Inequality does cause underdevelopment:

Comprehensive analyses of the relationship

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May 2013

Abstract

Whether inequality has a negative impact on development is still an unresolved debate. However, it is indisputable that it brings adverse effects in certain development measures. Taken largely from previous literatures, this paper seeks to use more recent data and more comprehensive data sets to show that inequality does in fact cause underdevelopment. We see that there are negative impacts of inequality on schooling and institutional qualities, which are some of the main indicators of countries' performance. In this paper we find that inequality's correlation with income growth, schooling and institutional qualities are mostly negative. Furthermore, this paper also uses HDI as a measure of development and shows that inequality does cause HDI growth to lag, and this is largely a negative implication for societies that are facing a worldwide increasing trend of inequality.

I. Introduction

Inequality is a serious issue on its own, and as it continues to increase worldwide, presumably affecting society in many ways. One way to estimate its harm in society would be to examine its impact on growth of per capita income, as it is a universal measure for economic performance and well-being. The relationship, however, still remains without an agreement.

This paper is an extended argument to literature on inequality's negative impact on development. It examines the relationship between inequality and economic development. Schooling and institutions serve as main channels by which inequality lowers per capita income, as suggested in past literature (Acemoglu et al., 2000, 2002, 2005 on institution; Schultz, 1963; Krueger, 1968; Easterlin, 1981; Mankiw, 1995 on schooling). Inequality will be measured by the gini coefficient and share of income accruing to the top 20%. Development cannot be defined alone by GDP, and thus I will use schooling and institutional measures of development in addition to GDP.

This paper largely follows Easterly's (2007) models, but is significant in that it uses more recent data in cross-country analysis in examining the relationship. Also, it uses different time periods and different measures of per capita income in order to examine if the results are consistent. Furthermore, the paper examines the relationship in a time-series method as previous literature saw nonlinear relationship using panel analysis growth (Forbes, 2000; Barro, 2000; Banerjee and Duflo, 2003) while some debates otherwise (that it is not an appropriate method or that it is not used in a right format (Easterly, 2007). Human development index will also be used as a dependent variable; it is a good measure of well-being as it captures education and health in addition to income.

Another significant contribution of this paper is that it uses human development index (HDI) as a dependent variable. It is a better measure of well-being, as it captures education and health in addition to income. I use the growth of HDI between 1980 and 2012 as one of the measures of development, taken from UNDP. Recent literature has emphasized the prominence of HDI (Human Development Report). Its relationship with inequality would be a significant indication of the effect of inequality on true development.

This paper finds first two cross-sectional analysis yield consistent results- that inequality has a negative effect on growth. The relationship is negative and highly significant. The relationship is especially strong when using secondary school enrollment as a measure for development – suggesting the adverse impacts of inequality that GDP alone does not capture. Section II will review past studies that have been influential in this study. Section III will discuss the two main data sets used in this paper. The third dataset using time-series panel method will also be examined. Section IV will analyze the results. Section V will do robustness checks, for potential omitted variables which may affect economic outcomes: ethnic fractionalization and legal origin. Section VI will conclude.

II. Literature Review

The relationship between inequality and economic development has been studied for a long time, and is still in contentious debate. There have been numerous arguments on all sides; that inequality does undermine economic growth, that inequality actually increases growth in the long term, or that they do not have any causal effect, or that the relationship is ambiguous.

Inequality may impede economic growth through the following channels: politics, imperfect capital market, and institutions. The first channel, politics, suggests that high inequality would cause increase in redistribution which would hinder economic growth (Alesina and Rodrk, 1994; Persson and Tabellini, 1994). Second, credit constraint, suggests that the asset-poor will be unable to make long term profitable investments due to short term credit constraints. Imperfect capital markets will prevent human capital accumulation (such as education) by the poor majority (Galor and Zeira, 1993; Alesina and Rodrik 1994; Perotti, 1996; Galor and Moav, 2006; Galor et al. 2006). And lastly, inequality could cause unstable institutions and political instability (Benabou, 1996; Perotti, 1996) that will lower growth (Alesina et al., 1996). Engerman and Sokoloff (1997, 2000) suggest that structural inequality causes bad institution, low human capital investment and underdevelopment. This is followed through by Easterly (2007) using wheat-sugar ratio as an instrument for inequality.

There have been numerous arguments that there is positive or nonlinear relationship between inequality and growth (Forbes (2000), Barro (2000), Banerjee and Duflo (2003). One of main theories suggests that accumulation of capital among the rich promotes efficiency as they are more likely to save more and increases their incentive to work hard and move up the ladder (Forbes, 2000). Recent literature has much focused on the nonlinearity of the relationship; that the relation is ambiguous or not related. Panel data analysis typically shows zero or positive relationship between the two (Banerjee and Duflo, 2003). This paper will does a time-series fixed effects regression and find an insignificant positive correlation. However, as Easterly (2007) mentioned in his paper, “there is some question as to whether panel methods using high frequency data are the appropriate test of a relationship whose mechanism seem to be long run characteristics that are fairly stable over time.” Barro (2000) suggests inequality encourages growth within rich countries but hurts growth in poorer countries.

III. Data

There are three different data sets used in this paper. All three data sets use countries taken from the World Bank. The list of countries is in Appendix A. Note that the use of countries slightly differs by data set and that not all countries are used in data analysis.

