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# Growth, Inequality, and Social Welfare: Cross-Country Evidence

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# Growth, Inequality, and Social Welfare: Cross-Country Evidence

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## 1. INTRODUCTION

Concerns about inequality are at the forefront of many policy debates today. From speeches by US President Barack Obama to the bestselling book "Capital in the 21st century" by Thomas Piketty, it is hard to escape the view that rising inequality poses major challenges in advanced economies. In the developing world too, much has been written about the adverse effects of high and rising inequality on the pace of poverty reduction. Concerns about inequality appear to be pervasive beyond policy elites as well, for example as manifested by the "we are the 99 percent" slogans of the Occupy Wall Street movement. Public opinion surveys suggest that strong majorities of respondents in advanced economies feel that the gap between rich and poor has been rising in recent years (Pew Research Center, (2013)).

These views no doubt in part reflect the fact that inequality has indeed been increasing in many countries. In the US over the past four decades, the Gini coefficient of income inequality has risen from around 0.3 to around 0.4. Roughly the same has happened in China, only more rapidly: between 1990 and 2009 the Gini coefficient has increased from 0.32 to 0.42. Much of this increase has happened at the upper end of the income distribution. According to Atkinson, Piketty and Saez (2011), the income share

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of the top 10 percent in the US has increased from around 33 percent in 1970 to nearly 50 percent in 2007, while in China it increased from 17 to 28 percent between 1986 and 2003.

However, it is also important not to lose sight of the fact that inequality has not increased in other countries, and has declined appreciably in still others. In the Atkinson, Piketty and Saez (2011) data, income shares of the top decile have been stable or even declining slightly since the mid-20th century in countries such as Germany, France, Switzerland, the Netherlands, and Japan. In Brazil, the Gini coefficient has declined from around 0.6 in the late 1990s to around 0.55 in the late 2000s. More systematically, in a large dataset of changes in inequality over periods at least five years long that we describe in more detail below, in almost half of episodes the Gini coefficient of inequality increases, while in the other half of episodes it decreases.

In this paper, we aim to shed light on a very simple question: how much do these changes in inequality, in either direction, matter? To answer this question we first need to be precise about what we mean by “matter”. Our approach here is unabashedly modest: we use standard tools of social welfare analysis to calculate how much more or less growth in average incomes a country would need over a given period in order to compensate for the observed change in inequality over the same period. We then document the size of this compensation, and its relationship to average income growth, in a large dataset of episodes of growth and changes in inequality covering 117 countries between 1970 and 2012.

A simple example helps to illustrate our approach. The World Bank has recently made a major public commitment to the goal of promoting “shared prosperity”, defined as growth in average incomes of those in the bottom 40 percent of the income distribution in each country in the developing world (World Bank (2013)). As a matter of simple arithmetic, growth in average incomes in the bottom 40 percent is the sum of growth in average incomes, and growth in the share of income accruing to the bottom 40 percent. In China, for example, between 1990 and 2009 average incomes grew at 6.7 percent per year. At the same time, inequality increased in the sense that the income share of the bottom 40 percent declined from 20.2 percent to 14.4 percent, corresponding to an average annual rate of -1.7 percent per year. Combining these two observations, average incomes in the bottom 40 percent grew more slowly than overall average income, at 5 percent per year. From the standpoint of promoting shared prosperity, therefore, the growth “cost” of the increase in inequality in China over this period is about 1.7 percentage points of growth per year. Or put differently, had inequality not increased in China during this time, a growth rate of 5 percent per year (instead of the 6.7 percent that actually happened) would have generated the same improvement in “shared prosperity”.

This example illustrates the two key ingredients in our approach. First, in order to understand how much inequality changes “matter”, we need to specify a social welfare function that assigns weights to individuals in a country based on their incomes. In the case of the World Bank’s “shared prosperity” target, the implicit social welfare function weights everyone in the bottom 40 percent of the income distribution in proportion to their incomes, and assigns zero weight to everyone in the upper 60 percent of the income distribution. In our empirical work, we will consider a variety of standard social welfare functions reflecting different preferences over how income is distributed across individuals in a country. Second, growth in social welfare between two points in time consists of growth in average incomes and growth in the relevant inequality measure implied by the particular social welfare function under consideration. In the case of the World Bank's "shared prosperity" target, the relevant inequality measure is the income share of the bottom 40 percent. For all of the social welfare functions we consider, this decomposition is additive, allowing for a straightforward quantification of the relative importance of growth and inequality changes, and the costs or benefits in terms of growth of the latter. In particular, the increase (decrease) in the relevant inequality measure in percentage points per year can be interpreted as the amount by which average income growth would have to be higher (lower) to deliver the observed growth rate of social welfare absent any changes in income distribution.

We work with a large dataset of income distributions covering 117 countries over the past four decades. This dataset combines the high-quality household survey data for developing countries underlying the World Bank's global poverty estimates (Chen and Ravallion (2010)), with the Luxembourg Income Study (LIS) data for advanced economies. We focus on within-country changes in average incomes and income inequality observed over episodes at least five years long. In a sample of 285 such non-overlapping episodes, we calculate the contribution of growth in average incomes, and the contribution of changes in inequality, to growth in social welfare, for a wide variety of social welfare functions.

Our main findings are easily summarized. For all of the social welfare functions we consider, social welfare on average increases equiproportionately with increases in average incomes. This reflects the fact that changes in the relevant inequality measures are not systematically correlated with changes in average incomes. For all but the most bottom-sensitive social welfare functions, the relationship between growth in social welfare and growth in average incomes is also quite precisely estimated. This reflects the fact that changes in inequality are small, in the sense that variation across episodes in inequality accounts for only a small fraction of the variation across episodes in changes in social welfare. And this in turn implies that the additional growth in average incomes required to "compensate" – in terms of social welfare growth – for a typical increase in inequality is quite small.

Although changes in social welfare driven by changes in the relevant inequality measures are on average small and uncorrelated with growth in average incomes, it is nevertheless useful to understand their correlates. In particular, if there were some combination of policies and institutions that supported a given growth rate of overall per capita incomes, but in addition led to declines in the relevant inequality measure, then from the standpoint of promoting social welfare, such policies would dominate others that delivered the same average growth rate but did not lead to declines in inequality. In the last part of the paper, we consider a range of variables that has been identified as important for growth and inequality in the large empirical cross-country literature. In the spirit of comprehensive data description, we use Bayesian Model Averaging to systematically document the partial correlations between these variables and growth in average incomes and in inequality, and through these channels, the correlations with social welfare. We find little compelling empirical evidence that any of these variables are robustly correlated with the relevant changes in inequality that matter for the set of social welfare functions that we consider. While we are unable to offer a well-identified causal interpretation of these regressions, the lack of any systematic partial correlation between these variables and inequality changes is, we think, an important stylized fact.

The main policy message of our work is the importance of overall economic growth for improvements social welfare. Inequality may be a “hot” current topic, but inequality changes in most countries over the past thirty years have been small, while differences average growth performance have been large. Our work also suggests that it is difficult to find robust correlations between policy and institutional variables and changes in inequality, indicating that there is no simple recipe for enhancing equality. Furthermore, the fact that changes in equality are uncorrelated with economic growth means that there are likely to be some equality-enhancing policies that also promote growth, while others reduce growth. With growing pressure to “do something” about inequality, it is important that policymakers are careful to avoid undermining growth in the quest for greater equality, as such policy measures are likely to be self-defeating in the sense of not improving social welfare.

This paper builds on our previous work in Dollar and Kraay (2002) and Dollar, Kleineberg and Kraay (2013). In those papers we studied the relationship between growth in average incomes and growth in average incomes in the bottom 20 percent and bottom 40 percent of the income distribution. Our findings in this paper are broadly consistent with this earlier work – in these papers we also found that changes in the income share of the poorest quintiles typically are small and uncorrelated with changes in average incomes. The present paper expands on this earlier work by considering a much broader class of social welfare functions, which allows us to connect our previous findings specific to the income shares of the poorest quintiles with more general inequality measures. Our emphasis in this paper on decomposing changes in social welfare into a growth component and a distribution component is related to the large literature that has followed Datt and Ravallion (1992) in decomposing changes in poverty measures into growth and distribution components (see Kraay (2006) for an application to absolute poverty measures in a large cross-country dataset).

In Section 2 we describe the social welfare functions we study, and discuss the decomposition of social welfare growth into growth in average income and changes in inequality. Section 3 briefly describes the data, and Section 4 contains our main results on the relative importance of growth and inequality changes for growth in social welfare. Section 5 uses Bayesian Model Averaging to systematically relate changes in social welfare to a variety of policy variables that have been considered in the cross-country empirical literature. Section 6 elaborates on the policy implications and concludes.

## 2. Growth, Changes in Inequality, and Social Welfare

We study the relationship between growth in average incomes and growth in social welfare. Economists have long used social welfare functions as a tool for representing preferences over how income is distributed across individuals. We consider a variety of such social welfare functions, that assign weights to individuals based on their incomes. Overall social welfare is then defined as the average of these weights across individuals.[1] As noted in the introduction, average income in the bottom 40 percent of a country is a simple example of a social welfare function. This particular social welfare function weights individuals in the bottom 40 percent of the income distribution in proportion to their incomes, and assigns zero weight to everyone above the $40^{th}$ percentile. Overall social welfare, i.e., average incomes in the bottom 40 percent, is then the average of these weights, i.e., their incomes, across individuals.

Social welfare functions are intimately related to measures of inequality (see for example Blackorby and Donaldson (1978) and Dagum (1990)). All of the social welfare functions that we consider in this paper can be multiplicatively decomposed into a term reflecting average income, and a term reflecting how equally incomes are distributed. Holding constant equality, social welfare is higher when average incomes are higher. And conversely, holding constant average incomes, social welfare is higher when equality is higher. Returning to our simple example, average income in the bottom 40 percent is the product of average income and the income share of the bottom 40 percent. For a given level of average income, social welfare is higher the higher is the income share of the bottom 40 percent, i.e. when this particular measure of equality is higher, as well as when average incomes are higher.

A little notation is helpful in order to summarize this decomposition. Let $\mu$ denote average income, and $I$ denote an inequality measure that is bounded between zero and one, as will be the case for the inequality measures associated with the social welfare functions that we consider. Social welfare can be expressed as $W = \mu(1-I)$, i.e. social welfare is higher if average incomes are higher, i.e. if $\mu$ is higher, and if inequality is lower, i.e. if equality $(1-I)$ is higher. The simple multiplicative form of these social welfare functions implies that *growth* in social welfare is simply the sum of growth in average incomes and growth in equality, i.e.

$$\text{(1)} \qquad \frac{dW}{W} = \frac{d\mu}{\mu} + \frac{d(1-I)}{(1-I)}$$

This additive decomposition of welfare changes into growth in average incomes and changes in equality allows a natural interpretation of changes in equality in terms of growth. In particular, the second term in Equation (1) is just the difference between growth in social welfare and growth in average incomes, and can be interpreted as the

[1] While we consider only social welfare functions defined over current income, one could, more generally, consider social welfare functions that reflect the lifetime utility of individuals, which in turn depends on present and future consumption, labour supply, and longevity, among many other things. See for example Jones and Klenow (2011), Basu et al (2013) for cross-country applications in a representative agent setting, and Perri and Krueger (2003) for an individual-level application in the US.

