

# The Welfare Implications of Growth Regressions

Donal O'Neill\*†

May 10, 2005

## Abstract

Regressions relating the growth rate in income to initial income have been the source of much recent debate in growth economics. Recent research has emphasised the importance of allowing for non-linearities in these models when explaining the evolution of income over time. In this paper we argue these extended growth regressions are also useful in facilitating welfare comparisons across income distributions, in a way that is not possible using alternative measures of convergence. To do this we exploit the similarities between the income convergence literature and work on tax progressivity in the public finance literature. We illustrate our approach using both regional data across the United States, Japan and Europe and countrywide comparisons.

Keywords: Growth Regressions, Welfare, Equality of Opportunity, Progressivity

JEL Codes: O47

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\*I would like to thank Olive Sweetman and Philippe Van Kerm for helpful comments on earlier versions of this paper.

†Economics Dept., NUI Maynooth, Co. Kildare, Ireland. e-mail:donal.oneill@may.ie.

# 1 Introduction

The early literature on income convergence across countries was dominated by cross-section studies that regressed the growth rate of income on initial income to examine whether or not poor countries grew faster than richer countries. These regressions are sometimes called “Barro-regressions” (e.g. Quah 1993a)<sup>1</sup> and faster growth among poor countries has become known as  $\beta$ -convergence (e.g. Barro and Sala-i-Martin (1992) and Sala-i-Martin (1996a)). However, this approach has been the subject of much debate and has been criticised by many.<sup>2</sup> At a fundamental level a number of authors, including Friedman (1992) and Quah (1996), point out that, by itself,  $\beta$ -convergence tells us little about the dynamic evolution of incomes. Friedman (1992), quoting Hotelling (1933), argues that "the real test of a tendency towards convergence would be in showing a constant decline in the variance...among individual enterprises." In the growth literature this type of convergence has been labelled as  $\sigma$ -convergence. As noted by Islam (2003) one of the main arguments for the rejection of Barro’s conclusions centered on the failure of traditional growth equations to accommodate non-linear specifications. As a result more recent developments in growth econometrics has emphasised nonlinearities in the growth process (Kalaitzidakis et al (2001), Fiaschi and Lavezzi (2003) and Maasoumi et al (2005)). These procedures provide a more detailed description of the evolution of the distribution of realised incomes over time than was possible using traditional linear Barro-regressions.<sup>3</sup>

Although there have been significant econometric and theoretical devel-

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<sup>1</sup>Some authors refer to these regressions as *growth-initial level* regressions and reserve the label "Barro-Regression" only for cases in which the growth regressions include other controls in addition to initial income. This distinction is somewhat arbitrary and unnecessary for our study.

<sup>2</sup>For recent summaries of this literature see Islam (2003) and Durlauf et al (2005).

<sup>3</sup>Other critics of traditional growth regressions include Quah (1996), who argues that the speed of convergence estimated from growth regressions may simply reflect small-sample biases. However, he later acknowledges that the degree of precision reported in standard Barro-Regression casts doubt on this explanation. Lee, Pesaran and Smith (1997) discuss the econometric problems that arise when using Barro-Regression to estimate the structural parameters of a growth model. Although important, this issue is distinct from, and not relevant for the question we address in our paper. For detailed summaries of these issues and the alternative approaches to measuring convergence see de la Fuente (1997), Durlauf and Quah (1999) and Islam (2003).

opments in the analysis of growth models over time there has been very little empirical work devoted to characterising the welfare properties of the observed processes. When making welfare comparisons economists have traditionally focused on the distribution of observed outcomes. However in recent years a number of economists have argued that welfare comparisons should place greater emphasis on equality of opportunities rather than observed outcomes (e.g Fleurbaey (1995), Roemer (1998)). The equal-opportunity framework stresses the link between the opportunities available to an agent and the initial conditions which are inherited or beyond the control of these agents. At the individual level these conditions may include characteristics such as race, gender or parental income. At a country-level analysis one may be interested in knowing to what extent the future opportunities of a country are determined by their initial income level. From this perspective one possible goal of policy makers could be to ensure that the opportunities available to agents are unrelated to initial endowments. This need not necessarily eliminate inequality in observed outcomes. Proponents of equality of opportunity accept inequality of outcomes that arise from genuine choice or shocks that are unrelated to initial conditions.

The question that we address in this paper is whether growth regressions can contribute in a meaningful way to studies that focus, not on the the evolution of realised outcomes, but rather on the equality of opportunity across agents. We show that appropriate consideration of nonlinearities in the growth process is not only desirable when documenting the evolution of income over time but is also an essential component of a coherent equal-opportunity based welfare framework. In particular, we extend the work of Benabou and Ok (2001) to show precisely how flexible form growth regressions can facilitate welfare comparisons in ways that are not possible using some of the alternative convergence concepts that have been proposed.

