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TESTING THE CONVERGENCE HYPOTHESIS: A COMMENT

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Abstract—In a recent paper Lichtenberg (1994) proposes a test of the convergence hypothesis that the variance of productivity across countries decreases over time. He argues that the ratio of the variance in the first period to that in the last period of the time series is F -distributed but overlooks the dependency between these two variances. As a consequence, probabilities of committing a type II error of incorrectly rejecting the convergence hypothesis are large. This problem manifests most strongly in short time periods. Lichtenberg, for example, rejects the convergence hypothesis for a data set of 22 OECD countries over the 1960–1985 period. Using two alternative test statistics, we claim that there is strong empirical evidence for convergence in that time period.

I. Introduction

The Solow growth model and endogenous growth models give opposite predictions about the development over time of productivity differences across countries. A convergence of productivities is considered empirical evidence in favor of the Solow growth model while it is considered difficult to reconcile with endogenous growth theories. Recently a discussion has emerged about the precise way to test for convergence (see, e.g., Bernard and Durlauf (1996), Den Haan (1995), Islam (1995), Lichtenberg (1994), and Oxley and Greasley (1995)). A common test of the convergence hypothesis has been to investigate whether poor countries grow faster than rich countries. Lichtenberg (1994) criticizes this practice of testing convergence. He emphasizes the difference between convergence and mean reversion and shows that a negative effect of initial productivity on the growth rate does not automatically imply convergence. That is, Lichtenberg claims that empirical studies have *overestimated* the rates of convergence. He argues that convergence is equivalent to a decrease over time in the variance of productivity across countries. In more technical terms, Lichtenberg, like Friedman (1992), asserts that research should focus on σ convergence instead of β convergence, and he shows that β convergence is a necessary but not a sufficient condition for σ convergence. Therefore, he suggests to use a ratio of variances statistic to test the convergence hypothesis, which he claims to be F -distributed. We show that this claim is incorrect, and we discuss a likelihood-ratio test statistic and an adjusted ratio of variances test statistic which may be used to test the convergence hypothesis. We compare the performance of the test statistics in a simulation experiment. Finally, the test statistics are applied to a data

set of 22 countries of the Organization for Economic Cooperation and Development (OECD) over the 1950–1994 period and some subperiods. The results indicate that the variance of productivity across these countries has decreased significantly since 1950, and the alternative test statistics both reverse the earlier Lichtenberg finding of nonconvergence for the OECD countries for the 1960–1985 period.

II. Testing the Convergence Hypothesis

Lichtenberg proposes a test of the convergence hypothesis that the variance of productivity across countries decreases over time. If $y_{it} = \ln(Y_{it})$, where Y_{it} is the productivity in country i at time t , and $\hat{\sigma}_t^2 = \sum_i (y_{it} - \bar{y}_t)^2/N$ is the variance of y_{it} across countries, then Lichtenberg claims that $\hat{\sigma}_1^2/\hat{\sigma}_T^2$ is $F(N-2, N-2)$ -distributed in case productivities do not converge over time, where N is the number of countries and T is the end of the period of investigation. We do not agree with this claim and show that this test procedure is biased toward finding no convergence. Assume that productivities are determined by the following autoregressive process:

$$y_{it} = \rho y_{i,t-1} + v_{it}, \quad t = 2, \dots, T, \quad i = 1, \dots, N \quad (1)$$

where the intercept is suppressed. The y_{it} are supposed to be identically and independently distributed (i.i.d.) $N(\mu_1, \sigma_1^2)$ and to be independent of the v_{it} , which are i.i.d. $N(0, \sigma_v^2)$. The null hypothesis of no convergence is equivalent to the parameter restriction $\rho^2 = 1 - \sigma_v^2/\sigma_1^2$. Productivities converge over time in case $\rho^2 < 1 - \sigma_v^2/\sigma_1^2$. From equation (1) we derive Lichtenberg's equation (4),

