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ON CONVERGENCE EMPIRICS: SOME EVIDENCE FOR SPANISH REGIONS

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This paper examines the dynamics of the cross section distribution of GDP per capita across 50 Spanish regions (provincias) to seek evidence of income convergence. It also studies the role that interregional migration has played in the convergence process. The main findings are that there is no evidence of income convergence across Spanish regions and that the role of migration flows has not been significant for the dynamic of Spanish income. If migration has had any effect, it seems to be a negative one. The approach in this paper exploits both cross-section and time series information in the data, overcoming most of the drawbacks of the traditional empirical literature on convergence.

Palabras clave: Convergence, conditioning, growth, stochastic kernel.

(*JEL* C21, C22, C23, O41)

1. Introduction

Income convergence is an important policy issue[1]. Economic policy should depend on whether the income inequality across countries or regions is vanishing or not, in other words, whether poor economies are catching up with the richest ones or on the contrary the income disparities persist over time. Economic theory does not provide much guidance in this issue; there is a conflict between growth models that predict convergence across economies, and those models, which do not. Also, the empirical literature does not give clear evidence about convergence.

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[1] In the first two sections of this paper we refer to 'income' in general, thereafter we take it to be GDP *per capita*.

The numerous and varied empirical studies on convergence in the recent growth literature can be classified in three different groups depending on the empirical approach they use to test convergence. Not every econometric approach is able to test for all the aspects involved in the convergence issue.

The empirical approach, which so far, has generated the widest literature, is the so-called cross-section regression analysis. It examines the regression of (averaged) growth rates on initial levels of income across economies. A negative coefficient on the initial condition is understood as poor economies growing faster than the richer ones and thus catching up *(beta convergence)*. Additionally, this approach looks at the dispersion of incomes across economies *(sigma convergence)*, and tries to account for convergence formulated in the following way: each economy eventually becomes as rich as all the others, the cross section dispersion diminishes over time.

A second approach to convergence is time series analysis. It tests the convergence hypothesis, formulated as a lack of persistence in income disparities across economies, studying persistence in the context of unit roots analysis In other terms, time series analysis tests whether disparities across economies have neither unit roots nor diverging deterministic time trends.

A third approach has been recently developed by Quah[2]. It models directly the dynamics of the entire distribution of income across economies as a natural way to study convergence. The evolution of the cross-section distribution of income involves two kinds of dynamics occurring simultaneously: changes in the exterior shape of the distribution and intra-distribution mobility. It takes into account both, cross-section dimension (transitional characteristics) and time series dimension information (dynamics).

The basic idea of convergence as a process of homogenization across economies over time already suggests that testing for convergence must involve the characterization of the behavior of a broad cross-section of economies over long periods. A cross-economies distribution of income tending over time towards a mass point (exterior shape) will indicate convergence, income equality. But also, changes in the relative position of the economies within the distribution (intra-distribution-mobility)

[2] Bianchi (1995), Desdoigts (1994), Paap and Van Dijk (1998) among others have also followed this approach.

are indicative of poor regions catching-up or rich ones falling behind. Therefore, testing the convergence hypothesis must involve the characterization of both, changes in the exterior shape and intra-distribution mobility dynamics.

We argue that the standard approaches, cross-section regression and time series analysis, in general, are not adequate to draw conclusions about convergence[3]. On one hand, regressing growth rates on initial levels of income across economies (growth equations), in spite of its popularity, is not very informative about convergence. In fact, it might be misleading, as argued below. On the other hand, time series analysis is not the most appropriate approach to study large cross-sections and it is not able to account for transitional characteristics. Analyzing the dynamics of the cross-section distributions embraces the other two approaches and seems to be a more adequate way to study large cross-sections, although it is not free from criticisms as we will point out below.

The remainder of this paper is organized as follows· Section 2 describes briefly the cross-section regression and time series approaches, explaining why these standard approaches may fail to examine convergence. Section 3 presents the cross-section distribution approach as an alternative empirical framework for studying the income dynamics of a broad cross-section of economies and offers some evidence for the regions in Spain (50 *provincias*, NUTS3 level in the Eurostat nomenclature). Section 4 studies the notion of conditional convergence and examines the role of inter-regional migration flows in the process of convergence for the Spanish *provincias*. Section 5 summarizes the economic findings.

2. The standard empirical approaches to convergence

2.1 Cross-section regression analysis

Standard cross-section regression approach relies on the concept of β convergence, which is a property of the classical CRS Solow gro-

[3]The current paper focuses on the empirics of income convergence across economies i.e. states, countries, regions, provinces, etc. The empirical study of convergence in other areas of economics, like industrial organization or labor markets, deserves similar comments to those we will make for growth theory

wth model[4]. One of the well-known predictions of this model is that the average growth rate of income over a period is a function of the gap between the steady state and the initial income. β convergence analysis consists of estimating growth equations in which the (average) growth rate of income over time for each economy is regressed on the initial levels of income. It interprets a negative correlation between the growth rate of income per capita and its initial level, as economies converging toward a common steady state *(absolute β convergence).* Alternatively, one can control for the steady state differences by regressing the average growth rate on the initial level of income and a bunch of steady variables; in this case a negative coefficient in the initial condition is interpreted as economies converging to their own steady state *(conditional β convergence).* The conditioning variables (government expenditure, investment, schooling, etc.) determine the long run, and the initial income level controls the transitory dynamics.

The results are surprisingly uniform: a negative and significant estimate of the initial income coefficient, when conditioning on the steady state variables, of about 2% for different samples and periods. Absolute convergence has also been found for some of the samples, like the US states, Japanese prefectures and OECD countries.

A fundamental question is whether this conditional convergence prediction of the Solow model has any practical interest. In other words, what is the practical interest of economies converging to their own steady states if such a steady states differ among economies and they do not tend to converge?[5] Moreover, in claiming that economies converge toward their steady state it is been assumed that the estimated steady state is the true one[6].

Some ideas (which apply to both *conditional* and *absolute convergence*) have suggested that the β test fails. The cross-section regression analysis, and in particular the concept of β convergence, is based on a model for a single "representative" economy but it extracts conclusions about the cross-section. In other words, the adjustment process

[4]See for example Baumol (1986), Barro (1991) Barro & Sala-i-Martin (1991) & (1992), Mankiw, Romer & Weil (1992).

[5]Canova and Marcet (1995) conclude divergence by showing that there is conditional β convergence but the steady state levels for each economy are far apart from each other. Similar *redutio ad absurdum* argument is used in Andrés and Lamo (1995).

