WHAT KIND OF REGIONAL CONVERGENCE?

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Abstract

Recent estimates of convergence equations using panel data techniques tend to produce theoretically unpalatable results which run counter to the views prevailing in the literature. This paper argues that these results (and in particular the very high convergence coefficients obtained in many of these studies) may be partly due to the difficulty of empirically separating short-term fluctuations around trend from long-term growth dynamics. Using data for the Spanish regions, I find that explicitly allowing for short-term noise reduces the estimated convergence rate to values which are consistent with an extended neoclassical model. On the other hand, the dispersion of estimated steady states remains high, but these estimates do not seem to be particularly reliable as predictors of long-run equilibrium income levels.

JEL Classifiction: O40, C23

Key words: convergence, panel data

Non-technical summary

Just a few years ago, researchers seemed to be close to reaching a consensus on the basic mechanics of economic growth. The dominant view in the literature was that the growth experience of countries and regions was broadly compatible with an augmented Solow-type neoclassical model built around and extended concept of capital which included investment in intangibles such as education and R&D.

This conclusion was largely based on empirical estimates of growth equations by authors such as Barro and Sala (1992) and Mankiw, Romer and Weil (1992). Starting from simple but fully specified growth models, these authors derive empirical specifications that relate the growth rate of income per capita or output per worker to the initial level of income and other conditioning variables. One of the key parameters of these equations is a convergence coefficient that measures the speed at which an economy approaches a long-run equilibrium whose position is determined by a set of underlying "fundamental" variables which is typically held to include the rate of population growth and investment rates in various types of assets. This parameter can be shown to be closely related to the degreee of returns to scale in the different types of capital, with convergence being faster the faster diminishing returns set in. Most early studies in the field found evidence of slow convergence for a variety of national and regional samples. This finding was interpreted as an indication that the aggregate production function exhibited close to constant returns to scale in a broad capital aggregate. Subsequent research confirmed this result as well as the statistical significance of the relevant investment rates, thereby reinforcing the view, common in the new growth literature, that the accumulation of human and technological capital was an important engine of growth.

In recent years, however, this view has been challanged by a series of papers that find evidence of extremely fast convergence but to very different steady states which cannot be explained by differences in investment rates or other commonly used conditioning variables. These findings, which are particularly striking at the regional level (where no important differences in unobserved fundamentals are expected), are disturbing because i) they suggest that we can explain only a fraction of observed income differences across economies in terms of the variables commonly held to be crucial for growth and ii) they may be interpreted as evidence in favour of old-fashioned neoclassical models in which human and technological capital play no role.

This paper investigates the possibility that these theoretically unpalatable results may be due to econometric problems arising from the difficulty of empirically distinguishing between long-term growth dynamics and short-term fluctuations. Its starting point is the observation that differences in existing estimates of convergence rates and the dispersion of long-run equilibria seem to arise mostly from the choice of econometric specification. In particular, high convergence rates are generally found only in studies which make use of panel data techniques in order to control for potential unobservable differences across economies. In practice, however, these techniques involve discarding most of the information contained in cross-country or cross-regional differences and produce parameter estimates which reflect only the variation in growth rates and structural characteristics over time within a given economy. Since the application of these techniques, moreover, involves working with averages over relatively short periods in order to increase the number of observations, it seems likely that much of the information left in the data has to do with short-term fluctuations around trend or capacity output. If economies oscillate around their trends due to business cycles and other transitory disturbances, the estimation of a single convergence coefficient is likely to produce a high value which can be mistakingly interpreted as a measure of the speed at which the economy approaches its steady state.

To explore this possibility, I write down a simple variation on the standard convergence model and use it to try to disentangle short- and long-term dynamics. Using a sample of Spanish regions, I try to "split" the estimated rate of convergence into a long-term and a short-term component which capture, respectively, the forces described by a standard growth model and short-term adjustments to transitory deviations from trend output. I also perform a series of experiments which involve torturing different sets of panel estimates in an attempt to extract from them some information on the likely importance of various econometric problems which beset alternative specifications of convergence regressions. The results seem to confirm that panel estimates of the (long-run) convergence rate tend to be too high due to the difficulty of distinguishing convergence from short-term fluctuations. On the other hand, steady-state dispersion, remains quite high even after correcting for this problem. While this result points to the need for further research into the determinants of growth rates and income levels, some of my findings also cast doubt on the reliability of panel data estimates of long-run equilibria. These estimates, in particular, are either too sensitive to the length of the sample or track observed end-of-sample values too closely to be considered reliable predictors of long-term income levels.

1.- Introduction

A plausible theoretical case can be made for the proposition that income per capita, or at least output per worker, should display a strong tendency towards equalization across the regions of a given country. Membership in the same nation state ensures that regional economies share a common set of policies and institutions and face no legal obstacles to the free flow of goods, productive factors and ideas across them. Language and other cultural barriers also tend to be relatively low, as most countries are reasonably homogeneous in this respect. In a neoclassical world, free trade and factor mobility together with the rapid diffusion of technology should reinforce the basic tendency towards convergence in closed economies that follows from the assumption of decreasing returns to scale in reproducible factors. To the extent that cross-regional differences in "fundamentals" can be expected to be minor, such convergence should be roughly absolute, i.e. towards a common level of income. Complete equality cannot of course be expected due to the inevitable shocks but in the long run we should observe a compact and fluid distribution in which, under "normal" conditions, regions display only minor fluctuations around a common trend and exchange relative positions frequently.

Is the empirical evidence consistent with this view? Although regional growth patterns have been subjected to very careful scrutiny in recent years, the literature does not yet provide a conclusive answer to this question. Practically all the relevant studies find evidence of some sort of convergence, in the sense that (possibly after holding other things constant) poorer regions within a given country do indeed tend to grow faster than richer ones. This finding implies that, in the absence of some sort of structural change, regional relative incomes will eventually stabilize, asymptotically approaching a stationary distribution characterized by a constant and finite variance. There is, however, considerable disagreement about the speed of convergence to this asymptotic distribution and about the degree of income dispersion likely to remain in the long run.

Some of these disagreements are more apparent than real, as the stationary distributions characterized in different studies are often very different animals. While some of them are indeed intended as estimates of the asymptotic distribution of regional income, others are conditional on a set of factors which can only be expected to change over time. Hence, estimates of convergence rates and steady-state income variances must be interpreted with care and are often more compatible with each other than they seem at first sight. Even so, two distinct and clearly opposed views can be found in the literature on the issue of where the regional convergence process is heading in the long run. While some researchers argue that the evidence is compatible with absolute, although very slow, convergence, others report extremely fast convergence but to very different steady states.

Which of these views is right makes some difference for policy purposes, but probably not that much. If convergence were both absolute and rapid, there would be no need for traditional regional development policies, although room would remain for some sort of risk-pooling mechanism which might help mitigate the effects of adverse short-term shocks. Since this is apparently the only possibility we can rule out with some confidence, one can make the case for regional policies on two alternative grounds. If convergence is absolute but slow, government policy may be useful as an instrument to accelerate the transition towards the steady state, helping eliminate more rapidly initial differences in per capita income levels. If convergence is only conditional, with important regional differences tending to persist indefinitely (and if the resulting degree of inequality is considered unacceptable on political or ethical grounds), then the need for an active regional policy would remain even in the long run. Such a policy, moreover, should be aimed at correcting thoose cross-regional differences in "fundamentals" which presumably account for persistent income disparities.

The theoretical implications of alternative convergence results are potentially more important. Until recently at least, the consensus view in the literature seemed to be that slow cross-regional or cross-national convergence should be interpreted as evidence in favour of some sort of extended neoclassical model with only slightly diminishing returns to scale in a broad capital aggregate.[1] From this perspective, recent findings of fast but only conditional convergence, both across countries and across regions, are deeply unsettling for two reasons.[2] The first is that one possible interpretation of high convergence rates takes us back to the old-fashioned neoclassical model with narrowly defined capital and sharply diminishing returns to scale. The second is that the size and significance of the coefficients of the regional dummies which lie behind estimates of widely dispersed steady states suggest that regions are much more different from each other than we used to think, and that they differ in ways we do not understand very well. In a very real sense, these two findings together take us back to 1957, right after the discovery of the Solow residual, and negate much of what we thought we had learned since then. While it now arises in a cross-section rather than a time-series setting, the problem is essentially the same one: we cannot really explain why output varies across time or space in terms of the things we think are important and know how to measure.

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1 See de la Fuente (1997) for a survey of the convergence literature.

2 While we will focus on studies of regional convergence, similar issues arise at the national level. Using panel data techniques, Knight et al (1993), Islam (1995) and Caselli et al (1996), among others, find evidence of rapid convergence across countries toward very different steady states whose dispersion is due to a large extent to permanent differences in total factor productivity rather than to investment rates. In these papers, moreover, human capital variables generally lose their significance.

If this is indeed the case, it is probably a good thing that we found out, as this may push us toward richer models and a better understanding of the growth process. But I would argue that such pessimism is at least premature. Perhaps the main reason is that there are other possible explanations for some of the recent empirical findings which are theoretically more agreeable than sharply diminishing returns. One possibility is that fast convergence may reflect the operation of other convergence mechanisms (such as technological diffusion, sectoral change or extremely high factor mobility across regions) that are generally not considered by the standard models in the literature. In de la Fuente (1996), I provide some evidence that suggests that this is in fact the case. A second possibility is that panel estimates of growth equations may systematically overestimate the rate of convergence due to econometric problems having to do with the difficulty of empirically distinguishing long-term convergence from short-term fluctuations around trend output.

