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Income Inequality and Macroeconomic Volatility: An Empirical Investigation

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Abstract

We explore the impact of macroeconomic volatility on the distribution of income. Using a cross-section of developed and developing countries, we find that greater output volatility, defined as the standard deviation of the rate of output growth, is associated with a higher Gini coefficient and income share of the top quintile. The coefficients suggest that a strong effect on inequality resulting from a reduction in volatility: the Gini coefficient of a country like Chile would fall by 6 points if it were to reduce its volatility to the same level as Sweden or Norway. Our results seem not to be driven by the high-inequality/high-volatility Latin American countries.

1. Introduction

Does the degree of output volatility in an economy affect the distribution of income across individuals? The possibility of a link between inequality and output volatility has been pointed out by Hausmann and Gavin (1996), who show that countries in Latin America are much more unequal and much more volatile than industrial economies. In this paper we use data for a cross-section of countries over the period 1960–90 to examine in detail this relationship.

The magnitude of the differences in income distribution across countries is large. For example, it is well-known that the middle-income Latin American economies are associated with much greater income inequality than are the East-Asian "tigers". In 1990, the Gini coefficients of the distribution of income in Brazil, Chile, Mexico, and Venezuela ranged between 55 and 64%, while those of Hong Kong, Korea, Taiwan, and Singapore, were between 30 and 41%. At the same time, the former were subject to much greater fluctuations in their respective growth rates than were the latter: during the 1980s, the standard deviation of the rate of output growth was, on average, 5.9% for the four Latin American economies, and 2.8% for the East Asian countries.

Our empirical results indicate that greater macro-economic volatility (measured as the standard deviation of the rate of growth of GDP) is associated with higher income inequality, as captured by the Gini coefficient. This relationship is robust to controls for a number of explanatory variables, and in particular to the inclusion of regional dummies, indicating that our results are not driven by the high-inequality/high-volatility Latin American countries. Furthermore, we show that high volatility increases the share of income of the highest quintile at the expense of those in the second and

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third quintiles, implying that there is a redistribution from the middle class to the upper-income group.

Our estimates suggest a sizable effect of volatility: the Gini coefficient of a country like Chile would fall by 6 points if it were to reduce its volatility to the same level as Sweden or Norway. Although attributing causality in a cross-section is always problematic, the time structure of our analysis gives some indication of cause and effect: inequality in 1990 is correlated with volatility during the previous decades. On the other hand, measures of income distribution in the 1960s seem not to affect subsequent output fluctuations. This does not imply that the distribution of income has no effect on instability, just that with the limited number of observations we have available for inequality in 1960 we find no support for such hypothesis.

This paper adds to the recent revival of interest in the factors shaping the distributions of earnings and income, both within countries and across countries (Atkinson, 1997; Gottschalk and Smeeding, 1997; Li, Squire, and Zou, 1998). It is to this latter strand that the present paper contributes. For decades empirical work on cross-country differences in the distribution of income consisted of tests of the Kuznets hypothesis taking the form of regressions of inequality on the level of GDP and its square. Only recently have variables other than the level of income been considered.

Bourguignon and Morrisson (1998) argue that the Kuznets process is too complex to be simply proxied by GDP per capita, and stress the importance of labour market imperfections in determining the extent of rural-urban migration. They propose the use of relative labour productivity (RLP), that is, labour productivity in the non-agricultural sector relative to that in agriculture, as a measure of the extent of labour market imperfections, and find, in a cross-section of developing countries, that a higher RLP is found in more unequal economies. Other macroeconomic variables have been found to be associated with the distribution of income. Li, Squire and Zou (1998) find that a higher level of secondary schooling, civil freedom and financial development all reduce a country's inequality, while the more unequal the distribution of land, the more unequal that of income. Bourguignon and Morrisson (1990) point to the role of trade liberalisation in increasing inequality.

Our analysis indicates that, together with output volatility, relative labour productivity is a major determinant of a country's degree of inequality. The resulting policy implications are attractive. Instead of pointing towards the traditional trade-off between growth and equality, they suggest the possibility of attaining distributional goals through policies that also foster growth, namely, by removing labour market rigidities and enhancing macroeconomic stability.[1]

The organization of the paper is as follows. We start by discussing some reasons why output volatility may affect the distribution of income. Section 3 describes our dataset, which comprises a cross-section of 80 developed and developing countries. Section 4 examines the impact of output volatility on inequality, using both the Gini coefficient of income and quintile shares. We then check the robustness of our results by computing other measures of volatility, and using a panel dataset. The last section concludes.

2. Why Does Volatility Matter to Inequality?

The literature on the relationship between distribution and fluctuations is meagre. Two recent papers by Alesina and Perotti (1996) and Aghion, Banerjee, and Piketty (1999) have examined some possible links. Alesina and Perotti maintain that greater inequality in the distribution of income generates social discontent, which in turn leads to socio-political instability, and find that their hypothesis is supported by the data. Aghion, Banerjee and Piketty argue that inequality—in the form of unequal access to investment opportunities across agents—results in output and investment volatility.

But does volatility itself affect the distribution of income? Rodrik (1999) explores some of the mechanisms—such as the exchange rate regime—that can magnify the impact of output fluctuations on the incomes of workers. However, the symmetry of shocks implies that the effect in downturns would be compensated by that in upswings and therefore have no impact on inequality in the medium- and long-term. If volatility is to have permanent effects on distribution it must be because the *perception of risk* affects economic decisions. In this section, we briefly discuss three mechanisms through which this may happen: wage setting, human capital investments, and labour supply decisions.