## 2 Progressivity, Growth and Welfare

Transition probabilities,  $M_T(x|y)$ , specify the probability that an individual with income  $y$  today will earn at most  $x$  at time  $T$ . A number of authors have estimated associated transition matrices in the context of income convergence (e.g Quah (1993)). However, they are almost always presented as descriptive tools for understanding the evolution of observed incomes over time. However, in his survey of welfare theoretic approaches to the measurement

of mobility Maasoumi (1998) notes that "Mobility in any social hierarchy is an indication of opportunity." Benabou and Ok (2001) make a similar point when noting that many people care about mobility "not because income movements are intrinsically valuable, but primarily because of the hope that it helps attenuate the effects of disparities in initial endowments on future income prospects (pg. 2)." In their paper they derive conditions under which a mobility process can be characterised as opportunity-equalising, as well as providing criteria to determine if one process is more equalising than another.<sup>4</sup> To do this they abstract from agents' aversion to risk and summarise future available opportunities or income prospects using the conditional expectation function determined by the underlying mobility process:<sup>5</sup>

$$e_T(y) = \int_0^\infty x dM_T(x|y) \quad (1)$$

Thus  $e_T(y)$  summarises the opportunities available at time  $T$  to an agent with current income  $y$ .<sup>6</sup> <sup>7</sup> While Benabou and Ok (2001) characterise future available opportunities using the underlying transition process,  $M$ , it is relatively straightforward to recast their results in terms of the underlying growth process. To do this we note that final realised income,  $y_T$ , can always be written as the sum of initial income ( $y_0$ ), the expected change in income given the initial level ( $g(y_0)$ ) and a mean zero residual term ( $v_T$ ); that is:

$$y_T = y_0 + g(y_0) + v_T \quad (2)$$

In this case the opportunities available to agents at time  $T$ , with initial income  $y_0$ , can be written as:

$$e_T(y_0) = y_0 + g(y_0) \quad (3)$$

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<sup>4</sup>They consider monotonic mobility processes such that for any  $y_1, y_2$  with  $y_2 > y_1$  then  $M_T(x|y_1) \geq M_T(x|y_2)$  for all  $x$ . This implies  $e_T(y_2) > e_T(y_1)$ .

<sup>5</sup>The use of conditional means to summarise opportunity sets is discussed in more detail in their paper. A major advantage of this approach is that it significantly simplifies the comparison of different opportunity sets. For a general discussion of some of the problems that arise when evaluating opportunity sets see Sen (1985).

<sup>6</sup>Benabou and Ok (2001) consider only monotonic mobility processes such that for any  $y_1, y_2$  with  $y_2 > y_1$  then  $M_T(x|y_1) \geq M_T(x|y_2)$  for all  $x$ . This implies  $e_T(y_2) > e_T(y_1)$ .

<sup>7</sup>For extensions that consider discounted lifetime utilities see Benabou and Ok (2001) and Dardanoni (1993).

Writing the model in this way allows us to draw close parallels between the income convergence literature and the public economics literature on tax/benefit progressivity (Lambert (1993)).<sup>8</sup> Following the tax literature we define a growth process as progressive if  $\frac{d\left(\frac{g(y_0)}{y_0}\right)}{dy_0} < 0$ , regressive if  $\frac{d\left(\frac{g(y_0)}{y_0}\right)}{dy_0} > 0$  and proportional if  $\frac{d\left(\frac{g(y_0)}{y_0}\right)}{dy_0} = 0$ . Intuitively a growth process is progressive if low income countries experience faster growth rates than higher income countries.

This framework is sufficient to allow us to characterise the welfare properties of growth processes based on the progressivity or otherwise of the process. To see this let  $U(e)$  denote the utility accruing to an agent with future opportunities summarised by  $e$ . We assume  $U'(e) > 0$ . Following an established tradition in public economics define social welfare as the average utility across initial income levels. That is

$$W_F = \int U(e_T(y)) f(y) dy \quad (4)$$

where  $f(y)$  is the distribution of initial incomes.<sup>9</sup> We can then establish the following theorem:<sup>10</sup>

**Theorem 1**

*A monotone growth process increases (decreases) welfare more than an equal yield proportional growth process applied to the same pre-growth income distribution for all strictly concave  $U$  and for all possible initial income distributions if and only if the growth process is progressive (regressive).*

Proof: See Appendix

This theorem states that progression in the growth process, over the entire range of income, is a necessary and sufficient condition for the resulting

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<sup>8</sup>In the tax/benefit literature,  $y_0$  would represent the tax/benefit base,  $e$  would represent final income and  $g(y_0)$  would represent net benefits. See also Benabou and Ok (2001).

