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GROWTH AND INEQUALITY: IS THERE ANY CLEAR-CUT RELATIONSHIP?

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ABSTRACT: *Theory predicts complex and multidimensional relationships between inequality and growth. Indeed, previous studies on inequality and growth using various estimation techniques, inequality measures, country samples and time frames have found conflicting results ranging from positive , negative, non-linear to insignificant and inconclusive relationships. In this study, we follow the model of Forbes (2000) to examine whether or not inequality affects growth. With the newly improved inequality data provided by the University of Texas Inequality Project (UTIP, 2013), we used the System-GMM to estimate the relationship in a panel of 65 countries over the period 1965-2005 on 5-year interval. We found a positive but statistically insignificant co-efficient of inequality on growth.*

KEYWORDS: Growth, Inequality, Income Distribution, System GMM.

INTRODUCTION

Whether or not countries with more equal income distributions grow faster than those that are less egalitarian has remained a fundamental question in economic research. Theory predicts complex and multidimensional relationships between inequality and growth. Indeed, previous empirical studies on inequality and growth using various estimation techniques, inequality measures, country samples and time frames have found conflicting results ranging from positive, negative, non-linear to insignificant and inconclusive relationship.Several reasons may account for why one theoretical question might lead to conflicting empirical evidences. These include the quality of data set used, the model specification used to examine the relationship, control variables included, country samples and the time frame examined whether long-run, medium or short-term.

In this study, we follow the model of Forbes (2000) to examine whether inequality affects growth. With the newly improved inequality data provided by the University of Texas Inequality Project (UTIP, 2013), we used the System GMM developed by Arellanoand Bover (1995) and Blundell and Bond (1998)to estimate panel data on 65 countries over the period 1965 – 2005 on 5-year interval. We found a positive but statistically insignificant co-efficient of inequality on growth. Also, in a non-linear specification, both squared and cube inequality variable has no impact on growth. These findings show that various theoretical links through which inequality affects growth are counter-acting; the relationship between inequality and growth is linear.

The rest of this paper is organised as follows. Section 2 provides a summary of the literature review and theoretical underpinnings for the study. Section 3 discusses data selection and methodology for the study. In section 4, the estimated results were presented while section 5 discusses the findings of the work. Section 6 highlights the implication of the work for research

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and practice by sensitivity analysis. In section 7, summary of the findings of the research was presented and section 8 concludes the paper by indicating other areas for future research work.

LITERATURE/THEORETICAL UNDERPINNING

Literature Review

There have been various studies on the relationship between income inequality and growth. However, they have failed to come to a consensus on the direction of income inequality impact on economic growth. In this section, we examine the findings of previous empirical studies on the relationship between growth and inequality.

Classical Studies on Growth-Inequality Nexus

Classical economists like David Ricardo and Karl Marx were concerned with the central role that resource distribution played in the process of growth. Distribution was viewed as an outcome of the opposing forces and interests of the various economic entities that made production possible. They were concerned about theoretical explanation of political laws governing the distribution of economic output (Atkinson, 1997). Kuznets (1955) seminal work was the first major attempt to explain the relationship between inequality and economic growth postulating that if inequality between sectors was more substantial than that within each sector, then in the process of growth, inequality would first rise – as people moved across sectors - and then fall, as most of them found themselves in the new sector, or the economy reached a point where factor movement was equalizing returns across sectors. This is the stylized Kuznets 'inverted-U' curve (Ferreira, 1999). Though these studies laid foundations for much more research to be done on inequality and growth, their results did not predict precisely how a unit change in inequality would impact growth and so, lack quantitative policy implications.

Pre-Deininger and Squire Dataset Studies

Neoclassical economists presented their works without much regards to the heterogeneity in resource endowments of economic agents in the dynamism of the growth process by simply analysing the economic behaviour of homogenous "representative agent". Despite the seemingly departure from growth-inequality nexus to theoretical expositions based on the idea of the homogenous representative agent, the quest to establish the link between inequality and growth was revived in early 1990s. While it can be argued that many economists worked on this area almost simultaneously, credit must be given to Galor and Zeira (1993) who concluded that "the distributions of wealth and income are very important from a macroeconomic point of view. They affect output and investment in the short and in the long run and the pattern of adjustment to exogenous shocks. It is, therefore, our belief that this relationship between income distribution and macroeconomics will attract more studies in the future" (1993, p.51).

Post-Deininger and Squire Dataset Studies

Earlier studies before the Deininger and Squire (D&S) data set on this relationship are highly suspicious. Weede (1997) questioned the robustness of their findings. In 1996, a milestone achievement in the study of growth-inequality nexus was made with the compilation of the 'high quality' inequality data set of Deininger and Squire (1996) concerning inequality levels. Subsequently, a number of studies have been carried out using this data set with conflicting results. While some studies find negative relationship between growth and inequality, some reported positive relationship and yet in some other studies, the link is inconclusive. Deininger and Squire (1996) find a negative correlation between initial asset (land) inequality and long-

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run growth. Further, they find that inequality retards income growth for the poor, but not for the wealthy.

Perotti (1996) finds a negative association between inequality and growth. Although he finds some evidence that this association is stronger in democracies, he concludes that this finding is not very robust towards alternative specifications. Barro (2000) in a panel study finds little overall relationship between income inequality and growth concluding that inequality tends to impede growth in poor countries and promote it in rich countries. Forbes (2000) also studies a panel data set and finds that in the short and medium term, an increase in a country's level of income inequality has a significant positive relationship to subsequent economic growth. Forbes' result was robust across samples, variable definitions, and model specifications. Knowles (2005) argues that most recent empirical findings on growth-inequality nexus employed inconsistently measured inequality data. Hence, the reported negative relationship between income inequality and growth across countries is not robust when income inequality is consistently measured. However, he found a significant negative relationship between expenditure inequality and growth in a sample of developing countries.

Banerjee and Duflo (2000), estimate a non –linear relationship between growth and inequality. They find that the growth rate is an inverted U-shaped function of net changes in inequality. While the paper argues that the non-linearity captures multiplicity of findings in previous studies, it could not assert whether inequality impedes growth or not.

In a recent work, Herzer and Vollmer (2012) employ panel co-integration technique to estimate growth-inequality relationship for a panel of countries between. They conclude that inequality has negative and statistically significant impact on growth. Their result is robust across country samples irrespective of the level of development or type of government which result is a major departure from Barro (2000).Despite the fact that most of the post-D&S dataset studies used seemingly appropriate control variables in standard growth regression, none but Voitchovsky (2005) paid attention to the nature of within-country and cross-country variations of inequality measures in choosing their estimation methods. We therefore argue that exclusion of this crucial innovation could have led to biased results in their findings.

Economic Theory

There are numerous theoretical literatures on how inequality affects economic growth which can be discussed under four headings. These include political economy, saving rate, credit-market imperfections and social unrest. We shall examine each of these in turn.

