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Growth Convergence and Spillovers among Indian States: What Matters? What Does Not?

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Abstract

Convergence and spillovers across countries and within countries are old, but recurrent policy concerns, and India is no exception to this rule. This paper examines convergence and spillovers across Indian states using non-stationary panel data techniques. Results on convergence among Indian states are generally found to be similar, but more nuanced, than previous studies. Generally speaking, there is evidence of divergence over the entire sample period, convergence during sub-periods corresponding to structural breaks, and club convergence. There is strong evidence of club convergence among the high- and low-income states; the evidence for middle-income states is mixed. Dynamic spillover effects among states are small.

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Contents

I. Motivation

Convergence and spillovers across countries and within countries are old, but recurrent policy concerns. The concerns stems from a need to understand the drivers of growth, to look out for which policies work and which do not, and a search for spillovers across geographical domains. From a policy perspective, the genesis of the concerns is obvious. Regions that get left behind are, globally, more prone to disruptions and fissiparous tendencies, and represent lost opportunities and wasted human potential. And India is no exception to this rule. Not surprisingly, the need to understand what promotes growth, both in absolute and relative terms, is a perennial policy preoccupation.

This paper examines convergence and spillovers across Indian states. If much has been written on the issue, what more can be said? This paper aims to situate itself in an arguably dense literature, both from a technical standpoint and on the basis of some new results. From a methodological standpoint, it stands with a recent literature on non-stationary panel data econometrics, where techniques have been developed to examine convergence in other countries, including China (Pedroni and Yao, 2006). In particular, these techniques allow an analysis of spillovers across constituent units, which is not possible in standard cross-section or time series studies. These techniques also provide more reliable parameter estimates of convergence and spillovers.

Among the other innovations of this paper are a ranking procedure to group states on their performance, a restatement of convergence and divergence across states during 1960-2004, and explanation of per capita income disparities by indicators, such as sector shares, infrastructure, private investment, and spillovers, similar to past studies, but more nuanced. In addition, club convergence and dynamic spillover effects among states are studied. The analysis of dynamic spillovers has, to the best of our knowledge, not been undertaken in any other study of Indian states.

This paper is organized as follows. Section II provides an overview of studies on convergence across Indian states, aiming to contextualize this paper in the literature. Section III describes the data and establishes some preliminary stylized "facts". Section IV provides a sketch of the non-stationary panel data techniques that characterize the econometrics of this paper. Section V gives the empirical results. Section VI concludes.

II. Literature Survey

A. Old Wine in Old Bottles?

Income convergence across Indian states has been explored previously in a number of studies using neoclassical growth regressions. These regressions estimate a relationship between (per capita) output growth rate and initial (per capita) level of output, providing a measure of β-convergence coefficient (Barro and Sala-i-Martin, 1992, 1995). Absolute convergence implies that initially poor states grow faster than the initially rich ones, regardless of heterogeneity across states. Conditional convergence defines a tendency to catch-up, controlling for heterogeneity across states. The studies include Cashin and Sahay (1996), Bajpai and Sachs (1996), Rao, Shand, and Kalirajan (1999), Nagaraj, et. al. (2000), Aiyar (2001), Sachs, Bajpai, and Ramiah (2002), Kochhar et. al. (2006), Purfield (2006) and Misra (2007). The studies differ across a number of dimensions, including the sample period, coverage of states, data sources, and estimation methodology (Table 1). The main points relate to:

- Sample period, estimation technique and controls for heterogeneity.

➢ The initial- and end-point incomes vary across the studies. Some authors directly apply annual growth rates and use one-lagged initial income such as Bajpai and Sachs (1996), Nagaraj, et al. (2000), and Sachs, et al. (2002). Misra (2007) uses compound annual growth rates. Others attempt to take into account the business cycle by constructing the data on 5 years apart (Aiyar, 2001) or the data on 5 years average over non-overlapping periods (Purfield, 2006). Others apply their own justification for the time interval.

➢ Earlier studies in the literature estimated cross-section growth/income regression equations, while later studies use panel regressions. Aiyar (2001) uses simple OLS and incorporates cross-section fixed effects. Nagaraj, et al. (2000) and Purfield (2006) use generalized method of moments (GMM) and take into account both cross-section and period fixed effects.

➢ Control variables vary across the studies. Nagaraj, et al. (2000), Baddeley, et al. (2006), and Purfield (2006) find sector shares and infrastructure explain the bulk of the growth dispersion. The studies find strong positive correlation between states' per capita output growth rate, and change in share of service sector, improvements in infrastructure (using number of telephone lines and transmission and distribution losses ratios as proxies).[1] Aiyar (2001) and Purfield (2006) also record the positive effect of credit growth (to proxy for private investment), but Misra (2007) does not. Higher literacy rates also appear to support growth in some studies (Aiyar, 2001), but not in others (Purfield, 2006).

- Absolute/conditional convergence.

➢ Generally speaking, most studies conclude absolute and conditional convergence for the pre-1990s. Including the post-1990s period, a number of studies point to income divergence. This indicates the possibility of a structural change around 1990.

➢ Cashin and Sahay (1996) finds absolute convergence, as well as conditional convergence with controls added for shares of economic sectors. Bajpai and Sachs

[1] Kochhar et. al. (2006) and others use the ratio of transmission and distribution (T&D) losses to generating capacity of state level electricity boards to indicate the quality infrastructure and institutions.

(1996) find absolute convergence across 19 states only in the 1960s. Rao, Shand, and Kalirajan (1999) find income divergence across 14 states over 1965-1995. Nagaraj, et al. (2000), Aiyar (2001), Kochhar et. al. (2006) and Misra (2007) document absolute divergence, with conditional convergence using share of agricultural sector, price shocks, infrastructures, literacy rate, and state's private investment as controls. Sachs, Bajpai, and Ramiah (2002) demonstrate overall income divergence across 14 Indian states during the period of 1980-1998, where the divergence within poorer states is more noticeable. Purfield (2006) confirms both absolute and conditional convergence during 1975-2003., with states' growth determined mainly by their own policies in 1990s, private sector investment, size of government, and institutions.

Other studies also examine the distribution of states' incomes. Cashin and Sahay (1996), Rao, Shand, and Kalirajan (1999), Bajpai and Sachs (1996), and Sachs, et. al. (2002) assess σ-convergence (which indicates convergence when the standard deviation of the logarithm of per capita states' incomes falls). However, a reduction of dispersion measure over time does not provide information about income dynamics. Bandopadhyay (2003) estimates non-parametric stochastic kernels and transition probability matrices, and concludes that Indian states' incomes are converging, but into two clubs.