[6]Levine and Renelt (1992) found that results are very sensible to small changes in the set of explanatory variables.

of the Solow model tells us whether or not each economy, after being perturbed from its steady state path, returns to it approaching monotonically. This is a single-country implication and consequently has nothing to say about economies approaching each other. In addition, β convergence test is assuming implicitly that the permanent component of income for each economy is well described by a linear or log-linear deterministic time trend. In fact, the averaged growth rate is simply the slope of the deterministic trend.

More elaborated studies in this approach analyze models of representative economies using panel data econometric methods, where the heterogeneity across economies takes form of "individual effects". These individual effects are (usually) eliminated, by using fixed effects techniques on the estimation. In other words, they leave unexplained significant differences across economies. These differences are precisely, what we want to understand. Canova and Marcet (1995) and Evans (1998) are interesting exceptions, which accommodate the unobserved heterogeneity.

Besides all the limitations just mentioned, Quah (1993b) has shown that convergence tests based on regressing growth rates on initial levels are uninformative since a negative cross-section regression coefficient on the initial level is compatible with cross-economies behaviors that are far from the idea of convergence. This is the so-called Galton's Fallacy. Quah (1993b) shows that, when estimating growth equations the initial condition coefficient can be negative when assuming that the cross-section distribution is time-invariant, or even if there is divergence. This holds for cross-section data, panel data or any other structure. Exactly the same reasoning applies to the idea of *conditional convergence*, just by taking the variable of analysis to be the residuals of the output after conditioning on the exogenous variables

The standard approach, in the light of the Galton's fallacy criticism, introduces the concept of σ convergence, which tries to contribute to the measurement of convergence with some kind of information about the dynamics of the cross-section distribution[7] There is σ convergence if the dispersion of the real income across economies tends to fall over time, the dispersion is measured as the sample standard deviation[8].

[7] σ convergence is model free in the sense that is not linked to a particular model as beta convergence to the classical model. It does not depend on the model specification

[8] Obviously, one can define both absolute and conditional σ convergence. depending

The idea is that both a negative coefficient of the initial condition and a decreasing cross-section dispersion over time would be sufficient to show convergence[9]. There are cases in which the sample standard deviation says little about the cross-section dynamics. It is only a point in time statistic and may not be sufficient to describe the cross-section distribution dynamics. For example, observations from a bi-modal distribution may have the same sample variance as observations from a uni-modal one, while the interpretation of these distributions in terms of convergence is obviously quite different. In other words, s convergence cannot account for clusters, stratification, etc. Also, σ convergence cannot account for the intra-distribution mobility.

Summarizing, the main limitation of the conventional approach is that it relies on two single statistics (mean and standard deviation) that are not always sufficient to describe the cross-section distribution dynamics.

2.2 Time series

There is a bunch of papers that addresses long run convergence using time series unit roots and cointegration techniques. Time series approach tests for convergence in a stochastic framework, where stochastic technological changes generate permanent movements of income, which may lead to patterns of persistence on income. Convergence in this setting will take place if the permanent movements in the income of an economy are associated with movements in the income of others.

A group of economies converge if the long run forecasts of income for all economies are equal at a fixed time. This may be directly tested by using multivariate cointegration tests. Differences in income vanishing in the long run means that the series of income disparities are not integrated or alternatively the incomes are cointegrated series. In this framework, it is possible to define clubs of convergence or to arrange groups of economies by measuring the number of common trends in the multivariate setting.

The results from this approach are in conflict with those of the cross-section regression analysis. Bernard and Durlauf (1995) implement a bivariate and multivariate test for cointegration and convergence for

on whether one refers to the dispersion of income before or after conditioning out the steady state variables effect.

[9] β convergence is a necessary condition for s convergence but not sufficient.

15 OECD economies, they do not find evidence of convergence.

Time series tests of convergence are not able to account for transitional characteristics. Additionally, they are not well suited to study large cross-sections because the multivariate tests are not very operative when the number of economies is large.[10]

3. Cross-section distribution dynamics. Absolute convergence across Spanish regions

When analyzing convergence we are interested in the relative performance of economies in terms of income, and on its evolution. On whether income inequality across countries or regions is vanishing or not. In other words, whether poor economies are catching up with the richest ones or on the contrary the income disparities persist over time This suggests the need of characterizing the dynamics of the entire cross-economies distribution of income, instead of focusing on some moments of the distribution.

Quah (e.g. 1993a, 1996a,c) develops an alternative approach to empirics of convergence which studies the evolution over time of the entire cross-section distribution of income. This evolution involves changes of the exterior shape and intra-distribution mobility, which give relevant information in characterizing convergence. The exterior shape of the income distribution tending over time to a limit point (income equality) indicates convergence. If this is not the case, we are still interested on whether poor regions are catching up (rich ones falling behind). The dynamics of each country's relative position is also a crucial component of the notion of convergence. In other terms, in order to characterize convergence we need to look also for intra-distribution mobility.

Quah's approach has been designed to deal with large cross-sections of data. In probability theory these structures, where both dimensions (cross-section and time series) have the same order of magnitude, are called *random fields*. At each point in time there is a cross-section distribution of income, which is simply the realization of a random element in a space of distributions. The cross section distributions have to be estimated from the data, we will use nonparametric techniques to do so. The idea is to model the dynamics of the distributions

[10] Although, there is an expanding literature on panel cointegration techniques that could be an answer to this limitation.

and capture both, the exterior shape and the intra-distribution mobility dynamics. This will allow identification of twin peaks (clustering in two groups), stratification (clustering in several groups), convergence, etc., and to answer questions as: how economies transit from the poorest tail of the distribution to the richest one, or for instance, how the richest 20% approaches the median. It also allows us to characterize situations in which some portions of the distribution display convergence and the others do not.

Studying the entire cross-section distribution dynamics encodes the standard approaches and overcomes some of their difficulties. In particular, it does not suffer from Galton's fallacy. It does not impose any structure on the data and is model free, in this sense its robustness does not depend on model specification. Additionally, conditioning in this context gives information on the causes of that dynamics and allows accounting for endogenous interaction across regions. For instance, spatial spillovers and international trade account for part of the distribution of incomes across countries in the world (Quah, 1996c), and across regions in the European cohesion countries (Quah, 1997). The current paper studies the role of migration across Spanish regions.

