Testing for convergence: evidence from nonparametric multimodality tests

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The views in this paper are those of the author and not necessarily those of the Bank of England. The author thanks Danny Quah for encouragement and advice and Robert Barro for useful comments. The usual disclaimer applies.

Issued by the Monetary Analysis Division, Bank of England, London, EC2R 8AH to which requests for individual copies should be addressed: envelopes should be marked for the attention of the Publications Group. (Telephone: 0171-601-4030).

ISSN 0142-6753

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Abstract

The convergence hypothesis in growth theory implies that the frequency of the density distribution of GDP in a cross–section of countries tends to approach unimodality as we move forward in time. In this paper, we test the convergence theory in a cross–section of 119 countries by means of bootstrap multimodality tests and nonparametric density estimation techniques. By looking at the density distribution of GDP across countries in 1970, 1980 and 1989, we find increasing evidence for *bimodality.* The finding stands in contrast with the convergence prediction.

1 Introduction

There is a debate in growth economics as to whether less developed economies are catching up with richer economies — what is commonly known as the "convergence hypothesis". At the heart of the debate stands a fundamental controversy among researchers about the 'correct' answers to a number of relevant questions like (Quah, 1995b):

- Are poor countries becoming poorer and rich countries richer, or is there a tendency for the poor to catch up with the rich?
- Are countries converging towards each other only within groups or "clubs"?
- Is most of the world becoming middle class, or is it that the middle class is vanishing?

Much empirical work has been devoted in the literature to support or question different views about the convergence hypothesis. However, no widely accepted conclusion has been reached so far.

Conventional empirical analyses employing cross–section, time–series or panel data techniques have found evidence to support the convergence hypothesis (see, among the others, Sala–i–Martin, 1994, 1995, and references therein). However, as recently pointed out by Quah (1995a,b), the limitation of conventional approaches is the modelling of the behaviour of an *average* or representative economy, rather than the *entire* cross–section of countries. Empirical evidence from cross section convergence regressions rely only on a few coefficients estimated from a linear model, without being able to clarify the dynamics of the entire income distribution.

In this paper, we follow the recommendation of Quah (1995b) to study "*growth and convergence in terms of the dynamically evolving cross-country distribution of income*".[1] Consistent with

[1]Quah (1995), page 2.

previous studies (Quah, 1995a,b), we find substantial evidence against the convergence hypothesis between less and most developed economies, in favour of the convergence hypothesis within groups of economies or "clubs". We also find some evidence of a vanishing of the middle class (again, as suggested in Quah 1995a,b).[2]

The remainder of the paper is organised as follows. In Section 2 we briefly consider nonparametric techniques for the estimation of the density distribution of incomes across countries. We also discuss nonparametric multimodality tests. We report the empirical results in Section 3. Section 4 briefly summarises and concludes.

2 The Statistical Framework

Consider a random variable x with realizations x_i, $i = 1, \ldots, n$. In our application, x_i denotes the GDP per capita in US dollars in country i, in a cross-section of n countries. Also denote by $f(x)$ the density of per capita incomes across countries.

With two groups of countries, say a group of "rich" and a group of "poor" countries, the convergence hypothesis predicts a catching-up of poor countries. In the presence of m^* groups of countries, the density of the frequency distribution has the form

$$f(x) = \sum_{i=0}^{m^*} p_i \cdot g_i(x; \mu_i, \sigma_i^2), \tag{1}$$

where p_i's are mixture proportions with $\sum_{i=0}^{m^*} p_i = 1$, and g_i are unimodal densities with first and second moments μ_i and σ_i^2. Assuming that the differences in the centrality parameters μ_i's (mean

[2] It must be stressed nevertheless that our analysis, representing a purely statistical investigation of stylised facts, does not provide theoretical justifications or economic rationales as of why convergence may or may not occur. With this respect, interested readers are referred to the monograph by Barro and Sala-i-Martin (1994).

incomes in different groups) are "large" relative to the dispersion parameters σ_i^2's (income variances in different groups), equation (1) implies that $f(x)$ is multimodal with m^* modes (the modes of the density are said to be "well–separated" in this case).