"growth cost" of the observed increase in inequality, i.e. the amount by which growth would have to be higher in order to compensate for the increase in inequality, in the sense of delivering the same welfare growth. In the remainder of this paper we implement and analyze this decomposition in a large cross-country dataset of income distributions over the past forty years.

Before turning to the data, we first discuss the specific social welfare functions we use, which are listed in Table 1. The first column identifies the social welfare function by the inequality measure to which it is related. The second column reports the social welfare function itself, while the third column reports the welfare weights that the social welfare function assigns to individuals based on their incomes. Readers uninterested in the mathematical formalities of these functions can skip Table 1 and move directly to Figure 1, which plots the key feature of each social welfare function listed in Table 1: the welfare weights assigned to individuals (on the vertical axis) against individuals' percentile ranks in the income distribution (on the horizontal axis).

The top panel of Figure 1 plots the welfare weights implied by social welfare functions that focus on average incomes of the bottom X percent of the population (for X=20, 40, and 90 percent). Such social welfare functions reflect a particular concern for the less well-off in a society, since they assign zero weight to those above the Xth percentile. However, within the bottom X percent, welfare weights are proportional to incomes, and so assign greater weight to the richer individuals and lower weight to poorer individuals. For comparison purposes, Figure 1 also reports the welfare weights implied by average income, as a very common benchmark social welfare function. Overall average income implies a pattern of welfare weights on individuals that are increasing, and are non-zero throughout the entire income distribution. Clearly, overall average income places a greater weight on the rich than any of the other social welfare functions reported in this graph, which place zero weight on the richest 100-X percent of the income distribution.

The second panel of Figure 1 reports the welfare weights associated with the Atkinson social welfare function. The Atkinson social welfare function is in effect an average of incomes raised to the exponent $1-\theta$. When $\theta=0$, this simplifies to overall average income, which is again shown for reference. As $\theta$ increases above zero, social preferences become more egalitarian. For example, when $0<\theta<1$, the welfare weights are upward sloping, but less steeply than for overall average income, implying relatively more weight on the poor and less weight on the rich than in the case of average incomes. When $\theta>1$, the welfare weights are downward sloping, implying a greater weight on the poor than on the rich. Finally, the case of $\theta=1$ is an interesting benchmark social welfare function in which all individuals are weighted equally.

The third panel of Figure 1 reports the welfare weights associated with the three remaining social welfare functions reported in Table 1, and again shows the welfare weights associated with mean income as a reference point. The social welfare function based on the Gini coefficient is the Sen (1976) measure of "real national income", defined as average income scaled by one minus the Gini coefficient. Sen (1976) shows that this corresponds to a weighted average of incomes, with weights proportional to individuals' ranks in the income distribution. Since these welfare weights are decreasing with individuals' ranks in the income distribution but increasing in income, this generates an inverted U-shaped patter of weights, with the most weight in the middle of the distribution.

The last two social welfare functions shown in Figure 1 are based on more exotic inequality measures. The first is based on the Donaldson and Weymark (1980) generalization of the Gini coefficient, and is drawn for the parameter value $\theta = 0.5$. It implies a U-shaped pattern of weights, with least weight on the middle of the distribution and most on both extremes. However, it places less weight on the rich than average income does, and of course considerably more weight on the poor. As $\theta$ approaches 1, the welfare weights on the poor decrease, and the function simplifies to mean income when $\theta = 1$. The second is based on the Bonferroni (1930) inequality index, which, like the Atkinson measure with $\theta > 1$, assigns lower weights to richer individuals.[2]

Figure 1 is useful because it provides a graphical summary of how different social welfare functions treat individuals at different points in the income distribution. To get a more concrete sense of the strength of preferences for equity implied by each social welfare function, we perform the following simple calculation. We consider two distributions of income, one with high inequality and one with low inequality. Then for each social welfare function, we ask how much lower average incomes in the second distribution would have to be in order for the social welfare function to value the two distributions equally. To discipline the exercise, we assume that high inequality corresponds to the average pre-tax-and-transfer Gini coefficient across all of the OECD observations in our dataset (described in more detail in the next section), while low inequality corresponds to the average post-tax-and-transfer Gini coefficient in the same group of countries. This corresponds to Gini coefficients of 0.43 and 0.29, respectively. To transform this assumption into an entire distribution over which we can evaluate social welfare, we assume that income is lognormally distributed, so that the Gini coefficient fully specifies the dispersion in log per capita incomes.

The corresponding percent reductions in income are reported in the last column of Table 1 for each social welfare function. The most striking feature of these numbers is that they are quite large: the standard social welfare functions that we consider imply that societies would be willing to forgo between 10 and 40 percent of average income in order to achieve a redistribution similar to what a typical OECD economy does through its tax and transfer system. There is also quite a bit of heterogeneity across different social welfare functions, indicating that the social welfare functions we consider span a substantial range of preferences for redistribution. Not surprisingly, more bottom-sensitive social welfare functions value redistribution much more strongly than less

[2] One prominent class of inequality measures not included here is the Generalized Entropy class, which includes the mean log deviation and the Theil index of inequality as its most common members. Since these measures are not bounded between zero and one, they do not fit easily into the framework of $W = \mu(1 - I)$. Instead, for these measures Chakravorty (2009) proposes social welfare functions of the form $W = \mu e^{-I}$ which also imply an additive decomposition between growth and changes in inequality. To conserve space, we do not report results for these two measures here. However, we do note that with this formulation (a) the social welfare function based on the mean log deviation implies equal weights across individuals exactly as does the Atkinson(1) measure, and (b) the social welfare function based on the Theil index in practice implies a downward-sloping pattern of weights very similar to the Atkinson(0.5) measure.

bottom-sensitive ones. For example, if our social welfare function is average incomes in the bottom 20 percent, redistribution that leads to a Gini reduction of 14 points is "worth" 41 percent of average income, while it is "worth" only 10 percent of average income when the social welfare function is average incomes in the bottom 90 percent. Despite the fact that the social welfare functions we consider imply strong preferences for redistribution, we will see that the actual changes in inequality observed over the past 30 years worldwide contribute relatively little to changes in social welfare – even when measured with more bottom-sensitive social welfare functions.

## 3. Data

Our starting point is a large dataset of 963 irregularly-spaced country-year observations for which household surveys are available, covering a total of 151 countries between 1967 and 2011. 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 summary statistics on average incomes and income distribution are based directly on household survey data. Roughly half of the surveys in the POVCALNET database report income and its distribution, while the other half report consumption expenditure and its distribution. When we construct within-country changes in the distribution of income or consumption, we focus only on episodes where the initial and final surveys are of the same type, i.e. both refer to income or both refer to expenditure. For terminological convenience, however, we refer only to income throughout the paper.[3] All survey means are expressed in constant 2005 US dollars adjusted for differences in purchasing power parity. For each survey, in addition to the survey mean, POVCALNET reports data on 10 points on the Lorenz curve, from which we calculate the income share of each decile, as well as average incomes within each decile. Absent more detailed information on the distribution of income within deciles, we calculate the social welfare functions in Table 1 based on decile average incomes, i.e. assuming that incomes are equally distributed within each decile.

For countries that are not covered in POVCALNET, we rely on the LIS database[4]. This expands our sample by adding 19 OECD economies. For these countries we construct mean income and decile shares 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 household total income, which is expressed in the raw data in current local currency units. We convert the survey means

[3] As a robustness check, we replicate our benchmark analysis in the first panel of Table 3 separately for income- and expenditure-based household surveys and find similar results in the two subsamples. To conserve on space we report results only for the full sample combining both types of surveys.

[4] 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.

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. Also for consistency with the POVCALNET data, we use LIS data on household size and equivalence scales to convert to average income and its distribution across individuals rather than households. Figure 2 gives an overview of the annual data availability from these two sources. LIS survey data starts earlier, going back to 1967, while POVCALNET observations start in the 1980s. Both databases have better country coverage in more recent years.

For our empirical analysis, we organize the data into consecutive non-overlapping episodes or "spells", defined as within-country changes in variables of interest between two survey years at least five years apart. Specifically, we calculate the average annual log differences of social welfare and its components, mean income and the relevant equality measure, for each spell, recognizing that different spells cover periods of different length, depending on the availability of household survey data.

While the data we rely on comes from the most reliable cross-country datasets on income distribution currently available, there nevertheless are some spells where the changes in average income and/or changes in decile shares over the spell are extreme. To prevent these from unduly influencing our results, we clean the data by truncating the sample at the first and 99th percentiles of the distribution of average growth and of average growth in each of the 10 decile shares. This leaves us with a final sample consisting of 117 countries, with a median length between the first and last available surveys of 16 years. For these countries we are able to construct 285 spells with a median spell length of 6 years. Appendix Table A1 summarizes the country coverage and data availability.

## 4. Results

### 4.1. Basic Description

We begin with some very simple descriptive analysis of the relative importance of growth and changes in inequality for growth in social welfare. The four panels of Figure 3 plot growth in social welfare (on the vertical axis) against growth in average incomes (on the horizontal axis) for our 285 spells, and for the following selected social welfare functions: average incomes in the bottom 20 and 40 percent of the income distribution, the Atkinson social welfare function with $\theta = 2$, and the Sen index. Since growth in social welfare is the sum of growth in average incomes and the growth rate of the relevant equality measure, the vertical distance between each point and the 45 degree line reflects the contribution of inequality changes to growth in social welfare. The striking feature of these graphs is that the vast majority of data points cluster quite closely around the 45-degree line. This is true for all the social welfare functions shown in Figure 3, and is particularly clear in the case of the Sen social welfare function. This is also the case for the remaining social welfare functions (bottom 90 percent, Atkinson (θ =0.5 and θ =1, Donaldson-Weymark (θ =0.5) and Bonferroni) which are omitted to save on space. This indicates that changes in social welfare due to inequality changes (in either direction) generally are small, particularly in comparison with the large variation in growth rates in average incomes apparent on the horizontal axis of each graph. Only in the case of very bottom-sensitive social welfare functions that place a high weight on the poorest deciles (such as average incomes in the bottom 20 percent, or the Atkinson measure with $\theta = 2$), do we begin to see more dispersion around the 45-degree line.

Figure 4 provides a complementary perspective on the relative size of changes in growth and changes in inequality. We first plot the distribution of average income growth rates across all spells. This distribution has a mean of 1.5 percent per year, and very substantial variation: its standard deviation is 4.2 percent, and the 10th and 90th percentiles are -2.8 percent and 6.3 percent respectively. In short, growth in mean income is positive on average, and exhibits very large variation across spells.

We then superimpose the distribution of growth rates of inequality changes in the same sample, for each of the nine social welfare functions we consider. The contrast between the distribution of growth rates and the distribution of inequality changes is stark. Consider for example the Sen social welfare function, where the relevant inequality measure is (one minus) the Gini index. The mean annual average growth rate of this inequality measure across all spells is essentially zero. There is also substantially less variation across spells in changes in inequality than there is in growth: the standard deviation of changes in inequality for the Sen social welfare function is 1.2 percent, and the 10th and 90th percentiles of the distribution of inequality changes are -1.5 percent and 1.6 percent respectively.