Political Economy

Political economy theory asserts that unequal societies would be necessarily forced to implement redistributive policies which would be detrimental to investment in physical and human capital and thus growth. Alesina and Rodrik (1994) whose ideas were related to political economy literatures on voting on tax rates in a dynamic setting argued that distributive struggles harmful to growth are more likely to take place when resources are distributed unevenly. Using an endogenous growth model with government spending, Alesina and Rodrik (1994) reported that tax rates above the optimal level that maximises capital accumulation and growth might be imposed. When tested they found that inequality in land and income ownership is inversely related to growth thus supporting their hypothesis. Li and Zou (1998) extended the model with the inclusion of public consumption in the endogenous growth model

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and obtained a positive relationship between income inequality and economic growth resulting in the political economy not coming to a consensus on which direction inequality affects growth. Persson and Tabellini (1994), relate equilibrium growth to income inequality and political institutions. In their model they expect that with inequality, implementation of policies that allow for less private appropriation through taxation on investment and thus less growth would occur. When tested income inequality is harmful to growth because it leads to policies that do not protect property rights.

Credit-Market Imperfections

With restricted access to credit usually due to inadequate collateral and poor contract enforcement, uptake of investment opportunities would depend on the individual's level of income or asset and usually for the poor households they would forego human capital investment that offer high rates of return thus reducing the rate of economic growth (Barro, 2000). Galor and Zeira (1993), whilst analysing the role of wealth distribution through investment in human capital showed that in the presence of credit market imperfections the initial distribution of wealth affects aggregate output and investment in human capital both in the long run and short run.

With high interest rates on the part of the borrowers, inequality would result in the under investment in human capital which adversely affects economic development (Galor, 2009). Also, Banerjee and Newman (1993) look at the interplay between occupational choices and the process development, given that the pattern of occupational choice is determined by the initial wealth distribution, they argued that in the presence of capital market imperfections, individuals would have limited credit thus forcing the poor people to engage in contractual employment rather than investing in being self-employed which negatively affect economic development.

Labour empowerment in an economy necessitates giving access to the less endowed financially in the society. However, in the absence of a perfect credit market, there is a limit to human capital development and hence economic growth. Moreover, it is noteworthy that high initial inequality could be self-perpetuating in an economy over a very long period of time. This mechanism is quite easy to understand because functional distribution of income from growth determines personal accumulation of wealth. Factors' share in output depends on the proportional contribution to the production of the output.

Socio-Political Unrest

More unequal societies are prone to agitations for political reforms that would bring about redistribution of incomes in favour of the lower income group. Barro (2000) posited that these agitations could bring about higher crime rate, riots etc. In extreme cases, there may be revolutions. The resulting instability of the political institutions coupled with greater uncertainty in the system may constitute threats to sustainable investment and hence growth. Moreover, the participation of the poor in antisocial activities connotes direct waste of valuable economic resources. A redistribution culminating into greater income equality would engender growth.

Saving Rates

Under this view, studies argue that the rate of savings would have impact on the level of income in the society. If the rich in the society save more than the poor then redistribution policies

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would adversely affect savings, investment and thus growth. Thus with inequality, saving and investment rises thus economic growth but this effect arises if the economy is partly closed so that domestic investment depends on the national saving (Barro, 2000). It could be possible that redistribution of resources from the rich to the poor would promote economic growth if the rich spend a high percentage of their income on luxuries or unproductive activities.

DATA AND METHODOLOGY

This paper uses a model that is similar to those used in most empirical work on inequality and growth to estimate the effects of inequality, income, total human capital, market distortions, country and period dummy variables on growth.

Description of variables

Inequality

Measuring income inequality is not an easy task. That is why scientists have come up with a variety of ways in their attempt to measure income inequality as accurately as possible. We will make here a brief description of three inequality indicators: gini coefficient, Theil index and Palma ratio.

a) The Gini Coefficient and the Lorenz Curve

In order to understand the meaning of the gini coefficient, we should understand the meaning of the Lorenz curve first, since it relies heavily on that. The Lorenz Curve is a graphical representation of the wealth distribution. The straight diagonal 45^{o} line that we see in Figure 1 represents perfect equality in wealth distribution. The curved line below is the Lorenz Curve, which shows the reality in wealth distribution, i.e., is the actual amount of wealth that corresponds to a certain percentage of the population (Lorenz, 1905). The gini coefficient is the difference between those two lines (A). Gini coefficient takes prices between 0 and 1; where 0 is perfect equality (everybody has the same) and 1 is perfect inequality (one person has everything in the economy). The smaller the shaded area, the more the economy tends to equal distribution (45^{o} line). This is the most frequently used inequality index. However, it has the disadvantage that the diagram itself is not based on any model of a distribution process. In Figure 2, we can see how income inequality is spread worldwide, using the gini coefficient as a measure. As the number of the index is getting bigger (tends to red), the income inequality is increasing.

b) Theil index

This is a better mathematically modelled index than the gini coefficient, but lucks an intuitive picture. This statistic is calculated as follows:

$$T = \sum_{p=1}^{n} \left\{ \left(\frac{1}{n}\right) * \left(\frac{y_p}{\mu_y}\right) * \ln\left(\frac{y_p}{\mu_y}\right) \right\}$$

where n is the number of individuals in the population, y_p is the income of the person indexed by p, and μ_y is the populations' average income. The natural logarithm determines whether the element will be positive, negative or zero. In short, this statistic is created in a way so that each person should contribute a Theil element. Positive and negative deviations from the mean contribute positive and negative elements, while the group of people who stands at the mean actually contributes nothing to the index(Theil, 1979).

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c) Palma ratio

Palma ratio is based on the assumption that middle class incomes in general represent about half of gross national income. So, the difference is at the tails, and to be more specific at the lower 40% and the top 10%. What this index actually does, is dividing the share of Gross National Income of the population's richest 10%, with the share of GNI of the poorest 40%. Despite its simplicity, the components of the Palma ratio alone are able to 'explain' between 99% and 100% of Gini variation. In practice, it is found that no more information is contained in the Gini –a measure of the entire income distribution –than in the Palma ratio, which excludes completely the 5^{th} to 9^{th} deciles(Cobham and Sumner, 2013).

Measuring Income Inequality

The availability of data has always been a crucial factor on determining the quality of a work in every project a researcher has to deal with. In the household income inequality field that we are interested in, the major breakthrough in the search of quality and reliable data was made in 1996 by Klaus Deininger and Lyn Squire of the World Bank, who used as an indicator the gini coefficient. Although it was the best work in the field until then, it had a lot of drawbacks. Some of them are that the coverage was sparse and unbalanced between countries and that it had infrequent measures of inequality for many developing countries, which made it impossible to find the time trend of inequality (Galbraith and Kum, 2004).

