INEQUALITY AND GROWTH: A PANEL DATA DYNAMIC APPROACH

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Özet: Bu çalışma son zamanlarda yapılan çalışmalarda elde edilen gelir dağılımı eşitsizliği ve ekonomik büyüme arasındaki pozitif ilişkiyi yeniden sınamaktadır. Çalışmada, zaman içinde değişmeyen ülke karakteristiklerini control etmek amacıyla genişletilmiş bir gelir dağılımı panel ve veri seti kullanılmaktadır. Aynı zamanda daha önceki çalışmalarda kullanılan model genişletilerek spesifikasyon hataları en aza indirgemeye çalışılmıştır. Bulunan sonuçlar daha önceki çalışmaların aksine, gelir dağılımı ile büyüme arasında bulunan pozitif ilişkinin daha çok sayıda ülke, özellikle de gelir düzeyi düşük olan ülkelerin dahil edilmesine direnç olmadığını ve bu ilişkinin anlamsızlaştığını göstermektedir.

Abstract: This paper retests some recent findings that income inequality is positively related to economic growth. It uses an extended income inequality panel data set that reduces selection bias, while controlling for time-invariant country specific effects and extends the model used in previous studies. Results suggest that in contrary to the recent findings, the positive significant relationship is not robust to the inclnsion of more countries, which are mostly poor countries, and it becomes insignificant, although remains positive.

I.Introduction

The topic of growth and inequality is back with us; yet this time in reverse order. After Solow's exogenous (old) growth model, the debate, in the late 50s and 60s, was how economic growth influenced the distribution of income; after Romer's endogenous (new) growth model the question is now how inequality along with some other socio-political variables affects growth. Recent studies both in empirical and theoretical areas show that the relation between income and growth can be both negative and positive. A theory rises or falls with its assumptions and with what it includes and hence with what it excludes. Therefore, it is theoretically almost always possible to prove any result. So the contradictory theoretical results should not be a great surprise. Perhaps the more interesting thing is why empirical results are contradicting each other. But again in this camp, the division appears along the line of methodology.

Comprehensive surveys of the relationship between inequality and economic growth are given by Benabou (1996) and Aghion, Caroli, and Garcia-Penalosa (1999). Cross-country regressions using the OLS method such as Alesina and Rodrik (1994), Perrotti (1996), and Persson and Tabellini (1994) find a negative relationship between inequality and growth in the subsequent

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period. For example Perrotti (1996) finds that "More equal societies have lower fertility rates and higher rates of investment in education. Both are reflected in higher rates of growth. Also, very unequal societies tend to be politically and socially unstable, which is reflected in lower rates of investment and therefore growth." Another line of empirical research uses panel data techniques to explore the relationship between inequality and growth.

After Deininger and Squire (1996) made available a much larger and comparable panel data set about income distribution, studies using panel data techniques on income distribution and growth have multiplied. Among them we can mention Li and Zou (1998), Forbes (2000), and Barro (2000). The first two of these papers use the fixed effects estimates and argue that there may be omitted country specific effects which may bias the OLS estimates. They find a positive and significant relation between inequality and growth. Whereas, Barro uses a three-stage least squares (3SLS) instead of fixed effects estimation, which, he argues, eliminates cross-country information. He finds no significant relation between inequality and growth. But after that he breaks up his sample into two groups rich and poor, he finds a negative relation between inequality and growth in the sample of poor countries and a positive one in the sample of rich countries.

Usually, the theoretical relationship between inequality and growth is divided into three channels. First one is the credit market imperfections which may be caused by higher inequality in the distribution of wealth and income. In such capital market imperfections the poor may have limited access to credit and might be prevented from investing in human capital or other sorts of capital (Aghion and Bolton, 1997). The second channel usually termed as the political economy channel. Here if the median voter's income is less than the arithmetic mean, then the median voter might vote for redistributive policies (Alesina and Rodrik, Persson and Tabellini, 1994). Another possibility is the social unrest. Higher inequality in the distribution of assets and income might lead to social unrest which might increase violence and theft (Alesina and Perotti, 1996).

