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Growth Still Is Good for the Poor

David Dollar (Brookings Institution)
Tatjana Kleineberg (Yale)
Aart Kraay (World Bank)

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Abstract: Average incomes in the poorest two quintiles on average increase at the same rate as overall average incomes. This is because, in a global dataset spanning 121 countries over the past four decades, changes in the share of income of the poorest quintiles are uncorrelated with changes in average income. The variation in changes in quintile shares is also small relative to the variation in growth in average incomes, implying that the latter accounts for most of the variation in income growth in the poorest quintiles. In addition, we find little evidence that changes in the bottom quintile shares are correlated with country-level factors that are typically considered as important determinants for growth in average incomes or for changes in inequality. This evidence confirms the central importance of economic growth for improvements in living standards at the low end of the income distribution. It also illustrates the difficulty of identifying specific macroeconomic policies that are significantly associated with the growth rates of those in the poorest quintiles relative to everyone else.

Keywords: growth, inequality

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ddollar@brookings.edu, tatjana.kleineberg@yale.edu, akraay@worldbank.org. We would like to thank, without implication, Kaushik Basu, Stefan Dercon, Phil Keefer, Luis Serven, and Martin Ravallion for helpful comments. Financial support from the Knowledge for Change Program of the World Bank is gratefully acknowledged. The views expressed here are the authors' and do not reflect those of the Brookings Institution, the World Bank, its Executive Directors, or the countries they represent.

1. Introduction

Absolute poverty has fallen sharply in the developing world over the past three decades. In 1980, 52 percent of the world's population lived below the World Bank's $1.25/day poverty line. By 1990, the incidence of poverty had fallen to 42 percent, and to 21 percent in 2010. Much of this reduction has been due to rapid growth in large and initially poor developing countries such as China and India. But in all regions of the world, rapid growth has been systematically associated with sharp declines in absolute poverty.

This success in poverty reduction has meant that low global absolute poverty lines, like the World Bank's $1.25/day standard, have become less relevant for many developing countries where today only a small fraction of the population lives below this austere threshold. This led the World Bank to put a new institutional emphasis on tracking "shared prosperity", in addition to monitoring absolute poverty. "Shared prosperity" is defined in terms of the growth rate of incomes in the bottom 40 percent of households, and the World Bank has made a public commitment to supporting policies that foster "shared prosperity" in the developing world.[1] Concerns about "shared prosperity" are also widespread in advanced economies, where many fear that growth no longer benefits those near the bottom of the income distribution.[2]

This emphasis on "shared prosperity" naturally raises the question of the extent to which it differs from simply "prosperity", where the latter could be defined as overall aggregate income growth. In this paper, we address this question, updating and elaborating on our earlier work in Dollar and Kraay (2002). In that paper, we studied the relationship between growth in average incomes of the poorest 20 percent of the population, and growth in average incomes, using a large cross-country panel dataset on average incomes and inequality. Our main findings in that paper were that (i) mean incomes in the poorest quintile on average increase equiproportionately with average incomes, reflecting the lack of a systematic correlation between growth and changes in the first quintile share, and (ii) this relationship is very strong, reflecting the fact that most of the variation in growth in incomes in the poorest quintile is

[1] See World Bank (2013).

[2] As an example of this, in a recent speech at Knox College in Galesburg, Illinois on July 24, 2013, President Barack Obama described the US economy as *"... a winner-take-all economy where a few do better and better, while everybody else just treads water"*. More systematically, a recent Pew Global Survey found that a strong majority of respondents in 14 advanced economies felt that the gap between rich and poor was increasing in recent years. The fraction holding this view ranged from a low of 58 percent in Japan to a high of 90 percent in Spain (Pew Research Center, 2013).

attributable to growth in average incomes, rather than changes in the share of income accruing to the poorest quintile.

Over the past 15 years since we began work on that paper, the quality and quantity of available household survey data on income distribution have improved dramatically, providing rich new information that can be used to revisit the evidence on the relationship between overall growth and growth in the poorest quintiles. We work with a large cross-country dataset of high-quality survey-based measures of average incomes and income distributions, drawing on the POVCALNET database[3] of the World Bank for developing countries, and the Luxembourg Income Study (LIS) data[4] for advanced economies. Using this combined dataset, which covers 121 countries for which household surveys are available for at least two years since the 1970s, we revisit the relationship between growth in average incomes and growth in the poorest quintiles. Updating the work in Dollar and Kraay (2002), we consider growth rates of average incomes in the poorest 20 percent of the population, and given the new emphasis at the World Bank on "shared prosperity", we also consider growth rates of average incomes in the poorest 40 percent of the population.

Echoing our earlier work, this expanded and updated dataset reveals a very strong equiproportionate relationship between average incomes in the poorest quintiles, and overall average incomes. In our benchmark specification, covering 285 non-overlapping within-country growth episodes at least five years long, the slope of the relationship between growth in average incomes in the poorest quintiles and growth in overall average incomes is very close to – and not significantly different from – one. Moreover, a standard variance decomposition indicates that 61 percent (77 percent) of the cross-country variation in growth in incomes of the poorest 20 percent (40 percent) is due to growth in average incomes. This basic result underscores the central importance of overall growth for improvements in living standards among the poorest in societies.

Although the portion of the variation in growth in incomes in the poorest quintiles due to changes in inequality is -- on average -- both small and uncorrelated with growth in average incomes, it is nevertheless important to understand its other correlates. In particular, if one combination of macroeconomic policies and institutions that supports a given aggregate growth rate also leads to an increase in the share of incomes accruing to the poorest quintiles, while another combination did the

[3] See PovcalNet Database (2013).
[4] See Luxembourg Income Study (LIS) Database (2013).

opposite, then the former would be preferable from the standpoint of promoting shared prosperity. We therefore investigate how growth in the income share of the poorest 20 and 40 percent correlates with a variety of country-level variables commonly thought to matter for growth (e.g. financial depth, financial openness, the inflation rate, the budget balance, trade openness, life expectancy, measures of internal and external conflicts, population growth, life expectancy, and civil liberties), as well as a number of variables often considered to matter directly for inequality (e.g. initial inequality, primary school enrollments, inequality in educational attainment, and agricultural productivity).

In the spirit of systematic data description, we use Bayesian Model Averaging to document the partial correlations between these variables and growth in the income share of the poor for all possible combinations of these variables. We find at best very modest evidence that any of the policies and institutions reflected in these variables are significantly correlated with changes in the income share of the bottom 20 and 40 percent of the income distribution. These findings illustrate the difficulty in using cross-national data to identify specific country-level correlates of growth in the income share of the poorest income quintiles. Moreover, the particularly strong relationship between growth in incomes of the bottom 40 percent and growth in average incomes, and the lack of evidence of systematic correlates of the difference between the two, underscores the central importance of rapid growth in average incomes as a means to achieving "shared prosperity".

Of course, this largely inconclusive finding on the links between the explanatory variables we considered and inequality changes does not imply that policymakers should not care about changes in inequality and how they matter for incomes at the low end of the income distribution. Purely from an econometric standpoint, a reasonable interpretation of our empirical findings in the last part of the paper is that cross-country regressions such as those we estimate are too blunt a tool to conclusively identify systematic correlates of inequality changes. Moreover in at least some episodes in our dataset, we observe large inequality increases that have resulted in growth in average incomes in the poorest quintiles lagging substantially behind growth in average incomes, while the opposite is true in other spells. It is a truism that all policies have distributional consequences that policymakers should consider before pursuing them. However, the fact that in the data we observe essentially a zero correlation between growth and inequality changes suggests that some policies that are good for growth in average incomes will also lead to increases in inequality, while others will lead to decreases in inequality. Similarly, other policies that might reduce inequality will lead to faster growth, while others to slower growth. The challenge for policymakers who often find themselves under pressure to "do something"

about inequality is to avoid choosing combinations of policy interventions that reduce inequality but that might decrease "shared prosperity" if these policies at the same time undermine growth.

This paper contributes to a large empirical literature on the relationship between growth and changes in inequality. Most immediately, this paper updates, extends, and improves upon Dollar and Kraay (2002). In that paper, we studied the relationship between growth and inequality changes using data available at the time through the late 1990s, and drawing primarily on the Deininger and Squire (1996) compilation of cross-country data on income inequality (the predecessor of the UN WIDER World Income Inequality Database). While this dataset was the largest cross-national compendium of inequality data available at the time, it suffered from a number of shortcomings, that are discussed in detail in Atkinson and Brandolini (2001) and more recently by Jenkins (2014). Relative to our previous work, the main innovation in this paper is to rely instead on two much more reliable compilations of cross-country data on income inequality discussed in more detail below: the World Bank's PovcalNet database for developing countries and the Luxembourg Income Study database for OECD economies. Not only are the quality and comparability of the inequality data in these two compilations much better, but also both sources provide data on household average income taken from the same survey as the inequality data. This allows us to relate changes in survey mean income to changes in inequality, rather than using growth in per capita GDP as we did in our previous paper.

This paper is also closely related to -- and shares a common dataset with -- our companion paper Dollar, Kleineberg and Kraay (2015). In that paper, we empirically document the relationship between growth in average incomes and growth in a wide variety of social welfare functions, of which average incomes in the bottom 20 and 40 percent are two specific examples. Finally, our work in all three papers can be viewed as contributing to a larger literature that has also documented a lack of any systematic correlation between growth and inequality changes (see for example Bruno, Ravallion and Squire (1998), Ravallion (2007), and Ferreira and Ravallion (2009)).

The rest of this paper proceeds as follows. Section 2 describes our empirical framework, as well as the cross-country panel of household survey data on which our results are based. Section 3 presents our core results on the bivariate relationship between growth in incomes of the poor and growth in average incomes, documenting two key features of the data: growth in average incomes and growth in the income share of the poorest quintiles are uncorrelated, and the variance of the former generally is much larger than the variance of the latter. Section 4 provides additional empirical evidence on the

correlation between growth in the income shares of the poorest quintiles and an array of variables from the cross-country growth literature. Section 5 concludes.

2. Empirical Strategy and Data

2.1. Basic Setup

Our starting point is the identity that relates incomes of the poor to average incomes:

(1) $$Y^P = S^P Y$$

where Y^P denotes average income in either the bottom 20 or 40 percent of the income distribution; S^P denotes the income share of the first quintile divided by 0.2 ($\frac{Q_1}{0.2}$) or the share of the bottom two quintiles divided by 0.4 ($\frac{Q_1+Q_2}{0.4}$); and Y denotes overall average income. As discussed below, in roughly half of the surveys in our dataset, the relevant welfare measure is consumption expenditure, while in the other half it is income. However, for terminological convenience we will refer only to income. Also, while our dataset is an unbalanced and irregularly-spaced panel of country-year observations where survey data are available, for notational convenience in this section we will suppress country and year subscripts. Taking log differences over time between two survey years for a given country results in the following expression for growth in incomes of the poor:

(2) $$\Delta \ln Y^P = \Delta \ln S^P + \Delta \ln Y$$

That is, growth in average incomes of the poor can mechanically be decomposed into growth in overall average incomes, and growth in the share of income accruing to the poor.