First data set uses cross-section analysis, with 2008 GDP per capita as dependent variable and inequality measures, averaged over 1970 to 2002, as independent variables. Easterly (2007) used GDP per capita for 20002 and inequality measures for 1960 – 1998; by using data for more recent years, I check if they yield consistent results. The gini coefficient and top quintile income share are used to measure inequality, and I also use wheat-sugar ratio as an instrument for the two measures of inequality. Wheat-sugar ratio is a good instrument for inequality, as they are highly relevant, shown in figure 1. This ratio has a strong correlation with tropical areas, but there are considerable variations in the wheat-sugar ratio both in tropical and non-tropical areas (Easterly 2007). Appendix B, taken directly from Easterly (2007), shows the different variations of wheat-sugar ratio for 118 countries.

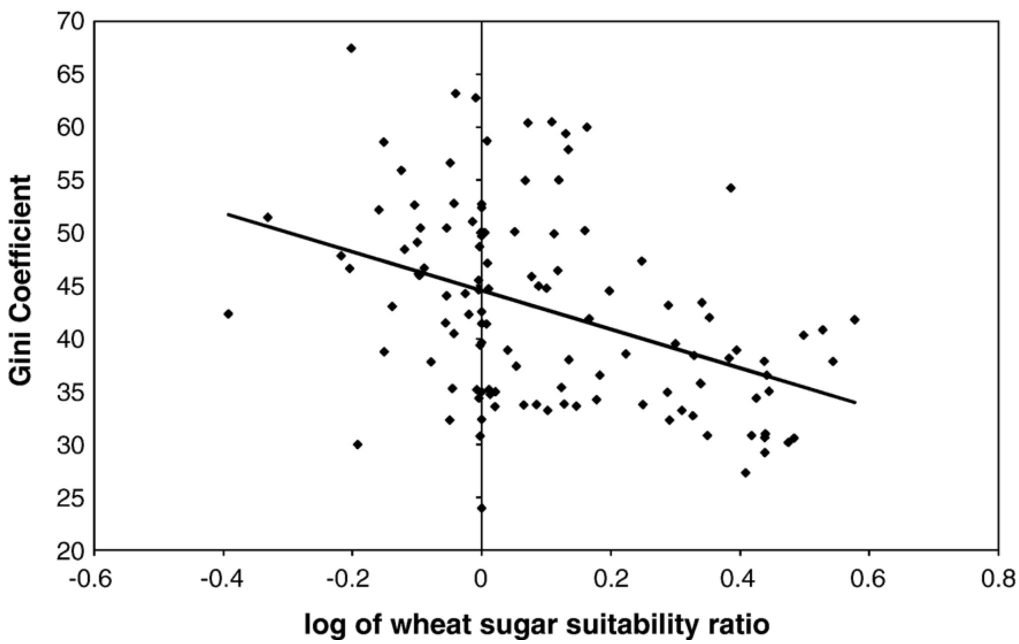
The use of instrumental variable analysis allows us to address the issue of causality. The log of the ratio of land suitable for wheat to that for sugarcane is strongly predictive of inequality (although this relationship does weaken over time). The "wheat-sugar ratio" is defined as lwheatsugar = log [(1 + share of arable land suitable for wheat) / (1 + share of arable land suitable for sugarcane)].

Using IV method:

1. Instrument Relevance: the instrument is strongly correlated with the endogenous variable, inequality. The ratio is negatively correlated with both inequality measures, and at 1% significance levels: Corr(lwheatsugar, inequality) $\neq 0$

2. Instrument Exogeneity: instrument is not affected by other variables that lead to different inequality measures. There should be no reverse causality; that development does not affect wheat-sugar ratio. In this paper, we largely assume this to hold true. That is, corr(lwheatsugar, u_i) = 0
3. Exclusion restriction: Instrument may affect development outcomes only through inequality, for it to be a valid instrument. We check for other possible channels in section V by robustness checks.

Figure 1. Inequality and log of wheat-sugar ratio



Source: Easterly (2007)

The data for GDP per capita, a measure for development, and share of income held by the top quintile, another measure for income inequality, are from World Development Indicator (World Bank), and the Gini index is from the UN-WIDER dataset (World Income Inequality database). I use the same regional assignments as Easterly (2007) taken from the world bank, and development measures with different time periods – secondary school enrollment rate averaged over 2002 to 2010 (World Bank), and institutional measures (QoG taken from World Bank governance indicators, Kaufmann et al (KKZ), 2009) averaged for 2008.

The second dataset differs in that I use GDP growth per capita, averaged over 1980 to 2008 and from 1990 to 2008, using cross-sectional analysis. I also hold for initial GDP per capita in 1980 and 1990 respectively, assuming that initial GDP would inversely affect subsequent growth (developing countries have a bigger area to improvement than the already developed countries). Rest of the data remains the same as those used in the first analysis.

Both cross-section analyses estimate the relationship without and with the presence of regional dummies. The World Bank's classifications are defined on the basis of income. Easterly (2007) corrects this. Countries are split into four regions: East/South Asia and Pacific, Western Hemisphere, Europe and Central Asia, and Middle East and Africa.

Lastly, I run a time-series regression to see if the relationship changes when comparing countries over time, rather than doing a cross-sectional analysis. Forbes mentions that there is a nonlinear relationship when using panel analysis. Easterly argues that panel analysis is inappropriate in estimating the relationship, as the frequency is too high. Thus, I adjust the time frequency to five year periods to control for some of the fluctuations to see if this yields any different results. However, I find that panel data, even with five year periods, estimates a positive relationship between inequality and income growth. Its correlation with schooling and institutions are, however, negative and becomes significant when using the five year periods.

Another contribution of this paper is the use of human development index (HDI) as a measure for development. The human development index is composed of health, education and living standards. Health is measured in terms of life expectancy at birth; education is measured by mean years of schooling and expected years of schooling; living standard is measured by gross national income per capita (GNI). The scores for these three components are aggregated using geometric mean. UNDP also introduced inequality-adjusted HDI, but I do not use this. I use the inequality unadjusted index since inequality obviously affects inequality-adjusted index. The HDI allows us to estimate the relationship between inequality and an inclusive measure of development.

