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Productivity growth in Indian agriculture: is there evidence of convergence across states?

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Abstract

This paper explores the question of convergence in total factor productivity (TFP) in agriculture across fourteen major agricultural states of India. Using a Törnqvist–Theil index for TFP growth for the period 1973–1993, we find no evidence to support convergence to a single TFP level (σ-convergence). After grouping the various states on the basis of their productivity performance, we find that the high-performing states show a gradual movement towards the trend, whereas the low-performing states generally show more volatility. Testing for long-run convergence in levels of agricultural productivity, we find evidence of conditional beta-convergence after controlling for state-specific factors and idiosyncratic year-specific volatility. The results are robust to alternative specifications of tests of unit root in panel data developed recently.

JEL classification: O13; C23

Keywords: Total factor productivity; Convergence; Panel data

1. Introduction

Agriculture in India has shown remarkable growth over the last three decades after the introduction of Green Revolution technologies in the late 1960s. This has led to an intensive investigation of the sources of this growth as well as its effect on poverty and inequality in the rural areas.

A representative cross-section of such studies focusing on poverty (Ahluwalia, 1985; Saith, 1981; Bell and Rich, 1994; and others) suggests that while there has been some reduction in poverty over the years of rapid agricultural growth, the impact of exogenous shocks such as inflation is still large in the determination of wages and income in the rural areas. There is also enough empirical evidence in the literature to suggest that poverty and inequality are still persistent in rural India in spite of substantial gains in land and labour productivity in agriculture.

The overall growth in productivity at the national level can mask significant differences between those states that have progressed rapidly, such as Punjab and Haryana, and those that have lagged behind. Das and Barua (1996) show that there were substantial inequalities in income among the states of India from the beginning of the Green Revolution period until the first half of the 1990s. They use a maximum entropy method to investigate the determinants of the persistence of regional inequality, and find that differences in agriculture and infrastructure are the

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largest sources of inequality among the various regions of the country. A more recent study by Fan et al. (2000a,b) shows that in India, governments tend to underinvest in regions that have low levels of productivity and infrastructure, that they call 'less-favoured areas'. They also show that the effect of investment in land and infrastructure on poverty in these areas would be much higher than in 'more-favoured areas'. In a separate study, Fan et al. (2000a,b) also show that gains in total factor productivity (TFP) can result through increases in government spending on physical and social infrastructure in rural areas.

TFP indices capture the effects of improved infrastructure such as irrigation, roads and electricity, as well as technology in the form of research and development. Higher TFP would imply a shift in the production possibilities frontier of the agricultural sector away from the origin, leading to higher output from the application of technology and better utilisation of resources. Ultimately, higher TFP leads to a reduction in the levels of poverty in the rural sector (Fan et al., 2000a,b). However, the persistence of regional inequality in agriculture found by Das and Barua (1996) can also be the result of differing rates of TFP growth in the states under consideration. Therefore, from a policy perspective, it is important to understand the long-run movement of regional productivity differences and to take effective measures (such as higher infrastructure investment, research and development, etc.) to correct such imbalances.

In this paper, therefore, we focus on the question of whether there has been a tendency towards convergence in agricultural productivity in the last two decades in India over a representative cross-section of Indian states. As pointed out in the studies mentioned above, differences in agricultural development are one of the major sources of persistence of inequality among the regions of the country. Our contribution to the existing literature is to explicitly test for the existence of convergence in agricultural TFP across a panel dataset of fourteen Indian states from 1973 to 1993, using a battery of tests recently developed for estimating convergence in panel data models.

The plan of the paper is as follows. In Section 2, we outline the TFP data on the different states and demonstrate that productivity growth across states has been uneven. In Section 3, we estimate an econometric model and test for convergence. Section 4 provides a discussion of the results and their relation to the earlier literature on convergence. Section 5 concludes.

2. TFP growth in agriculture in Indian states

2.1. Data sources and measurement

The dataset employed is a panel of fourteen major agricultural states for the period 1973–1993.[1] This dataset has been compiled by the World Bank and the International Food Policy Research Institute (IFPRI) in collaboration with various agencies of the Government of India.[2] Productivity in agriculture is measured using a TFP index, which is the ratio of total output to total input. In several inter-country studies of convergence in TFP, Malmqvist indices under the frontier production function framework are used (see Fulginiti and Perrin, 1998; Gutirrez, 2000; Thirtle et al., 1995). Other studies employ growth accounting techniques using elasticities of labour and capital to estimate TFP (Bernard and Jones, 1996; Martin and Mitra, 2001). This is due to the fact that the complete and comparable sets of input and output prices are not available for the countries under consideration. Where data are available (as in our case), the Divisia indices is the best approximation to capture the effects of unaccounted inputs in agriculture (TFP), such as irrigation, electricity, research and development, etc.