In the cross-country regressions the guiding idea is the notion of "conditional convergence" which is a compromise of exogenous and endogenous growth theories. A weakness of these cross-country regressions is measurement error. Because of the sample size and variety of sources it is hard to impose a unity on the data. Yet this weakness is also very much the strength of these studies; because of the variation in so many countries, assessment of long run implications from factors such as government policies, institutional arrangements, income inequality would be more reliable.

In contrast to cross-country regressions the interpretation of panel regressions is harder to make because of much shorter time period. Moreover, with short time periods, panel data techniques that do not control for time variant variables, such as policy changes or technological innovations, may not be suitable in a conditional convergence model. Forbes (2000) in her panel study of growth and income shows that there is a short run positive relationship between the two, which is in opposition to cross-country long-term results. She claims that by using higher quality data she reduces the measurement error and by using panel data she reduces omitted variable bias. Most importantly she does not control for time-variant variables. Her model as an artifact of endogenous growth models relies on the basic structure of growth models that assume conditional convergence according to which steady state level of output depends on government size, monetary or fiscal policies, or some other political-economic variables. During the relevant time period, a change in any of these variables will affect the target level of output, which will in turn affect the current growth rate; in fact this implies a structural change in the system.

Her contribution is the use of better estimation techniques and high quality data to reduce the estimation bias. The Arellano-Bond estimator, by allowing certain amount of endogeneity in the regressors, addresses the dynamic nature of the panel data estimation. But perhaps still in some cases some compromises can be found. Galor and Maov (2001) show that in the initial stage of development, inequality can be positively related to growth because the rich have a higher marginal saving rate, which will be channeled to investment in physical capital. But because of complementarities of physical and human capital and imperfections in credit markets, inequality will eventually have a negative effect on growth. The model again is unrealistic under the assumption of private savings will be invested in physical capital. Because, it is well known that many developing countries have huge government budget deficits and private savings and foreign borrowings are used to make up the government budget deficit.

In theoretical papers inequality refers to the distribution of wealth stock among the people in a certain country. But clearly the income distribution in a given year or a period is a proxy for this. Inequality is a dynamic notion and the Gini coefficient clearly does not control for that. First of all, as a result of growth in previous periods, share of quintiles in the income distribution might change but this may not be very well reflected in the Gini coefficient, namely, Lorenz curves from different periods might cross over yet the area between the diagonal and the Lorenz curve might stay the same. Consequently this might have different implications for growth in the long run. Secondly, Gini coefficient is not affected by the social mobility, which might have quite drastic implications for economic growth. Besides time lag between inequality and growth is not well established, especially in short period panels the relationship may not show clearly.

This paper differs from Forbes (2000) in two ways. First of all I use a much bigger data set for the inequality measures. In her study Forbes has 45 countries and most of these countries are the OECD countries and at least middle-income countries. This clearly results in a selection bias, by excluding poorer countries. By using the data set from Dollar and Kraay (2002), I include

78 countries. This might reduce the sample selection bias. Secondly, I am controlling for the quality of the human capital by including a variable that accounts for the schooling quality. This also helps to reduce the endogeneity in the model because quality of the schooling might very well be correlated with the inequality in a population. Also because of known properties of the Kuznet's curve the data might have a nonlinear structure. By adding a quadratic term for the inequality variable, I change her specification from linear to nonlinear relationship between inequality and growth.

The paper is organized as follows: section 2 discusses the data set and summarizes the descriptive aspects of the data; section 3 presents the empirical model and the estimation results; section 4 does the sensitivity analysis; section 5 presents concluding remarks; and in the last section there are variable definitions, regression tables, and figures.