According to the convergence hypothesis, if we start with a bimodal density in a given point in time, indicating the presence of two groups in a population of countries, there will be a tendency in the distribution to progressively move towards unimodality over time. Such a prediction indicates the way the convergence hypothesis can be tested empirically: we can estimate the density of the frequency distribution of incomes across countries at two (or more) distant points in time and evaluate at what points in time unimodality is most strongly rejected. We accomplish the former task by means of nonparametric kernel density estimators; the latter, by the bootstrap methodology.

2.1 Nonparametric Density Estimation

The purpose of density estimation in statistics and data analysis is to evaluate where observations occur more frequently in a sample. In nonparametric density estimation, the "true" probability density function $f(x)$ is estimated from a sample $\{x_i\}_1^n$ of independent and identically distributed observations. The estimated density is constructed by centring around each observation x_i a kernel function $K(u)$, with $u = (x - x_i)/h$, and averaging the values of this function at any given x. The estimator in its general form is defined as (see Silverman, 1986; Härdle, 1990)

$$\hat{f}_h(x) = (nh)^{-1} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) = (nh)^{-1} \sum_{i=1}^{n} K(u), \qquad (2)$$

where $h > 0$ is the *bandwidth* or *window width* and $K(u)$ is the Gaussian kernel

$$K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}u^2\right). \qquad (3)$$

Bandwidth h governs the degree of smoothness of the density estimate. With small values of h, wiggly estimates showing spurious structure in the data can often be obtained; with big values of h, on the contrary, important features of the underlying density can be smoothed away.[3] Figure 1 illustrates the construction of a kernel density estimator.

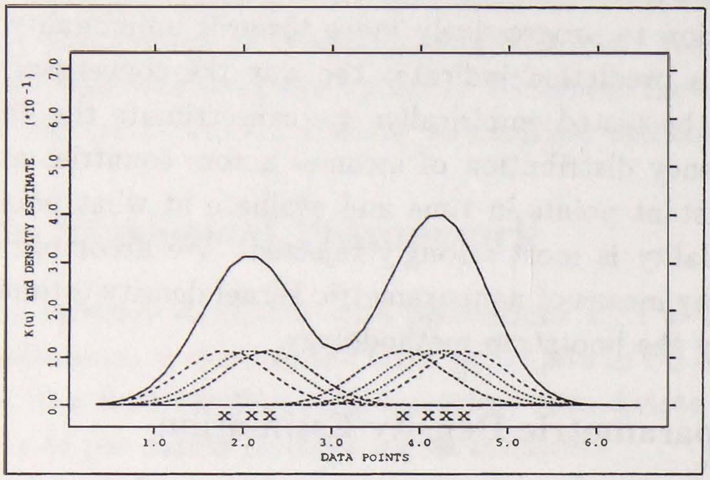


Figure 1: Construction of a nonparametric density estimate (solid line) by averaging the value of the kernel functions (Gaussian kernels represented by dotted lines), centred on the data points (x). Bandwidth: $h = 0.5$.

[3] Several data–driven bandwidth selectors have been proposed in the literature. As reviewed in Bianchi (1995), these aim to achieve an objective choice of the bandwidth by identifying a value of h which minimises some distance (or discrepancy) between the true and estimated density — such as for example the Mean Squared Error (MSE), its expected value, the Mean Integrated Squared Error (MISE), or the Taylor expansion of the MISE, the Asymptotic Mean Integrated Squared Error (AMISE). Other selectors, like those based on the bootstrap methodology, select a value of h consistent with the number of modes in the density, thus approaching the problem of bandwidth selection in the perspective of hypothesis testing.

2.2 Bootstrap Multimodality Tests

Well-known procedures for testing the number of modes in a density distribution include the parametric approach, based on maximum likelihood estimation, and the nonparametric approach, based on the bootstrap or resampling techniques (see Izenman and Sommer, 1988, for a comparison of the two approaches). We briefly consider in the following the nonparametric approach.

Bootstrap tests are built on the concept of *critical bandwidth* introduced by Silverman (1981, 1983, 1986). A critical bandwidth $h_{crit}(m)$ is defined as the smallest possible h producing a density with at most m modes, what means that for all $h < h_{crit}(m)$ the estimated density $\hat{f}_h$ has at least $m+1$ modes.