Volatility can affect distribution if agents with different endowments have different attitudes towards risk. Consider an economy with workers and entrepreneurs, and suppose that entrepreneurs are less risk-averse than workers. Entrepreneurs have access to the industrial technology, which is subject to aggregate shocks. The marginal product of workers hence fluctuates from period to period. Workers will therefore be willing to accept a reduction in their average earnings in exchange for a fixed wage. Entrepreneurs, by virtue of being less risk-averse, can capture the resulting risk-premium, and thus increase their share of income. The more volatile the technology the larger the risk-premium the workers are willing to forgo, and hence the greater the share of output captured by entrepreneurs.[2]

An alternative mechanism, explored by Checchi and García-Peñalosa (2004), concerns the effect of risk on human capital accumulation. Suppose output is risky, and that at least part of this risk is reflected in wages. Young individuals decide whether or not to invest a fixed cost in acquiring human capital. They also receive a bequest from their parents, although borrowing in order to invest in education is possible. When old, they work as skilled or unskilled workers depending on whether or not they have invested, and leave a bequest to their offspring. If agents have decreasing absolute risk-aversion, then inherited wealth acts as an insurance mechanism, so that only individuals with a sufficiently high inheritance will undertake the risky human capital investment. As risk increases, the level of inheritance required in order to study rises. An economy with greater risk will then exhibit fewer average years of education and a more unequal distribution of human capital, and hence of income.

Lastly, García-Peñalosa and Turnovsky (2005b) examine the effect of greater production uncertainty on the average growth rate, its volatility, and the distribution of income when individuals have an elastic supply of labour.[3] As is well known from this type of model, greater output has an income and a substitution effect on savings and the accumulation of capital. For realistic values of the degree of risk-aversion, the former dominates, and greater uncertainty increases savings and accelerates growth.[4] Faster growth implies higher future wages, and hence higher consumption for any extra time spent at work. It therefore increases the labour supply, raising the return to capital and lowering that to labour. Since capital endowments are more unequally distributed than labour time, this change in factor prices will increase income inequality.

3. Data Description

Our analysis of cross-country differences in inequality is limited by the availability of data on the distribution of income. We draw on the Deininger and Squire (1996) dataset, which brings together data for almost 200 economies. Each observation relates to a particular country in a particular year and includes the Gini coefficient of income and, in some cases, quintile shares. In general, there is no consistency in the surveys either across countries or over time within a country. Surveys differ in their coverage: some are national, others only rural or urban. Following the arguments of Atkinson and Brandolini (2001), we do not consider only the “high quality” subset of the Deininger-Squire data set. Instead, we select all the observations that were obtained from surveys of national coverage (see the appendix for a more detailed description of the data). Inequality is measured in 1990, the most recent year for which a substantial number of observations is available.

The data within this subset still presents a problem because the income units, the source of income, and whether it is measured net or gross of tax all differ among the observations. Whenever possible, we have used observations on the distribution of gross, personal income. In order to control for the differences in definitions, we will include dummy variables in our regression equations. An alternative is to adjust the raw data by calculating the average difference between, say, income and expenditure measures and adding it to all the observations that report expenditure measures.[5] This will be done as a robustness check on our results.

To obtain a measure of volatility we calculate the annual rate of growth of real per capita GDP over the period 1960 to 1990. Growth volatility is then defined as the standard deviation of the annual growth rate over this 30-year period as in Kormendi and Meguire (1985), and Ramey and Ramey (1995). The use of a long-run measure is consistent with our idea that it is risk rather than shocks that matter. The resulting sample consists of 80 countries for which we have data on inequality and GDP for the period. It incorporates 22 developed countries, 17 Latin- and Central-American, 5 New-industrializing countries, 11 other Asian countries, and 25 African economies. Table A.1 in the appendix gives the list of countries.

Recent work on growth and inequality, such as Forbes (2000), has exploited the panel dimension of the Deininger and Squire dataset. Panel data has the advantage that it allows us to control for unobserved heterogeneity, such as might arise from social and institutional determinants of inequality that are not directly measured. However, it presents problems for our analysis. First, it reduces dramatically the number of countries included in the sample. More importantly, controlling for country fixed-effects is not very useful when most of the variation in the dependent variable is between countries rather than over time. In this case, fixed-effects models leave unexplained what is most important in the data.[6] This problem is particularly acute since under 91% of the variation in the inequality data is due to variations across countries. Cross-country analysis is consequently more appropriate if we aim at explaining the bulk of the observed differences in the distribution of income, and most of the paper will consequently focus on it. Nevertheless, an analysis of panel data will be undertaken as a robustness check.

4. The Influence of Volatility on the Distribution of Income

Gini Coefficient Analysis

A simple regression of the Gini coefficient in 1990, denoted G_i, on volatility, SD_i, and its square yields the following equation

$$\begin{aligned} E(G_i) &= 18.879 + 8.278SD_i - 0.590SD_i^2 \\ &\quad\;(3.963)\quad\;(1.505)\qquad(0.117) \end{aligned}$$

Table 1. Gini Coefficient Analysis

	Gini	*Gini*	*Gini*	*Gini*	*Gini*
SD	10.260***		5.313***	6.018***	4.259***
	(1.547)		(1.685)	(1.866)	(1.608)
SD^2	–0.694***		–0.418***	–0.488***	–0.319***
	(0.120)		(0.124)	(0.132)	(0.109)
Net	–6.335***	–7.917***	–8.208***	–9.793***	–8.730***
	(2.370)	(2.110)	(2.581)	(2.163)	(2.013)
LnGDP		29.322**	10.136	6.872	–1.997
		(13.692)	(14.821)	(14.278)	(1.611)
$LnGDP^2$		–2.220***	–0.888	–0.740	
		(0.835)	(0.928)	(0.899)	
Sec85			–0.161**	–0.200***	
			(0.076)	(0.076)	
Growth				–1.384	
				(0.847)	
Investment				41.086	
				(26.312)	
Institutions				6.289	
				(7.791)	
Latin America					13.155***
					(3.204)
Africa					11.446 **
					(4.708)
Asia					4.225
					(4.740)
NIC					1.678
					(3.662)
N	80	80	70	68	80
Adjusted R^2	0.264	0.390	0.458	0.515	0.516
Standard error	8.663	7.886	7.674	7.216	7.026

Note: Standard errors in parentheses. *Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level.