B. Old Wine in New Bottles?

More recently, convergence has been addressed using newly developed non-stationary panel techniques. Quah (1993) and Evans (1998) argue that the strict conditions required for the derivation of growth regression are unlikely to be satisfied, potentially producing biased parameter estimates. Specifically, growth regressions provides valid inference if and only if the economies follow exact first-order autoregressive dynamics; the vector of control variables can account for all heterogeneity across economies; and the economies are not cross-sectionally dependent (Evans and Karras, 1996).

To address these problems, time-series methods for panel application have been proposed in the literature. In this approach, the definition of income convergence comes from the notion of unit roots and cointegration. This approach has several advantages. It is robust to problems of endogeneity, omitted variables, simultaneity, and measurement error. More importantly, it does not require arbitrary start and end point assumption. In particular, time series panels assume that states are close to limiting distributions, despite their initial conditions. It, therefore, allows for a better understanding of the actual path of the series involved, which is crucial to understanding potential convergence over time. The approach is especially suitable to Indian states, as the short data span is compensated for by variation in the cross-section dimension.

Non-stationary panel techniques have been applied to examine convergence for developed and some developing economies. Fleissig and Strauss (2001) test stochastic convergence for OECD countries and a European subsample. Choi (2004) implements multiple unit root tests in panel data for 48 US states. McCoskey (2002) applies the technique to a panel data set of Sub-Saharan

African countries. Pedroni and Yao (2006) explore regional income divergence in China, comparing pre- and post-reform periods.

The structure of the panel time series models is similar to the neoclassical growth regression. Typically, the cross-sectional growth regression takes the form:

$$(1/T)\log(y_{i,T}/y_{i,0}) = \alpha_i + \beta \log y_{i,0} + \gamma X_{i,0} + \varepsilon_{i,t} \qquad i = 1, 2, ..., N \tag{1}$$

where y is per capita income, X_i is a vector of controls for cross-section heterogeneity in levels and growth rates of per capita income, α, β, γ and are parameters, and $\varepsilon_{i,t}$ is an error term with a zero mean and finite variance. Nagaraj, et al. (2000) and Purfield (2006) apply Arellano-Bond multivariate dynamic model to this regression, with a first-order autoregressive-distributed lag model so that (1) can be rewritten as:

$$y_{i,t} = \delta_i + \lambda . y_{i,t-1} + \varepsilon_{i,t}$$

or

$$\Delta y_{i,t} = \delta_i + \varphi . y_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

where

$$\delta_i = [(\lambda - 1)\gamma / \beta]' X_i , \lambda \equiv (1 + \beta T)^{1/T} , \varphi \equiv (\lambda - 1) .$$

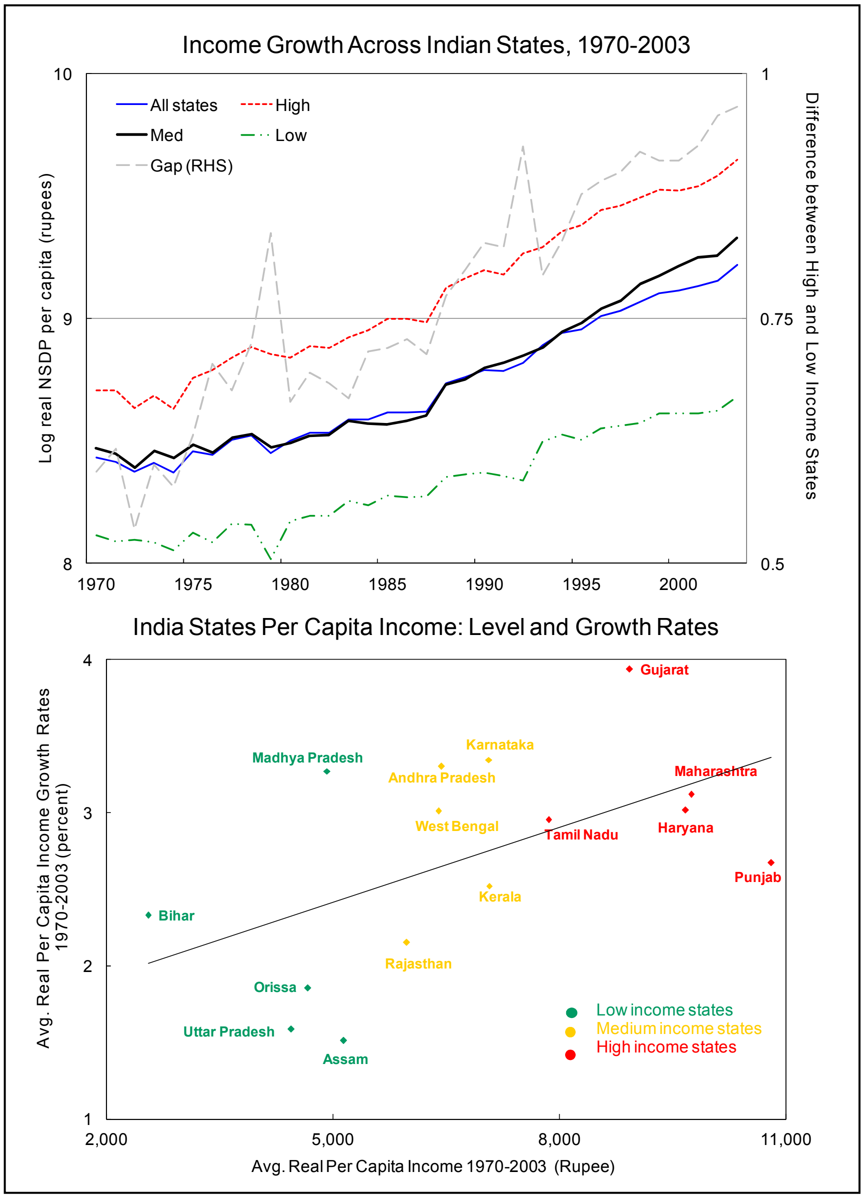
Equation (2) is then comparable to an ADF regression of the form:

$$\Delta y_{i,t} = \delta_i + \rho_i y_{i,t-1} + \sum_{L=1}^{p_i} \phi_{i,L} \Delta y_{i,t-L} + u_{i,t} \tag{3}$$

However, the conceptual frameworks are different. The dynamic panel regression (2) utilizes a vector of controls to remove the heterogeneity across states, pools all states, and interprets the convergence directly from the first-order lagged coefficient. As shown in Section IV, the non-stationary panel approach does not explicitly allow for controls, but instead uses deviations from mean in the estimating equation to control for heterogeneity, and uses lagged differences to capture serial correlation patterns. Moreover, the estimating equation for each state is done separately, and then the t-statistics or p-values are combined to conduct a panel unit root test. Convergence is then determined by the stationarity of differences across series (Appendix 1).

