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Persistence in inequalities across the Spanish regions[#]

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RESUMEN

En este artículo investigamos varios temas relacionados con la persistencia de las desigualdades regionales en renta per cápita en España entre 1980 y 2002. Para ello adoptamos un enfoque bayesiano que extiende el trabajo de Canova y Marcet (1995). Primero, estudiamos en qué medida existe un sesgo por efectos fijos en las regresiones de sección cruzada, y confirmamos su existencia. Segundo, proporcionamos una batería de estimaciones de velocidades de convergencia y estados estacionarios para un continuo de distribuciones a priori. Tercero, comprobamos que las disparidades regionales en España se han mantenido, con una elevada influencia de las condiciones iniciales sobre la distribución de estados estacionarios.

Palabras clave: Convergencia, desigualdades, econometría bayesiana, Gibbs sampling.

ABSTRACT

In this paper we investigate several issues concerning persistence in inequalities of relative income per capita among the Spanish regions over 1980-2002. For that purpose we take a Bayesian approach which extends the work by Canova and Marcet (1995). Firstly, we study to what extent there exists a fixed effect bias in the standard cross-section estimates, and we find that the speed of convergence is indeed underestimated. Secondly, we provide a battery of results in which steady states and convergence rates have been obtained for a continuum of prior distributions. Finally, we also deal with persistence in inequalites by determining whether initial conditions matter in the distribution of regional steady states, and our conclusion is that regional disparities tend to persist over time in Spain.

Keywords: Convergence, Inequalities, Bayesian Econometrics, Gibbs sampling.
JEL classification: C11, O47, R11.

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1 Introduction

Debate among economists and policy makers on the existence of convergence across countries and regions remains on the table. On the basis of the textbook Solow model, a huge number of empirical studies have been carried out to elucidate not only whether economic convergence exists but also which factors should be identified as engines of growth. A relevant part of this literature is motivated by the following questions: Will disparities in income per capita disappear as time goes by? What is the speed at which this convergence process takes place? Can governments follow adequate policies to increase growth rates or, by contrast, are economies doomed to keep their positions in comparative rankings?

The standard approach in growth empirics is running cross-section regressions à la Barro. Barro and Sala-i-Martin (1992) and Mankiw *et al.* (1992) detect convergence in several samples and estimate a speed of convergence of about 2% a year. However, an important caveat has to be kept in mind when assessing such results and those coming from subsequent literature: the analysis is based on the assumption that steady states and speeds of convergence are the same for all economies involved in the sample. Indeed, a seminal paper by Islam (1995) showed the fixed effect bias arising from regressions that do not control for heterogeneity across units. The main consequence of allowing for such a degree of heterogeneity is a substantial increase in the convergence rates, which achieve values of about 9%. This finding has been confirmed by other papers such as Caselli *et al.* (1996), Maddala and Wu (2000) and Canova and Marcet (1995).

In this article we follow the works by Canova and Marcet (1995), Maddala and Wu (2000) and Canova (2004), who applied Bayesian techniques to the analysis of the persistence in inequalities among European regions and OECD countries. Particularly, we borrow from Canova and Marcet (1995) the idea of exchangeability on some key parameters of the model. In turn, we slightly extend their Bayesian technique in three directions. *First*, speeds of convergence will be truncated on the unit circle, that is, equations will be forced to revert to a long run level. *Second*, we assume that the variance matrix of the residuals is non diagonal, due to the presence of cross correlations among the equations of the system. Canova and Marcet (1995) instead consider that this matrix is diagonal and estimate it using maximum likelihood principles. *Third*, once the Bayes rule is applied, we will use the Gibbs sampling method to obtain a numerical approximation of the marginal distributions of the parameters.

By extending the Bayesian techniques proposed by Canova and Marcet

(1995), the main aim of the paper is to investigate the persistence in inequalities in the Spanish regions over the period 1980-2002. This covers the eighties and nineties which are the years in which a sudden stop in regional convergence has been detected in Spain (see, for instance, López-Bazo *et al.*, (1999)). This contrasts with the extended claim that convergence rates increase during the expansionary stages of the cycle. Along these lines, this paper supplies additional evidence on this issue as our sample includes one of the lengthiest expansionary period in decades.

Three main questions are taken on board in our analysis. First, we check whether a convergence analysis for the Spanish regions using standard cross-section regressions appears to be contaminated by the fixed effects bias. Second, we study how the speed of convergence varies once we gradually alter the precision of the prior distribution of the parameters. At this point, we extend the contribution by Shioji (2004) by using his forecasting exercise in order to select the best prior assumptions on the distribution of relevant parameters. Third, we investigate the issue of persistence in inequalities across the Spanish regions.

Our main findings are as follows. Firstly, we corroborate previous findings by Canova and Marcet (1995) in the sense that the cross-section approach renders a biased estimate of the speed of convergence. In that regard, when steady states and speed of convergence parameters are not constrained to be common across regions, we find a much higher speed of convergence. Secondly, we strongly reject the hypothesis of unconditional convergence since regions are found to be converging to their own steady states rather than to a common steady state. Thirdly, we consistently find evidence of persistence in inequalities across the Spanish regions, showing that income differences have hardly narrowed down over the period under analysis. Thus initial conditions appear to be the most important determinant of the relative position in the distribution of estimated steady states.

The rest of the paper is organized as follows. Section 2 describes the econometric methodology employed in the study. Section 3 presents a brief description of the data and the results of the analysis. Section 4 puts forward some policy implications and concludes.

2 Econometric method

This section presents the Bayesian tools used in this paper. The model to estimate is an $N-$equation Gaussian panel with an $AR(1)$ structure. Let y_{nt} denote (the log of) *per capita* income of region n (for $n = 1, ...N$) at time t relative to (the log of) the mean across regions at period t, *i.e.*

$$y_{nt} = \log(Y_{nt}) - \log\left(\frac{1}{N}\sum_{n=1}^{N} Y_{nt}\right),$$

where Y_{nt} represents *per capita* income of region n at time t. The observation y_{nt} is then generated by

$$y_{nt} = \alpha_n + \rho_n y_{nt-1} + u_{nt}, \tag{1}$$

for $t = 1, ...T$. For equation n, stationarity requires $\rho_n \in (-1, 1)$, then mean reversion gives an equilibrium or steady state value for equation n equal to

$$SS_n = \frac{\alpha_n}{1-\rho_n}. \tag{2}$$

In a growth context, $v_n = 1 - |\rho_n|$ is interpreted as the speed of convergence of region n to the *relative* steady-state. As ρ_n gets closer to the limits of the unit circle, the degree of mean reversion decreases. If ρ_n is equal to 0, any deviation from the equilibrium value is automatically corrected, given that the data generating process (1) is white noise. Accordingly, the term SS_n is interpreted as the difference of the $n-$th region's steady state from the national steady state. Hence, a negative value for SS_n means that the $n-$th region's steady state is below average, thereby implying that region n grows at a lower rate along the balanced growth path than the average does.