($R^2 = 0.224$, standard errors in parenthesis). This simple regression equation is capable of explaining a substantial fraction of the variation in inequality across countries. Countries where output is very volatile are more unequal, except for very high levels of volatility. According to the above equation, volatility reduces inequality when the former variable takes a value greater than 7. However, when we divide our sample into two subsets, we find that for the 16 observations with a value of SD above 7 the coefficients on volatility are not significant. This indicates that relationship between the two variables breaks down for very high levels of volatility.

Table 1 reports alternative specifications of the determinants of the Gini coefficient. All equations in Table 1 (as in the rest of the paper, unless otherwise specified) are OLS estimations with heteroskedastic consistent errors. We included three dummy variables (for net income, for household income, for expenditure measures) in order to control for differences in the measurement of inequality. Of these, only the dummy

Table 2. Gini Coefficient Analysis (continued)

	Gini	*Gini*	*Gini*	*Gini*	*Gini*	*Gini*
SD		4.441**	5.005***	6.250**	4.001***	2.091**
		(1.883)	(1.445)	(2.855)	(1.489)	(1.058)
SD^2		−0.371***	−0.413***	−0.513*	−0.332***	−0.177
		(0.143)	(0.116)	(0.273)	(0.112)	(0.123)
Net		−8.768***	−10.34***	−10.094***	−10.02***	−9.132***
		(2.746)	(2.350)	(2.294)	(2.396)	(2.320)
LnGDP		−3.748*	−10.52***	−8.021**	−8.046***	−1.120
		(2.005)	(2.702)	(3.971)	(2.493)	(3.440)
Sec85		−0.143*	−0.160**	−0.056	−0.138*	−0.039
		(0.079)	(0.074)	(0.067)	(0.074)	(0.083)
MYSch	1.025					
	(1.759)					
CIVLIB	2.463***	0.949		2.003**	1.108	2.800***
	(0.749)	(0.839)		(0.932)	(0.736)	(0.849)
FNDV	−13.625**	−0.112		−4.076		
	(5.578)	(5.805)		(9.581)		
Land pc			1.622*			
			(0.958)			
AgEmp			−0.302***	−0.340**	−0.227**	−0.028
			(0.111)	(0.133)	(0.101)	(0.137)
RLP			1.032***	1.691***	1.032***	0.855***
			(0.369)	(0.535)	(0.332)	(0.319)
SPI				0.029		
				(0.097)		
Growth				−0.212		
				(1.298)		
Investment				−1.037		
				(32.698)		
Institutions				4.549		
				(8.931)		
Regional dummies	No	No	No	No	No	Yes
N	63	62	68	46	67	67
Adjusted R^2	0.322	0.494	0.574	0.602	0.603	0.688
Standard error	8.309	7.124	6.817	6.650	6.556	5.810

Note: Asterisks as in Table 1.

for net income has a significant coefficient. Our basic equation, column 1, is then augmented to test for the robustness of the effect of volatility to the inclusion of other variables previously found to affect inequality. For many of these variables, data are only available for a limited number of countries. In an attempt to maximize sample size, we report regression equations in which only a number of variables are tested at a time. The results when all potential explanatory variables are simultaneously included will be presented in Table 2 above.

We start by examining the Kuznets effect and role of education. A simple regression of the Gini coefficient on the level of output and its square yields the familiar bellshaped relationship between the level of income and inequality, usually interpreted as evidence of a Kuznets curve.[7] This relationship weakens once we include a measure of human capital, the secondary schooling enrollment rate, Sec85 (results not reported), and entirely disappears when we control for volatility, as seen in column 3.[8]

Next we examine the impact of the rate of output growth and investment. As already mentioned, a number of papers have found an association between growth and volatility. If growth then affects inequality through some sort of Kuznets mechanism, it could be the case that the coefficient on volatility is capturing an indirect relationship going from volatility to growth and from growth to inequality. It has also been suggested by Acemoglu et al. (2003) that a factor determining both greater inequality and greater volatility are weak government institutions. The relationship between inequality and volatility just reported could then be caused by a common factor—weak institutions—that affects both variables. Column 4 introduces as explanatory variables the growth rate, the share investment in GDP, and the measure of quality of government institutions used by Hall and Jones (1999).[9] The coefficients indicate that the effect of volatility on the income distribution is not mediated by the rate of growth or physical capital accumulation. Despite the high correlation between inequality and institutional quality, the coefficient on this variable is not significant and has no impact on that on volatility.