Therefore, the Törnqvist–Theil approximation of the Divisia index is used to measure the growth in TFP for each state between periods t and $t-1$. The state productivity indexes thus created are normalised using 1970 as the base year. The expression for the calculation of the index for each state is given by:

$$\ln\left(\frac{\mathrm{TFP}_t}{\mathrm{TFP}_{t-1}}\right) = \sum_i 0.5 \times (S_{i,t} + S_{i,t-1}) \times \ln\left(\frac{Y_{i,t}}{Y_{i,t-1}}\right) - \sum_j 0.5 \times (W_{j,t} + W_{j,t-1}) \times \ln\left(\frac{X_{j,t}}{X_{j,t-1}}\right)$$

[1] The states in alphabetical order are: Andhra Pradesh, Bihar, Gujrat, Haryana, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh and West Bengal.

[2] For details of the dataset and sources, see Fan et al. (1999)

where the left hand side is the log of the TFP index; $S_{i,t}$ and $S_{i,t-1}$ are output i's share in total production value at time t and $t-1$, respectively; and $Y_{i,t}$ and $Y_{i,t-1}$ are quantities of output i at time t and $t-1$, respectively. Farm prices are used to calculate the weights of each crop in the value of total production. $W_{j,t}$ and $W_{j,t-1}$ are cost shares of input j in total cost at time t and $t-1$, respectively; and $X_{j,t}$ and $X_{j,t-1}$ are quantities of input j at time t and $t-1$, respectively. Thirty crops (rice, wheat, jowar, bajra, maize, ragi, barley, gram, other pulses, groundnut, sesame, linseed, rapeseeds and mustard, castorseed, safflower, nigerseed, coconut, soybeans, sunflower, potato, tapioca, sweet potato, banana, cashewnut, coffee, jute, sugarcane, onion and fruits) and three major livestock products (milk, chicken and sheep and goat meat) are included in total production.

Five inputs (labour, land, fertiliser, tractors and animals) are included. Labour input is measured as total female and male labour (including both family and hired) engaged in agricultural production. A conversion ratio of 0.7 has been used to convert female labour to its male labour equivalent.[3] Land is measured as net cropped area; fertiliser input is measured as the total amount of nitrogen, phosphate and potassium used; tractor input is measured by the number of four-wheel tractors (including both private- and government-owned); and animal input is measured as the number of draft animals (total buffalos). Agricultural wages are used as the price of labour; rental rates of tractors and animals are used as their respective prices; and the fertiliser price is calculated as a weighted average of the prices of nitrogen, phosphate and potassium. The land price is measured as the residual of total revenue per hectare net of measured costs for labour, fertiliser, tractors and bullocks.

Table 1 presents the data on TFP for the states under consideration and Fig. 1 plots the data for convenience of exposition. Since agricultural production and consequently TFP is prone to fluctuations, the base year (1970) is chosen such that it can be considered a 'normal' year in terms of absence of any year-specific shock.

[3] The ratio 0.7 is calculated on the basis of the ratio of the rural wage rate for male and female labour in India. Previous studies have also used this ratio for India and China (Fan et al., 2000a,b), whereas 0.8 has been used for Japan by Kuroda (1995).

2.2. Performance of Indian agriculture

For the whole of India, the rate of TFP growth accelerated from the early 1970s to the late 1980s. While from 1973 to 1980, the trend growth rate was 1.45%, it increased to 2.33% in the 1980s. However, from the late 1980s onwards, there has been a discernable decline in the rate of TFP growth, being only 1.21% from 1989 to 1993. Recent data coming out of India confirms this trend.

The 1970s was the time when TFP was being affected by the introduction of new technology, known as the Green Revolution. It gathered strength in the first half of the 1980s, when the growth in TFP peaked. The experience of the years from the second half of the 1980s can be taken as an indication of the fact that the Green Revolution technologies have run their course, and it would be difficult to sustain a high rate of TFP growth in the absence of further major technological breakthroughs in the field of agricultural science.