II.Data and Model

Following the fast growth in computing power, interest in collecting and modeling panel data has greatly increased in recent decades. However, it is much harder to find a panel data set that belongs to the pre 1960s. Because of data availability most of the panel studies are restricted to the periods after the 1960s and admittedly the available number of periods are quite few. In a panel data set each unit must have at least two consecutive periods of observation. Besides the limitation of time, the data collected from international resources have definitional problems. In any international study, comparisons of data which are collected by different agencies and over many years are hardly feasible. Especially the index of inequality might show variation depending on whether it is based on expenditure or income or according to the recipient unit whether it is household or individual. Recently, attempts have been made to eliminate these discrepancies by Deininger and Squire (1996). So the resulting data set is a good improvement over the existing data sets and facilitates a study that will tentatively address the issues of measurement error and country specific time invariant effects.

I need to mention, however, that although Deininger and Squire Data is good improvement over the existing data sets, Atkinson and Brandolini (1999) draw attention to a few problems in this data set. They especially show that data might be problematic using overtime and within countries. Yet this is the best data available to use. Hence, we need to interpret the results we obtained cautiously.

In this paper, I use a similar data set as Forbes did except the inequality data. Here I extend her inequality data set by including observations from Dollar and Kraay (2002) data set which they claim to be the largest data set available up to date. This data set largely builds on the Deininger-Squire data set. But it also includes many observations which are from a recompilation of the UN-WIDER data set which was also used by Deininger and Squire to construct their "high quality data set". This is a panel data set of 137 countries spanning the years from 1955 to 1999.

Real GDP and per capita real GDP data (in 1995 constant American dollars) come from the World Bank's *World Development Indicators*. It is calculated using the Atlas method of the World Bank and the resultant growth rate is calculated from the income data as a five-year period average. Education data come from Barro and Lee (1996) and are available on the NBER website. The observations are the average years of secondary schooling in the female and male population separately. It is used as a proxy for human capital.

Here I also include a measure of the quality of education given in a country by including the expenditure share of primary education per pupil in National Income. As a measure of market distortions, I use *PPPI* which comes from *Penn World Tables mark 5.6*. It is the value of the investment deflator, which is calculated at the Purchasing Power Parity with respect to the United States. This variable proxies market distortions in a given country. Control variables such as the share of agriculture in GDP, the share of urban population in total population, the ratio of money supply to GDP (used as a measure of financial development), the inflation rate, the share of exports and imports in GDP also come from the World Bank CD, *World Development Indicators*.

A weakness of regression models, either cross-country or panel data, that try to understand the factors affecting the growth rate is that they assume that all countries follow the same path and have the same aggregate production function whereas in fact there are many differences regarding history, culture, geography among countries. Yet regression is practical and there still may be some common factors that might be captured by cross-country across-time regressions.

The specification I employ in this paper was first used by Barro and Sala-i-Martin (1995). Perrotti (1996) and Forbes (2000) use the same model. However, the first two models originally employed cross-country regression data and Forbes extends it to the panel data model by adding a time dimension and country dummies. The choice of independent variables can be defended on three grounds. First, comparability with the existing literature: many papers in the existing literature use similar specifications so that my results will be comparable with the literature. Second, there is a limited number of variables: this is due to restricted availability of inequality data. Inclusion of many variables will severely reduce the number of degrees of freedom. Thirdly, on theoretical grounds: as control variables only stock variables are used in order to reduce a possible endogeneity which can be a nuisance especially in panel data that have shorter periods. In my model I will also include a square term for the inequality measure. The need to do that rises from an empirical regularity that higher income countries tend to have lower inequality levels, which is also known as the inverted Kuznet's curve after Kuznets (1955). We can write the model as follows

$$\begin{aligned} Growth_{it} = {} & \beta_0 + \beta_1\, Inequality_{it-1} + \beta_2\, Inequality^2_{it-1} + \beta_3\, Income_{it-1} \\ & + \beta_4\, MaleEducation_{it-1} + \beta_5\, FemaleEduation_{it-1} \\ & + \beta_5\, TeaPri_{it-1} + \beta_6\, TeaSec_{it-1} + \beta_6 PPPI_{it-1} + \alpha_i + \eta_t + u_{it}, \end{aligned} \tag{1}$$