$$y_{iT} = \pi y_{i1} + u_i, \quad i = 1, \dots, N \quad (2)$$

where $\pi = \rho^{T-1}$ and $u_i = \sum_{t=2}^T \rho^{T-t} v_{it}$. The case of no convergence is equivalent to $\pi^2 = 1 - \sigma_u^2/\sigma_1^2$. It is clear that $\hat{\sigma}_T^2$ and $\hat{\sigma}_1^2$ are not independently distributed if $\pi \neq 0$. Therefore, Lichtenberg's claim that $T_1 = \hat{\sigma}_1^2/\hat{\sigma}_T^2$ would be F -distributed is incorrect in the common sense of $\pi > 0$. The deviation of the test statistic from an F -distribution is stronger, the larger is π . The implication of incorrectly using critical values of an $F(N-2, N-2)$ -distribution is that probabilities of committing a type I error are smaller than the significance level.¹ This is a consequence of the larger variability of $\hat{\sigma}_1^2/\hat{\sigma}_T^2$ (when $\sigma_1^2 = \sigma_T^2$) in case $\hat{\sigma}_1^2$ and $\hat{\sigma}_T^2$ are supposed to be uncorrelated when compared to the case of positively correlated $\hat{\sigma}_1^2$ and $\hat{\sigma}_T^2$. The main problem is of course

¹ Lichtenberg also incorrectly takes the degrees of freedom of both the nominator and the denominator of his ratio of variance statistic to be $N-2$ instead of $N-1$, although this will not affect empirical results substantially if N is larger than about 15.

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TABLE 1.—PERFORMANCE OF RATIO OF VARIANCES TEST STATISTIC T_1

Hypothesis	σ_v^2	N, T ρ	10, 10	10, 25	10, 40	25, 10	25, 25	25, 40	100, 10	100, 25	100, 40
H_0	0.0100	0.995	0.0	0.1	0.3	0.0	0.1	0.3	0.0	0.0	0.2
		0.99	0.0	0.4	1.9	0.0	0.7	6.4	0.0	7.7	38.6
		0.985	0.0	2.0	9.1	0.0	8.9	36.3	0.2	74.5	97.9
		0.98	0.1	6.0	24.9	0.1	34.8	73.9	7.6	99.4	100.0
H_0	0.0199	0.99	0.1	0.5	1.3	0.0	0.5	1.1	0.0	0.2	0.9
		0.985	0.1	1.7	4.1	0.0	2.8	8.1	0.1	10.5	28.2
		0.98	0.2	3.9	10.0	0.1	11.0	26.1	1.6	56.0	82.3
		0.985	0.1	1.0	2.1	0.1	1.0	2.2	0.0	0.7	1.8
H_0	0.0298	0.985	0.1	1.0	2.1	0.1	1.0	2.2	0.0	0.7	1.8
		0.98	0.3	2.4	5.0	0.2	4.1	8.5	0.4	10.9	22.1
H_0	0.0396	0.98	0.3	1.5	2.6	0.1	1.6	2.9	0.1	1.3	2.5

Note: Table shows percentage of 20,000 replications in which test statistic exceeds the $F_{95\%}(N-2, N-2)$ level.

not the low probabilities of committing a type I error but the attendant high probabilities of committing a type II error.

We propose two alternative test statistics of the hypothesis that the variances in the first and last periods are equal. Asymptotic distributions for both test statistics will be given, while small sample performances will be investigated in the next section. The first test statistic, T_2 , is derived using the likelihood-ratio principle. The second test statistic, T_3 , is found by deriving the correct (asymptotic) distribution of Lichtenberg's T_1 -statistic.

