Cross-Country Variability in Inequality Change*

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Abstract: Due to the availability of international and longitudinal data and sophisticated statistical applications, it has been possible to examine cross-country inequality changes from many different angles. In most studies, however, the variability of inequality across countries and years has been taken into account in a limited sense. This paper re-examines the findings of Galbraith and Kum (2005) and makes clear the implications of the assumptions on which the statistical models depend. As a general conclusion, inequality appears closely related to the sectoral share of employment in the overall state of economic development, and this finding appears robust even with various assumptions on cross-country variability in intercept and coefficients of covariates.

Keywords: Inequality, cross-country variability, Kuznets hypothesis

"No society can surely be flourishing and happy, of which the far greater part of the members are poor and miserable."

Adam Smith, The Wealth of Nations

INTRODUCTION

Many theoretical and empirical factors have been suggested to account for inequality dynamics, but still largely in progress. There are at least two streams of research on theoretical aspects of this issue: one focuses on the impact of inequality on economic development or growth; the other tries to account for the dynamics of inequality. The former comprises arguments such as the following: high inequality can help growth by directing more income to high-saving capitalists (Kaldor 1961); inequality harms

* This study is based on "Inequality and Structural Change," a working paper for the United Nations Research Institute for Social Development (Kum 2008).

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growth though political economic channels or though constraints on human capital accumulation or occupational choice (Birdsall, Ross, and Sabot 1995; Galor and Zeira 1993; Banerjee and Newman 1993; Alesina and Rodrik 1994; Persson and Tabellini 1994). Recent additions to this debate have been contributed by Forbes (2000) and Barro (2000), who again argue that inequality has a positive relationship with growth (Easterly 2007).

Relatively restrained but still heated debate has focused on the latter approach. Since Kuznets (1955) identified the transition from agriculture to industry as the main factor in a process of increasing inequality in the early stages of economic development, contributors to a vast empirical literature have tried to verify his inverted-U curve hypothesis (Ahluwalia 1976; Robinson 1976; Ram 1997; Tsakloglow 1988, Anand and Kanbur 1993; Ravallion 1997). In this line, Galbraith (1998) raised the point that a key to understanding inequality lies in understanding intersectoral transition or "structural change," since change in the structure of wages occurs because of changes in the relative positions of sectoral employees during economic development, and this change is likely to be reflected in the overall change in inequality. He saw that as economic development matured, the weight of agriculture in the whole economy would shrink, and dynamics within the industrial sector, such as the growth of labor unions and democratic politics, would come to dominate the evolution of inequality. In this account, the change of sectoral patterns of employment through the course of industrialization is regarded as the main force of structural change; technology, finance, commodities, and people themselves are also seen as plausible determinants.

Galbraith and Kum (2005) took this argument and tested its empirical relevance using industrial wage inequality data from the University of Texas Inequality Project (UTIP).[1] They began with close examination of the quality of the data. Since Kuznets's original suggestion, the quality of the data on inequality has often been criticized.[2] In order to see the change in sectoral patterns of employment and its effect on inequality, a data set that can reflect the intersectoral change of labor and corresponding wages should be prepared and transformed into an inequality measure. Further-

1. UTIP inequality data is based on the industrial data on wages and employments collected by the United Nations International Development Organization (UNIDO 2005).
2. In terms of income inequality data, Deininger and Squire (1996), using what they termed high quality cross-country and time-series data, made an important contribution in this regard. But they soon came under attack by critics who considered their data sparse and incompatible, since it was just a compilation of existing inequality measures based on different concepts and reference terms such as individual vs. household, income vs. expenditure, and net vs. gross. See Atkinson and Brandolini (2001) and Galbraith and Kum (2003) for more detail.

more, data should be collected based on the same categorical classifications in a comprehensive manner to ensure comparability (Berman 2000; Rodrik 1999). For these reasons, the UNIDO industrial wage data at the three-digit level were employed and transformed into an inter-industry wage inequality measure from 1963-2003 with 3,452 observations for 155 countries.

There are also many attempts in the literature to address the statistical modeling issue. Due to the availability of international and longitudinal data, sophisticated statistical applications have been applied from many different angles. Various factors and empirical strategies for estimation have been proposed and revised, and the fixed and random effects model of regression has been one of the most frequently employed techniques in this line. By taking the variability of inequality across countries and years into account, for instance, Galbraith and Kum (2005) extracted reasonable estimates to uncover the underlying mechanisms of inequality dynamics in terms of the GDP per capita, the share of manufacturing employment, and serial patterns.