We can see from the data in Table 1 that there has been a wide variation in the rate of TFP growth across regions of India over the period 1973–1993. Some states have done better than others in terms of agricultural performance, with Haryana, Punjab and West Bengal having the highest growth rates in the initial period. The divergence in productivity is captured by Fig. 1, which shows the fluctuations in the TFP growth across states over the entire time period.

A closer examination reveals that the states can be broadly divided into ones that are 'high-performing' and those that are 'low-performing' on the basis of their performance ranking over the entire period (Fig. 2). In the former case, the states have shown very substantial improvement in agricultural productivity (over 2% throughout the period, which is the national average). On the other hand, the 'low-performing' states have managed moderate improvements in TFP, while two states, Gujrat and Kerala, have recorded negative rates of TFP growth over the entire period. Therefore, the all-India data on TFP masks important and widespread regional disparities in agricultural performance.

The slowdown in overall TFP growth is brought into focus if we analyse the growth rates over the three subperiods across states. In the first period from 1973 to 1980, the two major agricultural states of North India, Punjab and Haryana, had the best performance

Table 1
Index of TFP growth, various states and all-India (1970 = 100)

Year	Andhra Pradesh	Bihar	Gujrat	Haryana	Karnataka	Kerala	Madhya Pradesh	Maharashtra	Orissa	Punjab	Rajasthan	Tamil Nadu	Uttar Pradesh	West Bengal	All-India
1973	114.52	82.44	83.53	81.22	100.41	105.2	90.84	116.95	102.61	106.92	82.9	109.3	91.23	95.35	99.38
1974	119.75	90.63	49.38	78.54	102.92	104.16	103.98	120.48	86.49	113.13	74.96	86.46	95	106.51	95.59
1975	118.05	101.32	98.76	107.49	104.43	106.37	111.57	137.16	106.7	123.74	91.69	114.83	104.51	113.45	109.28
1976	94.57	98.97	96.24	109.29	79.11	99.57	90.15	141.92	89.65	126.55	90.89	106.68	109.32	111.41	103.74
1977	112.21	103.24	89.43	115.95	113.28	101.63	105.16	147.31	106.07	141.37	90.09	125.55	112.48	120.8	112.82
1978	113.01	104.01	91.48	130.53	110.61	101.87	99.59	142.08	105.97	147.68	101.42	130.02	116.57	127.11	114.82
1979	94.16	87.19	83.94	95.74	103.31	102.56	72.34	145.11	88.12	142.5	77.55	123.99	85.13	118.16	98.48
1980	96.77	109.78	85.85	116.29	92.3	100.11	108.39	146.35	120.51	142.16	88.95	106.69	121.98	131.45	112.08
1981	117.34	101.55	99.17	114.67	100.53	98.12	111.68	156.57	122.34	154.75	98.09	127.82	124.72	122.34	117.71
1982	106.69	106.66	82.39	120.63	97.57	98.98	112.05	147.96	115.13	156.04	109.62	101.22	132.42	119.16	115.85
1983	117.41	127.52	109.59	121.21	107.41	94.8	132.76	159.9	142.02	157.25	118.61	118.36	138.39	144.82	128.48
1984	95.85	129.18	99.08	132.45	104.31	94.06	120.09	148.19	151.51	167.57	107.56	131.31	135.34	150.38	124.83
1985	102.14	133.32	54.8	153.36	94.74	89.1	130.03	130.43	150.99	174.27	108.43	148.78	137.69	187.19	128.07
1986	100.29	131.08	72.22	143.44	108.39	86.51	113.43	115.78	140.71	164.27	92.03	120.37	148.55	179.37	123.85
1987	121.52	124.75	36.11	113.28	107.5	82.66	124.68	157.54	130.2	171.62	89.15	140.75	145.97	183.9	126.23
1988	142.77	135.43	72.22	193.67	116.26	82.53	143.3	158.6	154.8	173.25	154.01	136.24	158.48	203.64	148.25
1989	127.49	131.79	53.11	125.35	107.38	86.98	132.92	210.08	152.03	188.69	114.5	143.37	150.27	211.95	140.18
1990	125.08	136.62	49.28	140.42	103.49	88.45	149.17	150.64	147.79	184.41	130.71	138.83	148.46	217.13	138.64
1991	121.16	129.67	62.78	137.89	109.24	97.62	134.4	141.52	173.87	183.25	115.03	135.49	147.55	227.14	138.75
1992	119.97	119.94	64.18	156.95	123.32	103.6	140.42	161.02	196.51	182.41	129.74	137.75	149.9	225.91	144.11
1993	127.27	137.71	49.86	158.78	130.69	109.78	149.19	167.91	210.58	189.73	113.27	136.13	150.26	236.36	146.10
Trend growth rate (%)															
1973–80	−2.71	2.31	3.02	4.93	−0.04	−0.63	−0.91	3.14	1.62	4.51	1.13	2.58	2.19	3.79	1.45
1981–88	1.92	3.46	−9.74	4.76	1.71	−2.91	2.24	−0.82	2.65	1.71	1.16	2.71	2.85	7.85	2.33
1989–93	−0.45	−0.43	1.37	5.84	5.68	6.23	1.71	4.54	9.36	0.32	−0.29	−1.11	0.01	2.58	1.21
1973–93	0.77	2.25	−2.64	2.74	1.01	−0.61	2.41	1.14	3.73	2.49	1.07	1.56	2.63	4.62	2.02