A useful thought experiment here is to ask the following question: from the perspective of rapid expected growth in social welfare, would we prefer to take a random draw from the distribution of average income growth or a random draw from the distribution of inequality changes? If our preferences for equity are captured by the Sen social welfare function, the answer is unambiguously to prefer a draw from the distribution of growth rates. As noted above, the mean of the distribution of growth rates is 1.5 percent per year, while for inequality changes it is essentially zero. Even if we were to get a very good draw from the distribution of inequality changes (say at the 90th percentile), this would deliver a growth rate of social welfare only slightly faster than what we could get at the average of the distribution of mean income growth (1.6 versus 1.5 percent per year).

These results on the relative importance of growth hold roughly the same for most of the social welfare functions we consider, with the exception of the most bottom-sensitive ones, such as average incomes in the bottom 20 percent, and the Atkinson social welfare function with $\theta = 2$. For these social welfare functions, we continue to find that the distribution of the relevant inequality changes is centered on roughly zero: the average change in inequality across spells is 0.1 percent per year. However, changes in inequality exhibit considerably more variation. For example, for the bottom 20 percent and the Atkinson social welfare function with $\theta = 2$, the standard deviation of inequality changes is 3 percent, which is closer to that for growth in average incomes which is 4 percent.

Table 2 reports summary statistics on the distributions of growth rates and inequality changes more systematically, and for different subsamples. The first column refers to average income growth, while the remaining nine columns correspond to growth in the relevant inequality measure for each of the nine social welfare functions in Table 1. Each horizontal panel corresponds to a different sample of observations, and within each panel we report the number of observations, the mean and the standard deviation of the distribution of growth rates within each sample. In addition we report the 10th and 90th percentiles of the distribution of growth rates for the pooled sample in the top panel of Table 2. All panels report summary statistics for the sample of minimum-five-year spells. The first panel reports the results for the pooled sample. The second panel disaggregates the sample into low-income, middle-income, and high-income countries. The third panel disaggregates the minimum-five-year spells by decades[5].

The summary statistics in the first panel reflect the previous discussion on the mean and relative variability of changes in average incomes and changes in inequality. Looking across income categories in the second panel, we see that growth on average was substantially higher in the low-income country spells (2.5 percent per year versus 1.3 and 1.6 percent per year in the middle- and high-income categories). Across all the different social welfare functions, however, we still see that growth in the relevant inequality measure was on average close to zero in all three income categories. Looking across decades, we see clear evidence of an acceleration in average growth rates of survey mean income, from near zero in the 1980s and 1990s to 2.9 percent per year in the 2000s. There was however little change in the growth rate of any of the inequality measures across decades, with the implication that social welfare increased on average by roughly as much as average incomes increased.

## 4.2. Regression Analysis

We next document the joint distribution of growth rates and inequality changes, using a series of simple ordinary least squares regressions of growth in social welfare on growth in average incomes. Since the former is the sum of growth in average incomes and changes in the relevant equality measure, the slope coefficient from this regression is one plus the slope coefficient of a regression of changes in inequality on growth. If the estimated slope coefficient in our regression of social welfare on growth is equal to one, this implies that on average, social welfare increases equiproportionately with average incomes. If, on the other hand, the slope coefficient is greater (less) than one, social

[5] A practical challenge for data description here is that only a small fraction of spells fall entirely within a single decade, and so 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.

welfare increases more (less) than equiproportionately with average incomes, reflecting a decline (increase) in the relevant inequality measure when average incomes increase.

In addition, the goodness of fit of these regressions is informative about the relative importance of growth and inequality changes for growth in social welfare. To capture this, we report the R-squared from the regression, as well as the share of the variation (across spells) of growth in social welfare that is attributable to variation (across spells) in growth in average incomes.[6]

Panel A of Table 3 reports the benchmark regression in our sample of 285 spells at least five-years long. As before, the nine columns correspond to the nine social welfare functions in Table 1. The regressions confirm the visual impressions from Figure 3, as the estimated slopes are all very close to one. In all cases we cannot reject the null hypothesis that the estimated slope coefficient is equal to one, indicating an absence of any statistically significant correlation between changes in average income and changes in inequality that are relevant for the social welfare measures we consider.

Turning to the variance decompositions, we see that for most social welfare functions, most of the variation in growth in social welfare is due to growth in average incomes. For example, for the Sen and bottom 40 percent social welfare functions, the shares of the variance of growth in social welfare due to growth in average incomes are 92 and 77 percent, respectively.

One clear regularity in Table 3 is that the share of the variance of growth in social welfare due to growth in average incomes is lower for more bottom-sensitive inequality measures. This is perhaps clearest in the case of the Atkinson social welfare function. When $\theta = 0.5$, the share of the variance in growth in social welfare due to growth is 98 percent, while this falls to 69 percent when $\theta = 2$. Mechanically, this finding reflects the fact that the growth rate of the income shares of the poorest deciles are the most volatile across spells in our dataset. This in turn means that social welfare functions that place greater weight on poorer individuals will be more responsive to variations in the income share of the poorest. While there are various plausible reasons why the income shares of the poorest may be more volatile, in the working paper version of this paper we provide a simple illustration of one mundane consideration. We show that simply standard sampling variation in the surveys on which the income share data are taken can generate the same pattern of more volatile income shares in the bottom deciles as we observe in the data. This suggests that some caution is in order in interpreting the differences across social welfare functions in the share of the variance of growth in social welfare that is attributable to growth.

In the lower panels of Table 3, we disaggregate our results by income level. The results are very similar for low-income, middle-income, and high-income countries. In all cases we cannot reject the hypothesis that the slope is equal to one. We also continue to see that the share of the variance of growth in social welfare due to growth in average

[6] We follow Klenow and Rodriguez-Clare (1997) in defining the share of the variance of $X+Y$ due to $X$ as $(V(X)+COV(X,Y)/V(X+Y)$, where X is the growth rate of average income and Y is the growth rate of the corresponding equality measure. Since the correlation between growth and inequality changes is small, the term $COV(X,Y)$ plays a minimal role in the decompositions that follow.

incomes is somewhat lower for the more bottom-sensitive social welfare functions such as the bottom 20 percent and Atkinson social welfare function with $\theta = 2$, but is generally high for all social welfare functions. This is particularly the case in high- and middle-income countries. In contrast, among low-income countries we find that the share of the variance of growth in social welfare due to growth is somewhat lower than in the middle- and high-income countries.

In Table 4, we repeat the pooled sample results in Panel A for comparison and then we disaggregate our results by decade. Across all periods and for all social welfare functions, we continue to find a slope coefficient that is very close to, and not statistically significantly different from one, indicating an absence of a significant relationship between changes in inequality and changes in average incomes. One consistent pattern, however, is that the share of the variance of growth in social welfare due to growth in average incomes declines slightly as we move from the 1980s to the 1990s to the 2000s. For example, for the bottom 40 percent social welfare function, this variance share declines from 85 percent in the 1980s to 72 percent in the 2000s[7].

In all of our results so far, we have relied exclusively on household survey means to construct growth rates in average incomes. 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.

The results are shown in Table 5. Panel A repeats our benchmark regression for all nine social welfare functions using the survey data. Panel B alternatively uses the growth rate of real private consumption from the national accounts. We estimate the regressions in identical samples to allow for a direct comparison. The slopes all continue to be very close to one. The main difference is that the share of welfare growth attributed to income growth declines modestly when we move to national accounts data. For example, for the Atkinson social welfare function with $\theta = 1$, this share is 92% using the survey data; it declines to 85% using the alternative measure from the national accounts.[8]

[7] Interestingly, this decline in the variance share does not appear to be due to compositional effects (noticing that the sample size increases significantly over time). As a robustness check, we constructed a sample of 43 countries with one survey available near the middle of each of the three decades. We then constructed two sets of spells, from the mid-1980s to the mid-1990s, and from the mid-1990s to the mid-2000s. In this smaller set of spells we also find that the share of the variance of growth in social welfare due to growth in average incomes falls in the second set of spells relative to the first.

[8] A number of authors have argued that the discrepancy in levels between national accounts-based and household survey-based measures of average living standards reflects the under-representation of the rich in household surveys, particularly in developing countries. To investigate this possibility, we identify a subset of spells where the national accounts-based measure of average income or private consumption exceeds the corresponding household survey based measure of income or consumption. We then assign the gap between the two measures to the richest decile in the household survey. We do this only for gaps of no more than 30 percent of the national accounts mean, to avoid implausibly large adjustments to survey-based measures of income of the rich. We then re-estimate our benchmark regressions using a much smaller sample of 90 spells where this adjustment is made to both endpoints of the spell. We find estimated slopes that are on average around 0.9, and generally are significantly less than one. This indicates that the national accounts-household survey discrepancy tends to increase during periods of growth, and conditional on the (in our view somewhat implausible) assumption that this exclusively reflects mismeasurement at the high end of the distribution, this also implies that inequality increases during such spells.

### 4.3. Social Welfare Functions That Value Absolute Income Differences

So far we have discussed social welfare functions that depend on *relative* inequality measures. In particular, for all the social welfare functions we have considered, if all incomes double, social welfare also doubles, and the contribution of inequality change to social welfare is zero. This feature of standard inequality measures can be questioned on the grounds that popular perceptions of inequality often appear to be shaped by absolute income differences as much as relative ones. This is particularly important in our context, since absolute income differences increase even when growth is distribution-neutral in the relative sense.

To analyse the importance of growth in average incomes for changes in social welfare functions that penalize absolute inequality, we use a social welfare function based on the Kolm (1976a,b) inequality measure.[9] Unlike the relative inequality measures discussed so far, the Kolm inequality index has the key property that inequality is unchanged if the same absolute amount is added to everyone's income. In contrast, such a pattern of transfers would imply lower inequality for relative inequality measures, since the proportional transfer to the rich is smaller than it is for the poor. Conversely, an equiproportionate transfer to everyone does not affect relative inequality, but would raise inequality as measured by the Kolm index since the absolute transfer received by the poor is smaller than the absolute transfer received by the rich. This absolute property of the Kolm inequality measure is reflected in the corresponding social welfare function: when average incomes increase with unchanged relative incomes, social welfare increases by less than average incomes since the Kolm inequality index increases as well.

As before, we are interested in the importance of changes in average incomes for changes in social welfare. To document this, we follow the approach of the previous subsections, and regress growth in the Kolm social welfare function on growth in average incomes in our benchmark sample of 285 spells. This regression delivers a slope coefficient of 0.5, which is significantly less than one. This reflects the fact that, by construction, the Kolm inequality index increases with growth in average incomes. As a result, social welfare grows more slowly than average incomes, and the slope coefficient in the regression is less than one. Beyond this mechanical effect driven by the Kolm social welfare function's aversion to absolute income differences, changes in how income is distributed contribute surprisingly little to the overall variation in growth in social welfare. One way of seeing is is to consider the correlation between growth

[9] The Kolm social welfare function is $W = -\frac{1}{\theta} log\left(\frac{1}{N}\sum_{i=1}^{N} e^{-\theta Y_i}\right)$, with the Kolm inequality index implicitly defined by $W = \mu - I$, and with welfare weights on individuals of $\varepsilon_i \propto Y_i e^{-\theta Y_i}$. For a given distribution of incomes, larger values of $\theta$ imply greater weight on poorer individuals. In addition, for a given value of $\theta$, as the entire distribution of income shifts up, the relative weight on poorer individuals increases. This implies that, for a fixed value of $\theta$, we would have very different preferences for redistribution across the countries with the very different average income levels represented in our dataset. To avoid this, we choose country-specific values for $\theta$ that are fixed over time, and that are calibrated to ensure that the weight on the poorest decile is 10 times larger than the weight on the richest decile.

and social welfare changes. For the Kolm social welfare function in our data, this correlation is around 0.8, which is quite similar to the correlation between growth and social welfare based on relative inequality measures discussed in the previous subsections.