The idea of critical smoothing is naturally related with hypothesis testing. If the true underlying density has two modes, for example, then a large value of $h_{crit}(1)$ is expected, because a considerable amount of smoothing is required to obtain a unimodal density estimate. This suggests that $h_{crit}(m)$ can be used as a statistic to test

$$H_0\text{: } f(x) \text{ has } m \text{ modes;} \quad H_1\text{: } f(x) \text{ has more than } m \text{ modes.}$$

A 'large' value of $h_{crit}(m)$ indicates more than m modes, thus rejecting the null.

How large is large in this context is assessed by the bootstrap, as discussed by the same Silverman in his works, and, among the others, by Efron and Tibshirani (1993), section 16.5. Given the vector of observations $\mathbf{x} = (x_1, \ldots, x_n)'$, a sample $\mathbf{y}^* = (y_1^*, \ldots, y_n^*)'$ is obtained by resampling with replacement from $\mathbf{x}$. To ensure that the realizations obtained from the bootstrap have the same first and second moment properties of the observations $\mathbf{x}$, the following transformation is considered

$$x_i^* = \bar{y}^* + \left(1 + \frac{h_{crit}^2(m)}{s^2}\right)^{-1/2} (y_i^* - \bar{y}^* + h_{crit}(m)e_i), \qquad (4)$$

where $i = 1, \ldots, n$, $\bar{y}^* = \text{mean}(\mathbf{y}^*)$, s^2 is the sample variance of $\mathbf{x}$, and e_i standard normal variables generated by the computer. A p-value for $h_{crit}(m)$, called the 'achieved significance level' (ASL) of the test, is obtained by generating a large number of samples from $f_{crit}(m)$ and counting the proportion of samples for which $h^*_{crit}(m) > h_{crit}(m)$, where $h^*_{crit}(m)$ is the smallest value of h producing a density estimate with m modes from the bootstrap data $\mathbf{x}^*$. We have formally

$$ASL_m = \text{Prob.}\{h^*_{crit}(m) > h_{crit}(m)\} \tag{5}$$

where $h_{crit}(m)$ is a fixed value obtained from the data $\mathbf{x}$. Denoting by B the number of bootstrap replications, and defining the indicator variable[4]

$$I_{m,b} = \begin{cases} 1 & \text{if } f_{h_{crit}(m)}(x^*) \text{ has more than } m \text{ modes} \\ 0 & \text{otherwise,} \end{cases}$$

an estimate for the p-value or achieved significance level of the test is given by

$$\widehat{ASL}_m = B^{-1} \sum_{b=1}^{B} I_{m,b}. \tag{6}$$

We fail to reject the null hypothesis of m modes in the density whenever the p-value is larger than standard levels of significance.

[4]It has been proven by Silverman that the event $h^*_{crit}(m) > h_{crit}(m)$ is equivalent to the event that $\hat{f}_{h_{crit}}(m)(x^*)$ has more than m modes. This results implies that it is not necessary to compute $h^*_{crit}(m)$ for each bootstrap sample; one needs only to check the proportion of cases when $f_{h_{crit}}(m)(x^*)$ has more than m modes.

3 Empirical Results

In this section, we consider per capita GDP at constant US dollars for $n = 119$ countries, measured in 1970, 1980 and 1989. Prior to testing for multimodality using kernel density estimation and the bootstrap methodology, we standardise the data by dividing income differentials from the mean value by the sample standard deviation. For the standardised data, the critical bandwidths are shown in Table 1 and Figure 2.

The results of nonparametric multimodality tests are shown in Table 1. It appears that the most likely hypothesis is that the underlying density has $m^* = 2$ modes in 1980 and 1989, whereas the unimodality hypothesis is not rejected in 1970 at a 5% level of significance. This provides evidence against the convergence hypothesis.

In the three years, by selecting a value of the bandwidth consistent with bimodality, we obtain the density estimates reported in Figure 3. The densities are all skewed to the right, indicating the presence of a large mass of "poor" countries, with a small proportion of "rich" countries. In 1980 and in 1989, a pronounced mode appears in the long right-end tail of the distribution suggesting the formation of "clubs" or clusters in the data, in support of the so called "polarisation hypothesis".