At any time t, residuals across equations are assumed to be serially uncorrelated and are distributed according to $u_t = (u_{1t}, ..., u_{Nt})' \sim i.i.d.\mathcal{N}_N[0, \Sigma]$, for all t, where $\Sigma : N \times N$, is non-diagonal.

- **Assumption 1:** The data $y_n = (y_{n1}, ..., y_{nT})'$ are generated by equation (1), for $n = 1, ...N$.

- **Assumption 2:** The value of ρ_n lies inside the unit circle, i.e., $\rho_n \in (-1, 1)$, for $n = 1, ...N$. Formally, $\rho_n \in S(\rho)$, for all $n = 1, ...N$, where

$$S(\rho) = \{\rho_n : |1 - \rho_n z| \neq 0, \forall z \in [-1, 1]\}. \tag{3}$$

Given these conditions and assumptions, the system of equations (1) can be reduced to the following expression

$$y = X\beta + u, \tag{4}$$

with $u \sim \mathcal{N}_{NT}(\mathbf{0}_{NT}, \Sigma \otimes I_T)$, and matrices in (4) have the form: $y = (y_1, ...y_N)' : NT \times 1$,

$$X = [(I_N \otimes \mathbf{1}_T), \text{diag}(y_{1,-1}, ...y_{N,-1})] : NT \times 2N, \tag{5}$$

with $y_{n,-1}$ denoting the one period lagged matrix for region n, $T \times 1$. Matrix $\text{diag}(y_{1,-1}, ...y_{N,-1})$ is block diagonal, $NT \times N$, and $\beta = (\alpha_1, ...\alpha_N, \rho_1, ...\rho_N)' : 2N \times 1$. This implies that the likelihood function is $y\,|\beta, \Sigma = p(y\,|\beta, \Sigma) = \mathcal{N}_{NT}[X\beta, \Sigma \otimes I_T]$.

2.1 Priors

Two blocks of parameters are to be estimated, β and Σ. We borrow from Canova and Marcet (1995) the idea of exchangeability for β, with a slight variation, namely, all the slopes ρ_n will be truncated into the stationarity set $S(\rho)$ defined in (3). In addition, we differ from Canova and Marcet (1995) in the prior for Σ. In their work, a diagonal matrix for $\Sigma = s^2 I$ is proposed, where the scalar s^2 is derived from maximum likelihood estimation. In turn, the prior probability for the estimated s^2 is assumed to be 1. From a Bayesian perspective, this implies that Canova and Marcet (1995) pose an absolute confidence that the ML estimate of s^2 is the true value. This allows to directly extract the relevant posterior distribution for β.

In our case, we will not assume a diagonal prior on Σ nor employ maximum likelihood techniques for the choice of its value. Instead, we propose a Wishart distribution as prior for Σ, and then exploit the Bayes rule to compute the posterior for β and Σ. These posterior distributions, however, have the uncomfortable form that β is conditional on Σ and, at the same time, that the distribution of Σ appears conditional on β. In an attempt to overcome this problem, we will use a Montecarlo integration technique, *i.e.* the Gibbs sampling method, to produce a numerical approximation of the marginal (not conditional) distributions of β and Σ. We shall now explain the priors.

[β]: *Parameters.* Priors are said to be exchangeable if equations are sharing a common value of parameters, regardless the ordinality of equations. In our model (1), if equation n is assumed to have the same intercept and slope than some other *given* equation m, no matter if $n \lesseqgtr m$, then under normality one may write

$$\begin{aligned} \alpha_n\,|\alpha_m &\sim \mathcal{N}\left[\alpha_m, \sigma_\alpha^2\right], \ \forall n \neq m, &(6)\\ \rho_n\,|\rho_m &\sim \mathcal{N}\left[\rho_m, \sigma_\rho^2\right]. \ \forall n \neq m. &(7)\end{aligned}$$

Expression (6) says that when equation m is given equation n is expected to have the same intercept as m, with a precision represented by $1/\sigma_\alpha^2$, i.e. the inverted prior variance. As long as σ_α^2 approaches 0, an econometrician reveals to feel extremely confident about such a belief, the precision tends to zero, and intercepts are fully exchangeable between equations n and m in the system. The opposite happens when σ_α^2 tends to infinity. An identical interpretation has the prior for the slope parameter in (7).

Canova and Marcet (1995) show that this is equivalent to imposing a prior on the difference of these parameters (see their appendix 3), that is

$$\alpha_n - \alpha_m \sim \mathcal{N}\left[0, \sigma_a^2\right], \ \forall n \neq m, \tag{8}$$
$$\rho_n - \rho_m \sim \mathcal{N}\left[0, \sigma_\rho^2\right]. \ \forall n \neq m. \tag{9}$$

where σ_α^2 and σ_ρ^2 are assumed to be given.

For the $2N$ $\beta-$parameters in the system, we shall assume a Gaussian prior, truncated to the set $S(\rho)$ in (3)

$$(I_2 \otimes R)\,\beta \sim \mathcal{N}_{(N-1)2}\left[\mathbf{0}_{(N-1)2}, (D \otimes \Omega)\right] \cdot S(\rho), \tag{10}$$

where $R : (N-1) \times N$, is a difference matrix given by

$$\begin{aligned} R(n,n) &= -R(n,n+1) = 1, \\ R(n,n-j) &= 0, \text{ for any } j \geq 1. \\ R(n,n+j) &= 0, \text{ for any } j \geq 2. \end{aligned}$$

The variance matrix is $D \otimes \Omega$,

$$D = \begin{bmatrix} \sigma_\alpha^2 & 0 \\ 0 & \sigma_\rho^2 \end{bmatrix} : (2 \times 2),$$

with $\Omega : (N-1) \times (N-1)$ and

$$\begin{aligned} \Omega(n,n) &= 1, \\ \Omega(n,n+1) &= \Omega(n+1,n) = -1/2, \\ \Omega(n,n+j) &= \Omega(n,n-j) = 0, \text{ for any } j \geq 2. \end{aligned}$$

Matrix Ω is so designed to prevent parameters from having variances that increase with the order of equations (see appendix 3 of Canova and Marcet (1995), where they show that matrix Ω makes the order totally neutral).