Our goal in the first part of this paper is simply to document the relative importance of these two factors in accounting – in a mechanical sense – for growth in average incomes of the poorest quintiles. We do this using two complementary and purely descriptive techniques. The first is to estimate a bivariate regression of growth in incomes of the poor on growth in average incomes (and an intercept) and to test whether the slope coefficient from this regression is equal to one. The (population) slope coefficient from this regression is:

(3) $$\frac{COV\ (\Delta \ln Y^P,\ \ \Delta \ln Y)}{V(\Delta \ln Y)} = 1 + \frac{COV\ (\ \Delta \ln S^P\ ,\ \ \Delta \ln Y)}{V(\Delta \ln Y)}$$

where the equality follows from the definition of growth in incomes of the poor. When the estimated slope coefficient is equal to one, incomes of the poor increase on average at the same rate as overall average incomes. This is because the income share of the poorest does not vary systematically with changes in average income, i.e. $\frac{COV\ (\Delta \ln S^P,\ \ \Delta \ln Y)}{V(\Delta \ln Y)} = 0$. If however the estimated slope coefficient is greater (less) than one, incomes of the poor rise faster (slower) than average incomes, reflecting a positive (negative) correlation between growth and the income share of the poor. Obviously, we cannot assign any causal interpretation to this correlation. Rather, by documenting whether this estimated OLS slope coefficient is equal to one, we are simply documenting whether the correlation between growth and changes in the log income share of the poor is equal to zero.[5] As we shall shortly see, in most cases we cannot reject the null of zero correlation.

The second technique is useful to describe the relative importance of these two sources of growth in average incomes of the poor. We document this using a standard variance decomposition, which starts from the observation that:

(4) $$V(\Delta \ln Y^P) = V\ (\Delta \ln Y) + 2\ COV\ (\Delta \ln S^P,\ \ \Delta \ln Y) + V(\Delta \ln S^P)$$

i.e. the (population) variance of growth in average incomes in the poorest quintiles reflects the (population) variance of the growth rate of the mean, the (population) variance of the growth rate of the income share of the poor, and the (population) covariance between the two. As already noted, we find that this covariance term is small and not significantly different from zero in most specifications.

[5] It is worth noting that measurement error in the growth rate of average income and in the growth rate of the income share of the poor can introduce biases in our estimates of the relationship between the two. Specifically let ε and u denote these two measurement errors, and assume that they are classical in the sense of being uncorrelated with growth in average incomes and growth in the income share of the poor. In this case, the slope estimator in Equation (2) becomes $1 + \frac{COV\ (\ \Delta \ln S^P + u\ ,\ \ \Delta \ln Y + \varepsilon)}{V(\Delta \ln Y + \varepsilon)} = 1 + \frac{COV\ (\ \Delta \ln S^P\ ,\ \ \Delta \ln Y)}{V(\Delta \ln Y)} \frac{V(\varepsilon)}{V(\Delta \ln Y + \varepsilon)} + \frac{COV(\varepsilon, u)}{V(\Delta \ln Y + \varepsilon)}$. The term $\frac{V(\varepsilon)}{V(\Delta \ln Y + \varepsilon)}$ captures standard attenuation bias due to classical measurement error and implies that our estimated slopes will be biased towards one. The term $\frac{COV(\varepsilon, u)}{V(\Delta \ln Y + \varepsilon)}$ reflects any correlation between measurement error in the growth rate of the mean and the growth rate of the income share of the poor, and could bias our estimates up or down depending on the sign of this correlation which is *a priori* ambiguous.

Nevertheless, it is not exactly zero and therefore needs to be taken into account in the variance decomposition. Specifically, we follow Klenow and Rodriguez-Clare (1997) in defining the share of the variation of growth in incomes of the poorest due to growth in average incomes as:

$$S = \frac{V\ (\Delta \ln Y) + \ COV\ (\Delta \ln S^P,\ \ \Delta \ln Y)}{V(\Delta \ln Y^P)} \tag{5}$$

Given that the covariance is small, the share of the variance of growth in average incomes of the poorest quintiles due to growth in average incomes will primarily reflect the relative variances of the two. Finally, we note that this variance share is closely related to the R-squared from the regression described above. Specifically, some simple arithmetic shows that $S^2 = R^2\ \frac{V\ (\Delta \ln Y)}{V\ (\Delta \ln Y^P)}$. We report the share of the variance of growth in average incomes of the poorest quintiles due to growth in average incomes in the tables of results that follow, as a useful summary of the relative importance of growth and changes in inequality in driving growth in incomes of the poor.

2.2. Measuring Growth in Average Income and Income of the Poor

Our starting point is a large dataset of 963 country-year observations for which household surveys are available, covering a total of 151 countries between 1967 and 2011. As noted in the introduction, this is the same dataset as we use in our companion paper, Dollar, Kleineberg and Kraay (2015). This dataset is the merger of data available in two high-quality compilations of household survey data: the World Bank's POVCALNET database, covering primarily developing countries, and the Luxembourg Income Study (LIS) database, covering primarily developed countries. The POVCALNET database is the dataset underlying the World Bank's widely known global poverty estimates. Its data on average incomes and income distribution are based on primary household survey data. In most cases, surveys are representative for the whole country.[6] Roughly half of the surveys in the POVCALNET database report income and its distribution, while the other half report consumption expenditure and its distribution. As noted earlier, however, for terminological convenience we will refer only to income. All survey means are expressed in constant 2005 US dollars adjusted for differences in purchasing power parity.

[6] In the case of Argentina and Uruguay, survey data is only available for urban areas; however, due to high urbanization rates (over 90%) this seems to be an acceptable proxy for the national income distribution.

For countries that are not covered in POVCALNET, we rely on the LIS database.[7] This expands our sample by adding 20 OECD economies. For these countries we construct mean income and income shares of the poorest directly from the micro data at the household level. The underlying surveys are nationally representative and intended to be comparable over time. We focus on the LIS measure of total household income, which is expressed in the raw data in current local currency units. We convert the survey means to constant 2005 USD and then apply the 2005 purchasing power parity for consumption from the Penn World Table, in order to be consistent with the POVCALNET data.[8] While the LIS data has a few observations in the 1960s and 1970s, the vast majority of the surveys fall in the 1980s, 1990s, and 2000s.

For our empirical analysis, we organize the data into "spells", defined as within-country changes in variables of interest between two survey years. Specifically, we calculate average annual log differences of average incomes, incomes of the poor, and quintile shares for each spell, recognizing that different spells cover periods of different length, depending on the availability of household survey data. We work with three sets of spells corresponding to different time horizons. The first set consists of all possible consecutive non-overlapping spells, beginning with the first available survey for each country. This largest sample consists of 701 spells in 121 countries, with a median spell length of 2 years. This sample is the least balanced panel in the sense that there is a great deal of variation in the number of spells per country, ranging from just one in countries like Algeria and Malawi, to 20 and 21 in countries such as Brazil and Costa Rica where annual household surveys are available frequently and for long periods of time. At the other extreme, we construct a sample of just one spell per country, taking the earliest and latest available year for each country, covering 117 countries with a median spell length of 16 years. Finally, as an intermediate sample, we construct a set of all possible consecutive non-overlapping spells by country, but imposing a minimum length of five years for each spell. This results in a set of 285 spells in 115 countries. The median spell length is 6 years.[9] Compared with the set of all

[7] A handful of countries have surveys available both through POVCALNET and LIS. For these countries we use only the POVCALNET data, i.e. we do not switch within countries between POVCALNET and LIS.

[8] The POVCALNET data refers to mean income/consumption and its distribution across individuals, while the LIS data are reported at the household level. We follow the LIS practice of using an equivalence scale equal to the square root of the number of household members to convert variables to per capita terms, and we construct the distribution measures across individuals, not households.

[9] In all three sets of spells, we trim extreme observations by dropping observations beyond the 1st and 99th percentiles of the distribution of the growth rates of mean income and the income shares of each of the 10 deciles. The numbers of countries and spells in the discussion above refer to those included in each sample after trimming extreme observations.

spells, the sample of minimum five-year spells and the sample of long spells will reflect fluctuations in growth and inequality over longer horizons.

Table 1 provides summary statistics on annual growth in overall average incomes, the first quintile share, and the sum of the first two quintile shares, for the three sets of spells.[10] The basic story is clear from the summary statistics. Consider for example Panel A which combines all spells in each of the three samples. For the 285 observations in the minimum-five-year-spell sample, the mean growth rate of average income is 1.5 percent per year and the mean change in the share of the bottom 40 percent is 0.0 percent per year. This implies that the growth rate of income of the bottom 40 percent is also 1.5 percent per year on average. Furthermore, growth rates in average incomes vary considerably more across spells than growth rates of the income share of the bottom 40 percent: the standard deviations of these two growth rates are 4.2 versus 2.3 percent. Finally, we will shortly see that the correlation between the two growth rates is statistically indistinguishable from zero. Taken together, this implies that the bulk of the variation in growth in incomes of the poor is attributable – in a variance decomposition sense -- to growth in average incomes. While the details vary a bit, a similar story emerges for growth rates of the income share of the bottom 20 percent, and considering the samples of spells of differing lengths.

The second panel of **Error! Reference source not found.** reveals some interesting heterogeneity by disaggregating by geographical region (the assignment of countries to geographical regions is noted in Appendix Table A1). Unsurprisingly, growth rates in average incomes vary greatly across regions, ranging from less than one percent per year in the Middle East North Africa sample, to a high of 3.6 percent per year in East Asia (for the sample of all spells). In contrast, average growth rates of the income shares of the bottom 20 and 40 percent are universally small and exhibit substantially less variation across spells than does growth in average incomes. As a consequence, growth in average incomes of the bottom 20 and 40 percent closely follows growth in average incomes.

The last panel in **Error! Reference source not found.** disaggregates the summary statistics by decade, to see whether the patterns noted above are stable over time. A practical challenge for data description here is that many spells "cross" decades, having a start year in one decade and an end year in

[10] Since the dataset for this paper coincides with that in our companion paper, the summary statistics in the middle panel are identical to those reported in Table 2 of Dollar, Kleineberg and Kraay (2015), where we focused on the sample of minimum 5-year spells. Relative to that paper, we provide additional detail here by reporting a full set of summary statistics for all the sample of all spells, and the sample of long spells as well.

the next decade, while only a small fraction of spells fall entirely within a single decade. As a result it is not obvious how to assign the remaining spells to decades. To circumvent this problem, for each spell we define three variables measuring the fraction of years in the spell falling in each of three decades. For example, a spell lasting from 1989 to 1994 would have one-fifth of its years in the 1980s and four-fifths in the 1990s, and none in the 2000s. We then report weighted summary statistics by decade, weighting each spell by the fraction of observations falling in each decade. We do this only for the sample of all spells, and the sample of minimum 5-year spells, as the disaggregation by decade is less meaningful when there is only one spell per country as in the sample of long spells.

