ESTIMATING THE LONG RUN RELATIONSHIP BETWEEN INCOME INEQUALITY AND ECONOMIC DEVELOPMENT

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Abstract

The relationship between income inequality and economic growth has been one of the most studied questions in the field of economics in recent years. Despite of this there is very little knowledge on the effect on income inequality to long-run growth. This paper addresses that issue using new measure of income inequality and panel data cointegration methods. Results imply that negative effect of income inequality on long-run growth is a dominant feature, but in some countries the effect of inequality is positive. Observed heterogeneity in the long-run effect also explains the controversial findings made on the short-/medium term effect.
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1 Introduction

The decades long empirical research on the relationship between income inequality and economic development has produced controversial results, with the direction and the statistical significance of the effect on income inequality to economic growth changing between studies. Some form of non-linearity between the variables, omitted-variables bias, inconsistent measure of income distribution, and flaws in the estimation procedure have usually been suggested

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as reasons for the controversy (Barro 2000, Banerjee & Duflo 2003, Forbes 2000, Malinen 2007). In theoretical literature the endogeneity of income inequality in growth regressions has usually been suggested as a reason for the controversy in empirical studies (Benabou 2005). The data on income distribution has also commonly been unevenly distributed among nations and over time. This has led studies trying to assess the time trend or effect on inequality to some other variable to use only a subset of the data or some form of interpolation between sparse observations. Especially the effect of income inequality on long-run economic growth has remained an open question mostly due to insufficient data on income distribution.

Fortunately, James Galbraith and Hyunsub Kum (2004) have gathered a Gini-index that has a consistent, long time series for several countries. Recent developments have also provided some insight on to what might be biggest contributor to the controversy. Deininger and Squire's (1996) Gini index, which has been used as a proxy on income distribution in many of the most cited studies in the field, has received serious criticism concerning its accuracy and consistency (Atkinson & Brandolini 2001, Hyunsub & Kum 2004). A more detailed analysis shows that Deininger and Squire's (1996) Gini index is very likely to be inconsistent and flawed.

Within the last decade or so there has been a growing interest towards incorporating time series analysis methods to analysis of panel data. Growing volume of time series data on many different countries has led to a intensive testing of macroeconomic theories with panel data. Although the panel unit root and panel cointegration tests have been intensively studied, their use in macroeconometric studies have been limited. Their restrictions and the somewhat immature theory of the inference in cointegrated panels have also limited the use of panel data time series methods in econometrics. However, the developments in the theory and methods on the analysis of panel data already enable the use of panel data time series analysis within a general economic framework. Many of the problems encountered in empirical studies on the relationship between income inequality and economic development can be approached with time series methods.

In previous studies, economic growth rates averaged over 5-10 years have usually been regressed against Gini index to find out the effect on income inequality to economic development (Barro 2000, Forbes 2000, Chen 2003). This has provided estimates only on the short- or medium term growth elasticity of income inequality. To find out the long term growth elasticity of income inequality, averages of 20 years or more would have to be used. These multidecade averages would lose a lot of information, and the risk of spurious parameter estimates would be great, because there would be no control for possible structural changes in the relation between income inequality and economic development. Thats why we could learn more on factors affecting on the long-run growth by using the original version of the production function where GDP is stated in levels. Unfortunately this brings out a new dilemma, if estimated function includes cointegrating relationships between GDP and explanatory variables.

The inference and estimation in panel cointegrated data differs from that in regular time series, because the asymptotic properties of the estimators of the regression coefficients in panel cointegrated regression models are different from those in time series cointegrated regression models (Baltagi 2008, Phillips and Moon 1999). The time series regression may be spurious, while the panel regression utilising all cross sections is not (Phillips and Moon 1999). Many estimators are also inconsistent in panel cointegrated data, including OLS and (by definition) the standard GMM estimator (Baltagi 2008). However, Choi (2002) has shown that an instrumental variables estimation can be used to consistently estimate nearly integrated panel data.

According to panel unit root tests both the EHII2.1 Gini index and GDP series seem to follow a $I(1)$ process in countries in question. The possible cointegration between EHII2.1 Gini index and GDP is tested with Pedroni's (2004) panel cointegration tests. According to it the Gini and GDP series seem to be cointegrated of order one.

Results obtained using average growth rates of 15-30 years in cross-country estimation imply that income inequality has no general statistical linear long run effect on GDP. According to panel estimation inequality has a negative statistically linear effect on long-run growth in developed economies. However, the results of the sensitivity analysis show that the effect on Gini to long-run growth is negative in majority of countries, but there are also few countries in which the effect of Gini to GDP was positive. This does, on its part, explain the controversy of the results of previous studies.

This paper is organized as follows. Section 2 presents the theories that have mostly been used to explain the long-run dependency between income inequality and economic development. Section 3 presents the data and conducts panel unit root and cointegration tests. Estimation details and results are given in section 4 and section 5 concludes.

2 The theoretical effects on income inequality to long run growth

Credit market imperfections have an effect on growth rates by limiting the division of labor (Fishman & Simhon 2002). When credit-market imperfections are present, people cannot borrow against future incomes. Generally this will affect on the level of education that household can acquire. As the growth enhancing effect of education is delayed due to the fact that schooling takes time, credit market imperfections may result to lower long-run growth rates. When credit market imperfections are present the initial level of capital and income inequality will determine the level of specialization. When level of capital in the economy is small, unequal income distribution will encourage capital owners to invest in specialization. This will lead to higher level of division of labour and to higher economic growth. When the level of capital in the economy is large, more equal distribution of incomes will lead to wide based demand for goods and to higher level of division of labour. Because educating workforce takes many years, changes in income inequality has an delayed effect on the level of specialization and on economic growth.

Unequal incomes may also result to an unstable sociopolitical environment. This will diminish investments and economic activity. Unequal incomes also usually have more destabilizing effect on society developed economiesw, where money is highlighted as a norm of success (Merton 1938). Usually this effect takes a long time to materialize, because societal changes are gradual.

Income inequality may decrease fertility and accumulate less human capital (De La Croix and Doepke 2004). Growing income inequality may also increase pressured to use redistributive taxation. This might lower consumption and deter investments. Because societal changes are slow, this effect takes a long time to materialize. Effect may also be worse in developing economies (Benhabib & Rustichini 1996).

3 Time series analysis of panel data

3.1 Data

There are 60 countries in EHII2.1 data set where the time series for Gini index is consistent and at least 20 years long. Gross domestic product is stated in real terms with the base year of 1996. Investments are gross investments as a portion of the GDP. The data on GDP and investments is from Penn World Tables (Heston et al. 2006). The EHII2.1 Gini index is from the University of Texas Inequality Project (UTIP) (Galbraith & Kum 2004). Male-education is from World Bank series.

Many of the previous studies made on the relationship between inequality and economic development have used the Deininger and Squire's (1996) Gini index as a measure on income distribution. These include Barro (2000), Banerjee and Duflo (2003), Forbes (2000), and Chen (2003). The main reason why so many researchers have relied on the Deininger and Squire's Gini index has been its alleged "high quality". However, as pointed out by Atkinson and Brandolini (2001, p. 780), Deininger and Squire's dataset includes so many different datasets that in many cases it would be "highly misleading to regard the Deininger and Squire's "high quality" estimates as a continuos series". This is also clearly illustrated in the study by Galbraith and Kum (2004). The different country-related datasets in Deininger and Squire's "high quality" dataset may also not be comparable with each other (Atkinson & Brandolini 2001). These are serious problems for estimation, because the statiscal inference requires that observations are from the same parent population. If the observations are not comparable, there is no one coherent parent population and the parameter estimates will be spurious.