However, the model is still based on the assumption that only the overall level of inequality is allowed to vary over countries after controlling for relevant covariates. In other words, the relationship between inequality and covariates is assumed to be the same for all countries except for intercepts (fixed or random) for each country. This assumption of parallel patterns of inequality change across countries seems reasonable at first glance, but it ignores the important point of varying effects of covariates on inequality in different countries. If we take the inequality changes in the United States and Zambia as an example, it is hard to accept this assumption of parallel patterns of inequality and, for instance, GDP per capita due to the huge difference in the latter, which seems to be the most plausible factor in explaining inequality change.

This paper continues the work started in an earlier paper, which tested the effect of structural change in the process of economic development (measured by manufacturing employment share) on inequality change through fixed and random effects models (Galbraith and Kum 2005). The present paper takes these results further by specifying a varying coefficient in addition to varying intercept and examines the sensitivity of structural change with other competing factors hypothesized by the earlier paper. By allowing varying effects of covariates on inequality, the suggested model can estimate the robustness of the relationship the structural change has on inequality. A key finding is that low inequality is closely associated with low variability in inequality through time, and that labor force movement out of agriculture is associated with high variability in the inequality of manufacturing wages. And this relationship is still maintained even when allowing cross-country variations in covariates' effect on inequality.

EMPLOYMENT SHARES AND INEQUALITY

According to Kuznets (1955), employment transition from agriculture to industry is the main factor in increasing inequality. As the size of agriculture shrinks, the size of industry grows, and inequality increases due to the large gap between the two sectors. But when the agricultural sector shrinks so far as to become an unimportant share of total employment, trends inside the industrial sector come to dominate, and with income growth and the development of aspects of social democracy such as labor unions and democratic politics, inequality decreases again, which leads to the Kuznets inverted curve relating inequality to income (Galbraith 2008). Thus, intersectoral migration of labor is one notable factor in the evolution of inequality, and changes in employment share among sectors, or intersectoral transitions in employment, could shed light on the underlying change in economic structure.

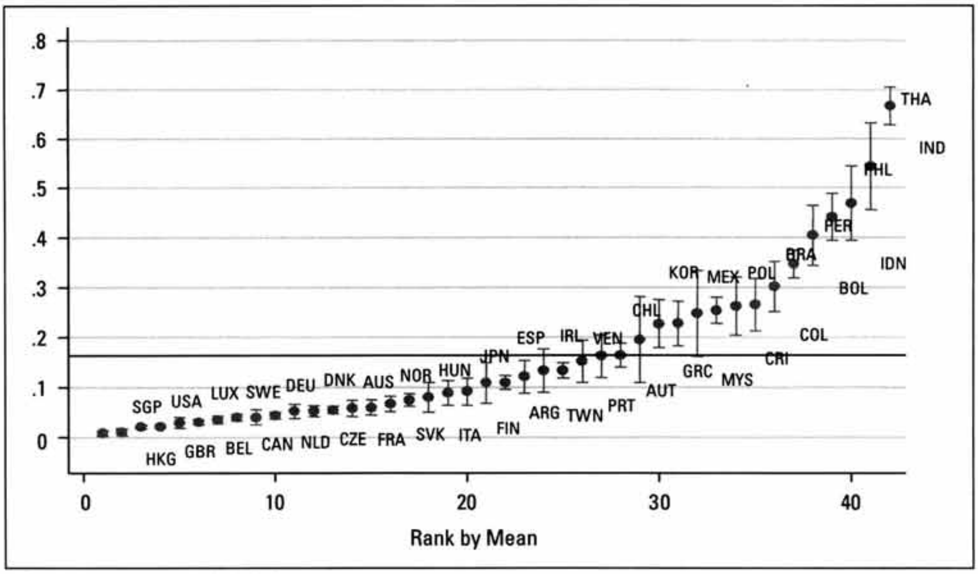
In reality, the employment share of agriculture had fallen in most countries by the late 20th century. To see the magnitude of change, 42 countries that have non-missing information for the agriculture, manufacturing, and service sectors for 1979-2003 were selected for comparison.[3] These comprised 25 OECD countries and 17 developing countries with the same sectoral classifications, assuring the compatibility of comparison. The mean and standard deviation of the employment share by sector for each country were calculated as a measure of variation over time (25 years) within each country and arranged in the order of mean value of employment share for agriculture, manufacturing, and services as shown in figures 1-3.

As shown in figure 1, the mean employment share of agriculture in 42 countries was less than 20%, and countries with smaller shares experienced smaller changes. In contrast, countries in which agriculture had a higher employment share tended to have larger reductions in the labor force in last 25 years. For instance, in Indonesia, agriculture had a 46.9% employment share with a standard deviation of 7.5%, whereas in the United Kingdom, agriculture had an employment share of 2.2% with only a 0.3% standard deviation in last 25 years.