The importance of overall growth for incomes of the poor can be seen by comparing the statistics for the 1980s and the 2000s: for the observations in the all-spell sample in the 1980s, mean income growth averaged 0.2 percent per year, but this increased to 3.4 percent per year in the 2000s. In contrast, growth rates of the income shares of the bottom 40 percent averaged close to zero percent across all three decades, and moreover exhibited less variation across spells than growth in average incomes.

3. Decomposing Growth in Average Incomes of Bottom 20 and 40 Percent

In this section we present a series of bivariate regressions of growth in average incomes of the bottom 20 and 40 percent on growth in average incomes. As outlined in the previous section, we use these regressions to document the correlation between growth and inequality changes that matter for incomes in the bottom 20 and 40 percent, as well as the share of the variance of growth in average incomes in the bottom 20 and 40 percent that is due to growth in average incomes. We begin in Table 2 with regressions for the full set of spells. The first (second) set of three columns report results for the growth rate of the bottom 20 (40) percent, while within each set we show results for the sample of all spells, the sample of long spells, and the sample of long spells. The results are quite consistent across all six specifications. In all cases the point estimate of the slope is very close to one, and we cannot reject the null hypothesis that the slope coefficient is equal to one, indicating the absence of a statistically significant correlation between growth in average incomes and growth in the income shares of the poorest. This in turn implies that average incomes in the poorest quintiles on average increase equiproportionately with mean income. This holds both when the poor are defined as those in the bottom 20 percent, and in the bottom 40 percent, the latter corresponding to the “shared prosperity” measure advocated by the World Bank. Turning to the variance decompositions, we find that between 72 and 80 percent of the variance of growth in average incomes of the bottom 40 percent is attributable to

growth in average incomes, depending on the sample of spells under consideration. For the bottom 20 percent, the corresponding proportion is somewhat smaller, ranging from 56 to 61 percent.[11]

Figure 1 provides a visual summary of these results. The top panel shows the relationship between growth in average incomes (on the horizontal axis) and growth in incomes in the poorest two quintiles (on the vertical axis), focusing on the sample of spells at least five years long. Consistent with the results in Table 2 , the slope of the fitted relationship is nearly indistinguishable from the 45-degree line. Moreover, it is clear that this relationship is quite strong, which in turn is reflected in the variance decomposition results noted above. The bottom panel of Figure shows the same relationship, in the three sets of spells. In all three sets of spells, the estimated slopes are close to one, and the corresponding R-squareds are large, ranging from 69 to 78 percent.

We next investigate how this relationship varies across geographical regions and over time. Table 3 shows that our basic finding of a tightly estimated equiproportional relationship between growth in incomes of the poor, and growth in average incomes, holds in most geographical regions, and particularly so for average incomes in the bottom 40 percent of the population. In 34 out of the 42 specifications reported in Table 3, we do not reject the null hypothesis that the estimated slope coefficient is equal to zero, at the 10 percent significance level.[12] This indicates that in the majority of subsamples, there is no statistically significant correlation between growth in average incomes and the income share of the bottom 20 or 40 percent. Out of the remaining 8 cases where the slope is significantly different from 1, it is significantly greater than 1 in 3 cases (indicating a significantly positive correlation between growth and the income share of the poor, i.e. declining inequality), while in the remaining 5 cases the slope is significantly less than 1 (indicating a pattern in which growth is associated with a decline in the income share of the poor, i.e. rising inequality). The most striking case of this is the East Asia and Pacific region, where the estimated slopes for the sample of all spells, and the sample of minimum 5-year spells, range from 0.58 to 0.77 and are statistically significantly less than one in two cases. This indicates that in these cases, spells with faster growth in average incomes were more likely to also have decreases in the income share of the poorest quintiles. However, this does not imply that

[11] As discussed in the working paper version of our companion paper, this smaller share of the variance due to growth may in part be the result of measurement error due to sampling variation in the underlying surveys. See Dollar, Kleineberg and Kraay (2014), Section 4.3.

[12] A standard caveat here is that the sample size is quite small in the sample of long spells in the Middle East/North Africa, South Asia, and East Asia samples since there are not many countries included in these regional groupings. As a result, the estimates, and particularly the robust standard errors, should be treated with some caution.

those in the poorest quintiles fared particularly poorly in such spells. Recall from Table 1 that average incomes in East Asia grew fastest among all regions at over 3 percent per year, and that average incomes in the bottom 20 and 40 percent also grew faster than in any other region.

In Table 4 we investigate how the relationship between growth in average incomes and growth in incomes of the poor varies by decade. As in Table 2, we assign spells in the sample of all spells, and the sample of minimum 5-year spells, to decades according to the fraction of the length of the spell falling in each decade. We report weighted least squares estimates of our bivariate regression of growth in average incomes of the poor on growth in average incomes, assigning greater weight to spells with more years in the corresponding decade. For spells falling in the 1990s and 2000s, across all specifications we find estimated slopes that are quite close to, and not statistically significantly different from one. However, for spells in the 1980s, there is a more systematic tendency for inequality to increase during periods of higher growth, as reflected in estimated slope coefficients that are significantly less than one. As in the previous two tables, we find that the share of the variance of growth in average incomes of the poorest quintiles due to growth in average incomes is substantial but lower for the bottom 20 percent (ranging from 0.52 to 0.74) than for the bottom 40 percent (ranging from 0.70 to 0.86).

In all of our results so far, we have relied exclusively on household survey data to construct measures of average income growth and growth in incomes of the poor. However, many past studies, including our own work in Dollar and Kraay (2002), have relied on national accounts growth rates to measure overall average income growth, and then combined this with household-survey based measures of how this growth was distributed across individuals. A large literature has discussed substantial differences between growth in survey mean income and corresponding aggregates in the national accounts in some countries (see for example Deaton (2005) and Deaton and Kozel (2005) for the case of India in particular). Without taking a stand on relative merits of national accounts versus household surveys as a measure of average living standards, we perform some simple robustness checks to see how our findings change if we rely on national accounts growth rates instead of household survey mean growth rates. [13]

The results are presented in Table 5. The first panel reproduces our benchmark specification in the slightly smaller samples of spells for which both national accounts growth and household survey

[13] As we have noted earlier, the household survey data are a mix of income and consumption surveys. This raises the question of which national accounts aggregate is the closest corresponding measure. Here we compare with real private consumption growth in all countries, following Ravallion and Chen (2008).

growth rates are available. Dropping these few spells makes very little difference for our benchmark results, which are quite similar to those in Table 2. The second panel reports results replacing household survey growth with the corresponding national accounts growth rate (and of course also using the national accounts growth rate plus the growth rate of the relevant quintile shares to compute growth in incomes of the poor). The estimated slope coefficients are very similar to those estimated using household survey mean growth rates, indicating that the correlation between changes in inequality and changes in average income based on national accounts data is not very different from the correlation between changes in inequality and changes in household survey means.

The main difference between the first and second panels is in the variance decompositions, where we see a lower share of the variance of growth in average incomes of the poor attributable to growth in average incomes when using national accounts growth rates. This is the case for the sample of all spells, and also for the sample of minimum 5-year spells, although not for the sample of long spells. Mechanically, the reason for this is straightforward – over the shorter horizons captured in the first two sets of spells, household survey growth mean rates are considerably more variable than national accounts growth rates. Given that the covariance term in our variance decomposition is close to zero, this immediately leads to a smaller share of the variance of growth in incomes of the poor due to growth in average incomes. Finally, in the third panel of Table 5, we follow the approach suggested in Chen and Ravallion (2008), using a simple average of the household survey mean and national accounts growth rates.[14] Since household survey mean growth rates vary much more than consumption growth rates in the national accounts, they dominate these average growth rates. As a result, this mixed method leads to findings that are very similar to those in the first panel of Table 5.

Overall, our findings show that the poor on average benefit equiproportionally from overall growth, and these findings hold across most geographical and temporal disaggregations of the data. In most cases this relationship is also fairly tightly estimated, particularly for income growth in the poorest 40 percent, where our benchmark findings suggest that around three quarters of the variation in growth in average incomes of the poorest 40 percent is attributable to growth in average incomes. These

[14] Chen and Ravallion (2008) show that under certain strong assumptions (a lognormal distribution of incomes and equal variance of measurement error across the two sources), treating national accounts data on consumption as a prior, and household surveys as data, the natural posterior estimate of mean living standards is an equally-weighted geometric average of the two. In log-differences this implies a simple average of the two growth rates.

findings confirm that, in our sample of spells, growth is distribution-neutral on average, and that changes in relative incomes tend to be substantially smaller than growth in overall average income.

4. Policies, Institutions, and Growth in the Income Share of the Poor

The previous section has shown that average incomes of the poor tend to rise at the same rate as overall average incomes, reflecting a lack of any systematic correlation between growth and changes in the income share of the poor. Moreover, we have seen that the majority of the cross-country variation in growth in incomes of the poor reflects growth in average incomes, rather than changes in the share of income captured by the poorest quintiles. While an extensive literature has investigated correlates of growth in average per capita incomes, which account for most of the variation in growth in incomes of the poor, relatively less is known about systematic correlates of growth in measures of income distribution such as the income shares of the poorest quintiles.[15] In this last section of the paper we empirically investigate how growth in the income shares of the poorest quintiles is correlated with a set of explanatory variables intended to proxy for a variety of policies, institutions, and initial conditions. To the extent that these variables are also correlates of growth in average incomes, knowledge of their associations with changes in inequality may be useful in helping policymakers seeking to pursue the goal of "pro-poor" growth or "shared prosperity" through reductions in inequaltiy.

We loosely group our explanatory variables into one set that serves as proxies for a variety of policies and institutions that might matter for growth, and a second set that might plausibly be relevant for changes in relative incomes. The growth correlates include a measure of financial development, the Sachs-Warner indicator of trade openness, the Chinn-Ito Index of financial openness, the inflation rate, the general government budget balance, life expectancy, population growth, the Freedom House measure of civil liberties and political rights, the frequency of political revolutions, and a dummy indicating participation in an in international or domestic conflict. Most of these variables have been identified as important correlates of growth in one or more of three prominent meta-analyses of growth determinants (Fernandez, Ley and Steel (2001a), Sala-i-Martin (2004) and Ciccone et al. (2010)). The second set of four variables is motivated by the much smaller existing cross-country literature on determinants of inequality. These consist of the initial level of inequality at the beginning of the spell (as

[15] For a recent contribution providing new evidence on correlates of growth at different points in the income distribution, see Jaumotte et. al. (2013).

emphasized by Ravallion (2003)), primary enrollment rates, a measure of educational inequality[16] (as emphasized by De Gregorio et. al. (2002)), and finally the share of agriculture in GDP (as emphasized for example in Datt and Ravallion (2002) in the context of Indian states).[17] Table A2 provides a detailed description of the definitions and sources of all of these variables.