The problems concerning the accuracy and consistency of Deininger and

Squire's "high quality" estimates can best be demonstrated with the help of some examples.[1] The time series of Deininger and Squire's "high quality" Gini index for Denmark, Norway, and India are presented in figure 1. The first thing that attracts attention are the wild changes in the values of Gini in Norway. The value of Gini drops by 6 points between the years 1976-79, and elevates almost 3 points between the years 1984-86. Why would a Nordic Welfare State have experienced such a violent changes in its income distribution, when there were no major economic or societal developments or crisis during those eras?

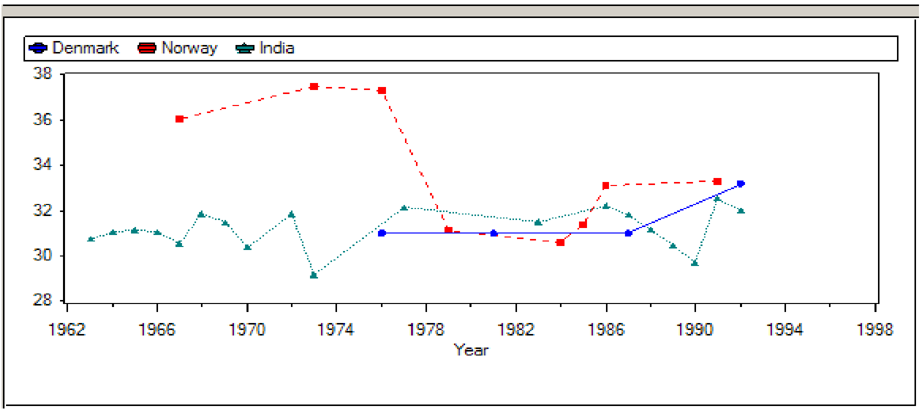

Figure 1. Values of Deininger and Squire's "high quality" Gini index for Denmark, Norway, and India

There is, however, far more stranger result present in figure 1. According to Deininger and Squire's Gini index, India had a more equal income distribution than Norway in the 1960s, 1970s, and 1990s, and a more equal income distribution than Denmark in the beginning of 1990s. This result is highly questionable, because India's level of poverty was one of the highest in developing economies in the 1990s, and the level of poverty had clearly declined from the 1970s (Justino 2007). Both Norway and Denmark also had highly progressive taxation and extensive publicly financed social services already in the 1970s.

For comparison, the time series of EHII2.1 Gini index for Denmark, Norway,

[1] All the values presented here are from the updated version of Deininger and Squire's dataset.

and India are presented in figure 2. The changes in the series are gradual as it should be with a slowly changing societal variable like income distribution in the absence of economic or other crises. Values of India's Gini index are also clearly above those of Denmark and Norway, which is reasonable concidering the differences in the level of economic development and poverty (Justino 2007). The effect of the economic downturn in Nordic countries in the beginning of the 1990s is also present in both series.[2]

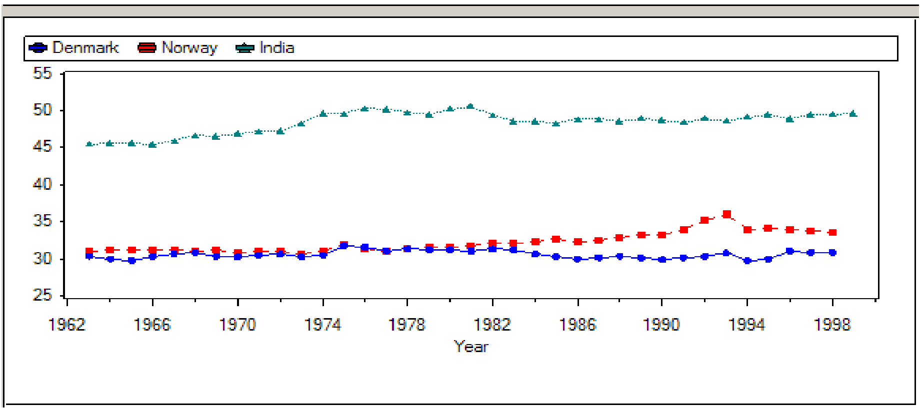

Figure 2. Values of EHII2.1 Gini index for Denmark, Norway, and India

As pointed out by Atkinson and Brandolini (2001) the most severe problem in Deininger and Squire's "high quality" dataset is its inconsistency. Like in Norway there are many other countries, which, according to Deininger and Squire's Gini index, encounter some rather aggressive changes in their income distribution within a relative short time periods.

Figures 3, 4, and 5 plot the time series of Deininger and Squire's "high quality" and EHII2.1 Gini indexes for Australia, Canada, and Sri Lanka. As in Norway, the changes in the values of Deininger and Squire's Gini in Australia

[2] Aaberge et al. (1997) argue that very generous unemployment benefits, different type of unemployment compared to many previous economic downturns, and methods used to calculate Gini index have probably contributed on the small changes in the income distribution in Denmark and Norway during the economic downturn in the beginning of 1990s. In other Nordic countries, i.e. Finland and Sweden, the economic downturn and the growth of unemployment were more severe.

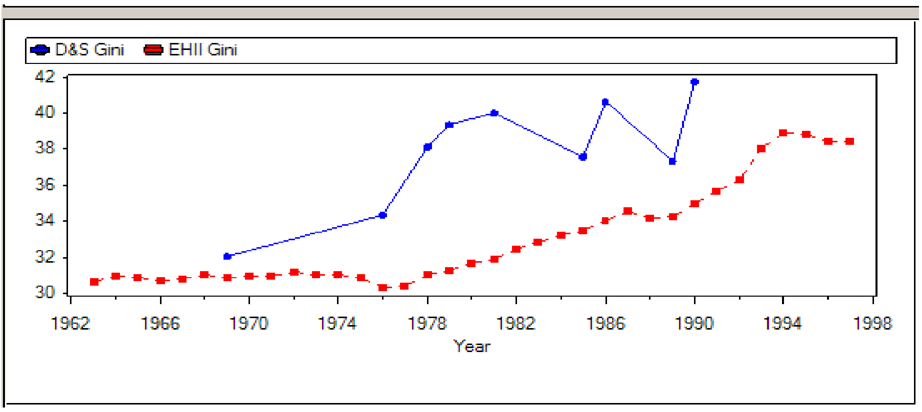

Figure 3. The values of Deininger and Squire's "high quality" and EHII2.1 Gini index for Australia

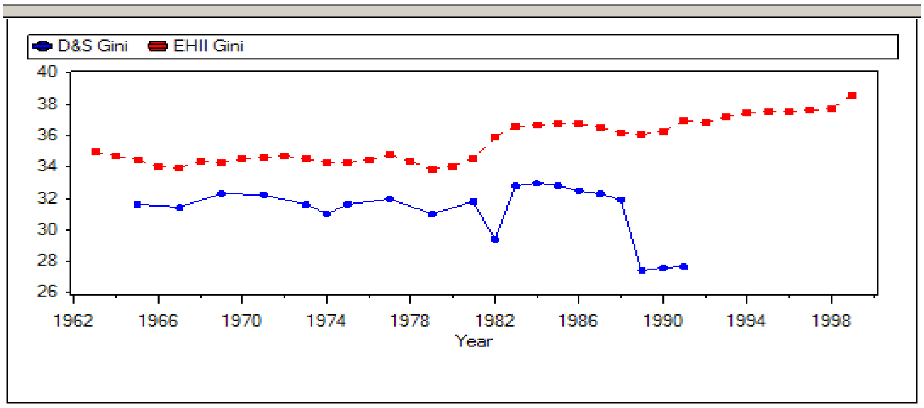

Figure 4. The values of Deininger and Squire's "high quality" and EHII2.1 Gini index for Canada