III. Data and Stylized “Facts”

We use data for Indian states over the period 1960-2004.[2] More recent data are perhaps available, but a part of the motivation is to keep the dataset comparable with other studies. An analysis with more recent data would be instructive as well, but is kept for further research. Moreover, the addition of a few more additional years would be preferable, but is unlikely to change the main results of the analysis given the relative weight of the observations in the sample. Annual per capita real net state domestic product is used to proxy for state-level income. The sample includes 15 major Indian states: Andhra Pradesh, Assam, Bihar, Gujarat, Haryana, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal. From this data, with the admitted caveat on sample length, the following stylized “facts” may be noted.



- All states grew, but differentially so that income gaps widened. By 2003, average per capita income in India was twice as high as in 1970.

- Over this period, ranked by per capita income (Table 2), states can be grouped into three categories: high-income states (Gujarat, Haryana, Maharashtra, Punjab, and Tamil Nadu); medium-income states (Andhra Pradesh, Karnataka, Kerala, West Bengal, and Rajasthan), and low-income states (Assam, Bihar, Orissa, Madhya Pradesh, and Uttar Pradesh).

[2] For an excellent discussion of data sources, see Purfield (2006).

- States' growth rates were positively correlated with average per capita income. Moreover, growth accelerated in the richer states; poorer states grew moderately. High-income states grew at average annual rates of 3-4 percent over 1970-2003, while low-income states grew at only at 1½ -2 percent.

- Among the medium-income group states, Andhra Pradesh and Karnataka grew at much higher rates than the group average; Kerala, Rajasthan, and West Bengal at lower than average rates. As a result, income difference between high- and low- income states more than doubled. By the end of the period, the average per capita income of the five richest states in 2003 was 2½ times as much as that of the poorest states.

- Reforms of the 1980s/1990s appear to have intensified divergence across states.[3] The reforms of the early 1980s included liberalization of international trade and relaxation of business-related rules and regulations. The reforms of the early 1990s induced further trade liberalization, financial liberalization, and privatization of non-financial enterprises as well as banks. A casual examination of the data suggests two surges in income gap, corresponding to the launch of the two waves of policy reforms.[4] Numerically, the gap between log real net SDP per capita of the five richest and five poorest states increased by around 20 basis points in 1980, as well as 13 basis points in 1992. The surges went down after a year, but the income gap continued to expand. Accordingly, we conclude two structural break dates in 1980 and 1992.

IV. THE ECONOMETRICS OF NON-STATIONARY PANELS

In time-series analysis concepts, two series are defined as convergent if the difference between them is "stable". Specifically, stochastic income convergence implies that income disparities between the series follow a mean stationary stochastic process. This can be characterized as follows. Let y_{it} be the logarithm of per capita income for state *i* at time *t*, *i* =1, 2, ... , N and *t* =1,2, ..., T. y_{it} contains a unit root or is integrated of order 1. Generally, convergence implies that any pair of states *i* and *j* converge, pair wise, if the difference $y_{it} - y_{jt}$ is stationary or $\lim_{k\to\infty} E(y_{i,t+k} - y_{j,t+k} \mid I_t) = \mu_i$. Then, y_{it} and y_{jt} are cointegrated. If the mean, μ_i , is zero, there is *absolute convergence* in per capita incomes; if μ_i is not zero, there is *conditional convergence*.

[3] Existing studies examine structural breaks using aggregative data for India, such as the growth rate of real GDP, real per capita GNP, and international trade (Table 3). Wallack (2003), Rodrik and Subramaniam (2004), Hausmann et. al. (2005), Virmani (2005), and Kohli (2006) find evidence of a break around 1980. Wallack (2003) alone records another break in 1993, although the evidence is weak.

[4] In addition, the possibility of structural breaks in state level data is tested, following Andrew (1993) and Bai (1994) structural break tests at unknown date, using the difference between the growth paths of high and low income groups. Two possible break dates are found, 1980 and 1992.

Conditional convergence implies that income growth paths for the states are parallel by the distance, μ_i, in limit.

For panels, convergence can be similarly defined between the elements of the panel. It is equivalent to convergence of every pair of y_{it} and y_{jt} within the set. Testing pair wise convergence for all states, however, tends to have low power for short samples, thus increasing the probability of failing to reject the null hypothesis of no cointegration. Evans and Karras (1996) show that all members y_{it} and y_{jt} cointegrating pair wise implies that all members cointegrate individually with a common time effect, $\bar{y}_t$.[5] Deviations of $y_{1,t+k}, y_{2,t+k}, \ldots, y_{N,t+k}$ from their cross-economy average, $\bar{y}_t$, are expected to approach a constant value as k goes to infinity, conditional on current information, $\lim_{k\to\infty} E(y_{i,t+k} - \bar{y}_{t+k} \mid I_t) = \mu_i$ for all i. Taking into account the serially-correlated nature of the series, empirically, an augmented Dickey-Fuller (ADF) test can be conducted using:

(4)
$$\Delta(y_{i,t} - \bar{y}_t) = \delta_i + \rho_i(y_{i,t-1} - \bar{y}_{t-1}) + \sum_{L=1}^{p_i} \phi_{i,L}\Delta(y_{i,t-L} - \bar{y}_{t-L}) + u_{i,t}$$

The autoregressive coefficient, ρ_i, is crucial to test income convergence, while δ_i takes into account idiosyncratic differences across states. The lagged difference terms capture higher order serial correlation, and the number of lags, p_i, is chosen to eliminate serial correlation in the error term.

In the convergence tests, we employ three panel tests for unit root (Appendix 1):

- Levin, Lin, and Chu (2002, hereafter LLC) test uses pooled within-dimension estimators. It treats parameter of interest as common across members of the panel, while other parameters can vary across members.

- Im, Pesaran, and Shin (2003, hereafter IPS) test allows all parameters to vary across members of panel. The test statistics are based on the group mean between-dimension of the individual test statistics.

[5] If $(y_{it} - y_{jt}) \sim I(0)$ for all i, j pairs, then $\frac{1}{N}\sum_{j=1}^{N}(y_{it} - y_{jt}) \sim I(0)$

But $\frac{1}{N}\sum_{j=1}^{N}(y_{it} - y_{jt}) = \frac{1}{N}\sum_{j=1}^{N} y_{it} - \frac{1}{N}\sum_{j=1}^{N} y_{jt} = y_{it} - \bar{y}_t$

So $(y_{it} - y_{jt}) \sim I(0)\forall i, j \Leftrightarrow (y_{it} - \bar{y}_t) \sim I(0)\forall i$ and similarly for the case with fixed effects.

