Regional convergence of growth, inequality and poverty in India—An empirical study

Samarjit Das a,*, Gouranga Sinha b,1, Tushar K. Mitra b

a Indian Statistical Institute, India
b University of Kalyani, India

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1. Introduction

Growth, inequality, and poverty are the three subjects of interest to development economists and policy makers in developing countries. Neoclassical growth theory underlines the mobility of supply side factors, in particular capital stock, labour and technology, as being the main factors which finally lead to reduction of disparities. However, contrary to this theory, it is also a fact that in a large economy like India, regions with different resource bases and endowments along with rigidity in factor mobility may result in regional disparities — at least in the short run. If differences are allowed to cumulate year after year, then these may create social and political unrest which might ultimately become a threat to national integration (Alesina and Perotti, 1996; Benhabib and Rustichini, 1996; Chowdhury, 2003), and eventually such growths become unsustainable. To cite an instance, Wei and Kim (2002) have found that increasing regional inequality is widely considered to be the primary reason for the existing regional problems in China and thus an obstacle to its stability and development.

Following the pioneering work of Baumol (1986), a good deal of efforts has been made for investigating the convergence hypothesis in different national and regional samples, based on two methodological approaches. Barro and Sala-i-Martin (1992, 1995) were the first who introduced the notion of β and σ convergences to assess whether the poor states grow faster than the richer ones, implying that they will catch up (β-convergence) in the long run, and/or whether the dispersion of the income diminishes (σ-convergence) over time. Barro and Sala-i-Martin’s work is based on cross-section data. Bernard and Durlauf (1995) have questioned the cross-sectional approach and defended the use of time-series methods. Barro and Sala-i-Martin (1992) have found, based on a time series of 100 years that US states converge unconditionally. More recently, de la Fuente (2002) has recorded evidence of convergence across Spanish regions. Juan-Ramon and Rivera-Batiz (1996) have found mixed evidence of convergence of income for the states of Mexico, namely, that convergence holds for the period 1975–85 and divergence for the period 1986–93. In this context, it may be worth mentioning that selection of sample is crucial since any inference is susceptible to sample selection bias, as has been pointed out by De Long (1988).

The literature on disparities across Indian states is relatively scanty. Nagaraj et al. (1997) have considered the growth performance of Indian states during the 1960–94 period and found evidence of conditional convergence. Cashin and Sahay (1996) have used a cross-section regression covering the period of 1960–92, and reported evidence of unconditional β-convergence, although the estimated convergence rate is not statistically significant. Baijai and Sachs (1996) have considered the same sample and found evidence of statistically significant unconditional convergence during the period...
1960–70, but not thereafter. They have argued that this could be due to high growth in the agricultural sector in India during the 1960s. In contrast to these findings, a number of studies (see for example Raman, 1996; Marjit and Mitra, 1996; and Dasgupta et al., 2000) have reported significant divergence across Indian states.

A number of econometric concerns are quite evident in these studies. The econometric literature has been critical of traditional growth regressions for studying economic convergence across countries and regions, based on the popular notions of β and σ convergences (Barro and Sala-i-Martin, 1992). In particular, these methods fail to allow for unobserved (and persistent) differences across countries, and they are susceptible to measurement errors, endogeneity biases and spatial autocorrelation (Temple, 1999). Subsequent researches based on either long-run behavior of output differences across countries (Bernard and Durlauf, 1995) or panel unit root tests (Evans and Karras, 1996), have motivated a new generation of convergence tests which address some of these serious econometric issues.

More recently, new testing procedures for the convergence hypothesis using panel data have been developed. These new methodologies ameliorate the inadequacy of the single cross-section method which essentially implies a too low growth rate and too large share of capital (Islam, 1995). Moreover, single cross-section method does not incorporate country specific differences. Two different approaches using panel data have been proposed. The first approach has essentially extended the methodologies, designed for cross-sectional data, to the analysis of panel data (Knight et al., 1993; Islam, 1995). The other one has used panel unit root testing procedures for examining convergence hypothesis (Quah, 1994; Bernard and Jones, 1996; Evans and Karras, 1996). The different testing procedures can be distinguished according to the models used for carrying out the tests and the restrictions imposed under the unit root null hypothesis.