where i represents each country and t represents each time period. The growth rate here is the annual average growth rate for country i during period t. As Forbes does, I will also average annual growth rate over five-year periods. Accordingly, growth in one period will be regressed on variables from the previous period.\footnote{In practice that means right hand side variables will come from the beginning of the period over which growth is averaged. e.g., average growth from the period 1965-1969 is regressed on the right hand side variables from the year 1965.} In this model I also use a square term for the inequality. The reason for this comes from the Kuznet's curve. It is empirically well known at the first stages of economic development, higher growth rates leads to higher inequality, at the later stages and development levels, inequality tend to be reduced. This very well suggests a quadratic relation between inequality and level of development. For the inequality variable I will experiment with various measures of inequality such as the Gini index, the ratio of the top quintile to bottom quintile.[i]

III.Estimation

As estimation techniques I use three different Panel Estimation methods: fixed effects, random effects, and Arellano-Bond method. Among these, fixed effects method is the least efficient but it has better consistency properties than random effects if the country specific effects are correlated with other explanatory variables. But both estimation techniques suffer from endogeneity such as a lagged dependent variable in the right hand side and clearly this is the case in (1). A generalized method of moments (GMM) technique was proposed by Arellano and Bond (1991). This technique aims to correct for the bias introduced by the lagged endogenous variable as well as some other endogeneity that might exist in other regressors. The way it does this by first differencing and then instrumenting for each regressors by using their lagged values.

Table 2 reports fixed effects and random effects estimation using the data set of Dollar and Kraay (2002). This dataset includes 256 observations, in contrast to Forbes' 177 observations. My specification of the model will be similar to that of Forbes but I will extend it by adding a square term for inequality, education quality, and period dummies. Moreover I will change the measures of inequality and the estimation techniques which are fixed effects and random effects. They are both given in Table 2, along with various measures of inequality.[ii] For each estimation technique I use two different measures of inequality, which are the Gini coefficient and top to bottom quintile ratio.[iii] Top of each column shows which inequality measure is used in this particular specification. Estimations in the first two columns are given by fixed effects, and the last two by random effects. According to the estimation results shown in table two, lagged GDP per capita variable, *pGDP*, as predicted by the conditional convergence theory, is consistently estimated as negative and significant. Also stock human capital variables such as female education, *FemEd*, and male Education, *MalEd*, although individually insignificant, joint hypothesis test shows that they are jointly significant. The same also true for the quality of education variables, *TeaPri* and *TeaSec*. Yet their total effect is not clear. The relation of market distortions, *PPPI*, to economic growth, is insignificant in the case of fixed effects but significant in the case of random effects. But a Hausman specification test rejects random effects in favor of fixed effects. Consequently, I conclude that the most reliable specification in Table-2 is in column (2), which also has the highest R^2. In order to be able to assess the right relationship between inequality and economic growth we have to consider the partial effect of inequality on economic growth. Column (2) estimates the coefficient of inequality as negative, although not significant; but when we consider the combined effect of inequality along with its square, the relationship becomes a parabola. Therefore, the apparent insignificance of inequality coefficients, both the linear term and the square term should not be misleading. Because of possible multicollinearity both can become insignificant. To be able to understand the overall effect of inequality on growth I take the partial derivative of equation according to the following equation

$$\frac{\partial Growth_{it}}{\partial Inequality_{it-1}} = \beta_1 + 2\beta_2 Inequality_{it-1}. \qquad (2)$$

Hence we cannot talk about a one type of relationship between inequality and economic growth. It is positive up to a point and then becomes negative. The turning point for the parabola is around 44 which is around the arithmetic mean of Gini coefficient in my sample. Considering the fact that in the sample Gini coefficient and per capita GDP is negatively correlated, higher inequality leads to faster economic growth in richer countries but it slows down economic growth in poorer countries.