<sup>9</sup>See Lambert (1993) section 4.2 for a rationalisation of this social welfare function.

<sup>10</sup>See also Corollary 3 of Benabou and Ok (2001) .

distribution of opportunities to welfare dominate the distribution of opportunities derived from an equal yield proportional mobility process, irrespective of the initial income distribution. An immediate corollary of this theorem is that a distribution of future opportunities across agents generated by a progressive growth process will welfare dominate the initial distribution of opportunities provided average income does not decline.

It is important to note the role of progressive growth in the above analysis. Since we are only considering monotone growth processes then progressivity must reduce the variance of future available opportunities across agents relative to those available in the initial distribution.<sup>11</sup> However, in general it is possible for the process to be monotonic, for mean income to rise and for inequality (as defined by the variance or Gini coefficient of opportunities) to fall and yet for Generalised Lorenz curves to cross so that unambiguous welfare rankings are not possible. A simple example which illustrates this possibility is given in Table 1. The first column shows the distribution of initial incomes (opportunities) and the second column shows a hypothetical distribution of future opportunities derived from this distribution. The last 4 rows summarise the respective distributions. The example is constructed so that on average opportunities have improved and dispersion in opportunities has fallen. This is true for each of the three standard measures of inequality reported. Furthermore the growth process is monotonic in that the rankings of countries in both distributions are preserved. Despite all of this it can be easily shown that the Generalised Lorenz Curves for these two distributions cross, which prevents unambiguous welfare rankings across the two distributions. The reason for this is that the growth process in this example is not progressive over the entire range. For example the growth rate for the second richest person is larger than the growth rate for the second poorest, which is a violation of progressivity.

Lambert (1993) provides a more detailed discussion of the restrictions that must be imposed on preferences in order for the social welfare function to be completely summarised by mean income and a scalar index of inequality. He also discusses the limitations that these restrictions place on the type of inequality indices which could summarise social welfare. This latter discussion may have interesting implications for how one should measure  $\sigma$ -convergence in cross-country studies of income inequality. However, the key

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<sup>11</sup>As mentioned earlier, this need not imply a reduction in the dispersion of observed outcomes.

result that emerges from this analysis is that *in order to make unanimous welfare comparisons across distributions of opportunities it matters how the reduction in inequality is generated. Simply comparing the variance of future available opportunities with current opportunities is not sufficient to establish welfare rankings.*

The above analysis shows how progressivity in the growth process can be used to facilitate welfare comparisons across alternative growth processes. We now establish the relationship between progressivity in the growth process and measures of  $\beta$ -convergence derived from a traditional growth regression. To determine the progressivity of the growth process we need to establish whether  $\frac{d\left(\frac{g(y_0)}{y_0}\right)}{dy_0} \leq 0$  for all  $y_0$ . Using the fact that  $\frac{d\left(\frac{g(y_0)}{y_0}\right)}{dy_0} \leq 0$  for all  $y_0$  if and only if  $\frac{d\left(\frac{g(y_0)}{y_0}\right)}{d \ln(y_0)} \leq 0$  for all  $y_0$ , we can use the following model of log income to characterise progressivity:

$$\ln y_T = \ln y_0 + m(\ln y_0) + \varepsilon_T \quad (4)$$

where  $\varepsilon_T$  is a mean zero error term. Progressivity of the growth process requires  $\frac{dm(\ln y_0)}{d \ln y_0} \leq 0$  everywhere. However, equation (4) is simply a flexible form Barro-regression and our progressivity condition is nothing more than a negativity condition on the slope of a non-parametric cross-sectional growth-initial level regression. Thus the progressivity requirements needed for welfare comparisons of alternative growth processes can be stated in terms of the  $\beta$ -convergence estimates obtained from a flexible specification of a Barro-regression. This highlights a potentially important role for growth regressions that extends beyond their ability to distinguish between competing theories of growth or their capacity provide a useful summary of the evolution of realised outcomes.