### 4.4. General Social Welfare Functions and Lorenz Dominance

In all of our results thus far, we have relied on specific social welfare functions in order to be able to explicitly measure the contribution of inequality changes to growth in social welfare. The benefit of this approach is that it allows us to express inequality changes in terms of growth in average incomes, which in turn leads to straightforward variance decompositions. Although we have considered a wide variety of common social welfare functions, a drawback of this approach is that our conclusions do depend on the specific functional form of the selected social welfare function. And this in turn raises the possibility that there might be other social welfare functions for which the contribution of growth to improvements in social welfare is different than for the ones we have considered.

To address this possibility, we draw on the concept of generalized Lorenz dominance to determine the direction, although not the magnitude, of welfare changes for a much broader class of social welfare functions than those considered here. Shorrocks (1983) shows that as long as the social welfare function is increasing and concave in incomes (i.e. the social welfare function prefers more income to less, and less inequality to more), then social welfare is unambiguously higher if and only if the growth rate of cumulative average income of each percentile of the population is positive. In our case where we focus on decile grouped data, this corresponds to the case where growth in average incomes of the first decile, the first two deciles, etc. all the way up to growth in overall average incomes, are all positive over a given spell. If this is true, then social welfare will have improved over this spell for any social welfare function that satisfies the minimum requirements of being increasing and concave in incomes.

To implement this, we divide our sample into 203 spells with positive average growth rates and 82 with negative average growth rates. In the first group, we count the number of spells where the final distribution in each spell generalized-Lorenz-dominates the initial distribution. In the second group, we do the opposite, counting up the number of spells where the initial distribution (before the negative average growth experience) generalized-Lorenz-dominates the final distribution. In both cases, these correspond to cases where positive (negative) growth unambiguously raised (lowered) social welfare for *any* increasing and concave social welfare function. In the sample with positive average growth, social welfare unambiguously increased in 81 percent of all spells. Conversely, social welfare unambiguously fell in two-thirds of the 82 spells where average income fell. Combining all spells, welfare changes in the same direction as average incomes in 76 percent of all spells. The small number of spells in which mean income and social welfare have not unambiguously moved in the same direction are generally ones in which the income growth rate is close to zero. Overall, this suggests that it would be very difficult to find episodes of sustained growth in incomes that did not also unambiguously increase social welfare.

## 5. Policies, Growth, and Social Welfare

A large existing empirical literature has sought to identify policies and institutions that are correlated with cross-country differences in growth. Since we have seen that most of the variation in growth rates in social welfare across countries is due to cross-country differences in average growth performance, these findings from cross-country growth empirics have direct implications for social welfare growth as well. Beyond this, it is useful to document the correlates of the remaining variation in social welfare growth due to changes in inequality. In particular, if there were a combination of policies and institutions that resulted in the same growth rate of average incomes as some other combination of policies, but also delivered a reduction in inequality, then the inequality-reducing combination of policies would be preferable from the standpoint of improving social welfare. In this section we use cross-country regression analysis to document more systematically the relationship between a set of variables proxying for a variety of policy and institutional factors on the one hand, and growth in social welfare and its components on the other.

Our starting point is the observation from Equation (1) that growth in social welfare over a given spell consists of two components: growth in average incomes and growth in equality. We regress both of these components on the same set of right-hand-side variables: log initial income, i.e. $\log(\mu)$ at the beginning of the spell; initial equality, i.e. $\log(1-I)$ at the beginning of the spell; and a set of explanatory variables drawn from the cross-country growth literature. The estimated coefficients from these regressions capture the partial correlations between each of the explanatory variables and growth in average incomes and growth in equality. Since growth in social welfare is the sum of these two components, the sum of the estimated coefficients across these two equations captures the partial correlations of the explanatory variables with overall social welfare growth.

The explanatory variables include a measure of financial development (credit to the private sector as a percentage of GDP), 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 revolutions, and a dummy variable indicating whether the country was party to a civil or international war in a given year. 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)). We also consider some additional variables that have been found to be significant correlates of inequality in the much smaller existing cross-country literature on determinants of inequality. These consist of primary school enrolment rates, a measure of educational inequality[10] (as emphasized by De Gregorio et. al. (2002)), and the share of agriculture in GDP (as emphasized for example in Datt and Ravallion (2002))[11]. Annex Table A1 provides a detailed description of the definitions and sources of all of these variables.

A well-known concern with cross-country growth empirics is that results can be sensitive to the precise set of explanatory variables included in the regression equation. To address this concern, we consider all possible combinations of these 13 explanatory variables, i.e. we estimate the growth and the inequality change regressions $2^{13} = 8192$ times for each possible combination of explanatory variables. We then use Bayesian Model Averaging (BMA) to summarize our results from this large number of regression models. In particular, BMA assigns a posterior probability to each model, which indicates the relative likelihood of each model compared with all of the other models considered. Intuitively, these posterior probabilities reflect a tradeoff between goodness of fit and parsimony: for two models with the same number of explanatory variables, the model that delivers the higher R-squared receives a higher posterior probability. Similarly, for two models with the same R-squared, the model with fewer explanatory variables receives a higher posterior probability.

We calculate these model posterior probabilities for the regression of growth in social welfare on each set of explanatory variables. We then use them to calculate probability-weighted averages of the estimated slope coefficients across all models, for both the regressions of growth and equality changes on all the combinations of explanatory variables. For each variable, we also calculate a posterior inclusion probability. This is simply the sum of the posterior probabilities of each model in which the variable appears, and is a useful summary of the relevance of that variable for growth in social welfare. Explanatory variables with high posterior inclusion probabilities are ones that appear in models that are more likely relative to other models.

Table 6 summarizes our results. To conserve on space, we report results only for three social welfare functions: average incomes in the bottom 40 percent, the Atkinson social welfare function with $\theta = 2$, and the Sen social welfare function. Our findings are qualitatively similar for the other social welfare functions considered in the paper. Our dataset consists of the same set of 285 spells at least five years long. However, each model is estimated in the smaller set of spells for which all the right-hand-side variables included in that model are available. Lagged log-levels of mean income and equality are measured at the beginning of each spell, while the remaining 13 explanatory variables are measured as averages over the spells. Our sample differs from the common practice in the cross-country empirical growth literature, which is to measure growth over regularly-spaced five- or ten-year intervals. The advantage of our approach of working

[10] 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.

[11] 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)).

with an irregularly-spaced panel is that it avoids the need to impute the household survey data across different years within a country, but instead relates actual changes in equality to explanatory variables observed over the same period. On the other hand, the disadvantage of this approach is that the coefficients on initial income and initial equality reflect changes over different time periods. All of the regressions are estimated by ordinary least squares, and so should be interpreted in terms of estimated partial correlations rather than causal effects.[12]

The first column in each panel reports the posterior inclusion probabilities for each variable. The remaining three columns report the posterior probability-weighted estimated coefficients for growth in social welfare, growth in average incomes, and growth in equality, respectively. As discussed above, the slopes in the first column are the sum of the slopes in the remaining two columns, i.e. the overall effect of a given variable on growth in social welfare is the sum of its effects on growth in average incomes and on growth in equality. To aid in the interpretation of the slopes, we scale each one to show to the effect on growth (in percentage points per year) of a one standard deviation increase in the corresponding right-hand-side variable. Below each estimated coefficient, we report in parentheses the percentage of all models in which the estimated slope coefficient is statistically significant at the 95 percent level and is of the same sign as the probability-weighted slope. Finally, note that the only difference across the three panels in the growth regression is the choice of the initial equality measure, which is different for each social welfare function. As a result, the estimated coefficients on the remaining variables in the growth regression are in most cases quite similar across the three panels.

Consider first the partial correlations between growth in social welfare and initial income and initial equality. We assume these variables appear in all specifications, so by construction their posterior inclusion probabilities are equal to one. The posterior probability-weighted estimated slopes in the social welfare regression are negative in all cases, and are highly significant in the vast majority of specifications, i.e. higher initial income levels, and higher initial equality, are significantly negatively correlated with subsequent growth in social welfare. To understand this finding, it is useful to consider separately the coefficients on these variables in the regressions for growth in average incomes, and growth in equality. Consistent with the large empirical growth literature, we find that lower initial income levels are associated with faster subsequent growth in average income. The same is true of equality: lower initial levels of equality, i.e. higher

[12] Our growth and inequality change regressions are dynamic panel regressions, and the error terms are likely to include a country-specific time-invariance component (i.e. country effects). As such, they are subject to the usual concerns in the empirical growth literature about Nickell bias, as well as the usual concerns about potential endogeneity of other right-hand-side variables. Many papers in the empirical growth literature have sought to address these problems using the system-GMM estimator proposed by Arellano and Bond (1991). However, an under-appreciated concern with this approach is that the internal instruments based on appropriate lags and differences of explanatory variables are often weak in standard cross-country growth settings (see for example Bazzi and Clemens (2012)). This is the case in our dataset as well – standard weak instrument diagnostics indicate that instruments in the first-stage regressions underlying the system-GMM estimator of the growth and inequality change regressions are very weak. We instead follow the recommendation of Hauk and Wacziarg (2009), who, following extensive Monte Carlo analysis of alternative estimators of growth regressions, conclude that pooled OLS performs best in practice.

initial inequality, are significantly associated with faster subsequent growth in equality, reflecting a tendency of equality to mean-revert.

On the other hand, we find little evidence that higher initial levels of equality are significantly associated with subsequent growth in average income, nor are initial income levels significantly associated with subsequent changes in equality. Specifically, initial equality is significantly positively correlated with growth in only 7 percent of models (when the social welfare function is average incomes in the bottom 40 percent), and in 15 percent of models (when the social welfare function is the Sen measure). This in turn casts some doubt on the frequently-heard concern that higher initial inequality might undermine subsequent growth in average income. In fact, it is striking that even though the probability-weighted slope coefficients on initial equality are positive in the three growth regressions (indicating a positive partial correlation between greater equality and subsequent growth), the corresponding slope coefficient is strongly negative in the social welfare regression. This is because any beneficial effects of higher equality on subsequent growth in average incomes are offset by the tendency of equality to mean-revert, which reduces social welfare through an increase in inequality.

Turning to the other variables in Table 6, some interesting patterns emerge. A few of them have consistently high posterior inclusion probabilities, indicating that they are important partial correlates of growth in social welfare in our sample. These include inflation (high inflation consistently is negatively correlated with growth in social welfare); population growth (faster population growth is associated with slower growth in social welfare); political instability as measured by revolutions (greater instability leads to slower growth in social welfare); and the share of agriculture in GDP (a higher share is associated with slower growth in social welfare).