The main shortcomings of this approach are of two kinds. Firstly, it is not sufficiently integrated in structural econometric analysis. Secondly, it suffers from problems inherent to nonparametric estimation and Markov chains estimation; this will become more obvious below[11]. The study of distributions (non parametric) and their dynamics have long been a central part of economic analysis of personal income, occupations, earnings, firms and industry shares, etc.

The current section analyzes convergence across Spanish regions using the cross-section distribution dynamics approach.

3.1 The data

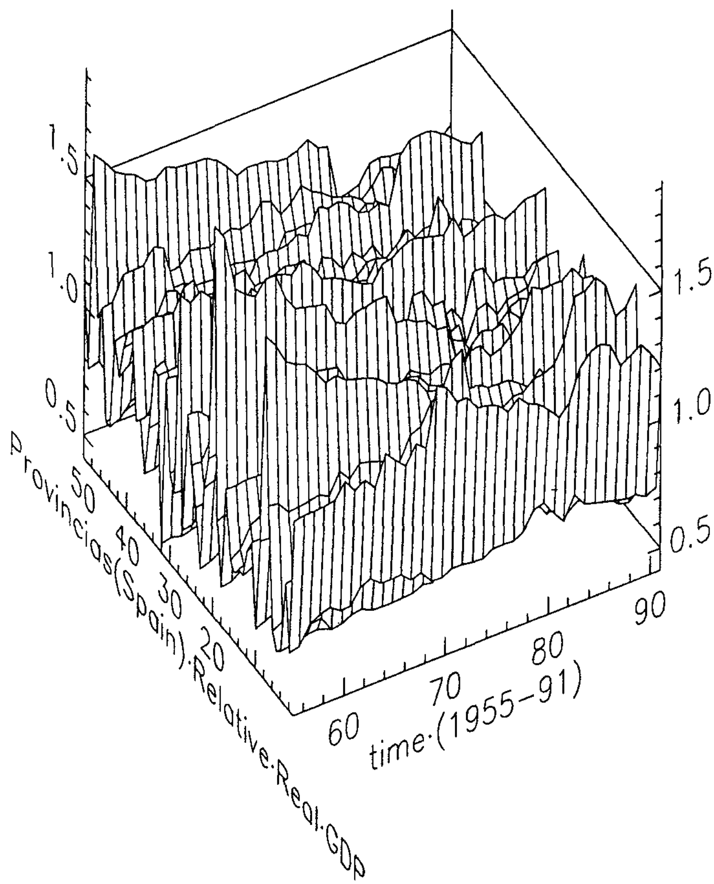
The basic variable is real GDP per capita (as a proportion of the labor force) in each individual region *(provincias)*, relative to the same variable for the country[12]. *Provincias* are the traditional administrative

[11] We model the dynamics of the cross section distribution in a discrete space as a Markov process.

[12] This normalization is a way to abstract each individual region from the country growth and fluctuations Although, this implies to assume that the regions move with the cycle in the same way as the aggregate

division in Spain, they correspond to NUTS3 in Eurostat nomenclature of statistical territorial units The GDP and labor force data were drawn from Banco de Bilbao and BBV series which are published every other year, see references. Some interpolation was required to get yearly data, for which we used the sectoral structure of each region and the sectoral GDP growth rates[13]. The sample covers 50 *provincias* over a period of 35 years (1955-1991). Figure 1 is a three dimensional plot of the variable. The main message of this graphic is that both dimensions of variation in the data are very important. These dynamics are the ones that this approach tries to account for.

FIGURE 1
Relative real GDP per capita across Spanish regions *(Provincias)*



[13]In particular, the GDP series for each region was completed using GDP growth rates. These growth rates were calculated as a weighted average of the aggregate growth rate for each sector in Spain, taking as weights the share that each sector's GDP represented in the total GDP of the region Thanks to J. Dolado for kindly providing the sectoral data

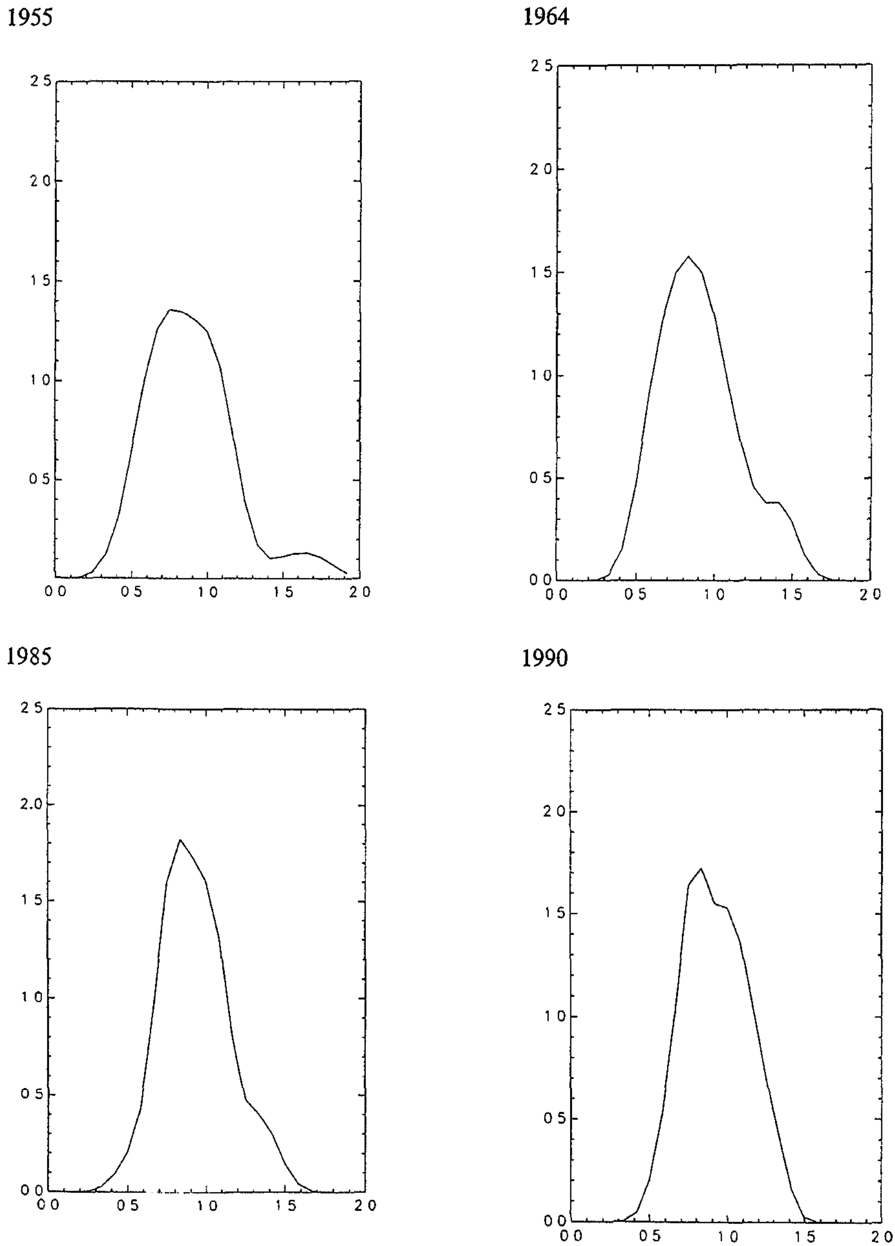
3.2 *The random element: cross section distribution*