This paper focuses on the second possibility. I will concentrate on regional growth because the theoretical and empirical issues we have just discussed arise in a particularly stark way in this context. To set the stage, Section 2 provides an overview of recent research on regional growth. The discussion will focus on the implications of different studies for the rate of convergence and the persistence of regional inequality, and on the differences in econometric specifications that seem to underlie conflicting empirical results. At the risk of oversimplifying, we can identify two opposing views on regional convergence (fast and conditional vs. slow and absolute) which, to a large extent, can be traced back to the choice of estimation technique (dummy-variable fixed effects models or other panel estimators vs. cross-section or pooled data regressions).

In Section 3 I will turn to the data to explore the relative merits of these alternative views and estimation techniques. Using a sample of Spanish regions, I will try to "split" the estimated rate of convergence into a long-term and a short-term component which capture, respectively, the forces described by a standard growth model and short-term adjustments to transitory deviations from trend output. I will also perform a series of experiments which involve torturing different sets of panel estimates in an attempt to extract from them some information on the likely importance of various econometric problems which beset alternative specifications of convergence regressions. The results are consistent with Shioji's (1997a,b) conclusion that the extremely high convergence rates obtained by some recent panel studies considerably overestimate the long-run convergence parameter -- which is the relevant one for growth theory issues. My findings are much less conclusive regarding the persistence of inequality. While there seem to be clear indications in the data that the Spanish regions are not converging to a common long-term income level, fixed-effect estimates of the asymptotic distribution do not seem to be particularly trustworthy, as steady state estimates are either extremely sensitive to the length of the sample or seem to track rather mechanically observed end-of sample incomes and to mirror the evolution of this variable as we change the length of the sample. Hence, standard panel techniques do not seem to be able to provide a reliable test of the absolute convergence hypothesis and may give the misleading impression of extremely high persistence of inequality.

2.- A bird's eye view of the literature

In a series of influential papers, Barro and Sala (BS (1990, 1991, 1992a,b), Sala (1996)) have argued that the empirical evidence is consistent with the hypothesis of absolute regional convergence. Starting from a standard neoclassical model of growth, these authors derive a convergence equation which they estimate using different national and regional samples. In both cases, they find clear evidence of convergence (i.e. of a negative partial correlation between initial income per capita and subsequent growth), although at a very slow rate (around 2% per year). There is, however, one significant difference between their national and regional results: while converge across broad country samples emerges only when they control for educational levels, investment and fertility rates and indices of political instability, convergence regressions at the regional level typically yield a negative slope coefficient even without introducing additional variables. Barro and Sala interpret these results as evidence that, while cross-country convergence is only conditional, regional convergence, at least within advanced industrial countries, has been absolute. This interpretation is reinforced by the the apparent stability of the estimated convergence coefficient across national and regional samples. Since regions seem to converge (unconditionally) at approximately the same rate as countries do once we control for human capital and other factors, one can plausibly argue that there is no need for additional variables in regional convergence equations.

Barro and Sala's results have been confirmed by a number of studies that have applied their techniques to various regional samples. Coulombe and Lee (1993), Dolado et al (1994), Shioji (1996) and Svensson (1997), among others, have investigated the regional convergence process in Canada, Spain, Japan and Sweden. While their estimates of the convergence rate vary somewhat and tend to be higher when regional price deflators are used, they are generally consistent with the hypothesis of slow but absolute beta convergence.

One potential objection to this conclusion is that in most of these studies absolute convergence is closer to a maintained assumption than to a tested hypothesis. The reason probably has to do with the existence of a strong prior belief that regional economies must be very similar in terms of their underlying fundamentals. In fact, this perceived homogeneity is probably the main reason why researchers turned to regional samples in their attempt to discriminate among competing growth models. It can be argued that by working with regional data we are implicitly holding constant a bunch of factors which are very difficult to control for in cross-country comparisons (because we do not have the necessary data and are not even sure of what these factors are). This is important because it allows us to get a clearer picture of the interactions among the variables highlighted by the theoretical models we are interested in testing.

Whatever the cause may be, the fact remains that most BS-type studies of regional growth do not make a determined effort to test the assumption of absolute convergence by including in the equation a sufficiently rich set of conditioning variables which may capture relevant cross-regional differences in steady states.[3] There are a number of studies that do this, however, and their results would seem at first sight to point to the strong rejection of the hypothesis of absolute convergence.[4] Many of these studies estimate conditional specifications of a convergence equation patterned loosely after the one proposed by Mankiw, Romer and Weil (1992), and interpret the control variables as determinants of steady-state income. Many of these variables are found to be significant, including investment rates in (or stocks of) physical, human, infrastructure and technological capital, migration and population growth rates, various proxies for sectoral structure, geographical indicators and dummies for subgroups of regions. Some of these papers also provide evidence of the existence of convergence clubs and of significant changes in convergence patterns over time.

Taken together, these studies do suggest that Barro and Sala's simple characterization of the regional convergence process as slow reversion towards a common mean does not adequately capture the rich dynamics of the regional income distribution. (This, by the way, is a point which Danny Quah has made repeatedly, e.g. in (1993)). By and large, however, their findings are not necessarily fatal for the view that absolute convergence may be a reasonable description of the basic long-run tendency in the data. Most (though not all) of the conditioning variables included in these studies may (and indeed do) themselves tend to become increasingly similar across regions over time. Hence, there is no necessary contradiction between the results of conditional and unconditional convergence equations -- provided we keep in mind that their respective slope parameters are measuring different things: the unconditional convergence rate summarizes the overall intensity of a tendency towards the reduction of regional disparities which works partly through the gradual equalization of steady-state determinants, while the conditional parameter measures the speed of convergence to a pseudo-steady-state which is itself changing over time

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[3] Barro and Sala's regional equations typically control only for some measure of the sectoral composition of output. In addition, the authors interpret the inclusion of this variable as a way to control for aggregate shocks which may be correlated with the initial level of income, rather than as a determinant of the steady state. This interpretation seems to be validated by their results. While the sectoral variable is generally significant, its inclusion does not significantly alter the estimated rate of convergence over the whole period and tends to make its value much more stable across subperiods.

[4] See for example Dolado et al (1994) and Mas et al (1995) for the Spanish provinces, Herz and Röger (1996) for the German Raumordnungsregionen, Grahl and Simms (1993), Neven and Gouyette (1995) and Faberberg and Verspagen (1996) for various samples of European regions, Holtz-Eakin (1993) for the states of the US and Paci and Pigliaru (1995), Fabiani and Pellegrini (1996) and Cellini and Scorcu (1996) for the regions of Italy.

(Cohen, 1992). In most cases, there is no obvious conflict between the estimated values of the two parameters.

But if conditioning on things like investment rates and sectoral structure does not necessarily allow us to discriminate between conditional and absolute convergence, how can we go about it? One possible approach is to search the abundant regional literature for indirect evidence that may throw some light on long-term convergence tendencies. One potentially useful tool in this regard are the Markov models of distribution dynamics popularized by Quah (1993). In this approach, the data are used to estimate a matrix of transition probabilities across discrete income classes which can then be iterated to forecast the future evolution of the income distribution. While results vary depending on the sample and the choice of income classes, they do not generally seem to support the absolute convergence hypothesis. Gardeazabal (1996), for instance, reports that the asymptotic distribution of per capita income across the Spanish provinces looks pretty much like the current one. Magrini (1998) finds that the distribution of income across (functional) European regions tends to split into two unconnected components, with a handful of very rich regions (from several of the central countries) pulling well ahead of a larger group characterized by a bi-modal and not excessively tight distribution.

Another indirect indication of the likely failure of absolute convergence is the well-documented tendency for both beta and sigma convergence to slow down over time and the almost complete interruption of the convergence process in many regional samples starting in the mid 1970s or early 1980s.[5] Although it is probably still too soon to rule out the possibility that the "convergence slowdown" is just a temporary setback due to the oil shocks and the assorted macroeconomic turbulences of the last decades, it may also be an indication that regional disparities are approaching their stationary levels.

A second approach which seems particularly promising is to turn to panel techniques in order to control for unobserved characteristics which may account for cross-regional differences in steady states. After all, this is what panel data econometrics is all about, and in the present context, this approach offers the attractive possibility of an explicit test of the absolute convergence hypothesis by the simple expedient of adding a bunch of dummy variables to the right-hand side of a convergence equation. This procedure allows us, in fact, to obtain a direct estimate of the asymptotic income distribution towards which the economy would presumably tend in the absence of structural change. While the exercise is certainly risky, it seems worth undertaking if only as a way to ascertain the likely degree of persistence of regional inequality.

[5] See for instance Barro and Sala (1991) for the US and Europe, Faberberg and Verspagen (1996) and Tondl (1997) for various EU regional samples, Dolado et al (1994) and Mas et al (1995) for Spain, Herz and Röger (1996) for Germany and Shioji (1996) for Japan.

There are a number of works in the convergence literature which have followed this approach or used it as a complement of more "structural" models. Marcet (1994), Raymond and García (1994), Canova and Marcet (1995), de la Fuente (1996) and Tondl (1997), for instance, all estimate fixed effects models using panel data for a variety of regional samples. Their results suggest a view of the regional convergence process with stands in sharp contrast with the one advanced by Barro and Sala: instead of slow convergence to a common income level, regional economies within a given country seem to be converging extremely fast (at rates of up to 50% per year) but to very different steady states.[6] Regional inequality is therefore found to be extremely persistent. In the "pure" panel studies the variance of estimated steady-state income or productivity levels is typically very close to the one observed towards the end of the sample period. In de la Fuente (1996), this falls to somewhere between one half and two thirds of observed end-of-sample inequality once we allow the diffusion of (transferable) technology to run its full course and assume that educational levels and capital-labour ratios (in efficiency units) are equalized across regions.