In the spirit of comprehensive data description, we use Bayesian Model Averaging (BMA) to systematically document the partial correlations between various combinations of these covariates and growth in the income shares of the poorest quintiles. This approach follows a growing literature which relies on BMA to show the robustness of empirical findings in the cross-country growth literature to variation in the set of included explanatory variables.[18] The basic idea of BMA is to consider the large set of 2^K empirical models defined by all possible combinations of the set of $K = 15$ variables added to our benchmark specification, rather than to base conclusions on just a few pre-selected models. Let $j \in \{1,2,3, \dots, 2^K\}$ index the universe of potential models defined as all possible combinations of explanatory variables, and let X_j denotes the particular set of explanatory variables included in model j. For each model j we estimate the following very simple OLS regression of growth in the income share of the poor on the corresponding set of included regressors in that model, i.e.:

$$\Delta S^P = \alpha_j + \beta_j' X_j + \varepsilon_j . \tag{6}$$

The estimated slope coefficients in β_j capture the partial correlations between growth in incomes of the poor and the variables included in model j. BMA provides an algorithm for assigning posterior probabilities to each model reflecting their relative likelihoods. These likelihoods in turn reflect the "fit" of the model as summarized by the R-squared, but with a model size penalty that rewards more parsimonious models with fewer regressors. These posterior model probabilities can then be used to combine inferences across different models in a way that reflects their relative likelihood. For each variable, we calculate the Posterior Inclusion Probability (PIP), which is the sum of the posterior model

[16] Specifically, we use data on educational attainment by different levels of attainment from the Barro-Lee dataset to construct a (grouped) Lorenz curve summarizing the distribution of the total number of years of education across individuals, and from this calculate a corresponding Gini coefficient.

[17] We also considered several other variables found to be significant correlates of inequality in some papers in the literature, but did not include them in our analysis because data coverage was very poor for many of the developing countries in our sample. These included indicators of labour market regulation and progressivity of tax systems (Checchi et. al. (2008)), public sector employment (Milanovic (2000)), and social transfers (Milanovic (2000), De Gregorio et. al. (2002)).

[18] See Fernandez, Ley and Steel (2002) for the seminal application of this technique to cross-country growth empirics.

probabilities for each model in which the given variable is included. High values of the PIP indicate that this variable appears in models that are relatively more likely. In addition, we calculate the posterior probability-weighted average of the estimated slope coefficient for each variable, averaging across all models.[19]

Before turning to the empirical results, we briefly note that this empirical exercise is very closely related to part of the empirical work in the last section of our companion paper, Dollar, Kleineberg and Kraay (2015). In that paper, we consider the same set of explanatory variables, and document their partial correlations with growth in social welfare for a variety of social welfare functions, including average incomes of the bottom 40 percent. In that paper, we also empirically unbundle the effects of each variable on social welfare growth into effects operating through changes in average income and changes in the inequality measure relevant to each social welfare function. Here we focus only on correlates of changes in inequality. However, relative to our other paper we extend the analysis to consider correlates of changes in average incomes of the bottom 20 percent as well, and we also provide more detail on the robustness of the conclusions suggested by the BMA analysis to variations in the assumptions required to implement BMA. A final difference is that in our other paper, we forced both initial income and initial inequality to be included in all models, while here we consider only initial inequality, and moreover we treat it symmetrically with all other explanatory variables, i.e. it appears in half of all models and does not appear in the other half.

The two panels of Table 6 summarize the results of the BMA exercise for growth the income share of the bottom 20 percent, and bottom 40 percent, respectively. In both tables we focus on the sample of spells at least five years long.[20] The rows of the table correspond to the 14 variables included in the BMA analysis. In each panel, we first report the posterior inclusion probability for each variable. The distribution of these PIPs across variables is quite stark. The initial income share of the poor (i.e. its value at the beginning of the spell) has a very high PIP that is indistinguishable from 1 up to 3 decimal places. This indicates that virtually none of the posterior model probability is assigned to any model that

[19] We implement BMA using a standard g-prior for the parameters of each individual regression model, and a prior that assigns a equal probability of μ/K that each individual variable is included in a given model (see for example Fernandez, Ley and Steel (2001a) for a seminal application to cross-country growth empirics). We set $g = 0.01$ and $\mu = 0.25K$. Since the total number of models is not very large, we implement BMA by exhaustively estimating all possible models, rather than use common numerical algorithms to visit only a subset of relatively more likely models.

[20] We have also performed the same BMA analysis in the set of all spells, and find broadly similar results. These results are not reported for reasons of space.

does not include initial inequality. Beyond this, the PIPs for the remaining variables are quite small, with only primary schooling having a PIP that is greater than 0.5. This is true for both the income share of the bottom 20 percent and the bottom 40 percent, illustrating the difficulty in identifying robust correlates of changes in the income share of the bottom quintiles from among this large set of candidate explanatory variables.

In the next column we report the posterior probability-weighted slopes. To aid in comparing these across variables, each is scaled by the sample standard deviation of the corresponding explanatory variable, so that it is interpretable as the effect on growth in the income share of the poor of a one-standard deviation increase in the variable. Echoing the finding of Ravallion (2003) for the Gini coefficient, initial equality enters negatively and with a very high PIP, indicating a tendency for equality to fall (increase) when it is initially high (low). These estimated slopes for the remaining variables are for the most part quite small – in fact only inflation and primary schooling have posterior probability-weighted estimated slopes that are not zero to three decimal places. In the case of inflation, the coefficient is negative, suggesting that higher inflation is associated with a slower growth rate of the income share of the poorest quintiles, i.e. an increase in inequality. This echoes our similar findings in Dollar and Kraay (2002). In the case of primary schooling, we find a puzzling negative association with growth in the income share of the poorest. However, since this effect is quite small, and is significant at conventional levels only in a minority of models, it probably should not be overinterpreted.

In Table 7 we provide more detail on the set of "top" models with highest posterior probabilities identified by BMA. The first 10 columns of this table report the 10 models with the highest posterior probabilities, and show the explanatory variables included in each. To conserve space, we show the top models only for the growth rate of the income share of the bottom 40 percent – results for the bottom 20 percent are quite similar. As already apparent from Table 6, the initial income share of the bottom 40 percent appears in all of the top 10 models. Turning to the other variables, a few of the top models include inflation and population growth, both of which are negatively associated with changes in the income share of the bottom 40 percent. Table 7 also shows that the somewhat puzzling negative association between primary schooling and the growth rate of the income share of the poorest quintiles noted in Table 6 is a feature of the top models, six of which include this variable.

One perennial concern in applications of BMA is the extent to which the conclusions are robust to different prior assumptions. A particularly important prior assumption governs the rate at which BMA trades off improvements in model fit versus reductions in parsimony when comparing models with

differing numbers of regressors. If this tradeoff assigns too great a weight to improvements in model fit, it is possible that most of the posterior probability ends up concentrated on just a few models, dubbed a "supermodel effect" by Feldkircher and Zeugner (2009). If this supermodel effect is present, it can distort the conclusions of BMA by suppressing the influence of other models that perform just slightly worse in the tradeoff between parsimony and fit. To investigate this possibility, we report the posterior model probabilities of the top 10 models at the bottom of Table 7. The first set of posterior model probabilities reflects our baseline prior assumptions underlying the results in Table 6. The posterior model probabilities are fairly strongly concentrated on the top 10 models, which collectively account for 81 percent of the posterior probability.

The second (third) sets of posterior model probabilities reflect prior assumptions that assign greater (less) weight to improvements in R-squared and therefore are more (less) likely to be prone to supermodel effects.[21] Despite these differing assumptions governing the tradeoff between model fit and number of regressors, we find a very similar set of top models. Of the 10 top models in our benchmark specification, 9 are included in the set of top 10 models in the two alternatives specifications. Naturally, there are some differences in the ordering of top models, and there are also some differences in the combined posterior probability assigned to the top 10 models. Specifically, there is somewhat greater concentration of posterior probability on the top 10 models in the first alternative which assigns relatively more weight to models with higher R-squareds than the benchmark (0.87 vs 0.81), while the opposite is true for the second alternative that assigns relatively less weight (0.64 vs 0.81). Nevertheless, since in all three cases most of the posterior probability is assigned to similar and fairly small set of models, the overall conclusions from BMA appear to be reasonably robust to how the tradeoff between model fit and model size is parameterized.

Finally, as a reference point we also report coefficient estimates from the "encompassing" regression that includes all 14 of the explanatory variables in the last column of Table 7. The pattern of signs, size and estimated significance of the coefficients on these variables is generally consistent with the preceding results. The main difference of course though is that the posterior probability assigned to

[21] Specifically, we vary the parameter g in the g-prior used by Fernandez, Ley and Steel (2001a). As noted above our baseline estimates use $g = 0.01$. In the second row, we come closer to the recommendation of Fernandez, Ley and Steel (2001b) to set $g = \frac{1}{N}$ or $g = \frac{1}{K^2}$, which in our case implies values of $g = \frac{1}{285} = 0.004$ or $g = \frac{1}{14^2} = 0.005$, so we set $g = 0.005$. In the third row, we follow the suggestion in Feldkircher and Zeugner (2012) that a value as large as $g = 0.05$ is sufficient to eliminate the influence of a supermodel effect in their critique of the application of BMA to cross-country growth regressions in Ciccone and Jarocinski (2010). (Note that Feldkircher and Zeugner define their g as the inverse of g as we use it here).

this model is very small, reflecting the lack of parsimony in this specification relative to the top models that include many fewer regressors.

Overall, these results suggest that a large set of plausible macro variables are remarkably unsuccessful in explaining growth in the income share of the poorest 20 and 40 percent. This finding in turn implies that historical experience in a large sample of countries does not provide much guidance on which combinations of macroeconomic policies and institutions might be particularly beneficial for promoting "shared prosperity" as distinct from simply "prosperity".

5. Conclusions

Incomes of the bottom 20 percent and bottom 40 percent of the income distribution generally rise equiproportionally with mean incomes as economic growth proceeds. We document this finding in a large cross-country dataset, updating and expanding the results of Dollar and Kraay (2002). The result holds across decades, including in the 2000s -- hence the conclusion in our title that "growth still is good for the poor." This finding reflects the fact that changes in the income shares of the bottom 20 percent and bottom 40 percent generally are small and uncorrelated with economic growth. This in turn implies that much of the variation in growth in incomes of the poor is attributable to growth in average incomes. For example, in the sample of 285 minimum 5-year spells, 77 percent of the variation of growth in average incomes of the bottom 40 percent is due to differences across spells in growth in average incomes.

Our data also suggests that the income shares of the bottom 20 percent and bottom 40 percent show no systematic tendency to decline over time; that is, there is no worldwide trend towards greater inequality within countries. In the sample of 285 minimum-five-year spells, the average annual growth rate in the income share of the bottom 40 percent is zero. Furthermore, there is little tendency for that result to change over time. The average change was -0.2 percent per year in the 1980s, -0.3 percent per year in the 1990s, and 0.4 percent per year in the 2000s.