The dataset we will use as an indicator of inequality within countries is the University of Texas Inequality Project database, and specifically the Estimated Household Income Inequality dataset (EHII), which uses as a measure of inequality the gini coefficient. The data on income dispersion comes from the United Nations Industrial Development Organization (UNIDO). The dataset is in panel data form.

The way the EHII dataset is constructed is as follows. The starting point is the Deininger and Squire database that we mentioned above. The first step is to separate the useful from the doubtful information. The gaps are filled with data sourced from UNIDO. This is achieved using regressions of the Gini indices from the Deininger-Squire inequality measure on the UNIDO variable and on a matrix of dummy variables including those that control for the type of data source. By employing this set of dummies they differentiate between income and expenditure Ginis, household versus per capita coverage and gross versus net distributions, The EHII indices (which can be conceived as the gini indices) vary in the (0,1) interval and are computed using the coefficients derived in the regression. Therefore, the dataset is assembled in a comprehensive and consistent manner (Roser and Cuaresma, 2012).

3.1.2 Growth

- Measured by GNI per capita growth (annual %)

This is the average annual growth of a country's gross national income. It is measured as the difference in logs of GNI per capita between two consecutive periods. This will be our dependent variable in the model.

Source: (World Development Indicators, 2013)

3.1.3 Income

- Measured by GNI per capita, Atlas method (current US $) and PPP

GNI per capita is the gross national income divided by the midyear population. GNI is the sum of value added by all resident producers plus any product taxes (less subsidies) not included in

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the valuation of output plus net receipts of primary income (compensation of employees and property income) from abroad. GNI is usually converted to U.S. dollars at official exchange rates for comparisons across economies. The Atlas method of conversion helps to smooth fluctuations in prices and exchange rates. The log of GNI per capita is an appropriate measure of income and economic growth.
Source:(World Development Indicators, 2013)

3.1.4 Human Capital

- Measured by Average years of secondary schooling in the total population aged over 25
Human capital achieved through education, is of crucial importance to economic growth (Mankiw, et al. 1992). Growth increases as the level of investment in human capital increases. Average years of secondary schooling in the total population ages 25 and older is a good proxy for the stock of human capital. This data is measured in 5 year intervals. These current estimates are an improvement on the previous estimates by utilizing more information and better estimation methodology.
Source: (Barro and Lee, 2013)

TABLE 1 - Summary Statistics

Variable	**Definition**	**Source**	**Year**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Inequality	Measured by the	UTIP	1965	40.66	7.17	28.01	52.20
	gini coefficient	upd. 30/10/13	1970	41.48	6.94	27.83	51.91
			1975	40.63	6.92	26.52	52.48
			1980	40.17	7.30	23.50	51.42
			1985	40.62	7.23	21.63	50.68
			1990	41.40	7.56	21.75	54.59
			1995	43.04	6.99	27.84	56.68
			2000	43.27	6.52	29.42	56.20
			2005	43.54	6.43	32.30	54.66
Income	Gross national income	World Bank	1965	6.29	1.07	3.98	8.17
	(GNI) converted to		1970	6.45	1.10	4.13	8.42
	international dollars		1975	6.96	1.20	4.62	8.87
	(2013 US$) using		1980	7.57	1.25	5.04	9.71
	purchasing power parity		1985	7.82	1.24	5.16	9.79

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	Rates		1990	8.02	1.38	5.08	10.04
			1995	8.24	1.51	5.25	10.54
			2000	8.40	1.53	5.19	10.71
			2005	8.55	1.53	5.23	10.83
PCF	Price level of investment,	Penn World	1965	0.18	0.18	0.05	1.17
	measured as the PPP of	Tables	1970	0.19	0.16	0.07	1.22
	investment/exchange rate	version 8.0	1975	0.25	0.15	0.07	1.28
	relative to the United		1980	0.41	0.19	0.06	1.57
	States		1985	0.49	0.19	0.09	1.22
			1990	0.60	0.26	0.19	1.56
			1995	0.67	0.42	0.29	2.92
			2000	0.70	0.52	0.17	3.93
			2005	0.71	0.54	0.06	4.38
Total Human	Average years of secondary	Barroand Lee	1965	0.86	0.80	0.02	3.74
Capital	schooling in the total	version 1.3	1970	1.04	0.92	0.07	4.28
	population aged over 25	upd. 09/04/13	1975	1.26	1.02	0.13	4.77
			1980	1.49	1.09	0.20	5.10
			1985	1.76	1.11	0.22	5.08
			1990	2.03	1.14	0.30	5.08
			1995	2.34	1.17	0.31	5.34
			2000	2.57	1.21	0.38	5.41
			2005	2.80	1.26	0.41	5.57

Sources: (University of Texas Inequality Project, 2013), (World Development Indicators, 2013), (Penn World Tables, v8.0)(Barro and Lee, 2013)

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Market Distortions

- Measured by Price level of capital formation (PCF) (price level of USA GDP_o in 2005=1)

Market distortions arise when the capital market fails to function efficiently which leads to distorted prices. This creates a borrowing constraint in the economy, as individuals cannot easily borrow against future income, therefore, the initial distribution of resources has a large impact on the economy's investment decisions and hence, growth (Perotti, 1996). Price level of Capital Formation is a good proxy of market distortions, as it measures how the cost of investment varies between each country and the United States by capturing market distortions that affect the cost of investment, such as tariffs, government regulations, corruption, and the cost of foreign exchange (Forbes, 2000).
Source: (Penn World Tables, v8.0)

Data Selection

As we mentioned at the beginning, finding data on the field of inequality is usually problematic. The initial UTIP database is consisted of 3,872 observations, regarding 149 countries for the years 1963-2005. Unfortunately, we had to decrease the amount of countries we are using in our sample due to the great gaps in data availability for a significant amount of years. In this paper, we are examining a 43-year period, from 1963 to 2005. The countries we selected to have at our sample are those that for the specified period have at least 25 observations.
Also, we faced the problem of time-inconsistency in our data due to political factors. For example in Germany we have data from 1991 and afterwards as a united country. For the previous years the data was split between the Federal Republic (West Germany) and Democratic Republic (East Germany). Other examples are the states of the former USSR (Union of Former Soviet Republics) and the states of the SFRY (Socialist Federal Republic of Yugoslavia).

Our final dataset is consisted of 65 countries, 49 of which are characterised as "rich" and 16 as "poor". This is a usual problem that most researchers confront when facing those kinds of datasets, since "rich" countries tend to keep better statistics than the "poor", so they are much more often included in samples. For making the simplified determination of "rich" and "poor", we used the World Banks' classification method. In the category "poor" we measured the countries that are characterised by the World Bank as: "Low income" and "Lower middle income". In the category "rich", we had the countries characterised as: "High income: OECD, "High income: non-OECD" and "Upper middle income".