- Maddala and Wu (1999, hereafter MW) is similar to IPS test, but pools marginal significance values across members of panel.[6]

In addition to the above tests, we also use bootstrap techniques to get better sample specific IPS adjustment terms and MW *p*-values. While a distinct advantage of the IPS and MW tests is that they allow for heterogeneous dynamics which are useful for panel applications, the tests could suffer from a small-sample size distortion as they depend on asymptotic properties. Pedroni and Yao (2006) suggest that, in practice, the test performance can be improved by replacing the IPS large-sample adjustment terms and MW *p*-value by a bootstrap to condition the Monte Carlo simulation on both sample size and specific number of fitted lags. The bootstrap procedures are elaborated in Appendix 1.

Finally, we examine closely the transition across periods and cross-sectional dimensions. McCoskey (2002) and Choi (2004) argue that stochastic convergence could be problematic in the presence of structural breaks in the data, and the standard tests may be biased and size-distorted.[7] Convergence across all states through the entire period is first tested. Then possible break dates are explored. The full sample is divided into subsamples and again tested for convergence according to each break. As regards the cross-section dimension, the possibility of club convergence is explored.

V. Convergence Revisited: A Non-stationary Panel Approach

This section presents the empirical results of application of the non-stationary panel approach to Indian states. First, diagnostic tests are conducted for the 15 states' income per capita. All series are integrated of order one, i.e. are I(1).[8] The remainder of the section presents: (i) income convergence tests, for the entire sample period, subsamples, and cross-sectional subsets; and (ii) macroeconomic determinants of income dynamics.

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[6] The common parameter hypothesis of LLC test is restrictive. The IPS and MW tests are considered generalizations of the LLC test. The IPS test is at least as flexible as MW test, and both are more flexible than LLC test as they do not require any parameter commonality. Computationally, the IPS test is easier than the LLC and MW tests. The IPS test simply averages individual ADF tests and use adjustment values to render the asymptotic standard normal distribution. MW test, on the other hand, requires simulation of the p-value. The distributions for individual ADF based unit root tests are nonstandard and depend on Brownian motion functions, and the simulation is non-trivial. The MW test is more conservative in which it is invariant to cross-sectional dependencies than the other two tests.

[7] The test might fail to capture the transition property toward stochastic convergence although the actual path is converging.

[8] Detailed results are available on request.

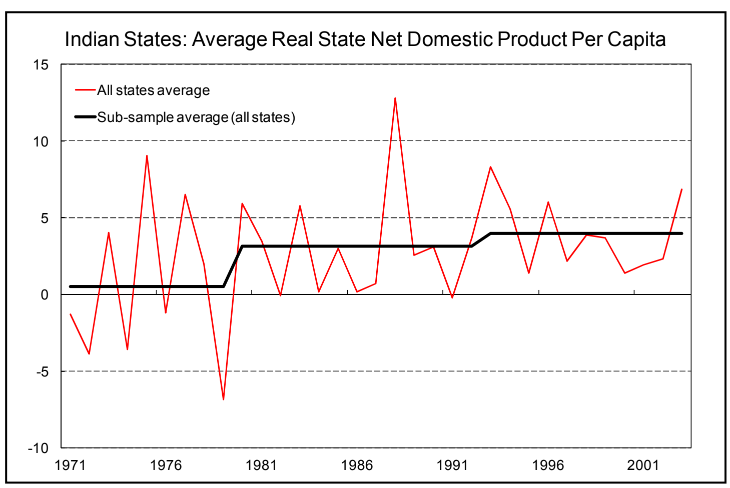
A. Convergence and Structural Change

Results on convergence among Indian states are generally found to be similar, but more nuanced, than previous studies. Generally speaking, there is evidence of divergence over the entire sample period, convergence during sub-periods corresponding to structural breaks, and club convergence. Over the entire sample period, non-convergence in states' per capita income is not rejected. Table 4 shows the numerical results. Individually, only two states, Madhya Pradesh and Rajasthan, displayed income convergence to the common trend, $\bar{y}_t$. Once accumulated into the panel, the null hypothesis of non-convergence (where the differences, $y_{i,t} - \bar{y}_t$, contain unit roots) cannot be rejected. The results are confirmed by all three tests.

There was convergence during subsamples.

- In the pre-1980s, Indian states' per capita incomes were cointegrated. Of the 15 states in the sample, 7 states displayed strong tendency toward convergence (the null of non-convergence is rejected at less than 5 percent), and Assam's ADF statistic rejects the null at around 8 percent. Combining these results into panel, all test statistics except the LLC ADF statistic now reject the null.
- During 1980-1992, the rejection of the null of nonconvergence is individually weaker, but mutually stronger than in the pre-1980s. Only 3 out of 15 states show income convergence to the group, and only one rejects the null at less than 5 percent significance level. The combined results suggest conditional convergence in the panel. All test statistics firmly reject the unit root null at less than 1 percent significance level.
- Post-1992, the results are similar to 1980-1992. The individual results shows 5 out of 15 states can reject the null hypothesis of unit root in the differences, $y_{i,t} - \bar{y}_t$. The panel results yet robustly reject the null where LLC, IPS, and MW tests reach the agreement. These results again indicate overall income convergence.

Income convergence/divergence broadly corresponds to periods of structural change during the sample period, along the lines of the three growth episodes. Pre-1980, the states' growth per capita rates were low (around ½ percent per annum) and volatile. Starting 1981, growth picked up strongly (3 percent in 1980-92), and the reforms seemed to benefit all states equally. After 1992, on average, the states continued to grow at nearly 4 percent, but differentially. Thereafter, the growth momentum was sustained in the high-income states,



and some medium income states also speeded up. However, growth slowed down in most low-income states. There was thus a tendency for income divergence among the low-income states post-1992, but not enough to overpower convergence among other states, pointing to possible "club convergence". We now turn to this phenomenon of club convergence which is examined using sub-group analyses through time and cross-sectional dimensions to further pinpoint the sources of income dispersion.[9]

B. The determinants of per capita income differentials

To examine the determinants of per capita differentials across states, we follow the literature and test for the role of the share of service sector in total output, private sector credit per capita, the share of development expenditure in total government expenditure, infrastructure measures (T&D loss ratio and number of telephone lines), literacy rate, and the share of private sector employment (Figure 1).[10]

In addition to these "conventional" measures, we construct a spatial distance index to capture possible spillover effect among states as a potential determinant of growth. We construct six indicator variables which take a value of 1 when the pair i, j is high-high, high-medium, high-low, medium-medium, medium-low, and low-low income states respectively and zero otherwise. Then, we weigh the indicator by the reciprocal of spatial distance between capital city of state i, j in hundreds of miles. The coefficient on spatial distance index captures the interaction between state i, j and is scaled down by the distance between two states.