Also, in the decade from 1970 to 1980, we notice the mode centred about -0.5 shifts to the left and the mode centred about 1.5–1.6 shifts to the right; this indicates a widening gap between less and more developed countries. In the decade from 1980 to 1989, there are no shifts in the modes, but a larger proportion of poor countries (larger than in 1980), together with a smaller proportion of middle–income countries, is now observed; this result appears consistent with the hypothesis of vanishing of the middle class.

GDP in	$h_{crit}(m)$			$\widehat{ASL}_m$; $B = 10000$		
	$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 2$	$m = 3$
1970	0.495	0.290	0.265	0.07	0.33	0.05
1980	0.565	0.220	0.150	0.00	0.36	0.63
1989	0.570	0.190	0.160	0.00	0.68	0.51

Table 1: Bootstrap tests for multimodality.

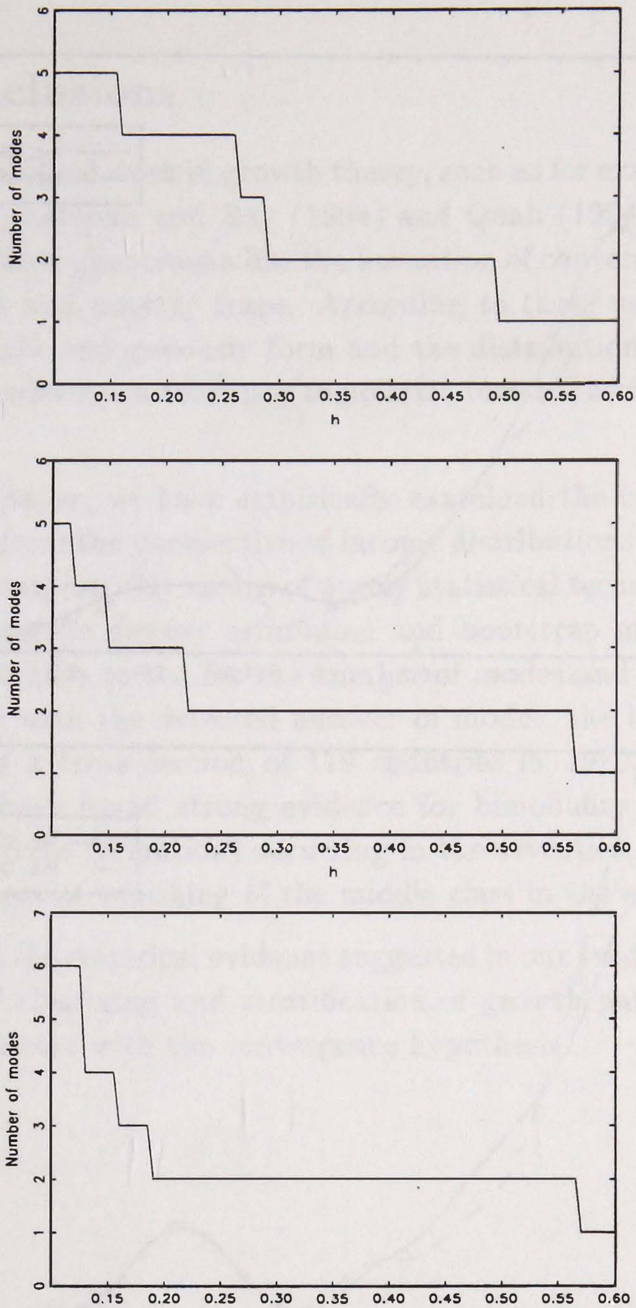
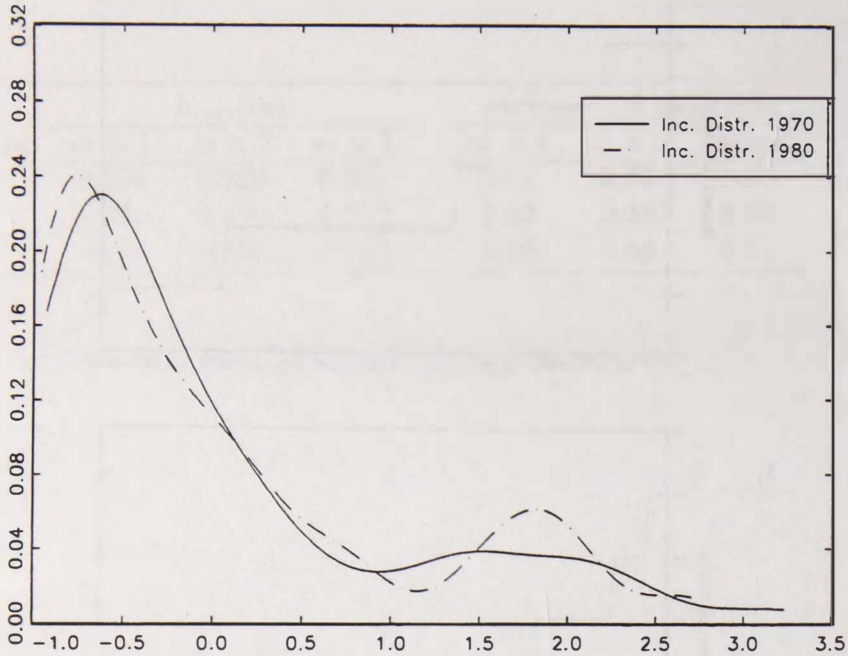