IV. Analysis of the results

(4.1) Cross-section analysis using instrumental variables analysis

First, I examine the cross-section regression to assess the relationship between inequality and development, using wheat-sugar ratio as instrument. Table 1 shows the first stage regression for instrument and inequality measures, average gini coefficient and average share of income held by the top quintile, from 1970 to 2002. The equation for first stage of IV regression is as follows:

$$\text{Inequality measure}_i = \alpha_1 + \beta_1(\text{lwheatsugar}_i) + \varepsilon_{1,i}$$

where ε is the noise term, i is for country, and β_1 shows the average correlation between lwheatsugar and inequality.

Table 1 shows that the correlation between average gini and lwheatsugar as well as average top quintile share and lwheatsugar are all significant at 1% level (P = 0). The F-statistics are also high for both measures. From this, we can say that lwheatsugar is a strong instrument for inequality.

Table 1. First stage regression for inequality on wheat-sugar ratio - to see if the instrument is strong

Dependent variables	Average Gini, 1970-2002	Average share of income held by top quintile, 1970-2002
Lwheatsugar	-29.297	-21.879
	(2.87)**	(2.53)**
Constant	44.178	49.34

	(0.87)**	(0.73)**
Observations	113	108
F-statistic	104.29	74.33
R-squared	0.36	0.34

Robust t statistics is in parentheses; ** implies significant at 1%

Table 2 shows the summary statistics for the variables used for the first dataset. I show that there are enough observations for lwheatsugar – as it has 117 observations, not much different from observations for gini and share of quintile.

Table 2. Summary statistics for dataset 1

Variable	Observations	Mean	Std. Dev.	Min	Max
lgdpc2008	165	8.659	1.275	5.67	11.185
gini7002	140	40.948	10.358	22.881	73.9
quintile7002	134	47.637	8.563	32.59	78.25
lwheatsugar	118	0.105	0.205	-0.393	0.578
institution2008	189	-0.053	0.916	-2.499	1.796
school0210	140	40.948	10.358	22.881	73.9

Lgdpc2008: log per capita GDP in 2008; gini7002: gini averaged over 1970 – 2002; quintile7002: the share of top quintile averaged over 1970 to 2002; lwheatsugar: log of wheat-sugar ratio; institution2008: institutional measures averaged in 2008; school0210: secondary school enrollment rates for 2002-2010.

Next I estimate the relationship between development outcomes – per capita income, institutions, and schooling - and inequality measures. Data on income measures, 2008 GDP per capita, and on schooling, 2002 - 2010 secondary school enrollment rate, is from World Bank Development Index (2013 version); institution measures are derived from World Bank governance indicators (2013 version), taken from Kaufmann, Kraay, and Zoido-Lobaton2003 (KKZ). The institutional measures compose of voice and accountability, rule of law, control of corruption, political stability, regulatory quality, and government effectiveness. The following equation is the second stage of the IV model, the main interest of this model: how inequality is associated with development.

$$\text{Development measure}_i = \alpha_2 + \beta_2(\text{inequality measure}_i) + \varepsilon_{2,i}$$

where ε is the noise term, i is for observed countries, and β_2 is the coefficient for inequality's average correlation with development measures.

Both OLS and IV regression results presented in Table 3 show that inequality is, on average, associated with a lower per capita income, worse institutional quality, and lower level of schooling. When using instrumental variable, lwheatsugar, the relationship is stronger. When regional dummies (endogenous to development measures) are included in the IV regressions, there is a stronger correlation but relationship is less significant than without regional dummies, although still significant.

Table 3. Results for development outcomes and inequality: Ordinary least squares and instrumental variables, using first data set

	Dependent variable: log per capita income, 2008 (lgdpc)					
	Inequality measure: Gini coefficient, 1970-2002			Inequality measure: share of top qunitle, 1970-2002		
	OLS	IV	IV	OLS	IV	IV
Inequality measure	-0.0587	-0.1038	-0.17	-0.053	-0.1399	-0.216
	(6.58)**	(7.03)**	(3.24)**	(4.83)**	(6.21)**	(3.40)**
East and South Asia and Pacific Americas			-2.415 (3.46)**			-2.876 (3.45)**
Europe and Central Asia			-2.374 (2.36)*			-2.394 (2.57)*
Middle East and Africa			-1.7297 (4.84)**			-2.271 (4.91)**
Constant	11.126	13.017	17.44	11.249	15.357	20.834
Observations	132	111	111	131	106	106
R-squared	0.222	0.137	0.053	0.134		
F-statistics from first stage	43.29	43.29	15.65	23.3	38.62	12.79

	Dependent variable: institutional measures in 2008 (KKZ)					
	Inequality measure: Gini coefficient, 1970-2002			Inequality measure: share of top quintile, 1970-2002		
	OLS	IV	IV	OLS	IV	IV
Inequality measure	-0.037	-0.076	-0.1595	-0.0339	-0.102	-0.188
	(5.23)**	(6.49)**	(3.11)**	(3.74)**	(5.76)**	(3.16)**

East and South Asia and Pacific Americas			-1.868 (2.76)**			-2.161 (2.80)**
Europe and Central Asia			-2.24 (2.23)*			-2.053 (2.31)*
Middle East and Africa			-0.651 (2.14)*			-1.145 (2.89)**
Constant	1.506	3.12	7.8345	1.603	4.798	10.228
Observations	141	113	113	134	108	108
R-squared	0.1798	0.0877		0.109		
F-statistics from first stage	27.39	42.14	8.48	13.99	33.13	6.76