Our random element, which turns out to be a cross-section distribution function, has to be estimated from data. There are two approaches to density estimation. The *parametric approach* which assumes that the data are drawn from one of the known parametric families of distributions with unknown parameters. The underlying distribution can then be estimated by estimating these parameters from the observed data set. And the *nonparametric approach*, which requires weaker assumptions. The data are allowed to speak for themselves in determining the estimate of the density function. The latter is the approach we are using in our analysis because it does not require imposing any assumption on the exterior shape or about the moments of the density function from which the data are drawn. Due to their flexibility, nonparametric methods are able to detect structures deviating from traditional parametric forms.

Figure 2 presents some nonparametric estimated density functions of relative per capita GDP across the 50 Spanish regions for some years of the sample. The estimation was done using gaussian kernels. The bandwidth was optimally chosen by least squared cross-validation (see Silverman (1986), section 2.10). Obviously, the bandwidth choice affects the estimation. A bandwidth higher than the optimal should smooth the estimation and the opposite should happen with a bandwidth smaller than optimal. We tried the estimations using bandwidths 10% and 15% higher and smaller than the optimal; these estimators hardly differ from the ones presented in this paper. In this context of *random fields*, looking at the cross-section distributions is equivalent to looking at the values of the variable, observation by observation, in time series analysis. A few conclusions may be extracted from this exercise. At the beginning of the sample our estimates show a small group of regions concentrated at around one and a half times the average income of the country, during the 1960s the distribution turns to be uni-modal. It is mainly during the period 1955-63 when the range of relative differences among regions' incomes diminishes. This first look at the density estimates suggests that the first and second moment do not entirely describe the behavior of the distribution. Consequently, β and σ convergence may be misleading[14]. In general, it would be beneficial to provide some measure of uncertainty for the estimated

[14] The cross-section distribution for every year of the sample is available upon request. All the calculations in this paper were done with Danny Quah's shell *tSrF*.

FIGURE 2
Estimated density functions of relative GDP per capita across Spanish regions
(Provincias)



densities. However, in this case, given the size of the sample, these measures would be quite inaccurate. Figure 2 is shown here for merely illustrative purposes.

Looking at the density estimates is very intuitive but the distributions are just point estimates for the sample period and cannot be assumed to reflect out-of-sample patterns. This does not give any information about the long run steady state nor about the intra-distribution mobility.

3.3 Modeling the distribution dynamics

In order to respond to these objections and make progress in the analysis it becomes necessary to develop a law of motion for the cross-section distribution of income as realizations of a random element in the space of distributions. Then, we need a model for a stochastic process that takes values that are probability measures associated with the cross-section distribution.

This paper builds up on Quah (1993a,b, 1996a,c). Let λ_t be the probability measures (one each year) associated with the cross-section distribution. The simplest way of modeling their dynamics is using the following probability model:

$$\lambda_t = T^*(\lambda_{t-1}, u_t), \qquad [1]$$

which is the analogous to a first order autoregression model in time series.

The stochastic difference equation in expression [1] is unmanageable. By ignoring the disturbance and iterating it can be written as [2].

$$\lambda_{t+s} = (T^*)^s \lambda_t, \qquad [2]$$

So that, as s goes towards infinity it is possible to characterize the long run distribution of income across economies, i.e. to characterize the existence and uniqueness of the steady state. T^* maps probability measures into probability measures. It encodes information on, for example, whether or not the income levels of economies get closer. T^* must be estimated from the data.

An easy way to work out T^* is to approximate it by assuming a countable state-space for income levels (states) $S_t = \{s_{1t}, s_{2t}, .., s_{rt}\}$. The discretization defines a grid that can be thought of as an estimator of the initial unconditional probability λ_t. In this case, T^* is simply a *transition probability matrix* (Q_t) such that the difference equation [1] is a Markov process.

Under some regularity conditions, Q_t defined for the fixed grid ($S_t = S$) is time-invariant (Q) and the long run calculation in [2] can be done in an explicit way. The sequence of powers of this matrix converges to a matrix whose rows (all of them identical) are the *ergodic distribution*, which allows us to talk about steady state.

TABLE 1
Spanish relative *per-capita* income
First order transition matrix, time stationary 1955-91

Uper end of the States	0.756	0 906	1.061	1 879
(r)	(1)	(2)	(3)	(4)
412	0 90	0.10	0.00	0 00
412	0 09	0.91	0 10	0 00
415	0.00	0 09	0 82	0 09
411	0.00	0 00	0.09	0 91
Ergodic distribution	0.205	0 246	0.281	0 268

Table 1 presents some estimates of the transition matrix Q. The length of the defined states varies in order to provide a uniform distribution for the observed sample. In fact, the lengths are quite different, much wider for low and high income states than for the intermediate ones. The first row of table 1 shows the upper limits of these states. For example, the state $s_2 = (0.75, 0.90)$ includes the regions which have an income between 0.75 times and 0.90 times the mean (aggregate) for the country. The first column is the total number of transitions over the whole time sample, starting at each state. The rest displays an estimator of the time-invariant transition probability matrix for a single year, calculated as an average over the total sample, and an estimate of the ergodic distribution (last row) which is the closest concept to the steady state in this setting. Each element of the Q matrix indicates the probability of transition from one state to another in one period; the q_{hg} entry is the probability that a region in state h transits to the state g (intra-distribution mobility). Each row is a conditional probability vector. For instance, the first row of the matrix gives the probabilities of transition from the first state to all the states (including the first) in one year. The ergodic distribution tells us the unconditional probability for an economy to end up in a particular range of relative GDP per capita, independently of where it started from, under the assumption that there is no structural change and the system keeps evolving in the same fashion.