[Σ]: *Cross correlations.* A Wishart distribution will be assumed for the prior of Σ^{-1},

$$\Sigma^{-1} \sim \mathcal{W}_N\left[v_0, S_0\right]. \tag{11}$$

v_0 and S_0 are assumed to be known. If $v_0 = 0$ and $S_0^{-1} = \mathbf{0}_{N\times N}$, one imposes a non-informative prior for Σ^{-1}, where the posterior distributions will be led by the information content in the data set.

- **Assumption 3**: The prior distribution for the whole set of hyper parameters is given by

$$[\beta, \Sigma] = \mathcal{N}_{(N-1)2}\left[\mathbf{0}_{(N-1)2}, (D \otimes \Omega)\right] \cdot S(\rho) \times \mathcal{W}_N [v_0, S_0].$$

2.2 Posterior distributions and the Gibbs sampling

Under assumptions *1, 2* and *3*,[1] the posterior for β, given Σ and the data set information, is $\beta\,|y, \Sigma \sim \mathcal{N}_{2N}\left[\beta_1, B_1^{-1}\right] \cdot S(\rho)$, where

$$\begin{aligned} B_1 &= \left(D^{-1} \otimes R'\Omega^{-1}R\right) + X'\left(\Sigma^{-1} \otimes I_T\right) X, &(12)\\ \beta_1 &= B_1^{-1} X'\left(\Sigma^{-1} \otimes I_T\right) y. &(13) \end{aligned}$$

The posterior for Σ, given β and the data set information, is $\Sigma^{-1}|y, \beta \sim \mathcal{W}_N [v_0 + T, S_1]$, where $S_1 = \left[S_0^{-1} + S_u\right]^{-1}$, with $S_u = \left[s^u_{n,m}\right] : N \times N$ for $n, m = 1, ...N$, and

$$s^u_{n,m} = (y_n - \alpha_n - \rho_n y_{n,-1})' (y_m - \alpha_m - \rho_m y_{m,-1})$$

Notice that $\beta\,|y, \Sigma$ and $\Sigma^{-1}|y, \beta$ are *conditional* posterior distributions, that is, they both require some given conditional value from the other block. However, as we are rather concerned about the joint posterior distributions of β and Σ, these unconditional distributions can be obtained through the Gibbs sampling method. Here we provide a very basic description of this numerical algorithm.[2] Consider a sequence of steps labeled as $i = 1, ...I$. Then, for a given collection of initial conditions for $\{\beta, \Sigma\}$, which we denote $\psi_{(0)}$, set $j = 1$ and start the process as follows:

1. Draw $\beta^{(j)}$ from $\beta \left| y, \Sigma^{(j-1)} \right.$.
2. Draw $\Sigma^{-1(j)}$ from $\Sigma^{-1} \left| y, \beta^{(j)} \right.$.
3. Call $\psi_{(j)} = \left\{\beta^{(j)}, \Sigma^{(j)}\right\}$, replace the step-index by $j + 1 \leq J$, and go again to step 1 in the process. Otherwise, for $j = J + 1$, stop the sampling.

[1] Proof is available from the authors upon request.
[2] For a detailed description of this algorithm, see Casella and George (1992).

This process should be iterated for J large, say $J = 15000$, and after removing a "reasonable" number of initial draws on $\psi_{(j)}$, say $J_0 = 1000$, the rest of draws can be used for inference and calculation of relevant moments, which are computed as follows:

$$\widehat{\beta}_1 = \frac{1}{J - J_0} \sum_{j=J_0+1}^{J} \beta^{(j)}, \tag{14}$$

$$\widehat{B}_1^{-1} = \frac{1}{J - J_0} \sum_{j=J_0+1}^{J} \left(\beta^{(j)} - \widehat{\beta}_1\right) \left(\beta^{(j)} - \widehat{\beta}_1\right)', \tag{15}$$

$$\widehat{\Sigma} = \frac{1}{J - J_0} \sum_{j=J_0+1}^{J} \Sigma^{(j)}. \tag{16}$$

By using the weak version of the law of large numbers, for $J \to \infty$, these moments converge to the moments of the relevant marginal and joint distributions.

3 Results

3.1 Data

Our data set consists of per capita output series for the 17 Spanish regions.[3] More specifically, we use PPP per inhabitant gross domestic product at NUTS level 2 which is retrieved from the Regio data set of Eurostat. As it is well-known, the use of data defined at NUTS-2 level is preferable to a more aggregated definition as implied by NUTS-1 level data, which usually define broad regions comprising territories that are very different in terms of economic and socio-cultural structures. It is important to note that there has been a change in the base in 1995 and data are provided from 1980 to 1994 following ESA79, while data from 1995 onwards follows ESA95. Since that change may give rise to a break in the series, we have extended backwards the ESA95 series from 1994 to 1980 with the growth rates of per capita GDP calculated with the ESA79 series.

[3]The Spanish regions are as follows: Andalusia, Aragon, Asturias, Baleares, Basque Country, Canary Islands, Cantabria, Catalonia, Castile-Leon, Castile-La Mancha, Extremadura, Galicia, Madrid, Murcia, Navarre, La Rioja and Valencia.

3.2 A helicopter tour

If a non-informative prior for Σ is assumed (i.e. $S_0^{-1} = \mathbf{0}$), the only priors that remain to be chosen is the pair $\left(\sigma_\alpha^2, \sigma_\rho^2\right)$. Assuming that $\sigma_\alpha^2 = \sigma_\rho^2 = 0$ forces equations in the panel to share the same intercept and slope, that is, both parameters are fully exchangeable across equations. The system is then viewed as a single equation. If one sets $\sigma_\rho^2 = 0$ together with σ_α^2 increasing, there is only full exchangeability for the $\rho_n' s$ across equations. As long as prior variances in $D = \text{diag}\left(\sigma_\alpha^2, \sigma_\rho^2\right)$ have values different from zero, both intercepts and slopes will start differing. Under the non-informative prior that $\left(\sigma_\alpha^2 \to \infty, \sigma_\rho^2 \to \infty\right)$, whatever resemblance among the $\alpha' s$ and the $\rho' s$ across equations is a dictum from data.

Figure 1 represents the positive orthant for the $\left(\sigma_\alpha^2, \sigma_\rho^2\right)$ hyper-parameter space. The choice of $\left(\sigma_\alpha^2, \sigma_\rho^2\right)$ is crucial for the estimation of the speed of convergence and steady state parameters. Under our Bayesian framework, three polar standard approaches can be written in terms of some specific priors: the cross-section (CS), the LSDV and the SUR case. Empirical studies on growth and convergence usually adopt at least one of these three corner approaches. When both $\left(\sigma_\alpha^2, \sigma_\rho^2\right)$ approaches 0, the system tends to be associated with the CS case, where all the equations in the system are forced to have the same intercept and the same speed of convergence. Once the speed is fixed (i.e., σ_ρ^2 is close to zero), thereby increasing the value σ_α^2 one gradually moves from CS to LSDV (i.e., $\sigma_\alpha^2 \to \infty$ and $\sigma_\rho^2 = 0$). Assuming a value of σ_α^2 tending to infinity, as long as the prior σ_ρ^2 is enlarged, one moves from LSDV to the SUR case where $\left(\sigma_\alpha^2 \to \infty, \sigma_\rho^2 \to \infty\right)$.