Interestingly, for each of these variables, the main effect operates through the relationship with growth in average incomes: the coefficients in the third column of each panel (which measure the partial correlations with growth) are much larger in absolute value than the coefficients in the third column (which measure the partial correlations with changes in equality). Consider for example the relationship between inflation and growth in social welfare. A one standard deviation increase in inflation reduces average annual growth in social welfare by between 1.8 and 2.1 percent per year, depending on which social welfare function we consider. Nearly all of this effect comes through lower growth in average incomes, which declines by 1.7 percentage points. This estimated coefficient is significantly different from zero in all of the models in which it appears[13]. The probability-weighted slope coefficient from the equality regression is negative, suggesting that high inflation is disequalizing on average. However, the estimated effect is much smaller than the estimated effect on growth, and is rarely statistically significant.

Another interesting case is the relationship between growth in social welfare and the share of agriculture in GDP, which is the one case among these four variables suggestive of a tradeoff. On the one hand, a higher share of agriculture in GDP is

[13] This finding is in part driven by a fairly small number of spells with quite high inflation rates.

associated with substantially slower growth in average incomes, and this effect is significant in nearly all specifications. On the other hand, a higher share of agriculture in GDP is positively associated with subsequent growth in equality. However, this latter effect is once again much smaller than the effect on growth in average incomes, and moreover is never statistically significant at conventional levels. As a result, the growth effect dominates, and the effect of a larger share of agriculture in GDP on subsequent growth in social welfare is substantially negative.

It is however noteworthy that the remaining variables mostly have quite low posterior inclusion probabilities, and rarely show up as significant correlates of either growth in average incomes or growth in the relevant inequality measures. This is at least somewhat surprising, given that these variables were selected for their prominence in the empirical growth literature. However, there are at least two important differences between our empirical specifications, and those used in the majority of papers in the broader growth literature. The first is that in our work, growth in average incomes is measured as growth in average income or consumption from the underlying household surveys. As we have noted earlier, there are substantial differences between these growth rates and measures of mean growth taken from national accounts data. Second, the vast majority of papers in the empirical growth literature examines growth over regularly-spaced spells of fixed length, typically five or ten years long, and with a much larger set of observations. This contrasts with our sample, which is much smaller and irregularly-spaced, as dictated by the limited availability of household survey data in particular years.

One way to assess the importance of these considerations is to re-estimate the results in Table 6, but replacing growth in household survey-based measures of average income with corresponding data from the national accounts. In particular, we use real per capita GDP growth from the national accounts, in order to be consistent with the empirical growth literature. However, we keep the structure of our irregularly-spaced panel of observations determined by the availability of survey data, needed to construct the social welfare measures. For most variables, our findings are broadly similar to when we use household survey mean growth rates. In addition, for some of our social welfare functions, we find that the budget balance has a posterior inclusion probability greater than 0.5, and enters positively in the growth regressions, suggesting that higher budget deficits are correlated with slower growth. One further notable finding is that when we switch to national accounts growth rates, initial equality enters positively and significantly in roughly three-quarters of all specifications for the growth regression, suggesting that initial inequality is bad for subsequent growth. However, this does not imply that higher initial equality is good for growth in social welfare. This is because, as we have already seen in Table 7, higher initial equality is significantly correlated with subsequent declines in equality, and this effect is quantitatively larger than the positive effect on average income growth. As a result, the posterior probability-weighted slope coefficient on initial equality in the social welfare regression is still negative.

## 6. Conclusions

This paper is motivated by the widespread concerns about inequality and its consequences that are often heard in current policy discussions. Our objective in this paper is to provide some simple descriptive evidence on the implications of observed inequality for changes in social welfare. By specifying a social welfare function, it is possible to quantify the welfare effects of changes in inequality, and compare them with the welfare effects of growth in average incomes. In particular, we exploit the fact that growth in a number of standard welfare functions can be decomposed into growth in average incomes, and growth in a particular measure of inequality specific to each social welfare function.

We implement these decompositions in a large dataset of high-quality data on income and its distribution across individuals, covering 117 countries over the past four decades. Using this data, we construct a large set of non-overlapping episodes or spells of changes in average income and changes in its distribution that are at least five years long, and measure the contribution of growth and changes in inequality to growth in social welfare over each spell. Our basic findings are easily summarized. Most of the cross-country and over-time variation in changes in social welfare is attributable to growth in average incomes. In contrast, the contribution of changes in relative incomes to social welfare growth is on average much smaller than growth in average incomes, and moreover is on average uncorrelated with average income growth. These findings suggest that the welfare impacts of changes in inequality observed over the past four decades are small when compared with the welfare impacts of growth in average incomes. These findings are generally quite robust across different social welfare functions that reflect a wide variety of preferences for redistribution, across different regions, and in different time periods.

While the variation in the growth rate of social welfare functions that is due to changes in inequality is on average substantially smaller than the share due to growth, it is nevertheless potentially important to understand the factors underlying this variation. If, for example, there were some combination of policies that generated the same rate of average growth as another combination, but at the same time reduced inequality, then the former combination might be preferable from the standpoint of social welfare growth. To investigate this we consider a set of variables intended to proxy for factors commonly thought to be conducive to growth in average incomes. We use Bayesian Model Averaging as a tool to systematically document the partial correlations between these variables and social welfare growth. We find that the relationship between these variables and social welfare growth, to the extent that they are quantitatively important, comes mostly through their effects on growth in average incomes, rather than through changes in inequality.

These findings indicate that the historical experience of a large set of developed and developing countries does not provide much guidance regarding the set of macroeconomic policies and institutions that might be particularly conducive to promoting growth in social welfare beyond their effects on aggregate growth. This of course does not imply that there are no policies that can influence inequality in ways that raise social welfare – it is just that our cross-country empirical tools are too blunt to clearly identify what such policies might be. While this is somewhat disappointing, the patterns in the data do nevertheless give some hints as to the likely returns in terms of social welfare growth of policies specifically directed at influencing inequality, relative to policies aimed at influencing overall growth. Consider for example a country at the mean of the distribution of overall growth performance, that adopts some combination of policies that turn it into a "top" growth performer at the $90^{th}$ percentile of the distribution of growth rates. Absent any changes in inequality, average annual social welfare growth would increase from 1.5 percent per year to 6.3 percent per year, or an increase of nearly five percentage points of growth. Now instead consider what would have happened had this country chosen another combination of policies that turned it into a star performer in terms of reduced inequality, at the $90^{th}$ percentile of the distribution of inequality changes. Looking across the different social welfare functions and associated inequality measures in Table 2, this would add considerably less to growth: an increment of 0.7 to at most 4.2 percentage points of growth per year..

In summary, our findings underscore the importance of growth for improvements in social welfare. At the same time, as the social welfare function puts more and more weight on those at the extreme lower tail of the income distribution, growth becomes less important for raising social welfare. At the extreme, if we wanted to help the single poorest person in a society, promoting economic growth would be a highly indirect way of meeting that objective. The fact that there are no robust correlates of changes in inequality in our dataset suggest that there is no simple recipe for raising social welfare growth through reductions in inequality. However, the fact that changes in inequality are uncorrelated with growth means that there are likely to be some policies that reduce inequality without harming growth, or even enhancing it – for example, early childhood education for all may be such a policy. However, it cannot be the case that all policies that reduce inequality are good for growth, because that would imply a positive correlation between growth and reductions in inequality, which we do not see in the data. As policy-makers are under increased pressure to "do something" about inequality, it is important to keep in mind that equality-enhancing policies that are neutral to or supportive of growth will be good for social welfare, whereas equality-enhancing policies that reduce growth are likely to be self-defeating in the sense that, while they may lead to a more equal society, their net effect may well be to reduce social welfare.

**Table 1: Social Welfare Functions**

| Inequality Measure (I) | Social Welfare Function (W) | Weight Assigned to Individuals | Willingness to Pay for Redistribution That Reduces Gini from 0.43 to 0.29 (Percent of Mean Income) |
|---|---|---|---|
| Income Share of Bottom X% | $W=\frac{1}{NX}\sum_{i=1}^{NX} Y_i$ | $\varepsilon_i \propto \begin{cases} Y_i, & i \leq NX \\ 0, & i > NX \end{cases}$ | 41 (X=20%)<br>34 (X=40%)<br>10 (X=90%) |
| Gini Index | $W=\frac{2}{N^2}\sum_{i=1}^{N}(N+1-i)Y_i$ | $\varepsilon_i \propto (N+1-i)Y_i$ | 20 |
| Atkinson Index | $W=\left(\frac{1}{N}\sum_{i=1}^{N} {Y_i}^{1-\theta}\right)^{\frac{1}{1-\theta}}$ | $\varepsilon_i \propto Y_i^{1-\theta}$ | 10 ($\theta=0.5$)<br>15 ($\theta=1$)<br>31 ($\theta=2$) |
| Bonferroni Index | $W=\frac{1}{N}\sum_{i=1}^{N}\frac{1}{i}\sum_{j=1}^{i} Y_j$ | $\varepsilon_i \propto \sum_{j=i}^{N}\frac{1}{j}\,Y_i$ | 26 |
| Donaldson-Weymark Index | $W=\frac{1}{N}\sum_{i=1}^{N}\left(\left(\frac{i}{N}\right)^{\theta}-\left(\frac{i-1}{N}\right)^{\theta}\right)Y_i$ | $\propto\left(\left(\frac{i}{N}\right)^{\theta}-\left(\frac{i-1}{N}\right)^{\theta}\right)Y_i$ | 10 ($\theta=0.5$) |

*Notes*: $Y_i$ refers to income of individual $i$, ordered from poorest to richest so that $Y_1 < Y_2 <, \ldots, < Y_N$. $\varepsilon_i$ refers to the weight assigned by the social welfare function to an individual with income $Y_i$, i.e. $\varepsilon_i \equiv \frac{\partial W}{\partial Y_i}\frac{Y_i}{W}$. The last column reports the percentage reduction in average income that ensures that the social welfare function is indifferent between a lognormal income distribution with a Gini coefficient of 0.43 versus one with a Gini coefficient of 0.29.

*Sources*: Authors compilation.