In this paper, we attempt to examine whether the Indian states are really converging or diverging in terms of three commonly-used indicators viz., per capita consumption, inequality and poverty. The present paper attempts to examine convergence hypothesis by using panel unit root tests in the framework of Evans and Karras (1996). However, most of these panel unit root literature including Evans and Karras, assume that each of the time series in the panel is cross-sectionally independent. Due to a single currency, near-free factor movements, common policies adopted by the central authority and spatial correlation, various socio-economic variables in different regions in India are expected to be contemporaneously correlated. Recent studies by O’Connell (1998) and Breitung and Das (2005) have highlighted that, in the presence of contemporaneous correlation, standard panel unit root test like those proposed by Maddala and Wu, 1999; Levin et al., 2002; Im et al., 2003 suffer from severe over-size problem. Hence, such tests are likely to suggest acceptance of convergence hypothesis more often. Moreover, the occurrence of cross-sectional dependence is certain due to the observation made by Pearson (1897). Pearson’s work points out the fallacy of correlation coefficient between ratios that have a common divisor. What he showed is that even when X and Y are completely uncorrelated random variables, ratios like \( Z \) and \( \frac{X}{Z} \) where Z is another random variable; may have a misleadingly large value of correlation coefficient (see also Kim, 1999). Due to the very construction of panel unit root tests by using a common numeraire as in Evans and Karras (1996), the time series are most likely to be cross-sectionally dependent.

Another distinctive advantage of incorporating contemporaneous cross-sectional dependence in a panel framework is that any series may be decomposed into a number of common factors and idiosyncratic components. The idiosyncratic components may be considered as the effect of policies that are reserved for the state governments, whereas common factors may be looked upon as the effect of policies adopted by the central government for this divergence. Therefore, such decomposition enables one to identify the source of inter-state divergence if such a divergence exists and also to find the responsible entity — central or state governments. This is important from the consideration of policy implications because if the idiosyncratic shocks are dominant or have unit roots, primary responsibility lies with the state governments for creating growth-friendly conditions, maintaining efficient delivery system, and for implementation of various developmental programmes undertaken by the central government. If, for example, there are credit market imperfections in any state, the poor in that state may not be able to utilize growth-promoting opportunities and so with the rise in the proportion of the poor, the growth rate would be lower (see Stiglitz, 1969; Loury, 1981; Aghion et al., 1999). On the contrary, if common factors are predominant or having unit roots, then decline in growth rate accompanied by increase in poverty or rise in inequality should be of concern to central authorities.

The plan of the paper is as follows. Section 2 presents a brief discussion on the methodology. A preliminary analysis of the data with traditional convergence tests is done in Section 3. The next section presents the empirical results based on panel unit root tests. Section 5 discusses further analysis of panel unit root tests based on groups which are formed to find if convergence is achieved within groups. Finally, the paper concludes with some comments in Section 6.

2. Econometric methodology

To test cross-sectional dependence, we use the Lagrange multiplier (LM) type tests as proposed by Breusch and Pagan (1980). A simple modified Lagrange multiplier (MLM) test, as suggested by Pesaran (2004), is also considered as it precludes the inherent oversize problem of the LM test.

We consider tests which explicitly incorporate cross-sectional dependence viz., the tests developed by Chang (2002, 2004) and by Breitung and Das (2005). Consider the data generating process:

\[
\Delta y_t = \mu_t + \rho \Delta y_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta y_{t-j} + \epsilon_t
\]