It could also be that there are differences between regions of the world—in policies, geography, or the structure of production—which affect both inequality and volatility. Figure 1 depicts the relationship between volatility and inequality in the various geo-

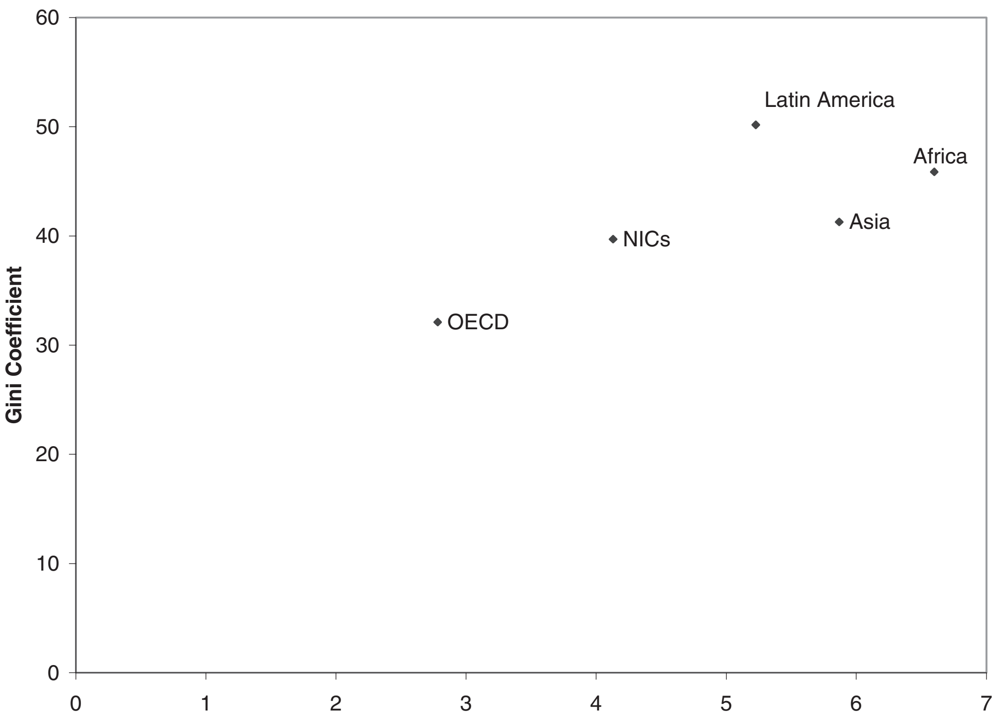

Figure 1. Gini Coefficient and Volatility, Averaged by Region

graphical regions. Countries have been divided into five groups: Africa, Latin America, the New Industrializing Countries, other Asian economies, and OECD economies. Each point in the graph represents the (unweighted) average volatility and average inequality for each group. Those regions with high levels of volatility also tend to exhibit high levels of inequality.

The last column of Table 1 reports estimates obtained when we include regional dummies in our basic regression equation for the Gini coefficient. Dummies for Latin America, Asia, and Africa have positive and statistically significant coefficients, but, although their presence reduces the impact of volatility on inequality, the effect nevertheless remain substantively and statistically significant. Volatility seems to be able to explain differences in inequality both across regions of the world and within those regions.

The first column of Table 2 examines the impact of the variables used by Li, Squire, and Zou (1998): schooling measured as mean years of secondary schooling of the population in 1960, denoted MYSch; an index of civil liberties, CIVLIB; and financial development, FNDP, measured by the ratio of liquid liabilities to GDP averaged over 1960–89.[10] A regression equation similar to that estimated by Li, Squire, and Zou[11] implies that, as in their paper, fewer civil liberties—a higher value of CIVLIB—increase inequality, and more financial development reduces it. Although MYSch has no significant effect, when we replace it with Sec85, that is a measure of human capital at a point in time closer to our measure of inequality, all three variables have a significant effect (not reported). However, once we control for volatility and the level of GDP, the coefficients on civil liberties and financial development become insignificant.

We then run regression equations similar to those in Bourguignon and Morrisson (1998), except that we also include our measure of volatility and its square. In line with the results reported in their paper, GDP per capita and education have a weak effect, sensitive to which other variables are included. We find that cultivable land per capita has a positive impact on inequality, in contrast with the negative (though often insignificant) coefficient obtained by Bourguignon and Morrisson. In our sample, the coefficient on this variable is driven by one observation, Australia, and becomes insignificant once it is excluded from the sample. Because of the sensitivity of the coefficient to one outlier, we remove this variable from further estimations. The share of agriculture in total employment, AgEmp, has a negative and significant effect, while relative labour productivity has a positive and significant effect, indicating that the greater the extent of macroeconomic dualism, the more unequally income is distributed. Lastly, we included in our regression equation a measure of socio-political instability, SPI, which proves to have no impact on the Gini coefficient.[12]

Column 4 allows us to compare the various hypotheses proposed, although at a cost in terms of the number of observations (there are only 46 countries for which all variables are available). There seem to be only four variables that are systematically significant: volatility, civil liberties, relative labour productivity, and the share of agricultural employment. Of these, only the first three are robust to the inclusion of regional dummies. This is not very surprising as the variation in the last variable within regions is small compared to that across regions.

The impact of output volatility on inequality is not only statistically significant, but also economically significant. Consider the penultimate equation in Table 2, our preferred specification. For the US, an increase in volatility of one standard deviation of the distribution of volatility in our sample—up to the level of Malaysia, Jamaica, or India—would result in an increase in the Gini coefficient of four points, which represents 40% of the standard deviation of Gini in our sample. The Gini coefficient of a high-volatility country like Chile would fall by six points if it were to reduce its volatility to the same level as Sweden or Norway. The effect is, of course, weaker if we use the coefficients obtained when regional dummies are included.

Quintile Shares

In order to understand better the way in which volatility affects inequality we examine the impact it has on the income shares of various groups. Table 3 reports regressions of the shares of the five quintiles on volatility and other variables (data is available for only a small subset of our sample). Greater volatility increases the income share of the top 20% of the population, and reduces that of all other quintiles. The effect is particularly strong on the shares of the 2nd and 3rd quintiles, indicating that volatility results in redistribution from the middle class towards the wealthiest households. The weak impact of volatility on the 4th quintile is probably due to the fact that we are not using an appropriate division of income groups, as volatility may increase the income share of the richest in this group (those close to the top 20%) and reduce that of individuals close to the 3rd quintile.