Although panel models lead to a seemingly clear rejection of the absolute convergence hypothesis, the issue is still far from settled. Currently, the controversy seems to focus largely on econometric issues. Proponents of panel techniques argue that the cross-section specifications used in much of the "classical" convergence literature do not make use of all the relevant information and that failure to control for unobserved regional characteristics can bias cross-section or pooled data estimates of the convergence rate toward zero.[7] On the other hand, panel estimates are certainly not free of problems, as Shioji (1997a,b) has pointed out. One basic objection is that it may be very dangerous to use (relatively) high frequency data to estimate a growth model which focuses on long-term dynamics. In addition, it is well known that some of the standard panel estimators of the convergence rate may be subject to a potentially serious upward bias in short samples (Nickell (1981) and Hsiao (1986)) and that "within" panel estimates which rely mainly on the time-series variation of the data may exacerbate measurement error problems (e.g. Griliches and Hausman, 1986).

Canova and Marcet (1995) argue that existing data on macroeconomic aggregates in relatively recent periods are unlikely to contain enough measurement error to generate a significant bias. Shioji (1997a, b), however, notes that the variable we would really like to "see" is not income per se but something like trend or capacity output. Hence, he argues, cyclical fluctuations and other short-term noise in the data should be treated as measurement error. Using what he calls a skipping

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6 Similar results are also reported by Evans and Karras (1996) for a sample of US states using time series techniques.

7 This is what Canova and Marcet (1996) call the fixed effects bias. The intuition is simply that we will underestimate the speed at which a region approaches its steady state if we have the wrong destination. As an illustration, imagine a train which approaches Paris from Berlin at a constant rate. If we believe the train's destination is Madrid and measure its rate of approach to this point, we will get a number which i) is too low and ii) decreases over time.

estimator, Shioji makes a plausible case for the view that the degree of measurement error in the data (in this extended sense) is considerable, and goes on to show that the combination of measurement error and the small sample bias may be sufficient to generate extremely high estimates of the convergence rate even when the true value of the parameter is around 2%.

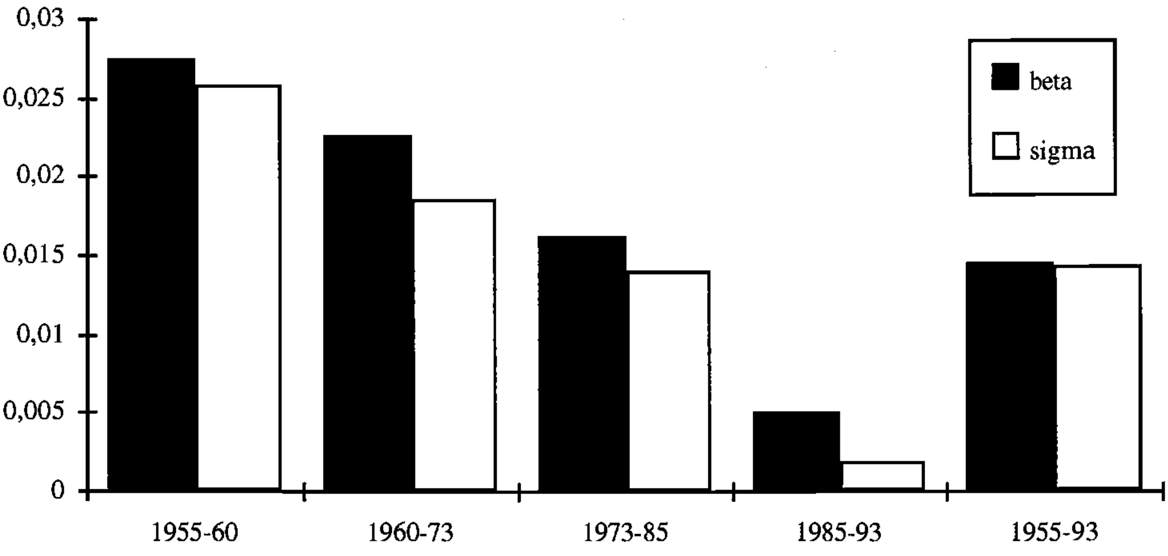
In conclusion, existing discrepancies between alternative estimates of the convergence rate and the steady state income distribution can be traced back to the use of different econometric specifications. While cross-section or pooled regressions typically yield low convergence rates (and impose a common steady state), fixed effects and time-series estimates generally point in the opposite direction and imply very significant steady-state differences across regions. Given that both types of specifications present potentially serious econometric problems, it is far from obvious *ex ante* which one provides a more accurate characterization of the regional convergence process. To try to make some headway on this issue, we have to turn to the data and try to devise ways to gauge the likely seriousness of the various problems that have been identified in the literature. This will be the objective of the next section.

3.- Convergence across the Spanish regions

The research department of a large Spanish bank (Banco Bilbao-Vizcaya) provides estimates of regional gross value added for the 17 Spanish regions covering the period 1955-1993 at two- (and occassionally three-) year intervals. Using these data I will construct series of relative regional incomes (income per capita in log deviations from the national average) and relative regional growth rates and use them to estimate various specifications of a standard growth equation. As Canova and Marcet (1995) argue, this normalization should eliminate at least part of the cyclical noise in the data.

First of all, we should note that the pattern of regional convergence in Spain seems to be representative of those found in many other industrial countries. The level of regional inequality (measured by the standard deviation of relative income per capita) decreases rapidly during the first part of the sample and roughly stabilizes after the late seventies (see Figure 2). Using only the cross-section dimension of the data, the estimation of an unconditional convergence regression in relative income per capita over the entire period 1955-93 yields an estimated rate of convergence of 1.5% per year, which is not far from the usual cross-section estimates. If we repeat the exercise for each of four natural subperiods, we detect a clear tendency for the unconditional convergence rate to fall over time. This is illustrated in Figure 1, where we also display the evolution of the rate of sigma convergence, defined as the average annual percentage reduction of the standard deviation of relative income per capita during each period.

Figure 1: Unconditional beta and sigma convergence rates by subperiod



To illustrate the sharp contrast beween pooled and fixed-effects estimates of the convergence rate we now pool the biennial observations and estimate two versions of the following convergence equation,

(1) $\Delta y_{rt} = \alpha_r - \beta y_{rt} + \varepsilon_{rt}$

where Δy_{rt} is the average annual growth rate of relative income over the subperiod starting at time t and α_r a region-specific constant which can be used to recover an estimate of the steady state income level ($y_r^* = \alpha_r/\beta$). First, we estimate a restricted or unconditional version of equation (1) with the pooled data after imposing the assumption of a common intercept (and therefore a common steady state) for all regions. The estimated convergence rate is 2.2% and the standard deviation of the implied asymptotic distribution of income per capita (which reflects only the variance of the shocks ε_{rt}) is 0,10 (column [1] of Table 1). Next, we estimate an unrestricted or conditional version of equation (1) using ordinary least squares with dummy variables (LSDV) to allow for regional fixed effects (equation [2]). With this specification, the conditional convergence rate (β_c) increases almost four-fold to 8% per year[8] and more than half of the regional dummies are highly significant. The implied steady states look a lot like the end-of-sample incomes and the standard deviation of the implied stationary distribution (taking into account the estimated variance of the shocks) is $\bar{\sigma}_y = 0.21$, which is quite close to the observed dispersion in the final year of the sample ($\sigma_y^{93} = 0.20$).

[8] This figure is significantly higher when we work with output per employed worker rather than income per capita.

As we have already noted, one problem with this second estimate of the convergence rate is that it is likely to be biased upward in short samples. To obtain an alternative estimate which should in principle be consistent, we reestimate the fixed effects model using a version of Arellano's (1988) orthogonal deviations (OD) procedure.[9] Surprisingly, this procedure yields an estimate of the convergence parameter which is only slightly smaller than the previous one and leaves unaltered the dispersion of the estimated regional steady states (see equation [3]). This suggests that i) the short sample bias is not the primary reason for the high values of the convergence parameter obtained with fixed effects specifications and/or ii) the conditions for the consistency of Arellano's instrumental variables estimator (which include the absence of serial correlation) do not hold.

Table 1: Estimated convergence rates and long-term income dispersion with various specifications

	[1]	*[2]*	*[3]*
β	0.022	0.080	0.076
(t)	(4.76)	(5.63)	(3.91)
s.e. regression	0.0207	0.0201	
std deviation y_r^*	[0.0000]	0.2057	0.2056
$\bar{\sigma}_y$	0.0995	0.2120	
σ_y^{93}	0.1980	0.1980	0.1980
fixed effects	no	yes	yes
specification	OLS	LSDV	OD

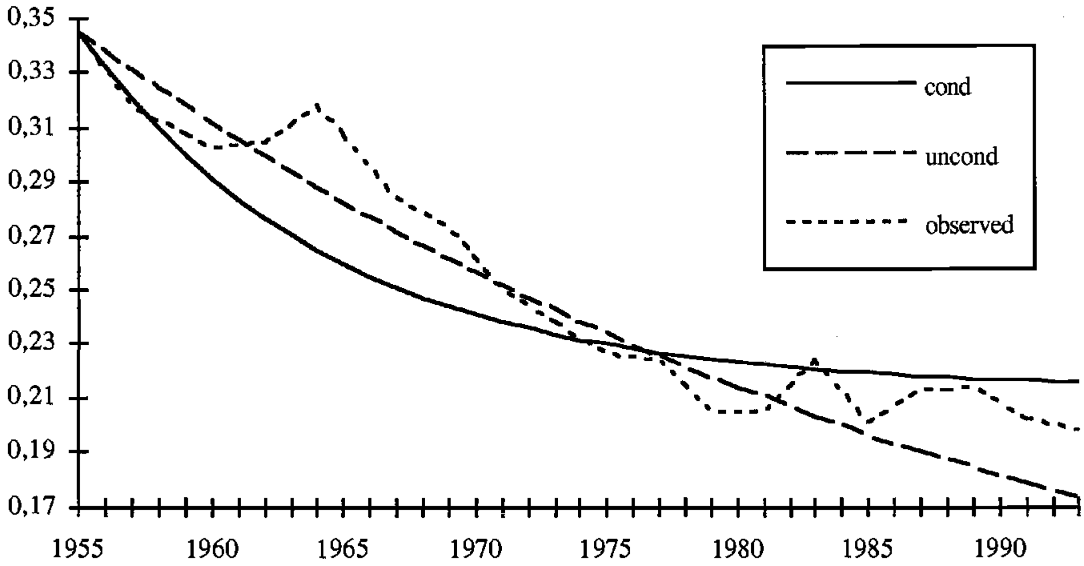
As expected, the conditional and unconditional versions of equation (1) tell very different stories. In the first case the conclusion is that we have pretty much reached the steady state. Hence, the substantial degree of inequality we observe today is likely to persist indefinitely in the absence of "structural change." If we believe the restricted equation, however, we can still hope that regional inequality will eventually fall to about one half its current level.