The manufacturing and service sectors, however, showed somewhat different patterns of change, as shown in figures 2 and 3. The employment share of manufacturing was around 20% on average with relatively small estimated standard deviations. In most countries, at least 10% but less than 30% of employees worked in the manufacturing sector, and only a handful of countries, such as Hong Kong (11.9%) and Malaysia (5%), experienced relatively large changes in employment share; the former

3. The comparisons of employment share by sectors are based on data from the Groningen Growth and Development Centre (GGDC 2007), in particular the 10-sector database.

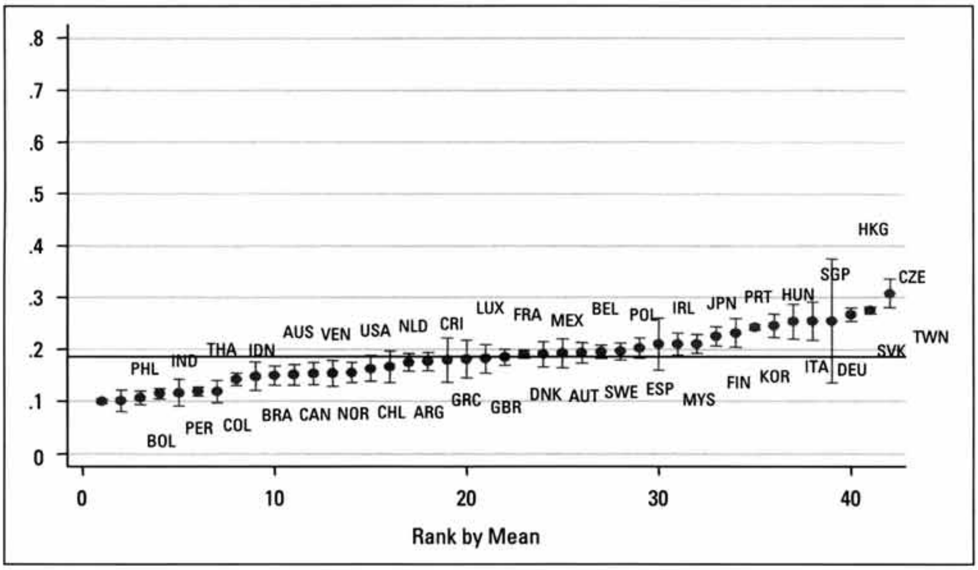
Figure 1. Employment Share of Agriculture, 1979-2003



* Bar indicates 1 standard deviation across years

** Cross line indicates overall mean

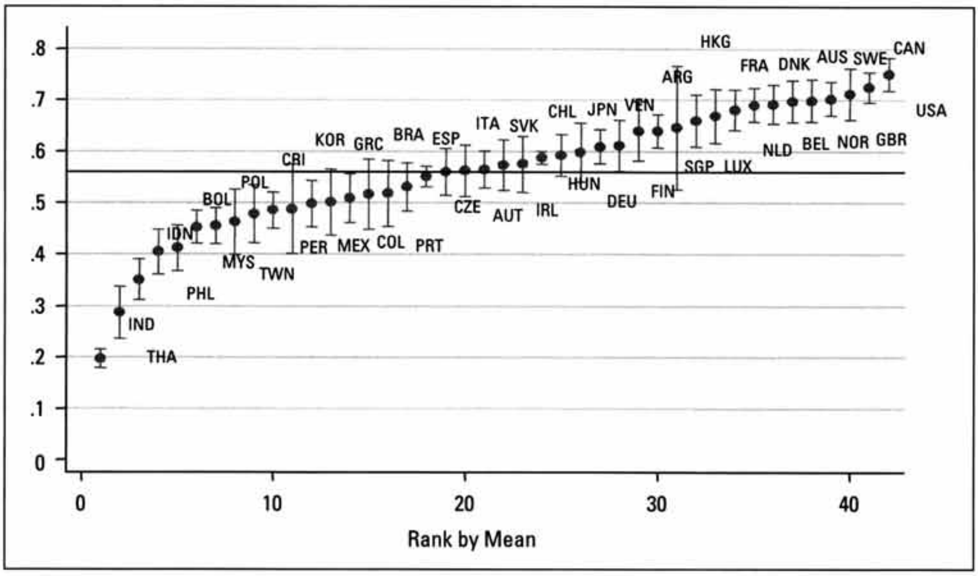
Figure 2. Employment Share of Manufacturing, 1979-2003