where the starting values of \( y_{0}, y_{1}, \ldots, y_{p} \) are set equal to zero. To take care of autocorrelations/short run dynamics, Eq. (1) includes the term \( \sum_{j=1}^{p} \gamma_j \Delta y_{t-j} \). Individual specific intercepts \( \mu_t \) have also been included because series means may not be zeroes. The error vector \( \epsilon_t = (\epsilon_{t1}, \epsilon_{t2}, \ldots, \epsilon_{tn}) \) is i.i.d with \( E(\epsilon_t) = 0 \) and \( \epsilon_t \epsilon_t' = \Omega \), where \( \Omega \) may not necessarily be a diagonal matrix. The null hypothesis is \( H_0: \rho = 0 \), that is, all time series are random walks. Under the alternative, it is assumed that all the time series are stationary with \( H_1: \rho < 0 \). Testing the hypothesis of regional convergence with respect to an indicator typically involves conducting unit root tests for the log-ratio of a regional indicator to that of a common numeraire. If the unit root null hypothesis is rejected, then this ratio is mean reverting and any deviations from the numeraire should diminish over time suggesting thereby deviation from the numeraire is temporary, and hence it may be concluded that regional convergence with respect to the particular indicator holds. In contrast, if the unit root tests fail to reject the null hypothesis, then the evidence suggests that these ratios follow random paths and hence the deviation from the numeraire becomes permanent rejecting the convergence hypothesis.\(^3\)

Chang (2002) proposed a nonlinear instrumental variable (IV) approach which is applicable under heterogeneous alternatives as well. Chang’s work showed that the usual individual OLS-based \( t \)-statistics constructed from this transformed model are asymptotically independent even in the presence of cross-sectional dependence. Thus, the panel test statistic is simply defined as a standardized sum of individual \( IV \ t \) ratios and it asymptotically follows \( N(0, 1) \) under \( H_0 \).

Another testing procedure developed by Chang (2004) is based on bootstrap methodology, which takes care of the oversize problem.

\(^2\) Some tests are applicable with heterogeneous alternatives.

\(^3\) As we have allowed the possibility of non-zero intercepts in Eq. (1), convergence may be considered to be conditional one, as opposed to absolute convergence (see Evans and Karras, 1996).
involved in the standard OLS or GLS-based t-statistics. In this method, one first estimates Eq. (1) and then re-samples the residual vectors (instead of individual residuals) keeping the dependence structure in the data, and finally uses them to generate pseudo observations. The OLS or GLS t-statistics are calculated based on these pseudo observations. These t-statistics form the bootstrap distribution under $H_0$.

A simple method that works even when $N$, the number of cross-sectional units, is greater than $T$, the total number of time-series observations, is the one proposed by Breitung and Das (2005). As the OLS standard error is biased under cross-sectional dependence, Breitung and Das (2005) have used modified standard error that is robust to cross-sectional dependence and showed that under $H_0$, the test statistic, $t_{rob}$, follows $N(0,1)$. We denote four statistics discussed so far, as the IV ($t_{iv}$), OLS-based bootstrap $t$ ($t_{bs}$), GLS-based bootstrap $t$ ($t_{gs}$), and robust $t$ ($t_{rob}$), test statistics, respectively.

It may be worthwhile to note that all these tests are appropriate only under ‘weak’ dependence structure. But cross-sectional dependence may be ‘weak’ or ‘strong’ depending on the nature of the eigenvalues of the error variance–covariance matrix, $\Omega$. As discussed in Breitung and Das (2008), ‘weak’ dependence means all the eigenvalues of the error variance–covariance matrix are bounded (‘weak’), even for large $N$, whereas ‘strong’ dependence implies and is implied by the presence of unbounded eigenvalues. Under strong dependence, each series may be decomposed into two components viz. (i) a few common factors and (ii) the idiosyncratic term (Forni et al., 2000).

However, as shown by Breitung and Das (2008), the aforementioned tests are not appropriate in the presence of strong dependence. Under strong dependence, unit root tests may be applied to estimated factors and idiosyncratic errors separately. Factors are estimated using the method of principal components. After estimating factors, one can apply standard univariate unit root test to each of the factors. Each factor, as estimated by principal component analysis, follows the standard Dickey–Fuller test under the null hypothesis of unit root (Bai and Ng, 2004). Similarly, one can test for stationarity of idiosyncratic errors using panel approach. Moon and Perron (2004) have developed panel unit root test on idiosyncratic errors after removing the factors from the data. Further, Breitung and Das (2008) have shown that the robust test follows the standard Dickey–Fuller test under strong dependence.