A grid of distributions will be presented where values for $\left(\sigma_\alpha^2, \sigma_\rho^2\right)$ will be picked within an interval that goes from 10^{-6} up to 10^6. The goal is to analyze how robust the estimate set β is along this tour.

Figure 1 about here

3.3 Speed of convergence to the steady states

In tables 1-3 we present the estimates of the speed of convergence for different models characterized by a broad range of values of σ_α^2 and σ_ρ^2. In the three panels of table 1, we show the estimates for the three corner cases: CS, LSDV and SUR. The first of them restricts both the α_n and ρ_n parameters to be the same across regions as in the cross-section approach. Not surprisingly, the estimate of a common speed of convergence towards a common steady state appears very low (lower than 1%).

We then allow the intercepts to vary across regions (case where $\sigma_\alpha^2 = 10^6$ and $\sigma_\rho^2 = 10^{-6}$) as in those studies employing a fixed effects or LSDV estimator (see Islam (1995) and Caselli *et al.* (1996)). This renders a much higher speed of convergence to region-specific steady states as held by the conditional convergence hypothesis. The speed of convergence appears of the order of 40% a year, which seems to be an extraordinarily high value as compared to previous studies employing the LSDV estimator that rendered a speed not higher than 20%. In this regard, two issues are worth noting. Firstly, as noted by Canova and Marcet (1995), when we do not appropriately account for the heterogeneity of intercepts across regions, the estimates of ρ are overstated (fixed effects bias), since the estimate of the parameter is pooled towards the cross-sectional mean, thus yielding low speeds of convergence. Secondly, we have found that the estimate of ρ is very sensitive to the number of iterations employed in estimating the variance-covariance matrix[4]. In fact, when the FGLS estimator with only two iterations is used the value of ρ substantially increases, and consequently a convergence rate close to 20% is found.

Once we lift any restriction on the α_n and ρ_n parameters (SUR case where $\sigma_\alpha^2 = \sigma_\rho^2 = 10^6$), we obtain an average speed of convergence of around 35% which is a bit higher than the 29% estimated by Lee *et al.* (1997) and substantially higher than the 23% estimated by Canova and Marcet (1995) for the European regions. Our estimates range from a low convergence speed of around 12% for Castile-La Mancha and Madrid to an extremely high value of almost 90% for Andalusia. This thus indicates that Andalusia adjusts almost instantaneously to any deviation of current income levels from steady state values. If we cluster the regions on the basis of their speed of convergence towards their steady states, we find that Castile-La Mancha, Castile-Leon, Madrid and Murcia appear to converge at a speed lower than 20% per annum. Regions with a convergence speed in the range of $20-40\%$ are Asturias, Baleares, Cantabria, Catalonia, Canary Islands, Extremadura, La Rioja and Valencia. The Basque Country, Aragon and Galicia appear to converge at a rate between 40 and 60%, and Navarra and Andalusia converge at a rate above 60%.

In table 2, we further explore how the speed of convergence behaves in a range of intermediate cases between the cross-section and the LSDV cases. We do that by setting $\sigma_\rho^2 = 10^{-6}$ and gradually increasing σ_α^2 from 10^{-5} to 1. We observe that the speed of convergence gradually increases from a low 0.5% when $\sigma_\alpha^2 = 10^{-5}$ to 40% when $\sigma_\alpha^2 = 1$, which is pretty much

[4] Results are available from the authors upon request.

similar to the case when $\sigma_\alpha^2 = 10^6$. In table 3 we explore the intermediate cases between the LSDV and the SUR approach by setting $\sigma_\alpha^2 = 10^6$, and gradually increasing the value of σ_ρ^2 from 10^{-5} to 1. We find that the average speed of convergence takes on a value of 40% when $\sigma_\rho^2 = 10^{-5}$ and decreases to about 32% when $\sigma_\rho^2 = 10^{-3} = 10^{-2}$, and again increasing to about 41% when $\sigma_\rho^2 = 1$.

Taken as a whole, we find evidence of the fixed effect bias associated with the cross-section approach, which tend to pull the estimated speed of convergence to a very low value. Once we allow the intercepts and slope coefficients to vary, we find overwhelming evidence that the average speed of adjustment is much higher than that previously found in the literature. An average speed of convergence of around 35% a year implies that regions quickly adjust to any shock leading current income levels to deviate from their expected steady state values.

Tables 1, 2 and 3 about here

3.4 Persistence in inequalities

Table 4 provides some descriptive numbers that will be helpful in supporting one of our findings, *i.e.* the persistence in inequalities in the Spanish regions. Two different sources of Spanish relative *per capita* income are confronted, that of BBVA for 1955 (a widely used biannual data source of Spanish income) *versus* that of Eurostat (actually used in this paper) for 1980 and 2002. Standard deviations of Eurostat series from 1980 through 2002 produce an average value of about $\sigma_y = 0.2127$ (years in between not shown). The first of the two columns labeled as BBVA reports the same variable, with a standard deviation $\sigma_y = 0.3690$. Figure 2 plots the standard deviations of relative income per capita as measured in both sources. The longer series of BBVA collects a continuous decay in the dispersion from 1955 until 1980. Interestingly, both data sources overlap for the period 1980-2002. Hence, they reflect an identical measure of dispersion. The stability exhibited by the standard deviation leads to the conclusion that inequalities have remained unaltered throughout 1980-2002.

A comparison of BBVA versus Eurostat data reveals that there are not substantial changes between 1955 and 1980. Only two regions, La Rioja and Aragon, experience a shift in sign. Indeed, only for the former the change in sign is remarkable, provided that Aragon could be clustered within those borderline regions wandering around the horizontal $0-$axis. For the remaining regions, figures are apparently the same, both in sign and magnitude.

In addition, in a more rigurous attempt to establishing whether there is persistence in inequality across the Spanish regions, we examine whether region-specific steady states are determined by initial conditions. For that purpose, we estimate simple OLS regressions of the type: $SS_n = a + by_{n,1980} + \xi_n$, where SS_n is the estimated steady state defined in (2) and $y_{n,1980}$ stands for the log of relative *per capita* output at the beginning of the period. We are particularly interested in the size of b, since the closer its value to 1, the more evidence there is for persistence in inequalities[5].