* Bar indicates 1 standard deviation across years

** Cross line indicates overall mean

Figure 3. Employment Share of Services, 1979-2003



* Bar indicates 1 standard deviation across years
** Cross line indicates overall mean

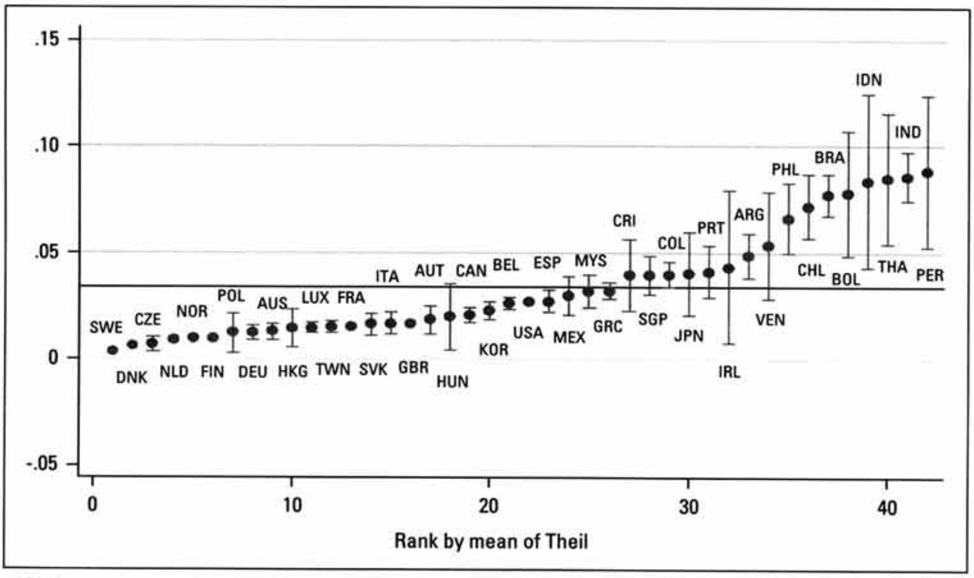
decreasing and the latter increasing.

In contrast, the employment share of the services sector in most countries has been growing rapidly. In financially advanced countries such as the United States, Canada, and GBR, the service sector took the highest rank and kept increasing its share. But most developing countries experienced more volatile changes in the service sector's share of employment. On average, the change was much larger than that of manufacturing sector.

In this exercise, it is noteworthy that agriculture's share of employment has had the largest span of dynamics and its volatility was greater where the share was larger. That is, agrarian countries and less developed countries have experienced more volatile reductions in the employment share of agriculture. While employment share changes across sectors show some historical experience of economic structural change, it is still hard to connect this to inequality changes directly. To see this relationship, the change of inequality with respect to its variability is presented in figure 4.

As figure 4 makes clear, the higher the inequality level is, the larger its standard deviation over time. For instance, several northern European countries have had both the lowest inequality levels and the smallest fluctuations over the past 40 years. In contrast, several Latin American countries had much higher levels of inequality with much greater fluctuations. In short, countries with lower inequality levels also had

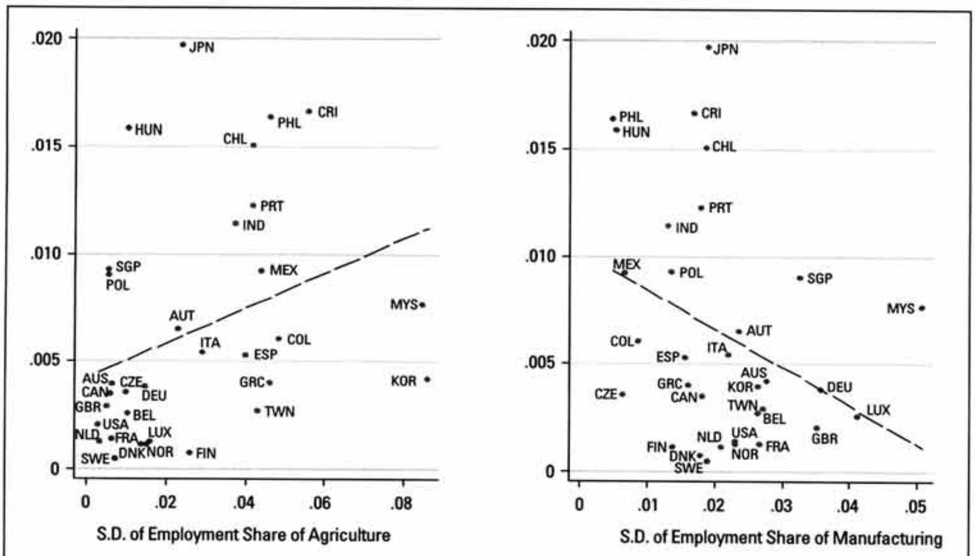
Figure 4. Mean and Standard Deviation of UTIP-UNIDO Inequality, 1963-2002