The estimated regression takes the form:

$$y_{ij} = \alpha + x_{ij}\beta + \varepsilon_i \quad , \text{i = 1,2,..,N; j = 1,2,..,N} \tag{5}$$

where

$$y_{ij} \text{ is a } \frac{N(N-1)}{2} x\, 1$$

vector of difference in log of per capita income between state i and j, i.e.,

$$y_{ij} = \frac{1}{T}\sum_{t=1}^{T}(\ln y_{it} - \ln y_{jt}) \; \forall \; i \neq j$$

and

$$x_{ij} \text{ is a } \frac{N(N-1)}{2} x\, K$$

[9] Although the set-up of the convergence tests allows for time and cross-sectional fixed effect, the instruments are not enough to filter out structural changes.

[10] Development expenditure includes spending on education, public health, family planning, water supply, and relief after natural calamities.

matrix of difference in factors between state *i* and *j*, i.e.,

$$x_{ijk} = \frac{1}{T}\sum_{t=1}^{T}(x_{ikt} - x_{jkt}) \; \forall \; i \neq j; k = 1,\dots,K$$

and β is a $K \times 1$ vector of coefficients.

Our main empirical results are as follows (Table 7). The main determinants of per capita income differentials among states are share of the service sector, private sector credit per capita, and development expenditure. The factor loadings for these variables are always positive and significant in all specifications. Specifically, a 1 percent difference in share of service sector contributes to about 0.02 percent difference in per capita income between states; a 1 percent difference in development expenditure results in approximately 0.07 percent difference in per capita income; private investment is the largest contributor to per capita income differentials (0.5 percent).

Other variables are not statistically significant: the number of telephone lines is the only variable that is significant, but the effect is almost negligible; T&D loss ratio has correct sign as expected, but is not significant; literacy rate and employment in private sector are statistically insignificant.

From a policy perspective, these results are intuitive and important. The results confirm the significant role for development policy and expenditures and of the availability of credit. They also affirm the role of the private sector in promoting growth. The statistical insignificance of some factors, in particular the literacy rate, should not be interpreted as these factors not being important. It is possible that spending on education and other key areas such as health, which are included in development spending, are already good proxies.

Interestingly, spillover effects among states are not strong. Most of the parameter estimates are not significantly different from zero, except for low-low income state pairs. The negative estimates show potential crowding out effect between high-high income states, while positive spillover effects are noticeable in all other combination.

C. Club Convergence and Dynamic Spillover Effects

There is strong evidence of club convergence among the high- and low-income states; the evidence for middle-income states is mixed (Table 5).

- High- and low- income states display convergence for both entire period and each sub-period. For high-income group, over the full sample, the non-convergence hypothesis is firmly rejected by bootstrapped IPS and MW tests, while the IPS test using large sample adjustment is rejected at 10 percent significance level. The rejection of non-convergence is much stronger in all sub-periods (less than 1 percent significance level; all tests). For low-income group, over the full sample, non-convergence is rejected with the large sample adjusted IPS together with bootstrapped IPS tests (not rejected with LLC and MW tests). For the sub-samples, the rejection of non-convergence is uniform and stronger.

- Medium-income states exhibit divergence over the full sample period; convergence for pre-1980 and 1980-1992, but not for post-1992. Individually, Kerala is the only state that can reject the null of non-convergence. These nonrejections are also accumulated into the panel. Medium-income states appear to be converged in pre-1992, but diverged in subsequent periods. All tests solidly reject the null in pre-1980 and 1980-1992. Nonetheless, in post-1992, states never reject the null for neither individual nor panel.

- Divergence among the medium income group results from two states, Andhra Pradesh and Karnataka. The growth rate of Andhra Pradesh increased from 1¼ percent in pre-1980s to 3½ percent in 1980-1992, then to almost 5 percent post-1992. For Karnataka, the growth rate surged from 1¾ percent, to 2¾ percent, to 5¼ percent, respectively. Both states emerge as the leaders in the information technology, and positioned themselves as the top IT exporting states. Andhra Pradesh is also a mineral rich state, while Karnataka is a manufacturing hub for the largest public sector industries.

- Excluding these two states, there is evidence of convergence among the medium-income states also. While previous results indicate divergence for the entire sample period as well as post-1992, there is now convergence in all periods, and the results are robust (Table 6). For the entire period, the null of individual unit roots for Kerala and West Bengal is rejected at less than 5 percent significance level. All tests reject the null of non-convergence. Post-1992 results are slightly weaker. Only Kerala can reject the unit root null. Panel-wise, non-convergence is rejected with both IPS and MW statistics (but not with LLC statistics).

The dynamic panel approach also allows an examination of spillover effects between groups of states over time. We characterize the dynamic relationship among high-, medium- and low-income states as a system of equations:

$$
\begin{aligned}
y_{it}^{H} &= \sum_{j=1}^{p}\alpha_j^H y_{i,t-j}^H + \sum_{j=1}^{q}\alpha_j^M y_{i,t-j}^M + \sum_{j=1}^{r}\alpha_j^L y_{i,t-j}^L + f_i^{y^H} + u_{it}^{y^H} \\
y_{it}^{M} &= \sum_{j=1}^{p}\alpha_j^H y_{i,t-j}^H + \sum_{j=1}^{q}\alpha_j^M y_{i,t-j}^M + \sum_{j=1}^{r}\alpha_j^L y_{i,t-j}^L + f_i^{y^M} + u_{it}^{y^M} \qquad (6)\\
y_{it}^{L} &= \sum_{j=1}^{p}\alpha_j^H y_{i,t-j}^H + \sum_{j=1}^{q}\alpha_j^M y_{i,t-j}^M + \sum_{j=1}^{r}\alpha_j^L y_{i,t-j}^L + f_i^{y^L} + u_{it}^{y^L}
\end{aligned}
$$

y_{it}^H = log of per capita income of high income states; i =1,..,5 and t=1,…,30

$f_i^{y^H}$ = fixed effects of high income state i

y_{it}^M = log of per capita income of medium income states; i =1,..,5 and t=1,…,30

$f_i^{y^M}$ = fixed effects of medium income state i

y_{it}^L = log of per capita income of low income states; i =1,..,5 and t=1,…,30

$f_i^{y^L}$ = fixed effects of low income state i

The number of lags is chosen by minimizing the AIC and SBIC.