TABLE 2 - Inequality Coefficients

Country	**1965**	**1970**	**1975**	**1980**	**1985**	**1990**	**1995**	**2000**	**2005**
Australia	31.05	31.02	31.17	31.46	33.38	35.06	36.56	36.28	36.27
Austria	34.79	34.77	33.21	33.22	34.19	34.64	35.50	35.70	35.69
Bangladesh		41.34	42.67	44.09	44.45	46.79	49.06	50.16	
Barbados		45.25	44.78	44.43	42.90	44.34	45.75	44.97	

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Belgium	32.42	32.45	32.73	34.87	36.61	37.17	37.22	37.81	39.10
Bolivia		42.63	43.86	45.63	48.68	49.22	50.51	50.38	51.35
Bulgaria	29.21	27.83	27.24	27.34	27.27	26.53	35.76	40.10	40.40
Cameroon		48.82	45.72	46.62	50.00	52.75	55.26	56.20	54.66
Canada	35.14	34.58	34.88	34.66	36.43	36.68	37.93	38.02	38.49
Chile	46.07	44.10	41.60	45.00	48.37	48.38	46.55	47.71	49.32
China (Hong Kong)			27.78	23.50	24.49	26.44	34.33	40.79	44.02
China (Macao)				25.06	21.63	21.75	27.84	32.19	34.04
Colombia	43.68	44.29	44.74	44.07	44.40	45.13	46.04	46.32	46.92
Cyprus	45.17	43.35	42.24	41.45	38.87	38.57	38.87	39.46	37.88
Denmark	30.45	30.94	30.95	31.70	31.61	30.71	30.52	30.94	32.30
Ecuador	47.44	47.20	44.43	42.47	45.25	46.24	48.52	49.61	45.81
Egypt	44.06	42.08	41.17	40.53	43.51	43.87	47.08	48.49	52.26
El Salvador	47.88	45.64	44.85	43.63	44.43		50.03	47.03	
Fiji		41.83	41.90	42.99	46.50	47.50	49.00	41.97	42.12
Finland	32.99	33.06	31.11	30.97	30.90	31.95	33.09	32.82	33.65
France				32.97	33.82	35.13	37.12	36.48	36.80
Ghana	48.66	49.78	48.99	47.95	48.46	49.07	48.67		
Greece	43.42	42.56	41.65	41.46	41.75	41.56	43.14	43.48	44.05
Guatemala		46.64	45.94	45.03	45.31	47.63	54.58	49.45	
Honduras	45.09	44.95	43.02		42.14	41.97	47.56		
Hungary	29.46	27.96	26.52	26.08	27.39	29.90	37.32	40.10	40.06
India	47.07	47.77	49.72	51.16	50.32	50.01	50.02	50.63	51.87
Indonesia		51.56	50.88	51.42	50.57	49.83	47.07	48.74	48.20

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Iran	49.54	49.84	47.27	45.54	37.85	38.29	42.89	45.19	45.84
Israel	35.53	36.35	36.89	39.68	40.69	41.48	42.56	42.83	44.11
Italy		39.50	37.53	35.65	36.39	37.51	37.75	36.53	36.27
Jamaica	46.00	47.24	48.71	47.81	46.58	51.66	51.43	49.49	48.75
Japan	35.84	34.51	34.25	35.34	35.65	35.85	37.25	40.56	42.85
Jordan	49.02	49.88	49.34	49.48	49.38	49.58	46.28	47.10	49.07
Kenya	52.20	51.06	50.53	49.69	49.65	48.49	47.37	46.84	
Kuwait		51.62	52.48	50.20	50.68	54.16	56.68	53.01	54.06
Luxembourg	31.02	29.77	30.42	30.61	31.95	33.47	34.25	34.22	35.82
Malawi	47.36	46.00	47.75	48.15	48.98	54.59	53.42	54.46	54.11
Malaysia		46.36	44.36	41.60	41.52	42.96	38.94	38.66	39.99
Malta	40.15	36.93	35.87	31.60	30.88	31.88	33.98	35.19	36.04
Mauritius		40.85	46.49	46.34	44.90	37.23	36.22	37.66	38.36
Mexico		42.29	42.42	42.02	42.31	43.48	45.22	46.43	
Morocco				50.37	48.85	49.32	48.19	48.58	51.35
Netherlands	31.23	32.15	33.36	32.92	34.58	35.11	35.37	35.87	36.74
New Zealand	33.93	33.75	32.97	32.09	32.43		38.52	38.92	38.42
Norway	31.62	31.62	31.59	31.85	32.77	33.42	35.04	34.27	35.98
Pakistan	44.30	44.80	47.45	47.59	48.56	48.77	49.86	50.82	52.52
Panama	44.42	43.44	44.16	44.12	43.81	46.71	49.10	49.86	43.80
Philippines	46.80	47.74	46.86	46.42	46.56	48.32	48.79	46.84	47.67
Portugal	43.20	43.11	39.88	37.61	38.58	39.97		37.55	38.96
Senegal			40.07	41.21	46.11	44.48	48.60	48.77	49.59
Singapore	45.60	45.90	40.94	37.29	36.45	35.47	34.32	35.97	37.66

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South Africa	43.07	42.88	42.80	42.66	43.52	44.07	45.09	45.57	47.02
Spain	40.38	40.83	40.58	38.34	38.10	39.63	40.28	39.56	38.61
Sri Lanka		51.91		47.83	47.32	46.46	43.58	45.43	46.93
Sweden	28.89	28.28	27.65	27.57	28.65	29.11	30.00	29.42	
Syrian Arab Republic	47.04	46.15	43.95	44.92				46.70	48.55
Trinidad and Tobago		48.78	45.68	46.93	47.36	50.31	50.76	52.29	52.08
Tunisia	48.09	46.91	46.76	45.38	44.27		51.11	51.39	53.38
Turkey	45.09	43.77	43.46	44.43	44.08	45.01	48.74	48.57	48.19
United Kingdom	28.01	28.27	29.03	29.66	32.85	34.26	35.58	35.83	36.79
Uruguay		40.30		37.68	41.39	40.70	42.92	46.25	47.01
USA	35.31	34.18	35.27	36.09	37.16	37.55	38.24	38.24	39.41
Venezuela	46.34	43.98	42.05	39.75	41.28	42.81	45.00	47.67	
Zimbabwe	45.79	45.68	44.98	44.80	43.71	44.39	47.29	47.70	
Average	**40.66**	**41.48**	**40.63**	**40.17**	**40.62**	**41.40**	**43.04**	**43.27**	**43.54**

Source: (University of Texas Inequality Project, 2013)

In table 1 we can see the summary statistics (mean, standard deviation and range) of each of the variables in the final dataset. Following Forbes (2000) model, we have used our variables averaged over five-year periods, so we actually estimate 9 time-periods. Doing this, we are reducing serial correlation from business cycles. Table 2 shows the inequality coefficients for all the countries in the dataset.

In graph 1 we can see the correlation we have on our data when we plot the growth rate we have calculated from the World Development Indicators and the inequality measured by the gini coefficient that we have from the UTIP database. Here, we have the whole sample of countries and we notice a slightly negative correlation between the two variables, which we cannot yet say whether it is significant or not. This is exactly what Barro (2000) finds when plotting his data.