* Bar indicates 1 standard deviation across years

** Cross line indicates overall mean

Figure 5. Change of Employment Share of Agriculture and Manufacturing and Change of UTIP-UNIDO Theil Inequality, 1979-2002



* Bar indicates 1 standard deviation across years

** Cross line indicates overall mean

lower rates of change over time, whereas countries with higher inequality levels had higher rates of change.

Figure 5 combines the variability of inequality and the employment share of agriculture and manufacturing.[4] The variability of agriculture's employment share means the degree of shrinkage in agriculture, since the average share of agriculture has consistently decreased. Although the pattern is not so linear, it does indicate that countries with greater variability in the employment share of agriculture have experienced greater variability in inequality change. Furthermore, countries with greater variability in manufacturing employment share have had smaller variability in inequality change, which indicates some connection between intersectoral transition and inequality dynamics.

REGRESSION MODELS WITH USUAL ASSUMPTIONS

The relationship between UTIP-UNIDO inequality measures and several covariates was parametrically estimated to explain the behavior of inequality across countries and over time. Following Galbraith and Kum (2005), variables included in this analysis were GDP per capita in log term (ln_gdppc) and its square (ln_gdppc2), openness of the economy measured as the percentage of GDP (open), investment share of GDP (invest), percentage of people over 65 (oldpop), and manufacturing employment share out of population (mnfemp).[5] The World Development Indicators (World Bank 2007) and Penn World Table 6.2 (Center for International Comparisons 2006) are the data sources for these covariates; 2,607 observations for 86 countries that have at least 20 annual observations in the 1963-2002 period were used.

The rationale for using these covariates is straightforward. It has been a long tradition going back to Kuznets that inequality is related to income in quadratic form. Thus, GDP per capita and its square term were employed for nonlinear behavior of inequality. Kuznets proposed the inverted-U curve, but as Galbraith and Kum (2003) and Galbraith (2008) pointed out, a downward pattern with an upward tail at the high end is also possible. So the precise form is an object of empirical investigation. Openness and investment share in the GDP were employed to control for the economic factors that could affect the manufacturing industry and external terms of trade. A negative influence of investment share on inequality was expected, but the effect of openness

4. Indonesia, Bolivia, Ireland, and Hong Kong have been dropped as outliers.
5. The model specification follows the one in Galbraith (2008) and Galbraith and Kum (2005).

was not clear a priori. The share of the elderly in total population and the employment share of manufacturing in population were included to reflect demographic and economic structural change in a society. Our main interest is in the latter.

It is obvious that the importance of the manufacturing sector in total economic activity varies widely from place to place in the course of economic development. The ratio of manufacturing employment to population, however, provides a crude but effective measure of the relative size and importance of manufacturing, and conversely of the relative size and importance of the service and agriculture sectors. Furthermore, since manufacturing tends to be more heavily unionized than the other sectors, and since industrialization is associated historically with the development of the middle-class working population, we expect higher shares of manufacturing employment in population to be associated with lower inequality. With the same logic, however, for the elderly population share positive sign is expected.

The basic specification of the model is as follows:

$$Y_{ij} = \beta_1 + \beta_2 X_{2ij} + \beta_3 X_{3ij} + \beta_4 X_{4ij} + \beta_5 X_{5ij} + \beta_6 X_{6ij} + \beta_7 X_{7ij} + \varsigma_{1i}\varsigma_{2j} + \varepsilon_{ij}$$

where i and j indicate country and year respectively, and each X is a covariate; X_2 is GDP per capita in log term and X_3 is its square term, X_4 is openness, X_5 is investment share, X_6 is manufacturing employment share, and X_7 is older population share. For each explanatory variable, the corresponding regression coefficient will be estimated. Y is an inequality index, the UTIP-UNIDO Theil measure. The peculiar point in this specification is that there are two additional error terms: ς_{1i} and ς_{2j}, for country-specific (i) effects and year-specific (j) effects differentiated from the usual residual error (ε_{ij}). Since data consist of clusters of repeated inequality measures in the same country over time, it is unreasonable to assume that each inequality in the same country is independent. Also, since the behavior of inequality in each country is not deterministic, statistical models that allow the effects of either country or year to vary by specifying the two-way error-components have been heavily specified in the literature (Baltagi 2005).