3. Data and some preliminary analyses

This study is based on long and consistent time-series data across 14 major states$^6$ of India on consumption level, poverty and inequality-based measures assembled from the 34th round national sample surveys (NSS) conducted by the National Sample Survey Organization (NSSO), Govt. of India, for both rural and urban sectors spanning the period 1958 to 2005.$^{5,10}$ Datt (1998) has earlier constructed comparable and consistent summary information about poverty and consumption expenditure data based on the survey data provided by NSSO up to 1993–94. We have updated these series up to 2004–05, using the same method as followed in Datt (1998). A consistent set of price indices across states and across survey periods, using monthly data on consumer price indices from the Labour Bureau (available at the disaggregated level), has been constructed. The primary deflators are the Consumer Price Index for Industrial Workers (CPIIW) for the urban sector, and the Consumer Price Index for Agricultural Labourers (CPIAL) for the rural sector. The standard of living has been taken to be the average monthly per capita consumption expenditure (MPCE) at 1973–74 prices.$^{11}$ Here economic growth has been measured in terms of per capita consumption instead of per capita state GDP since it directly captures the well-being at the household level. Also, the preference for consumption reflects the present practice in the poverty measurement literature (Lipton and Ravallion, 1995). Poverty measures and the Gini coefficient measuring inequality have also been evaluated in terms of MPCE. The poverty measures considered are the widely used head count index (HCl), the poverty gap index (PG), and the squared poverty gap (SPG) indicating incidence of absolute poverty, the depth of poverty and the severity of poverty, respectively. Before going into the more formal analysis based on panel unit root tests, we first present the findings corresponding to traditional convergence tests so that the empirical results obtained in the former could be compared and better understood.$^{12}

To get a useful insight into the data we have computed the mean rank of each state for each period with respect to all the variables for both the sectors — urban and rural. It is useful to get an idea of a state’s average ranking relative to other states for all the periods. To that end, we have calculated the number of better (worse) years, that is, the number of years a particular state has exceeded (fallen short of) its average rank. In both the sectors, states such as Bihar, MP, Assam, Orissa, Rajasthan and Karnataka have been found to be the worse performers with respect to mean achievement in terms of all the indicators.

It is found that the dispersion of MPCE in both the rural and urban sectors of the cross-section of state economies decreases over time implying thereby the $\alpha$-convergence of MPCE in both the rural and urban sectors. The essence of such convergence analysis is to investigate whether the standard of living gap between regions falls over time or not. However, the $\alpha$-convergence test is not found to be satisfied for the two indicators of inequality measure and poverty indices.

In our study, we have also found a negative relationship between rates of MPCE growth of various states and the levels of their MPCEs at a chosen (1958) initial point of time for the rural sector only. This leads to the acceptance of absolute or beta-convergence. Interestingly absolute convergence has not been found for the other indicators considered in this study.

Following Boyle and McCarthy (1997), we have computed the indices of rank concordance for both the multi-annual (RC$_t$) and binary versions (RC$_a$) of the measures for the inter-temporal mobility of the various states in terms of the ranking of the states for all the indicators under study for both the rural and urban sectors. There have been downward trends in both RC$_t$ and RC$_a$ series for all the indicators. It has been found that for MPCE in urban sector, the values of RC$_t$ and RC$_a$ have decreased steadily from unity to values in between 0.78 and 0.58 over the chosen period of 48 years. Similar trend has been observed for other indicators as well at both the urban and rural levels. These findings essentially imply that there is significant inter-temporal mobility of states in terms of ranking of

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$^4$ Under strong dependence, data may be decomposed as $y_{it} = f_i + u_{it}$, where $f_i$ is a chosen (1958) initial point of time for the rural sector only. This

$^5$ Unfortunately, there is no test to examine the nature of dependence — strong or weak.

$^6$ In this paper, we have followed the procedures developed by Bai and Ng (2004) e.g., we use three $JCP$ criteria and three $JCP$ criteria.