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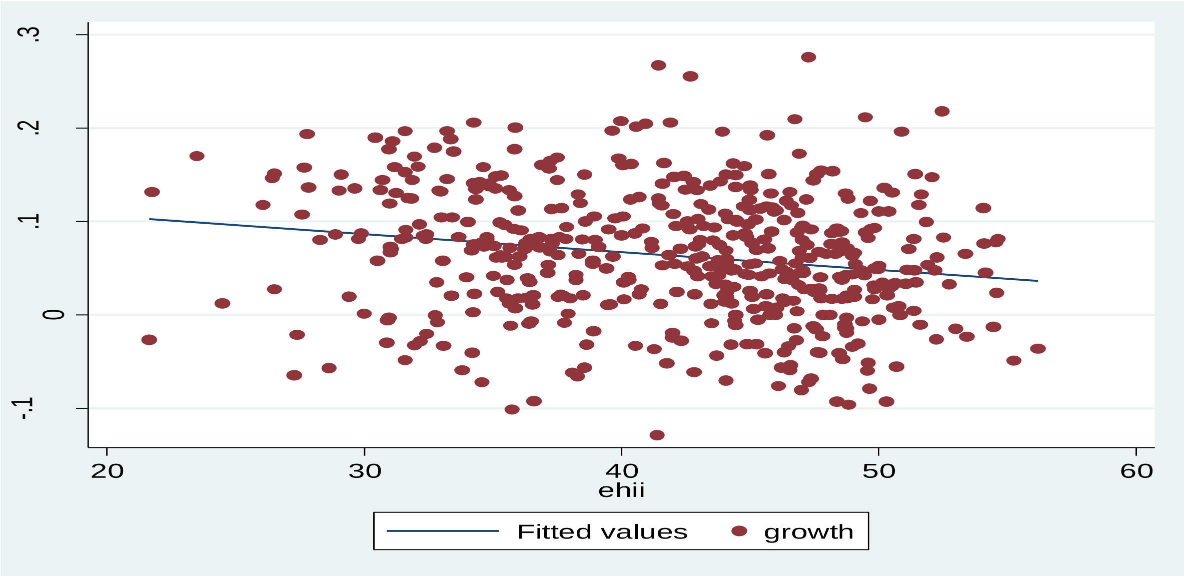

GRAPH 1 – Growth Rate vs Inequality

METHODOLOGY

The literature review is evidence to the fact that extensive research has been carried out to study the relationship between inequality and economic growth. In spite of this, scholars have not reached a definite consensus on the nature of this relationship. Some of the possible reasons for these conflicting results are data problems, such as -measurement errors in inequality data which leads to bias; non availability of data for some regions creating selection bias; and most of the equations' specifications are autoregressive, which systematically include the lagged GDP level which leads to endogeneity bias; model specification - linear models, e.g. (Forbes, 2000), or non-linear models, e.g. (Banerjee and Duflo, 2003); and estimation techniques – first difference GMM (Forbes, 2000); 3 stage least squares (Barro, 2000); and fixed and random effects (Banerjee and Duflo, 2003). In this study, we aim to analyse the relationship between inequality and growth by correcting for some of the possible problems that have been identified.

Model Specification

In light of an improved inequality data, which should reduce measurement error, we intend to estimate a linear model as Forbes (2000). Growth is estimated as a function of initial inequality, income, human capital, market distortions, and country and period dummy variables. The country dummies control for time-independent omitted-variable bias, while the period dummies control for global shocks, which might affect growth in any period but are not otherwise captured by the explanatory variables.

$$growth_{it} = \beta_1 Ehii_{i,t-1} + \beta_2 income_{i,t-1} + \beta_3 education_{i,t-1} + \beta_4 pcf_{i,t-1} + \alpha_i + \eta_t + u_{it} \quad \textbf{(1)}$$

Where i and t– represents country and each time period respectively

$growth_{it}$ - average annual growth for country i during period t

pcf_{it-1} – market distortions for country i during period $t-1$

$education_{it-1}$ – human capital for country i during period $t-1$

$income_{it-1}$ – income for country i during period $t-1$

$Ehii_{it-1}$ – inequality for country i during period $t-1$

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α_i – country dummies

η_t – period dummies

u_{it} – error term

In choosing our estimation methods, we give serious consideration to possibility of omitted variable bias, endogeneity of control variables and nature of the variations in inequality measure in our panel data. The standard panel estimation techniques (fixed and random effects) will be used. Fixed effects estimates are calculated from differences within each country across time; Random effects estimates are more efficient, since they incorporate information across individual countries as well as across periods. A Hausman specification test (a distance test) will be used to test the validity of the within and between moment conditions, i.e. it tests the independence of the time-invariant effects from the other explanatory variables. If the Hausman statistic is small the FE and RE moment conditions are valid, but the RE result is preferred, due to the independent/orthogonal of the time-invariant effects.

Though the within group estimation addresses omitted variable bias, the estimation technique would be biased, inconsistent, and inefficient for our analysis because we have a lagged dependent variable which is endogenous to the fixed effects in the error term that brings about the dynamic panel bias. This occurs when growth is written in terms of differences in income levels.

$$income_{it} = \beta_1 inequality_{i,t-1} + \gamma_2 income_{i,t-1} + \beta_3 human\ capital_{i,t-1} + \beta_4 pcf_{i,t-1} + \alpha_i + \eta_t + u_{it} \qquad \textbf{(2)}$$

$$\gamma_2 = \beta_2 + 1$$

To deal with this Forbes (2000) used the difference estimator by Arellano and Bond (1991). The GMM estimator takes first differences of the level equations to remove countryspecific effects and uses lagged values of $y_{i,t}$ and $\boldsymbol{X}_{i,t}$ as instruments for the first differences.

$$(y_{i,t} - y_{i,t-1}) = \alpha(y_{i,t-1} - y_{i,t-2}) + \beta(\boldsymbol{X}_{i,t-1} - \boldsymbol{X}_{i,t-2}) + (h_t - h_{t-1}) + (v_{i,t} - v_{i,t-1}) \quad \textbf{(3)}$$

Given that inequality is fairly persistent over time within country but vary largely across countries, the difference GMM estimator discards much of the information in the data. Voitchovsky (2005) pointed out that using the limited within country information is not the best option as the coefficients might be estimated imprecisely. Our study uses the system GMM estimator which was developed by Arellano and Bover (1995) and Blundell and Bond (1998). It estimates a system of equations in first differences and in levels. The model could be written as this:

$$y_{i,t} = \alpha y_{t-1} + \boldsymbol{X}_t'\beta + \eta_i + h_t + v_{i,t} \qquad \textbf{(4)}$$

For the equation in first differences, the estimator uses lagged levels as instruments, whilst for the equation in levels it uses lagged first differences as instruments. The system GMM estimator, rather than removing the country specific effectsη_i, the estimator differences the instruments to make them exogenous to the fixed effects assuming that changes in the instrumenting variable *x* are uncorrelated to the fixed effects - $\mathrm{E}\left[\Delta x_{\mathrm{i,t}}\eta_i = 0\right] \forall\ i, t,$ (Roodman, 2006). The system GMM estimator has better finite sample properties and should provide a more accurate and less biased estimate than the first differenced GMM estimator.