The fact that changes in quintile shares are zero on average does not mean that there are not some striking changes in inequality in particular countries at particular time periods. We attempt to explain these changes in inequality with variables used in the empirical growth literature, such as measures of macroeconomic stability, trade openness, and political stability. We also include variables that might plausibly have direct effects on the income share of the poor. This part of our work essentially

provides non-results: none of the macro country-level variables we consider robustly correlates with changes in the income shares of the poorest quintiles.

From the perspective of promoting "shared prosperity", the findings of this paper convey both good news and bad news. The good news is that institutions and policies that promote economic growth in general will on average raise incomes of the poor equiproportionally, thereby promoting "shared prosperity". The bad news is that, in choosing among macroeconomic policies, we do not find robust evidence that certain policies are particularly "pro-poor" or conducive to promoting "shared prosperity" other than through their direct effects on overall economic growth.

References

Atkinson, Andew and Andrea Brandolini (2001). "Promise and Pitfalls in the Use of 'Secondary' Datasets: Income Inequality in OECD Countries as a Case Study". Journal of Economic Literature39(3): 771-99.

Balakrishnan Ravi, Chad Steinberg, and Murtaza Syed. (2013). "The Elusive Quest for Inclusive Growth: Growth, Poverty, and Inequality," *IMF Working Paper WP/13/152.*

Bruno, Michael, Martin Ravallion and Lyn Squire (1998). "Equity and Growth in Developing Countries: Old and New Perspectives on the Policy Issues", in V. Tanzi and K. Chu (eds). Income Distribution and High-Quality Growth. Cambridge: MIT Press.

Checchi, Daniele; Garcia-Penalosa, Cecilia. (2008). "Labour Market Institutions and Income Inequality", *Economic Policy issue 56, pp. 601-34, 640-49.*

Chen, Shaohua, and Martin Ravallion. (2008). "The Developing World Is Poorer Than We Thought, But No Less Successful in the Fight against Poverty," *World Bank Policy Research Working Paper 4703.*

Chen, Shaohua, and Martin Ravallion. (2010). "The Developing World Is Poorer Than We Thought, But No Less Successful in the Fight against Poverty," *The Quarterly Journal of Economics.*

Ciccone, Antonia and Marek Jarocinski. (2010). "Determinants of Economics Growth: Will Data Tell?," *American Economic Journal: Macroeconomics 2, 2:4, 222-246*.

Datt, Gaurav and Martin Ravallion (2002). "Why Has Economic Growth Been More Pro-Poor in Some States of India than Others?". Journal of Development Economics. 68: 381-400.

Deaton, Angus, and Valerie Kozel. (2005). "Data and Dogma: The Great Indian Poverty Debate", *Oxford University Press 20:177-199.*

De Gregorio, Jose; Lee, Jong-Wha. (2002). "Education and Income Inequality: New Evidence from Cross-Country Data", *Review of Income and Wealth, v. 48, iss. 3, pp. 395-416.*

Deininger, Klaus and Lyn Squire (1996). "A New Dataset Measuring Income Inequality". World Bank Economic Review. 10(3): 565-91.

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

Dollar, David, Tatjana Kleineberg and Aart Kraay (2014). "Growth, Inequality, and Social Welfare: Cross-Country Evidence". World Bank Policy Research Department Working Paper No. 6842.

Dollar, David, Tatjana Kleineberg and Aart Kraay (2015). "Growth, Inequality, and Social Welfare: Cross-Country Evidence". Economic Policy. *Forthcoming*.

Feldkircher, M., and S. Zeugner (2009). "Benchmark Priors Revisited: On Adaptive Shrinkage and the Supermodel Effect in Bayesian Model Averaging". IMF Working Paper No. 09/202, International Monetary Fund.

Feldkircher, M., and Zeugner, S. (2012). "The Impact of Data Revisions on the Robustness of Growth Determinants—a Note on 'Determinants of Economic Growth: Will Data Tell?'. Journal of Applied Econometrics. 27(4):686-694.

Ferreira, Francisco H. G. and Martin Ravallion (2009). "Poverty and Inequality: The Global Context", in Salverda, Wiemer, Brian Nolan and Tim Smeeding, eds. The Oxford Handbook of Economic Inequality. Oxford: Oxford University Press.

Fernandez, C., Ley, E., and Steel, M.F.J. (2001a). Model Uncertainty in Cross-Country Growth Regressions. *Journal of Applied Econometrics*, 16(5), 563-576.

Fernandez, C., Ley, E., and Steel, M.F.J. (2001b). Benchmark prior for Bayesian model averaging. *Journal of Econometrics*, 100(2), 381-427.

Jaumotte, Florence, Subir Lall, and Chris Papageorgiou. (2013). "Rising Income Inequality: Technology, or Trade and Financial Globalization," *IMF Economic Review, v. 61, no. 2, pp. 271-309.*

Jenkins, Stephen (2014). "World Income Inequality Databases: An Assessment of the WIID and SWIID". Institute for Social and Economic Research Working Paper No. 2008-31.

Klenow, Peter and Andres Rodriguez-Clare (1997). "The Neoclassical Revival in Macroeconomics – Has It Gone Too Far?", in Ben Bernanke and Julio Rotemberg, eds. NBER Macroeconomics Annual. Cambridge, MIT Press, pp. 72-103.

Luxembourg Income Study (LIS) Database (2013). http://www.lisdatacenter.org (multiple countries; May 2013). Luxembourg: LIS.

Milanovic, Branko. (2000). "Determinants of Cross-Country Income Inequality: An 'Augmented' Kuznets Hypothesis", *Essays in honour of Branko Horvat, pp. 48-79.*

Pew Research Center (2013). "Economies of Emerging Markets Better Rated During Difficult Times". http://www.pewglobal.org/2013/05/23/economies-of-emerging-markets-better-rated-during-difficult-times/.

PovcalNet Database (2013). The on-line tool for poverty measurement developed by the Development Research Group of the World Bank, http://iresearch.worldbank.org/PovcalNet/index.htm; May 2013.

Ravallion, Martin (2003). "Inequality Convergence". Economics Letters. 80(3):351-56.

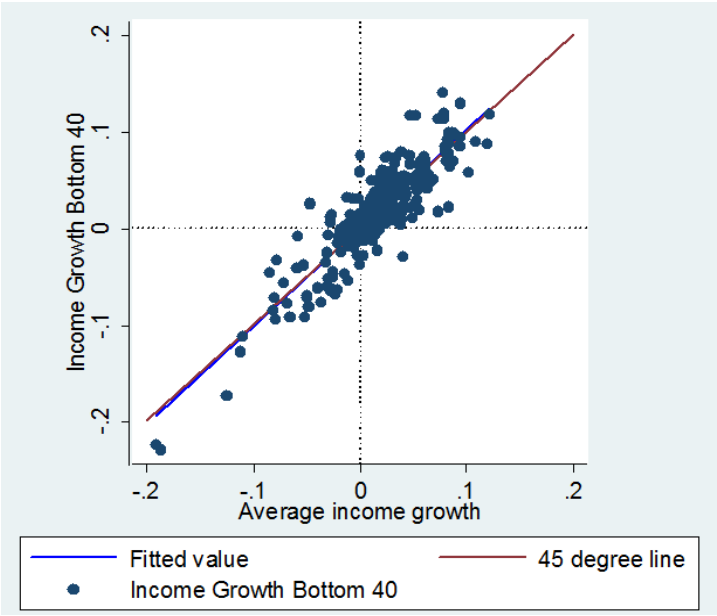
Ravallion, Martin (2007). "Inequality is Bad for the Poor", in J. Micklewright and S. Jenkins (eds.). Inequality and Poverty Re-Examined. Oxford: Oxford University Press.

Sala-i-Martin, Xavier, Gernot Doppelhofer, and Roland I. Miller. (2004). "Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach." *American Economic Review, 94(4): 813-35.*

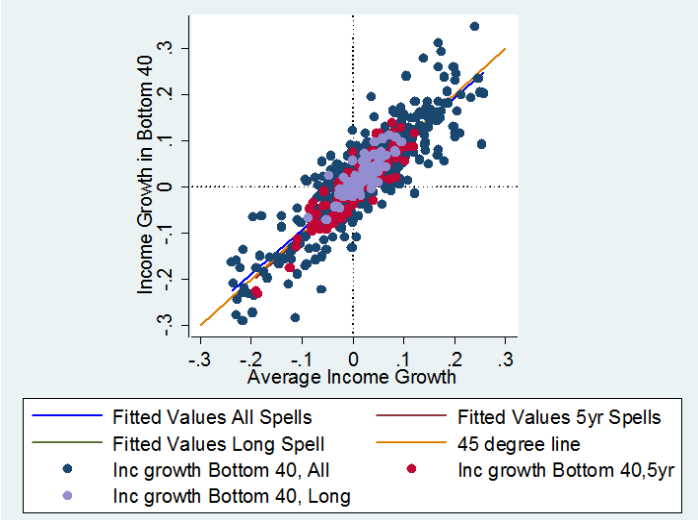
World Bank (2013). "The World Bank Goals: End Extreme Poverty and Promote Shared Prosperity". http://www.worldbank.org/content/dam/Worldbank/document/WB-goals2013.pdf.

Figure 1: Growth rates of Incomes of Poorest 40 Percent

(a) Sample of Minimum Five Year Spells



(b) Spells of Different Lengths



Notes: These figures show the correlation between growth in incomes of the poorest 40 percent and overall income growth. The top panel uses the sample of spells at least five years long. The bottom panel contrasts the findings in the three sets of spells: all available spells regardless of length, spells at least five years long, and the longest available spell for each country.