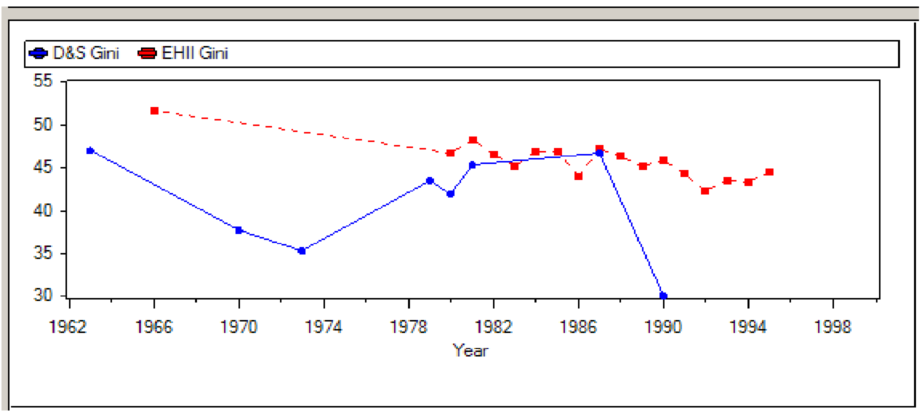

Figure 5. The values of Deininger and Squire's "high quality" and EHII2.1 Gini index for Sri Lanka

and Canada are doubtful. However, even more peculiar is the behaviour of the time series of Deininger and Squire's Gini in Sri Lanka. The value of Sri Lanka's Gini index plummets by 16 points between the years 1987 and 1990. During that period Sri Lanka was at war with the Tamil Tigers. Despite of it economy grew relatively fast with an average growth of 4.5 percent per annum, and there were no major changes in the tax or redistribution policies (Gunatilaka & Chotikapanich 2005). So, there should be no reason for the Gini index to suddenly plummet by 16 points, unless the indicator of income distribution has changed. This is actually just what has happened. In all of the previous "high quality" observations for Sri Lanka, incomes in Deininger and Squire's dataset were measured per household and by income surveys. In 1990 the incomes were measured per person and by expenditure surveys.[3]

In the light of the criticism presented on Deininger and Squire's "high quality" Gini index, it seems highly likely that many of its values are flawed, and the studies that have used it as a measure on income distribution are subject to errors. Atkinson and Brandolini (2001, p. 795) suggest that the construction of secondary data-sets "should be cumulative, with data from earlier data-sets only being excluded on grounds of inadequate quality". This is just what has been done in EHII2.1 Gini index. Galbraith and Kum (2004) have regressed Deininger and Squire's Gini coefficients on the values of explanatory variables, which include the different income measures of Deininger and Squire's data set, the set of measures of the dispersion of pay in the manufacturing sector, and the manufacturing share of the population. Unexplained variations in Deininger and Squire's income measures are treated as inexplicable, and they are discarded from the calculations of EHII2.1 Gini coefficients. According to Galbraith and

[3]The Deininger and Squire's "high quality" data uses the same income measures in Australia, Canada and Norway, and so the heterogeneity of income measures does not explain the variation in their Gini indexes.

Kum (2004) EHII2.1 Gini has three clear advantages over the Deininger and Squire's Gini index. It has more than 3000 estimates, while Deininger and Squire have only about 700 "high quality" estimates. EHII2.1 borrows its accuracy from the Industrial data published annually by the United Nations Industrial Development Organization (UNIDO). This way changes over time and differences across countries in pay dispersion are reflected in income inequality. All estimates are also adjusted to household gross income, which makes them congruent. Values of the EHII2.1 also correspond to the estimates of income distributions of other research institutes, such as the OECD, better than those of Deininger and Squire's Gini index (Föster & Pearson 2002, Galbraith & Kum 2004).

3.2 Panel unit root tests

Most of the time series analysis methods for panel data assume that there are no cross-unit cointegration relationships between series. When dealing with economic variables, this restriction is quite uncomfortable, because for example business cycles do usually transfer to neighboring countries quite easily in modern open economies. However, according to simulation tests it is still possible to obtain robust results from panel unit root and cointegration tests even in the presence of cross-unit cointegration (Banerjee et al. 2004, Banerjee et al. 2005).

All the panel unit root tests used in this study are based on the following regression:

$$\triangle y_{it} = \rho_i y_{i,t-1} + \delta_i + \eta_i t + \theta_t + \epsilon_{it}, \tag{1}$$

where δ_i are the individual constants, $\eta_i t$ are the individual time trends, and θ_t are the common time effects (Banerjee et al. 2005). All tests rely on the assumption that $E[\epsilon_{it}\epsilon_{js}] = 0 \; \forall \; t, s$ and $i \neq j$, which is required for the calculation of common time effects (Banerjee et al. 2005). The null hypothesis in all the tests is $H_0 : \rho_i = 0 \; \forall \; i$, but the tests have different assumptions about the heterogeneity of ρ. The inclusion of individual constants and time trends is also optional, but Breitung's (2000) test requires that individual trends are included.

Two different types of panel unit root tests are used. Levin, Lin and Chu (2002) (LLC), and Breitung tests assume a common unit root process, i.e. $\rho_i = \rho \; \forall \; i$. Im, Pesaran, and Shin (2003) test (IPS) and Fisher type ADF and PP tests, presented by Maddala and Wu (1999), allow for a individual unit root processes.[4]

There were 60 countries in the original dataset. After panel unit root tests 5 countries were discarded from the set because their series of Gini index did not follow a $I(1)$ process according to individual ADF tests. Descriptive statistics of the remaining 53 countries are presented in table 1 and country list of the 53 countries are presented in appendix 1.

Table 1: Descriptive statistics

variable	mean	std. deviation	min.	max.
GDP	6624.25	6740.03	145.24	43138.33
GDP growth (%)	2.533	4.860	-26.774	56.074
Gini index	39.571	6.631	23.074	58.975
investments (%)	18.112	8.525	0.191	52.531
male-edu (%)	24.204	15.633	0.700	78.900

Summary of the results of the five panel unit root tests are presented in table 2.[5] Individual trends and constants are included in the tests for GDP and Gini. For GDP it is natural to allow for both individual time trends and constants, because the time series of GDP usually follows a clear upward trend. The time series of Gini seems also to be trending in many countries,[6] and so it is also

[4] ADF and PP tests present also individual panel unit root test statistics. These were used to find the countries with stationary series of GDP and/or Gini index from the original set of countries.

[5] All the test were performed with Eviews 6.

[6] The time series were inspected visually.

allowed to have individual time trends. GDP growth and investments seem not to exhibit a trend, and so only individual constants are included in their tests.[7]

Table 2: Panel unit root tests

variable	LLC	Breitung	IPS	ADF	PP
log(GDP)	9.068	4.091	15.092	15.855	16.072
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
GDP growth	-24.486*	-	-25.639*	780.589*	788.040*
	(<.0001)		(<0.0001)	(<.0001)	(<.0001)
Gini	0.937	4.522	3.054	75.303	69.356
	(0.8256)	(1.0000)	(0.9989)	(0.9895)	(0.9977)
investments	-6.171*	-	-7.681*	247.757*	218.019*
	(<.0001)		(<.0001)	(<.0001)	(<.0001)

Probabilities of the test statistics are presented in parentheses. All tests include individual effects and trends except the test for GDP growth and investments which include only individual effects. * denotes the rejection of unit root hypothesis at 5
percent or smaller probability. The values of Breitung's test for DGP growth and investmens are missing, because Breitung's test requires the inclusion of individual trends.