It is hard to distinguish the effect of education and the level of income. In the particular formulation reported in Table 3, a greater level of income reduces the share of the top quintile and increases that of other groups, while education tends to have an insignificant impact. Dualism has a positive impact on the top quintile, a negative one

Table 3. Quintile Analysis

	Q5	*Q4*	*Q3*	*Q2*	*Q1*
SD	4.844***	–0.638*	–1.492***	–1.633***	–1.079**
	(1.521)	(0.389)	(0.422)	(0.496)	(0.450)
SD^2	–0.383***	0.047	0.119***	0.132***	0.085**
	(0.119)	(0.030)	(0.032)	(0.039)	(0.036)
Net	–8.950***	2.162***	2.413***	2.245***	2.129***
	(2.245)	(0.855)	(0.617)	(0.747)	(0.573)
LnGPD	–7.675***	1.493**	2.071***	2.440***	1.669**
	(2.773)	(0.671)	(0.754)	(0.966)	(0.791)
Sec85	–0.120*	0.023	0.039*	0.030	0.027
	(0.069)	(0.019)	(0.020)	(0.021)	(0.017)
CIVLIB	0.382	–0.246	–0.196	–0.040	0.099
	(0.752)	(0.191)	(0.206)	(0.252)	(0.231)
AgEmp	–0.229**	0.034*	0.066**	0.077**	0.051
	(0.103)	(0.021)	(0.027)	(0.037)	(0.032)
RLP	0.845***	–0.182**	–0.249***	–0.253***	–0.161***
	(0.269)	(0.076)	(0.079)	(0.083)	(0.069)
N	58	58	58	58	58
Adjusted R^2	0.530	0.432	0.581	0.438	0.329
Standard error	6.169	1.782	1.692	2.043	1.629

Note: Asterisks as in Table 1. For all these regressions, we have removed Burkina Faso, Central African Rep., Cote d'Ivoire, Egypt, Gambia, Germany, Guinea, Iran, Japan, Lesotho, Luxembourg, Madagascar, Malawi, Mali, Mauritania, Morocco, Nepal, Nigeria, Puerto Rico, Taiwan, Thailand, and Zambia, due to data availability.

on the rest, in accordance with the results obtained by Bourguignon and Morrisson (1998). In contrast to the strong effect of civil liberties on the Gini coefficient obtained above, the coefficient on this variable has an insignificant coefficient on all the quintile regressions.

5. Robustness Analysis

Alternative Measures of Volatility

The standard deviation of growth rates may, under some circumstances, be an unsatisfactory proxy for the level of output volatility experienced by an economy (see Pritchett, 2000). Consider, for instance, two countries with the following growth patterns: country A has annual growth rates of 4%, 2%, 4%, 2%, 4%, and 2%, while country B has 4%, 4%, 4%, 2%, 2%, and 2%. They will have the same average rate of growth and standard deviation (3 and 1.095%, respectively), but are clearly experiencing different levels of volatility. Country B has a low level of volatility, but has experienced a change in its trend rate of growth. Given the length of the period over which we are calculating volatility, such trend changes could well have taken place. A possible way of dealing with this problem is to define higher order measures, such as the standard deviation of the first differences of the annual growth rates. This alternative measure of volatility yields a value of 2.19 for the first series, and of 0.89 for the second one, fitting with the intuition that A is more volatile than B.

We calculated the standard deviation of *changes* in the annual rate of output growth, denoted SD(Δg), for our sample. The correlation between this measure and the standard deviation of the annual rate of growth is 0.95. When we re-estimate our basic regression equation using this new measure of volatility, we obtain the following equation:

$$E(G_i) = \underset{(3.403)}{21.102} + \underset{(0.973)}{6.395}\mathrm{SD}(\Delta g)_i - \underset{(0.055)}{0.315}\mathrm{SD}(\Delta g)_i^2 - \underset{(2.119)}{6.1787}\mathrm{Net}$$

(R^2 = 0.278, SE = 8.802, standard errors in parenthesis). These results are extremely similar to those reported in Table 1. Equivalent results are obtained when we use as our measure of volatility the average of the absolute values of the changes in the rate of growth, as suggested by Pritchett (2000). Substituting either of these two variables for SD in other specifications of the regression equation yielded results almost identical to those previously obtained (not reported).

Panel Data Analysis

Two things are missing from our regression equations in section 4. First, despite our use of measures like socio-political instability or the quality of government institutions, we may still be missing measures of some of the institutional and social factors that influence inequality, and which differ across countries. Second, since the data on the distribution of income are obtained, for the most part, from national surveys, there maybe country-specific discrepancies in the way in which they were collected.

In order to control for this unobserved heterogeneity and check the robustness of our results we use panel data on inequality. We use the panel constructed by Forbes (2000) from the Deininger and Squire dataset, which together with our dataset gives us a 39-country sample, with (at most) six, five-yearly observations per country, over the period 1961–90. This panel not only allows us to control for unobserved heterogeneity, but also for the robustness of the results to the inequality observations used.[13] However, we do not fit country fixed-effects models for two reasons. First, as we have already argued, most of the variation in inequality is across countries rather than over time. Conditioning out individual countries' heterogeneity would then remove most of what we want to explain. A second problem of this approach is that having short-run measures of volatility makes little sense. Given the availability of data on inequality, we would need to calculate volatility of the growth rate over a five-year period in order to have a reasonable panel. However, we are interested in the effect of risk, not of output shocks. A five-year measure would be a poor proxy for underlying risk in the economy as it is perfectly possible for an otherwise volatile economy to experience a five-year period of stable growth (the data is in fact full of such examples). We thus follow Ramey and Ramey (1995) and regress a time varying dependent variable on a time-invariant measure of volatility.