$^7$ This test will be called as direct Dickey–Fuller test (DDF).

$^8$ The 14 states taken together accounted for 96% of India’s total population. These are Andhra Pradesh (AP), Assam, Bihar, Gujarat, Karnataka, Kerala, Madhya Pradesh (MP), Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu (TN), Uttar Pradesh (UP) and West Bengal (WB).

$^9$ Data gaps have been cemented by the method of interpolation as developed by Friedman (1962). Various robustness checks have been conducted to gauge overall performances of the interpolated data.

$^{10}$ In this long period (48 years), India has certainly experienced several structural changes. However, it is very difficult to incorporate structural break analysis in our framework. To check robustness we have tried the same exercise with several relatively smaller time periods, and in all such cases our overall conclusion has remained the same.

$^{11}$ We have taken 1973–74 as the base period so as to maintain consistency with the series constructed by Datt (1998).

$^{12}$ To save space, we have not provided any detailed tables. These may be obtained from authors on request.
the states, and that the states have consistently changed their relative positions over the period.

4. Empirical results of panel data Analysis

Contemporaneous cross-sectional dependence is a major problem with panel unit root tests. Thus, we first apply the tests (LM and MLM) to verify if such dependence really exists in the present data under our study. In this paper, we have worked with the log-ratio of each regional time series to that of all-India average series as the numeraire. Keeping in mind the possible contrasting behaviors at rural and urban levels (see also Jha, 2000) we study the convergence hypothesis at both levels separately. Due to data limitations, we don‘t have the scope to address the sample selection problem, as defined in the text.

Table 1 summarizes the results of panel unit root tests. Table 1 also corroborates with the one in Table 2. Therefore, at urban level, convergence has been observed for all the indicators under both kinds of dependences. Thus, it reveals that the regional disparity in India is actually temporary in nature at urban level. It seems likely that the trickle down effect, urban development policies, and poverty alleviation programmes have probably led to such convergence. Here it may be mentioned that our study is based on consumption data whereas all other studies on India are based on per capita state GDP series. State level GDP is available only at aggregate level, and so decomposition of rural and urban is not possible. It is somewhat difficult for us to compare the present findings with those in the existing literature. However, the present findings may be considered to be similar to those of Nagaraj et al. (1997), Cashin and Sahay (1996), and Bajpai and Sachs (1996).

The extent of persistence of shocks may be observed from the estimated half-lives in Tables 1 and 2. Half-life estimates (a measure of speed of convergence) for urban levels (from Table 2) show that estimates are uniformly larger for common factor than for the idiosyncratic shocks. The difference in the speeds of convergence (measured by half-lives) for urban levels (from Table 2) show that estimates are uniformly larger for common factor than for the idiosyncratic shocks. The difference in the speeds of convergence between the lone common factor and the idiosyncratic errors could be explained in policy terms as well. It may be due to the fact that effective time for implementation of any developmental policy is less when it is the responsibility of the state government to implement it, whereas implementation and delivery time are more when these are carried out by the central government.

For the state-wise data in the rural sector, Table 1 suggests that unit root null hypothesis is rejected by all tests for poverty and inequality indices. Therefore, convergence is observed in terms of poverty and inequality indices at rural level. On the other hand, unit root null is accepted for MPCE at rural level implying that there is persistent divergence across states at rural level in terms of per capita consumption. It is possibly due to the fact that the high growth observed at national level has not percolated to the rural level uniformly. Second, at rural level, growth is primarily from farm sector. There are severe inter-state variations in terms of initial conditions, amount of rainfall, fertility condition of land etc. Third, as argued by Gaiha and Kulkarni (1999), anti-poverty and various development programmes are not very effective towards smoothening of consumption distribution and thereby reducing poverty in India. Reasons for such policy ineffectiveness could be due to the existence of powerful vested interest, on the one hand, and non-existence of

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To check robustness of numeraire, we have tried with few other alternatives like, for instance, Kerala. Overall findings have remained unchanged.