	Dependent variable: secondary enrollment rates averaged over 2002 - 2010					
	Inequality measure: Gini coefficient, 1970-2002			Inequality measure: share of top quintile, 1970-2002		
	OLS	IV	IV	OLS	IV	IV
Inequality measure	-1.454 (6.90)**	-2.278 (6.64)**	-2.439 (2.81)**	-1.308 (5.10)**	-3.007 (6.06)**	-3.224 (2.90)**
East and South Asia and Pacific Americas			-32.711 (2.93)**			-43.8099 (2.93)**
Europe and Central Asia			-24.553 (1.56)			-27.488 (1.68)
Middle East and Africa			-42.524 (6.45)**			-50.086 (5.93)**
Constant	134.419	169.418	201.758	136.719	217.437	257.514
Observations	131	107	107	131	104	104
R-squared	0.241	0.1897	0.429	0.142		0.3275
F-statistics from first stage	47.55	44.07	27.83	25.97	36.69	23.35

Robust t statistics in parenthesis (* significant at 5%; ** significant at 1%)

(4.2) Cross-section analysis for income growth rates as a new dependent variable

The second set of regressions is slightly different from the first, in that the growth rate of GDP per capita is used as a measure of economic development, along with secondary schooling enrollment rate and institutional quality. Secondly, the initial GDP is included a control variable, for initial development level would affect subsequent growth. Results are similar from the first data set; this increases our confidence of the negative relationship between inequality and growth. Inequality does in fact undermine development.

I do this for a few different time periods for all variables. First, I look at the relationship between log of growth of GDP per capita (1980-2008) and inequality measures averaged over 1970 to 2002 and then over 1970-1980 (for initial inequality) holding initial level of income per capital constant. I do this first without regional dummies and second with regional dummies.

Next, I estimate the relationship between GDP per capita growth from 1990-2008 on inequality measure from 1970-2002 and 1970-1990. I also estimate the same relationship using per capita income growth from 1980-1990 as the dependent variable. 1980-1990 is the period of low growth, 1990-2008 is for high growth; I compare the relationship between growth and inequality during the times of high growth and low growth. Again, I hold for initial level of income of countries. I do this first without controlling for regional dummies and second controlling for regional dummies.

Table 4 shows the summary statistics for main variables used in the second dataset. Gini7002, quintile7002, institution2008 and school0210 are the same as in the first dataset, so I leave them out from Table 4.

Table 4. Summary statistics for second dataset

Variable	Observations	Mean	Std. Dev.	Min	Max
lgdpcgr7008	188	1.138	.484	-.119	3.411
lgdpcgr8008	188	1.082	.536	-.268	3.411
lgdpcgr8090	99	.768	1.134	-3.585	2.914
lgdpcgr9008	187	1.085	.582	-.288	3.411
quintile7090	63	44.573	9.254	31.3	63.544
gini7090	116	38.648	11.058	19.65	63.7
gini7080	83	41.679	10.180	21.957	65.35
lgdpc1980	130	8.381	1.249	5.510	11.466
lgdpc1990	164	8.380	1.225	5.579	10.837

Lgdpcgr7008: log of per capita GDP growth averaged over 1970-2008; log of per capita GDP growth averaged over 1980-2008; lgdpcgr8090: log of per capita GDP growth averaged over 1980-1990; quintile7090: the share of income accruing to top quintile averaged over 1970-1990; gini7090: gini averaged over 1970-1990; gini7080: gini averaged over 1970-1980; lgdpc1980: log of per capita GDP in 1980; lgdpc1990: log of per capita GDP in 1990.

Table 5 shows results for the following OLS regression:

$$\text{Development measure}_i = \alpha + \beta(\text{inequality measure}_i) + c(\text{Initial GDP}) + \varepsilon_{i.}$$

where ε is the noise term.

Table 5 shows that the relationship is negative for all but the magnitude and significance differ. Comparing the relationship when there is low growth and high growth, we see that the correlation is higher during the period of low growth (1980-1990) and less so in the period of high growth (1990-2008). The significance is smaller in low growth, but this is due to smaller observations that make standard error larger. Thus, it is possible that growth is an important factor in how inequality may affect development.

Table 5. Results for development outcomes and inequality: Ordinary least squares, using second data set

Dependent variable: log per capita income growth, 1980 - 2008 (lgdpc)								
Inequality measure	Gini, 1970-2002		Gini, 1970-1980		share of top quintile, 1970-2002		share of top quintile, 1970-1980	
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Inequality measure	-0.0118 (2.64)**	-0.01195 (2.05)**	-0.0109 (2.21)**	-0.0141 (2.18)**	-0.00775 (1.44)	-0.00415 (0.65)	not enough data	
lgdpc1980	-0.0977 (2.28)**	-0.101 (1.84)*	-0.1437 (3)***	-0.1006 (1.43)	-0.05856 (1.41)	0.086 (1.48)		
East and South Asia and Pacific Americas		0.0507 (0.28)		0.0378 (0.18)		0.131 (0.73)		
Europe and Central Asia		-0.078 (0.5)		-0.256 (1.57)		0.033 (0.21)		
Middle East and Africa		-0.0972 (0.8)		-0.0522 (0.35)		-0.156 (1.23)		
Constant	2.241	2.322	2.627	2.46	1.7705	1.854		
Observations	106	106	74	74	99	99		
R-squared	0.0826	0.0997	0.1325	0.1779	0.032	0.0748		