Table 1: Descriptive Statistics

	Growth in Average Income			Growth in Inc. Share Bottom 20 %			Growth in Inc. Share Bottom 40 %		
	All spells	5-yr-spells	Long spells	All spells	5-yr-spells	Long spells	All spells	5-yr-spells	Long spells
Panel A: All observations (pooled)									
Pooled (N=701,285,117)									
Mean	0.020	0.015	0.020	0.001	0.001	0.005	0.001	0.000	0.003
Std. Dev.	0.077	0.042	0.028	0.065	0.034	0.025	0.041	0.023	0.018
P10	-0.061	-0.028	-0.011	-0.071	-0.039	-0.018	-0.047	-0.027	-0.015
P90	0.110	0.063	0.052	0.071	0.045	0.034	0.046	0.031	0.025
Panel B: By regions									
Europe & Central Asia (N=145,42,20)									
Mean	0.030	0.013	0.028	-0.003	-0.007	0.001	-0.001	-0.006	0.000
Std. Dev.	0.108	0.078	0.043	0.067	0.034	0.026	0.045	0.025	0.019
Latin America & Carribean (N=215,62,19)									
Mean	0.017	0.011	0.016	0.008	0.006	-0.001	0.005	0.003	0.000
Std. Dev.	0.085	0.045	0.018	0.089	0.044	0.020	0.051	0.026	0.014
Middle East & North Africa (N=21,14,7)									
Mean	0.009	0.003	0.009	0.010	0.007	0.014	0.007	0.005	0.010
Std. Dev.	0.032	0.024	0.025	0.027	0.022	0.025	0.021	0.018	0.018
High Income (N=160,75,28)									
Mean	0.017	0.016	0.014	-0.008	-0.004	-0.004	-0.006	-0.004	-0.004
Std. Dev.	0.057	0.026	0.026	0.038	0.021	0.015	0.026	0.014	0.010
Sub-Saharan Africa (N=81,50,27)									
Mean	0.010	0.017	0.017	0.009	0.009	0.016	0.005	0.006	0.011
Std. Dev.	0.051	0.034	0.027	0.058	0.041	0.031	0.044	0.031	0.023
South Asia (N=25,17,6)									
Mean	0.022	0.020	0.026	0.001	-0.001	0.009	0.000	-0.002	0.008
Std. Dev.	0.036	0.014	0.014	0.025	0.016	0.022	0.022	0.015	0.023
East Asia & Pacific (N=54,25,10)									
Mean	0.036	0.029	0.035	-0.004	0.001	0.007	-0.003	0.001	0.004
Std. Dev.	0.044	0.027	0.020	0.031	0.025	0.030	0.024	0.018	0.019
Panel C: By Decade									
1980s (N=85,80)									
Mean	0.002	0.002		-0.005	-0.001		-0.004	-0.002	
Std. Dev.	0.077	0.045		0.059	0.026		0.040	0.019	
1990s (N=202,198)									
Mean	0.005	0.008		-0.005	-0.004		-0.004	-0.003	
Std. Dev.	0.079	0.044		0.063	0.035		0.040	0.024	
2000s (N=171,167)									
Mean	0.034	0.029		0.006	0.007		0.004	0.004	
Std. Dev.	0.074	0.036		0.068	0.034		0.042	0.023	

Notes: This table reports descriptive statistics for growth rates in survey means and quintile shares. The first set of three columns report the growth rate of average income in the three indicated samples of spells. The second and third sets of three columns report the growth rate of the income share of the bottom 20 and bottom 40 percent, for the same three samples. Panel A pools all observations. Panel B disaggregates by region. Panel C disaggregates by decade. Results in this panel are not shown for the set of long spells because there is only one spell per country in this sample. See main text for a description of how the spells in the other two samples are assigned to decades. All growth rates are calculated as average annual log differences over the length of the spell.

Table 2: Full Sample Regression Results

Dependent. var.: Growth in incomes of the poor	Bottom 20 Percent			Bottom 40 Percent		
	All spells	Five-yr-spells	Long spells	All spells	Five-yr-spells	Long spells
Average growth	1.001***	1.075***	0.953***	0.957***	1.021***	0.955***
	(0.0553)	(0.0626)	(0.119)	(0.0332)	(0.0467)	(0.0785)
Number of Observations	701	285	117	701	285	117
R-squared	0.583	0.650	0.535	0.766	0.783	0.685
Share of variance due to growth	0.582	0.605	0.561	0.800	0.767	0.718
P-value of wald test, slope=1	0.980	0.234	0.696	0.193	0.654	0.569

Notes: *** (**) (*) denotes significance at the 1 (5) (10) percent level. Heteroskedasticity-consistent standard errors clustered at the country level reported in parentheses. This table reports results from OLS regressions of growth in incomes of the poor on growth in average incomes. Growth rates are calculated as average annual log differences over the indicated definitions of spells. Columns (1)-(3) define the poor as those in bottom 20 percent of income distribution, while Columns (4)-(6) refer to bottom 40 percent of income distribution. In addition to the usual regression outputs, we report the share of the variation in income of the poor that is due to variation in overall incomes. We also report the p-value corresponding to a Wald test of the null hypothesis that the estimated slope is equal to one.

Table 3: Results by Region

Dependent. var.: Growth in income of the poor	Bottom 20 Percent			Bottom 40 Percent		
	All spells	Five-yr spells	Long-spells	All spells	Five-yr spells	Long-spells
Panel A: Europe & Central Asia (N=145,42,20)						
Average growth	0.906***	1.130***	0.942***	0.935***	1.077***	0.951***
	(0.0811)	(0.0692)	(0.127)	(0.0553)	(0.0510)	(0.0896)
R-squared	0.686	0.877	0.706	0.840	0.924	0.822
Share of variance due to growth	0.757	0.777	0.750	0.898	0.858	0.865
P-val. Wald test, slope=1	0.259	0.0768	0.652	0.254	0.147	0.591
Panel B: Latin America & Carribean (N=215,62,19)						
Average growth	1.222***	1.037***	0.936***	1.052***	0.947***	0.951***
	(0.0749)	(0.160)	(0.218)	(0.0467)	(0.112)	(0.170)
R-squared	0.584	0.527	0.415	0.756	0.729	0.623
Share of variance due to growth	0.478	0.508	0.443	0.719	0.770	0.655
P-val. Wald test, slope=1	0.00798	0.817	0.771	0.283	0.642	0.778
Panel C: Middle East & North Africa (N=21,14,7)						
Average growth	0.950***	1.112***	1.836***	0.931***	1.110***	1.584***
	(0.193)	(0.130)	(0.238)	(0.144)	(0.100)	(0.172)
R-squared	0.570	0.601	0.918	0.671	0.685	0.934
Share of variance due to growth	0.601	0.540	0.500	0.721	0.617	0.590
P-val. Wald test, slope=1	0.803	0.427	0.0126	0.651	0.325	0.0145
Panel D: High Income (N=160,75,28)						
Average growth	0.880***	1.030***	0.793***	0.878***	0.950***	0.802***
	(0.101)	(0.156)	(0.135)	(0.0694)	(0.106)	(0.0706)
R-squared	0.641	0.600	0.678	0.802	0.755	0.841
Share of variance due to growth	0.728	0.583	0.855	0.913	0.795	1.049
P-val. Wald test, slope=1	0.244	0.850	0.138	0.0898	0.644	0.00907
Panel E: Sub-Saharan Africa (N=81,50,27)						
Average growth	0.796***	1.103***	0.807**	0.827***	1.083***	0.869***
	(0.126)	(0.188)	(0.368)	(0.104)	(0.126)	(0.230)
R-squared	0.337	0.450	0.339	0.487	0.590	0.517
Share of variance due to growth	0.423	0.408	0.420	0.589	0.544	0.596
P-val. Wald test, slope=1	0.116	0.589	0.605	0.109	0.515	0.573
Panel F: South Asia (N=25,17,6)						
Average growth	0.704**	0.772***	2.028**	0.757***	0.844***	2.052**
	(0.184)	(0.137)	(0.723)	(0.119)	(0.153)	(0.742)
R-squared	0.558	0.329	0.744	0.653	0.391	0.740
Share of variance due to growth	0.794	0.426	0.367	0.863	0.463	0.361
P-val. Wald test, slope=1	0.167	0.170	0.214	0.0964	0.364	0.215
Panel G: East Asia & Pacific (N=54,25,10)						
Average growth	0.582***	0.719**	1.288	0.690***	0.769***	1.117**
	(0.0713)	(0.256)	(0.757)	(0.0666)	(0.165)	(0.465)
R-squared	0.508	0.387	0.449	0.694	0.594	0.588
Share of variance due to growth	0.873	0.538	0.349	1.005	0.773	0.527
P-val. Wald test, slope=1	0.000239	0.302	0.713	0.00119	0.194	0.806

Notes: *** (**) (*) denotes significance at the 1 (5) (10) percent level. Heteroskedasticity-consistent standard errors clustered at the country level reported in parentheses. This table reports results from OLS regressions of growth in incomes of the poor on growth in average incomes. Growth rates are calculated as average annual log differences over the indicated definitions of spells. Panel A defines the poor as those in bottom 20 percent of income distribution, while Panel B refers to bottom 40 percent of income distribution. In addition to the regular regression outputs, we document the variance decomposition which summarizes the part of the variation in income of the poor that is due to variation in overall incomes. We also report the p-value corresponding to a Wald test of the null hypothesis that the estimated slope is equal to one. The assignment of countries to geographical regions is documented in Appendix Table A1.

Table 4: Results by Decade

Dependent. var.: Growth in income of the poor	Bottom 20 Percent		Bottom 40 Percent	
	All spells	Five-yr spells	All spells	Five-yr spells
Panel A: 1980 (N=113,80)				
Average growth	0.771***	1.061***	0.814***	1.016***
	(0.0947)	(0.0991)	(0.0679)	(0.0753)
R-squared	0.524	0.782	0.740	0.859
Share of variance due to growth	0.679	0.737	0.909	0.846
P-val. Wald test, slope=1	0.0184	0.542	0.00788	0.835
Panel B: 1990 (N=319,198)				
Average growth	1.012***	1.062***	0.968***	1.013***
	(0.0700)	(0.0757)	(0.0425)	(0.0590)
R-squared	0.614	0.650	0.784	0.779
Share of variance due to growth	0.607	0.612	0.810	0.769
P-val. Wald test, slope=1	0.869	0.417	0.451	0.824
Panel C: 2000 (N=435,167)				
Average growth	1.010***	0.996***	0.953***	0.970***
	(0.0783)	(0.0776)	(0.0438)	(0.0505)
R-squared	0.550	0.517	0.743	0.699
Share of variance due to growth	0.545	0.519	0.779	0.720
P-val. Wald test, slope=1	0.904	0.959	0.290	0.557

Notes: *** (**) (*) denotes significance at the 1 (5) (10) percent level. Heteroskedasticity-consistent standard errors clustered at the country level reported in parentheses. This table reports results from weighted OLS regressions of growth in incomes of the poor on growth in average incomes, for the indicated decades, with weights corresponding to the fraction of observations in each spell falling in the indicated decade. Growth rates are calculated as average annual log differences over spells at least five years long. In addition to the regular regression outputs, we report the variance decomposition which summarizes the part of the variation in income of the poor that is due to variation in overall incomes. We also report the p-value corresponding to a Wald test of the null hypothesis that the estimated slope is equal to one.