**Table 2: Descriptive Statistics**

| Social Welfare Function | Average incomes | Bottom 20% | Bottom 40% | Bottom 90% | Atkinson (θ=0.5) | Atkinson (θ=1) | Atkinson (θ=2) | Sen Index | Donaldson - Weymark (θ=0.5) | Bonferroni |
|---|---|---|---|---|---|---|---|---|---|---|
| **Pnael A: All Observations (Pooled)** | | | | | | | | | | |
| **Sample of Min-5-year Spells (N=285)** | | | | | | | | | | |
| Mean | 0.015 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| Std. Dev. | 0.042 | 0.034 | 0.023 | 0.010 | 0.006 | 0.012 | 0.028 | 0.012 | 0.006 | 0.014 |
| P10 | -0.028 | -0.039 | -0.027 | -0.012 | -0.007 | -0.014 | -0.028 | -0.015 | -0.008 | -0.019 |
| P90 | 0.063 | 0.045 | 0.031 | 0.012 | 0.007 | 0.016 | 0.031 | 0.016 | 0.008 | 0.018 |
| **Panel B: By Income Category (Min-5-year Spells)** | | | | | | | | | | |
| **Low Income (N=42)** | | | | | | | | | | |
| Mean | 0.025 | 0.007 | 0.004 | 0.001 | 0.001 | 0.002 | 0.005 | 0.002 | 0.001 | 0.002 |
| Std. Dev. | 0.035 | 0.040 | 0.029 | 0.015 | 0.008 | 0.016 | 0.029 | 0.017 | 0.007 | 0.019 |
| **Middle Income (N=168)** | | | | | | | | | | |
| Mean | 0.013 | 0.002 | 0.001 | 0.000 | 0.000 | 0.001 | 0.002 | 0.000 | 0.000 | 0.000 |
| Std. Dev. | 0.049 | 0.036 | 0.024 | 0.010 | 0.006 | 0.013 | 0.032 | 0.013 | 0.006 | 0.015 |
| **High Income (N=75)** | | | | | | | | | | |
| Mean | 0.016 | -0.004 | -0.004 | -0.002 | -0.001 | -0.001 | -0.002 | -0.002 | -0.001 | -0.003 |
| Std. Dev. | 0.026 | 0.021 | 0.014 | 0.006 | 0.003 | 0.006 | 0.014 | 0.008 | 0.005 | 0.010 |
| **Panel C: By Decade (Min-5-year Spells)** | | | | | | | | | | |
| **1980s (N = 80)** | | | | | | | | | | |
| Mean | 0.002 | -0.001 | -0.002 | -0.001 | 0.000 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| Std. Dev. | 0.045 | 0.026 | 0.019 | 0.010 | 0.005 | 0.009 | 0.018 | 0.011 | 0.006 | 0.013 |
| **1990s (N = 198)** | | | | | | | | | | |
| Mean | 0.008 | -0.004 | -0.003 | -0.001 | -0.001 | -0.001 | -0.003 | -0.002 | -0.001 | -0.002 |
| Std. Dev. | 0.044 | 0.035 | 0.024 | 0.011 | 0.006 | 0.013 | 0.029 | 0.013 | 0.006 | 0.015 |
| **2000s (N=167)** | | | | | | | | | | |
| Mean | 0.029 | 0.007 | 0.004 | 0.001 | 0.001 | 0.002 | 0.006 | 0.001 | 0.001 | 0.002 |
| Std. Dev. | 0.036 | 0.034 | 0.023 | 0.010 | 0.006 | 0.012 | 0.029 | 0.012 | 0.006 | 0.014 |

*Notes*: This table reports the mean, standard deviation, and $10^{th}$ and $90^{th}$ percentiles of the distribution of growth rates of average income (the first column) and the relevant inequality measure corresponding to the indicated social welfare function (the remaining nine columns). The top panel pools all countries and periods. The middle panel distinguishes countries by their income level. The bottom panel reports results by decades. In the bottom panel, each subsample consists of all spells with at least one end-point in the indicated decade, and spells are weighted by the fraction of years of the spell falling in the indicated decade. The dataset consists of a sample of 285 non-overlapping spells at least five years long.
*Sources*: Authors' compilation.

**Table 3: Regressions of Social Welfare Growth on Average Income Growth: Disaggregated By Income Level**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| **Social Welfare Function** | **Bottom 20%** | **Bottom 40%** | **Bottom 90%** | **Atkinson (θ=0.5)** | **Atkinson (θ=1)** | **Atkinson (θ=2)** | **Sen Index** | **Donaldson - Weymark (θ=0.5)** | **Bonferroni** |
| **Panel A: Benchmark : Pooled Sample (N=285)** | | | | | | | | | |
| Avg. growth | 1.075 | 1.021 | 0.991 | 1.001 | 1.008 | 1.043 | 1.003 | 1.014 | 1.014 |
| | (0.0626) | (0.0467) | (0.0223) | (0.0121) | (0.0238) | (0.0468) | (0.0273) | (0.0131) | (0.0311) |
| R-squared | 0.650 | 0.783 | 0.944 | 0.981 | 0.925 | 0.717 | 0.921 | 0.981 | 0.899 |
| Variance decomposition | 0.605 | 0.767 | 0.952 | 0.980 | 0.918 | 0.687 | 0.918 | 0.967 | 0.887 |
| **Panel B: Low Income Sample (N=75)** | | | | | | | | | |
| Avg. growth | 1.030 | 0.950 | 0.947 | 0.982 | 0.977 | 1.021 | 0.953 | 1.008 | 0.970 |
| | (0.156) | (0.106) | (0.0469) | (0.0253) | (0.0504) | (0.105) | (0.0635) | (0.0373) | (0.0758) |
| R-squared | 0.600 | 0.755 | 0.947 | 0.985 | 0.939 | 0.776 | 0.904 | 0.963 | 0.866 |
| Share of variance due to growth | 0.583 | 0.795 | 1.000 | 1.003 | 0.961 | 0.761 | 0.948 | 0.955 | 0.892 |
| **Panel C: Middle Income Countries (N=168]** | | | | | | | | | |
| Avg growth | 1.091 | 1.033 | 0.997 | 1.003 | 1.013 | 1.055 | 1.011 | 1.017 | 1.022 |
| | (0.0719) | (0.0544) | (0.0264) | (0.0143) | (0.0279) | (0.0544) | (0.0319) | (0.0152) | (0.0362) |
| R-squared | 0.693 | 0.819 | 0.958 | 0.985 | 0.936 | 0.728 | 0.939 | 0.986 | 0.922 |
| Share of variance due to growth | 0.636 | 0.793 | 0.960 | 0.981 | 0.924 | 0.690 | 0.929 | 0.970 | 0.902 |
| **Panel D: Low Income Countries (N=42)** | | | | | | | | | |
| Average growth | 0.951 | 0.967 | 0.975 | 0.989 | 0.978 | 0.947 | 0.975 | 0.989 | 0.973 |
| | (0.216) | (0.145) | (0.0535) | (0.0352) | (0.0742) | (0.159) | (0.0722) | (0.0348) | (0.0863) |
| R-squared | 0.409 | 0.569 | 0.836 | 0.945 | 0.820 | 0.569 | 0.801 | 0.955 | 0.760 |
| Share of variance due to growth | 0.430 | 0.588 | 0.858 | 0.956 | 0.839 | 0.600 | 0.821 | 0.965 | 0.782 |

*Notes*: This table reports the results from a regression of growth in the indicated social welfare function (in each column) on growth in average incomes, in the sample of non-overlapping spells lasting at least five years. The top panel reports the regression results in the pooled sample of 285 spells. The three lower panels correspond to sets of countries at different income levels, following the World Bank's classification for 2012. Heteroskedasticity-consistent standard errors are reported in parentheses. * (**) (***) indicate significant differences of the estimated slope coefficient from one at the 10 (5) (1) percent level.
*Sources*: Authors' compilation.

**Table 4: Regressions of Social Welfare Growth on Average Income Growth: Min 5-Year Spells Disaggregated By Decade**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| **Social Welfare Function** | **Bottom 20%** | **Bottom 40%** | **Bottom 90%** | **Atkinson (θ=0.5)** | **Atkinson (θ=1)** | **Atkinson (θ=2)** | **Sen Index** | **Donaldson - Weymark (θ=0.5)** | **Bonferroni** |
| **Panel A: Benchmark : Pooled Sample (N=285)** | | | | | | | | | |
| Avg. growth | 1.075 | 1.021 | 0.991 | 1.008 | 1.043 | 1.003 | 1.014 | 1.014 | 0.996 |
| | (0.0626) | (0.0467) | (0.0223) | (0.0238) | (0.0468) | (0.0273) | (0.0311) | (0.0131) | (0.0241) |
| R-squared | 0.650 | 0.783 | 0.944 | 0.925 | 0.717 | 0.921 | 0.899 | 0.981 | 0.931 |
| Variance decomposition | 0.605 | 0.767 | 0.952 | 0.918 | 0.687 | 0.918 | 0.887 | 0.967 | 0.934 |
| **Panel B: 1980s (N=80)** | | | | | | | | | |
| Avg. growth | 1.061 | 1.016 | 0.980 | 0.994 | 0.995 | 1.019 | 0.998 | 1.016 | 1.010 |
| | (0.0991) | (0.0753) | (0.0388) | (0.0196) | (0.0375) | (0.0689) | (0.0468) | (0.0225) | (0.0526) |
| R-squared | 0.782 | 0.859 | 0.956 | 0.989 | 0.959 | 0.870 | 0.943 | 0.986 | 0.930 |
| Share of variance due to growth | 0.737 | 0.846 | 0.975 | 0.994 | 0.964 | 0.854 | 0.945 | 0.971 | 0.921 |
| **Panel C: 1990s (N=198)** | | | | | | | | | |
| Avg growth | 1.062 | 1.013 | 0.983 | 0.996 | 0.999 | 1.025 | 0.998 | 1.013 | 1.009 |
| | (0.0757) | (0.0590) | (0.0297) | (0.0159) | (0.0306) | (0.0559) | (0.0349) | (0.0159) | (0.0390) |
| R-squared | 0.650 | 0.779 | 0.940 | 0.980 | 0.924 | 0.716 | 0.919 | 0.980 | 0.897 |
| Share of variance due to growth | 0.612 | 0.769 | 0.956 | 0.984 | 0.924 | 0.699 | 0.921 | 0.967 | 0.889 |
| **Panel D: 2000s (N=167)** | | | | | | | | | |
| Average growth | 0.996 | 0.970 | 0.985 | 0.994 | 0.990 | 0.991 | 0.982 | 0.995 | 0.983 |
| | (0.0776) | (0.0505) | (0.0189) | (0.0121) | (0.0261) | (0.0638) | (0.0260) | (0.0134) | (0.0312) |
| R-squared | 0.517 | 0.699 | 0.931 | 0.973 | 0.890 | 0.589 | 0.895 | 0.975 | 0.863 |
| Share of variance due to growth | 0.519 | 0.720 | 0.945 | 0.979 | 0.899 | 0.595 | 0.911 | 0.980 | 0.878 |

*Notes*: This table reports the results from a regression of growth in the indicated social welfare function (in each column) on growth in average incomes, in the sample of non-overlapping spells lasting at least five years. The top panel reports the regression results in the pooled sample of 285 spells. The three lower panels correspond to samples that cover the indicated time periods. The regression for each decade includes all spells with at least one end-point falling in the indicated decade. Spells are weighted by the fraction of the years of the spell falling in the indicated decade. Heteroskedasticity-consistent standard errors are reported in parentheses. * (**) (***) indicate significant differences from one at the 10 (5) (1) percent level.