According to all five tests the logarithmic GDP and Gini index seem to follow a $I(1)$ process, and the series of GDP growth and investments seem to be stationary. However, as mentioned above, it is highly likely that at least some of the series tested have cross-sectional cointegrating relations between them. This would violate the assumption of uncorrelated residuals among cross-sections, i.e. $E[\epsilon_{it}\epsilon_{js}] = 0 \ \forall \ t, s$ and $i \neq j$. Banerjee et al. (2005) have studied the effect of the violation of the assumption of no cross-unit cointegration to rejection frequencies of the null hypothesis. Their results show that in the presence of cross-unit cointegration ADF, PP, and IPS tests grossly overreject the null hypothesis of unit root with relatively small T and large N dimension of data. But, as all the unit root tests presented in table 2 accept the null hypothesis in the series of Gini index and GDP, they seem very likely to be unit root processes.[8]. Accordingly the rejection frequency of the LLC test was found to be fairly close

[7]If individual trends are included, the results change only marginally and both series are still stationary according to all five tests.

[8]First differenced series are stationary according to all panel unit root tests. The series of GDP and Gini index seem thus to be $I(1)$

to the 0.05 limit in the presence of cross-sectional cointegration with small T and large N dimensions of data. Thus the GDP growth and investments series can be assumed to be stationary with relative certainty.

3.3 Panel cointegration tests

The test for cointegration between Gini index and GDP is performed with Peter Pedroni's (2004) panel cointegration test, which consist of seven different test statistics. Pedroni´s panel cointegration test is based on a model:

$$y_{it} = \alpha_i + \delta_i t + \beta_i X_{it} + \epsilon_{it}, \tag{2}$$

where α_i:s and δ_i:s allow for member specific fixed effects and deterministic trends, X_{it} is an m-dimensional column vector of explanatory variables, and β_i in an m-dimensional vector for each member i. The disturbances are assumed to be independent and indentically distributed. The variables y_{it} and X_{it} are assumed to be integrated of order one. Thus, under the null of no cointegration the residual e_{it} will also be $I(1)$.

The model for testing the cointegration between Gini index and GDP is:

$$\log(GDP_{it}) = \alpha_i + \delta_i t + \beta_i Gini_{it} + \epsilon_{it}, \tag{3}$$

where the changes in GDP is explained by the changes in the Gini index and $E[\epsilon_{it}\epsilon_{js}] = 0 \ \forall s, t, i \neq j$. Model is extremely simple because Pedroni's test statistics does not identify the cointegrating relations. Pedroni's test only shows are there any cointegrating relations between variables in question, but does not tell how many cointegrating vectors there are and to which explanatory variable the cointegrating vectors are related. If there were additional variables in equation 2, there would be no way to tell are the possible cointegrating vectors related to Gini index. Results of the Pedroni's panel cointegration tests on equation 3 are presented in table 3.[9]

Table 3: Pedroni's panel cointegration test statistics for log(GDP) and Gini index

Within-dimension				
	statistic	prob.	weight. statistic	prob.
panel v-statistic	53.124	$<$.0001	47.575	$<$.0001
panel rho-statistic	6.519	$<$.0001	6.506	$<$.0001
panel PP-statistic	2.746	0.0092	2.836	0.0071
panel ADF-statistic	1.927	0.0624	2.113	0.0428
Between-dimension				
	statistic	prob.		
group rho-statistic	7.919	$<$.0001		
group PP-statistic	4.341	$<$.0001		
group ADF-statistic	1.346	0.1612		
countries	53			
observations	1998			

Within-dimension tests presuppose common AR coefficients among cross sections. Between-dimension presupposes individual AR coefficients.

According to 9 of the 11 test statistics presented in table 3 the series of Gini and GDP are cointegrated.[10] As with panel unit root tests, the presence of cross-sectional cointegration may have affected the results. However, according to Banerjee et. al. (2004) panel v, panel ρ, and panel PP-statistics perform well in the presence of cross-sectional cointegration even with relatively small T and N dimensions of data. Because all these test statistics reject the hypothesis of no cointegration, Gini index and GDP seem very likely to be cointegrated.

4 Estimation

4.1 Estimation using average growth rates

One of the major problems in empirical macroeconomics has been the lack of consistently measured data. In growth regressions the growth rate has usually

[9] The test is performed with Eviews 6.

[10] When values of the non-logarithmic GDP are used, 7 of the 11 test statistic find the Gini index and GDP to be cointregated.

been averaged over 5 years or more to eliminate the possible business cycles, which has also removed the need for consistently measured data. Five year business cycle "smoothing" is usually appropriate, because it is short enough to capture the possible structural changes appearing in the relation. Use of 5 year intervals has meant that estimated coefficients have represented short or medium term effects. The estimation of long run elasticities of growth would require that averages of 20 years or more would have to be used.

Here, average growth rates of 30 and 15 years are used. The risks related to use of multidecade averages in estimation are clear. When the dependent variable is averaged over long period of time, it loses a lot of information in estimation and the risk for spurious regressions is high, because there is no control over the possible changes in the relation between dependent and explanatory variable(s). It is also problematic for statistical inference to assume that the changes in some variable in one year would affect to some other variable for the next 20 years or more.

Two models are estimated. Both models are Barro-type extended versions of the neoclassical growth model:

$$\begin{aligned} growth30y_i = \alpha + \beta_1 log(GDP_{i,t-1}) + \beta_2 investments_{i,t-1} \\ + \beta_3 Gini_{i,t-1} + \beta_4 male-edu_{i,t-1} + \epsilon_i \end{aligned} \tag{4}$$

$$\begin{aligned} growth15y_{it} = \alpha + \beta_1 log(GDP_{i,t-1}) + \beta_2 investments_{i,t-1} \\ + \beta_3 Gini_{i,t-1} + \beta_4 male-edu_{i,t-1} + \epsilon_{it} \end{aligned} \tag{5}$$

Equation 4 is a cross-country estimation, while equation 5 is a panel estimation. All the countries whose 30 year average growth rate was negative, are discarded from the set. If country has experienced deceleration in GDP in 30 year period it is highly likely that this has resulted from some structural factors rather than changes in explanatory variables presented in equations 4 and 5. Results of estimation of equations 4 and 5 are presented in table 4.

Table 4: Regression results using 30 year growth rates

Dependent var.:	Growth 30y	Growth 30y	Growth 30y	Growth 15y
Constant	2.0746	8.6923	8.5074	0.9796
	(1.5427)	(4.5477)	(4.3789)	(5.0564)
log(GDP)	-	-0.5956	-0.6514	-0.0145
		(0.3918)	(0.4395)	(0.5022)
investments	0.0266	0.0395	0.0382	0.1045
	(0.0258)	(0.0277)	(0.0274)	(0.0578)
Gini index	-0.0082	-0.0712	-0.0614	-0.0319
	(0.0293)	(0.0485)	(0.0465)	(0.0638)
Male education	-	-	0.0105	0.0299
			(0.0179)	(0.0566)
estimator	OLS	OLS	OLS	GMM
countries	47	47	47	63
periods	1	1	1	2
observations	47	47	47	100
Hansen test	-	-	-	5.94 (11)

The estimated period is 1971-2000. Standard errors are presented in parentheses. Hansen stands for Hansens test for overidentifying restrictions and the number of instruments is presented in parentheses. All OLS estimations are done using White heteroskedasticity-consistent standard errors and covariances. First, second, and third lags of first difference are used as instruments for explanatory variables in GMM estimation.