One possible way to try to see which story is more plausible is by checking which specification produces a better match with the observed evolution of regional inequality. Using the estimated parameters, the standard error of the previous regressions and the initial income distribution, we can use the two models we have just estimated to compute the expected path of the standard deviation of income per capita and compare it with the observed path of this variable (σ_t).[10] As can be seen in Figure 2, the results are disappointingly ambiguous: σ_t seems to be trying very hard to

[9] The procedure works roughly as follows. First, we write the variables in equation (1) in deviations from the the average value of their corresponding future observations in order to eliminate the fixed effects. Then, we estimate a system of cross-section equations (one for each subperiod) by two-stage least squares, using all the lagged values of initial income as instruments. Once we have an estimate of the convergence parameter, the fixed effects can be easily recovered from the average values of the dependent and independent variables.
[10] See de la Fuente (1997).

keep us guessing as to which of the two estimated paths it likes better. It lies generally closer to the unconditional prediction in the first half of the sample period but it then levels off as predicted by the conditional model. The deviation from the unconditional path, however, is far too small to appear conclusive. Looking backwards in time, slow convergence towards a common income level does not look very different from fast convergence to where we are now. The important difference has to do with what is likely to happen in the future, but that is of little help to us today.

Figure 2: Observed vs. predicted sigma convergence



As we have seen in the previous section, one of the main concerns about panel estimates is that the short-term noise in panel observations (i.e. in average growth over relatively short subperiods) may make it difficult to "see" long-term dynamics clearly. If regional incomes fluctuate around the trend or capacity levels described by some growth model, quick reversion towards the trend may help create the illusion of fast convergence to the steady state. To avoid this problem, Shioji (1997a,b) suggests treating short-term noise as measurement error. It may be more informative, however, to try to incorporate short-term dynamics explicitly into the model and see whether this allows us to disentangle the short and long-term components of the convergence rate. In the rest of this section I will attemp to do just that using a very simple variation on the standard convergence model which expliticly introduces short-term noise.

a.- A convergence model with short-term noise

We will assume that log relative income per capita (y_{rt}) in region r at time t can be written as the sum of a "trend" or permanent component (q_{rt}) and a short-term component (x_{rt}) which captures temporary deviations from trend due to assorted short-term shocks. We will also assume that the permanent component of income behaves as predicted by some sort of roughly neoclassical growth model, asymptotically approaching a steady state determined by the region's fundamental characteristics (summarised by a constant parameter α_r), according to the following deterministic law of motion:

$$(2)\ \Delta q_{rt} = \alpha_r - \lambda q_{rt}.$$

Our last assumption will be that the transitory component of income follows an autoregressive process which also reverts to a (zero) mean; in particular,

$$(3)\ \Delta x_{rt} = -\rho x_{rt} + \varepsilon_{rt}$$

where ε_{rt} is an iid perturbation.

If ρ and λ are between zero and one, regional relative incomes tend to converge in the long run towards a stationary distribution whose constant variance is a function of the dispersion of regional fundamentals, α_r, and the variance of the shocks. Since the expected value of x_{rt} is zero in the long run, the expected income of region r is given by $y_r^* = q_r^* = \alpha_r/\lambda$.

Hence, the long-term predictions of the model are identical to those of equation (1) above. Under our new assumptions, however, there are two different sources of dynamics which may be hard to disentangle. Notice that the growth rate of income per capita in region r at time t is now given by

$$\Delta y_{rt} = \Delta q_{rt} + \Delta x_{rt} = -\lambda(q_{rt} - q_r^*) - \rho x_{rt} + \varepsilon_{rt}.$$

Multiplying and dividing the right-hand side of this expression by the deviation of income per capita from its long-term expected value,

$$y_{rt} - y_r^* = (q_{rt} - q_r^*) + x_{rt},$$

we have

$$(4)\ \Delta y_{rt} = -\beta_{rt}\,(y_{rt} - y_r^*) + \varepsilon_{rt}$$

with

$$(5)\ \beta_{rt} = \frac{q_{rt} - q_r^*}{y_{rt} - y_r^*}\,\lambda + \frac{x_{rt}}{y_{rt} - y_r^*}\,\rho.$$

Hence, the "overall" convergence coefficient, β, will vary both across regions and over time. In fact, β_{rt} will be a weighted average of the short- and long-term convergence rates, with weights proportional to the share of each income component in the total deviation from the steady state.

The previous discussion suggests that if short-term noise is important the usual practice of estimating a single convergence coefficient will give us only a very scrambled signal as to the true value of the long-term convergence rate. To illustrate this point, consider the LSDV estimator of the convergence parameter, given by

$$(6)\quad \hat{\beta}_{LSDV} = \frac{-\sum_{r=1}^{R}\sum_{t=0}^{T-1}(\Delta y_{rt} - \overline{\Delta y_r})(y_{rt} - \bar{y}_r)}{\sum_{r=1}^{R}\sum_{t=0}^{T-1}(y_{rt} - \bar{y}_r)^2}$$

where R is the number of regions and T the number of subperiods in the sample. Using (6) and the "true model" given by equations (4) and (5) it is easy to show that $\hat{\beta}_{LSDV}$ can be written in the form

$$(7)\quad \hat{\beta}_{LSDV} = \frac{\lambda\left(\sum_{r=1}^{R}\sum_{t=0}^{T-1}(q_{rt} - \bar{q}_r)^2\right) + \rho\left(\sum_{r=1}^{R}\sum_{t=0}^{T-1}x_{rt}^2\right)}{\sum_{r=1}^{R}\sum_{t=0}^{T-1}(y_{rt} - \bar{y}_r)^2} + S(\varepsilon, y, T)$$

where $\operatorname{plim}_{R\to\infty} S(\varepsilon, y, T) > 0$ for given T. Hence, $\hat{\beta}_{LSDV}$ is likely to overestimate the true value of λ for two reasons. The first one is the short sample bias captured by S(). But even in long samples, $\hat{\beta}_{LSDV}$ will be biased upward whenever $\rho > \lambda$. The size of the bias will increase with the weight of short-term noise (x_{rt}) in the total variation of y_{rt}.

Unlike the short-sample bias, moreover, this second problem will not disappear with either longer samples or alternative specifications which correct for the usual sources of inconsistency in dynamic panel models. The reason, of course, is that if equations (4) and (5) describe the true model then the usual convergence equation given in (1) is misspecified. In the remainder of this section we will attempt to establish whether or not this is in fact the case by obtaining rough estimates of ρ and λ and examining the sensitivity of panel estimates of β to changes in the length of the sample. My goal will not be to obtain precise estimates of these parameters (which would probably require the use of state space techniques), but to establish their order of magnitude in order to ascertain whether short-term noise is likely to be a serious problem in panel estimates of growth equations.

Table 2: Some Monte Carlo experiments

	$\sigma_\varepsilon = 0.01$		$\sigma_\varepsilon = 0.02$	
q_0	*avge.* $\hat{\beta}$	*std. dev.* $\hat{\beta}$	*avge.* $\hat{\beta}$	*std. dev.* $\hat{\beta}$
0	0.3377	0.1296	0.4338	0.2068
0.15	0.1028	0.0507	0.3500	0.1955
0.30	0.0434	0.0194	0.1025	0.0528
0.50	0.0284	0.0106	0.0543	0.0245
1	0.0265	0.0172	0.0437	0.0372

Before proceeding, I have checked that short-term noise can indeed generate misleadingly high estimates of the convergence coefficient even when the true parameter value is very low by running a series of Monte Carlo experiments. Assuming the true parameter values are $\lambda = 0.02$ and $\rho = 0.25$, I have simulated one thousand samples of forty annual observations each for a single economy. In all cases, the steady state value of q is assumed to be zero, but the initial distance from the steady state (q_o) and the standard deviation of the shocks (σ_ε) are allowed to vary across runs. For each simulated sample, I estimate a standard convergence specification with a single parameter (β) by OLS. The results, summarized in Table 2, show that the estimated value of β increases, from values close to λ to values well above ρ, as we increase the variance of the shocks and/or reduce the initial distance from the steady state.

b.- Some estimates of the short- and long-term convergence rates

The short-term noise model (STNM) presented in the previous section is observationally equivalent to the standard convergence specification when $\rho = \lambda$. Hence, we can try to estimate the "general model" given in equations (4) and (5) and then check the equality of the two coefficients in order to test whether the standard convergence equation is misspecified. Since q_{rt} and x_{rt} are not observed separately, however, this cannot be done directly. In this section we will consider two approaches which can be used to obtain rough estimates of the short- and long-term convergence rates, ρ and λ. They both involve manipulating equations (4) and (5) in order to derive two alternative expressions which can be used to separately identify the two parameters, at least approximately. One of these equations will allow us to identify the desired parameters in a clean way, but it may still be subject to a short-sample bias. The second one, by contrast, should be free of bias but will yield only an approximate estimate of λ whose quality will depend on initial conditions.