The model assumes that the residual error ε_{ij} includes both the interaction between year and country and any other effect specific to country i in year j, and ς_{1i} and ς_{2j} are uncorrelated with the residual error (ε_{ij}), and they are all normally distributed. Furthermore, each error component is assumed to be independent, and the total variance is the sum of the variance components conditional on included covariates.

$$Var(y_{ij}) = Var(\beta + \varsigma_{1i} + \varsigma_{2j} + \varepsilon_{ij}) = Var(\varsigma_{1i} + \varsigma_{2j} + \varepsilon_{ij}) = \varphi_1 + \varphi_2 + \theta$$

where φ_1 is the between-country variance, φ_2 is the between-year variance, and θ is within-country (or -year) variance. Depending on the assumption about the features of these error terms, fixed effects models and random effects models could be estimated.

Random effects (or random intercept) models assume that the random effects have zero means and are correlated neither with each other nor with the covariates in the model, which leads to the efficient estimator. Fixed effects models, however, do not take the orthogonality of ς_{1i} and ς_{2j}, which are uncorrelated with the included covariates. For this reason, it is necessary to treat them as additional constant terms for each country and/or year for the consistent estimator.[6]

But a more important point is that both the fixed effect model and the random effect model produce consistent estimates if the model is correctly specified. If there is a violation, such as some correlation between the random effects (or random intercept) and any of the covariates in the model, the estimates from the random effect model become inconsistent, whereas those from the fixed effects model remain consistent. This is because the random effects estimator is a weighted average of the between and within estimators,[7] and implicitly assumes that the between and within effects of the covariates are the same ($\beta^W = \beta^b = \beta^{true}$). If this assumption is not held, for instance, the between effects differ from the within effects due to the omitted country-specific variables, and estimates from the random effects model are different from those of the fixed effects model. This is why the Hausman specification test, even though it has limited power,[8] gets into this picture to examine the relevancy of the random and fixed effects estimators.[9]

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6. This leads the fixed effects model to be frequently termed the least-squares dummy variable (LSDV) model.
7. The between-effects estimator uses averages of the response and explanatory variables for each country over the years in a regression model. Thus, any information from the within-country variability is omitted, and only between-country variability is used in estimation. The within-effects estimator uses all deviation values from the respective country's mean in the regression model. Since only variability within country is left, this model is identical to the LSDV except for the grand intercept. It can show simply using a GLS estimator for the random effects model such that $\beta_{GLS} = (W + \omega^2 B)^{-1}(\omega^2 B\beta_B + W\beta_W)$, where W and B are matrix versions of the within-cluster and between-cluster sums of squares of the covariates respectively, and ω is the variance ratio of the within and between estimators.
8. The Housman test is known to be only sensitive to certain model misspecifications, so caution is needed.
9. For more information on the fixed effects model and random effects model, see Wooldridge (2002).

Table 1. Results of Fixed and Random Effects Models

	(1) OLS Ln_Theil	(2) Fix-one Ln_Theil	(3) Ran-one Ln_Theil	(4) Fix-two Ln_Theil	(5) Ran-two Ln_Theil
ln_gdppc2	-0.036	-0.174	-0.152	-0.144	-0.133
	(2.63)**	(7.62)**	(6.95)**	(6.48)**	(6.38)**
ln_gdppc	0.758	3.09	2.719	2.312	2.164
	(3.21)**	(7.79)**	(7.18)**	(5.87)**	(5.94)**
open	0.001	0.001	0.001	0.0001	0.0001
	(5.33)**	(2.74)**	(3.32)**	(0.38)	(0.49)
invest	-0.014	-0.008	-0.011	-0.0004	-0.003
	(7.85)**	(3.91)**	(5.19)**	(0.2)	(1.57)
mnfemp	-0.252	-0.268	-0.314	-0.159	-0.208
	(9.32)**	(8.10)**	(9.99)**	(4.93)**	(6.81)**
oldpop	-0.076	0.064	0.035	0.028	0.006
	(14.31)**	(5.65)**	(3.41)**	(2.43)*	(0.6)
constant	-5.651	-16.449	-14.491	-12.22	-11.328
	(5.69)**	(9.59)**	(8.89)**	(7.03)**	(7.14)**
obs.	2607	2607	2607	2607	2607
countries		86	86	86	86
R-squared	0.38	0.07		0.17	
log likelihood			-1658.37		-1571.43
RE_SD(country)			0.717		0.636
RE_SD(year)					0.191
RE_SD(resid)			0.425		0.404
RE_SD(gdppc)					