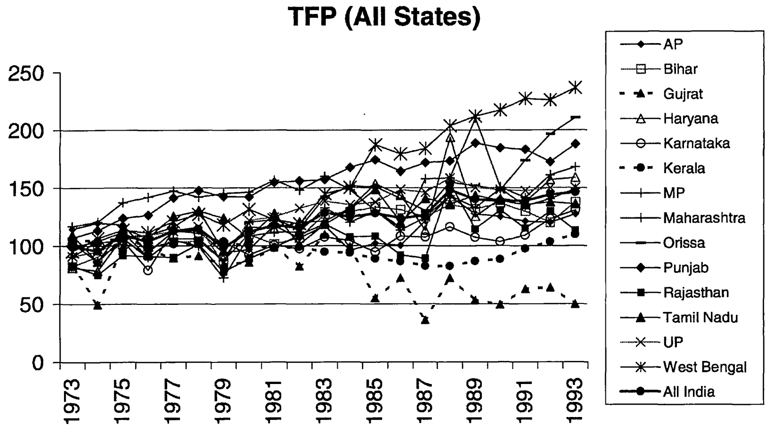
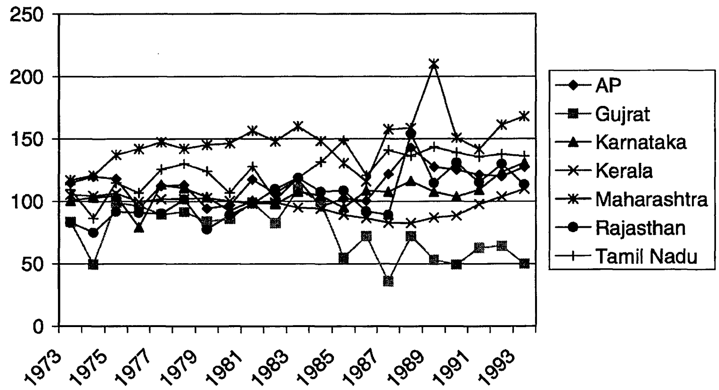


Fig. 1. Total factor productivity growth: states and all-India.

(a)



(b)

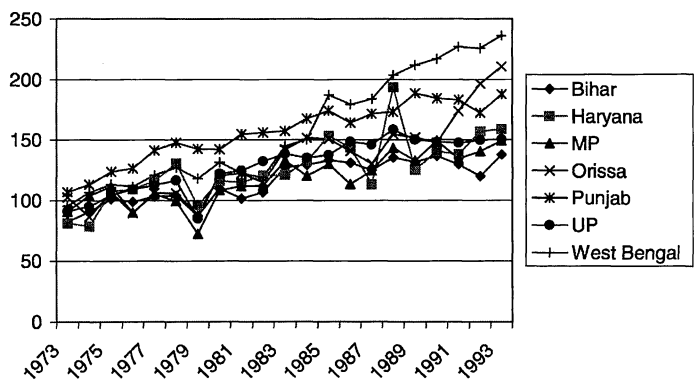


Fig. 2. TFP growth rates in different states: (a) low-performing states and (b) high-performing states.

among all the states. This is mainly because they got a head-start regarding the introduction of modern technologies in foodgrain production, which then spread to other states of the country. The second period from 1980 to 1988 saw better TFP performance in nearly all states (except Gujrat, Maharashtra and Kerala), but was marked by a slowdown in the TFP growth in Haryana and Punjab, possibly due to diminishing returns to technology in agriculture. Overall, this period saw the fruits of technology being harvested by most major agricultural states in India, resulting in significant progress towards the achievement of self-sufficiency in foodgrain production by the early 1980s.