As an alternative way of dealing with unobserved heterogeneity, we propose the use of lagged inequality as an explanatory variable. To the extent that the omitted variables change only slowly over time, they will also be a determinant of inequality in the previous period and, consequently, we can use the latter as a proxy for at least some of them. We thus estimate the Gini coefficient of country i at time t, G_{it}, as a function of G_{it-1}, and our time-invariant measure of volatility.

The models are estimated using OLS with standard errors corrected for the non-independence of observations from the same country. Table 4 reports the results of a number of different specifications that include initial Gini, volatility and the four most robust predictor variables from our earlier models—the level of output, education, relative labour productivity, and civil liberties. With the exception of civil liberties, for which we have only one measure per country for the entire period, these variables take values specific to each panel period. It is clear from Table 4, that the effect of volatility is robust in the panel, with a significant coefficient in all specifications except for that in column 3. That specification includes 11 explanatory variables (all our explanatory variables plus the four regional dummies), 7 of which are time-invariant, and 6 of which had already been shown to be insignificant. Given that we have only 39 countries, it is not surprising that most variables, including volatility and some of the regional variables, become insignificant. As soon as some of the insignificant variables are dropped from the regression equation (see the last two columns), volatility recovers its significance and the standard error of the equation actually falls.

In contrast to volatility, none of the other explanatory variables proves statistically significant. As was to be expected, most of the differences in current inequality are explained by differences in past inequality, and the coefficient on volatility is about half of that obtained when we were not controlling for previous period inequality.

Possible Channels of Causation

Growth volatility has been found to be strongly correlated with both the volatility of fiscal and monetary policy by a number of authors, such as Ramey and Ramey (1995), Rodrik (1999), and Easterly, Islam, and Stiglitz (2000). An important question is then whether what matters for the distribution of income is output volatility, or the variability of some other, correlated variable.

There are good reasons to expect that the variability of fiscal and monetary policy affects inequality. If reductions in public expenditures during bad times take the form of cuts in social expenditures, such as health and education, these cuts may have per-

Table 4. Panel Data Estimates

	Gini (t)	*Gini (t)*	*Gini (t)*	*Gini (t)*	*Gini (t)*
Gini (*t*–1)	0.879***	0.885***	0.744***	0.742***	0.746***
	(0.035)	(0.045)	(0.064)	(0.050)	(0.067)
SD	1.674***	2.169***	1.434	1.817*	1.470**
	(0.604)	(0.768)	(0.989)	(0.979)	(0.724)
SD^2	–0.139***	–0.171***	–0.111	–0.142*	–0.126**
	(0.055)	(0.062)	(0.077)	(0.076)	(0.058)
LnGDP (*t*)		0.224	–0.699		–0.135
		(0.502)	(0.524)		(0.395)
Sec (*t*)		0.016	0.027		0.027
		(0.014)	(0.018)		(0.017)
CIVLIB		–0.116	0.122		0.272
		(0.240)	(0.281)		(0.259)
RLP (*t*)		0.093	–0.076		–0.02
		(0.246)	(0.237)		(0.257)
Latin America			4.248***	4.077***	4.522***
			(1.299)	(1.381)	(1.002)
Africa			1.814	2.249**	1.940**
			(1.096)	(1.108)	(0.857)
Asia			0.214	0.349	
			(1.024)	(1.117)	
NIC			–1.542	–0.878	
			(1.415)	(1.255)	
# observations	122	122	122	122	122
# countries	39	39	39	39	39
R^2	0.852	0.854	0.875	0.873	0.874
RMSE	3.331	3.363	3.162	3.138	3.155

Note: Asterisks as in Table 1.

manent effects on the human capital of the lower income groups and thus will increase inequality. High volatility of monetary policy has been shown to result in high-output volatility and high—and volatile—inflation rates,[14] indicating that a possible transmission mechanism could be inflation. Because inflation is a regressive tax, the high-inflation rates could generate greater inequality, and thus be responsible for the correlation between output volatility and distribution.

Table 5 presents tests of these two hypotheses. We find that the standard deviation of the annual rate of growth of real government expenditure, SD(Gov), is a major determinant of the volatility of output growth. The coefficient on inflation, measured as the average rate over the period 1960–90, is significant, but its impact is very small: an increase of one standard deviation in inflation increases volatility by 0.3 point, just over 10% of the standard deviation of SD. The same result is obtained when we use the standard deviation of inflation over the period. We also checked for two other candidate explanatory variables, socio-political instability and initial inequality (measured by the Gini coefficient in 1960), both of which proved to have no impact. The lack of correlation between initial inequality and subsequent volatility seems to indicate that causation is likely to run from fluctuations to distribution, rather than the other way round. However, given the small sample size for this regression equation, it is not possible to rule out the possibility that inequality does affect output volatility.