### 3 Empirical Analysis

In this section we illustrate our approach using regional data sets taken from Barro and Sala-i-Martin (1995), as well as country level data taken from the Penn-World Tables Version 6.1. The regional data sets are those used by Sala-i-Martin (1996b) to study regional cohesion. Sala-i-Martin estimated linear Barro-regressions for the regions of the United States, Japan and Europe. In

order to apply Theorem 1 however we must consider flexible estimators of the growth process that allow for possible nonlinearities. To do this we extend Sala-i-Martin's empirical analysis by estimating flexible nonparametric growth equations for each of these data sets. In particular we estimate the following flexible form growth equation:

$$\ln \left( \frac{y_{i,T}}{y_{i,0}} \right) / N = m[\ln(y_{i,0})] + \epsilon_{i,T} \quad (5)$$

In each case we use the Nadaraya-Watson kernel estimator to obtain a flexible estimate of  $m[\ln(y_0)]$ .<sup>12</sup> The dates for which the analysis is conducted depends on data availability and differs across data sets. The data for the US refer to real annual personal income per capita for each of the 48 contiguous states from 1900 to 1990. The Japanese data measure real per capita income between 1955 and 1990 for the 47 prefectures, as collected by the Economic Planning Agency of Japan. Finally the European data measure GDP per capita in each of 90 regions of Europe covering Germany (11 regions), United Kingdom (11 regions), Italy (20 regions), France (21 regions), The Netherlands (4 regions), Belgium (3 regions), Denmark (3 regions) and Spain (17 regions).<sup>13</sup>

The nonparametric estimates,  $m[\ln(y_0)]$ , for the US states, the Japanese prefectures and the European regions are given in Figures 1-3 respectively. Our principal concern is the extent to which the growth process exhibits progression or regression over the income range; equivalently the extent to which the slope of  $m[\ln(y_0)]$  is negative or positive at each value of  $y_0$ . Recalling Theorem 1 we note that it is this feature of the growth process that facilitates welfare comparisons across the distribution of opportunities. Figures 1-3 show that all the regional growth processes exhibit progressivity over almost all of their respective income ranges. Indeed the only evidence of

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<sup>12</sup>For a more detailed discussion of kernel regression techniques see Blundell and Duncan (1998).

<sup>13</sup>Following Sala-i-Martin (1995) the European GDP figures are expressed as deviations from country specific means. Thus the estimated growth process we present for the regions of Europe should be interpreted as a common, within country growth, process. More details on these data, including maps illustrating the regions under consideration, are available in Barro and Sala-i-Martin (1995).



regressive growth for these data occurs among high income Japanese prefectures. However, even then the confidence intervals are such that we cannot rule out progressive growth over this income range. On the other hand we clearly reject the possibility that income growth is regressive over the entire income range for all the regional growth processes. In this case Theorem 1 implies that there exists *at least one* initial income distribution for which the observed growth process welfare dominates an equal yield proportional growth process. Furthermore, since the data strongly supports the hypothesis of progressivity over the entire range, our data are consistent with a scenario in which the distribution of future opportunities derived from the observed process unambiguously welfare dominates that obtained from a proportional growth process for *all possible initial income distributions* in all of the regions. Since average income has risen over this period in each of our regional data sets, and since we can always view the identity mapping as a proportional growth process, our data also support the hypothesis that the distribution of opportunities available today within each of these regions welfare dominates that available previously.

We can also apply our approach to examine income growth across countries using the Penn World Table version 6.1. These data provide national incomes converted to international prices from 1950-2000. We use data for the period 1960-2000. We begin by looking at the unconditional growth process for the OECD countries and for a world sample of 83 countries for which there were no missing data.<sup>14</sup> The non-parametric estimates of  $m[\ln(y_0)]$  for both these samples are given in Figures 4 and 5 respectively. The estimated growth process for the OECD countries exhibit a high degree of nonlinearity. Progressivity is most pronounced at low and high income levels. However, there is a middle range of incomes for which the estimated growth process is approximately proportional. Nevertheless the confidence intervals are such that the inferences that we can draw from the sample of OECD countries mirror those presented earlier for the regional data sets. We reject regressive income growth over the entire income range but cannot reject the hypothesis of progressivity over all initial income levels. Thus the data are consistent with welfare improving growth among the OECD countries.

The situation for the entire world sample is different however. Figure 5 highlights important nonlinearities in the estimated growth process for the world sample. For this sample however, the overall tendency is for regressive

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<sup>14</sup>A complete list of these countries is given in Table 2.

income growth, especially over a broad range of middle income countries. Unfortunately the confidence intervals are such that we cannot draw precise welfare inferences from the estimated growth process. All three processes, progressive, proportional and regressive are consistent with the data so that none of the competing welfare rankings can be rejected.