To derive the first equation, let us rewrite the short-term noise model introduced above in the form

(8) $y_{rt} = q_{rt} + x_{rt}$

(9) $q_{rt+1} = \alpha_r + \phi_\lambda q_{rt}$

(10) $x_{rt+1} = \phi_\rho x_{rt} + \varepsilon_{rt}$

where $\phi_\rho = 1-\rho$ and $\phi_\lambda = 1-\lambda$. Iterating equations (9) and (10) backward, it is easily seen that

$$x_{r,t+h} = \phi_\rho^h x_{rt} + e_{rt} \quad \text{with} \quad e_{rt} = \sum_{s=1}^{h} \phi_\rho^{s-1} \varepsilon_{r,t+h-s}$$

and

$$q_{r,t+h} = \phi_\lambda^h q_{rt} + (1-\phi_\lambda^h) q_r^* \quad \text{with} \quad q_r^* = \alpha_r/\lambda.$$

Using these expressions, we can derive the equation

(11) $y_{r,t+h} = q_{r,t+h} + x_{r,t+h} = \phi_\rho^h y_{rt} + (1 - \phi_\rho^h)\, q_r^* + (\phi_\lambda^h - \phi_\rho^h)\, \phi_\lambda^t (q_{ro} - q_r^*) + e_{rt}.$

Notice that the third term on the right-hand side of (11) vanishes whenever $\lambda = \rho$ or $q_{ro} = q_r^*$. Hence, we can use the coefficient of the initial condition q_o to test for the possible misspecification of the convergence equation -- provided the economies in the sample do not start out at their steady-state income levels, in which case the data provides no information on the long-term convergence parameter.

To get equation (11) into a form that is more convenient for estimation with our (irregularly dated) data rearrange terms, substract y_{rt} from both sides and divide by the length of the subperiod, h, to get

$$(12)\ \frac{y_{r,t+h} - y_{rt}}{h} \equiv g_{rt} = -\frac{1-(1-\rho)^h}{h} y_{rt} + \left(\frac{1-(1-\rho)^h}{h} - \frac{1-(1-\lambda)^h}{h}\right)(1-\lambda)^t (y_{ro} - x_{ro}) + \\ + \left\{\frac{1-(1-\rho)^h}{h} - \left(\frac{1-(1-\rho)^h}{h} - \frac{1-(1-\lambda)^h}{h}\right)(1-\lambda)^t\right\} q_r^* + e_{rt}$$

where we have also made use of the fact that $q_{ro} = y_{ro} - x_{ro}$. If λ and ρ are small, we can use the approximation

$$\frac{1-(1-\mu)^h}{h} \cong \mu$$

to replace (12) by the somewhat "more linear" expression,

$$(13)\ g_{rt} \cong -\rho y_{rt} + (\rho-\lambda)(1-\lambda)^t (y_{ro} - x_{ro}) + [\rho - (\rho-\lambda)(1-\lambda)^t]\, q_r^* + e_{rt}.$$

If either of the coefficients is large (as ρ will be in practice) we will want to check our results by estimating the following simplified version of (12) directly:

$$(12')\ g_{rt} = -\frac{1-(1-\rho)^h}{h} y_{rt} + \left(\frac{(1-\lambda)^h - (1-\rho)^h}{h}\right)(1-\lambda)^t (y_{ro} - x_{ro}) + \\ + \left\{\frac{1-(1-\rho)^h}{h} - \left(\frac{(1-\lambda)^h - (1-\rho)^h}{h}\right)(1-\lambda)^t\right\} q_r^* + e_{rt}.$$

We now proceed to estimate various versions of equations (12) and (13). First, we estimate equation (13) by NLS under the assumption that $x_{ro} = 0$ for all r (i.e. that the short-term disturbance was zero in the first year of the sample period for all regions), using dummy variables to obtain direct estimates of the regional steady states, q_r^*. This is equation [4] in Table 3. We then introduce an additional set of regional dummies in the previous specification in order to estimate the initial disturbances, x_{ro} (equation [5]) and repeat the procedure after eliminating all non-significant dummies (equation [6]). Finally, we estimate the ("fully non-linear") equation (12') including only those regional dummies which were significant in the previous stage (equation [7]).

The results on the convergence parameters are very robust to the chosen specification. Notice that accounting for short-term shocks brings our estimate of the long-term convergence parameter back to the 2% value obtained in our original unconditional specification (equation [1] in Table 1) but does not change the conclusion that convergence is only conditional. As in the standard LSDV specification, more than half of the regional steady states are significantly different from zero (i.e. from the national average). Moreover, the dispersion of the steady states actually increases relative to our prior estimates (see equation [2] in Table 1). Finally, the short-term convergence rate seems to be very high (between 0.24 and 0.30) and the hypothesis that the initial short term disturbance is zero cannot be rejected except in the case of two regions.

Table 3: Estimated short and long-term convergence rates and long-term income dispersion with various STNM panel specifications

	[4]	*[5]*	*[6]*	*[7]*	*[8]*
ρ	0.240	0.285	0.252	0.303	0.500*
	(9.33)	(10.41)	(10.04)	(8.14)	(9.30)
λ	0.0213	0.0223	0.0224	0.0225	
	(2.88)	(2.02)	(16.17)	(16.35)	
β					0.021
					(2.86)
s.e. regression	0.0184	0.0183	0.018	0.018	0.0385
std dev iation y_r*	0.2238	0.2351	0.2360	0.2352	0.2218
specification:	*(13)*	*(13)*	*(13)*	*(12')*	*(16)*
	$x_{ro} = 0$		*only dummies sign. in [5]*		*H-E*

- *Note:s*
- t statistics in parentheses below estimated coefficients.
- Estimation by NLS. Equations [4] - [7] are estimated sequentially in the order shown here, using the parameter estimates obtained at each stage as initial values for the next specification
- (*) See Footnote 11.
- Specification: refers to the appropriate equation in the text; H-E which stands for Holtz-Eakin.

As noted in the previous section, panel estimates of the convergence rate are likely to be subjet to an upward small sample bias in addition to the one generated by short-term dynamics. To try to get around the first problem, Holtz-Eakin's (1993) suggests the estimation of a fixed effects specification after pooling observations which correspond to increasingly longer differences of relative income starting on a common date. Our second specification will involve a variant of this procedure in which we give up some precision in the estimation λ in exchange for some insurance against a possible bias which may affect our first set of estimates (of ρ and indirectly of λ).

Fixing the initial year of the sample at zero, we define the long difference of y_r between dates zero and t by $\overset{t}{\underset{o}{\Delta}} y_{rt} = y_{rt} - y_{ro}$. It is then easy to check, using equations (2) and (3) that the following expression holds:

$$(14)\ \overset{t}{\underset{o}{\Delta}} y_{rt} = -\left([1-(1-\lambda)^t]\frac{q_{ro} - q_r^*}{y_{ro} - y_r^*} + [1-(1-\rho)^t]\frac{x_{ro}}{y_{ro} - y_r^*}\right)(y_{ro} - y_r^*) + u_{rt}$$

with

$$(15)\ u_{rt} = \varepsilon_{r,t-1} + (1-\rho)u_{r,t-1}$$

where $\varepsilon_{r,t}$ is the original iid "yearly" disturbance. Trying to approximate (14), we will estimate an equation of the form

$$(16)\ \overset{t}{\underset{o}{\Delta}} y_{rt} = -\ [1-(1-\beta)^t]\ (y_{ro} - y_r^*) + u_{rt}$$

with an AR(1) error term, using regional dummies to obtain a direct estimate of the steady state. Notice that the independent variable in this equation is always y_{ro} (regional income in 1955) and that the dependent variable is the total change in relative income per capita over 1955-57 for the first observation, the change in relative income over 1955-60 in the second, and so on. Comparison of (14) and (16) shows that, just as in the standard (LSDV) case, the estimation of a single convergence coefficient in (16) will yield some weighted average of λ and ρ. The main difference with respect to the LSDV specification is that the weigths of λ and ρ will now depend on the shares of the short- and long-term components of income in the deviation from the steady state at *time zero* (and not throughout the sample period). Since this permanent component of the variation of y around its steady state will presumably decrease over time, this procedure should yield a better estimate of λ than the usual approach (with pooled annual data). If the initial deviation of income from the steady state is mostly long-term in nature (as it seems likely in our sample), the estimated value of β should not be very far from the long-term convergence rate, λ.[11] Finally, notice that the AR(1) coefficient will give us a direct estimate of one minus the short-term convergence rate, $1-\rho$.[12]

The results obtained with this specification, summarized in column [8] of Table 3, are consistent with our first set of estimates. The long-term convergence rate is quite low (2.1%) while short-term convergence appears to be extremely fast (with $\rho = 0.50$ for a period of two years), and the dispersion of the estimated steady states remains high. Notice that, as in the previous specifications, the estimated values of λ and ρ are very different from each other, suggesting that the standard convergence equation is misspecified.

c.- Dispersion of the regional steady states

We have just seen that accounting for short-term error significantly reduces our estimate of the long-term convergence rate, bringing it back to the low values obtained in convergence studies which rely on cross-section or pooled data specifications. Our results, however, are not consistent with the hypothesis of absolute convergence that is generally imposed in these models.

Table 4 displays the regional steady states obtained with the various specifications of the convergence equation we have estimated above. (The column headings are the same as those of the corresponding equations in Tables 1 and 3). As we have already noted, the steady state estimates obtained using a LSDV specification of the standard convergence model (shown in column [2] of Table 4) are widely disperse and lead to the strong rejection of the absolute convergence

[11] In fact, (16) is correct, with $\beta = \lambda$, if x_{ro}, so equation [8] is directly comparable to equation [4] in the same Table. We tried using dummies to estimate x_{ro} using Holtz-Eakin's specification but (not surprisingly, given that all the variation in the right-hand side of the equation is coming only from t) the estimation procedure did not converge.