Table 5. Possible Channels of Causation from Volatility to Inequality

	SD	*SD*	*SD*	*Gini90*	*Gini90*
SD(Gov)	0.25***	0.20***	0.072*	5.718***	1.088
	(0.052)	(0.075)	(0.41)	(1.374)	(1.732)
SD(Gov)^2				–0.454***	–0.072
				(0.121)	(0.143)
INFLATION	0.002***	0.0005	0.0004	0.019***	0.007
	(0.0008)	(0.003)	(0.003)	(0.006)	(0.005)
Gini60			0.012		
			(0.030)		
LnGPD60	–0.92***	–0.35	–0.51		
	(0.39)	(0.57)	(1.72)		
Sec60		–3.65**	–1.70		
		(1.89)	(1.73)		
SPI		–0.025			
		(0.027)			
SD					4.053**
					(2.028)
SD^2					–0.375**
					(0.161)
Net				–5.184**	–10.376***
				(2.537)	(2.395)
LnGPD90					–7.183***
					(2.839)
Sec85					–0.200**
					(0.089)
CIVLIB					1.192*
					(0.728)
AGEmp					–0.239**
					(0.104)
RLP					0.915***
					(0.295)
N	73	51	29	73	63
Adjusted R^2	0.483	0.575	0.503	0.146	0.556
Standard error	1.821	1.540	1.132	9.341	6.939

Note: Asterisks as in Table 1.

Columns 4 and 5 indicate that although government expenditure volatility has a positive and significant impact on inequality, this effect disappears once we include the standard deviation of output growth, indicating that government expenditure affects inequality in so far as it makes output more volatile.[15]

6. Conclusions

Our analysis of cross-country data shows that greater volatility, measured by the standard deviation of the rate of growth of output, is associated with a higher degree of inequality.[16] This relationship is robust to changes in the definition of volatility, the particular inequality observations used, and controlling for lagged inequality in a panel. Some of the factors that previous research has shown to be determinants of income inequality, namely the degree of dualism and the extent of civil liberties, prove to have, together with volatility, a robust impact on the distribution of income. In order to understand how volatility affects inequality, we have examined its effect on the income shares of the various quintiles. Greater volatility results in redistribution from middle-income groups (second and third quintiles) to the top-income group (fifth quintile), while its effect on the share of the lowest 20% of the population is weaker.

The next question consists in identifying the mechanisms through which output fluctuations can affect the distribution of income. Two of the most obvious ones, fiscal policy variability and inflation, seem to be ruled out by the data. We have outlined other possible explanations, yet these are neither exhaustive nor, we suspect, mutually exclusive. A detailed examination of a variety of mechanisms is needed if we want fully to understand the impact of volatility on inequality. However, the relationship that we have identified has important implications for policy making as it challenges the long-standing argument that distributional targets may be incompatible with efficiency goals. Policies aimed at ensuring macroeconomic stability will at the same time reduce the degree of income inequality in an economy.

Appendix: Data Sources and Main Data

Inequality

The data is mainly from Deininger and Squire (1996), (World Bank Web Site, version 13/6/97). We selected all the observations obtained from surveys of national coverage, for the years of interest (or as close as possible). For some countries there were several observations for the same year. For the OECD we chose the observations recommended by Atkinson and Brandolini (2001), usually the LIS data. For Italy we have used the data available in the LIS Web site, following the suggestion of Atkinson and Brandolini. For developing countries, we selected the data from Chen, Datt, and Ravallion (1994) and the World Development Report. When the data from these two sources differed (Tanzania, Zambia and Venezuela), we computed the average value.

GINI: Gini coefficient of income in or around the year 1990.
Qy: Income share of the yth quintile in or around the year 1990.
Net: Dummy variable taking the value 1 if the inequality measure is based on net income.

Output and Volatility

LnGDP: Logarithm of real GDP per capita in the year 1990, in 1985 dollars.
SD: Standard deviation of the annual rate of growth of real per capita GDP, over the period 1960–90.
Growth: Average annual rate of growth of real per capita GDP over 1960–90.
Gov: Annual rate of growth of real government expenditure at 1985 prices.
SD(Gov): Standard deviation of Gov over the period 1960–90.
Source: Summers and Heston, Penn World Tables Mark 5.6.

Table A.1. Main Data

Country	*Gini*	*SD*	*Country*	*Gini*	*SD*
Algeria	38.73	7.553	Korea, R.	33.64	4.097
Australia	35.93	2.698	Lesotho	60.90	7.443
Austria	31.60	1.74	Luxembourg	23.81	4.203
Bangladesh	37.00	8.961	Madagascar	43.44	4.229
Belgium	29.24	2.218	Malawi	62.00	5.043
Bolivia	42.04	3.473	Malaysia	48.35	4.926
Botswana	54.21	8.582	Mali	54.00	5.371
Brazil	63.42	4.624	Mauritania	42.53	6.820
Burkina Faso	39.00	4.703	Mauritius	36.69	8.308
C. Afr. Rep.	55.00	4.171	Mexico	54.98	4.220
Canada	32.73	2.486	Morocco	39.20	5.514
Chile	56.49	6.458	Nepal	30.06	7.460
Colombia	51.32	2.448	Netherlands	29.10	2.139
Costa Rica	46.07	3.739	New Zealand	36.58	2.957
Cote d'Ivoire	38.00	6.562	Nicaragua	50.32	9.268
Denmark	28.75	2.726	Niger	36.10	9.841
Dom. Rep.	50.46	6.843	Nigeria	41.15	11.160
Ecuador	43.00	4.774	Norway	27.29	1.900
Egypt	32.00	3.362	Pakistan	32.38	4.231
Finland	26.31	3.000	Panama	56.47	5.726
France	33.52	1.879	Peru	44.87	6.598
Gambia	39.00	9.760	Philippines	45.73	3.585
Germany	26.00	2.250	Portugal	36.76	4.364
Ghana	36.74	7.069	Puerto Rico	50.86	3.672
Greece	37.67	3.732	Senegal	54.12	4.274
Guatemala	59.06	3.071	Singapore	41.00	4.802
Guinea	40.40	6.411	South Africa	62.30	3.689
Guin. Bissau	56.12	9.455	Spain	25.91	3.253
Guyana	40.22	11.773	Sri Lanka	46.70	4.643
Honduras	52.63	2.978	Sweden	26.31	1.760
Hong Kong	45.00	4.020	Taiwan	30.53	2.805
India	32.53	5.029	Tanzania	48.56	6.046
Indonesia	33.09	3.960	Thailand	50.80	3.408
Iran	42.90	9.468	Tunisia	40.24	3.362
Ireland	37.90	2.580	Turkey	44.09	3.536
Italy	29.00	2.667	UK	34.32	2.198
Jamaica	41.79	4.917	USA	38.51	2.439
Japan	35.00	3.526	Venezuela	48.96	4.276
Jordan	40.66	10.118	Zambia	47.46	6.509
Kenya	54.39	7.681	Zimbabwe	56.83	5.731
			Average	*41.98*	*4.99*
			St. Deviation	*10.05*	*2.71*