Table 3 employs the same specification as in Table 2, however, this time using the dynamic panel estimation technique of Arellano-Bond. In this table, I use two different measures of inequality: top of each column gives the inequality measure used. This table also gives similar estimates for variables other than inequality on which I will concentrate now. The consistent message given by the table is that this relationship between inequality and economic growth is individually insignificant and jointly insignificant. In column (4) although the coefficient of the top to bottom ratio looks negative, the partial effect takes on positive value after around 7 which is smaller than anything in my sample. According to the dynamic technique of Arellano-Bond, which is a better estimation technique in case of panel data, the relationship between inequality and economic growth is then is inconclusive.

IV.Conclusion

In this paper, I tried to retest the relation between inequality and growth. Two panel studies done earlier, in contrast to cross-country analyses, found a significant and positive relation between these two variables, albeit on a smaller data set. I tried to extend the model and data set of Forbes (2000). On a bigger data set, I extended her model by including a square term for the inequality and also by controlling for the quality of human capital. I retested her results by using three different estimation techniques and three different measures of inequality. The estimation results at their best still remain inconclusive. Although, a fixed effects specification yields a positive and significant estimation of the relation between inequality and economic growth, generalized method of moments estimation of Arellano and Bond do not yield any conclusive results. The apparent conflicts between this paper and Forbes' paper can be attributable to the model specification and using different data sets. The data set used in this paper is a much bigger data set, and this should reduce any possibility of sample selection bias. In Forbes' data set half of the countries are coming from the OECD which is known as the rich countries club. But as the fixed effects estimation show in this paper, inequality has different effects for the rich and the poor. Another possible source contributing to the conflict between this paper and her paper is the model misspecification. In the models tested in this paper, quadratic term for the inequality most of the time was jointly significant with the linear term, yet in some cases the relevant portion of the inequality was only either increasing or decreasing part of the parabola.

I also did some sensitivity tests to see whether the fixed effects estimations might become insignificant or negative as well as to see whether the dynamic panel estimation technique is affected by some sort of omitted variable bias issues. Inclusion of various sensitivity variables to my benchmark model do not change the earlier results: dynamic panel estimations still show insignificant relation between inequality and growth in all definitions of inequality or equality. Clearly, because the time period in the data is very short, only five years, it is hard to say anything about the long term or even medium term relationship between inequality and economic growth. Consequently, I find that the positive and significant short run relationship found by Forbes are not robust to a different model specification and a larger data set that includes a much wider selection of countries. In addition to a widely accepted theoretical model, inequality data are notoriously hard to compare. So it is not surprising that different estimation methods bring out different results. Hence, the relationship between inequality and economic growth, still awaits a much more widely accepted theory and better data collection methods.

References

Aghion, Philippe, Eve Caroli, and Cecilia Garcia-Penalosa, (1999) "Inequality and Growth: The Perspective of the New Growth Theories", *Journal of Economic Literature* 37, pp.1615-1660.

Aghion, Phillipe, and Patrick Bolton, (1997) "A Theory of Trickle-Down Growth and Development", *Review of Economic Studies* 64(2), pp.151-172.

Alesina, Alberto and Roberto Perotti, (1996) "Income Distribution, Political Stability and Investment", *European Economic Review* 81(5), pp.1170-1189.

Alesina, Alberto and Dani Rodrik (1994), "Distributive Politics and Economic Growth", *Quarterly Journal of Economics* 109(2), pp.465-90.

Arellano, Bond and Stephen R. Bond, (1991) "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations", *Review of Economic Studies* 58(2), pp.277-97.

Atkinson, A.B., and A. Brandolini, (1999) "Promise and Pitfalls in the Use of "Secondary" Datasets: Income Inequality in OECD Countries" Mimeo, Nuffield College, Oxford.