The dynamic estimated spillover effects are also small (Figures 2-5).[11] Over entire sample period, there are spillover effects among states where a positive shock had positive and permanent effect within the group as well as on other groups. The within-group effect appears to have been relatively large, while the between-group effects were smaller. In general, the spillovers between high-medium income groups are stronger than high-low and medium-low income groups. Numerically, the spillover effects are quite small. A one standard deviation increase in income in one state transfers to only 0.01-0.07 standard deviation increase in income in other states. The bottom line seems to be that states that are ahead do not seem to pull the lagging states along.

In the sub-sample analysis, the results confirm divergence across states, particularly in the post-1992 period. The interaction between states is not quite evidenced in pre-1980 as well as post-1992 periods. The shock dies out very quickly after a few years. In pre-1980, shock from one state, however, results in more volatile growth to other states. Similarly, in post-1992, the spillover effects are very small and negligible. Most responses are flat around zero. On the other hand, during the period 1980-92, states were possibly more interconnected, with evidence of spillover effects, albeit weak ones.

VI. Concluding Remarks

Convergence and spillovers across countries and within countries are old, but recurrent policy concerns, and India is no exception to this rule. With this motivation, this paper has examined convergence and spillovers across Indian states, using non-stationary panel data techniques. Results on convergence among Indian states are generally found to be similar to but more nuanced than previous studies. Generally speaking, there is evidence of divergence over the entire sample period (1960-2003), convergence during sub-periods corresponding to structural breaks, and club convergence. There is strong evidence of club convergence among the high- and low-income states; the evidence for middle-income states is mixed. Dynamic spillover effects among states are small.

There is evidence of three growth episodes for India. In these episodes, high income states experienced high and stable growth on average, medium income states grew fast, some catching up with high states; some low income stated picked up, but gaps with the high and middle

[11] We estimate the generalized impulses as in Pesaran and Shin (1998) which constructs an orthogonal set of innovations that does not depend on the VAR ordering.

income stated were persistent; and some states continued to lag in the race. From a policy perspective, states that forged ahead were those that benefited from advances in the services sector, those with better infrastructure and credit availability, and those that engaged efficiently in development spending. The lack of dynamic spillovers may also be pointing to a need for better infrastructure and connectivity throughout the country to allow a dissemination of the benefits of growth across the country.

Appendix 1: Test Procedures for Panel Unit Roots

1. Levin, Lin, and Chu Test

Levin, Lin, and Chu (2002) propose a parametric test analogous to the augmented Dickey Fuller test. They model serial correlation dynamics using autoregressive of order k specification in lagged differences. To perform the test, first estimate ADF regression by OLS for each member:

(1.1) $$\Delta y_{i,t} = \rho_i y_{i,t-1} + \sum_{L=1}^{p_i} \phi_{iL} y_{i,t-L} + \alpha_{mi} d_{mt} + \varepsilon_{i,t}, \qquad m=1,2,3;\ i=1,2,\ldots,N;\ t=1,2,\ldots,T$$

$d_{1t} = \phi$ (the empty set); $d_{2t}=\{1\}$; $d_{3t}=\{1,t\}$

The time effects for cross sectional dependence can be extracted by replacing y_{it} by

$\tilde{y}_{it} = y_{it} - \bar{y}_t$ where $\bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{it}$

Next, use the estimated residuals, $\hat{\varepsilon}_{it}$, to compute the estimated residual variance for each i:

(1.2) $$\hat{\sigma}^2_{\varepsilon i} = \frac{1}{T}\sum_{t=1+K_i}^{T} \hat{\varepsilon}^2_{it}$$

Then, run two auxiliary regressions to generate orthogonalized residuals by estimating the following for each member i:

(1.3) $$\hat{e}_{it} = \Delta y_{it} - \sum_{L=1}^{P_i} \hat{\pi}_{iL} \Delta y_{it-L} - \hat{\alpha}_{mi} d_{mt}$$

and

(1.4) $$\hat{v}_{it-1} = y_{it-1} - \sum_{L=1}^{P_i} \tilde{\pi}_{iL} \Delta y_{it-L} - \tilde{\alpha}_{mi} d_{mt}$$

After that, normalize $\hat{e}_{it}$ and $\hat{v}_{it-1}$ by regression standard error from (2) and get

(1.5) $$\tilde{e}_{it} = \frac{\hat{e}_{it}}{\hat{\sigma}_{\varepsilon i}} \text{ and } \tilde{v}_{it-1} = \frac{\hat{v}_{it-1}}{\hat{\sigma}_{\varepsilon i}}$$

Now, compute the panel test statistics by pooling all cross sectional and time series observations to estimate

(1.6) $$\tilde{e}_{it} = \rho \tilde{v}_{it-1} + \tilde{\varepsilon}_{it}$$

and so apply the t-test for $\delta = 0$ where t-statistic is given by

(1.7) $$t_\delta = \frac{\hat{\rho}}{STD(\hat{\rho})}$$

(1.8) $$\hat{\rho} = \frac{\sum_{i=1}^{N}\sum_{t=2+p_{ii}}^{T} \tilde{v}_{it-1}\tilde{e}_{it}}{\sum_{i=1}^{N}\sum_{t=2+p_{ii}}^{T} \tilde{v}^2_{it-1}};$$

$$STD(\hat{\rho}) = \hat{\sigma}_{\tilde{\varepsilon}}\Big[\sum_{i=1}^{N}\sum_{t=2+p_i}^{T} \tilde{v}^2_{it-1}\Big]^{-1/2}$$

The above t-statistic would require some adjustment to have a standard normal limiting distribution as follows:

(1.9) $t_\rho^* = \dfrac{t_\rho - N\tilde{T}\hat{S}_N \hat{\sigma}_{\tilde{\varepsilon}}^{-2} STD(\hat{\rho})\mu_{m\tilde{T}}^*}{\sigma_{m\tilde{T}}^*} \xrightarrow{d} N(0,1)$, under the null $\rho_i = 0$

where the mean adjustment $\mu_{m\tilde{T}}^*$ and standard deviation adjustment $\sigma_{m\tilde{T}}^*$ are from tables depending on cases.

The hypotheses for unit root test are as follows:

$H_0 : \rho_i = \rho = 0, \forall i$
$H_1 : \rho_i = \rho < 0, \forall i$

The rejection of the null hypothesis implies there is no unit root for all series in consideration.