We first derive a likelihood-ratio test statistic, which is a function of $\hat{\sigma}_1^2$ and $\hat{\sigma}_T^2$, like T_1 , and of the covariance of productivities in the first and last period, $\hat{\sigma}_{1T} = \sum_i (y_{i1} - \bar{y}_1)(y_{iT} - \bar{y}_T)/N$. The productivities in the first and last periods have a bivariate normal distribution

$$\begin{bmatrix} y_{i1} \\ y_{iT} \end{bmatrix} \sim N \left(\begin{bmatrix} \mu_1 \\ \mu_T \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & \sigma_{1T} \\ \sigma_{1T} & \sigma_T^2 \end{bmatrix} \right). \tag{3}$$

The null hypothesis of no convergence is equivalent to $\sigma_1^2 = \sigma_T^2 = \sigma^2$, and the maximum-likelihood estimator of σ^2 is $\hat{\sigma}^2 = \frac{1}{2}\hat{\sigma}_1^2 + \frac{1}{2}\hat{\sigma}_T^2$. The values of the log-likelihood functions in case of the null hypothesis of equal variances L_0 , and in case of no parameter restriction L_A are

$$L_0 = -\frac{1}{2}N \left(\ln(4\pi^2) + \ln(\hat{\sigma}^4 - \hat{\sigma}_{1T}^2) + \frac{\hat{\sigma}^2(\hat{\sigma}_1^2 + \hat{\sigma}_T^2) - 2\hat{\sigma}_{1T}^2}{\hat{\sigma}^4 - \hat{\sigma}_{1T}^2} \right) \tag{4}$$

$$L_A = -\frac{1}{2}N(\ln(4\pi^2) + \ln(\hat{\sigma}_1^2\hat{\sigma}_T^2 - \hat{\sigma}_{1T}^2) + 2). \tag{5}$$

If we substitute $\hat{\sigma}^2 = \frac{1}{2}\hat{\sigma}_1^2 + \frac{1}{2}\hat{\sigma}_T^2$, then two times the difference between L_A and L_0 equals

$$\begin{aligned} 2(L_A - L_0) &= N \left(\ln \left[\frac{(\hat{\sigma}_1^2 + \hat{\sigma}_T^2)^2}{4} - \hat{\sigma}_{1T}^2 \right] - \ln(\hat{\sigma}_1^2\hat{\sigma}_T^2 - \hat{\sigma}_{1T}^2) \right) \\ &= N \left(\ln \left[1 + \frac{1}{4} \frac{(\hat{\sigma}_1^2 - \hat{\sigma}_T^2)^2}{\hat{\sigma}_1^2\hat{\sigma}_T^2 - \hat{\sigma}_{1T}^2} \right] \right). \end{aligned} \tag{6}$$

This statistic has a limiting $\chi^2(1)$ -distribution using the standard asymptotic property of the likelihood-ratio test. From Morrison (1978, p. 250) we find that the χ^2 approximation is improved if we replace N

in equation (6) by $N - 2.5$. Hence, we define our testing statistic as²

$$T_2 = (N - 2.5) \ln \left[1 + \frac{1}{4} \frac{(\hat{\sigma}_1^2 - \hat{\sigma}_T^2)^2}{\hat{\sigma}_1^2\hat{\sigma}_T^2 - \hat{\sigma}_{1T}^2} \right]. \tag{7}$$

The second way of testing the equality of variances σ_1^2 and σ_T^2 is as follows. From equation (2) it can be derived that

$$\hat{\sigma}_T^2 = \pi^2\hat{\sigma}_1^2 + 2\pi\hat{\sigma}_{1u} + \hat{\sigma}_u^2. \tag{8}$$

The elements of the covariance matrix of y_{i1} and u_i have asymptotically a trivariate normal distribution (see, e.g., Wesselman (1987, p. 20)),

$$\sqrt{N} \begin{bmatrix} \hat{\sigma}_1^2 - \sigma_1^2 \\ \hat{\sigma}_{1u} \\ \hat{\sigma}_u^2 - \sigma_u^2 \end{bmatrix} \rightarrow N \left(0, \begin{bmatrix} 2\sigma_1^4 & 0 & 0 \\ 0 & \sigma_1^2\sigma_u^2 & 0 \\ 0 & 0 & 2\sigma_u^4 \end{bmatrix} \right). \tag{9}$$