None of the parameter estimates is statistically significant, although the parameter estimate of domestic investments in GMM estimation is quite close to the 5% limit with the estimated p-value for the regression coefficient being 0.074.

To test for possible structural breaks in the relation between economic growth rate and explanatory variables two different cross-country regression are performed. The estimated model is:

$$\begin{aligned} growth15y_i = \alpha + \beta_1 log(GDP_{i,t-1}) + \beta_2 investments_{i,t-1} \\ + \beta_3 Gini_{i,t-1} + \beta_4 male - education_{i,t-1} + \epsilon_i \end{aligned} \tag{6}$$

Model is estimated in two different periods. Explanatory variables from 1970 are regressed againts the average growth rate between 1971 and 1985, and explanatory variables from 1985 are regressed againts the average growth rate between 1986-2000. Table 5 reports the results. The countries with a negative average growth rate were discarded from the estimation.

Table 5: Regression results using two different 15 year periods

Dependent var.:	Growth 1971-85	Growth 1986-2000
Constant	8.3563	8.7065
	(4.8280)	(5.5209)
log(GDP)	-0.9162*	-0.9524
	(0.4506)	(0.4817)
investments	0.0745*	0.0747*
	(0.0221)	(0.0334)
Gini index	-0.0211	-0.0207
	(0.0601)	(0.0540)
male education	0.0077	0.0522*
	(0.0199)	(0.0243)
estimator	OLS	OLS
observations	43	56

Standard errors are presented in parentheses. All estimations are done using White heteroskedasticity-consistent standard errors and covariances. * denotes that the parameter estimate is statistically significant at 5% or smaller probability.

In the period 1971-1985 logarithmic GDP and domestic investments parameter estimates were statistically significant. In the period 1986-2000 parameter estimates of domestic investments and male-education were statistically significant, and the parameter estimate of logarithmic GDP was very close to the 5% limit (p-value 0.0534). Thus, there seems to some convergence at least in the period 1971-1985 within the 43 countries.

The effect of domestic investments on growth is almost the same in the two different periods with the value of the parameter estimate being 0.0745 in 1971-85 and 0.0747 in 1986-2000. Still, its parameter estimate in regression using 30 year averages is not statistically significant. So, even when there seems to be no structural breaks in the relation between explanatory and dependent variable the estimation using 30 year averages gives "plurry" estimates.

4.2 Estimation using GDP levels

4.2.1 Estimation and inference in cointegrated panels

Conventional limit theorems assumes one index to pass to infinity. The limit theory for panels with large n and T needs to allow both indexes to pass to infinity. This has some profound effects for estimators. For example OLS becomes inconsistent in panel cointegrated data, which is a sharp contrast to consistency of OLS in cointegrated time series data (Baltagi 2008). The possible endogeneity of regressors has also restricted the development of consistent and unbiased estimators for cointegrated panel data. Standard GMM estimator is also inconsistent if the underlying series of dependent variable or instruments include unit root processess (Binder et al. 2005).[11]

However, Choi (2002) has shown that an instrumental variables estimation can be used to consistently estimate nearly integrated panel data. In Choi's model the DGP is assumed to follow a one-way error component model of the form:

$$y_{it} = \alpha + \beta_1 x_{1it} + \beta_2 x_{2it} + u_{it}, i = 1, ..., N; t = 1, ..., T, \tag{7}$$

where $k_1 \times 1$ vector x_{1it} is $I(0)$, the $k_2 \times 1$ vector x_{2it} is $((I - exp(C_{x2i}/T)L)x_{2it} = \epsilon_{x2it}$, i.e. $I(0)$ but *nearly* nonstationary, and u_{it} is the $I(0)$ disturbance term.

The disturbance term is assumed to be decomposed as

$$u_{it} = \mu_i + v_{it},$$

where μ_i is an unobservable random variable of individual effects and v_{it} is a common disturbance term. The structure of v_{it} may be of $AR(p_i)$ form:

[11] This includes the Arellano and Bond's (1991) GMM estimator.

$$v_{it} + \rho_{i1} v_{i(t-1)} + ... + \rho_{ip_1} v_{i(t-p_i)} = w_{it},$$

where w_{it} is a white noice process with variance σ_w^2, $(0 < \sigma_w^2 < \infty)$, or a more general (e.g. linear) structure. All the roots of the characteristic equation $1 + \rho_{i1} z + ... + \rho_{ip_i} z_i^p = 0$ are assumed to lie outside unit circle for all i. This implies that

$$s_{pi} = \sum_{k=0}^{p_i} \rho_{ik} > 0, \ (\rho_{i0} = 1).$$

The autoregressive coefficients and orders are allowed to be heterogenous across individuals.

Explanatory variables are assumed to be endogenous:

$$E(x_{1it} v_{it}) \neq 0 \text{ and } E(\epsilon_{x_{2it}} v_{is}) \neq 0,$$

for some t and s. It is assumed that a $I(0)$ vector z_{1it} of size l_1, and a nearly nonstationary $((I - exp(C_{x2i}/T)L) z_{2it} = \epsilon_{z_{2it}}$, and $\epsilon_{z_{2it}} \sim I(0))$ vector of size l_2 are available as instruments. Instruments should satisfy the conditions

$$E(z_{1it} v_{it}) = 0 \ \forall t$$

and

$$E(\epsilon_{z_{2it}} v_{is}) = 0 \ \forall t, s,$$

which state that lags of x_{1it} may be used as instruments, but z_{2it} should be strictly exogenous.

Additionally, it is assumed that:

1. (a) $E(\mu_i) = 0$ and $0 < Var(\mu_i) = \sigma^2_\mu < \infty \ \forall i$
   (b) $E(\mu_i v_{jt}) = 0 \ \forall i, j$ and t.
2. Let $\Psi_i = (x'_{1it}, z'_{1it}, \epsilon'_{x_{2it}}, \epsilon'_{z_{2it}}, w_{it})^T_{t=1}$.
   Then $\Psi_1, ..., \Psi_N$ are independent.

Assumption 1 is required only for the IV-GLS estimator, because Within estimation eliminates the individual effects μ_i. Assumption 2 enables the use of central limit theorem and the law of large numbers to the weak limits of the time series sample moments (which are obtained by sending T to infinity) by sending N to infinity (sequential limits). Within these conditions, and when N is large, the use of central limit theorem and the law of large numbers leads to asymptotic normality result for the panel IV-estimators.

4.2.2 Estimation and results

As was shown in subsection 4.1, the estimation using multidecade averages loses a lot of information and may result to large standard errors of parameter estimators. Best way to mitigate these problems is to use the GDP level instead of the rate of GDP growth as a measure of economic development, and estimate time series within each cross-section.