Table 5 shows the results. The first specification uses as dependent variable the steady states estimated for the case of a common value for the $\alpha_n' s$ and $\rho_n' s$ across regions. This renders a statistically insignificant estimate of b of around 0.38, which implies that regional differences in income levels will not persist forever and eventually disappear. However, the fit of the CS specification is quite poor with an R^2 below 10%. As we move from the cross-section approach towards the LSDV case, the size of b increases up to a statistically significant value of about 0.95 which implies almost perfect persistence of inequalities across the Spanish regions. The fit of the regressions is very good with $R^{2\prime}s$ of almost 90%. If we further let the slope coefficient vary across regions, the average estimate of b slightly falls to 0.94 but remains significant at the 1% level and the R^2 remains about 90%. This again indicates the existence of almost perfect persistence of inequality, with only a small reduction in income inequality in the limit.

Tables 4 and 5 and Figure 2 about here

3.5 Too many priors?

Following partially Shioji (2004), we have carried out a simple forecasting exercise in order to select which prior distribution gets a better fit to the actual data generating process (DGP). The data point of BBVA regional per capita income for 1955 is considered to be a referential initial point. We use this reference point in order to check which of the available fifteen models defined for a different set of priors (as shown in tables 1, 2 and 3) displays the best accuracy for predicting the first observed period in the Eurostat series, 1980. For each prior, we use the posterior marginal distributions (14), (15) and (16) to generate random draws of $\left\{\alpha_n, \rho_n, \alpha_n/\left(1-\rho_n\right), [u_{nt}]_{t=1956}^{1980}\right\}_{n=1}^{N=17}$.

[5] A value of b equal to 1 would indicate that the position of the distribution of regional steady states has remained unchanged, and those regions beginning with a low steady state relative to national levels will not improve their relative position.

This step is repeated 15000 times, for any of which we calculate projections for 1980 $\widetilde{y}_{1980}^{(h,j)} = \left\{ \widetilde{y}_{n,1980}^{(h,j)} \right\}_{n=1}^{N=17}$, where the superindex $(h, \cdot)$ stands for the particular iteration (for $h = 1, ...15000$) and $(\cdot, j)$ labels the model $(j = 1, ...15)$. Then, we calculate the following distance to the observations in 1980, $y_{1980} = \{y_{n,1980}\}_{n=1}^{N=17}$

$$RMSE\,(j, y_{1980}) = \sqrt{\frac{1}{15000} \sum_{h=1}^{15000} \left[\frac{1}{17} \sum_{n=1}^{17} \left(\widetilde{y}_{n,1980}^{(h,j)} - y_{n,1980} \right)^2 \right]}.$$

This represents the root of the mean square errors (RMSE). Model (j) is said to better predict y_{1980} than model (j') if $RMSE\,(j, y_{1980}) < RMSE\,(j', y_{1980})$, that is, if the predictions from model (j) are closer to 1980 than the predictions from (j'). In a similar manner we also calculate a measure of the distance of the projections to the steady states, $RMSE\,(j, SS)$.

Table 6 shows that the prior distribution providing the best prediction is that of $\sigma_\alpha^2 = 10^6$ and $\sigma_\rho^2 = 10^{-4}$, that is, a distribution based on a prior close to the underlying assumption in LSDV estimation. It corresponds to a mean value for ρ of $0,5394$, that is, a speed of convergence of $46,06\%$. Again, due to the underlying heterogeneous value of α across regions, this high speed has to be interpreted as the adjustment of regional economies to *their own* steady states.

It is also interesting to show how the forecasting capability decreases by a higher extent when the model specification is close to the assumptions of cross-section analysis than when a more flexible probability distribution for the relevant parameters ($\sigma_\alpha^2 = 10^6$, $\sigma_\rho^2 = 10^6$) is considered. Note that the RMSE is about three times higher under a cross-section approach than with LSDV estimates. In line with previous contributions and above text, this is a clear argument in favor of taking into account a high degree of heterogeneity especially in terms of steady states. This is a clear indication in favor of the absence of unconditional convergence across the Spanish regions.

When comparing columns for $RMSE\,(j, y_{1980})$ and $RMSE\,(j, SS)$, a lower value for the latter is found provided one goes from CS to the SUR through LSDV. Shioji (2004) uses US state data and also concludes that LSDV predictions are closer to steady states than to actual observations. He thus interprets this result as a symptom that LSDV tend to overestimate the speed of convergence. In our view, this is a natural consequence of using a high speed convergence model as implied by the LSDV assumptions, i.e. the degree of mean reversion is so high that regions need no more than two years to correct deviations from their long run positions. In 25 years, from

1955 up to 1980, regions may have crossed over the steady state lines for about 10 to 12 times. A 2% speed would require 35 years for a half of the initial gap to vanish.

The above reasoning could be misleading if the series were affected by structural breaks. Indeed, the forecasting exercise would be invalid if the parameters distribution had experienced a permanent shock at any point during the period 1955-2002. However, as shown in Table 4, the relative income per capita in 1955, 1980 and 2002 have not substantially changed. Thus it seems quite unlikely that the occurrence of structural change has played a major role in determining the relative position of the Spanish regions over time.

Table 6 about here

4 Concluding remarks

In this article we have applied bayesian techniques to the analysis of the persistence in inequalities among the Spanish regions over the period 1980-2002. As argued, our methodology tries to overcome the difficulties posed by the standard cross-section approach which neglects the within variation of the data and forces the speed of convergence to be the same across units. Our analysis thus allows for a high degree of heterogeneity across units, thus rendering estimates of region-specific steady state and speed of convergence parameters.

Our study has dealt with three main questions. First, we have checked for the existence of a non-negligible fixed effects bias associated with previous work on the existence of convergence across regions and countries using cross-section regressions. Second, we have determined how the speed of convergence varies after gradually lifting some restrictions imposed on the estimated parameters on steady state income levels and speed of convergence. Third, we have investigated the issue of persistence in inequalities across the Spanish regions by determining to what extent steady state income levels are or not determined by initial conditions.

Our main findings have been the following. First, we have corroborated previous findings by Canova an Marcet (1995) in that the CS approach renders a biased estimate of a homogenous speed of convergence below 1% a year, which would be consistent with a Solow model with a very high capital share leading to a very slow adjustment along the transitional growth path. Second, when steady states and speed of convergence parameters are not constrained to be common across regions, we have found a much higher speed of convergence. Our estimates of the speed of convergence have appeared to range from a "low" value of around 12% a year for Castile-La Mancha and Madrid to almost 90% for Andalusia. This indicates that the latter has been permanently on its steady state. Third, we have strongly rejected the hypothesis of unconditional convergence since steady states have been found to significantly differ across regions. Fourth, we have provided consistent evidence of persistence in inequalities across the Spanish regions, showing that income differences have hardly narrowed down over the period under analysis. Thus initial conditions have been the most important determinant of the relative position in the distribution of estimated steady states.

