it} and write (9) as follows,

$$g_{it}=(3\beta+1)g_{i,t-3}+3(\eta_i+\mu_{it}) \quad (10)$$

A first difference of (10) gives

$$g_{it}-g_{i,t-1}=(3\beta+1)(g_{i,t-3}-g_{i,t-3-1})+3(\mu_{it}-\mu_{i,t-1}) \quad (11)$$

Based on the assumption, ($g_{i,t-3}-g_{i,t-3-1}$) is uncorrelated with ($\mu_{it}-\mu_{i,t-1}$).Standard OLS procedure thus is consistent and instrumental variables are not needed. To compare novel OLS estimates with GMM estimates, we apply GMM again for this dataset.

Table 4.13 reports estimates using novel OLS and GMM methodology based on the same dataset. The m statistic is only 0.4, which is statistically insignificant from 0 and the crucial assumption of no τ, (τ -1), and (τ +1)-order serial correlation for OLS estimations is satisfied. Both one-step and two-step GMM estimates are larger in magnitude, but less in significance than OLS estimates. Thus the convergence hypothesis is further corroborated and the OLS estimates show that the inequality levels across countries converge at about 0.3 percentage point. Apparently, for such small sample, OLS procedure is preferred since 126 observations are utilized, while GMM only makes use of 42 observations.

Table 4.13 Novel OLS tests and GMM tests for all countries: WIID

	1996-2005		
	OLS	GMM1	GMM2
Initial Gini	-0.33***	-0.54***	-0.63***
	(-8.05)	(-2.94)	(-5.32)
m statistic	0.40		
N. Obs	126	42	42

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

CHAPTER 5

CONCLUSION

In the study, convergence in income inequality is analyzed using the considerably enlarged data bases, from the World Bank (Povcal) and the World Institute for Development Economic Research (WIDER). Convergence in Gini indices of inequality is primarily tested across 55 countries over a period of 5, 10, 15, 20 and 25 years. Cross-section estimation (OLS) is applied first to the data as a benchmark case and we find that the regressions fit the data much better for longer periods in all samples. For instance, initial inequality explains as high as 69% (Povcal) and 76% (WIID) of the variance of the changes in the Gini coefficients of developing countries in the 1980-2005 periods against for instance, only 8% and 1% of the variances spanning the 1995-2000 period.

Then we use panel (GMM) estimation methods to mitigate the issue of small sample size in the unconditional test of convergence and find uniform convergence in income inequality across developing countries, developed countries and both combined. The overall annual speed of convergence for developing and developed countries together is about 0.09 percentage points, which is significantly slower than the speed within the U.S. We also compare the speed of inequality convergence between developing and developed economies. Results from the panel data model suggests that over the 25 year period, developing countries converged significantly more slowly than developed countries.

Finally, to augment the previous conclusion, we further implement a novel OLS procedure proposed by Bao and Dhongde (2009) to make more efficient use in data than GMM. The methodology requires high-frequency data and thus an annual frequency dataset from WIID for 21 countries has been compiled for analysis. The results signals even a stronger level of convergence than the GMM estimates. Hence, the inequality convergence has been corroborated in all tests.

APPENDIX A

M-STATISTIC

Equation (12) can be represented by a vector form,

$$y = \beta^* x + v$$

Here y, x and v are vectors of $N(T-\tau)\times 1$, Suppose

$$v' = (v_1^{'}, v_2^{'}, ..., v_N^{'}) = (v_{1,\tau+1}, ..., v_{1,NT})$$

$$v_{(-\tau)i} = (v_{i,\tau+1}, ..., v_{i,T-\tau})'$$

$$v_{*i} = (v_{i,2\tau+1}, ..., v_{i,T})'$$

Then $\hat{v}_{(-\tau)i}$ and $\hat{v}_{*i}$ can be obtained from the above equation. Similar, we can get $\hat{x}_{(-\tau)i}$ and $\hat{x}_{*i}$. The m statistic can be formed below,

$$m = \frac{\hat{v}_{(-\tau)i}^{'} \hat{v}_{*i}}{\sqrt{Q}}$$

where

$$Q = \sum_{i=1}^{N} (\hat{v}_{(-\tau)i}^{'} \hat{v}_{*i})^2 - 2(\hat{v}_{(-\tau)i}^{'} \hat{x}_{*i})(x'x)^{-1} \sum_{i=1}^{N} \hat{v}_{(-\tau)i}^{'} \hat{x}_{*i} (x_i^{'} \hat{v}_i) + ((\hat{v}_{(-\tau)i}^{'} x_*)(x'x)^{-1})^2 \sum_{i=1}^{N} (x_i^{'} \hat{v}')^2$$

REFERENCES

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. 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.

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.

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.

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).

Fum, R. and Hodler, R. (2010). 'Natural resources and income inequality: The role of ethnic divisions', Economics Letters, Elsevier, Vol. 107(3), pp. 360-363.

Gomez,M. and Ventosa-Santaularia, D. (2007). Income convergence: the Dickey-Fuller test under the simultaneous presence of stochastic and deterministic trends', Department of Economics and Finance Working Papers EM200703, Universidad de Guanajuato, Department of Economics and Statistics.

Gottschalk, P. and Smeeding, T. (1998). 'Empirical evidence in industrialized countries', LIS Working Paper 154.

Lin,P. and Huang, H.(2012). 'Inequality convergence revisited: evidence from stationarity panel tests with breaks and cross correlation', Economic Modelling, Vol. 29(2), pp.316-315.

Lin, P. and Huang, H. (2011). 'Inequality convergence in a panel of states', Journal of Economic Inequaliy, 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.

Paas, T. and Schlitte, F. (2007). ‘Regional income inequality and convergence processes in the EU-25’, HWWI Research Papers, pp. 1-11.

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

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