The estimated model is a simplified version of the neoclassical growth model presented in equations (4) and (5):

$$log(GDP_{it}) = \alpha + \beta_1 investments_{it} + \beta_2 Gini_{it} + u_{it}, \tag{8}$$

where annual values of GDP are regressed against annual values of investments and Gini index, and $u_{it} = \mu_i + v_{it}$ ($\mu_i \sim i.i.d.$ and $v_{it} \sim i.i.d.$). Domestic investments is assumed to be stationary and Gini index is assumed to be *nearly* nonstationary, i.e. $(I - exp(C_{Gini_i}/T)L)Gini_{it} = \epsilon_{Gini_{it}}$. Both variables are assumed to be endogenous, i.e. $E(investments_{it}v_{it}) \neq 0$ and $E(Gini_{it}v_{it}) \neq 0$. The income, profits, and capital taxes as a percent of GDP and government size on GDP are used as instruments for the Gini-index. Data on taxes is from the Global Development Network's Growth Database and the data on government size is from Penn World tables.

Taxes on income, profits and capital usually lowers the disposable incomes of the rich. As such taxes do even out the distribution of incomes even without the possible income transfers to lower income brackets. Larger proportion of government on the GDP usually means that government uses more money on health care, social services etc. This will even out the distribution of incomes. [12]

The proportion of taxes on GDP should also not be directly related to the level of GDP, because there is no clear economic "rule" for the correct level of taxation in different levels of economic development. On the contrary, some economic theories argue that the low level of taxation is the most growth enhancing policy in any phase of economic development. The heterogeneity in the levels of income taxation is confirmed by the data. For example in 1998 tax on income, profits, and capital was 14.2 percent on GDP in South Africa, 8.9 percent in Norway, 6.8 percent in Iceland, 4.5 percent in Germany, and 8.1 percent in Lesotho. Government size should also not be determined by the level of GDP. In 1998 the government size on GDP was 18.7 percent in Bolivia, 13.7 in Canada, 21.2 percent in Ecuador, 11 percent in the United States, 12.1 percent in Zimbabwe, 19.2 percent in Senegal, and 19.85 percent in Finland. Therefore, it is assumed that both instruments are not affected by the level of GDP, i.e. they are strictly exogenous.

[12] This could, of course, also mean that the money goes to some activity that does not even the distribution of incomes, e.g. spending on military. However, it is assumed here that *in general* government size implies the money spend in some redistributive functions.

Instruments need also have a consistent time dimension. Consistent time series for taxes between the years 1972-1996 is available for 22 of the 53 countries tested in section 3. Consistent time series for government size between the years 1972-1994 is available for 38 of the 53 countries tested in section 3 and for 24 countries for the time period 1963-1996. Country lists are presented in appedix 1. Instruments for Gini index should also be *nearly* nonstationary, and this is tested with the five tests used in section 3. According to PP tests the series of taxes of income, profits, and capital as a percent of GDP seem to follow a unit root process in countries in question. But, according to LLC, IPS, Breitung and ADF tests the series does not follow a unit root process. According to LLC, Breitung, and IPS tests the time series of government size follows a unit root process, but the ADF and PP tests reject the unit root hypotheses at the 5 percent level. These results leave some reasong for a doubt, but at least the series of government size seems to be a unit root process, and so we rely more on it.

Estimation is first performed by using just government size as an instrument for the Gini index to increase the time dimension and the number of countries included in estimation. First estimation includes the years 1963-1996. The first, second, and third lags of investments are used as instruments for investments, and GLS and Within-GLS estimators use cross-section weights, and the error structure of v_{it} in equation (8) is assumed to be $AR(1)$ form. Table 6 presents the results of OLS and feasible instrumental variables GLS and Within-GLS estimations of equation (8).

The estimated AR process is *nearly* nonstationary in all estimations. The parameter estimate of investments is statistically significant only in the OLS estimation. The different sign of the parameter estimate of investments in GLS and Within-GLS estimations implies that that the unobserved country-effect might correlate with investments. Thus, the results obtained with Within-GLS estimation can be concidered to be more reliable. The parameter estimate of Gini index is negative in all estimations, but statistically significant only in the OLS and GLS estimation.

To increase the number of countries included in the next estimation the time dimension is diminished to 25 years. The estimation now covers the years 1972-1996. As lagged instruments decrease the actual periods included in estimation, only first and second lags are used as instruments for investments. This should be enough for the identification because the series of investments was found to be a stationary in section 3.1. The last Within-GLS estimation uses the same set of countries as estimations presented in table 6. Table 7 presents the results.

The estimated AR process is nearly nonstationary in all estimations. The parameter estimate of investments is positive and statistically significant in OLS and Within-GLS estimations, but in GLS estimation it is negative and not statistically significant. As mentioned above this probably results from the

Table 6: Estimates of the long run effects of Gini index I

Dependent variable: log(GDP)				
	OLS	GLS	Within-GLS	
constant	16.442*	22.971*	15.886*	
	(1.2974)	(5.5801)	(3.0889)	
investments	0.0077*	0.0030		0.0039
	(0.0007)	(0.0045)	(0.0022)	
Gini index	-0.0053*	-0.0879*	-0.0526	
	(0.0014)	(0.0163)	(0.0295)	
AR process	0.9911*	0.9930*	0.9863*	
	(0.0014)	(0.0032)	(0.0046)	
countries	24	24	24	
years	31	31	31	
observations	792	744	744	

Standard errors are presented in parentheses. First, second, and third lag are used as instruments for investments. The government size is used as instruments for Gini index. * denotes that the parameter estimate is statistically significant at 5 percent or smaller probability.

correlation between unobserved country-specific effect and investments. The parameter estimate of Gini index is negative and statistically significant in all estimations. Interestingly, the parameter estimate of investments become statistically significant in the set of 24 countries when the first 8 years are dropped from estimation (63-71). This implies that there might have been some developments in the world that have affected on growth beyond these explanatory variables during that era. These may include the Vietnam war and civil unrest experienced in many developed nations.

Next, estimation is performed by using both taxes and government size as instruments for Gini index. Table 8 presents the results.

The estimated AR process is nearly nonstationary in all estimations. The parameter estimate of investments is positive in all estimations and statistically significant in all Within-GLS estimations. The not statistically significant parameter estimate on the GLS estimation probably, once again, results from the correlation between unobserved country-specific effect and the instruments of investments. The parameter estimate of Gini index is negative and statistically

Table 7: Estimates of the long run effects of Gini index II

Dependent variable: log(GDP)				
	OLS	GLS	Within-GLS	Within-GLS
constant	12.749*	18.216*	12.593*	12.489*
	(0.460)	(2.310)	(1.050)	(1.829)
investments	0.0048*	-0.0096	0.0062*	0.0063*
	(0.0008)	(0.0114)	(0.0023)	(0.0024)
Gini index	-0.0100*	-0.0871*	-0.0529*	-0.0498
	(0.0016)	(0.0299)	(0.0200)	(0.0356)
AR process	0.9814*	0.9869*	0.9620*	0.9617*
	(0.0021)	(0.0039)	(0.0044)	(0.0071)
countries	38	38	38	24
years	25	25	25	25
observations	912	874	874	552

Standard errors are presented in parentheses. First and second lag are used as instruments for investments in the second and third estimation. The last Within-GLS estimation uses also the third lag.. The government size is used as instruments for Gini index. * denotes that the parameter estimate is statistically significant at 5 percent or smaller probability.

significant when government size is used as its instrument. This enforces the view presented in the beginnig of section that taxes on income, profits, and capital might not be a suitable instrument for Gini index.

4.3 Sensitivity analysis

Because this is a first study presenting these results, some test of robustness of the results is reguired. One of the most studied questions in modern macroeconometric studies is the possible nonlinearity in the relation between growth and different explanatory variables in countries in different stages of economic development. Some studies have found that growing inequality would enhance short-/medium term growth in developing economies and diminish it in developed economies or *vice versa* (Barro 2000, Malinen 2007).