2. Im, Pesaran, and Shin Test

Im, Pesaran, and Shin (2003) propose a unit root test for dynamic heterogeneous panels based on the group mean between-dimension test. The test is also analogous to the augmented Dickey-Fuller test. The univariate ADF test is estimated for each member:

(2.1) $\Delta y_{i,t} = \rho_i y_{i,t-1} + \sum_{L=1}^{p_i} \phi_{iL} y_{i,t-L} + \alpha_i + \varepsilon_{i,t}$ $\quad$ *i=1,2,...,N; t=1,2,...,T*

Again, to extract the time effects, y_{it} can be replaced by $\tilde{y}_{it} = y_{it} - \bar{y}_t$ where $\bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{it}$.

Then, collect t-statistics of each ρ_i, and calculate the group-mean value of t-statistic for panel:

(2.2) $\bar{t}_\rho = \frac{1}{N}\sum_{i=1}^{N} t_{\rho_i}$

To obtain the asymptotically standardized normal distribution, the t-bar statistic requires some adjustments as follow:

(2.3) $\tilde{t}_\rho = \dfrac{\sqrt{N}(\bar{t}_\rho - \mu)}{\sigma} \xrightarrow{d} N(0,1)$, under the null $\rho_i = 0$

where μ and σ are tabulated mean and variance from IPS paper.

Unlike LLC test, the IPS hypotheses take into account the null hypothesis that all series in panel are unit-root against the alternative that at least one of them is stationary.

$H_0 : \rho_i = 0, \forall i,$
$H_1 : \rho_i < 0, \ni i$

The rejection of the null again indicates the panel does not contain unit root.

3. Maddala and Wu Test

Maddala and Wu (1999) propose somewhat different test. Similar to IPS test, they treat all parameters as heterogeneous among members and base their model on ADF type of regression. Instead, they combine significance values of ADF t-tests across members of panel to get the Fischer's test statistic. The procedure is as follows:

The first step is to estimate ADF regression for each member i.

(3.1) $\Delta y_{i,t} = \rho_i y_{i,t-1} + \sum_{L=1}^{p_i} \phi_{iL} y_{i,t-L} + \alpha_i + \varepsilon_{i,t}$ $\quad i=1,2,...,N;\ t=1,2,...,T$

or replacing y_{it} by $\tilde{y}_{it} = y_{it} - \bar{y}_t$ where $\bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{it}$ to extract time effects.

Then, collect the t-statistic, t_{ρ_i}, for $H_0 : \rho_i = 0$ for each member i and compute the corresponding p-values, $\pi_i (i = 1,2,..,N)$. In particular, π_i value must be obtained by simulation since t_{ρ_i} distribution is non-standard. If the test statistics are continuous, the significance levels $\pi_i (i = 1,2,..,N)$ are independent uniform (0,1) variables, and $-2\ln\pi_i$ has a χ^2 distribution with two degrees of freedom. With additive property of the χ^2 variables, the MW panel unit-root test statistic is $\lambda = -2\sum_{i=1}^{N}\ln\pi_i$ has a χ^2 distribution with *2N* degrees of freedom.

The MW test considers the same unit-root test hypotheses as IPS test.

$H_0 : \rho_i = 0, \forall i,$
$H_1 : \rho_i < 0, \ni i$

There is evidence of unit root in panel if the null cannot be rejected.

4. Step-Down Procedure for Choosing Lag Truncation

The number of lags is crucial. The lag truncation must be large enough to ensure the ADF residual is white noise. If the number of lags is too small, tests will be misspecified and potentially lead to serious size distortion. Nonetheless, if the number of lags is too large, tests are inefficient. Power of the test is gradually loss.

The time series literature often uses Akaike Information Criterion (AIC) and Schwarz Bayesian information criterion (SBIC). Pedroni and Yao (2006) argue that these are not sufficiently conservative for panel unit root tests as the two tests tend to undertruncate. On the other hand, panel unit root and panel cointegration procedures do best with less conservative "step down procedure".

This paper employs the procedure as in Pedroni and Yao (2006) to the above three tests. We first start with a sufficiently large number of lags. Specifically, we take the nearest integer of

1/5 of the sample length for an arbitrary initial starting number of lags relative to sample size. The ADF regression is then performed. If the largest lag is significance, we can stop the process and choose this truncation. If not, the number of lags is sequentially eliminated one at a time and continues the above process until significance. Additionally, the number of lags is allowed to be different across states.

5. Bootstrap Procedures

This paper applies bootstrap technique to simulate the IPS adjustment terms as well as MW p-value. The IPS test requires the appropriate adjustment values for mean and variance. Theoretically, values of the adjustment terms are asymptotically invariant to lag truncation, provided that the number of lags is large enough to ensure that the ADF residuals are white noise. For finite sample, however, the use of asymptotic value of adjustment terms can lead to substantial size distortion. The specific adjustment terms to each panel's members depend on its serial correlation nature, and so are very sensitive to the choice of lag truncation. Moreover, if the data are cross-sectional dependent, the test statistics are no longer the same as their asymptotic version. The MW test, too, needs simulation for non-standard t_{ρ_i} distribution to map between each member's t_{ρ_i} value and corresponding p-value.

Following Pedroni and Yao (2006), we use a bootstrap to condition the Monte Carlo simulation on both the sample size and the specific number of fitted lags. If the number of lag truncation in ADF regression is chosen so that its residuals are white noise, the ADF limiting distribution is asymptotically the same as DF distribution. One can then simulate the DF distribution using pure random walk and use this distribution to map t_{ρ_i} values into corresponding p-values. Specifically, we estimate serial correlation properties by running ADF regression for each member i.

(5.1) $$\Delta y_{i,t} = \rho_i y_{i,t-1} + \sum_{L=1}^{p_i} \phi_{iL} y_{i,t-L} + \alpha_i + \varepsilon_{i,t}$$

We draw 10,000 realizations of pure random walk of length T+100 for ε_{it}. We fix parameters, $\rho_i, \phi_{iL}, \alpha_i$, and replicate the serial correlated process. We repeat the ADF regression using these pseudo-innovations, y^*_{it}.

(5.2) $$\Delta y^*_{i,t} = \rho_i y^*_{i,t-1} + \sum_{L=1}^{p_i} \phi_{iL} y^*_{i,t-L} + \alpha_i + \varepsilon_{i,t}$$

We then discard the first 100 results to eliminate an arbitrary initial condition. We then collect the parameters of interest and generate the pseudo distribution. Finally, we compute corresponding mean and variance, as well as the probability distribution.