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Note: (i) $t_{\text{rob}}$, $t_{\text{OLS}}$, $t_{\text{GLS}}$, and $t_{\text{iv}}$ denote the $t$-statistics corresponding to bootstrap-OLS, robust-OLS, bootstrap-GLS and Chang’s (2002) instrumental variable methods, respectively. LM and MLM statistics are defined for testing cross-sectional dependence, as defined in the text.

(ii) 5% critical values are given in parentheses.

(iii) Half-lives are presented in years.
media attention, on the other hand. Therefore, the notion of persistent regional disparities in India seems to be true at rural level at least in terms of consumption level and these disparities are expected to cumulate over time. In the long run, all these regions seem to diverge from each other asking for a serious policy intervention. Effort must, therefore, be initiated to achieve robust and uniform consumption distribution.

From Table 2, it is observed that common factor as well as idiosyncratic effects have unit roots. As we also have pointed out earlier, the idiosyncratic components may be considered as the effect of policies that are reserved for the state governments. Therefore, state should take the primary responsibility of creating growth-friendly conditions, maintaining efficient delivery system, and implementing various developmental programmes undertaken by the central government. On the other hand, unit root in common factor implies that the central authority should take the responsibility of bringing the backward states at par with the developed states. This is possible by reformulating its fiscal and industrial policies and of course by initiating various welfare and developmental programmes.

The use of disaggregated (urban and rural) data provides much more revealing findings. Such data have the scope to indicate at which level disparity is severe. When we use aggregate data (state level GDP), such features may get lost and subsequently this may lead to misleading findings. The conflicting findings in the existing literature on disparities across Indian states may be due to the use of aggregated data as well as the different methodologies.

5. Further analysis of panel unit root tests based on groups

Since we have noted in the previous section that unit root null hypothesis is rejected for MPCE at rural level, it is natural to ask if there is heterogeneity across groups but convergence within each group. Accordingly, we have attempted to find if, among the 14 states, there exist few homogeneous groups of states across which MPCE converge/diverge over time. To that end, we have performed factor analysis using Kaiser’s (1958) varimax rotation\textsuperscript{15} technique on the basis of variance–covariance matrix. It has been found (see Table 3) that the first two factors, viz., $f_1$ and $f_2$ explain most of the variations (about 87%) in the data. Prominent factor loadings in factor $f_1$ have been attached to such states as AP, Gujarat, Kerala, Maharashtra, UP, Punjab, TN and WB and those in $f_2$ have been attached to such states as Orissa, Assam, Bihar, Karnataka, MP and Rajasthan. Since the two factors are orthogonal to each other we may identify the first factor as high-growth factor and the second as low-growth factor on the basis of the fact that all the states having prominent factor loadings in factor $f_1$ have high-growth rates (greater than the national growth rate) and those in factor $f_2$ have low growth rates (less than the national growth rate). This corroborates the findings in Section 3 that in respect of consumption level, the ranking performances of the states belonging to the high-growth group have been better than those of the states belonging to the other group. Thus, the fourteen states may be conspicuously classified into two groups as discussed above. As the factor analysis clearly shows the existence of two separate groups, it may be worthwhile to examine if there is convergence among the members in each group.

To examine this empirically, we have carried out panel unit root tests for both the groups for MPCE at rural level to find if each of them converges over time or not. From the results presented in Tables 4 and 5, we can conclude that all the tests uniformly suggest convergence within the members of their respective groups. Tables 6 and 7 present findings of convergence test under strong dependence. Here it may again be pointed out that under strong dependence, each series is decomposed into common factor and the idiosyncratic errors. For both the groups, the findings of DDF (direct Dickey–Fuller) test, as a