F-statistics from first stage	3.83	2.06	4.73	2.91	1.37	1.23		

Dependent variable: log per capita income growth, 1990-2008								
Inequality measure	Gini, 1970-2002		Gini, 1970-1990		share of top quintile, 1970-2002		share of top quintile, 1970-1990	
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	
Inequality measure	-0.022 (4.72)***	-0.0123 (1.9)*	-0.026 (6.58)***	-0.021 (3.57)***	-0.019 (3.75)***	-0.0053 (0.81)	-0.0286 (5.4)***	-0.0098 (0.96)
Initial GDP per capita (1990)	-0.128 (2.88)***	-0.213 (4.02)***	-0.185 (4.27)***	-0.237 (4.4)***	-0.071 (1.68)*	-0.194 (3.58)***	0.075 (1.31)	0.0321 (0.4)
East and South Asia and Pacific Americas		-0.012 (0.06)		-0.087 (0.4)		0.074 (0.43)		0.32 (1.38)
Europe and Central Asia		0.259 (1.48)		0.087 (0.46)		0.397 (2.48)*		0.517 (1.9)
Middle East and Africa		-0.337 (2.47)**		-0.255 (1.71)*		-0.342 (2.54)**		0.0524 (0.31)
Consant	3.029	3.373	3.69	3.988	2.55	2.89	1.88959	1.188
Observations	132	132	109	109	128	128	61	61
R-squared	0.1422	0.234	0.2658	0.2973	0.527	0.215	0.308	0.372
F-statistics from first stage	11.15	132	21.96	9.85	7.09	7.11	20.56	9.71

Dependent variable: log per capita income growth, 1980-1990			
Inequality measure	Gini, 1970-1980		share of top quintile, 1970-1980
	OLS	OLS	OLS
Inequality measure	-0.0397 (2.01)**	-0.043 (1.67)*	not enough data
Initial GDP per capita (1980)	-0.0137 (0.1)	0.091 (0.37)	
East and South Asia and Pacific Americas		0.1432 (0.19)	
Europe and Central Asia		-0.382 (0.97)	
Middle East and Africa		-0.0005 (0.999)	
Consant	2.368	1.704	
Observations	54	54	
R-squared	0.134	0.1534	
F-statistics from first stage	2.21	1.49	

Robust t statistics in parenthesis (* significant at 10%; ** significant at 5%; *** significant at 1%)

(4.3) Human development index growth as dependent variable

Next, we use HDI growth as a dependent variable. I define HDI growth in a following way for example:

hdigr8012 = (HDI 2012 – HDI1980)/ HDI1980.

Human development index constitutes various indicators that better illustrate countries' well-being. Table 6 lays out the summary statistics for HDI observations.

Table 6. Summary statistics for HDI

Variable	Observations	Mean	Std. Dev.	Min	Max
hdigr8012	110	.322	.197	.063	.979
hdigr9012	130	.203	.152	-.070	.863
hdi1980	110	.536	.185	.176	.857
hdi1990	130	.585	.181	.198	.88

Where hdigr8012: hdi growth over 1980-2012; hdigr9012: HDI growth over 1990-2012; hdi1980: HDI in 1980; hdi1990: HDI in 1990.

As before, I use the OLS model, IV model for HDI growth as dependent variables. Table 7 shows the results for regressing HDI growth from 1980 to 2012 on inequality measures, holding constant the initial HDI. I do this once with ordinary least squares model and then use instrumental variables regression, using wheat-sugar ratio as instrument. I do this once without regional dummies and once with the regional dummies; same classification as before.

Results show that the growth of human development indicator score from 1980 to 2012 is negatively associated with the average gini coefficient from 1970 to 2002, when holding for initial HDI score of 1980. The result is same when using the income share of top quintile as the measure for inequality. The relationships are highly significant.

Using IV approach with lwheatsugar as instrument for inequality, we observe similar results. First we make sure that inequality measures and the instrument are correlated (First stage in IV regression). We see that the correlation between gini7002 and lwheatsugar is -29.297 with t-stat of -10.21. Thus, the correlation is significant at under 0.01% significance level. The correlation between lwheatsugar and quintile7002 is -21.879 with t-stat -8.62. Hence, the relationship is significant at .01% confidence level. The following equation is the first stage of the IV model.

Inequality $\text{measure}_i = \theta_1 + \gamma_1(\text{lwheatsugar}_i) + \varepsilon_{1,i}$

where ε is the noise term, i is for countries, and γ_1 estimates the correlation between lwheatsugar (the instrument) and inequality.

Table 7 shows the basic relationship between HDI growth from 1980 to 2012, and inequality measures – the Gini coefficient and share of top quintile – from 1970 to 2002. We hold for intial HDI in 1980, as it is highly correlated with and may affect subsequent growth rate. The following equation is the second stage of the IV model:

HDI Growth $(1980\text{-}2008)_i = \theta_2 + \gamma_2(\text{Inequality measure}_i) + \delta_2\text{HDI 1980} + \varepsilon_{2,i}$

where ε is the noise term.

Table 7. Results for relationship between HDI growth from 1980-2012 and inequality measures from 1970-2002, using OLS and IV regressions.

	Dependent variable: HDI growth, 1980-2012					
	Inequality measure: Gini coefficient, 1970-2002			Inequality measure: share of top quintile, 1970-2002		
	OLS	IV	IV	OLS	IV	IV
Inequality measure	-0.007	-0.006	-0.015	-0.008	-0.007	-0.0199
	(4.83)***	(2.67)***	(1.9)*	4.69***	2.59***	1.66
HDI1980	-0.984	-0.971	-1.229	-0.953	-0.936	-1.221
	(10.98)***	(7.27)***	(5.82)***	(10.84)**	(7.52)***	(6.08)***
East and South Asia and Pacific			0.099 (1.05)			-0.142 (1.00)
Americas Europe and Central Asia			-0.155 (1.27)			-0.176 (1.15)
Middle East and Africa			-0.138 (2.37)**			-0.178 (2.05)**
Consant	1.165	1.127	1.734	1.247	1.193	2.071

Observations	95	81	81	86	77	77
R-squared	0.6592	0.684	0.693	0.657	0.656	0.6215
F-statistics from first stage		50.33	20.13	60.37		22.52

Robust t statistics in parenthesis (* significant at 10%; ** significant at 5%; significant at 1%)

The findings from the IV method tell us that inequality causes slower HDI growth. The OLS regressions show strong correlation between the inequality measures and HDI growth, both under 1% significance level. Using IV method also yields negative coefficients, although less significant. They show that the relationship is negative and significant at 5% level without holding for regional dummies. When controlling for regional dummies, we see that the relationship is close to 10% significance level. Thus, we do find a causal relationship of inequality and HDI growth rate.