From the late 1980s onwards, there is substantial evidence of an overall slowdown in TFP growth in India, as can be seen from Table 1. Major agricultural states in north India, such as Bihar, Uttar Pradesh, Punjab and Rajasthan recorded very minor or even negative rates of TFP growth in this period. However, Haryana, Karnataka, Kerala, Maharashtra, Orissa and West Bengal all recorded significant productivity gains.

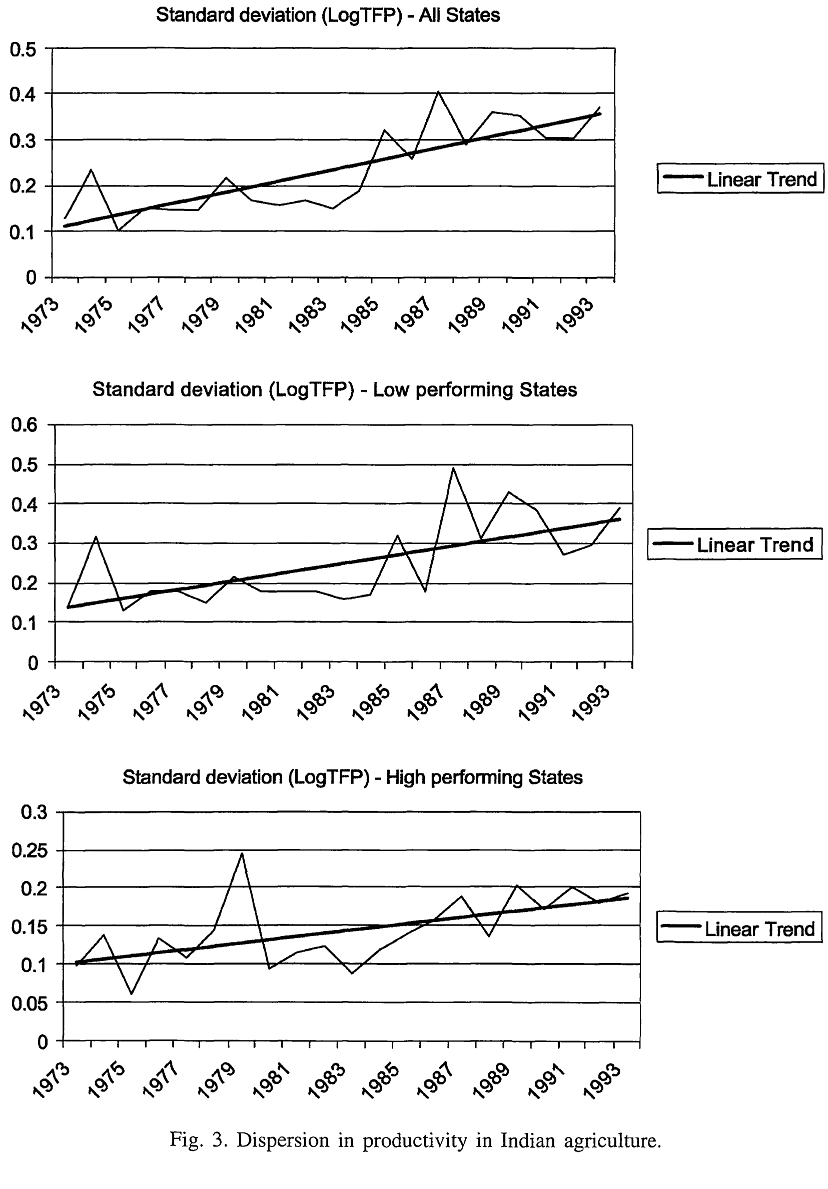


Fig. 3. Dispersion in productivity in Indian agriculture.

2.3. Divergence in productivity among states

To understand the divergence in productivity experience, we calculate the standard deviation of TFP for each year across states (following Barro and Sala-i-Martin, 1995; Bernard and Jones, 1996; and others). A few interesting points can be noted from Fig. 3. It seems apparent that overall, there has been an increase in the dispersion of TFP in agriculture across regions over the entire time period. The movement has been very uneven, with sharp increases followed by significant declines in productivity dispersion. The trend, however, has been unambiguously towards greater dispersion, since the trend line has a positive slope.[4]

However, as seen above in Table 1 and Fig. 1, a distinct pattern emerges when we distinguish between 'low-performing' and 'high-performing' states, taking the average annual rate of TFP growth at the national level as the benchmark. The lower panels of Fig. 3 show the dispersion according to performance level. We see that the aggregate dispersion is more or less identical to that of the 'low-performing' states.