An approximate distribution of the ratio of variances T_1 under the hypothesis $\pi^2 = 1 - \sigma_u^2/\sigma_1^2$ can now be derived using the delta method (see, e.g., Wesselman (1987, p. 22)),

$$\begin{aligned} &\sqrt{N} \left(\frac{\hat{\sigma}_1^2}{\hat{\sigma}_T^2} - 1 \right) \\ &\rightarrow N \left(0, \begin{bmatrix} \frac{\partial(\sigma_1^2/\sigma_T^2)}{\partial\sigma_1^2} \\ \frac{\partial(\sigma_1^2/\sigma_T^2)}{\partial\sigma_{1u}} \\ \frac{\partial(\sigma_1^2/\sigma_T^2)}{\partial\sigma_u^2} \end{bmatrix}^T \begin{bmatrix} 2\sigma_1^4 & 0 & 0 \\ 0 & \sigma_1^2\sigma_u^2 & 0 \\ 0 & 0 & 2\sigma_u^4 \end{bmatrix} \begin{bmatrix} \frac{\partial(\sigma_1^2/\sigma_T^2)}{\partial\sigma_1^2} \\ \frac{\partial(\sigma_1^2/\sigma_T^2)}{\partial\sigma_{1u}} \\ \frac{\partial(\sigma_1^2/\sigma_T^2)}{\partial\sigma_u^2} \end{bmatrix} \right) \\ &= N(0, 4 - 4\pi^2). \end{aligned} \tag{10}$$

By substituting the least-squares estimate $\hat{\pi}$ for the parameter π we derive an adjusted ratio of variances test statistic T_3 , which has

² Note that $\hat{\sigma}_{1T}$ can simply be computed as $\hat{\sigma}_{1T} = \hat{\pi}\hat{\sigma}_1^2$, where $\hat{\pi}$ is the least-squares estimate of π in equation (2).

TABLE 2.—PERFORMANCE OF LIKELIHOOD-RATIO TEST STATISTIC T_2

Hypothesis	σ_v^2	N, T ρ	10, 10	10, 25	10, 40	25, 10	25, 25	25, 40	100, 10	100, 25	100, 40
			H_0	0.0100	0.995	4.8	4.7	4.8	5.0	5.2	5.3
		0.99	7.0	9.3	10.0	10.4	17.0	23.2	29.1	56.7	71.4
		0.985	11.5	18.9	23.5	25.7	48.3	59.7	78.1	97.9	99.6
		0.98	19.1	34.1	40.4	47.8	77.1	84.4	97.8	100.0	100.0
H_0	0.0199	0.99	5.1	4.9	5.0	4.9	5.2	5.2	5.1	5.0	5.1
		0.985	5.7	6.9	7.2	7.5	10.8	12.2	16.3	29.8	38.1
		0.98	8.0	11.2	13.1	14.7	25.5	30.7	47.7	77.2	86.1
H_0	0.0298	0.985	5.0	4.9	4.9	5.0	5.0	4.8	5.1	4.6	5.0
		0.98	5.3	6.1	6.4	6.6	8.5	9.2	12.0	19.6	23.6
H_0	0.0396	0.98	5.3	4.9	4.7	4.9	4.9	4.8	4.9	5.0	4.9

Note: Table shows percentage of 20,000 replications in which test statistic exceeds the $\chi_{0.95}^2$ (1) level.

TABLE 3.—PERFORMANCE OF ADJUSTED RATIO OF VARIANCES TEST STATISTIC T_3

Hypothesis	σ_v^2	N, T ρ	10, 10	10, 25	10, 40	25, 10	25, 25	25, 40	100, 10	100, 25	100, 40
			H_0	0.0100	0.995	0.9	4.3	7.2	0.5	3.1	5.1
		0.99	2.3	14.6	24.3	2.8	20.9	36.9	18.8	62.1	80.7
		0.985	5.1	32.1	50.2	11.2	57.9	77.1	68.5	98.6	99.8
		0.98	10.5	54.3	71.2	29.5	85.9	94.3	96.3	100.0	100.0
H_0	0.0199	0.99	3.1	8.0	10.9	2.2	6.2	7.6	2.5	4.9	6.0
		0.985	5.1	17.1	23.6	6.0	20.1	27.4	16.1	41.9	55.5
		0.98	9.1	29.2	39.1	13.7	42.9	55.2	48.7	86.4	93.9
H_0	0.0298	0.985	5.0	10.3	12.6	3.5	7.3	9.1	3.4	5.4	6.9
		0.98	7.8	18.4	22.7	7.5	18.8	24.3	15.0	32.8	40.3
H_0	0.0396	0.98	6.8	11.9	13.9	4.7	8.3	10.1	3.9	6.4	7.1

Note: Table shows percentage of 20,000 replications in which test statistic exceeds the $N_{0.95}(0, 1)$ level.