(4.4)
Lastly, I conduct time-series analysis, to see how inequality affects development controlling for country-fixed effects. The positive relationship between GDP growth rate and inequality challenges the two previous analyses in section 4.1 - 4.3. However, Easterly mentions this challenge (2007), and refutes this point:

> “A challenge to this literature came from researchers who exploited the panel dimensions of the data (Forbes, 2000; Barro, 2000; Banerjee and Duflo, 2003). These authors found a zero, nonlinear, or even positive relationship between inequality and growth. The positive relationship of Forbes (2000) would seem to confirm a long tradition in economic thought of beneficent inequality that concentrates income among the rich who save more and increases the incentive to work hard to move up the ladder. However, there is some question as to whether

> panel methods using relatively high frequency data are the appropriate test of a relationship whose mechanisms seem to be long run characteristics that are fairly stable over time." (Easterly, 759)

Thus, I adjust the time periods to a 5 year span, to control for yearly fluctuations. Despite Easterly's argument, data still yields a positive relationship between inequality (gini) and income growth rate in time-series panel analysis. However, the results for schooling measure and institutional measure are different. Even when using yearly periods, there is a negative relationship between inequality and institutions and between inequality and schooling. The correlation is negative, but not significant at 20% significance levels. When using 5 year span, however, the correlation between inequality and schooling become significant at 1% level. For institutional measure, it still remains insignificant at 20% significant level, but comes close. Note that I use average schooling years for school indicator in time-series analysis, based upon data availability. I also only use gini as a measure for inequality (and do not use income share of top quintile) due to data availability.

Table 8 shows basic summary statistics for variables used in time-series analysis. Table 9 shows basic summary statistics when using 5 year span data. Table 10 shows the regression outputs for yearly time-series analysis. Table 11 shows regression results for time-series analysis when using 5year span data - containing less noise. The following shows the equation for time-series regressions:

$$\text{GDP Growth}_{it} = \gamma_1(\text{inequality measures})_{it} + \lambda_t + u_{i,t}$$

Where λ_t is time effects, the model has a different intercept, λ_t, for each time period, every 1 year in Table 10 and every 5 years in Table11.

Table 8. Summary statistics for time-series dataset, 1960- 2008

Variable	Observations	Mean	Std. Dev.	Min	Max
gdpcgr	6913	2.449	32.517		
Institution	1921	-0.047	0.922	-2.499	1.956
school	907	4.472	2.903	0.042	12.247
gini	2115	38.066	10.884	15.9	73.9

Gdpcgr: per capita GDP growth rate in 1960-2008; institution: institutional measures in 1960-2008; school: average schooling years in 1960-2008; gini: gini index in 1960-2008; top quintile: share of income accruing to the top quintile in 1960-2008.

Table 9. Summary statistics for time-series dataset using 5 year span data, 1960-2008.

Variable	Observations	Mean	Std. Dev.	Min	Max
gdpcgr	1483	2.504	14.359		
Institution	577	-0.046	0.916	-2.417	1.94
school	811	4.612	2.917	0.042	12.247
gini	834	39.508	10.622	16.63	73.9

Table 10. Time-series Regression of development outcomes on inequality

Dependent variables	growth of GDP per capita	Institution	Schooling
Gini	0.119	-0.002	-0.028
	(5.44)**	(1.1)	(2.01)*
Constant	-2.343	0.399	7.42
	(2.73)**	(5.09)**	(13.29)**
Observations	1915	515	301
F-statistic	29.6	1.21	4.06
R-sq (within)	0.0164	0.0031	0.0178

Robust t statistics in parenthesis (* significant at 5%; ** significant at 1%)

Table 11. Time Series Regression of development on inequality: with 5 year time periods, within 1960-2008

Dependent variables	growth of GDP per capita	Institution	Schooling

Gini	0.105	-0.004	0.942
	(4.25)***	(1.24)	(3.6)***
Constant	-1.945	0.313	7.355
	(1.94)*	(2.37)**	(15.15)***
Observations	767	273	504
F-statistic	18.06	1.53	12.92
R-sq (within)	0.0281	0.0107	0.0306

Robust t statistics in parenthesis (* significant at 10%; ** significant at 5%; *** significant at 1%)

V. Robustness checks

Robustness checks are necessary in order to see if the relationship between inequality and development still holds when controlling for other potential causal variables, which may affect development. These potential omitted variables are taken from Easterly (2007): ethnic fractionalization and legal origin. Ethnic fractionalization has been emphasized in affecting growth and developmental measures as schooling and institutions (Easterly and Levine, 1997; Alesina et al. 1999; Acemoglu, Johnson, and Robinson 2002). By doing robustness checks, we make sure that inequality affects development controlling for other plausible explanatory variables (aka omitted variables).

Table 12 and Table 13 show that the relationship still remains strong and significant (at 1%) when controlling for ethnic fractionalization or legal origin dummies. I estimate the relationship between development outcomes and these two explanatory variables. I find that ethnic fractionalization and legal origin are both highly correlated with development outcomes, all at 1% significance levels. Thus, by holding for these variables, we examine if the relationship between inequality and development changes.