Barro, Robert J., (1991) "Economic Growth in a Cross Section of Countries", *The Quarterly Journal of Economics* 106, pp.407-443.

Barro, Robert J., (2000). "Inequality and Growth in a Panel of Countries", *Journal of Economic Growth* 5, pp.5-32.

Barro, Robert J. and Jong Wha Lee (1996), "International Measures of Schooling Years and Schooling Quality", *American Economic Review, Papers and Proceedings* 86(2), pp. 218-13.

Barro, Robert J. and Xavier Sala-i-Martin (1995), Economic Growth, New York: McGraw-Hill.

Roland, Benabou, (1996) "Inequality and Growth", *NBER Working Paper*, No: 5658.

Deininger, Klaus and Lyn Squire, (1996) "A New Data Set Measuring Income Inequality", *World Bank Economic Review* 10, pp.565-591.

Dollar, David and Aart Kraay, (2002) "Growth is Good for the Poor", *Journal of Economic Growth* 7, pp.195-225.

Forbes, Kristin J. (2000) "A Reassessment of the Relationship Between Inequality and Growth", *American Economic Review* 90(4), pp.869-97.

Galor, Oded and Omer Moav, (2001) "From Physical to Human Capital Accumulation: Inequality and the Process of Development", Brown University Working Paper, pp.99-27.

Levine, R. and D. Renelt, (1992) "A Sensitivity Analysis of Cross-Country Growth Regressions", *American Economic Review* 82(2), pp.942-963.

Li, Hongyi and Heng-fu Zou, (1998) "Income Inequality is not Harmful for Growth: Theory and Evidence", *Review of Development Economics* 2(3), pp.318-334.

Kuznets, Simon, (1955) "Economic Growth and Income Inequality" *American Economic Review* 65, pp.1-28.

Perrotti, Roberto, (1996) "Growth, Income Distribution and Democracy" *Journal of Economic Growth* I(2), pp.149-87.

Persson, Torsten and Guido Tabellini, (1994) "Is Inequality Harmful for Growth?" *American Economic Review* 84(3), pp.600-621.

Table 1: *Summary Statistics*

	Year	Mean	Standard Deviation	Minimum	Maximum
Inequality: Gini Index	1965	40.00	10.02	22.23	62.00
	1970	40.82	11.34	21.50	61.88
	1975	38.87	9.41	17.83	57.90
	1980	38.72	8.96	21.54	57.78
	1985	36.72	8.77	20.97	61.76
	1990	39.83	10.34	23.34	63.42
log of per-capita GDP	1965	7.40	1.47	4.66	10.34
	1970	7.51	1.52	4.79	10.48
	1975	7.65	1.54	4.93	10.50
	1980	7.76	1.55	4.99	10.59
	1985	7.76	1.58	5.02	10.64
	1990	7.84	1.61	4.98	10.74
	1995	7.91	1.63	5.04	10.68
Female Education	1965	0.53	0.63	0.00	3.10
	1970	0.69	0.79	0.00	3.97
	1975	0.78	0.83	0.01	3.68
	1980	0.99	0.98	0.01	5.11
	1985	1.12	0.98	0.02	4.84
	1990	1.29	1.02	0.03	4.69
Male Education	1965	0.73	0.67	0.01	2.94
	1970	0.95	0.85	0.01	3.68
	1975	1.07	0.90	0.03	3.77
	1980	1.33	1.04	0.04	5.07
	1985	1.43	1.04	0.07	4.81
	1990	1.61	1.09	0.09	4.85
PPPI	1965	87.09	40.74	31.36	274.03
	1970	79.71	42.15	31.87	281.97
	1975	101.44	54.78	36.45	384.86
	1980	117.75	100.65	39.98	903.38
	1985	75.63	40.70	31.79	295.09
	1990	85.06	42.16	27.91	257.99