Figure 2: Critical bandwidths obtained by kernel density estimation in 1970 (top panel), 1980 (middle panel) and 1989 (bottom panel) are the values of h where jumps in the step function occur. Note that the number of modes in the estimated densities are a decreasing function of the window width.



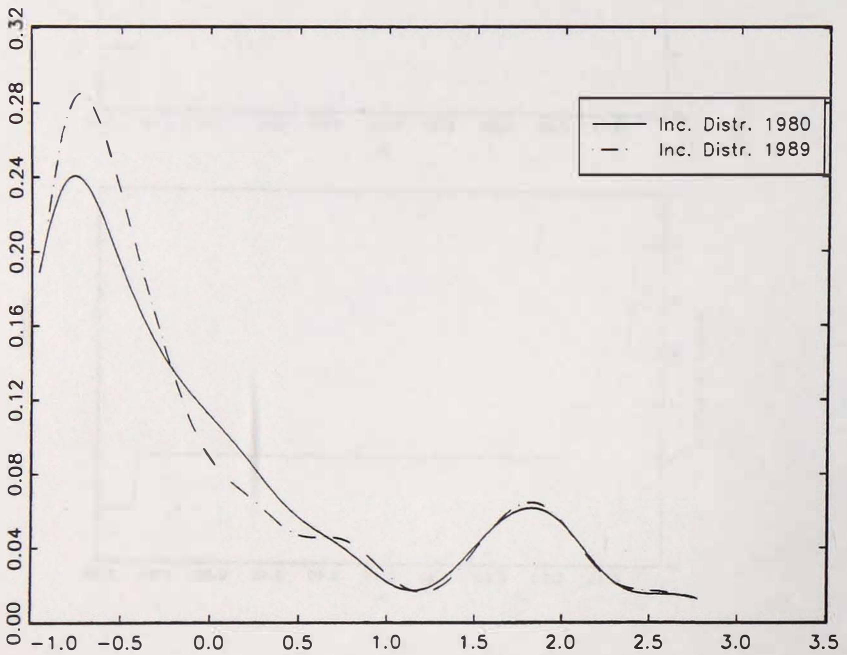


Figure 3: Density estimates of standardised income distributions in 1970, 1980 and 1989. Selected bandwidths are the critical bandwidths consistent with bimodality: 0.29, 0.22 and 0.19 respectively.

4 Conclusions

Recent theoretical work in growth theory, such as for example Baumol (1986), Esteban and Ray (1994) and Quah (1994, 1995a,b), has rationalised phenomena like the formation of convergence clubs, polarisation and poverty traps. According to these models, convergence clubs endogenously form and the distribution of income across countries has a tendency to polarise towards a bimodal distribution.