*Sources*: Authors' compilation

**Table 5: Regressions of Social Welfare Growth on Average Income Growth: Alternative Measures of Real Income Growth**

| | Different Welfare Measures | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | Bottom 20% | Bottom 40% | Bottom 90% | Atkinson (θ=0.5) | Atkinson (θ=1) | Atkinson (θ=2) | Sen Index | Donaldson - Weymark (θ=0.5) | Bonferroni |
| | **Panel A: Survey data - income or consumption (N=274)** | | | | | | | | |
| Avg. growth - Min 5 year spells | 1.006 | 0.965 | 0.963 | 0.987 | 0.983 | 1.005 | 0.967 | 0.995 | 0.973 |
| | (0.0695) | (0.0501) | (0.0238) | (0.0137) | (0.0275) | (0.0572) | (0.0283) | (0.0127) | (0.0321) |
| R-squared | 0.565 | 0.722 | 0.927 | 0.975 | 0.902 | 0.645 | 0.899 | 0.977 | 0.871 |
| Share of variance due to growth | 0.561 | 0.749 | 0.963 | 0.988 | 0.917 | 0.642 | 0.929 | 0.982 | 0.895 |
| | **Panel B: National Accounts data - Real private consumption per capita (N=274)** | | | | | | | | |
| Avg. growth - Min 5 year spells | 1.051 | 1.011 | 0.997 | 1.002 | 1.011 | 1.060 | 1.002 | 1.007 | 1.008 |
| | (0.0648) | (0.0463) | (0.0212) | (0.0120) | (0.0241) | (0.0513) | (0.0259) | (0.0124) | (0.0298) |
| R-squared | 0.463 | 0.634 | 0.891 | 0.961 | 0.855 | 0.552 | 0.851 | 0.963 | 0.814 |
| Share of variance due to growth | 0.440 | 0.626 | 0.894 | 0.959 | 0.846 | 0.521 | 0.849 | 0.956 | 0.807 |
| | **Panel C: Mixed measure - arithmetic average from A&B (N=274)** | | | | | | | | |
| Avg. growth - Min 5 year spells | 1.030 | 0.977 | 0.969 | 0.991 | 0.992 | 1.034 | 0.975 | 0.999 | 0.982 |
| | (0.0768) | (0.0551) | (0.0262) | (0.0149) | (0.0299) | (0.0607) | (0.0312) | (0.0144) | (0.0356) |
| R-squared | 0.457 | 0.621 | 0.888 | 0.961 | 0.852 | 0.543 | 0.847 | 0.963 | 0.809 |
| Share of variance due to growth | 0.443 | 0.636 | 0.916 | 0.970 | 0.859 | 0.526 | 0.869 | 0.964 | 0.823 |

*Notes:* This table reports the results from a regression of growth in the indicated social welfare function (in each column) on growth in average incomes, in the sample of non-overlapping spells lasting at least five years. The three panels correspond to the three different measures of mean income. Heteroskedasticity-consistent standard errors are reported in parentheses. * (**) (***) indicate significant differences from one at the 10 (5) (1) percent level.

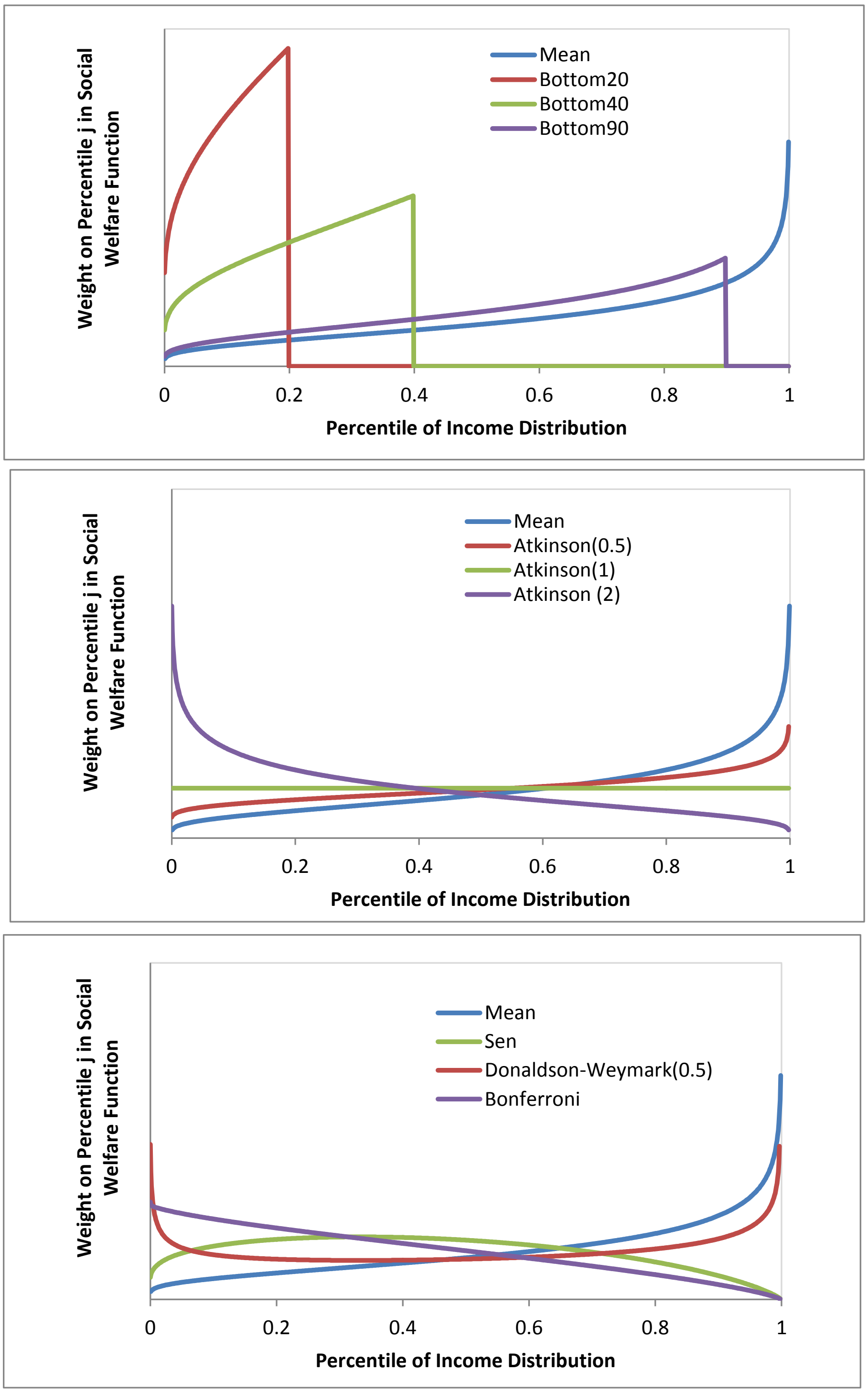
*Sources*: Authors' compilation

**Table 6: Regressions of Social Welfare Growth on Average Income Growth: Alternative Measures of Real Income Growth**

| | Panel A: Bottom 40 Percent | | | | Panel B: Atkinson (θ=2) | | | | Panel C: Sen | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Posterior Inclusion Probability | Social Welfare | Growth | Equality | Posterior Inclusion Probability | Social Welfare | Growth | Equality | Posterior Inclusion Probability | Social Welfare | Growth | Equality |
| Initial income level | 1.000 | -2.836 | -3.055 | 0.220 | 1.000 | -2.883 | -3.077 | 0.194 | 1.000 | -2.900 | -3.081 | 0.181 |
| | | (100) | (100) | (0) | | (99) | (100) | (0) | | (100) | (100) | (1) |
| Initial equality level | 1.000 | -1.011 | 0.078 | -1.089 | 1.000 | -1.427 | 0.029 | -1.456 | 1.000 | -0.496 | 0.118 | -0.615 |
| | | (89) | (7) | (100) | | (100) | (3) | (100) | | (5) | (15) | (100) |
| Credit to priv. sector to GDP | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | | (0) | (0) | (0) | | (0) | (0) | (0) | | (0) | (0) | (0) |
| Inflation rate | 1.000 | -1.980 | -1.692 | -0.288 | 1.000 | -2.073 | -1.706 | -0.368 | 1.000 | -1.841 | -1.694 | -0.147 |
| | | (99) | (97) | (8) | | (99) | (98) | (16) | | (98) | (97) | (6) |
| Budget Balance | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | | (18) | (45) | (0) | | (20) | (43) | (0) | | (29) | (48) | (0) |
| Trade Openness | 0.004 | 0.001 | 0.002 | -0.001 | 0.004 | 0.001 | 0.002 | -0.001 | 0.008 | 0.003 | 0.003 | -0.001 |
| | | (12) | (14) | (0) | | (11) | (14) | (0) | | (13) | (14) | (0) |
| Population growth | 0.575 | -0.508 | -0.395 | -0.114 | 0.768 | -0.789 | -0.519 | -0.270 | 0.563 | -0.452 | -0.381 | -0.071 |
| | | (46) | (9) | (27) | | (89) | (11) | (81) | | (20) | (7) | (58) |
| Life expectancy | 0.039 | 0.006 | 0.016 | -0.010 | 0.038 | 0.004 | 0.014 | -0.010 | 0.048 | 0.015 | 0.020 | -0.005 |
| | | (5) | (15) | (0) | | (8) | (17) | (0) | | (10) | (15) | (0) |
| Revolutions per pop. | 0.470 | -0.288 | -0.276 | -0.012 | 0.429 | -0.284 | -0.260 | -0.024 | 0.579 | -0.351 | -0.331 | -0.020 |
| | | (29) | (35) | (0) | | (28) | (36) | (0) | | (36) | (33) | (0) |
| Civil Liberties / Democracy | 0.031 | -0.008 | -0.010 | 0.003 | 0.027 | -0.004 | -0.009 | 0.005 | 0.035 | -0.010 | -0.012 | 0.002 |
| | | (0) | (3) | (0) | | (0) | (3) | (0) | | (1) | (4) | (0) |
| Internal/external conflict (dummy | 0.034 | 0.002 | -0.002 | 0.005 | 0.035 | 0.004 | -0.002 | 0.005 | 0.033 | 0.000 | -0.002 | 0.003 |
| | | (0) | (0) | (0) | | (0) | (0) | (0) | | (0) | (0) | (0) |
| Fin. openness (Chinn-Ito) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | | (16) | (14) | (0) | | (30) | (15) | (0) | | (17) | (14) | (0) |
| Primary school enrollment rate | 0.003 | 0.000 | 0.001 | -0.001 | 0.003 | -0.001 | 0.001 | -0.002 | 0.008 | 0.002 | 0.003 | -0.001 |
| | | (1) | (2) | (59) | | (11) | (1) | (97) | | (0) | (2) | (43) |
| Education Gini | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| | | (14) | (29) | (0) | | (16) | (29) | (0) | | (22) | (26) | (0) |
| Agriculture (% GDP) | 0.997 | -1.968 | -2.265 | 0.296 | 0.995 | -1.882 | -2.237 | 0.355 | 0.999 | -2.090 | -2.260 | 0.171 |
| | | (98) | (100) | (0) | | (88) | (100) | (0) | | (100) | (100) | (0) |