Table 5: Robustness Across Alternative Measures of Average Growth

Dependent. var.: Growth in income of the poor	Bottom 20 Percent			Bottom 40 Percent		
	All spells	Five-yr-spells	Long spells	All spells	Five-yr-spells	Long spells
Panel A: Survey data - income or consumption (N=677,274,110)						
Average growth	0.988***	1.006***	0.863***	0.943***	0.965***	0.895***
	(0.0597)	(0.0695)	(0.121)	(0.0360)	(0.0501)	(0.0792)
R-squared	0.561	0.565	0.498	0.751	0.722	0.665
Share of variance due to growth	0.568	0.561	0.577	0.796	0.749	0.743
P-value of wald test, slope=1	0.844	0.930	0.262	0.118	0.481	0.187
Panel B: National Accounts data - Real private consumption per capita (N=677,274,110)						
Average growth	0.993***	1.051***	0.839***	0.987***	1.011***	0.886***
	(0.0786)	(0.0648)	(0.0831)	(0.0488)	(0.0463)	(0.0614)
R-squared	0.344	0.463	0.536	0.570	0.634	0.704
Share of variance due to growth	0.346	0.440	0.638	0.577	0.626	0.795
P-value of wald test, slope=1	0.928	0.433	0.0559	0.792	0.805	0.0671
Panel C: Mixed measure - arithmetic average from A&B (N=677,274,110)						
Average growth	0.985***	1.030***	0.813***	0.936***	0.977***	0.863***
	(0.0832)	(0.0768)	(0.105)	(0.0486)	(0.0551)	(0.0726)
R-squared	0.380	0.457	0.441	0.588	0.621	0.623
Share of variance due to growth	0.386	0.443	0.543	0.628	0.636	0.722
P-value of wald test, slope=1	0.856	0.696	0.0768	0.190	0.677	0.0611

Notes: *** (**) (*) denotes significance at the 1 (5) (10) percent level. Heteroskedasticity-consistent standard errors clustered at the country level reported in parentheses. This table reports results from OLS regressions of growth in incomes of the poor on growth in average incomes. Growth rates are calculated as average annual log differences over the indicated definitions of spells. Panel A uses household survey means, in the slightly smaller sample of spells where national accounts growth rates are also available. Panel B uses national accounts growth rates as a measure of average income growth and to construct average income growth of the poor. Panel C uses a simple average of survey mean and national accounts growth rates. In addition to the regular regression outputs, we report the variance decomposition which summarizes the part of the variation in income of the poor that is due to variation in overall incomes. We also report the p-value corresponding to a Wald test of the null hypothesis that the estimated slope is equal to one.

Table 6: Bayesian Model Averaging Results: Summary

	Dependent Variable is Growth in Income Share of Bottom 20 %				*Dependent Variable is Growth in Income Share of Bottom 40 %*			
			Percent of Models With Slope Significantly:				Percent of Models With Slope Significantly:	
	PIP	Weighted Slope	Positive	Negative	PIP	Weighted Slope	Positive	Negative
Initial equality level	1.000	-0.015	0%	100%	1.000	-0.015	0%	100%
Credit to priv. sector to GDP	0.001	0.000	0%	0%	0.001	0.000	0%	0%
Inflation rate	0.190	-0.001	0%	7%	0.133	0.000	0%	4%
Budget Balance	0.004	0.000	0%	0%	0.004	0.000	0%	0%
Trade Openness	0.001	0.000	0%	0%	0.001	0.000	0%	0%
Population growth	0.103	0.000	1%	6%	0.140	0.000	4%	18%
Life expectancy	0.044	0.000	0%	0%	0.046	0.000	0%	1%
Revolutions per pop.	0.034	0.000	0%	0%	0.035	0.000	0%	0%
Civil Liberties / Democracy	0.044	0.000	0%	0%	0.046	0.000	0%	0%
Internal/external conflict	0.055	0.000	0%	0%	0.049	0.000	0%	0%
Fin. openness (Chinn-Ito)	0.003	0.000	0%	0%	0.003	0.000	0%	0%
Primary school enrollment rate	0.582	-0.003	0%	36%	0.630	-0.003	0%	29%
Education Gini	0.000	0.000	0%	0%	0.000	0.000	0%	0%
Agriculture (% GDP)	0.358	0.000	0%	0%	0.265	0.000	0%	0%

Notes: This table summarizes the results of the Bayesian Model Averaging exercise described in Section 4 of the paper. The two panels report results for growth in the average income share of the bottom 20 percent and bottom 40 percent. Within each panel, the first column indicates the posterior inclusion probability for each variable, i.e. the sum of the posterior probabilities of all models including the that variable. The second column reports the posterior probability-weighted slope coefficients. These are scaled by the standard deviation of the corresponding variable, and so can be interpreted as the effect on the dependent variable of a one-standard-deviation increase in the explanatory variable. The third and fourth columns report the fraction of estimated slope coefficients significantly greater (less than) zero across all models.

Table 7: Bayesian Model Averaging Results: Details for Growth in Income Share of Bottom 40 Percent

Dependent Variable: Growth in Share of Bottom 40%	Top 10 models with highest PMP in Benchmark Specification										
	1	2	3	4	5	6	7	8	9	10	All regressors
Initial equality level	-0.014	-0.013	-0.016	-0.016	-0.014	-0.013	-0.014	-0.014	-0.015	-0.015	-0.017
	(8.499)	(7.938)	(8.817)	(8.489)	(8.227)	(8.026)	(8.464)	(8.24)	(8.348)	(8.537)	(6.306)
Credit to priv. sector to GDP											0.002
											(0.739)
Inflation rate						-0.002	-0.002	-0.003			-0.001
						(1.983)	(1.307)	(2.163)			(0.729)
Budget Balance											0.000
											(0.122)
Trade Openness											-0.001
											(0.735)
Population growth				-0.003							-0.004
				(2.054)							(1.755)
Life expectancy									0.002		0.000
									(1.077)		(0)
Revolutions per pop.											-0.001
											(0.656)
Civil Liberties / Democracy										-0.001	0.000
										(0.49)	(0.106)
Internal/external conflict											0.002
											(0.955)
Fin. openness (Chinn-Ito)											0.001
											(0.39)
Primary school enrollment rate	-0.004		-0.004	-0.005			-0.003		-0.004	-0.004	-0.003
	(2.957)		(3.094)	(3.52)			(2.744)		(3.089)	(3.009)	(1.741)
Education Gini											-0.001
											(0.571)
Agriculture (% GDP)			-0.001		0.000			0.001			0.000
			(0.843)		(0.321)			(0.659)			(0.04)
N	280	285	269	280	273	284	280	273	280	279	207
Rsq	0.209	0.182	0.231	0.221	0.204	0.196	0.214	0.218	0.212	0.212	0.198
PMP	0.287	0.150	0.116	0.077	0.058	0.049	0.022	0.020	0.017	0.014	0.000
Number RHS variables	2	1	3	3	2	2	3	3	3	3	14
Posterior Model Probabilities (Baseline: g=0.01). Combined posterior probability of top 10 models is: 0.81											
PMP	0.287	0.150	0.116	0.077	0.058	0.049	0.022	0.020	0.017	0.014	0.000
Rank by PMP	1	2	3	4	5	6	7	8	9	10	15,021
Posterior Model Probabilities (Greater Weight on Model Fit: g=0.004). Combined posterior probability of top 10 models is: 0.87											
PMP	0.316	0.251	0.083	0.054	0.063	0.053	0.016	0.014	0.012	0.010	0.000
Rank by PMP	1	2	3	5	4	6	7	8	10	13	15,488
Posterior Model Probabilities (Less Weight on Model Fit: g=0.05). Combined posterior probability of top 10 models is: 0.64											
PMP	0.177	0.051	0.138	0.094	0.039	0.033	0.029	0.026	0.022	0.019	0.000
Rank by PMP	1	4	2	3	5	7	8	9	10	12	12,593

Notes: This table reports coefficient estimates and standard errors for the 10 models with the highest posterior probability. Coefficient estimates are scaled by the standard deviation of the explanatory variable. T-statistics based on heteroskedasticity-consistent standard errors are reported in parentheses. The bottom panel reports the corresponding posterior model probabilities, for the benchmark specification and for two alternatives prior specifications assigning greater (less) weight on improvements in model fit relative to model size. The last column reports the coefficient estimates and model probabilities for the encompassing model that includes all of the explanatory variables.

Appendix:

Table A1: Data availability by country

Country	Region	Database	Total obs	First year available	Last year available	Sample all spells (diff.)	Sample min-5-year-spells (diff.)	Sample long-spells (diff.)
Albania	ECA	PCN	5	1997	2008	4	2	1
Argentina	LAC	PCN	22	1986	2010	14	4	1
Armenia	ECA	PCN	10	1996	2008	8	1	1
Australia	HIINC	LIS	6	1981	2003	5	3	1
Austria	HIINC	LIS	6	1987	2004	5	2	1
Azerbaijan	ECA	PCN	3	1995	2008	2	2	1
Burundi	SSA	PCN	3	1992	2006	2	2	1
Belgium	HIINC	LIS	6	1985	2000	5	2	1
Burkina Faso	SSA	PCN	4	1994	2009	3	2	1
Bangladesh	SA	PCN	8	1984	2010	7	4	1
Bulgaria	ECA	PCN	8	1989	2007	6	3	1
Bosnia and Herzegovina	ECA	PCN	3	2001	2007	2	1	1
Belarus	ECA	PCN	12	1988	2008	10	3	1
Belize	LAC	PCN	7	1993	1999	0	0	0
Bolivia	LAC	PCN	11	1991	2008	7	2	1
Brazil	LAC	PCN	26	1981	2009	20	5	1
Bhutan	SA	PCN	2	2003	2007	1	0	1
Botswana	SSA	PCN	2	1986	1994	1	1	1
Central African Republic	SSA	PCN	3	1992	2008	2	2	1
Canada	HIINC	LIS	11	1971	2007	10	5	1
Switzerland	HIINC	LIS	5	1982	2004	4	2	1
Chile	LAC	PCN	10	1987	2009	9	4	1
China	EAP	PCN	9	1981	2005	7	3	1
Cote d'Ivoire	SSA	PCN	9	1985	2008	8	3	1
Cameroon	SSA	PCN	3	1996	2007	2	2	1
Colombia	LAC	PCN	12	1992	2010	9	3	1
Costa Rica	LAC	PCN	23	1981	2009	21	4	1
Czech Republic	HIINC	PCN	3	1988	1996	2	1	1
Germany	HIINC	LIS	5	1994	2010	4	2	1
Denmark	HIINC	LIS	5	1987	2004	4	2	1
Dominican Republic	LAC	PCN	16	1986	2010	15	4	1
Algeria	MENA	PCN	2	1988	1995	1	1	1
Ecuador	LAC	PCN	13	1987	2010	8	4	1
Egypt, Arab Rep.	MENA	PCN	5	1991	2008	4	2	1
Spain	HIINC	LIS	7	1980	2010	6	4	1
Estonia	HIINC	PCN	9	1988	2004	7	1	1
Ethiopia	SSA	PCN	4	1982	2005	3	3	1
Finland	HIINC	LIS	5	1987	2004	4	2	1
Fiji	EAP	PCN	2	2003	2009	1	1	1
France	HIINC	LIS	7	1979	2005	5	5	1
United Kingdom	HIINC	LIS	7	1991	2010	6	3	1
Georgia	ECA	PCN	12	1996	2008	9	2	1
Ghana	SSA	PCN	5	1988	2006	4	2	1
Guinea	SSA	PCN	4	1991	2007	2	1	1
Gambia, The	SSA	PCN	2	1998	2003	1	0	0
Guinea-Bissau	SSA	PCN	3	1991	2002	1	1	1
Greece	HIINC	LIS	5	1995	2010	4	2	1
Guatemala	LAC	PCN	8	1987	2006	6	1	1
Guyana	LAC	PCN	2	1993	1998	1	1	0
Honduras	LAC	PCN	20	1989	2009	12	4	1
Croatia	HIINC	PCN	7	1988	2008	5	1	1
Hungary	HIINC	PCN	10	1987	2007	7	2	1
Indonesia	EAP	PCN	8	1984	2005	7	3	1
India	SA	PCN	5	1978	2005	4	4	1
Ireland	HIINC	LIS	6	1987	2004	5	2	1
Iran, Islamic Rep.	MENA	PCN	5	1986	2005	4	2	1
Israel	HIINC	LIS	6	1986	2007	5	3	1
Italy	HIINC	LIS	11	1986	2010	10	4	1
Jamaica	LAC	PCN	7	1988	2004	6	3	1
Jordan	MENA	PCN	7	1987	2010	6	4	1
Kazakhstan	ECA	PCN	11	1988	2009	8	3	1