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We test for the validity of our instruments to ensure that our estimates are consistent and efficient. Since the system GMM estimator assumes that there is no serial correlation in the idiosyncratic error term$\nu_{i,t}$, the presence of time dummies in our model supports this assumption. First order serial correlation is usually accepted for the first differenced residuals but no second order serial correlation. We test for second order autocorrelation in the error terms and if not found, supports the validity of our instruments as the presence of autocorrelation would render some lags of the endogenous variable invalid. Also, we carry out a Hansen test of over identifying restrictions to identify if our moment conditions are valid which implies exogeneity of our instruments. Our instruments are drawn from within the dataset. For the first differenced equation, given that we have a lagged endogenous dependent variable, we use the second and third lags of the dependent variable as instruments$Income_{t-2}$and $Income_{t-3}$. The inequality, education and market distortions variable are treated as being predetermined and so we instrumented the variables with their first lags, $Ehii_{t-2}$, $Human\ capital_{t-2}$andPcf_{t-2}.

To be valid instruments for the equations in levels, the first differenced explanatory variables have to be orthogonal to the country specific effects - η_i. There is no potential correlation between the differences of the explanatory variable and the country specific effects therefore the lagged first difference of inequality, income, human capital and market distortions variables are included as instruments for the equation in levels, $\Delta Ehii_{t-2}$, $\Delta Human\ capital_{t-2}$,$\Delta PPPI_{t-2}$ and $\Delta Income_{t-2}$.
Our instrument matrix is collapsed to reduce instrument count and the Windmeijer - corrected cluster-robust errors is used in the two-step estimation without which the standard errors would be biased downward.

RESULTS/FINDINGS

Results and Diagnostics

All estimations were done using xtabond2 provided by Roodman (2009). The instrument counts reported were 17, which is less than the number of panels/groups, 65. According to Roodman (2009) a large number of instruments weaken the power of Hansen test to detect the invalidity of instruments which should not be taken for granted. As mentioned earlier the GMM estimator usually requires first order serial correlation but no second order serial correlation in the first differenced residuals. The null hypothesis states that there is no first or second serial correlation. From our regression output we have first order serial correlation but no second serial correlation with a p-value of 0.406 which is significant at the conventional significant levels. The overidentifying restrictions were tested using the Hansen J statistic to test the validity of the moment conditions i.e. the exogeneity of our instruments. We chose the Hansen statistic over the Sargan statistic as the former is robust to heteroskedasticity and clustering which we assume whilst the latter assumes conditional homoscedasticity (Baum et al, 2003). The null hypothesis states that all overidentifying restrictions are exogenous which we fail to reject. This indicates that our instruments are valid.

According to Baum et al.(2003) in a model containing a large set of excluded instruments, the Hansen test which uses all the entire set of overidentifying instruments may have little power. Therefore we test the validity of subsets of the instruments in levels and differences via the difference in Hansen tests which is also known as the C statistic (Roodman, 2009). There is no evidence against the null hypothesis therefore we fail to reject the null indicating that the subset

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of differenced instruments for the endogenous variable income and the level instruments are valid. The F-test of joint significance shows that we reject the null hypothesis that the explanatory variables are jointly equal to zero with a p-value of 0.000. After examining the diagnostic validity of our model results, we proceed with the economic interpretation of the estimates in Table 3. The Fixed and Random Effects estimators give conflicting results, and this is resolved using the Hausman specification test. The test shows that the random effect estimate is not valid because the independence assumption is not satisfied. Also, due to the presence of a lagged endogenous variable, the fixed effect estimate is biased and inefficient.

TABLE 3 - Regression Analysis

Variables	**Fixed Effects**	**Random Effects**	**Arellano and Bond/ Blundell and Bond SGMM**
ehiiL1.	0.0006	-0.0011**	0.0016
(Lagged income inequality)	(0.0009)	(0.0004)	(0.0029)
lnpc_gniL1.	-0.0694***	0.0032	0.0005
(Lagged log. of per capita income) 1st lag	(0.0078)	(0.0033)	(0.014)
hc_totalL1.	0.0092	-0.0008	0.0047
(lagged human capita) 1st lag	(0.0076)	(0.0033)	(0.0169)
pcfL1.	-0.0102	-0.0189**	-0.0075
(lagged market distortions) 1st lag	(0.0098)	(0.0081)	(0.0131)
Model Diagnostics			
R^2	0.63	0.52	
Groups	65	65	65
Observations	452	452	452
Period	1975 - 2005	1970 - 2000	1970 – 2005

Notes: Dependent variable is average per capita annual growth, standard error of estimates appear in parentheses, R^2 is the within- R^2 for fixed effects and the overall-R^2 for random effects.

*** Coefficient is significant at 1%

** Coefficient is significant at 5%

Source: Extracted by authors from STATA 12 regression outputs.

DISCUSSION

Our interest lies in interpreting the estimates of the System GMM. The inequality coefficient is positive, very low and statistically insignificant. While the positive coefficient of inequality suggests that countries with higher inequality tend to have higher growth rate of per capita income, its statistical insignificance putatively rules out this possibility. This corroborates the finding of Barro (2000) that inequality shows little overall effect on growth rates across countries. In contrast to Forbes (2000), the insignificant relationship between inequality and growth reveals that the various theoretical models linking inequality with growth and

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predicting varying outcomes are counter-acting leaving almost a neutral effect of inequality on growth.

It should be noted however, that, the coefficient of inequality on growth should be construed as different from earlier work on growth and inequality. Our estimate explains the medium-term impact of inequality on growth because our data was based on a 5-year average time interval of 9 periods from 1965 - 2005. Since this result contradicts earlier works which reported negative impact of growth on inequality such asAlesina and Rodrik (1994), Persson and Tabellini (1994), Perotti (1996), Acemoglu (1997),while Li and Zou (1998) and Forbes (2000) founda positive significant relationship between inequality and growth, we probe further to see if the result is robust to sample selection and estimation technique, the result is reported in the sensitivity analysis section below.