To make the estimation of groups asymptotically feasible, i.e. to make the groups large enough, countries are somewhat artificially divided to four groups: Countries whose income per capita was over $4000 in 1972 (rich), countries whose GDP per capita was under $2000 in 1972 (poor), countries whose GDP

Table 8: Estimates of the long run effects of Gini index III

Dependent variable: log(GDP)				
	Within-GLS	Within-GLS	GLS	Within-GLS
constant	13.830*	10.515*	15.026	13.238*
	(1.556)	(1.493)	(1.050)	(1.296)
investments	0.0082*	0.0076*	0.0007	0.0097*
	(0.0034)	(0.0024)	(0.0073)	(0.0029)
Gini index	-0.0737*	-0.0023	-0.0766*	-0.0628*
	(0.0299)	(0.0326)	(0.0188)	(0.0256)
AR process	0.9658*	0.9578*	0.9752*	0.9639*
	(0.0055)	(0.0049)	(0.0041)	(0.0048)
instruments	gs.	tax	tax & gs.	tax & gs.
countries	20	20	20	20
years	25	25	25	25
observations	460	460	460	460

Standard errors are presented in parentheses. First and second lags are used as instruments for investments. Taxes on income, profits, and capital as percent on GDP (tax) and government size (gs) are used as instruments for Gini index. * denotes that the parameter estimate is statistically significant at 5 percent or smaller probability.

per capita was between \$2000 and \$4000 in 1972 (middle-income), and to countries whose GDP per capita was under \$1000 in 1972 (very poor). Table 8 presents the results of Within-GLS estimation of equation 8.

Table 9: Effects of Gini index in different income groups

Dependent variable: log(GDP)				
	very poor	poor	middle-income	rich
constant	9.539*	9.468*	14.648*	11.983
	(1.0121)	(1.1098)	(2.2304)	(0.7564)
investments	-0.0041	-0.0058	0.0090*	0.0081*
	(0.0054)	(0.0058)	(0.0040)	(0.0023)
Gini index	-0.0128	-0.0079	-0.0784*	-0.0357*
	(0.0222)	(0.0247)	(0.0326)	(0.0163)
AR process	0.9486*	0.9424*	0.9721*	0.9536*
	(0.0063)	(0.0060)	(0.0096)	(0.0044)
countries	12	19	13	11
years	25	25	25	25
observations	276	437	299	253

Standard errors are presented in parentheses. First, and second lags are used as instruments for investments. Government size is used as instrument for Gini index. * denotes that the parameter estimate is statistically significant at 5 percent or smaller probability.

Estimated AR processes is nearly nonstationary in all groups. The parameter estimate of Gini index was negative in all groups, but statistically significant only in middle-income and rich economies. The parameter estimate of investments is positive and statistically significant in the middle-income and rich economies, but negative and not statistically significant in poor and very poor economies. This a somewhat odd result, because it implies that domestic investments would have no effect on the long run development of poor economies. However, if the estimated period is transformed to include only the years 1985-1996 the parameter estimate of investments becomes positive and statistically significant in the poor and very poor economies and the parameter estimate of Gini index becomes positive and statistically significant in very poor economies. In the period 1972-1985 both parameter estimates are negative and not statistically significant. This strange result may, at least in some part, be explained by the fact that many of these countries were planning economies before 1980s. In a planning economy governments make investment decisions in which case the most of the reguired "saving" for investments is done by the state. Because of this, changes in income distribution have a limited effect on the level of savings and investments. Investments may also be used as a political tool in planning economies. If the level of investments is too high compared to the level of demand for goods, then the excess capital may cause the growth to stagnate. Planned economy is also very rigid, which may cause risk-aversion.

Recently, there has been a growing concern about the possible heterogeneity bias in growth regression (Hineline 2007). If there are some individual or time-specific effects that exist between statistical or time-series units that are not captured by the explanatory variables the intercepts or slopes or both may be heterogenous between statistical units (Hsiao 2003). In these cases the obtained parameter estimates would be meaningless. To check this, individual parameter estimates of Gini index must be obtained. The problem with the traditional time series analysis methods is the lack of power in small samples, like the maximum sample of 37 years used in this study. However, although the power of the test will be low, the Johansen's cointegration test can be used to estimate the individual long run cointegrating coefficients between Gini index and GDP to test the results obtained in this study.

The results of the standard Johansen's cointegration tests for Gini index and logarithmic GDP for 40 countries are presented in table 10. In 13 of the 53 series tested in section 3 the vector autoregressive model's autocorrelations could not be eliminated, and their results are not present in table 10.[13] In 9 of the series the inclusion of investments as a exogenous explanatory variable led

[13] Johansen's cointegration test is based on the uncorrelatedness of residuals, and autocorrelated residuals would lead to a biased parameter estimates.

to autocorrelated residuals, and so in these the investments are discarded from the test. In 38 of the series the cointegrating relation between Gini index and GDP was trending, and so a deterministic trend was added to the Johansen's test. The assumption of *trending* cointegrating relation is reasonable, because the *non-trending* cointegrating relation would mean that the values of Gini index and GDP have moved to the same direction, or that the relation has changed.[14] If GDP, for example, is trending upwards, Gini index cannot follow it indefinitely, because there is a upper limit in Gini index, where all the wealth within nation is in the hands of one individual. However, within this relatively short time period it is quite possible that the series of GDP and Gini have moved to same direction, which may explain the observed *non-trending* cointegrating relation in some series. Also, if the values of Gini index and/or GDP have not increased or decreased, then the cointegrating relation can naturally be *non-trending*.

In majority of countries presented in the tables 10 and 11 the cointegrating coefficient of Gini index was negative. However, in 12 of the 40 series the long run effect of Gini to GDP was positive, and negative in the 28 series. In many countries the standard errors of the estimators are also quite small, which indicates that most of the estimated long run equilibrium relations are statistically robust. The coefficient of Gini index is statistically significant in 32 countries, and in 24 of these the coefficient is negative. This shows that the slopes of the parameter estimates of Gini index are heterogenous across the panel.

To find out the possible effect of the initial level of inequality on the sign of the coefficient of Gini index, the mean of Gini index in different income groups is calculated. The mean of the initial level of inequality was 44,49 in very poor

[14] This could also mean that there was a structural break in one or both series.

Table 10: The individual cointegrating coefficients of Gini index I

Dependent variable: log(GDP)					
	Gini	Trend	Inv.	Trace pr.	M-e pr.
Very poor:					
Bangladesh	0.1222* (0.0352)	No	Exog.	0.6452	0.5607
Bolivia(+)	-0.0889* (0.0301)	Yes	Exog.	0.0395	0.1058
Ecuador(+)	-0.1535* (0.0149)	Yes	Exog.	0.0742	0.0395
Egypt	-0.0572* (0.0211)	Yes	-	0.1855	0.1493
India(+)	0.5168* (0.1364)	Yes	Exog.	0.1076	0.2132
Indonesia(+)	0.4039* (0.1038)	Yes	Exog.	0.1643	0.2517
Madagascar(+)	-0.1328* (0.0297)	Yes	Exog.	0.1586	0.0814
Malaysia(+)	-0.2421* (0.0917)	Yes	-	0.0097	0.0117
Philippines(+)	-0.1686* (0.0293)	Yes	Exog.	0.2461	0.2077
Senegal	-0.0661* (0.0263)	Yes	-	0.4016	0.6177
Syrian A. R.(+)	-0.0727* (0.0168)	Yes	Exog.	0.3836	0.3100
Turkey	0.2267* (0.0599)	Yes	Exog.	0.0363	0.0501
N=12					
Poor:					
Colombia(+)	-0.3853* (0.0484)	Yes	Exog.	0.0152	0.0202
El Salvador(+)	0.0010 (0.0488)	Yes	Exog	0.3646	0.4439
Macao	-0.0162* (0.0049)	Yes	-	0.1204	0.0772
Mexico(+)	-0.1761* (0.0854)	Yes	Exog.	0.1021	0.2266
Nicaragua(+)	-0.0069 (0.0395)	Yes	Exog.	0.8333	0.7724
Panama(+)	-0.0760* (0.0067)	Yes	Exog.	0.0556	0.0547
Venezuela(+)	-0.0784* (0.0094)	Yes	Exog.	0.6419	0.3843
N=7					