The main results of the paper are consistent with previous contributions. In particular, high convergence rates have been also reported in Cuadrado (1998) -between 27% and 35% for the Spanish regions over 1980-1995- and De la Fuente (2002) -between 25% and 39% for 99 EU regions in the period 1980-1994. Along these lines, our results back up the finding of extremely high speeds of convergence towards region-specific steady states. These high convergence rates are compatible with a low share of private capital over output, with perfect private capital mobility across regions, and with a very close position of economies to their steady states.

Taken as a whole, our results point to the failure of EU regional policies instrumented through Cohesion and Structural Funds as a means for correcting regional disparities in Spain over the last decades. The absence of convergence has taken place despite the fact that growing resources have been allocated to the reduction of territorial income differences. Indeed, financial resources aimed at promoting convergence now account for over 30% of total EU budget, more than twice the share they represented in 1988. This lack of convergence casts doubts on the effectiveness of European development policies precisely when the EU enlargement leads to new challenges in the recipient territories. Therefore, our sample allows us to add new arguments to the debate on the impact of regional policies.

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Figure 1: A helycopter tour over the Hyperparameter space

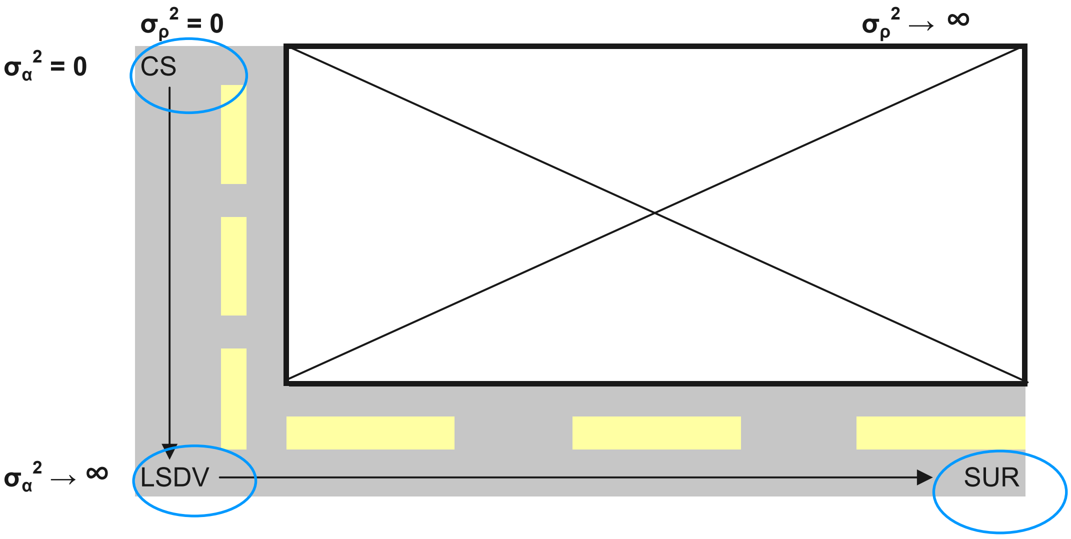

Figure 2: σ-convergence.