The coefficient of lagged income level on growth is positive but statistically insignificant. This negates the theoretical prediction of conditional convergence across countries. Romer (2012) suggests that convergence among countries theoretically follows from three main important issues. First, Solow model predicts that countries would converge to the balanced growth path relative to their positions in the transitory periods. Second, neoclassical growth models assume diminishing marginal productivity of capital. As a result, MPK is higher in poor countries causing capital flows across countries until MPK is equalized. Third, technology once available is diffused speedily across countries. This enables poor countries to catch-up because they might not necessary need to pay for innovation costs. However, the positive coefficient of lagged per capita income on growth shows that divergence exists in growth rates across countries in the sample of countries studied. Rich countries are getting richer while poor countries are getting poorer as predicted by Romer(1986) endogenous growth model.

The coefficient of lagged total human capital, which represents the impact of average year of secondary schooling for both male and female on growth, is positive but statistically insignificant. Though theory predicts that increase in human capital investment should have significant positive impact on growth, the insignificant nature of our estimate raises a concern. One reason for the insignificant positive relationship might be that rich countries have reached their steady states, which means increase in human capital accumulation has little effect on their growth rates. However, in poor countries where we expect higher returns on human capital, the quality of the education and training which indicates its tendency to impact growth is usually weak. Banerjee and Duflo (2011, p74) asserts that whereas increase in human capital investment is usually encouraged in developing countries, quality of the education so acquired is treated as being less important even in the drafting of global policy on development such as the Millennium Development Goals (MDGs). For example, MDGs goal number 2 specified achievement of universal primary education by 2015 but no mention was made of the quality and learning outcomes of such universal education. We therefore argue that poor quality of human capital investment in developing countries has affected the extent to which education influences growth. Hence, the overall positive insignificant relationship between human capital and growth in our result.We subject this finding to sensitivity analysis by using other sub-schooling category such as average year of schooling which includes all levels of education.

As expected, market distortion represented by lagged PCF has a negative impact on growth. However, it is statistically insignificant. We expect higher distortions in price of capital formation to negatively impact growth. However, our finding may suggest that while domestic

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investment decisions might be susceptible to distortion in prices of capital formation, cross country capital formation neglects this theoretical proposition. For example, despite the fact that investment climate in developing countries seems unfavourable, multinational companies (MNCs) majorly owned by investors in developed nations across the globe find their ways into the various sectors of the developing economies where returns on investment are very high regardless of the distortions and associated degrees of uncertainties. Hence, market distortions seem to be less effective in reducing investment and therefore growth.

IMPLICATION TO RESEARCH AND PRACTICE

To justify the findings of our work in line with acceptable standards of research practice, we attempt a sensitivity analysis. Our aim is to cross-check our results using other estimation techniques, models, country-samples and independent variables combinations. The table below shows the estimates of various modifications of our basic equation to check the robustness of our results in the light of previous work in this area, which employed different estimation techniques, used different country samples and explored non-linear relationship between inequality and growth. Using average year of total schooling as a proxy for average total years of secondary schooling in our basic equation does not substantially change the result.Although the coefficient of inequality on growth becomes negative, it remains statistically insignificant. When we estimate our basic equation for only the 46 rich countries (as classified by the World Bank) in our sample, inequality coefficient on growth was positive and statistically significant at 10% level.

TABLE 4 – Sensitivity Analysis

Variables	**EhiiL1. (Lagged income inequality)**	**Lagged Squared income inequality**	**Lagged Cube income inequality**	**Lagged average years of total schooling**	**F-stat [p-value]**	**Panel size**	**Obs.**	**Period**
Arellano and Bover/ Blundell and Bond SGMM								
Average year of total schooling	-0.0019 [0.0027]			-0.0075 [0.0093]	56.76 [0.000]	65	452	1970 – 2005
Rich countries	0.0055** [0.0029]				50.82 [0.000]	46	321	1970 – 2005
Poor countries	0.0029 [0.0061]				24.49 [0.000]	19	131	1970 – 2005
Excluding Outliers	0.0013 [0.0037]				55.02 [0.000]	55	388	1970 – 2005
Non-linear equation	0.0347 [0.0596]	-0.0011 [0.0015]	0.0000 [0.0000]		62.45 [0.000]	65	452	1970 – 2005
Ordinary Least Square estimation								
Equation 1	-0.0011*** (0.0005)				44.25 [0.0000]	65	452	1970 – 2000

*** Coefficient is significant at 1%
** Coefficient is significant at 5%
Note: Standard errors in parentheses; parentheses under F-Stat is p-value
Source: Extracted by authors from STATA 12 regression outputs.

Also, the coefficient of inequality on growth in the 16 poor countries was positive, though not statistically significant. With this finding, our result confirms the work of Barro (2000) that inequality promotes growth in rich countries and moreover, since we cannot confidently say anything on the effect of inequality on growth in poor countries, we suggest there is no significant impact of inequality on growth in poor countries.

We also remove 10 countries that we categorized as outliers for having extremely too high or too low average inequality coefficient in the sample. The coefficient of inequality on growth in this reduced sample does not however change significantly from our basic finding. In OLS specification on inequality and growth, the coefficient of inequality was negative and statistically significant at 5%. However, as noted earlier OLS estimates are inefficient owing to lagged endogenous variable and country fixed effects included in our model.

Finally, to confirm if we have estimated a linear relationship between inequality and growth where no such relationship exist, we include lagged square and lagged cube of inequality in our basic equation. The coefficient of inequality remains positive and statistically insignificant while the coefficient of lagged square (lagged cube inequality) was positive (zero) and also statistically insignificant. This contrasts sharply with the findings of Barro (2000) and Chen (2003) that there is non-linear (inverted-U) relationship between inequality and growth.

CONCLUSION

In this study we examined findings of previous empirical work on growth and inequality. We identified possible issues which might have contributed to conflicting results on this same question of whether inequality affects growth across countries. Briefly, we reviewed the work of Kuznets (1955) on the inverted-U' curve hypothesis, Galor and Zeira (1993) comprehensive work on the subject of inequality and growth and we argued that these works did not indicate precisely quantitative implication of policy objectives on how inequality affects growth.

With the innovation of Deininger and Squire (1996) high quality inequality data set, we also examined some subsequent empirical work which relied on it. For example Perotti (1996) finds a negative association between inequality and growth while Barro (2000) in a panel study finds little overall relationship between income inequality and growth concluding that inequality tends to impede growth in poor countries and promote it in rich countries. Forbes (2000) also studies a panel data set and finds that in the short and medium term, an increase in a country's level of income inequality has a significant positive relationship to subsequent economic growth. Forbes' result was robust across samples, variable definitions, and model specifications. Knowles (2005) argues that most recent empirical findings on growth-inequality nexus employed inconsistently measured inequality data. Hence, the reported negative relationship between income inequality and growth across countries is not robust when income inequality is consistently measured. However, he found a significant negative relationship between expenditure inequality and growth in a sample of developing countries.

Banerjee and Duflo (2000), estimate a non–linear relationship between growth and inequality. They find that the growth rate is an inverted U-shaped function of net changes in inequality. While the paper argues that the non-linearity captures multiplicity of findings in previous studies, it could not assert whether inequality impedes growth or not.