In this paper, we have empirically examined the convergence hypothesis from the perspective of income distributions in a cross–section of countries. By means of purely statistical techniques such as nonparametric density estimation and bootstrap multimodality tests, we have tested for the number of modes and estimated, consistently with the detected number of modes, the income distribution of a cross–section of 119 countries in 1970, 1980 and 1989. We have found strong evidence for bimodality (ie polarisation and clubs formation) occurring in the seventies, associated with a process of vanishing of the middle class in the eighties.[5]

Overall, the empirical evidence suggested in our study supports the view of clustering and stratification of growth patterns over time, in contrast with the convergence hypothesis.

[5]It is worthwhile noticing here that our method, although pertinent to testing for convergence, does not provide detailed information about intra–distribution dynamics. Quah (1995a,b), however, has already provided results for the latter.

Appendix

Income Data

The data set is taken from the database of the University of Pennsylvania, called Penn World Table (PWT), June 1993. The following countries were included in the cross section.

Country	Per capita GDP 1970	1980	1989
ALGERIA	1837	2778	2778
ANGOLA	1100	627	657
BENIN	1144	1111	953
BOTSWANA	863	1871	3218
BURKINA FASO	399	473	541
BURUNDI	324	463	518
CAMEROON	867	1275	1293
CAPE VERDE IS.	686	988	1269
CENTRAL AFR.R.	699	663	559
CHAD	549	425	380
CONGO	1579	1829	2216
EGYPT	1105	1572	1829
GABON	3692	4789	3618
GAMBIA	599	878	645
GHANA	1012	921	815
GUINEA	351	424	360
GUINEA-BISS	653	440	659
IVORY COAST	1320	1563	1282
KENYA	577	889	887
LESOTHO	386	917	958
MADAGASCAR	1123	959	672
MALAWI	429	541	504
MALI	389	498	544
MAURITANIA	985	958	860
MAURITIUS	2348	3892	5363
MOROCCO	1296	1866	2043
MOZAMBIQUE	1458	896	755
NAMIBIA	2602	2417	2054
NIGER	752	694	467
NIGERIA	769	1196	742

RWANDA	626	733	659
SENEGAL	1104	1087	1081
SEYCHELLES	1666	2825	3426
SIERRA LEONE	1050	1001	908
SOMALIA	845	836	865
SOUTH AFRICA	3146	3512	3316
SWAZILAND	2415	3015	2182
TOGO	626	726	628
TUNISIA	1398	2473	2743
UGANDA	764	513	901
ZAIRE	644	450	403
ZAMBIA	1091	930	722
ZIMBABWE	1063	1176	1292
BARBADOS	4758	6534	7727
CANADA	10175	14231	17690
COSTA RICA	2796	3694	3572
DOMINICAN REP.	1496	2305	2293
EL SALVADOR	1737	1923	1738
GUATEMALA	2003	2540	2099
HAITI	788	980	793
HONDURAS	1207	1491	1351
JAMAICA	2670	2274	2413
MEXICO	3950	5707	5165
PANAMA	2497	3291	2650
PUERTO RICO	5784	6768	9051
TRINIDAD&TOBAG	6725	11242	8355
U.S.A.	12725	15097	18354
ARGENTINA	4165	4745	3615
BOLIVIA	1614	1908	1597
BRAZIL	2401	4254	4133
CHILE	3687	3900	4024
COLOMBIA	2097	2892	3150
ECUADOR	1762	3181	2805
GUYANA	1706	1965	1184
PARAGUAY	1439	2516	2235
PERU	2648	2889	2177
SURINAME	3048	3969	2367
URUGUAY	3870	4955	4320
VENEZUELA	7624	7233	5692
BANGLADESH	919	1098	1254