Country	Region	Database	Total obs	First year available	Last year available	Sample all spells (diff.)	Sample min-5-year-spells (diff.)	Sample long-spells (diff.)
Kenya	SSA	PCN	4	1992	2005	2	1	1
Kyrgyz Republic	ECA	PCN	10	1988	2009	6	2	1
Cambodia	EAP	PCN	4	1994	2008	2	1	1
Lao PDR	EAP	PCN	4	1992	2008	3	3	1
Sri Lanka	SA	PCN	5	1985	2007	4	4	1
Lesotho	SSA	PCN	4	1987	2003	2	2	1
Lithuania	ECA	PCN	9	1988	2008	7	3	1
Luxembourg	HIINC	LIS	6	1985	2004	5	3	1
Latvia	ECA	PCN	11	1988	2008	9	2	1
Moldova	ECA	PCN	15	1988	2010	12	1	1
Madagascar	SSA	PCN	7	1980	2010	5	2	1
Maldives	SA	PCN	2	1998	2004	0	0	0
Mexico	LAC	PCN	13	1984	2010	10	3	1
Macedonia, FYR	ECA	PCN	9	1998	2009	8	2	1
Mali	SSA	PCN	4	1994	2010	3	2	1
Montenegro	ECA	PCN	4	2005	2008	3	0	1
Mozambique	SSA	PCN	3	1996	2008	2	2	1
Mauritania	SSA	PCN	6	1987	2008	4	3	1
Malawi	SSA	PCN	2	1998	2004	1	1	1
Malaysia	EAP	PCN	9	1984	2009	8	3	1
Namibia	SSA	PCN	2	1993	2004	1	1	1
Niger	SSA	PCN	4	1992	2008	3	1	1
Nigeria	SSA	PCN	5	1986	2010	4	3	1
Nicaragua	LAC	PCN	4	1993	2005	3	2	1
Netherlands	HIINC	LIS	6	1983	2004	5	3	1
Norway	HIINC	LIS	6	1979	2004	5	2	1
Nepal	SA	PCN	4	1985	2010	2	2	1
Pakistan	SA	PCN	8	1987	2008	7	3	1
Panama	LAC	PCN	14	1979	2010	10	2	1
Peru	LAC	PCN	16	1986	2010	12	3	1
Philippines	EAP	PCN	9	1985	2009	8	4	1
Poland	HIINC	PCN	17	1985	2009	14	4	1
Paraguay	LAC	PCN	14	1990	2010	13	2	1
Romania	ECA	PCN	14	1989	2009	11	2	1
Russian Federation	ECA	PCN	13	1988	2009	11	3	1
Rwanda	SSA	PCN	4	1985	2011	3	3	1
Senegal	SSA	PCN	4	1991	2005	3	1	1
El Salvador	LAC	PCN	15	1989	2009	13	3	1
Serbia	ECA	PCN	8	2002	2009	6	1	1
Slovak Republic	HIINC	PCN	9	1988	2009	7	2	1
Slovenia	HIINC	PCN	6	1987	2004	4	2	1
Sweden	HIINC	LIS	8	1967	2005	7	5	1
Swaziland	SSA	PCN	3	1995	2010	2	2	1
Seychelles	SSA	PCN	2	2000	2007	1	0	0
Thailand	EAP	PCN	13	1981	2009	12	4	1
Tajikistan	ECA	PCN	5	1999	2009	3	2	1
Turkmenistan	ECA	PCN	3	1988	1998	1	1	0
Timor-Leste	EAP	PCN	2	2001	2007	1	1	1
Trinidad and Tobago	HIINC	PCN	2	1988	1992	1	0	1
Tunisia	MENA	PCN	5	1985	2005	4	4	1
Turkey	ECA	PCN	9	1987	2008	8	3	1
Tanzania	SSA	PCN	3	1992	2007	2	2	1
Uganda	SSA	PCN	7	1989	2009	6	3	1
Ukraine	ECA	PCN	13	1988	2009	11	3	1
Uruguay	LAC	PCN	18	1981	2010	17	5	1
United States	HIINC	LIS	10	1974	2010	9	6	1
Venezuela, RB	LAC	PCN	13	1981	2006	9	3	1
Vietnam	EAP	PCN	6	1993	2008	5	2	1
West Bank and Gaza	MENA	PCN	2	2007	2009	1	0	1
Yemen, Rep.	MENA	PCN	2	1998	2005	1	1	1
South Africa	SSA	PCN	5	1993	2009	4	1	1
Zambia	SSA	PCN	6	1993	2006	4	1	1

Notes: Region codes refer to World Bank categories with the exception that all High income countries were pooled by pulling observations from the geographical regions: HIINC= High Income countries, ECA= Europe and Central Asia, MENA= Middle East & North Africa, LAC = Latin America and the Caribbeans, SSA=Sub-Saharan Africa, SA= South Asia and EAP=East Asia and Pacific. Database indicates whether the data come from POVCALNET (PCN) or LIS. Total observations, first year, and last year refer to the number and timing of household surveys in our combined dataset. The last three columns indicate the number of spells included in each of the three definitions of spells. Note that these spells refer to the sample used in the regression, following the removal of extreme observations as noted in the text. This is why there are some blank entries in the last three columns.

Table A2: Variable Description		
Variable	**Source**	**Description / Adjustments**
Survey means	POVCALNET, LIS	POVCALNET measures welfare by income or consumption as determined in the surveys. For LIS, we calculate survey means of total household income directly from the household level survey data.
Private consumption	Penn World Table 8	Household private consumption at constant national 2005 prices.
Covariates used in Bayesian Model Averaging:		
Population growth	WDI	Population growth in percentage points.
Life expectancy	WDI	Life expectancy in years.
Private Credit to GDP	Global Financial Development Indicators	Private Credit by Deposit Money Banks and Other Financial Institutions to GDP: the indicator isolates credit issued to the private sector by intermediaries other than the central bank.
Inflation rate	WDI	The inflation measure is calculated by taking log-differences from the WDI reported GDP deflator (in local currency units).
Budget balance	WEO and data from Easterly, Levine, Roodman (2004)	Data series on Budget Balance from Easterly, Levine, Roodman (2004) was used when available, after the last available year, we used WEO data.
Assassination; Revolution	Cross-National Time Series	Assassinations and revolutions as percentage per 100,000 habitants. Source: Banks, Arthur S., Wilson, Kenneth A. 2013. Cross-National Time-Series Data Archive. Databanks International. Jerusalem, Israel. http://www.databanksinternational.com
Trade Openness	Wacziarg-Welch (2008); extended through 2010.	Wacziarg-Welch (2008) extended the initial Sachs-Warner (1995) openness measure through 2001. We update the series to 2010 using underlying data on tariffs, black market premium and export marketing boards. A country is considered as closed if it has one of the following: Average tariff rates over 40 percent, black market exchange rate over 20 percent lower than the official exchange rate, or a state monopoly on major exports (export marketing board). We used the following data sources: 1. Tariffs: Source: Francis K.T. Ng "Trends in average applied tariff rates in developing and industrial countries, 1980-2006"; http://go.worldbnka.org/LGOXFTV550. Note that no tariffs higher than the 40 percent threshold were in place after 2000. 2. Black market premium: Sources: Economic Freedom in the World 2012 report; database from the Fraser Institute; http://www.freetheworld.com. Data shows a 0-10 ranking where 10 implies no black market premium and 0 implies a premium of 50 percent or more. The black market premium is defined as the percentage difference between the official and black market exchange rate. We assume that a score of 0-6 implies a premium of 20 percent or greater. 3. Export marketing board: In 2001 Wacziarg-Welch identified 12 countries as having an export marketing board based on various criteria. Clemens et al. update the classification through 2005, identifying three further countries as having liberalized, i.e. as having abolished their export marketing boards (Senegal (2002), Chad and Papua New Guinea (2005)). We don't make any other updates, thus considering the remaining 9 countries (Central African Rep, Congo Dem. Rep, Congo Rep., Gabon, Russia, Togo, Ukraine) as closed through 2010. Neither of these countries has tariffs over 40 percent or black market premiums over 20 percent, so they would be considered open when liberalizing their export marketing board.
Internal conflict; war participation	UCDP-PRIO Dataset	Data from UCDP dataset allows constructing one dummy for internal conflict and one for war participation. In the latter, we consider a country to be participating in a war only if it is listed either as the country of location, or a major participant (side A or B), omitting countries that are listed as allies.
Civil liberties, political rights	Freedom House	Sum of the civil liberties and the political rights indicator, both measured on a 1-7 scale. http://www.freedomhouse.org/report/freedom-world-2012/methodology

Financial Openness	Chinn-Ito Index	The Chinn-Ito index (*KAOPEN*) is an index measuring a country's degree of capital account openness. The variable is based on the binary dummy variables that codify the tabulation of restrictions on cross-border financial transactions reported in the IMF's *Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER).* http://web.pdx.edu/~ito/Chinn-Ito_website.htm
Primary schooling	WDI	Gross primary school enrolment rates (percent of population).
Gini coefficient on educational attainment	Barro-Lee dataset	The Barro-Lee dataset provides data on the percentage of the population that attained a given level of education: No education (0 years), complete primary (6 years), complete secondary (12 years), and complete tertiary (16 years). For non-complete primary, secondary, or tertiary we assume respectively 3 years, 9 years, and 14 years of schooling. With this information, we can construct a Lorenz curve measuring which percentage of population attained which percentage of total years of schooling. With this in hand, we construct a Gini coefficient that measures educational inequality analogous to the standard income inequality measure.
Agricultural productivity	WDI	WDI Indicator: NV.AGR.TOTL.ZS, "Agriculture, value added (% of GDP)". Constructing the log-difference provides a measure of change in agricultural productivity.