The values in the main diagonal are higher for the poorest and richest regions, being around 90%, which indicates that in average the probability of leaving both the lowest and highest income group in one period is around 0.10. There is less persistence for the intermediate groups, the probability of being off the diagonal for those reaches 0.19, and it is symmetrically distributed between the probability of moving up or down (to a higher and lower relative position). With regard to the long run, we end up with a distribution that has not degenerated, but gives a slightly higher probability of reaching the average state. The steady state distribution does not differ much from the observed one. Low intra-distribution mobility implies that the poor regions are not catching up with the rich ones (nor the rich falling behind). From these two facts together we conclude that (according to the current model) convergence across Spanish regions has not taken place.

A similar model is used in Gardeazabal (1996). He analyzes the dynamics of personal income per capita across Spanish regions for a similar time sample. Gardeazabal (1996) finds that the ergodic distribution is similar to the observed one at the final year of the sample and concludes that the Spanish economy is already in its steady state, and therefore convergence has taken place. His findings are not in conflict with ours, although, his conclusion is. It can be said that the economy is at its steady state but this equilibrium is not necessarily one of convergence, in the sense of economic homogenization (catching up/falling behind). In fact, from Gardeazabal's results one can see that the observed distributions in 1977 and thereafter are very close to the estimated ergodic distribution; i.e. already in 1977 the Spanish regions were close to the steady state. Whether that equilibrium distribution is one of economic convergence is a different issue. According to Gardeazabal's ergodic distribution the 14% of the regions have *low* income (in equilibrium), and only the 24% are around the average[15]. On top of this, the lack of high mobility across regions induces us to claim that Gardeazabal (1996) could provide more evidence for our conclusion than for his. In

[15] Gardeazabal (1996) works with deviations of regional income (in logs) from the time mean. He divides the rank of variation of his variable into 5 intervals whit approximately equal number of observations over the whole sample *Low* income regions are those in the lowest interval. The upper limits of Gardeazabal's intervals, expressed as regional income relative to the time mean, should be around 0 8, 0 9, 1.0, 1.2, and -∞, according to our calculations.

other words, the economy has reached a steady state but this is not one of economic convergence. Nevertheless, the results in Gardeazabal (1996) are not directly comparable with the ones in this paper since his variable of analysis is not the same as ours.

TABLE 2
Spanısh relative *per-capıta* income
First order transition matrıx, time statıonary 1955-64

Uper end of the States	0.724	0.872	1.050	1 882
(r)	(1)	(2)	(3)	(4)
113	0.86	0 14	0.00	0.00
114	0.12	0 78	0.10	0.00
111	0.00	0 09	0.83	0.08
112	0 00	0.00	0.10	0.90

TABLE 3
Spanısh relatıve *per-capıta* ıncome
First order transition matrix, tıme statıonary 1964-77

Uper end of the States	0 746	0 902	1.058	1 492
(r)	(1)	(2)	(3)	(4)
177	0.93	0.14	0 00	0 00
177	0 06	0 82	0 12	0.00
171	0.00	0.09	0 86	0 05
175	0 00	0 00	0 06	0.94

TABLE 4
Spanish relative *per-capıta* ıncome
First order transıtion matrix, tıme statıonary 1977-91

Uper end of the States	0.796	0 929	1.065	1 501
(r)	(1)	(2)	(3)	(4)
175	0 86	0 14	0 00	0 00
173	0.13	0 77	0 10	0 00
178	0 00	0.12	0 77	0 11
174	0 00	0 00	0 10	0.90

The calculations in this section as well as those in Gardeazabal (1996) require time-invariant transition probability, which is not always reasonable for long periods in which, for example, some economic structural changes may have happened. Following the analysis in Dolado *et al* (1994), we divide the whole sample into the three following subperiods. periods 1955-64, 1964-77 and 1977-91[16]. Table 2, 3 and 4 dis-

[16]The period 1977-91 is quite heterogeneous. beıng 1977-85 a period of crises or

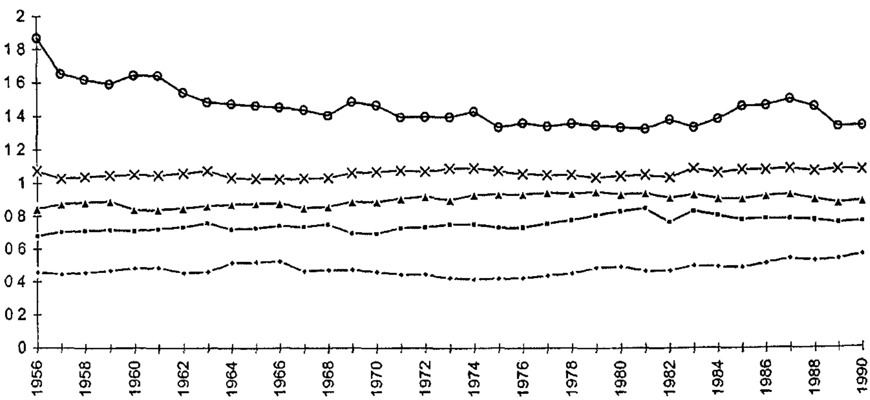
plays some estimates of the transition matrix Q for these sub-periods.

Alternatively, it is possible to construct time-variant transition matrices; by fixing the probability vectors to be uniform and identical for every time point ($\lambda_t = \lambda$) we define a time-variant grid $S_t = \{s_{1t}, s_{2t}, ..., s_{rt}\}$. Associated to that there is a sequence of transition probability matrices, Q_t.

For example, let r be 4, and define $\lambda_t = \lambda = (0.25, 0.25, 0.25, 0.25)$, then the set of quartiles defines the grid, and changes in the grid describe the evolution of the cross-section distribution. The associated sequence of transition probability matrices will show the intra-distribution mobility.

Convergence in this setting is a situation in which the sequences of quartiles tend to approach each other; i.e. the interquantil ranges tend to zero (and/or there is high mobility). Figure 3 shows the sequence of quantiles, although it does not give information on intra-distribution mobility[17]. Again the picture is one of persistence. There may be slight convergence during the first part of the sample.