Again, I use lwheatsugar as instrument in the IV regression to estimate the relationship between inequality and development when controlling for ethnic fractionalization and legal origin. Holding ethnic fractionalization constant, (taken from Alesina et al., 2003), the coefficient on inequality measures drops slightly but still remains significant at 1% significance level. The F-statistics on the first stage regression with the lwheatsugar instrument are high and satisfactory. Legal origin (taken from La Rota et al 1999) is held constant by using dummies for British, French, and Socialist legal origin, where German or Scandinavian origins are the omitted categories to avoid collinearity). We see that the relationship is still significant, at 1%, and the coefficient for inequality increases, suggesting the magnitude to which inequality affects development is even higher when controlling for legal origins. The first stage F-statistics with the instrument are strong and satisfactory. The results are consistent with Easterly's paper (2007) although this data employs a more recent time period for measures of inequality as well as development. Hence, inequality does cause underdevelopment.

Table 12. Robustness checks: effect of inequality on development outcomes controlling for ethnic fractionalization

	Inequality measure: Gini, 1970-2002			Inequality mere: share of top quintile, 1970-2002			OLS without inequality measures		
	lgdpc 2008	institution 2008	school 2002-2010	lgdpc 2008	institution 2008	school 2002-2010	lgdpc 2008	institution 2008	school 2002-2010
Inequality measure	-0.0898	-0.074	-1.792	-0.114	-0.092	-2.27			
	(-4.78)**	(4.66)**	(4.62)**	(4.6)**	(4.41)**	(4.5)**			
Ethnic Fractionalization	-1.0796	-0.369	-32.508	-1.42	-0.647	-38.304	-2.514	-1.504	-61.347
	(-2.07)*	(0.87)	(2.75)**	(2.68)**	(1.57)	(3.14)**	(7.31)**	(6.26)**	(7.93)**
Constant	12.916	3.206	163.447	14.746	4.615	199.072	9.77	0.619	101.56
	(21.31)**	(5.91)**	(13.02)**	(14.58)**	(5.2)**	(9.68)**	(54.09)**	(4.65)**	(26.43)**
Observations	109	111	106	105	107	103	160	184	171
R-squared	0.2515	0.135	0.317	0.1045	0.026	0.2113	0.2611	0.176	0.277
F-statatistics for first-stage on excluded instrument	42.47	33.37	36.08	34.31	26.2	29.71		39.15	

Robust t statistics in parenthesis (* significant at 5%; ** significant at 1%)

Table 13. Robustness checks: effect of inequality on development outcomes controlling for legal origin

	Inequality measure: Gini, 1970-2002	Inequality measure: share of top quintile, 1970-2002	OLS without inequality measures

	lgdpc 2008	institution 2008	school 2002-2010	lgdppc 2008	institution 2008	school 2002-2010	lgdpc 2008	institution 2008	school 2002-2010
Inequality measure	-0.147	-0.119	-2.785	-0.1999	-0.158	-3.815			
	(6.04)**	(6.31)**	(4.74)**	(5.12)**	(5.29)**	(4.28)**			
leg_british	0.2099	0.401	3.99	0.512	0.533	9.261	-1.667	-1.167	-25.788
	(0.44)	(1.02)	(0.39)	(0.86)	(1.23)	(0.72)	(7.35)**	(5.69)**	(4.77)**
leg_french	0.444	0.233	5.541	0.871	0.533	14.312	-1.895	-1.533	-36.772
	(1.08)	(0.69)	(0.57)	(1.66)	(1.23)	(1.17)	(8.91)**	(7.81)**	(7.24)
leg_socialist	-1.182	-1.321	-12.717	-0.736	-0.973	-4.888	-1.353	-1.517	-14.957
	(5.58)**	(6.01)**	(2.89)**	(3.4)**	(4.1)**	(1.14)	(6.44)**	(6.97)**	(3.26)**
Constant	14.826	5	189.501	17.847	7.297	247.862	10.2444	1.243	101.195
	(19.33)**	(7.95)**	(10.3)**	(12)**	(6.31)**	(7.37)**	(71.75)**	(7.22)**	(28.19)**
Observations	110	112	107	106	108	104	165	189	176
R-squared	0.057	0.052	0.141				0.146	0.1945	0.139
F-statatistics for first-stage on excluded instrument	24.71	20.89	16.06	23.67	20.02	16.07	32.51	22.09	19.06

Robust t statistics in parenthesis (* significant at 5%; ** significant at 1%)

VI. Conclusion

This paper suggests that inequality does in fact impede economic and human development, as suggested by Easterly (2007) as well as Sokoloff and Engerman's hypothesis that inequality does hinder growth through institutions and schooling. By combining past literature with new data, this paper seeks to see if the relationship holds when using different methods and different time periods. Following Easterly's 2007 paper, but going further to use growth rates as well as time-series analysis, this paper seeks to explain some of the missing data and evidence from Easterly's argument.

Instrumental variable analysis show that inequality is negatively correlated with all three development measures: per capita income, institutional performance, and secondary school enrollment rate. Per capita income growth rate is also negatively and significantly correlated with inequality. HDI growth is a more inclusive measure of development outcomes. This paper finds

HDI growth is also negatively affected by inequality, using both OLS and IV analysis. Thus, this paper through comprehensive analysis, finds that inequality does cause underdevelopment.