On the contrary, while the 'high-performing' states have shown a general increase in dispersion, the magnitude of this increase is lower than that of the low performers. Moreover, the oscillations around the trend line show signs of dampening, which indicates that the long-run dispersion is tending towards a steady state. As pointed out by Datt and Ravallion (1998), this might be due to initial conditions such as differences in natural endowments, physical and human infrastructure, etc. Therefore, in our empirical section, we set up our null hypothesis taking into account the heterogeneity in TFP performance among states and evaluate the different tests of convergence for their applicability to our data.

Based on these observations, we do not expect to find evidence of absolute decline in the productivity gap, that is, to get a negatively significant value for the time-trend in the subsequent empirical analysis. However, in the long run, the log of the TFP series across states should be cointegrated with the all-India rate of TFP growth, which we shall test for below. We would thus be able to determine whether the rates of TFP growth in agriculture across Indian states have been converging or not.

In the next section, we test for convergence of state TFP indices by analysing the panel of 14 major states of India between 1973 and 1993. The time period is long enough for us to use the asymptotic properties of the estimated convergence coefficients, taking into account recent developments in panel convergence analysis.

3. Tests of convergence in productivity across states

3.1. Basic model

The neoclassical growth model without technology predicts convergence in output per worker for similar, closed economies based on the accumulation of capital. However, even in the neoclassical model, if exogenous technology processes follow different long-run paths across countries, there will be no tendency for their output levels to converge. Analogously, in our case, we are interested in whether the different states in India, especially the major agricultural ones considered in this study, have managed to narrow their technology gap. To see this, we construct a simple model of sectoral output in which convergence in output occurs due to the improvement in TFP. The behaviour of TFP in this model is such that relatively backward regions can grow more rapidly by efficiently using the same technologies that are available to the leading regions.

Following Bernard and Jones (1996), we assume that the production process can be represented by a simple Cobb–Douglas production function with constant returns to scale.[5] We can write the log of the output in agriculture in state i at time t, $\ln Y_{i,t}$, as

$$\ln Y_{i,t} = \ln A_{i,t} + \alpha \ln K_{i,t} + (1-\alpha) \ln L_{i,t} \quad (1)$$

where $A_{i,t}$ is an exogenous technology process, $K_{i,t}$ is the capital stock, and $L_{i,t}$ is the number of workers in

[4] This might be one of the reasons behind Das and Barua's (1996) observation of increasing inequalities in agriculture in Indian states.

[5] Although it is a restrictive assumption, it simplifies our argument for the use of Divisia index where prices of factors and inputs are taken as the marginal product and marginal cost, respectively, in calculating TFP.

the sector. We assume that $A_{i,t}$ evolves according to

$$\ln A_{i,t} = \gamma_i + \lambda \ln D_{i,t} + \ln A_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

where γ_i is the asymptotic rate of growth of agriculture in state i; λ parameterising the speed of the catch-up denoted by $D_{i,t}$; and $\varepsilon_{i,t}$ represents the region-specific productivity shock. We allow $D_{i,t}$ to be a function of the productivity differential in agriculture in region i from that of the national average, A_{n}:

$$\ln D_{i,t} = \ln \hat{A}_{i,t-1} \quad (3)$$

where a hat indicates a ratio of the national average of a variable to the same variable in state i, i.e.

$$\hat{A}_{i,t} = \frac{A_{i,t}}{A_{\mathrm{n},t}}$$

This formulation implies that productivity gaps between states are a function of the lagged gap in productivity. We also assume that technological convergence occurs independent of capital deepening. Therefore, the model yields a simple equation for the time path of TFP given as

$$\ln \hat{A}_{i,t} = (\gamma_i - \gamma_{\mathrm{n}}) + (1 - \lambda) \ln \hat{A}_{i,t-1} + \hat{\varepsilon}_{i,t} \quad (4)$$

where $\hat{\varepsilon}_{i,t}$ are iid error terms.[6] If $1 > \lambda > 0$, the difference between the technology levels between the state and the national level will be stationary. Alternatively, if $\lambda = 0$, productivity levels would grow at different rates permanently and show no tendency to converge. In that case, the difference between the TFP in state i and the national average will be non-stationary.