Absolute value of t or z statistics is given in parentheses.
* significant at 5%; ** significant at 1%

Table 1 reports the results of the estimation. Column 1 is a result of the pooled-OLS model for overall reference for comparison, and columns 2 to 5 are results of the fixed effects model and the random effects model with one-way and two-way respectively. In every specification, the coefficients for both GDP per capita and its square term were significant at the 5% level, indicating an inverted-U shape. With regard to the range of GDP per capita, however, as the model under consideration is moving from the one-way fixed effects model (column 2) to the two-way random effects model (column 5), the turning points of the inverted-U curve gradually shift to the left, indicating that more and more predicted values are placed on the downward portion of the curve across the models. Hausman's specification test, however, indicates that the estimates from the random effects model are inconsistent.

The main indicator of economic structural change is significant. The sign of the estimated coefficient for manufacturing employment share is negative, as expected in all models with variations of specification (fixed and random or one-way and two-way). That is, the effect of manufacturing employment share on inequality is robust in terms of magnitude and statistical significance across models. Elderly population share, an indicator of demographic change, is estimated to have a significant positive effect on inequality, but the magnitudes of the estimated coefficients across the model are decreasing. The estimated coefficient of investment share is negative in all models but not significant when year-effects are included. Openness is estimated to have positive and statistically significant effects on inequality only when country-specific effects are considered, but the magnitude is very small.

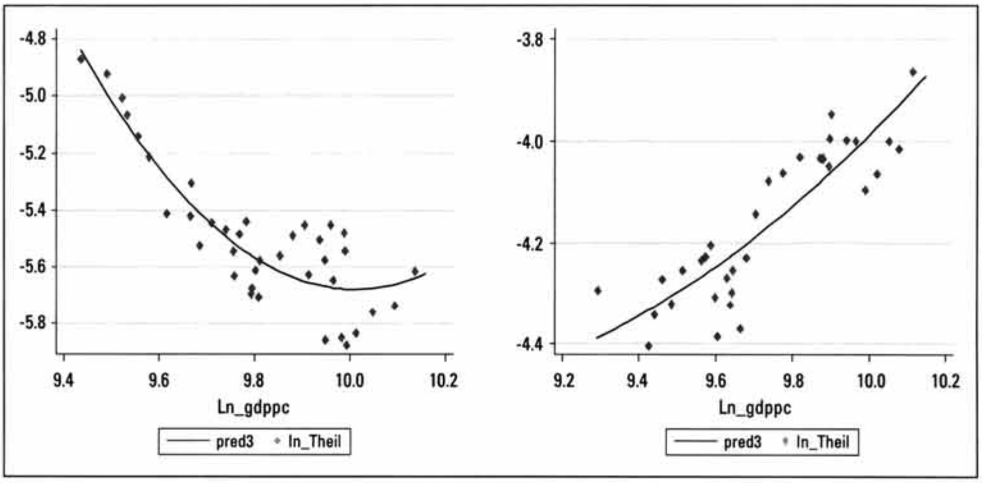
The random effects models provide additional parameter estimates, that is, estimated residual standard deviation (RE_SD). In a two-way random effects model (column 5), the estimated residual standard deviation between countries is 0.64, which is smaller than that of the one-way random effects model (0.72) in column 3. Also, the estimated residual standard deviation between years is 0.19, and the remaining residual variability, not due to additive effects of countries and years, is 0.4. Based on these estimated residual standard deviations, the intra-class correlation of countries given a year can be calculated as 0.67, and the intra-class correlation of years given a country as 0.06. That means there is a much higher correlation over years within a country than over countries within a year, given the covariates. In other words, the change of inequality within country is relatively small, while the differences in inequality between countries are relatively large. This confirms the conventional wisdom, which says that the variations of inequality across countries are larger than those from across years (Li, Zou, and Squire 1997; Goesling 2001; Korzeniewicz and Moran 1997; Schultz 1998). It also suggests that the effects of covariates on inequality across countries could be different rather than uniform.

REGRESSION MODEL WITH A NEW ASSUMPTION

This reasoning leads us to suspect the validity of the assumption that the country-specific regression lines are parallel with common time-specific effects in the additive sense. Since we have allowed the country-specific effects and year-specific effects to vary randomly but only as part of error terms, they would not affect the major relationship between inequality and covariates in the model. Thus, it is possible to assume that countries would differ in their overall rate of inequality change according to their GDP per capita in addition to random intercept.

Simple comparison shows this point clearly. If the relationship between inequality and covariates (GDP per capita, for instance) is estimated for each country separately, the result can be depicted as is done for Sweden and the United Kingdom in figure 6. Then we can see that the relationship for each country is different, but we cannot take any advantage of cross-country variations. Also, the small number of observations for each country allows us a limited degree of freedom in statistical inference.