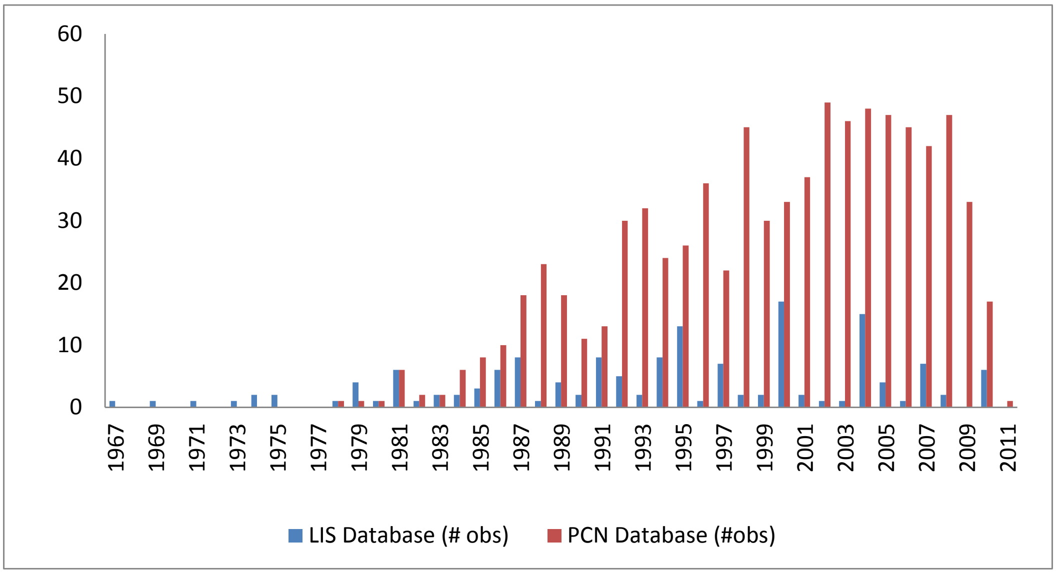
*Notes:* This table summarizes selected BMA results. The three panels correspond to specifications using the three indicated social welfare functions. Within each panel, the first column reports the posterior inclusion probability for the indicated explanatory variable. The second column within each panel reports the posterior probability-weighted estimated slope coefficients for the growth rate of social welfare (Equation (9)). The third and fourth columns within each panel report the corresponding posterior probability-weighted slopes for the regressions where growth in average incomes, and growth in the relevant equality measure, are the dependent variable. As discussed in the text, these two slope coefficients sum to the slope coefficient reported in the second column, and they are multiplied by the standard deviation of the corresponding right-hand-side variable. The numbers in parentheses indicate the fraction of models in which the estimated slope coefficient is statistically significantly different from zero and of the same sign as the posterior probability-weighted slope.
*Sources*: Authors' compilation.

**Figure 1. Weights On Individuals Implied by Social Welfare Functions**



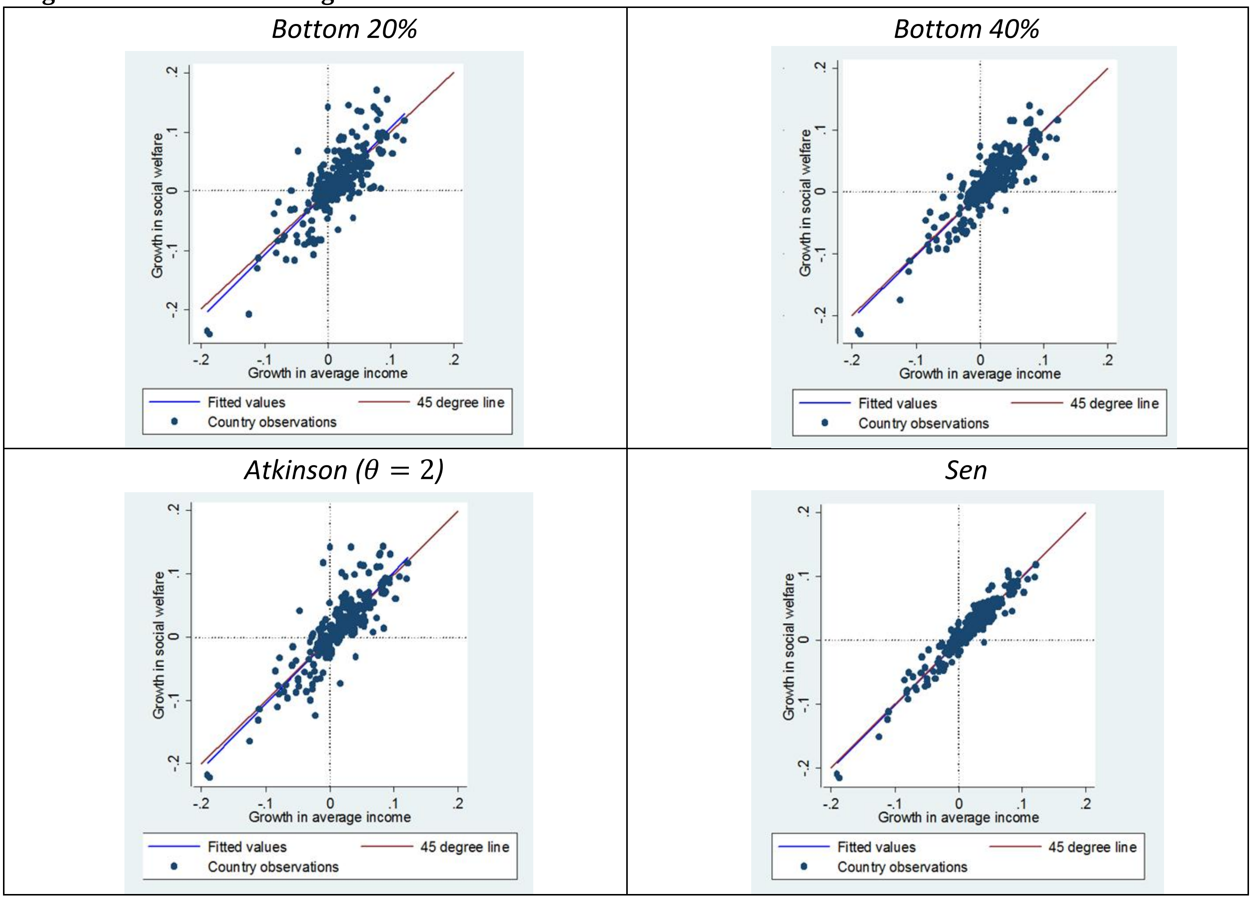

*Notes:* The graph shows the weights (on the vertical axis) assigned by the indicated social welfare functions to individuals at different points in the income distribution (on the horizontal axis). Weights are normalized to sum to one. Weights are in general data-dependent and are depicted for a hypothetical lognormal income distribution with a mean of $2000 per annum and a Gini coefficient equal to 0.30.
*Sources*: Authors' compilation.

**Figure 2. Availability of Household Survey Data (POVCALNET and LIS)**




*Notes:* This figure shows number of household surveys available in each year for the LIS and POVCALNET databases.
*Sources*: Authors' compilation.

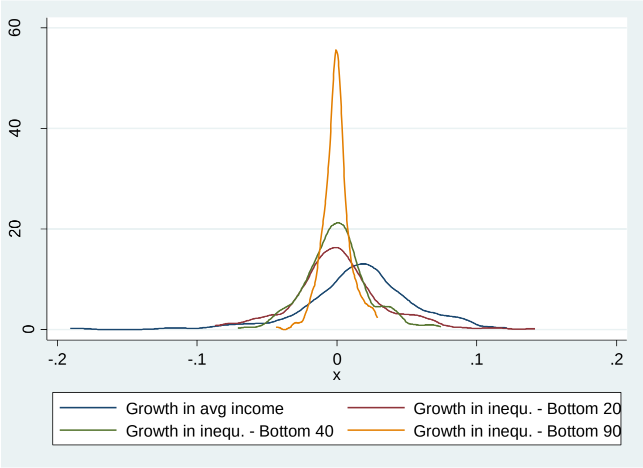
**Figure 3. Growth in Average Incomes and Growth in Social Welfare**



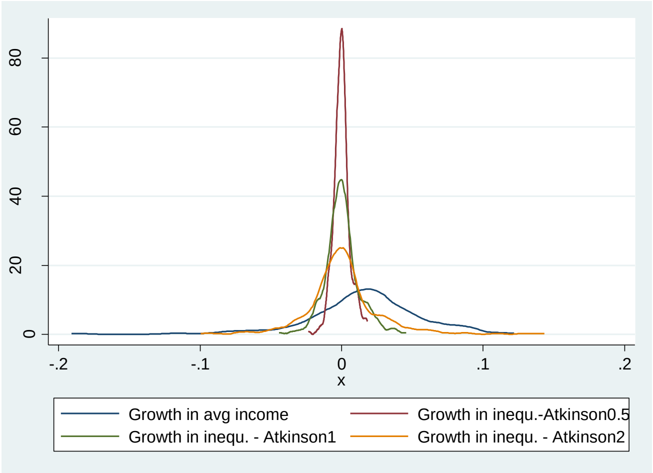

*Notes:* This graph plots the average annual growth rate in average income (on the horizontal axis) against average annual growth rate in social welfare (on the vertical axis), for a selected set of social welfare function. All growth rates are constant price annual average log-differences. The dataset consists of the sample of 285 non-overlapping spells lasting at least five years.
*Sources*: Authors' compilation.

**Figure 4. Distribution of Growth in Average Incomes and Growth in Inequality**

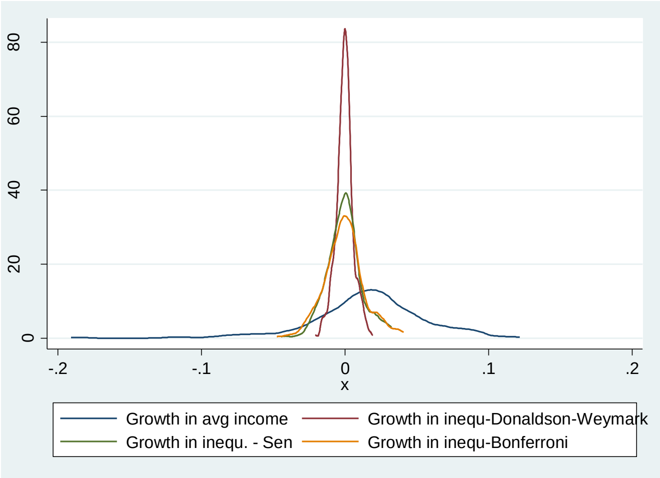
**Mean Income; Inequality Measures for Bottom 20, 40 and 90 Percent**




**Mean Income; Inequality Measures for Atkinson $(\boldsymbol{\theta} = \mathbf{0.5, 1, 2})$**




**Mean Income; Inequality Measures for Sen, Donaldson-Weymark $(\boldsymbol{\theta} = \mathbf{0.5})$ and Bonferroni**




*Notes*: This graph shows the kernel density estimate of the distribution of the growth rate of average income, and the growth rate of the inequality change component of the indicated social welfare functions. The dataset consists of 285 non-overlapping spells lasting at least five years.
*Sources*: Authors' compilation.

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## Appendix

**Table A.1: Description of control variables**

| 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:<br>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.<br>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.<br>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 |

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| | | 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. |
| Government expenditure on health and education (percent of GDP) | IMF social spending data, WDI, IMF GFS | Government expenditure on health and education is retrieved from various sources. We prioritize the data from Nozaki et al. (2011), we use WDI data for countries where the WDI coverage is better than the former, and as a third source we use the IMF Government Finance Statistics (GFS) for countries where this source offers the best coverage. We merge data sources only across but not within countries. Source: Nozaki Masahiro, Clements, Benedict and Gupta, Sanjeev. (2011). "*What Happens to Social Spending in IMF-Supported Programs?"*. http://www.imf.org/external/pubs/cat/longres.aspx?sk=25190.0 |
| 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. |