TABLE 4.—EMPIRICAL RESULTS FOR 22 OECD COUNTRIES

Period	T_1	T_2	T_3	$\hat{\rho}$	$\hat{\sigma}_\rho$	$\hat{\pi}$	$\hat{\sigma}_\pi$	$\hat{\sigma}_v^2$	$\hat{\sigma}_1^2$	$\hat{\sigma}_T^2$
1950–1994	2.60 ^a	8.04 ^a	4.19 ^a	0.9822	0.0016	0.446	0.096	0.00076	0.3160	0.1215
1960–1985	1.63	4.79 ^a	2.05 ^a	0.9794	0.0026	0.693	0.082	0.00076	0.2320	0.1424
1950–1961	1.39	5.03 ^a	1.55	0.9833	0.0039	0.807	0.058	0.00096	0.3160	0.2272
1961–1972	1.53	6.15 ^a	1.89 ^a	0.9812	0.0040	0.758	0.063	0.00076	0.2272	0.1488
1972–1983	1.09	0.94	0.62	0.9907	0.0045	0.941	0.041	0.00067	0.1488	0.1367
1983–1994	1.13	1.51	0.76	0.9891	0.0040	0.922	0.044	0.00050	0.1367	0.1215

Notes: ^a Significant at the 5% level. The critical values corresponding to this level of significance are 2.12 for the T_1 -statistic, 3.84 for the T_2 -statistic, and 1.645 for the T_3 -statistic.

asymptotically a standard normal distribution,³

$$T_3 = \frac{\sqrt{N}(\hat{\sigma}_1^2/\hat{\sigma}_T^2 - 1)}{2\sqrt{1 - \hat{\pi}^2}} \quad (11)$$

III. Simulation Experiment

In order to compare the small-sample performance of the three test statistics T_1 , T_2 , and T_3 we use a Monte Carlo simulation experiment with 20,000 replications for a total of 90 elements of the parameter space (N, T, σ_v^2, ρ) . In each of the experiments we fix μ_1 at zero and σ_1^2 at unity. We do not incorporate an intercept in equation (1), although we allow for it in the least-squares estimation. The test statistics are compared on basis of the nine (N, T) combinations from the set $(\{10, 25, 100\}, \{10, 25, 40\})$.

Table 1 shows the results of the simulation experiment for the test statistic T_1 , whereas tables 2 and 3 show the corresponding results for the likelihood-ratio test statistic T_2 and the adjusted ratio of variances test statistic T_3 , respectively. For each element of the parameter space

we compute the percentage of the replications that gave a larger test statistic than the value corresponding to the theoretical 5% significance level. In case $\rho^2 = 1 - \sigma_v^2/\sigma_1^2$ (H_0) this rejection frequency corresponds to the significance level, whereas in the case $\rho^2 < 1 - \sigma_v^2/\sigma_1^2$ it corresponds to the power of the test. We concentrate on values of ρ close to 1 because these are most common in empirical work concerning convergence.

Lichtenberg's T_1 -statistic only has a simulated significance level close to the theoretical significance level in experiments with $T = 40$ and $\rho = 0.98$. This was to be expected because T_1 will be approximately F -distributed only in cases in which $\pi = \rho^{T-1}$ is close to 0. The likelihood-ratio test statistic has simulated significance levels quite close to the theoretical significance level for all experiments. The simulated significance levels of the adjusted ratio of variances test statistic deviate somewhat more strongly from the theoretical level. They are below the theoretical level in the case where $\pi = \rho^{T-1}$ is close to 1, and they are above the theoretical level in the case where $\pi = \rho^{T-1}$ is close to 0. The speed of convergence of T_3 to a standard normal distribution appears to be quite low.