FIGURE 3
Relative real GDP per capita across Spanish regions. *(Provincias)*



It is well known that the arbitrary discretization may affect the characteristics of the ergodic distribution as well as the Markov property. To avoid this problem, we can take the number of cell tending to infinite, or put it differently, the length of the intervals being infinitesimally small. This leads to a continuous matrix: *stochastic kernel* (Stokey and Lucas,1989).

recession while 1985-91 one of expansion. Using alternative sub-period does not change our qualitative results

[17]Transition matrices are available upon request

FIGURE 4
Dynamics of relative real GDP per Capita across Spanish regions *(Provincias)*
1 year transition

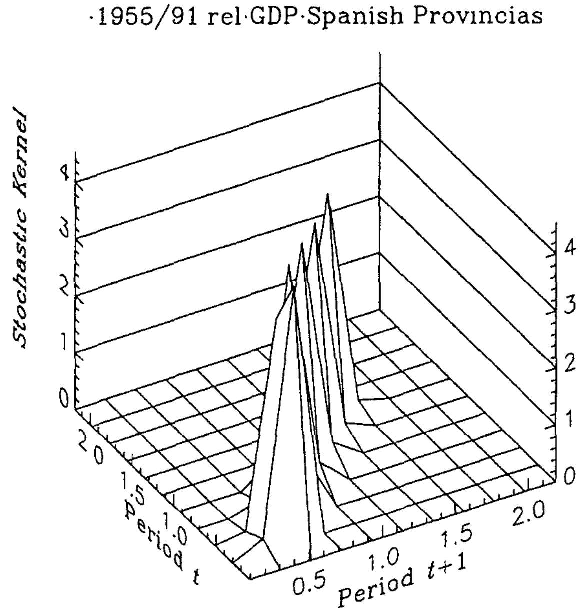
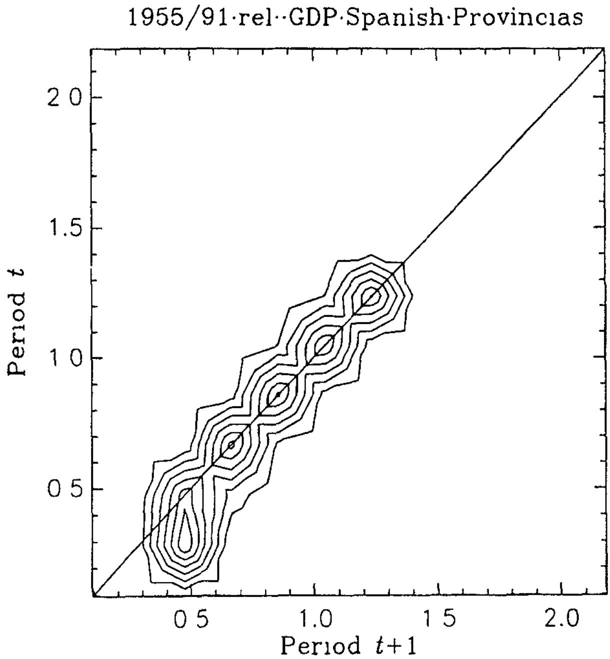


FIGURE 5
Dynamics of relative real GDP per Capita across Spanish regions *(Provincias)*
1 year transition. Contour plot. 1955-91



We can think of a *stochastic kernel* in terms of conditional probability density. Take any three dimensional plot of a *stochastic kernel* (e.g. Figure 4), a slice parallel to the $t+\tau$ gives a probability density that describes transitions from a part of the income distribution (the point where we slice) to any other in t periods; i.e. it describes the probability density in $t+\tau$ conditional on the density at period t. The location of the probability mass gives us the information about persistence and mobility allowing us to extract conclusions in terms of convergence. Concentration of the probability mass along the positive sloped diagonal would indicate high persistence in the economies' relative position, and consequently low mobility. The mass of probability under this diagonal indicates improvement in relative positions, i.e. catching up. If the mass of probability is orthogonal to the $t+\tau$ axis there is convergence. Peaks along the diagonal indicate the presence of convergence clubs. Concentration along the negative sloped diagonal would indicate that regions are overtaking each other in the income ranking. Finally, the transition probability describing horizontal lines (parallel to $t+\tau$) would show that there is very low persistence; the probability of being at any point in $t+\tau$ is independent of the position in t. The contour plots (e.g. Figure 5) give a clear impression of relative height and thus of the concentration of probability.

The *stochastic kernels* estimators in this paper (Figures 4 to 8) where obtained using the Epanechnikov kernels for estimating the joint density $f(X_{it}, X_{it+\tau})$ and then dividing it by the implied marginal distribution, to obtain the conditional probability. Where X_{it} is the per capita income for each individual region i relative to the same variable for the country in period t. The bandwidth was chosen automatically by least square cross-section validation (see Silverman, 1986, Section 3.4.3)[18].

Figure 4 displays a three dimensional plot of the transitions probability function for $\tau = 1$, while Figure 5 displays the contour of the function in Figure 4. According to these figures, during the sample period (1955-91), Spanish regions have a low probability of changing their relative position in one year, tending to remain where they are relative to each other Notice, as well, that the general picture is one of clubs of convergence, this can be observed in the contour (Fig 5), which shows several peaks (convergence clubs) all of them along the diagonal except for the poorest regions. The mass of probability for the poorest