For this sample however it may be possible to make some progress if we consider conditional convergence rates rather than absolute convergence. Following previous literature (e.g Mankiw, Weil and Romer (1992)) we condition on a country's average savings rate, average annual population growth rate and average human capital level.<sup>15</sup> Traditionally in the growth literature these conditioning regressors are interpreted as controls for differences in steady states, which facilitate tests of the traditional Solow growth model. When considering equality of opportunity one can alternatively think of these as controls to ensure that ex-ante, conditional on initial income, each country has access to the same set of choices.<sup>16</sup> To estimate the conditional Barro-regression we specify the following loglinear model:

$$\ln \left( \frac{y_{i,T}}{y_{i,0}} \right) / N = \theta \ln(S_i) + \phi \ln(n_i) + \delta \ln(H_i) + h[\ln(y_{i,0})] + \epsilon_{i,T} \quad (5)$$

The steady state control variables (the average share of real investment in real GDP ( $S$ ), the average population growth rate ( $n$ ), and the average years schooling ( $H$ )) enter parametrically but we allow the function measuring progression,  $h[\ln(y_0)]$ , to be estimated nonparametrically. To estimate this model we follow the procedure outlined by DiNardo and Tobias (2001). The data is sorted by ascending order of initial income. Estimates of  $\theta$ ,  $\phi$  and  $\delta$  are obtained from a differenced regression of the dependent variable on

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<sup>15</sup>Our measure of the savings rate is the average share of investment in GDP and our measure of human capital is average years of schooling of the population aged 15 or over. The schooling measure is taken from Barro and Lee (2000).

<sup>16</sup>In the latter case it may be more appropriate to condition on the levels of savings human capital and population growth at the start of the period  $S_{0,i}$ ,  $H_{0,i}$  and  $n_{0,i}$  rather than the average over the entire period. However, for these data the results are likely to be very similar irrespective of which sets of controls are used. We present the ones based on the average levels as they are in keeping with previous work on conditional growth (e.g Mankiw, Weil and Romer (1992)). For a nonlinear sensitivity analysis of cross-country growth equations to alternative sets of control variables see Kalaitzidakis et al (2000).

differenced values of  $\ln(S)$ ,  $\ln(n)$  and  $\ln(H)$ . These estimates are used to purge the original dependent variable of the effects of the variables that enter the model in a linear fashion. Finally, a non-parametric regression is carried out using the new purged dependent variable and the log of initial income to get an estimate of  $h[\ln(y_0)]$ .

The resulting estimate of  $h[\ln(y_0)]$  is given in Figure 6. While Kalaitzidakis et al (2001) and Fiaschi and Lavezzi (2003) estimated similar models so as to illustrate the role of nonlinearities in the growth process, our principal concern is more specific; the extent to which the growth process exhibits progression or regression over the entire income range. Looking at Figure 6 the only evidence of regressive growth occurs at very low incomes. However, we clearly reject the possibility that income growth is regressive over all incomes. However, we fail to reject the hypothesis of progressivity over the entire range. Thus **conditional on differences in steady state incomes**, the world growth process is consistent with a scenario in which the distribution of future opportunities derived from the observed process unambiguously welfare dominates that obtained from a proportional growth process for *all possible initial income distributions*.<sup>17</sup> However, introducing additional regressors into our growth regressions raises a number of additional issues. Firstly, conditioning on additional regressors may lead to biased estimates due to endogeneity. Some authors have used panel data techniques to address this issue (e.g Caselli et al (1996)). They find that controlling for endogeneity increases the rate of convergence to approximately 10% per year, which is equivalent to increased progressivity in the growth process. Although at face value this would only tend to strengthen our welfare conclusions there are reasons to believe that the rate of convergence reported by Caselli et al is implausibly high.<sup>18</sup> Furthermore the panel estimates available to date have not, as yet, adequately addressed the issue of nonlinearities in the growth process; as already noted, it is difficult to draw welfare conclusions on the basis of average measures of convergence or progressivity. A more fundamental objection to using conditional growth equations when making welfare comparisons

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<sup>17</sup>Similar welfare inferences can be drawn from the estimates provided by Fiaschi and Lavezzi (2003) (Figure 5 page 393). The results presented by Kalaitzidakis et al (2001) on the other hand are such that the confidence intervals around the regressive range in their estimated process led to rejection of **both** the regressive and progressive hypothesis. Hence in their data unambiguous welfare rankings are not possible at the world level even after conditioning on steady state differences.

<sup>18</sup>See Temple (1999) and Islam (2003).

was raised by Islam (2003). He notes that "the welfare implications of conditional convergence finding for global samples is rather limited, because it only means that poor countries are moving towards their own steady states, and knowing this may be of little solace if those steady states income levels are themselves very low." Our analysis provides an explicit theoretical and empirical basis for this assertion.