[12] See equation (15). Notice, however, that with our data and this specification, the estimated ρ will refer to a period of (roughly) two years. The "annual" ρ implied by the estimated coefficient will be approximately half the value reported in equation [8] of Table 3.

hypothesis. Since the model is apparently misspecified, however, these estimates are inconsistent. It is easily checked that the LSDV estimate of region's r steady state is of the form

$$(17)\ \hat{y}_r^* = \frac{\hat{\alpha}_r}{\hat{\beta}_{LSDV}} = \frac{\lambda}{\hat{\beta}_{LSDV}} y_r^* + \left(1 - \frac{\lambda}{\hat{\beta}_{LSDV}}\right)\overline{q}_r + \left(1 - \frac{\rho}{\hat{\beta}_{LSDV}}\right)\overline{x}_r + \frac{\overline{\varepsilon}_r}{\hat{\beta}_{LSDV}}$$

where $\hat{\beta}_{LSDV}$ is the LSDV estimator given in equation (6). Since the expected values of $\overline{x}_r$ and $\overline{\varepsilon}_r$ are zero, we have $E\overline{q}_r = E\overline{y}_r$; hence, we can approximate (17) by

$$(18)\ \hat{y}_r^* \cong \frac{\lambda}{\hat{\beta}_{LSDV}} y_r^* + \left(1 - \frac{\lambda}{\hat{\beta}_{LSDV}}\right)\overline{y}_r$$

and, solving this expression for the true value of y_r *, obtain a (naively) corrected estimate of the steady state as a function of the (assumed) true value of the long-term convergence parameter λ and the LSDV estimate of y_r*. The corrected estimates are shown in the column labeled [2c] under the assumption that $\lambda = 0.02$. Comparing these new figures with those shown in the first column we see that, although the correction is important for individual regions, the dispersion of the steady states does not change very much (and is actually higher than for the uncorrected estimates).

Table 4: Estimated regional steady states

region:	*[2]*	*[2c]*	*[3]*	*[4]*	*[5]*	*[8]*
Baleares	0.337	0.557	0.347	0.534	0.513	0.531
Madrid	0.261	0.165	0.250	0.102	0.152	0.099
Cataluña	0.218	-0.013	0.213	-0.039	0.014	-0.043
País Vasco	0.125	-0.408	0.119	-0.420	-0.361	-0.422
Navarra	0.118	0.070	0.128	0.055	0.073	0.052
Rioja	0.093	0.110	0.095	0.006	0.069	0.001
Aragón	0.076	0.146	0.079	0.147	0.107	0.148
Valencia	0.006	-0.073	0.010	-0.026	-0.038	-0.021
Cantabria	-0.018	-0.333	-0.017	-0.273	-0.441	-0.269
Canarias	-0.066	0.205	-0.072	0.126	0.218	0.116
Asturias	-0.068	-0.388	-0.075	-0.306	-0.320	-0.300
Castilla y León	-0.102	0.009	-0.104	-0.066	-0.032	-0.071
Murcia	-0.197	-0.074	-0.172	0.047	-0.018	0.055
Cast. la Mancha	-0.201	0.107	-0.201	0.031	-0.010	0.028
Galicia	-0.216	0.005	-0.217	-0.021	-0.003	-0.022
Andalucía	-0.357	-0.373	-0.349	-0.322	-0.279	-0.318
Extremadura	-0.428	-0.208	-0.440	-0.294	-0.320	-0.291
*std. dev. y_r**	*0.2057*	*0.2469*	*0.2056*	0.2238	0.2351	*0.2218*
specification	*LSDV*	*corr. LSDV*	*OD*	*STNM*	*STNM*	*HE*
assumed λ		0,020				
estimated β		0,080				

- Note: Column headings refer to the relevant equation numbers in Tables 1 and 3.

The same conclusion emerges when we examine the remaining columns of the table. The steady states recovered from the equation estimated using Arellano's orthogonal deviations procedure are quite similar to the LSDV estimates. The estimates obtained with our various short-term noise specifications, finally, lie close to the corrected LSDV estimates and also display a rather high variance.

d.- Sensitivity analysis

Our results so far indicate that, while Shioji seems to be right in his contention that both short-term noise and the short-sample bias will tend to inflate panel estimates of the (long-term) convergence rate, there are no signs that correcting for these problems will bring us any closer to accepting the hypothesis of absolute convergence. Before accepting these "salomonic" results at face value, we will examine the robustness of the fixed-effects parameter estimates to changes in the length of the sample. The exercise can be of interest for three reasons. First, it should give us some additional insight on the likely importance of sample length and short-term noise as sources of bias in the estimation of the (long-term) convergence coefficient. Second, it can serve as a quick check on the out-of-sample forecasting properties of the fixed effects models we have estimated, thereby allowing us to gauge the plausibility of their predictions concerning steady state incomes. And third, it will provide an indirect check on some of the testable implications of our short-term noise story.

The experiment we will carry out involves the repeated estimation of various fixed-effects specifications of the standard growth equation (with a single convergence parameter) as we reduce the number of observations along the time dimension, dropping either initial or final subperiods one at a time. If we fix the final period and look further and further back into the past, we can make some sort of guess as to what may happen to our estimates if we had longer series. If we proceed in the opposite way, fixing the initial date and taking increasingly longer samples, we can reconstruct the pattern uncovered by a hypothetical researcher who would have reestimated our panel regressions as new data came in.

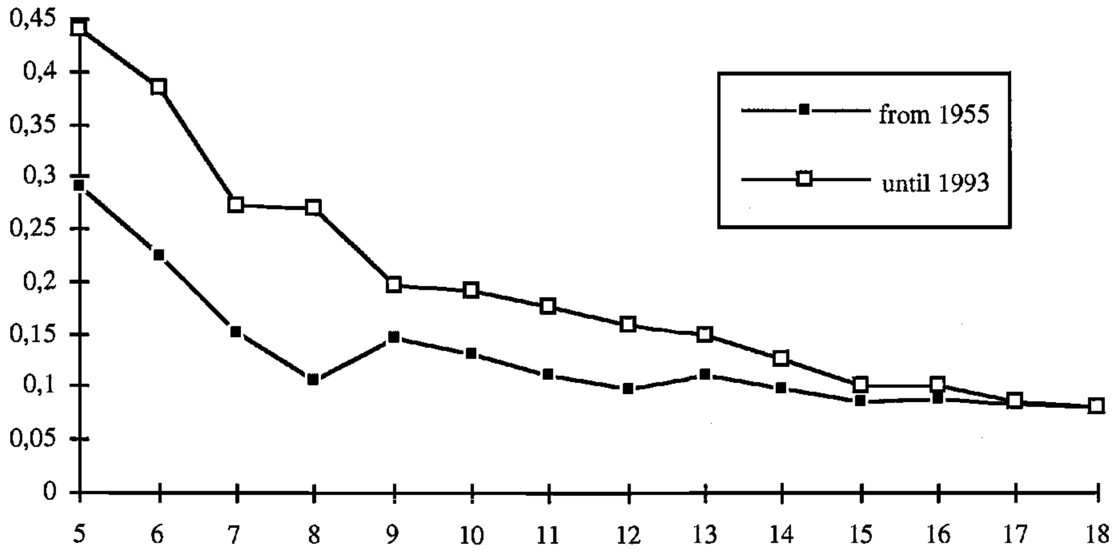
In view of the previous discussion we expect that LSDV estimates of β will tend to rise as the sample is shortened from either direction because this will worsen the small sample bias. Whether we drop observations from the beginning or from the end of the sample, however, should make a difference because the weight of short-term error (relative to permanent deviations from the steady state) is likely to be higher in later subperiods.[13] If this effect is sufficiently strong, the estimated

[13] As time passes, the permanent component of income should get closer and closer to its steady state value, losing importance relative to the short-term perturbations as a source of variation around the steady state. Hence, we should have

$$\frac{q_{rt} - q_r^*}{y_{rt} - y_r^*} \rightarrow 0 \text{ and } \frac{x_{rt}}{y_{rt} - y_r^*} \rightarrow 1 \quad \text{as } t \rightarrow \infty$$

value of β could actually decrease as we drop end-of-sample observations (because it should be getting closer to λ than to ρ), otherwise, we should at least observe a slower increase in β when we proceed in this manner than when we drop successive observations from the beginning of the sample. This is actually what happens, as can be seen in Figure 3, where we display the estimated value of β as a function of the length of the sample. The small sample bias seems to become extremely large as the number of observations falls below eight or ten, even in the more favourable case where we drop the final subperiods. This suggests that panel estimates of the convergence rate from short samples (such as Eurostat's data on EU regions) are likely to give highly misleading results, especially when the information comes from recent periods when permanent deviations from the steady state may be small. In fact, this may be true even when we abstract from the small sample bias: our short-term error model implies that an estimate of β which comes from a sample which is close to its steady-state distribution will give us almost no information on the value of the long-term convergence parameter, λ.

Figure 3: Estimated rate of convergence (β) as a function of the number of observations per region, LSDV estimates



Next, we repeat the experiment using Holtz-Eakin's specification of the convergence equation (with pooled long differences) and Arellano's procedure with the variables in orthogonal deviations and instrumental variables estimation. Since the short-sample bias should not be a problem (at least in the Holtz-Eakin case), we would expect the estimated convergence rate to rise as we drop early

which implies that $\beta_{rt} \rightarrow \rho$ as $t \rightarrow \infty$. If ρ is higher than λ, as seems to be the case, we should observe that panel estimates of β rise as we rely increasingly on information from the end of the sample period, and fall as we do the opposite.