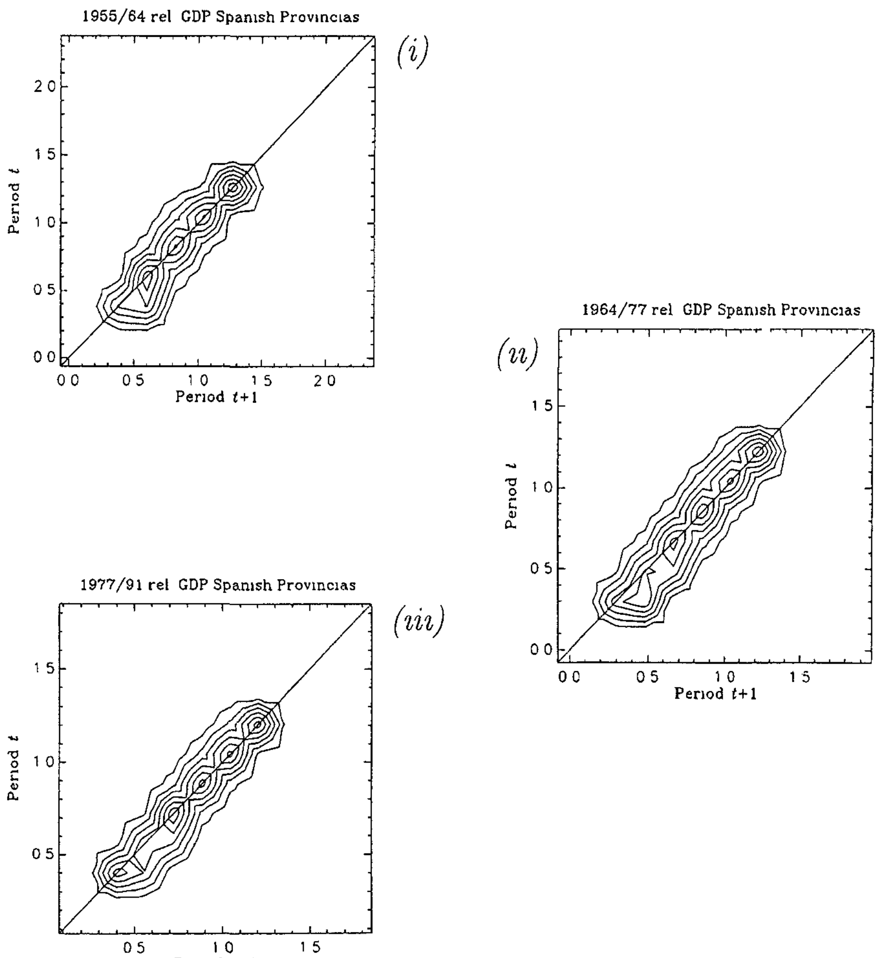
[18] Again, changing the bandwidth gives the expected results.

regions is under the diagonal, indicating some caching up among them, they have concentrated in a cluster around 50% of the average income.

Figures 6 display the contours of the *stochastic kernels* for the periods 1955-64, 1964-77 and 1977-91. The contour for the 1956-64 period (Figure 6(i)), again seemingly indicates that the poorest regions tend to approach the rest and concentrate in a club. For the period 1964-77 and 1977-91 (Figures 6(ii) and 6(iii)) the rank of relative income has slightly decreased. The probability of transition is mainly over the diagonal. We conclude that if some convergence has taken place, it has been in the first sub-period (1955-64). In particular, the richest club is weakened during the first sub period.

FIGURE 6

Dynamics of relative real GDP per Capita across Spanish regions *(Provincias)* 1 year transition. Contour plot.



So far, we have provided some evidence on the cross-sectional distribution dynamics across regions in Spain. The analysis in this section had a simple objective: characterizing convergence. The aim of the next section is to explain how this approach permits explicit ways of cross-section iteration and is able to give some information to understand the law of motion of the cross-section distribution by simply looking at how a set of conditioning factors alter the cross-sectional distribution of income.

4. Conditional information

This section departs from conditional convergence as understood by the classical model[19] In the context of our approach, conditioning may be useful to explore convergence. How a set of conditioning factors alters the distribution of income helps to understand the law of motion of the entire income distribution. It allows to consider the importance of endogenous interaction across regions (e.g. spillovers, trade effects, etc.).

We illustrate how to bring conditional information into the cross-section distribution dynamics approach and we obtain evidence on how interregional migration has affected the convergence process across Spanish regions. The idea is to analyze the income disparities after conditioning out the effects of some variables. It can be done in many different ways. Here, we analyze the residuals from a first stage regression, i.e the effects of the variables we are conditioning on are removed. This would be of little interest, if a great deal of information were removed.

4.1 Conditioning variables

For Spain, we choose as the conditioning variable the interregional migration flows (taken from INE, *Migraciones*, several years) as a percentage of the previous year labor force[20]. The sample covers the 50 regions above, over the period 1962 to 1991.

The whole exercise consists of studying the dynamics of the distribu-

[19] Andrés and Lamo (1995) analyze the distribution of income per capita for the OECD countries conditioned to the steady state as suggested by Solow model.
[20] In a different data set, Levine and Renel (1992) found that the significance of hardly any of the conditioning variables (except saving rates) can be claimed robust We are also aware of the interpretation problems of the variable migration Thanks to J de Lucio for providing the data

tion of income disparities, which migration flows cannot account for. We are considering the interrelation across regions via migration, a very simple and particular factor of interrelation The methodology in this exercise follows the one in Quah (1996a).

4.2 Conditioning regression

We face a clear case of endogeneity considering migration. Therefore, we estimate a two-sided projection of GDP growth rates on migration rates[21]. Then, we accumulate the residuals from this projection to get the corresponding residual components in regional GDP per capita, relative to the country's GDP per capita, which is going to be the basic variable of analysis. The intention is to remove the effects of migration from the GDP dynamics. Notice that the residuals have no explicit economic interpretation, but they capture the dynamics in the original data that has not been removed by the regression.

4.3 Some results

The evidence from studying the dynamics of these residuals seems to indicate that migration flows have had, if any, a negative effect on the convergence process across Spanish regions during the period 1966-87. This can be seeing, by comparing the results for the raw data with those derived from the data after conditioning. The sample now is restricted to the period 1966-87 for which the migration data are available[22]. The *stochastic kernel* before conditioning out the effect of migration (Figure 7) is one of persistence and clubs along the diagonal[23]. The regions with highest and lowest levels of relative income are particularly concentrated. After conditioning (Figure 8) there is also persistence, but now the richest regions' club is not that remarkable and the poor regions' club is under the diagonal, indicating some improvement in their relative position (catching up) Tables 5 and 6 show the conditional and unconditional time-invariant transition matrix. We found a small increase in mobility after conditioning. In summary, over the period 1966-87 migration flows across Spanish *provincias* had a small and negative influence on the convergence process in the country.

[21] Results from the conditioning regression are available upon request

[22] Some observations are lost during the conditioning process

[23] In the previous section this period already appeared as one of high persistence.