<table>
<thead>
<tr>
<th>Variable</th>
<th>$t$-value</th>
<th>Rural</th>
<th>Urban</th>
<th>$t$-value</th>
<th>Rural</th>
<th>Urban</th>
<th>$t$-value</th>
<th>Rural</th>
<th>Urban</th>
<th>$t$-value</th>
<th>Rural</th>
<th>Urban</th>
<th>$t$-value</th>
<th>Rural</th>
<th>Urban</th>
<th>$t$-value</th>
<th>Rural</th>
<th>Urban</th>
</tr>
</thead>
<tbody>
<tr>
<td>MPCE</td>
<td>(N = 14)</td>
<td>–1.91</td>
<td>–1.46</td>
<td>–1.59</td>
<td>–4.32</td>
<td>–1.42</td>
<td>–5.17</td>
<td>C</td>
<td>–</td>
<td>–</td>
<td>0.44</td>
<td>0.42</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HCl</td>
<td>(N = 14)</td>
<td>–1.56</td>
<td>–1.73</td>
<td>–2.67</td>
<td>–2.87</td>
<td>–3.17</td>
<td>–3.74</td>
<td>C</td>
<td>0.38</td>
<td>0.29</td>
<td>0.39</td>
<td>0.28</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PG</td>
<td>(N = 14)</td>
<td>–1.82</td>
<td>–1.48</td>
<td>–3.94</td>
<td>–2.52</td>
<td>–5.83</td>
<td>–3.54</td>
<td>C</td>
<td>0.49</td>
<td>0.26</td>
<td>0.35</td>
<td>0.31</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SPG</td>
<td>(N = 14)</td>
<td>–1.15</td>
<td>–1.50</td>
<td>–3.18</td>
<td>–2.13</td>
<td>–3.98</td>
<td>–3.26</td>
<td>C</td>
<td>0.37</td>
<td>0.32</td>
<td>0.41</td>
<td>0.30</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GINI</td>
<td>(N = 14)</td>
<td>–0.98</td>
<td>–2.38</td>
<td>–2.87</td>
<td>–4.31</td>
<td>–5.44</td>
<td>–6.12</td>
<td>C</td>
<td>0.33</td>
<td>0.40</td>
<td>0.68</td>
<td>0.35</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: (i) $DF$, $f_{uu}$ and MP denote the $t$-statistics corresponding to direct Dickey–Fuller test, robust-OLS, Moon and Perron (2004) methods, respectively. For all the tests, the nominal size is 0.05.
(ii) Half-lives are presented in years.
(iii) ‘D’ implies divergence and ‘C’ convergence.

\textsuperscript{15} Another way to split the sample is based on the characteristic at the beginning of the sample. This is a suggestion made by the referee. We tried to test for convergence hypothesis based on such criteria. We failed to accept convergence hypothesis for any of such groups. Sample selection seems to be a crucial issue as observed by De Long (1988).
Table 4
Cross-sectional dependence tests and panel unit root tests for high-growth states.

<table>
<thead>
<tr>
<th>Variable</th>
<th>LM</th>
<th>MLM</th>
<th>trow</th>
<th>tiv</th>
<th>t'shm</th>
<th>t'sgh</th>
<th>Half-life estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>MPCE</td>
<td>77.42</td>
<td>6.60</td>
<td>−2.25</td>
<td>−2.57</td>
<td>−2.84</td>
<td>−3.75</td>
<td>1.00</td>
</tr>
<tr>
<td>(N=8)</td>
<td>(16.92)</td>
<td>(1.96)</td>
<td>(−1.65)</td>
<td>(−1.65)</td>
<td>(−1.86)</td>
<td>(−1.68)</td>
<td></td>
</tr>
</tbody>
</table>

Note: 1. High-growth states are Andhra Pradesh, Punjab, Gujarat, Kerala, Maharashtra, Tamil Nadu, Uttar Pradesh, and West Bengal.
2. See note of Table 1 for all notations.

Table 5
Cross-sectional dependence tests and panel unit root tests for low-growth states.