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In a recent work, Herzer and Vollmer (2012) employ panel co-integration technique to estimate growth-inequality relationship for a panel of countries between. We argued that the results of the post D&S data set are still biased because most of them do not account for the importance of cross-country variation in inequality data as against little evidence of within country variation in inequality as reflected in the data. We further assert that the D&S data set has subjected most previous works to sample selection bias in their analysis.

To correct for some of the key issues identified in previous work, we employed the System GMM developed by Arellano &Bover (1995) and Blundell & Bond (1998) to estimate a panel dataset of 65 represented samples of rich and poor countries. We use the inequality data provided by the University of Texas Inequality Project (UTIP, 2013).

We found that relationship between inequality and growth is positive but insignificant. We suggest that various theoretical links between inequality and growth might be counter-acting to leave a neutral effect. Also, in a non-linear specification, both squared and cube inequality variable has no impact on growth. We therefore conclude that, policy makers interested in redistribution for improved welfare should be aware that such redistributive policy might not be Pareto optimal.

FUTURE RESEARCH

The findings of our work reveal that inequality has positive but statistically insignificant effect on growth. This should not be interpreted to mean that the relationship between inequality and growth is resolved. From our results and sensitivity analysis, we understand that inequality and growth exhibit varying relationships depending on country samples.

Moreover, ours has not been an attempt to analyse a long-run relationship between inequality and growth. As a result of data availability, we have been constrained to estimate short and medium-term inequality and growth nexus.

In our subsequent work, we would attempt to estimate a long-run relationship between inequality and growth as more up-to-date data becomes available. We would also like to re-examine more deeply the theoretical underpinnings of the channels through which inequality affects growth as it appears that the nexus between inequality and growth depends to a large extent on the conditions and efficiency of these channels in the various countries.

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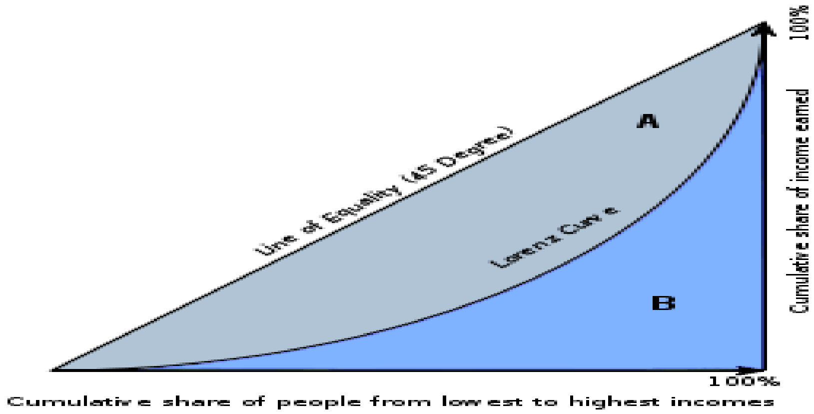
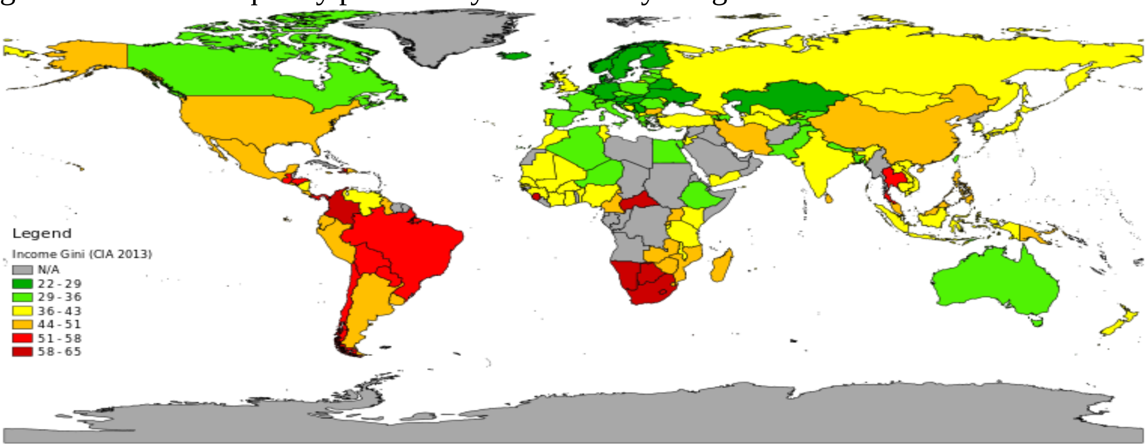
APPENDIX

Figure 1: The Lorenz Curve



Source: (Wikipedia)

Figure 2: Income Inequality per country measured by the gini coefficient.



Source: (CIA World Factbook)

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TABLE 4 – Regression Analysis and GMM Diagnostics

Variables	Coefficients	t-stat	p-value	Further Explanation
ehiiL1.	0.0016	0.56	0.579	"Lagged income inequality"
lnpc_gniL1.	0.0005	0.04	0.968	"Lagged log. of per capita income (1st lag)"
hc_totalL1.	0.0047	0.28	0.782	"Lagged human capita (1st lag)"
pcfL1.	-0.0075	-0.58	0.566	"Lagged market distortions (1st lag)"
Set of dummy variables				
yr1965	*dropped due*			
yr1970	-0.0045	-0.03	0.979	
yr1975	0.0768	0.43	0.669	
yr1980	0.0343	0.19	0.85	
yr1985	-0.0891	-0.48	0.631	
yr1990	0.0006	0	0.997	
yr1995	-0.0342	-0.18	0.858	
yr2000	-0.0605	-0.31	0.759	
yr2005	-0.0119	-0.06	0.952	
Model diagnostics				
Number of observations	452			
Number of groups	65			
Number of instruments	17			
F-test of joint significance		F(12, 65) = 68.83 Prob> F		H_0: Independent variables are jointly equal to zero
Arellano-Bond test for AR(1) first differences		z = -5.59 Pr> z = 0.000		H_0: There is no first-order serial correlation in residuals
Arellano-Bond test for AR(2) first differences		z= -0.83 Pr> z = 0.406		H_0: There is no second-order serial correlation in residuals
Hansen J-test of over-identifying restrictions:		chi2(5) = 7.50 Prob> chi2 =		H_0: Model specification is correct and all over-identifying restrictions (all over-identified
Difference-in-Hansen tests of exogeneity of GMM instrument subsets:for levels		chi2(4) = 7.45 Prob> chi2 = 0.114		Hansen test excluding System GMM instruments (the differenced instruments). H_0: system-GMM instruments are truly exogenous
Difference-in-Hansen tests of exogeneity of GMM instrument subsets:		chi2(3) = 2.82 Prob> chi2 =		H_0: system-GMM instruments are truly exogenous and they improve Hansen J-test are

Notes: Dependent variable is average per capita annual growth.
Source: Extracted by the Authors from STATA 12 regression output.

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