Education

Sec85: Percentage of "secondary schooling attained" in the total population in 1985.
MYSch: mean years of secondary schooling in the total population in 1960.
Source: Barro and Lee (1993).

Other Variables

AgEmp: Percentage of the economically active population employed in agriculture.
Land pc: Arable land and land under permanent crops in 1991 (in 1000 Ha) divided by the total population in 1990 (in 1000s).
Source: FAO Production yearbook, 1992, Tables 1 and 3.
AgShare: Share of agricultural output in GDP. Three-year averages (1988–90) are used to smooth fluctuations in agricultural prices. Source: World Bank World Tables 1993.
RLP: Relative labour productivity (non-agriculture/agriculture). Calculated as RLP = (1-AgShare)AgEmp/((1-AgEmp)AgShare).
CIVLIB: Index of civil liberties, averaged over 1960–89. A value of 1 is assigned to countries with the largest degree of civil liberties, and 7 to those with the smallest.
FNDV: Degree of financial development, measured by the ratio of liquid liabilities to GDP averaged over 1960–89.
INV: Investment share in GDP, averaged over the period 1960–89.
Source of all the above: King and Levine (1993).
SPI: Index of socio-political instability over the period 1960–85, where a higher value indicates more instability. Source: Alesina and Perotti (1996).
INFLATION: December over December CPI % change. Averaged over the period 1960–90. Source: Bruno and Easterly (1998).
INSTITUTIONS: Our measure of government institutions is an average of two indices. One is a measure of government antidiversion policies, itself an average of five indices (law and order, bureaucratic quality, corruption, risk of expropriation, government repudiation of contracts) over the period 1986–95. The other is a measure of openness defined as the fraction of years during the period 1950–94 that the economy has been open. Source: Hall and Jones (1999).

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Notes

1. In the last decade a number of theoretical and empirical analysis have suggested the absence of a trade-off between inequality and growth. See Aghion, Caroli and García-Peñalosa (1999) for a review.
2. In the previous version of the paper we develop a simple model that explores this mechanism. See also Caroli and García-Peñalosa (2002).
3. See also García-Peñalosa and Turnovsky (2005a) for an analysis of the relationship between volatility and the factor distribution of income.
4. The idea that greater uncertainty increases precautionary savings and hence capital accumulation is consistent with the early empirical literature on growth and volatility, such as Kormendi and Meguire (1985). Although it contrasts with the finding of Ramey and Ramey (1995) that greater volatility is associated with lower average growth rate, these authors mainly focus on the 'unexpected' component of volatility.
5. Deininger and Squire (1996) recommend the use of dummy variables, although there are no strong reasons for preferring one methodology to the other. Atkinson and Brandolini (2001) discuss the problems of both methodologies.
6. For a discussion of the problems of using panel techniques to analyse macrodata, see Easterly et al., (1993) and Quah (2003).
7. Anand and Kanbur (1993) find no support for the inverted-U relationship on a cross-section of countries. Barro (2000), using the Deininger and Squire data, obtains significant coefficients on log(GDP) and its square, but finds that they explain only a small fraction of the international variation.
8. Throughout the paper, human capital is measured as the percentage of individuals in the total population in 1985 who have attained secondary schooling, Sec85. We also estimated equations including other measures of education, such as primary or tertiary enrollment rates or the average number of years of education, which usually had insignificant coefficients.
9. This measure of government institutions is a combination of an index of government anti-diversion policies (GADP) and an openness measure. The same results were obtained when we used only GADP.
10. All results were replicated when we used the ratio of M1 to GDP as our measure of financial development.
11. Except that we have not included the Gini coefficient of land amongst the regressors as we could find the data only for a small number of countries.
12. We also tested for whether openness affects the link between volatility and inequality. The measures of openness used (the ratio of either exports or imports plus exports to GDP over the 1960–89 period, and the change in openness over the same period) had no significant effect and the coefficients on volatility were unaffected by their inclusion.
13. Forbes uses observations which are often different from the ones we chose, and she adjusts the raw data by adding average differences between the various income concepts rather than using dummies as we have done (for more details on the construction of the data, see the original article).
14. See Okun (1971) and Taylor (1981).
15. We tried alternative specifications, and obtained similar results when we used as our measure of volatility the standard deviation of government expenditure as a proportion of GDP. The average rate of growth of government expenditure proved to have no significant effect.
16. Inevitably, the Deinenger and Squire data measure true income inequality with error. It is, however, impossible to assess the precise extent to which this influences our conclusions. To do

so would require that, as in Krueger and Lindahl's (2001) attempt to assess the reliability of cross-national measures of schooling, we had multiple measures of inequality (and, even then, we would have to make assumptions about the distribution of the error in each of these). In the absence of such measures we can only say that, as is well known, random measurement error attenuates regression estimates towards zero; and on this basis our results may understate the strength of the relationship between volatility and inequality.