## 4 Conclusion

Cross-Section regressions in which growth rates are regressed on initial values are widespread in economics. These regressions have been criticised on the grounds that they do not fully incorporate the range of restrictions imposed by alternative growth models and for failing to provide much insight into the evolution of income distributions over time. Accepting these criticisms, our paper draws on similarities between the convergence literature and the tax progressivity literature in public economics to show that appropriately specified growth regressions may, nevertheless, facilitate welfare comparisons that are not possible from analyses based on alternative measures of convergence. To do so we must allow for possible nonlinearities in the growth process. We illustrate the approach by examining the growth process for the US states, the prefectures of Japan, the regions of Europe, the OECD countries and the world as a whole. For almost all of these data sets the results are similar. Flexible non-parametric growth regressions indicate that the growth processes observed over recent times have been unambiguously welfare improving. The only exception occurs when we consider the growth process at the world-level. For this process our analysis explicitly highlights the fact that welfare comparisons at the world level depend crucially on how one interprets differences in long-run income levels.

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# Appendix:

## Proof of Theorem 1

Define the expected growth rate for person with initial income  $y_0$  as  $\gamma(y_0) \equiv \left(\frac{g(y_0)}{y_0}\right)$ .

$\implies$  Under proportional growth then the Lorenz curve of opportunities at time  $T$ ,  $(e_T(y_i))$ , must equal the Lorenz curve for initial incomes or opportunities ( $e_0 \equiv y_0$ ).

That is  $L_{e_{prop,T}}(p) = L_{e_0}(p)$  for all  $p \in [0,1]$

By definition  $e_T(y_0) = y_0 + g(y_0)$ .

Taking the average across agents we get that  $\bar{e}_T = \bar{e}_0(1 + \bar{\gamma})$ , where  $\bar{\gamma}$  is the average expected growth rate across agents  $\left(\bar{\gamma} = \frac{\sum \frac{g(y_0)}{y_0}}{N}\right)$  and  $\bar{e}_0$  is average initial income or opportunities.

Hence the Generalised Lorenz Curve for future opportunities derived from a growth process characterised by  $\gamma(y)$  can be expressed as :

$$GLC_{e_{\gamma T}}(p) = \bar{e}_0(1 + \bar{\gamma})L_{e_T}(p),$$

where  $L_{e_T}(p)$  is the Lorenz curve of future opportunities.

If our observed growth process is progressive, that is  $\gamma'(y) < 0$  for all  $y$ , then we can use the Jakobsson-Fellman theorem (Lambert (1993) page 150) and our assumption of monotonicity to conclude that :

$$GLC_{e_{\gamma T}}(p) = \bar{e}_0(1 + \bar{\gamma})L_{e_T}(p) \geq \bar{e}_0(1 + \bar{\gamma})L_{e_0}(p) = \bar{e}_0(1 + \bar{\gamma})L_{e_{prop,T}}(p) \text{ all } p \in [0,1].$$

The first inequality follows from our assumptions of monotonicity and progressivity and the last equality follows from step 1 of the proof.

By definition this implies that:

$$GLC_{e_{\gamma T}}(p) \geq GLC_{e_{prop,T}}(p) \text{ all } p \in [0,1].$$



Referring to Shorrocks' (1983) completes the proof in this direction.

$\Leftarrow$  Suppose  $GLC_{e_{\gamma T}}(p) \geq GLC_{e_{prop,T}}(p)$  for all  $p$  and any pre-growth income distribution.

Then following the logic above we can establish that

$$L_{e_T}(p) \geq L_{e_0}(p) \text{ for all } p \text{ and all pre-growth income distributions}$$

From the Jakobsson-Fellman theorem we can then conclude that the mobility process is progressive for all  $y_0$ .

Table 1: Ambiguous Welfare Rankings in the Presence of Declining Income Dispersion.

| $y_{i,0}$               | $e(y_{i,0})$             |
|-------------------------|--------------------------|
| 10                      | 17                       |
| 20                      | 20                       |
| 30                      | 21                       |
| 40                      | 45                       |
| 50                      | 48                       |
|                         |                          |
| Mean Income=30          | Mean Income=30.2         |
| Gini=.266               | Gini=.23                 |
| Coefficient of Var=.527 | Coefficient of Var.=.496 |
| $\sigma_{\ln}$ =.636    | $\sigma_{\ln}$ =.489     |