3.2. Estimation procedure

Tests for convergence in panel data models are a subject of ongoing theoretical investigation.[7] Most earlier studies have tested for unit roots using the methodology proposed by Levin and Lin (1992). Bernard and Jones (1996) further extended this discussion to include non-zero drift terms in the framework.

Levin and Lin (1992) proposed a method of testing for unit roots in a finite sample panel data. For estimation purposes, we consider the general version of Eq. (4)

$$\ln \hat{A}_{i,t} = \rho \ln \hat{A}_{i,t-1} + \mu_i + \upsilon_{i,t} \quad (5)$$

where $\upsilon_{i,t} \sim iid(0, \sigma_\upsilon^2)$ and $\mu_i \sim iid(\bar{\mu}, \sigma_\mu^2)$ is an individual-specific effect. We also assume, following Levin and Lin (1992), that $\upsilon_{i,t}$ has $2+\Delta$ moments for some $\Delta > 0$ and $E\mu_i\upsilon_{i,t} = 0$ for all i and t, and other regularity conditions hold.

The null hypothesis that we test is H_0: $\rho = 1$ for all i against the alternative hypothesis H_0: $\rho < 1$ for all i. This means that we are testing whether the group of states as a whole are converging or not. Under this alternative hypothesis, the states are taken as homogenous, controlling for state-specific fixed effects. The t-values are asymptotically centred and normal, and therefore we can test for convergence using the significance level of the t-statistics.

In case a deterministic element such as a time-trend is present in the data, we can include a state-specific parameter $\eta_i \cdot t$ in Eq. (5) to control for idiosyncratic yearly shocks to the agricultural sector. Moreover, we also specify the model to take into account the persistence in the error terms likely to result from presence of cross-sectional elements in the panel dataset.

The assumption of homogeneity in the panel convergence test has been criticised in several papers (Im et al., 1997; Harris and Tzavalis, 1999; Hadri, 2000). Recently, Levin and Lin (2002) have improved the earlier model to allow for the degree of persistence in individual panel to vary freely. Extending Eq. (5) and taking into account the individual and trend variations, the following equation tests for unit root in panel data

$$\Delta y_{i,t} = \delta_{i,t} y_{i,t-1} + \sum_{L=1}^{p_i} \theta_{i,L}\, \Delta y_{i,t-L} + \alpha_{0i} + \alpha_{01} \cdot t + \zeta_{i,t} \quad (6)$$

where the error term is distributed independently across individuals and follows a stationary invertible ARIMA process for each individual. The procedure involves performing augmented Dickey–Fuller (ADF) regressions with the lag order permitted to vary across individuals. For reasons of simplification, we test for the same lag-length across all panels, choosing p_i in accordance with the method proposed by Levin and

[6] Since our dataset includes cross-section observations, we shall subsequently set up our tests of convergence for serially correlated errors as well.

[7] For a review, see Banerjee (1999).

Lin (2002). These estimations have been carried out using NPT1.2 and Coint 2.0 on GAUSS.[8]

4. Estimation results

4.1. Results from Levin and Lin (LL) method

Tables 2 and 3 present the results of the tests for convergence using the two methodologies described above. From the results of Table 2, we observe that all specifications reject the null of non-stationarity. LL1 is specified without intercept and time-trend but with individual-specific effects. LL2 includes all three, while LL3 is estimated without intercept and time-trend but considering serial correlation across time periods.

A closer look at the results indicates that among the three, LL2 has the lowest coefficient but the highest t-statistic. LL3 shows a significant improvement in the estimated coefficient when serial correlation is accounted for. Therefore, these preliminary results indicate that there is a tendency for the levels of TFP across states in India to converge. The rejection of the null hypothesis implies that all the states are converging at the same rate towards a steady state.

Table 3 provides the estimation results for LL4 and LL5 based on the improved model of Levin and Lin (2002). We estimate the two models with one- and two-period lags in the ADF regressions. LL4 includes an individual-specific effect only whereas LL5 includes individual time-trends as well. The results point to a rejection of the null hypothesis and a substantial improvement in the estimated coefficients. The test statistic t_δ is obtained from pooling the individual test statistics in the final stage of the estimation. Therefore, for LL5 with one lag, the rate of convergence is nearly 10%, decreasing to 1.5% when both lags are included in the ADF regression.