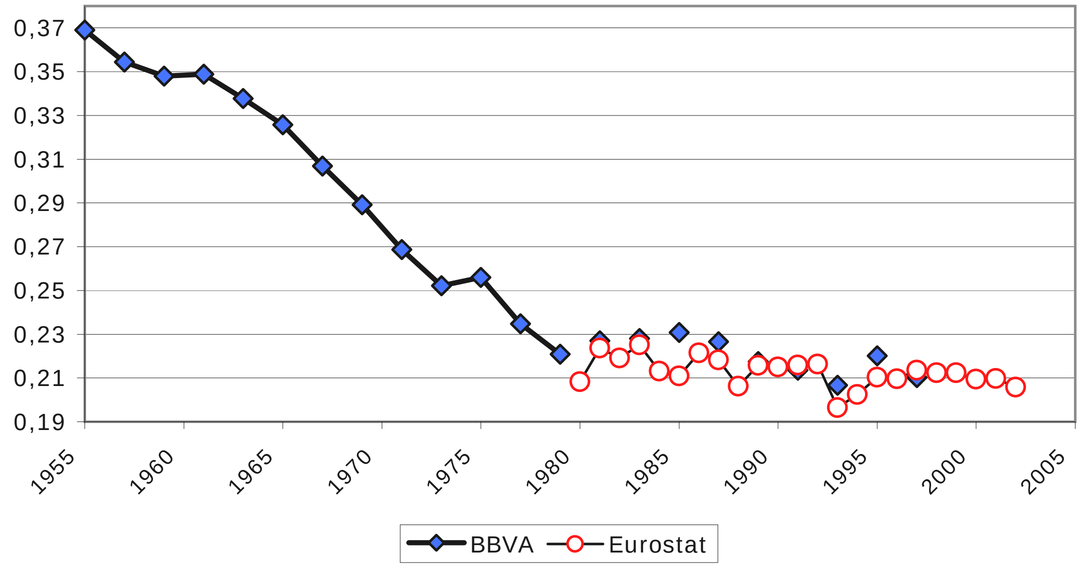

Table 1: Corner cases

	CS ($\sigma_\alpha^2 = 10^{-6}$, $\sigma_\rho^2 = 10^{-6}$)				LSDV ($\sigma_\alpha^2 = 10^{6}$, $\sigma_\rho^2 = 10^{-6}$)				SUR ($\sigma_\alpha^2 = 10^{6}$, $\sigma_\rho^2 = 10^{6}$)			
	α	ρ	α / (1-ρ)	1-ρ	α	ρ	α / (1-ρ)	1-ρ	α	ρ	α / (1-ρ)	1-ρ
Galicia	-0,0005	0,9979	-0,2597	0,21%	-0,0844	0,5970	-0,2095	40,30%	-0,0976	0,5324	-0,2087	46,76%
Asturias	-0,0007	0,9978	-0,3312	0,22%	-0,0451	0,5970	-0,1120	40,30%	-0,0318	0,7397	-0,1222	26,03%
Cantabria	0,0004	0,9976	0,1599	0,24%	-0,0199	0,5968	-0,0492	40,32%	-0,0132	0,7532	-0,0537	24,68%
País Vasco	0,0005	0,9979	0,2139	0,21%	0,0834	0,5971	0,2071	40,29%	0,1120	0,4591	0,2071	54,09%
Navarra	-0,0003	0,9978	-0,1581	0,22%	0,0898	0,5971	0,2228	40,29%	0,1438	0,3564	0,2234	64,36%
Rioja	-0,0002	0,9978	-0,0965	0,22%	0,0597	0,5970	0,1481	40,30%	0,0540	0,6323	0,1470	36,77%
Aragón	0,0007	0,9980	0,3533	0,20%	0,0215	0,5970	0,0534	40,30%	0,0300	0,4197	0,0518	58,03%
Madrid	0,0016	0,9983	0,9552	0,17%	0,1064	0,5972	0,2642	40,28%	0,0367	0,8793	0,3041	12,07%
Castilla-León	0,0002	0,9979	0,0799	0,21%	-0,0294	0,5971	-0,0729	40,29%	-0,0124	0,8411	-0,0780	15,89%
Castilla-La Mancha	0,0000	0,9979	-0,0134	0,21%	-0,0877	0,5970	-0,2175	40,30%	-0,0264	0,8838	-0,2274	11,62%
Extremadura	0,0001	0,9978	0,0594	0,22%	-0,1919	0,5970	-0,4763	40,30%	-0,1013	0,7815	-0,4634	21,85%
Cataluña	-0,0005	0,9979	-0,2386	0,21%	0,0696	0,5971	0,1726	40,29%	0,0650	0,6248	0,1734	37,52%
Valencia	-0,0007	0,9978	-0,3027	0,22%	-0,0062	0,5971	-0,0155	40,29%	-0,0055	0,6715	-0,0166	32,85%
Baleares	0,0002	0,9980	0,0954	0,20%	0,0882	0,5970	0,2189	40,30%	0,0770	0,6481	0,2188	35,19%
Andalucía	-0,0006	0,9979	-0,2743	0,21%	-0,1143	0,5970	-0,2837	40,30%	-0,2471	0,1207	-0,2810	87,93%
Murcia	-0,0002	0,9979	-0,0921	0,21%	-0,0671	0,5971	-0,1667	40,29%	-0,0323	0,8089	-0,1692	19,11%
Canarias	-0,0004	0,9980	-0,1944	0,20%	-0,0145	0,5973	-0,0360	40,27%	-0,0039	0,7999	-0,0195	20,01%

Table 2: Intermediate cases (between CS and LSDV)

PRIOR	σ_α^2 10^{-5}	σ_ρ^2 10^{-6}	σ_α^2 10^{-4}	σ_ρ^2 10^{-6}	σ_α^2 10^{-3}	σ_ρ^2 10^{-6}	σ_α^2 10^{-2}	σ_ρ^2 10^{-6}	σ_α^2 10^{-1}	σ_ρ^2 10^{-6}	σ_α^2 1	σ_ρ^2 10^{-6}
	α	ρ	α	ρ	α	ρ	α	ρ	α	ρ	α	ρ
Galicia	-0,0020	0,9949	-0,0083	0,9613	-0,0226	0,8960	-0,0431	0,7990	-0,0754	0,6414	-0,0844	0,5979
Asturias	-0,0034	0,9948	-0,0079	0,9613	-0,0158	0,8960	-0,0260	0,7991	-0,0409	0,6414	-0,0451	0,5979
Cantabria	0,0010	0,9946	-0,0027	0,9611	-0,0068	0,8958	-0,0113	0,7989	-0,0180	0,6412	-0,0198	0,5978
País Vasco	0,0017	0,9949	0,0063	0,9613	0,0203	0,8961	0,0414	0,7991	0,0743	0,6415	0,0833	0,5981
Navarra	-0,0012	0,9949	0,0034	0,9614	0,0207	0,8961	0,0439	0,7991	0,0797	0,6415	0,0896	0,5981
Rioja	-0,0011	0,9949	0,0001	0,9614	0,0105	0,8961	0,0270	0,7991	0,0524	0,6414	0,0595	0,5979
Aragón	0,0026	0,9950	0,0066	0,9615	0,0087	0,8961	0,0122	0,7991	0,0195	0,6414	0,0215	0,5980
Madrid	0,0056	0,9951	0,0138	0,9615	0,0312	0,8962	0,0563	0,7992	0,0955	0,6416	0,1062	0,5981
Castilla-León	0,0005	0,9949	0,0009	0,9614	-0,0057	0,8961	-0,0147	0,7992	-0,0262	0,6415	-0,0293	0,5980
Castilla-La Mancha	-0,0011	0,9950	-0,0055	0,9614	-0,0216	0,8961	-0,0441	0,7991	-0,0780	0,6414	-0,0873	0,5980
Extremadura	0,0009	0,9949	-0,0046	0,9615	-0,0387	0,8961	-0,0913	0,7991	-0,1699	0,6415	-0,1913	0,5980
Cataluña	0,0009	0,9951	0,0079	0,9616	0,0197	0,8962	0,0363	0,7991	0,0623	0,6415	0,0695	0,5980
Valencia	-0,0022	0,9949	-0,0041	0,9614	-0,0041	0,8961	-0,0043	0,7991	-0,0058	0,6415	-0,0062	0,5980
Baleares	0,0006	0,9950	0,0064	0,9615	0,0221	0,8962	0,0440	0,7992	0,0783	0,6415	0,0878	0,5980
Andalucía	-0,0021	0,9949	-0,0107	0,9614	-0,0305	0,8960	-0,0580	0,7990	-0,1019	0,6414	-0,1141	0,5979
Murcia	-0,0015	0,9949	-0,0092	0,9614	-0,0205	0,8961	-0,0345	0,7991	-0,0599	0,6415	-0,0671	0,5980
Canarias	-0,0002	0,9951	0,0017	0,9615	0,0008	0,8962	-0,0039	0,7993	-0,0121	0,6417	-0,0143	0,5982

Table 3: Intermediate cases (between LSDV and SUR)