If we consider the power of the tests, then it can simply be seen that both the likelihood-ratio test statistic and the adjusted ratio of variances test statistic outperform Lichtenberg's test statistic T_1 for all

³ If $|\hat{\pi}| > 1$, then T_3 cannot be determined. When this case occurred in the simulation experiment, we decided not to accept convergence.

experiments. Whether to prefer test statistic T_2 to test statistic T_3 depends on the value of $\pi = \rho^{T-1}$ and the sample size N . A clear advantage of the likelihood-ratio test statistic is that it appears to have already a distribution close to the asymptotic $\chi^2(1)$ -distribution for small values of N . However, in those cases in which the adjusted ratio of variances test statistic has a simulated significance level close to the theoretical level it often has a much higher power than the likelihood-ratio test statistic.

IV. Empirical Results for 22 OECD countries

We computed the statistics for a data set of gross domestic product (GDP) per capita for 22 OECD countries for the 1950–1994 period (Maddison (1995, tables D-1a and 1b)). We did the same for the period 1960–1985, which was used by Lichtenberg. The results can be found in table 4. For the period 1950–1994 all three statistics indicate that the variance of productivities has decreased indeed. In 1950 it was 0.3160, while it was only 0.1215 in 1994. For the period 1960–1985 the T_1 -statistic suggests that there has not been convergence of GDP per capita while the other two test statistics report convergence. It is clear from table 1 that the use of the T_1 -statistic for short time periods has a large probability of committing a type II error. We conclude that there has also been convergence for the period 1960–1985, in which the variance decreased from 0.2320 to 0.1424.

We also examined some shorter time periods, namely, the time period 1950–1994 divided into four subperiods of 12 years each. For such short time periods the T_1 -statistic is likely to be insignificant, and the results in table 4 confirm this. For example, while the likelihood-ratio test statistic and the adjusted ratio of variances test statistic indicate that there has been convergence in the 1961–1972 period, the T_1 -statistic never indicates convergence for the shorter time periods. Overall, the pattern seems to correspond well with the formulation of equation (1). From this equation we find that the variance σ_t^2 of y_{it} is determined as follows:

$$\sigma_t^2 = \rho^2 \sigma_{t-1}^2 + \sigma_v^2, \quad t = 2, \dots, T. \quad (12)$$

In the case that $\rho^2 < 1 - \sigma_v^2/\sigma_1^2$, the variance decreases over time, but the decrease becomes less severe over time and the variance converges to $\sigma_v^2/(1 - \rho^2)$. From table 4 one can compute that the estimates of the value of this limiting value lie between 0.019 (period 1960–1985) and 0.036 (period 1972–1983). A similar pattern is found by Den Haan (1995) for 49 states from 1940 to 1990. The dispersion of per-capita

income in his sample has become much smaller over this time period, but seems to have settled down in the 1970s and 1980s.

V. Conclusion

Lichtenberg (1994) claims that the ratio of the variance in the first period and the variance in the last period can be used as a test statistic of the convergence hypothesis. He argues that this statistic is $F(N-2, N-2)$ -distributed, which we show to be an incorrect claim as the variances are not independently distributed. Using a simulation experiment, we show that the test procedure proposed by Lichtenberg leads to a low probability of accepting the hypothesis of convergence regardless of whether or not it is true. As a consequence, one is biased toward finding empirical support for the endogenous growth models, especially in short time periods. We discuss two alternative test statistics, which outperform Lichtenberg's statistic for "short" time periods.

We apply the three test statistics to a data set of 22 OECD countries for the time periods 1950–1994 and 1960–1985. For the period 1950–1994 all statistics indicate convergence. For the period 1960–1985, as used by Lichtenberg, only his test procedure indicates no convergence. We claim that this is due to the low power of his test statistic. Overall, the results indicate that the degree of convergence across OECD countries has diminished since 1950.

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