Figure 6. Predicted and Observed Inequality against GDP per Capita (Sweden and United Kingdom)



This deficiency can be overcome through the following model:

$$Y_{ij} = (\beta_1 + \varsigma_{1i}) + (\beta_2 + \varsigma_{2j})X_{2ij} + \beta_3 X_{3ij} + \beta_4 X_{4ij} + \beta_5 X_{5ij} + \beta_6 X_{6ij} + \beta_7 X_{7ij} + \varepsilon_{ij}$$

where a random intercept (ς_{1i}), a deviation of country i's intercept from the global mean intercept β_1, and a random slope coefficient for GDP per capita (ς_{2j}), a deviation of country j's slope from the global mean slope β_2, are included. With this specification, it is assumed that a country-specific slope of GDP per capita is not parallel to the average (or grand) slope, while we still assume that the random intercept and slope coefficient have a bivariate normal distribution with zero mean and uncorrelated with ε_{ij}. Put simply, we would like to estimate the covariability of the slope of GDP per capita and intercept with respect to inequality rather than grand slopes of GDP per capita and varying intercepts. The estimated coefficients are reported in table 2 with those of the previous random effects model for comparison.

Table 2. Results of Random Effects and Random Coefficient Models

	(1) OLS Ln_Theil	(3) Ran-one Ln_Theil	(5) Ran-two Ln_Theil	(6) Ran-coeff Ln_Theil
ln_gdppc2	-0.036	-0.152	-0.133	-0.284
	(2.63)**	(6.95)**	(6.38)**	(6.22)**
ln_gdppc	0.758	2.719	2.164	4.718
	(3.21)**	(7.18)**	(5.94)**	(5.93)**
open	0.001	0.001	0.0001	0.001
	(5.33)**	(3.32)**	(0.49)	(2.11)*
invest	-0.014	-0.011	-0.003	-0.002
	(7.85)**	(5.19)**	(1.57)	(1.15)
mnfemp	-0.252	-0.314	-0.208	-0.149
	(9.32)**	(9.99)**	(6.81)**	(4.13)**
oldpop	-0.076	0.035	0.006	0.089
	(14.31)**	(3.41)**	(0.6)	(6.08)**
constant	-5.651	-14.491	-11.328	-22.812
	(5.69)**	(8.89)**	(7.14)**	(6.47)**
obs.	2607	2607	2607	2607
countries		86	86	86
R-squared	0.38			
log likelihood		-1658.37	-1571.43	-1402.26
RE_SD(country)		0.717	0.636	0.712
RE_SD(year)			0.191	0.024
RE_SD(resid)		0.425	0.404	0.005
RE_SD(gdppc)				0.084

Absolute value of t or z statistics is given in parentheses.
* significant at 5%; ** significant at 1%

A likelihood test was performed to see whether the random coefficient model fit better than the random effects model, and the test showed confirmative for this specification. That is, compared with the one-way random effects model (labeled 3) and two-way random effects model (labeled 5), the random coefficient model (labeled 6) improved log likelihood from -1,658 and -1,571 to -1,402 respectively. This indicates that the inclusion of random slopes makes the model fit better. The sign and the magnitude of the estimated coefficients were similar to those of the previous models and all were statistically significant, which indicates the robustness of the relationship between inequality and the covariates. Also, the estimated residual standard deviation decreased from 0.425 (labeled 3) and 0.404 (labeled 5) to 0.029, again reflecting the better fit of the inequality change trajectories with random slope.

CONCLUSION

This paper has presented and summarized the cross-country variability of inequality dynamics in the years 1963-2002, and has shown the relationship between inequality and indicators of structural change for 42 countries during this period. As a general conclusion, inequality appears closely related to the sectoral share of employment in the overall state of economic development. Further, it is clear that countries with high inequality experience much more variability of inequality than countries with low inequality. This finding appears robust even with various assumptions on the cross-country variability in intercept and coefficients of covariates.

Another objective of this paper is to make clear the logic of fixed and random effects model specifications. Since this model appears to be a standard form of model specification on cross-country studies, it is better to understand the basic assumptions of the model and the pros and cons it conceives. This paper has also tried to emphasize the importance of robustness in statistical estimates with respect to the changes of assumptions, factors, and observations. Only the aspect of model specifications on robustness check was pursued here, but other issues should also be further investigated. Finally, previous findings of a Kuznets relation and a global pattern in the evolution of inequality seem to be relevant, though the future direction is hard to predict at this moment.

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