Standard errors are presented in parentheses. Trace pr. and M-e pr. are the probabilities of rejection of no cointegration hypothesis in Trace and Maximum-eigenvalue tests. Trend describes the trend specification made on the cointegration relation. Inv. describes is investments included as exogenous variable or not included at the test. * denotes that the coefficient is statistically significant at 5% or smaller probability.

Table 11: The individual cointegrating coefficients of Gini index II

Dependent variable: log(GDP)					
	Gini	Trend	Inv.	Trace pr.	M-e pr.
Middle-income:					
Barbados(+)	-0.1565* (0.0545)	Yes	Exog.	0.9944	0.9978
Chile(+)	-0.0048 (0.0073)	Yes	Exog.	0.0338	0.0239
Finland	-0.1393* (0.0188)	Yes	Exog.	0.9436	0.9954
Greece(+)	-0.2407 (0.2785)	Yes	-	0.0124	0.0064
Hong Kong	-0.0311 (0.0091)	Yes	Exog.	0.0002	0.0001
Ireland	-0.0461* (0.0167)	Yes	Exog.	0.3148	0.3168
Israel	0.1482* (0.0665)	Yes	Exog.	0.3862	0.3301
Italy(+)	-0.8547* (0.3107)	Yes	-	0.5993	0.7247
Japan	-0.1563* (0.0412)	Yes	Exog.	0.0461	0.1258
Singapore(+)	-0.0940 (0.0099)	Yes	Exog.	0.2919	0.1447
Spain(+)	0.0099 (0.0723)	Yes	Exog.	0.3333	0.5758
N=10					
Rich:					
Australia	-0.1066* (0.0091)	Yes	Exog.	0.0040	0.0005
Austria	-0.0813* (0.0246)	Yes	Exog.	0.0024	0.0003
Belgium	0.1181* (0.0250)	Yes	Exog.	0.1953	0.0412
Canada(+)	-0.5400* (0.1616)	Yes	-	0.4624	0.4061
Germany	0.2442* (0.0423)	Yes	Exog.	0.0052	0.0247
Kuwait(+)	0.4109 (0.2141)	No	Exog.	0.4726	0.8093
New Zealand(+)	-0.0406* (0.0060)	Yes	Exog.	0.0347	0.0158
Norway	-0.6520* (0.1448)	Yes	Exog.	0.4980	0.2274
Sweden	0.0048 (0.0238)	Yes	-	0.0336	0.0321
UK	0.1631* (0.0321)	Yes	Exog.	0.3246	0.3091
USA(+)	0.0677 (0.0513)	Yes	-	0.0078	0.0335
N=11					

Standard errors are presented in parentheses. Trace pr. and M-e pr. are the probabilities of rejection of no cointegration hypothesis in Trace and Maximum-eigenvalue tests. Trend describes the trend specification made on the cointegration relation. Inv. describes is investments included as exogenous variable or not included at the test. * denotes that the coefficient is statistically significant at 5% or smaller probability.

economies, 41,27 in poor economies, 38,98 in middle-income economies, and 34,09 in rich economies in 1970. The countries whose Gini index was above these thresholds are marked with (+). In developing economies the effect of initial inequality seems to be mixed, but in the middle-income and rich economies all countries who had a statistically significant positive cointegrating coefficient of Gini index are below this limit. It thus seems that the initial level of income inequality defines the extent of the positive effect of income inequality on long-run growth in developed economies. However, the negative cointegrating coefficient is clearly a dominant feature in developed economies. This implies that there may be some other factor dividing developed countries to economies who can benefit from greater income inequality, given that the initial income distribution is equal enough, and to economies where income inequality has a negative effect on long-run growth despite the initial level of income distribution.

5 Conclusions

Results show that the distribution of incomes and economic development are integrated, but they also open new questions on the direction of the effect of income inequality has on economic development. The effect of income inequality on of economic development was negative in majority of countries, but the effect was also positive in some countries. In developed economies all robust positive effects of inequality were restricted to those countries whose initial level of income inequality was below the mean of inequality of their income groups. This implies that the effect of income inequality may be restricted by the initial level of inequality in more developed economies. In many developed economies with a negative effect of income inequality on economic development the initial level of inequality was very equal, and in developing economies the initial level of inequality did not have an effect on the sign of the coefficient of inequality. Thus, there seems to be some factor determining the influence that initial income distribution can have on the effect on income inequality to economic growth.

There are several restrictions that have to be attached to the results. Sample selection bias, omitted-variables bias, and measurement errors may have affected the results. In statistical studies based on insufficient data availability for random sampling there is always the possibility of systematic errors. There were, for example, only two Sub-Saharan African countries and only one country from the former Eastern bloc included in estimations. Estimated equation was also very simple including just two explanatory variables. Several countries were discarded from the sensitivity analysis because their vector autoregressive model's autocorrelations could not be eliminated. This implies that there may have been explanatory variables missing from the estimation. Although the EHII2.1 Gini index is clearly more consistent measure of income distribution than Deininger and Squire's Gini index, it is still just a representation of statistical summaries. Thus, the level of inequality given by EHII2.1 Gini may not have represented the true level of inequality in the countries in question.

Results show that future research should concentrate on understanding the different cultural, institutional, socio-political, and/or economical factors that contribute to the inequality-growth nexus. Observed heterogeneity also explains, at least to some degree, the highly conflicting results reported in previous studies, although the short or medium term effect of income inequality on economic growth may differ from the long-run effect.

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7 Appendix

Table 12: Country list I

Country	observations
Australia	35
Austria	37
Bangladesh	21
Barbados	28
Belgium	30
Bolivia	30
Canada	37
Chile	37
Colombia	37
Cyprus	37
Denmark	36
Ecuador	37
Egypt	36
El Salvador	28
Fiji	23
Finland	36
Germany	25
Greece	37
Hong Kong	27
Hungary	30
India	37
Indonesia	29
Ireland	36
Israel	34
Italy	32
Japan	37
Korea, Republic of	37
Kuwait	38
Macao	20
Madagascar	22
Malaysia	32
Malta	27
Mauritius	32
Mexico	30
Netherlands	37
New Zealand	34
Nicaragua	21
Norway	36
Panama	32
N=39	

Observations notifies the maximum number of simultaneous observations in the series of Gini and GDP.

Table 13: Country list II

Country	observations
Papua New Guinea	20
Philippines	35
Portugal	27
Senegal	24
Singapore	37
Spain	37
Sweden	37
Syrian Arab Republic	36
Taiwan	25
Turkey	36
UK	32
USA	37
Uruguay	23
Venezuela	29
N=14	

Observations notifies the maximum number of simultaneous observations in the series of Gini and GDP.