<table>
<thead>
<tr>
<th>Variable</th>
<th>LM</th>
<th>MLM</th>
<th>trow</th>
<th>tiv</th>
<th>t'shm</th>
<th>t'sgh</th>
<th>Half-life estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>MPCE</td>
<td>40.38</td>
<td>4.63</td>
<td>−2.67</td>
<td>−1.87</td>
<td>−2.69</td>
<td>−2.75</td>
<td>1.03</td>
</tr>
<tr>
<td>(N=6)</td>
<td>(7.26)</td>
<td>(1.96)</td>
<td>(−1.65)</td>
<td>(−1.65)</td>
<td>(−2.16)</td>
<td>(−1.83)</td>
<td></td>
</tr>
</tbody>
</table>

Note: 1. Low-growth states are Assam, Bihar, Karnataka, Orissa, Rajasthan and Madhya Pradesh.
2. See note of Table 1 for all notations.

Table 6
Panel unit root tests under common factor models for high-growth states.

<table>
<thead>
<tr>
<th>Variable</th>
<th>toffs</th>
<th>trob</th>
<th>t'shm</th>
<th>Half-life estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rural</td>
<td>Rural</td>
<td>Rural</td>
<td>Common factor</td>
<td>Idiosyncratic error</td>
</tr>
<tr>
<td>MPCE</td>
<td>−0.17</td>
<td>−2.22</td>
<td>−4.29</td>
<td>0.20</td>
</tr>
<tr>
<td>(N=8)</td>
<td>(−1.95)</td>
<td>(−1.95)</td>
<td>(−1.65)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Notations are same as in Tables 2 and 4.

Table 7
Panel unit root tests under common factor for low-growth states.

<table>
<thead>
<tr>
<th>Variable</th>
<th>toffs</th>
<th>trob</th>
<th>t'shm</th>
<th>Half-life estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rural</td>
<td>Rural</td>
<td>Rural</td>
<td>Common factor</td>
<td>Idiosyncratic error</td>
</tr>
<tr>
<td>MPCE</td>
<td>−1.32</td>
<td>−2.15</td>
<td>−5.47</td>
<td>0.73</td>
</tr>
<tr>
<td>(N=6)</td>
<td>(−1.95)</td>
<td>(−1.95)</td>
<td>(−1.65)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Notations are same as in Tables 2 and 4.

test for common factor, suggest that unit root is present in the factor. However, Moon–Perron (MP) test, as a test for idiosyncratic error, suggests that error components are stationary. Therefore, these two findings jointly imply that each series is decomposed into a nonstationary common factor and stationary idiosyncratic errors. In other words, we may conclude that underlying series are nonstationary (due to the presence of nonstationary factor), there exists a common factor which is the binding force, and this makes the member states not to diverge from each other. This phenomenon is termed as cross co-integration (Banerjee et al., 2005).16 In other words, findings based on Tables 4–7 uniformly suggest that there is convergence among the group members under both kinds of cross-sectional dependence. A tentative explanation for such non-overlapping groupings could be that few states are pulling away from the rest and thereby causing a second peak.

6. Conclusions

This paper has attempted at examining if disparities in consumption level, poverty and inequality among major states of India have converged with the passage of time. Using panel unit root tests that are robust to cross-sectional dependence, we have found that inequality and poverty indicators have converged across both rural and urban levels. Consumption has also converged at urban level. However, divergence has been observed at rural level for per capita consumption. We have also tried to find if there exist homogeneous groups such that heterogeneity may be present across groups but convergence may be achieved among the members of the same group. Based on factor analysis, we have found two such groups of states for rural sectors, viz., low-growth and high-growth states. It has been found that the level of consumption has converged among the members in each group separately. Finally, we have attempted at identifying the responsible entities for such divergences — central or state governments or both. It has been argued that both the central authority and state governments have the responsibility to bring back the alienated states at par with the developed states. The emergence of the two groups at the rural level is an issue of major concern for policy makers. Divergence across regions may have negative effects on subsequent growth and development, and may consequently worsen economic, social and political conditions. Further explorations using state specific characteristics for explaining the emergence of such groups may be very interesting and useful.

References


16 As idiosyncratic errors are stationary, we may think that all the group members are co-integrated among themselves, and common factor represents the common trend.
Pearson, K., 1897. On a form of spurious correlation which may arise when indices are used in the measurement of organs. Proceeding of Royal Society, London Series A 60, 489–498.