Table 2: Full Sample of 83 countries included in the analysis

|                    |                    |            |             |                          |
|--------------------|--------------------|------------|-------------|--------------------------|
| Argentina          | Costa Rica         | India      | Malawi      | Sweden                   |
| Australia          | Denmark            | Ireland    | Malaysia    | Switzerland              |
| Austria            | Dominican Republic | Iran       | Nigeria     | Syria                    |
| Belgium            | Algeria            | Iceland    | Nicaragua   | Chad                     |
| Benin              | Ecuador            | Israel     | Netherlands | Togo                     |
| Bangladesh         | Egypt              | Jamaica    | Norway      | Thailand                 |
| Bolivia            |                    | Jordan     | Nepal       | Trinidad and Tobago      |
| Brazil             | Finland            | Japan      | New Zealand | Turkey                   |
| Barbados           | France             | Kenya      | Pakistan    | Tanzania                 |
| Canada             | Ghana              | Korea      | Panama      | United Kingdom           |
| Chile              | Gambia             | Sri Lanka  | Peru        | Uganda                   |
| China              | Guinea-Bissau      | Lesotho    | Philippines | Uruguay                  |
| Cameroon           | Greece             | Mexico     | Portugal    | United States of America |
| Congo, Republic of | Guatemala          | Mali       | Paraguay    | Venezuela                |
| Colombia           | Hong Kong          | Mozambique | Romania     | South Africa             |
| Spain              | Honduras           | Mauritius  | Rwanda      | Zambia                   |
| El Salvador        | Indonesia          |            | Senegal     | Zimbabwe                 |

Table 3: Summary Statistics

| Variable   | Average   | Minimum      | Maximum        |
|------------|-----------|--------------|----------------|
| $H_i$      | 4.6 years | .5 (GNB)     | 10.8 (NZL)     |
| $n_i$      | 3.2%      | .3% (BEL)    | 11.68% (JOR)   |
| $S_i$      | 16.6%     | 2.06% (UGA)  | 31.80% (NOR)   |
| $y_{1960}$ | 3699      | 381.5 (TZA)  | 14978.25 (CHE) |
| $y_{2000}$ | 9560      | 481.87 (TZA) | 33292 (USA)    |

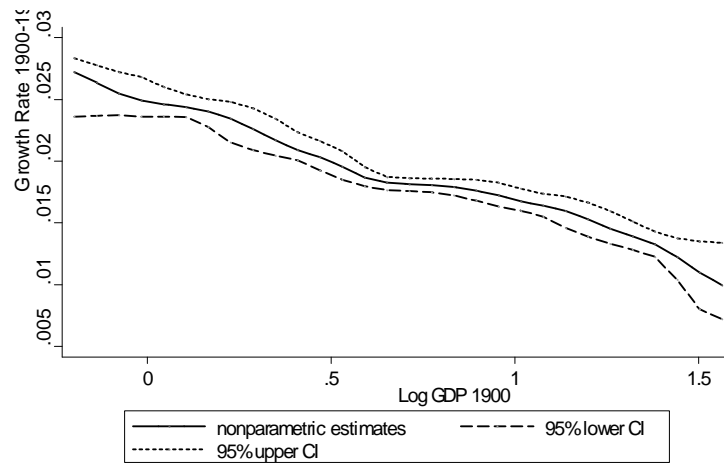


Figure 1: Nonparametric Estimates of the Growth Process across the US States.

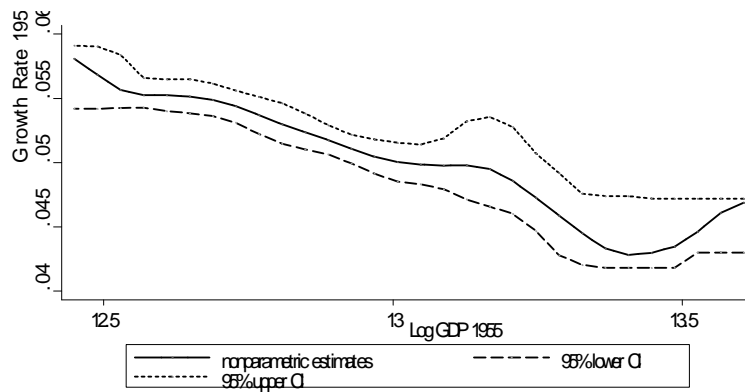


Figure 2: Nonparametric Estimates of the Growth Process across the Japanese Prefectures.