4.2. Further tests of convergence

Although Levin and Lin (2002) is a substantial improvement over the previous series of tests, the question still remains whether pooling has any effect on the outcome of the convergence tests. Im et al. (1997) and Hadri (2000) provide two instances in which the independence assumption across cross-sections is utilised to test for unit roots. On the other hand, in small-sample estimations with the time dimension limited, the asymptotic distributions of the test statistics can be different from the Levin and Lin results (Harris and Tzavalis, 1999). Therefore, it is necessary to carry out these additional tests to determine whether panel heterogeneity and sample-selection have any effect on the outcome of the LL tests.

Table 4 outlines the result of Im et al. (1997); Hadri (2000) and Harris and Tzavalis (1999) tests

Table 2
Unit root estimates according to Levin and Lin (1992)

Model	Coefficient (ρ)	t-value	Critical probability
LL1	0.543	−5.031	0.000
LL2	0.117	−9.816	0.000
LL3	0.872	−8.091	0.000

Note: LL1, Levin and Lin (1992) individual-specific effect only; LL2, Levin and Lin (1992) individual-specific effect and individual time-trend; LL3, Levin and Lin (1992) serially correlated errors, without intercept and time-trend.

Table 3
Unit root tests according to Levin and Lin (2002)

Model	Lag length	Coefficient (ρ)	t_δ value	Critical probability
LL4	1	0.559	17.868	0.000
	2	0.818	26.066	0.000
LL5	1	0.898	40.874	0.000
	2	0.985	51.354	0.000

Note: LL4, Levin and Lin (2002) with individual-specific effect; LL5, Levin and Lin (2002) with individual-specific effect and individual time-trend.

Table 4
Other tests of convergence

Model	Test statistic	Critical probability
IPS97	−2.696	0.043
HT1	3.609	0.000
HT2	24.018	0.000
Hadri	362.896	0.000

Note: IPS97, Im et al. (1997) with time-trend; HT1, Harris and Tzavalis (1999) with intercept; HT2, Harris and Tzavalis (1999) with intercept and time-trend; Hadri, Hadri (2000) with time-trend.

[8] The GAUSS code for NPT1.2 can be downloaded from http://web.syr.edu/~cdkao.

for the specifications including a time-trend for Im et al. (1997) and Hadri (2000), and both intercept and time-trend for Harris and Tzavalis (1999). As is evident, the test statistic in all the three cases rejects the null of non-stationarity. Therefore, we can say that the Levin and Lin (2002) test results are robust to alternative specifications of panel independence and small-sample bias. The above results unambiguously point to a rejection of the hypothesis of a unit root, indicating long-run convergence in TFP levels taking into account individual-specific variations.

Recently, McCunn and Huffman (2000) investigated the convergence in TFP for agriculture in forty-two US states. They find no evidence of σ-convergence but characteristics of conditional β-convergence in the data. In our study, we use panel unit-root tests under various specifications to test for β-convergence, and come to exactly the same conclusions. Although we cannot decompose the convergence rates into their components due to data limitations, our conjecture is that in the long run, elimination of differences in infrastructure, R&D, social services, etc. would have a significant impact on the rate of convergence across states in India, which is consistent with McCunn and Huffman (2000).

5. Conclusion

We analyse the growth in productivity in Indian agriculture over the last two decades. The agricultural sector has performed admirably after the introduction of modern technology and high-yielding 'Green Revolution' varieties since the late 1960s. However, an analysis of the disaggregated data at the state level underscores the regional variation in the rate of TFP growth within the country. We find that broadly, the states can be categorised according to their growth in TFP in agriculture between 'high-performing' and 'low-performing' regions. There is no evidence of a reduction in the productivity gap between these groups of states over time, leading us to conclude that until now, the rates of productivity growth have not become equal in all regions of the country.

The convergence analysis, on the other hand, shows that the TFP gap as measured by the distance of each state's productivity level from the all-India average is stationary, and thus there is evidence of long-run convergence. This result is robust to specifications that take into account cross-sectional variations across states and idiosyncratic yearly shocks in the panel dataset under consideration.

The causes underlying the results of our analysis may suggest the importance of increasing investment in infrastructure, including irrigation, electricity, roads, government social spending, research and extension services, among others, in regions in which the TFP level is below the national average. The tendency in developing countries to concentrate resources in the 'more-favoured areas' would lead to the persistence of the productivity differential as we have found in our analysis. Along with direct support for agriculture, the impact on agricultural productivity of infrastructure as broadly defined above needs to be analysed.

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