	Year	Mean	Standard Deviation	Minimum	Maximum
Student Teacher Ratio Primary School	1965	34.52	10.70	13.50	67.10
	1970	33.43	10.28	9.40	63.70
	1975	31.32	11.00	8.30	66.50
	1980	30.63	11.76	8.20	64.60
	1985	28.75	11.58	6.90	65.60
	1990	28.75	14.34	6.10	90.40

Student	1965	18.70	5.87	7.20	35.00
Teacher Ratio	1970	19.17	6.25	7.30	36.50
Secondary	1975	20.49	6.90	6.10	39.30
School	1980	20.35	7.90	6.30	62.40
	1985	19.82	8.27	6.70	64.30
	1990	18.65	6.68	6.70	37.30

Table 2- *Fixed Effects and Random Effects, Dollar-Kraay Data Set*

	Fixed Effects		Random Effects	
	(1)	(2)	(4)	(5)
	Gini	Q51	Gini	Q51
Inequality	-0.00066	0.00311	0.00077	0.00108
	(0.00187)	(0.00082)***	(0.00155)	(0.00063)*
LpGdp	-0.02806	-0.02941	-0.00011	0.00022
	(0.00810)***	(0.00896)***	(0.00256)	(0.00220)
FemEd	0.00269	-0.00013	-0.00787	-0.01235
	(0.00974)	(0.01011)	(0.00691)	(0.00616)**
MalEd	-0.00017	0.00263	0.00745	0.01199
	(0.00917)	(0.00963)	(0.00632)	(0.00564)**
PPPI	-0.00014	-0.00018	-0.00017	-0.00019
	(0.00009)	(0.00010)*	(0.00006)***	(0.00006)***
SqInq	0.00002	-0.00007	-0.00001	-0.00003
	(0.00002)	(0.00002)***	(0.00002)	(0.00001)**
TeaPri	-0.00007	0.00002	-0.00005	-0.00007
	(0.00035)	(0.00036)	(0.00026)	(0.00024)
TeaSec	0.00045	0.00050	0.00013	0.00015
	(0.00047)	(0.00050)	(0.00036)	(0.00034)
Observations	256	236	256	236
Countries	76	73	76	73
R-squared	0.26	0.28		

Notes: Dependent variable is the average annual per-capita growth.
Standard errors are in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%. R^2 is the within - R^2 for Fixed Effects.

Table 3: *Arellano-Bond, Dollar-Kraay Data Set*

	(1) Gini	(2) Gini	(3) Q51	(4) Q51
Inequality	0.00043	0.00030	0.00045	-0.00026
	(0.00037)	(0.00206)	(0.00048)	(0.00166)
LpGdp	-0.08173	-0.08164	-0.08272	-0.08610
	(0.01088)***	(0.01164)***	(0.01200)***	(0.01309)***
FemEd	0.01103	0.00765	0.00198	-0.00175
	(0.01069)	(0.01143)	(0.01215)	(0.01323)
MalEd	-0.00261	0.00048	0.00679	0.01070
	(0.01029)	(0.01084)	(0.01217)	(0.01307)
PPPI	-0.00025	-0.00022	-0.00027	-0.00023
	(0.00009)***	(0.00010)**	(0.00010)***	(0.00012)*
SqInq		0.00000		0.00002
		(0.00002)		(0.00005)
TeaPri		-0.00060		-0.00056
		(0.00041)		(0.00046)
TeaSec		0.00084		0.00069
		(0.00054)		(0.00059)
Obs No	145	134	128	118
Countries	44	42	42	40

Notes: Dependent variable is the average annual per-capita growth. Standard errors are in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

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[i] I also experimented with the sum of middle quintiles, Q_2, Q_3, and Q_4 as a measure of equality rather than inequality. But this measure does not change the results dramatically at all.

[ii] I did an extensive set of regressions both on Forbes' own dataset using different specifications. These estimations usually show that Forbes' results are robust to various specifications of the model as well as the different measures of inequality. These results are available from the author on request.

[iii] Estimations with the sum of middle quintiles are done as well but not reported.