FIGURE 7
Dynamics of relative real GDP per Capita across Spanish regions *(Provincias)* 1 year transition. Contour Plot. 1966-87

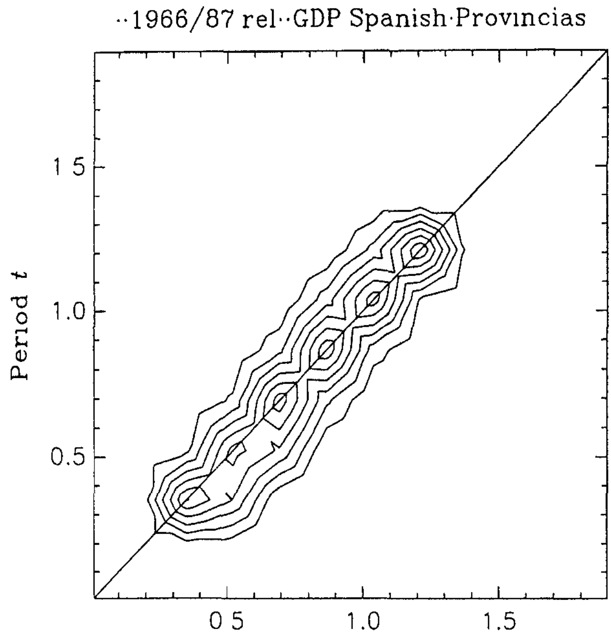
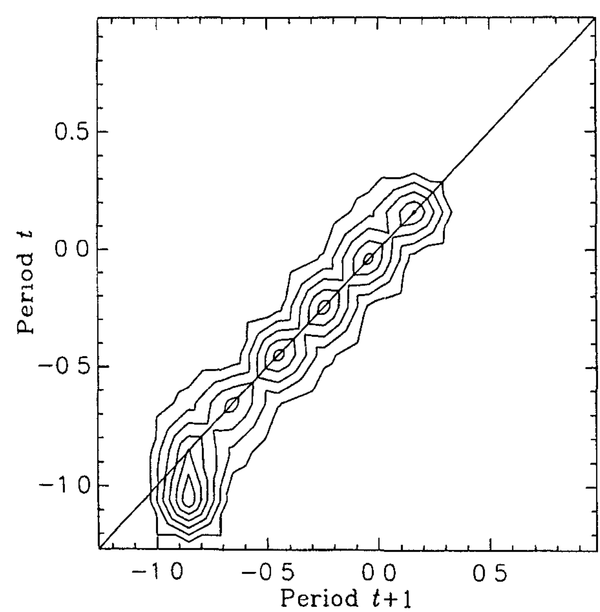


FIGURE 8
Dynamics of relative real GDP per Capita across Spanish regions *(Provincias)* conditioning on migration 1 year transition Contour plot 1966-87



During the second part of the sample migration flows decreased reaching a quite low level. Therefore, we divide the sample into two sub-periods; 1966-77 when the migration flows are quite important compared to 1977-87.

TABLE 5
Spanish relative *per-capita* income
First order transition matrix, time stationary 1966-87

(r)	(1)	(2)	(3)	(4)
282	0 91	0.09	0.00	0 00
281	0 08	0 80	0.12	0 00
284	0 00	0.11	0.79	0 10
275	0.00	0 00	0.09	0 91

TABLE 6
Spanish residuals first stage regression. Conditioning out migration flows
First order transition matrix, time stationary 1966-87

(r)	(1)	(2)	(3)	(4)
275	0.90	0 10	0 00	0 00
276	0 08	0.79	0.12	0 00
277	0.00	0 12	0.76	0 12
272	0 00	0 00	0.11	0 89

CUADRO 7
Spanish relative *per-capita* income
First order transition matrix, time stationary 1966-77

(r)	(1)	(2)	(3)	(4)
155	0.94	0.06	0 00	0 00
155	0.06	0.83	0 12	0.00
148	0 00	0.07	0 86	0 07
154	0 00	0.00	0 06	0.94

CUADRO 8
Spanish residuals first stage regression Conditioning out migration flows
First order transition matrix, time stationary 1966-77

(r)	(1)	(2)	(3)	(4)
151	0.90	0 10	0 00	0 00
150	0 07	0 81	0 11	0.00
149	0 00	0 11	0 77	0 12
150	0 00	0 00	0 13	0 87

For the period 1966-77 (Tables 7 and 8) the conditional and unconditional results differ considerably. The matrix for the residuals (conditioning out migration) displays much more mobility than the unconditional one, especially for the regions on both extremes of the distribution. In other words, the observed data (GDP per capita) show a lower probability of poor and rich regions approaching the average over the period 1966-77 than the data where the influence of migration has been removed from GDP dynamics. During the period 1977-87 (Tables 9 and 10) the picture is about the same before and after conditioning. Migration did not play a role in convergence, recall that in this period migration is rather low.

CUADRO 9
Spanish relative *per-capita* income
First order transition matrix, time stationary 1977-87

(r)	(1)	(2)	(3)	(4)
138	0 87	0.13	0.00	0.00
143	0 13	0.77	0.10	0.00
143	0 00	0.12	0.75	0.13
137	0 00	0.00	0.13	0.87

CUADRO 10
Spanish residuals first stage regression Conditioning out migration flows
First order transition matrix, time stationary 1977-87

(r)	(1)	(2)	(3)	(4)
135	0 87	0 12	0 01	0 00
139	0.13	0 75	0.12	0.01
141	0 00	0.13	0.74	0 12
135	0 00	0 00	0.13	0 87

Dolado *et al* (1994) find the effect of migration to be also negative and not very significant. As they explain, this could be due to the fact that the migrants were the ones with relatively high human capital in the region[24].

5. Conclusion

This paper has analyzed the cross-section distribution of relative GDP per capita across regions in Spain to characterize convergence and has studied the role of interregional migration in convergence. The main conclusions from the analysis are the following:

(i) There is no evidence of income convergence across Spanish regions.

[24] Raymond and Garcia (1994), on the contrary, claim that migration flows have played an important role in favor of convergence across Spanish regions during the 60s and 70s.

Although, GDP disparities in Spain have narrowed (slightly) during the period 1955-64.

(ii) If migration flows across Spanish regions have played any role in convergence during the period 1966-88, it has been negative. When removing the influence of migration on the dynamics of regional GDP, the richest and poorest regions move towards the average income level over the period 1966-77. This phenomenon could possibly be explained in terms of the skills of the migrants during this period. The role of migration is insignificant during the 80's.

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Resumen

Este artículo analiza la evolución de la distribución del PNB per cápita en 50 provincias españolas, con el objetivo de obtener evidencia sobre la convergencia de la renta de dichas regiones. También estudia el papel que la migración interprovincial ha desempeñado en el proceso de convergencia. Los principales resultados indican que no hay evidencia de convergencia de la renta entre las provincias españolas y que el efecto de los flujos migratorios sobre la convergencia ha sido nulo o incluso negativo. El enfoque adoptado en este artículo tiene en cuenta tanto la información de sección cruzada como de series temporales contenida en los datos, y no esta sujeto a la mayoría de las críticas realizadas a la literatura empírica tradicional sobre convergencia.

Keywords: Convergencia, convergencia condicional, crecimiento

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