PRIOR	σ_α^2 10^6	σ_ρ^2 10^{-5}	σ_α^2 10^6	σ_ρ^2 10^{-4}	σ_α^2 10^6	σ_ρ^2 10^{-3}	σ_α^2 10^6	σ_ρ^2 10^{-2}	σ_α^2 10^6	σ_ρ^2 10^{-1}	σ_α^2 10^6	σ_ρ^2 1
	α	ρ	α	ρ	α	ρ	α	ρ	α	ρ	α	ρ
Galicia	-0,0852	0,5934	-0,0974	0,5336	-0,0726	0,6554	-0,0837	0,6007	-0,0982	0,5296	-0,1129	0,4578
Asturias	-0,0454	0,5935	-0,0530	0,5126	-0,0384	0,6680	-0,0398	0,6548	-0,0306	0,7527	-0,0295	0,7643
Cantabria	-0,0201	0,5919	-0,0229	0,5250	-0,0165	0,6760	-0,0158	0,6948	-0,0142	0,7322	-0,0167	0,6714
País Vasco	0,0840	0,5951	0,0950	0,5417	0,0585	0,7180	0,0850	0,5903	0,1019	0,5084	0,1186	0,4277
Navarra	0,0902	0,5951	0,0992	0,5548	0,0673	0,6974	0,1166	0,4776	0,1510	0,3244	0,1756	0,2149
Rioja	0,0602	0,5936	0,0678	0,5462	0,0455	0,6852	0,0525	0,6418	0,0679	0,5453	0,0600	0,5950
Aragón	0,0217	0,5938	0,0254	0,5162	0,0211	0,6053	0,0279	0,4634	0,0345	0,3264	0,0352	0,3117
Madrid	0,1069	0,5953	0,1215	0,5362	0,0890	0,6677	0,0765	0,7185	0,0586	0,7908	0,0636	0,7703
Castilla-León	-0,0294	0,5948	-0,0330	0,5448	-0,0211	0,7165	-0,0132	0,8292	-0,0113	0,8578	-0,0168	0,7788
Castilla-La Mancha	-0,0883	0,5937	-0,1024	0,5280	-0,0545	0,7521	-0,0385	0,8274	-0,0225	0,9017	-0,0268	0,8820
Extremadura	-0,1935	0,5939	-0,2080	0,5643	-0,1198	0,7435	-0,1093	0,7652	-0,0660	0,8533	-0,1006	0,7826
Cataluña	0,0699	0,5948	0,0751	0,5631	0,0488	0,7231	0,0516	0,7064	0,0523	0,7021	0,0503	0,7138
Valencia	-0,0063	0,5944	-0,0069	0,5380	-0,0054	0,6691	-0,0065	0,5766	-0,0056	0,6602	-0,0062	0,5957
Baleares	0,0887	0,5940	0,1037	0,5251	0,0662	0,6977	0,0689	0,6853	0,0697	0,6814	0,0968	0,5570
Andalucía	-0,1153	0,5935	-0,1338	0,5273	-0,0960	0,6627	-0,0913	0,6794	-0,1776	0,3699	-0,2826	-0,0069
Murcia	-0,0676	0,5947	-0,0767	0,5393	-0,0535	0,6807	-0,0567	0,6604	-0,0458	0,7271	-0,0447	0,7342
Canarias	-0,0145	0,5965	-0,0157	0,5728	-0,0072	0,7355	-0,0021	0,8326	-0,0019	0,8370	-0,0031	0,8146

Table 4: Relative income figures

	BBVA	Eurostat	
	1955	1980	2002
Galicia	-0,3945	-0,1467	-0,2000
Asturias	0,0319	0,0061	-0,1579
Cantabria	0,0549	0,0379	-0,0248
País Vasco	0,4633	0,2272	0,2305
Navarra	0,0522	0,2386	0,2247
Rioja	-0,0151	0,2115	0,1026
Aragón	-0,0582	0,0076	0,0565
Madrid	0,6388	0,1640	0,3158
Castilla-León	-0,3381	-0,0234	-0,0531
Castilla-La Mancha	-0,6025	-0,1838	-0,2187
Extremadura	-0,6681	-0,5552	-0,4189
Cataluña	0,3802	0,1187	0,1922
Valencia	0,0603	0,0002	-0,0416
Baleares	0,2592	0,1544	0,1616
Andalucía	-0,3619	-0,2328	-0,2770
Murcia	-0,3677	-0,1587	-0,1790
Canarias	-0,2369	-0,1933	-0,0481
Standard Deviation	0,3690	0,2083	0,2059

Table 5: Persistence in inequalities

Prior		$SS_n = a + b*y_{80,n}$					
σ_α^2	σ_ρ^2	a_{OLS}	t-statistic	b_{OLS}	t-statistic	R^2	mean(ρ)
10^{-6}	10^{-6}	0,0047	0,06	0,3762	0,99	6,1%	0,9979
10^{-5}	10^{-6}	0,0011	0,01	0,5041	0,97	5,9%	0,9949
10^{-4}	10^{-6}	0,0021	0,06	0,5468	3,07	38,6%	0,9614
10^{-3}	10^{-6}	-0,0019	-0,08	0,8433	6,95	76,3%	0,8961
10^{-2}	10^{-6}	-0,0026	-0,13	0,9269	9,15	84,8%	0,7991
10^{-1}	10^{-6}	-0,0025	-0,13	0,9437	10,30	87,6%	0,6415
1	10^{-6}	-0,0025	-0,13	0,9454	10,47	88,0%	0,5980
10^{+6}	10^{-6}	-0,0025	-0,14	0,9459	10,48	88,0%	0,5971
10^{+6}	10^{-5}	-0,0025	-0,13	0,9458	10,49	88,0%	0,5942
10^{+6}	10^{-4}	-0,0023	-0,13	0,9461	10,64	88,3%	0,5394
10^{+6}	10^{-3}	-0,0021	-0,11	0,9380	9,98	86,9%	0,6914
10^{+6}	10^{-2}	-0,0012	-0,06	0,9355	9,65	86,1%	0,6709
10^{+6}	10^{-1}	-0,0007	-0,03	0,9262	9,25	85,1%	0,6530
10^{+6}	1	-0,0013	-0,07	0,9356	9,57	85,9%	0,5921
10^{+6}	10^{+6}	-0,0003	-0,01	0,9433	9,34	85,3%	0,6443

Table 6: Shioji's experiment

σ_α^2	σ_ρ^2	RMSE($\hat{y}_{80}$,y_{80})	RMSE($\hat{y}_{80}$,SS)	mean(ρ)
10^{-6}	10^{-6}	0,2413	0,9864	0,9979
10^{-5}	10^{-6}	0,2472	0,7918	0,9949
10^{-4}	10^{-6}	0,1745	0,1312	0,9614
10^{-3}	10^{-6}	0,1186	0,0516	0,8961
10^{-2}	10^{-6}	0,0934	0,0369	0,7991
10^{-1}	10^{-6}	0,0799	0,0296	0,6415
1	10^{-6}	0,0781	0,0288	0,5980
10^{+6}	10^{-6}	0,0781	0,0289	0,5971
10^{+6}	10^{-5}	0,0781	0,0290	0,5942
10^{+6}	10^{-4}	0,0760	0,0278	0,5394
10^{+6}	10^{-3}	0,0830	0,0314	0,6914
10^{+6}	10^{-2}	0,0854	0,0320	0,6709
10^{+6}	10^{-1}	0,0925	0,0390	0,6530
10^{+6}	1	0,0864	0,0322	0,5921
10^{+6}	10^{+6}	0,0915	0,0341	0,6443