Figure 4: Estimated rate of convergence as a function of the number of observations per region
Holtz-Eakin panel estimates

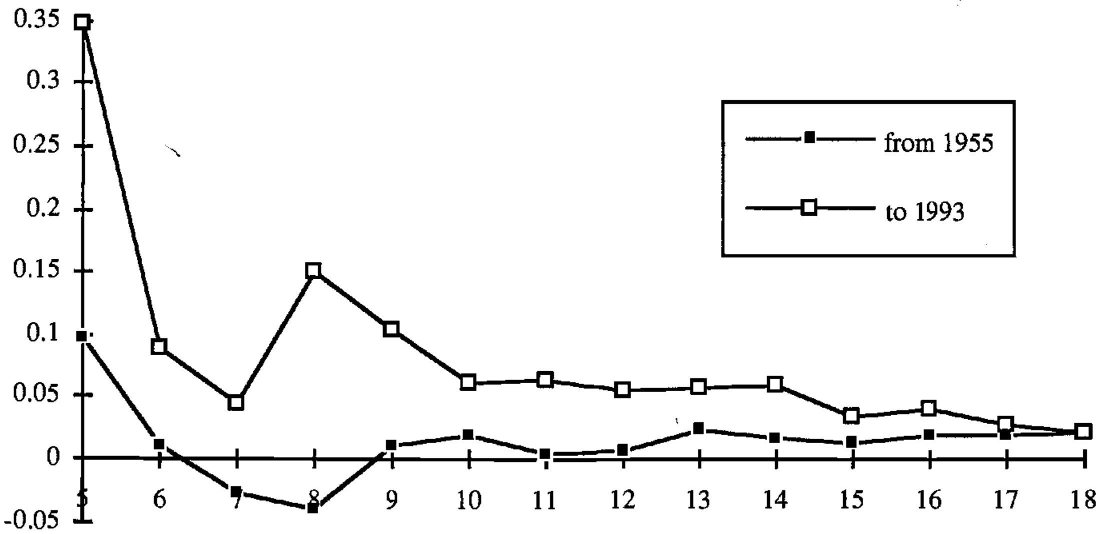
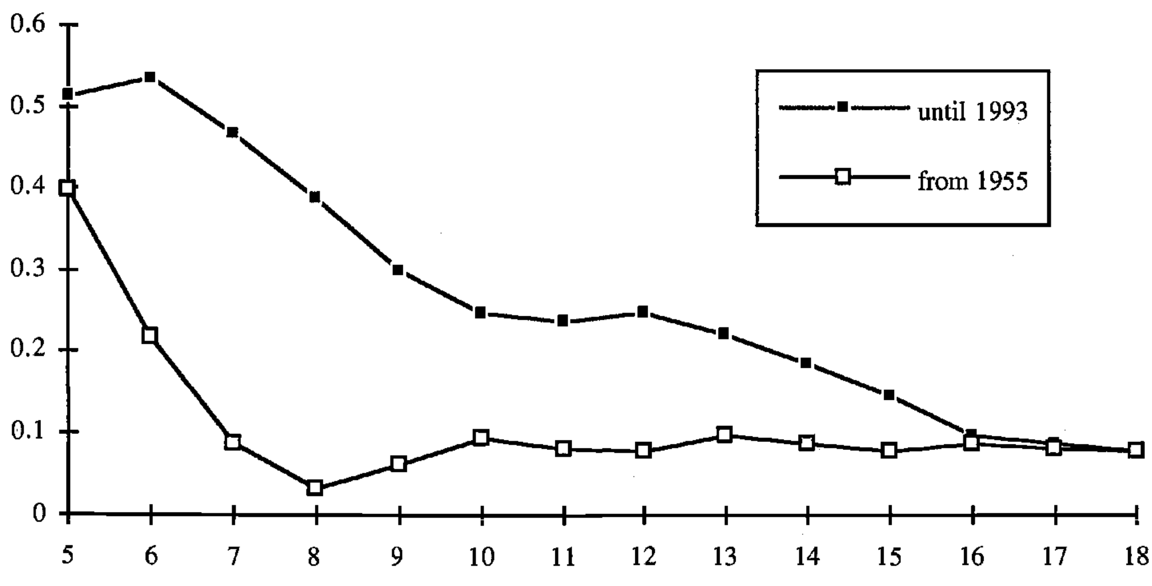
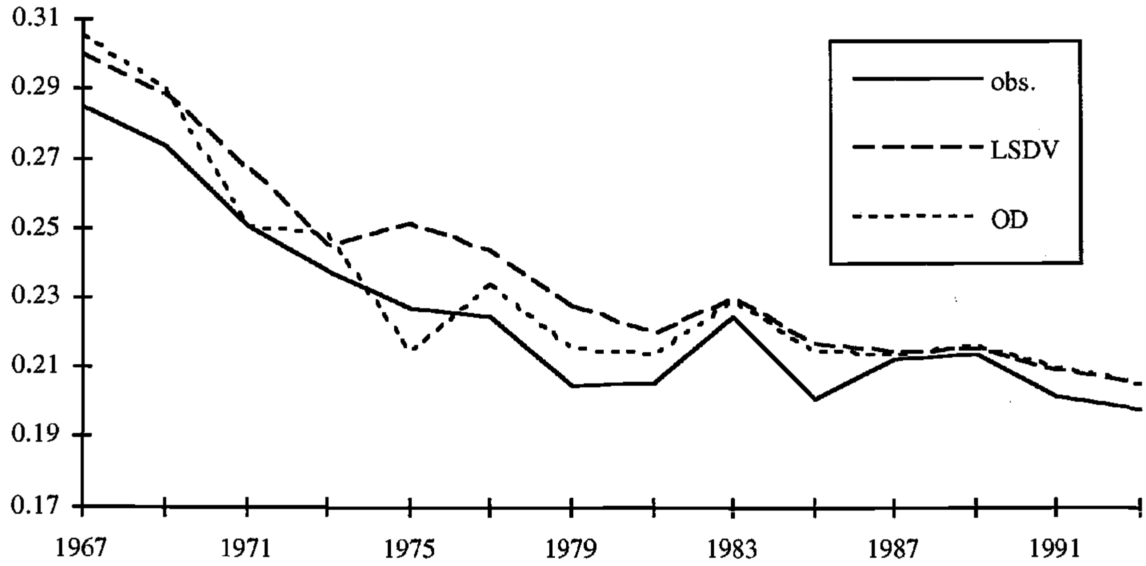


Figure 5: Estimated rate of convergence as a function of the number of observations per region
Arellano's OD panel estimates



observations because this will increase the relative importance of short-term shocks as a source of initial-period deviations from the steady state. Although the behaviour of the estimated β is a bit more erratic than in the LSDV case, Figures 4 and 5 show that the results roughly conform to the expected pattern. In the Holtz-Eakin case, the convergence rate tends to increase as we drop beginning of sample observations, but remains quite low when we keep the initial date fixed at 1955 until the number of observations per region becomes small. Its behaviour then becomes a bit erratic, with negative values followed by a sharp rise to around 10%. In the OD case, the pattern is similar, except that the convergence rate remains fairly high even as we shorten the sample from its end.

Figure 6: Dispersion of estimated steady states (LSDV and OD estimates) vs. dispersion of income in the final year of the sample period



Turning now to steady-state predictions, we ask whether the estimates produced by these alternative specifications can be considered plausible estimates of long-term equilibrium relative incomes. The answer to this question is a resounding no. We find that the LSDV and OD estimates of y_r* and their variance remain largely unchanged as we drop observations from the beginning of the sample period. When we proceed in the opposite direction, however, the dispersion of the estimated steady states drops significantly as we lengthen the sample by including later and later observations. Moreover, the variance of the estimated steady states (and their values for specific regions) seem to track rather well the observed end-of-sample values as shown in Figures 6, 7 and 8. Hence, a hypothetical researcher who relied on panel techniques to estimate the asymptotic distribution of regional incomes in the sixties and seventies would have been warning about the end of regional convergence in Spain since at least 1967 -- and would have been proved wrong by the data for over a decade thereafter. In view of this finding, the plausibility of estimates of asymptotic distributions obtained by panel techniques becomes extremely suspect.

Things are even worse when we use Holtz-Eakin's procedure (or our alternative specification of the short-term noise model). The estimated steady states now become very sensitive to the sample period and, in some cases, imply steady state levels of income dispersion which are up to eight times higher than the observed standard deviation of relative income. This instability is illustrated in Figure 7, where we compare observed income at time t with the steady state prediction obtained with a sample ending at t using the two alternative specifications.