CHINA	825	1241	2290
HONG KONG	4456	8801	14035
INDIA	704	763	1042
INDONESIA	700	1252	1798
IRAN	4212	3148	3046
ISRAEL	5718	7494	8431
JAPAN	7500	10292	14045
JORDAN	1412	2600	2280
KOREA, REP.	1688	3123	6209
MALAYSIA	2117	3772	4470
MYANMAR	392	475	576
PAKISTAN	997	1076	1340
PHILIPPINES	1368	1869	1727
SINGAPORE	3155	6958	10240
SRI LANKA	1315	1851	2218
SYRIA	2201	4286	3705
TAIWAN	2387	4827	8209
THAILAND	1508	2146	3231
YEMEN	586	1031	1615
AUSTRIA	7565	10586	12378
BELGIUM	8453	11354	13097
CYPRUS	3757	5294	7827
CZECHOSLOVAKIA	3825	5583	6171
DENMARK	9675	11234	13579
FINLAND	8247	10985	14371
FRANCE	9621	11798	13664
GERMANY, WEST	9557	12013	13937
GREECE	4234	5895	6622
HUNGARY	3382	5051	5623
ICELAND	7086	11909	13092
IRELAND	4884	6785	8406
ITALY	7669	10445	12367
LUXEMBOURG	10000	12029	16079
MALTA	2367	4387	6482
NETHERLANDS	9228	11323	12434
NORWAY	8129	12249	14647
POLAND	2999	4465	4583
PORTUGAL	3323	5048	6281
SPAIN	6017	7495	9305
SWEDEN	10643	12290	14534

SWITZERLAND	13274	14653	16799
TURKEY	2179	2853	3370
U.K.	7695	10028	13050
U.S.S.R.	2873	4270	5457
YUGOSLAVIA	3337	5641	5090
AUSTRALIA	10917	12622	14904
FIJI	2501	3557	3541
NEW ZEALAND	9352	10260	11811
PAPUA N.GUINEA	1740	1658	1445

Programs

The following GAUSS programs were used to derive the results. The programs, which can be used to replicate the results in the paper, are available upon request from the author (but free of charge only to academic institutions and/or non–profit organisations).

File	Output of the program
hcrit1.prg:	Figure 2, and $h_{crit}(m)$, $m = 1, 2, 3$ reported in Table 1.
boot-h1.prg:	p-values in Table 1.
denest.prg:	densities plotted in Figure 3.

References

[1] **Barro, R J** and **Sala-i-Martin, X** 1994, 'Economic growth', *Mc Graw Hill.*

[2] **Baumol, W J** 1986, 'Productivity growth, convergence, and welfare', *American Economic Review*, 76(5), pages 1072–85.

[3] **Bianchi, M** 1995, 'Bandwidth selection in density estimation', *"The XploRe Book", W. Härdle, S. Klinke and B. Turlach editors*, Springer Verlag, Berlin.

[4] **Efron, B** and **Tibshirani, R J** 1993, 'An Introduction to the Bootstrap', *Chapman and Hall, Monographs on Statistics and Applied Probability, 57, New York.*

[5] **Esteban, J M** and **Ray, D** 1994, 'On the measurement of polarization', *Econometrica*, 76(5), pages 1072–85.

[6] **Härdle, W** 1990, 'Smoothing techniques. With implementation in S', *Springer-Verlag, Berlin.*

[7] **Sala-i-Martin, X** 1994, 'Cross sectional regressions and the empirics of economic growth', *European Economic Review*, 38(3/4), pages 739–747.

[8] **Sala-i-Martin, X** 1995 (forthcoming), 'Regional cohesion: Evidence and theories of regional growth and convergence', *European Economic Review*, 38(3/4), pages 739–747.

[9] **Izenman, A J** and **Sommer, C J** 1988, 'Philatelic mixtures and multimodal densities', *Journal of the American Statistical Association*, 83(404), pages 941–953.

[10] **Quah, D T** 1994, 'Ideas determining convergence clubs', *LSE Working Paper.*

[11] **Quah, D T** 1995a, 'Empirics for economic growth and convergence', *European Economic Review*, forthcoming.

[12] **Quah, D T** 1995b (forthcoming), 'Convergence empirics across economies with (some) capital mobility', *Journal of Economic Growth.*

[13] **Silverman, B W** 1981, 'Using kernel density estimates to investigate multimodality', *Journal of the Royal Statistical Society, Series B*, 43, pages 97–99.

[14] **Silverman, B W** 1983, 'Some properties of a test for multimodality based on kernel density estimates', *In Probability, Statistics, and Analysis. Edited by J.F.C. Kingman and G.E.H. Reuter, Cambridge University Press*, pages 248–260.

[15] **Silverman, B W** 1986, 'Density estimation for statistics and data analysis', *Chapman and Hall, Monographs on statistics and applied probability no. 26, London.*

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