Appendix A. List of country names

Andorra	Cote d'Ivoire	Equatorial Guinea
Afghanistan	Cameroon	Greece
Angola	Congo	Grenada
Albania	Colombia	Guatemala
United Arab Emirates	Comoros	Guyana
Argentina	Cape Verde	Honduras
Armenia	Costa Rica	Croatia
Antigua and Barbuda	Cuba	Haiti
Australia	Cyprus	Hungary
Austria	Czech Republic	Indonesia
Azerbaijan	Germany	India
Burundi	Djibouti	Ireland
Belgium	Dominica	Iran
Benin	Denmark	Iraq
Burkina Faso	Dominican Republic	Iceland
Bangladesh	Algeria	Israel
Bulgaria	Ecuador	Italy
Bahrain	Egypt	Jamaica
Bahamas	Eritrea	Jordan
Bosnia and Herzegovina	Spain	Japan
Belarus	Estonia	Kazakhstan
Belize	Ethiopia (1993-)	Kenya
Bolivia	Finland	Kyrgyzstan
Brazil	Fiji	Cambodia
Barbados	France	Kiribati
Brunei	Micronesia	St Kitts and Nevis
Bhutan	Gabon	Korea, South
Botswana	United Kingdom	Kuwait
Central African Republic	Georgia	Laos
Canada	Ghana	Lebanon
Switzerland	Guinea	Liberia
Chile	Gambia	Libya
China	Guinea-Bissau	St Lucia

Liechtenstein
Sri Lanka
Lesotho
Lithuania
Luxembourg
Latvia
Morocco
Monaco
Moldova
Madagascar
Maldives
Mexico
Marshall Islands
Macedonia
Mali
Malta
Myanmar
Montenegro
Mongolia
Mozambique
Mauritania
Mauritius
Malawi
Malaysia
Namibia
Niger
Nigeria
Nicaragua
Netherlands
Norway
Nepal
Nauru
New Zealand
Oman
Pakistan (1972-)
Panama
Peru
Philippines
Papua New Guinea
Poland
Korea, North
Portugal
Paraguay
Qatar
Russia
Rwanda
Saudi Arabia
Sudan
Senegal
Singapore
Solomon Islands
Sierra Leone
El Salvador
San Marino
Somalia
Serbia
Sao Tome and Principe
Suriname
Slovakia
Slovenia
Sweden
Swaziland
Seychelles
Syria
Chad
Togo
Thailand
Tajikistan
Turkmenistan
Tonga
Trinidad and Tobago
Tunisia
Turkey
Tuvalu
Taiwan
Tanzania
Uganda
Ukraine
Uruguay
United States
Uzbekistan
St Vincent and the Grenadines
Venezuela
Vietnam
Vanuatu
Yemen
South Africa
Congo, Democratic Republic
Zambia
Zimbabwe

Appendix B. lwheatsugar by country

Algeria	0.0404
Argentina	0.2895
Armenia	0.112
Australia	0.1347
Austria	0.438
Azerbaijan	0.0877
Bangladesh	0.128
Belarus	0.4833
Belgium	0.4392
Bolivia	-0.1195
Bosnia and Herzegovina	0.5281
Botswana	0.0088
Brazil	-0.0491
Bulgaria	0.4086
Burkina Faso	0
Burundi	0.011
Cambodia	-0.0201
Canada	0.1019

Central African Republic	-0.0407
Chad	0
Chile	0.2481
China	0.085
Colombia	-0.0946
Costa Rica	-0.1385
Cote d'Ivoire	-0.0428
Czech Republic	0.4749
Denmark	0.4419
Dominican Republic	-0.2175
Ecuador	-0.0257
Egypt	0
El Salvador	-0.0138
Estonia	0.3529
Ethiopia	0.1664
Fiji	-0.0961
Finland	0.0206
France	0.4375
Gabon	-0.2017
Gambia	0
Georgia	0.3854
Germany	0.4452
Ghana	-0.0078
Greece	0.2231
Guatemala	-0.3314
Guinea	-0.0035
Guyana	-0.0997
Honduras	-0.1246
Hungary	0.4383
India	-0.0045
Indonesia	-0.0454
Iraq	0.1628
Ireland	0.1005
Israel	0.2877
Italy	0.3287
Jamaica	-0.3926
Japan	0.2908
Jordan	0.0071
Kazakhstan	0.0129
Kenya	0.1298
Korea, South	0.2493
Kyrgyzstan	0.0104
Laos	-0.0497
Latvia	0.4253
Lebanon	0.119
Lesotho	0.1342
Lithuania	0.4986
Macedonia	0.1828
Madagascar	-0.0544
Malaysia	-0.0889
Mali	0
Mauritania	0
Mexico	0.0047
Moldova	0.1976
Mongolia	0
Myanmar	0.0212
Nepal	0.0776
Netherlands	0.3398
New Zealand	0.1234
Nicaragua	-0.1593
Niger	0
Nigeria	-0.0048
Norway	0.0535
Pakistan	0.1462
Panama	-0.1036
Papua New Guinea	-0.0431
Paraguay	-0.1519
Peru	-0.0979
Philippines	-0.2045
Poland	0.3491
Portugal	0.3409
Romania	0.3268
Russia	0.3002
Rwanda	-0.0027
Senegal	0
Serbia	0.3944
Sierra Leone	-0.0096
Slovenia	0.4173
South Africa	0.1088
Spain	0.0649
Sri Lanka	-0.0565
Sudan	-0.0025
Suriname	-0.1921
Swaziland	0.0719
Sweden	0.1777
Switzerland	0.5439
Tanzania	0.0671
Thailand	-0.0054
Tunisia	0.1173
Turkey	0.1601
Turkmenistan	0
Uganda	-0.1508
Ukraine	0.3094
United Kingdom	0.3385
United States	0.383
Uruguay	0.5775
Venezuela	-0.0544
Vietnam	-0.0786
Zambia	0.0508
Zimbabwe	0.0084

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