Figure 7: Observed relative income at time t vs. steady state prediction from a sample ending in the same year. LSDV and Holtz-Eakin estimates

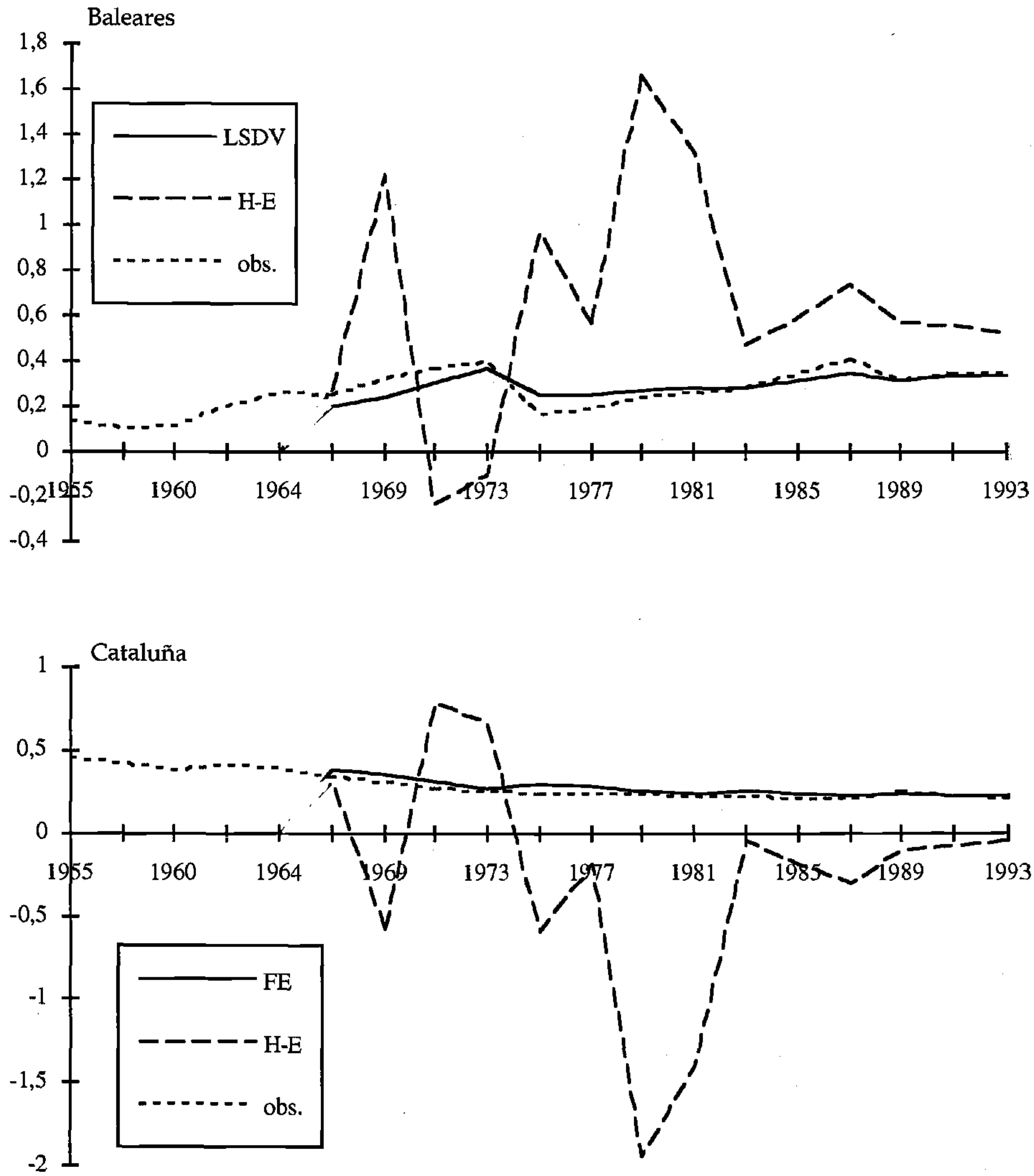
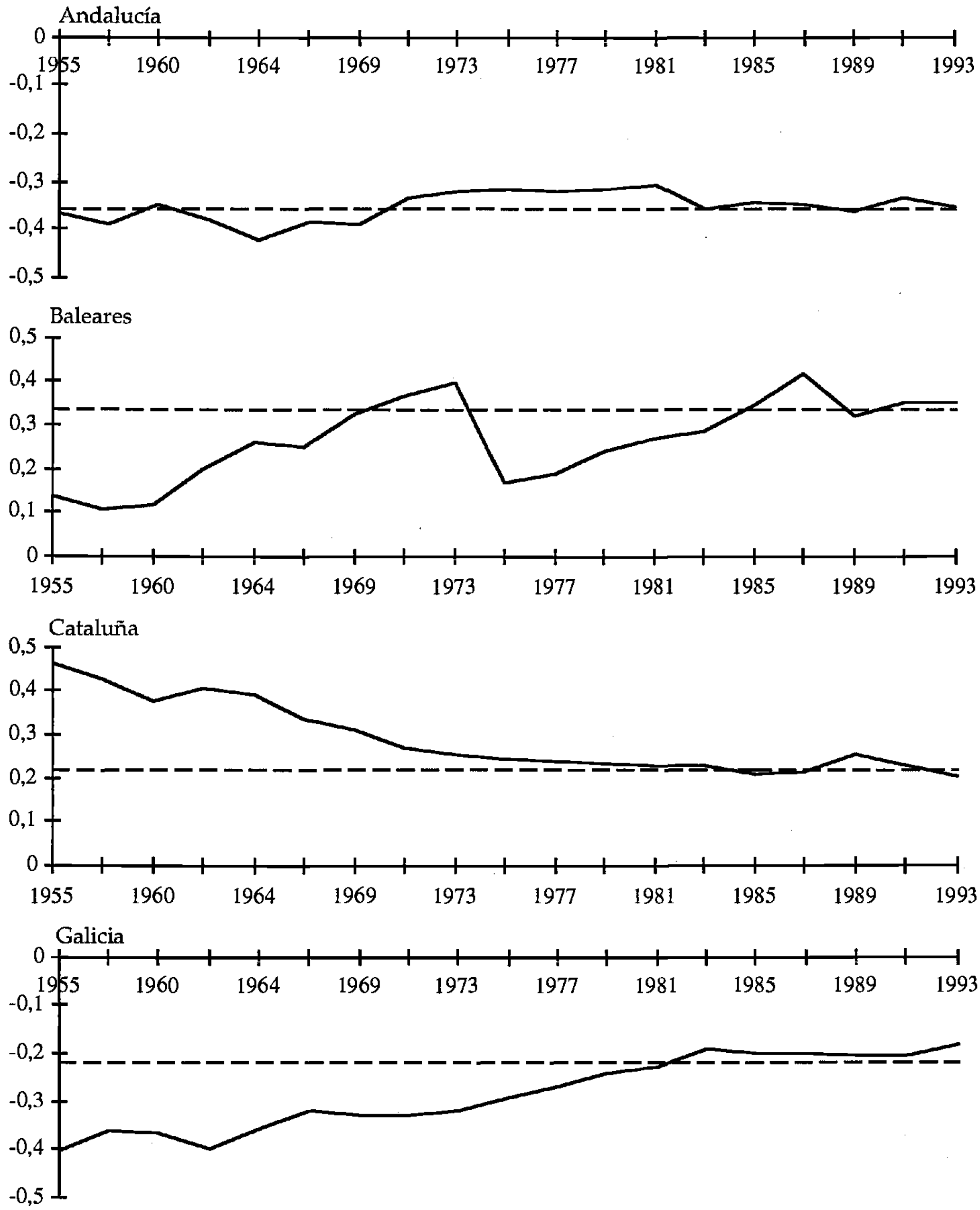


Figure 8: Observed relative income and estimated steady state (LSDV)



Perhaps the only fair conclusion one can draw from this exercise is that, as Canova and Marcet (1995) warn, forecasting asympotic distributions is a risky business at best. In fact, the risk may be large enough to justify the conjecture that the absolute convergence hypothesis cannot be tested in a reliable way with available time series. This does not mean, however, that absolute convergence is necessarily a good assumption or that the concern voiced by some authors about the persistence of regional inequalities is unfounded. To make this point, I will close this section with a figure which displays the time path of income per capita in a handful of Spanish regions together with their estimated steady states. The reader will have to look at Figure 8 very hard to find any indication that some of these regions have any plans of ever reverting back to the national mean.

4.- Conclusion: Much ado about nothing?

In order to get good estimates of the parameters of a convergence equation we need to solve two difficult problems. The first one involves a trade-off between two opposing biases which tend to render different estimates of the convergence rate inconsistent. The second problem is finding a way to avoid the danger that short-term noise may obscure the long-term relationships we would like to capture. Different views on the likely importance of these problems have led researchers to choose alternative specifications which yield very different characterizations of the convergence process: slow and absolute convergence in cross-section or pooled regressions, and extremely fast but only conditional convergence in fixed effects and related ("within") panel specifications.

After briefly reviewing the relevant literature, in this paper I have used data on the Spanish regions to assess the plausibility of these two views. Since the analysis has been rather informal and restricted to a single sample which may not be representative in various ways, it would be dangerous to try to draw general conclusions from it. With this caveat, the results are suggestive and they do seem to indicate that the extremely high convergence rates obtained in some recent panel studies are likely to contain a substantial upward bias and should probably not, in any event, be interpreted as estimates of the long-term convergence rate which is the parameter of interest in the context of growth theory. The reason for this is that convergence estimates based on the within-region variation in relatively high-frequency data are likely to reflect not only the rate at which trend output approaches its steady-state value, but also the speed of adjustment back toward trend output after a transitory shock. In this respect, therefore, my findings tend to confirm those of Shioji (1997a,b) using a different methodology.

My results are much less conclusive on the issue of the likely persistence of regional inequality -- i.e. on the absolute or conditional nature of regional convergence. I find that correcting in various ways for the factors that may bias panel estimates of the convergence rate does not have a substantial effect on the dispersion of the estimated steady states. Hence, a case can probably be made for the view that "long-term" convergence is rather slow but only conditional. A simple check on the robustness of the results to the length of the sample, however, strongly suggests that standard panel data methods do not provide a reliable test of the absolute convergence hypothesis. Estimated steady states are either too erratic or tend to track end-of-sample values much too closely for us to be comfortable with their interpretation as estimates of long-term equilibrium incomes.

On the whole, the exercise may serve as a warning that the panel techniques which are becoming increasingly popular in growth empirics may lead to misleading results. While there is no denying that the more traditional cross-section and pooled regression estimates present significant problems, perhaps one of the clearest lessons we can draw from the current exercise concerns the importance of handling dummy variables (and related devices) with extreme care.

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