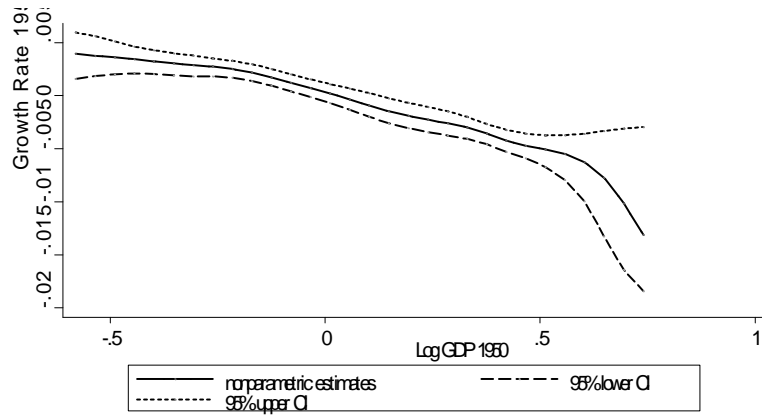


Figure 3: Nonparametric Estimates of the Growth Process Across the European Regions.

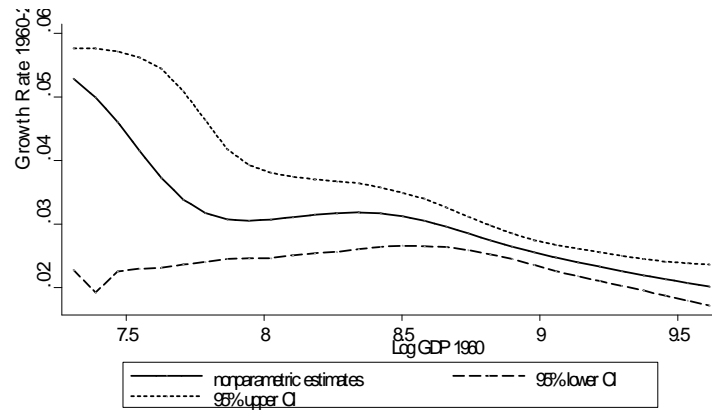


Figure 4: Nonparametric Estimates of the Growth Process Across the OECD Countries.

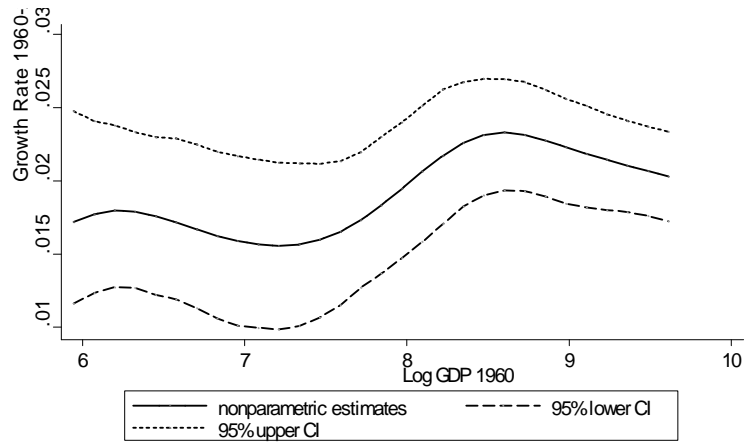


Figure 5: Nonparametric Estimates of the Unconditional Growth Process Across the World.

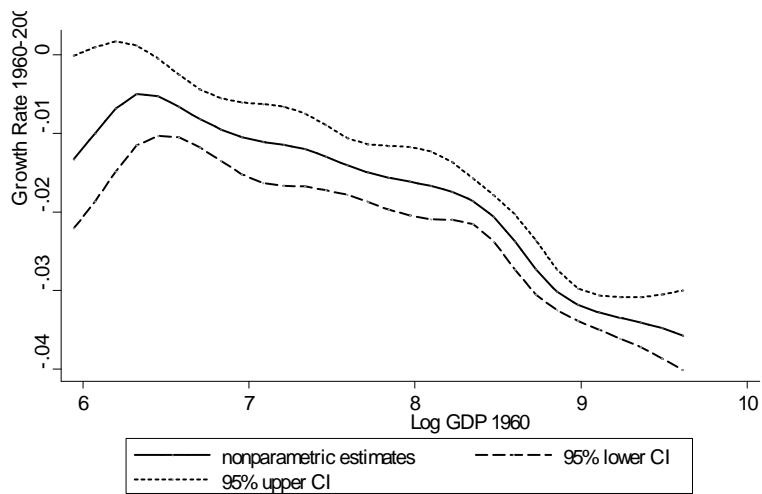


Figure 6: Nonparametric Estimates of the Conditional Growth Process Across the World.