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Table 1. Indian States: Growth and Convergence Literature--A Survey of Results

	Variable	States	Estimation	FE/TE 1/	1961-65	1966-70	1971-75	1976-80	1981-85	1986-90	1991-95	1996-00	2001-05	Absolute Convergence	Conditional Convergence	Controls
Cashin &Sahay (1995)	Log real per capita states' income	20	cross-sectional	n.a.										yes	yes	Sectoral shares
Bajpai and Sachs (1996)	Log real per capita states' income	19	cross-sectional	n.a.										no yes no no	 yes no no	Initial agriculture share
Rao, et al. (1999)	Log real per capita states' income	14	cross-sectional											no	no	Share of agricultural sector
Nagaraj, et al.(2000)	Real per capita states' income	17	panel regression on lagged per	FE/TE										no	yes	Share of agricultural sector Relative price shocks Infrastructure variables
Aiyar (2001)	Log real per capita states' income annual data 5 years apart	19	panel regression	FE										no	yes	Literacy rate Real private sector credit per capita
Sachs, et. al. (2002)	Log real per capita states' income	14	panel regression on lagged per	n.a.										no	n.a.	
Kochhar, et al. (2006)	Annual avg. decadal rate of growth in per capita	14	panel regression on Log initial per	FE/TE										yes/no (depends on estimation procedures)	no (post 90s)	Decadal dummies
Purfield (2006)	Log real per capita states' income 5 years average on non-overlapping periods	15	panel regression	FE/TE										yes	yes no (post90s)	Female literacy rate Private/government investment Infrastructure variables Employment indicators Sectoral shares Reform dummies
Baddeley, et al. (2006)	Growth rate of real states' per capita income	15	cross-sectional regression	n.a.										no	yes (OLS) no (GLS)	Economic structure Physical and human capital formation 1990 reform dummies
Misra (2007)	Compound annual growth rates	14	panel regression on lagged per	FE/TE										no	yes	
Bandyopadhyay (2003)	per capita income	17	distributional approach	n.a.										no (2 club convergence)	no	

Sources: Authors.

1/ FE/TE: Fixed effects/Time effects

Table 2. Rank of Indian States Income, 1970–2003

Year	Punjab	Maharashtra	Haryana	Gujarat	Tamil Nadu	Kerala	Karnataka	West Bengal	Andhra Pradesh	Rajasthan	Assam	Orissa	Madhya Pradesh	Uttar Pradesh	Bihar
1970	1	3	2	4	6	5	8	9	11	7	12	10	14	13	15
1971	1	4	2	3	6	5	8	7	10	9	11	12	13	14	15
1972	1	4	2	6	5	3	9	7	12	10	8	11	13	14	15
1973	1	2	3	4	6	5	7	9	10	8	11	12	13	14	15
1974	1	2	3	6	5	4	7	8	9	11	10	12	13	14	15
1975	1	3	2	4	6	5	7	8	10	9	11	12	13	14	15
1976	1	3	2	4	5	6	9	8	11	7	10	12	14	13	15
1977	1	2	3	4	5	6	7	8	11	9	12	10	14	13	15
1978	1	3	2	4	5	6	7	9	10	8	12	11	14	13	15
1979	1	2	3	4	5	6	7	8	9	10	11	12	14	13	15
1980	1	3	2	4	6	5	8	7	10	11	9	12	14	13	15
1981	1	3	2	4	5	6	8	10	7	11	9	12	14	13	15
1982	1	3	2	4	6	5	7	10	8	11	9	14	13	12	15
1983	1	4	2	3	5	10	6	9	8	7	11	12	14	13	15
1984	1	4	2	3	5	7	6	8	10	11	9	12	14	13	15
1985	1	3	2	4	5	6	9	8	10	11	7	12	14	13	15
1986	1	3	2	4	5	8	6	7	11	10	9	12	14	13	15
1987	1	3	2	4	5	8	6	7	9	11	10	12	14	13	15
1988	1	4	2	3	5	9	6	10	7	8	11	12	14	13	15
1989	1	3	2	4	5	8	6	10	7	9	11	12	14	13	15
1990	1	3	2	4	5	7	9	10	6	8	11	14	13	12	15
1991	1	3	2	5	4	8	6	9	7	10	11	13	14	12	15
1992	1	2	3	4	5	7	6	10	9	8	11	13	14	12	15
1993	1	2	3	4	5	6	7	9	8	11	12	14	10	13	15
1994	1	2	3	4	5	6	7	10	8	9	12	14	11	13	15
1995	2	1	4	3	5	6	7	9	8	10	12	14	11	13	15
1996	1	2	4	3	5	7	6	9	8	10	12	14	11	13	15
1997	2	1	4	3	5	7	6	9	10	8	12	14	11	13	15
1998	1	2	4	3	5	7	6	9	8	10	12	13	11	14	15
1999	2	1	3	4	5	7	6	9	8	10	12	13	11	14	15
2000	1	2	3	5	4	7	6	9	8	10	12	14	11	13	15
2001	1	2	3	4	5	7	6	9	8	10	12	13	11	14	15
2002	2	1	3	4	5	7	6	8	9	10	12	13	11	14	15
2003	3	2	4	1	6	7	5	8	9	10	12	13	11	14	15
Avg. rank	1	3	3	4	5	6	7	9	9	9	11	13	13	13	15
SD of rank	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
Avg. RNSDPPC	10,805	9,745	9,672	8,930	7,857	7,072	7,067	6,399	6,440	5,975	5,146	4,667	4,925	4,452	2,555

Sources: Indian authorities; and IMF staff estimates.

Table 3. Survey of Structural Breaks in Indian Economic Data

Author (s)	Sample	Method	Variables	Break date (s)	
				1980s	1990s
Wallack (2003)	1951–2001	Andrew test, Bai test	Growth rate of real GNP, real GDP, etc.	1980	1993
Rodrik and Subramanian (2004)	1960–2000	Bai and Perron (1998, 2003)	-real per capita GDP -per capita GDP at PPP prices -GDP per worker -total factor productivity	1979	no
Balakrishnan (2005)	1980–2000	Chow test	Log annual GDP	n.a.	no
Hausmann, Pritchett, Rodrik (2005)	1957–1992	Growth episodes	Growth rate of GDP per capita	1982	n.a.
Virmani (2005)	1950–2002	Chow test	Annual rate of GDP growth	1980-81	no
Kohli (2006)	1950–2004	Compare growth rate	-GDP growth -Industrial growth -Agricultural growth -Gross investment/GDP	1980	no

Table 4. Panel Unit Root Test Results for All Indian States

State	Whole		pre-1980		1980–1992		post-1992		post-1980	
	ADF	p-value	ADF	p-value	ADF	p-value	ADF	p-value	ADF	p-value
Andhra Pradesh	-2.12	0.26	-3.98	0.04	-2.24	0.20	-1.21	0.63	-2.05	0.30
Assam	-0.30	0.96	-1.84	0.08	-0.76	0.74	-2.26	0.23	-1.20	0.69
Bihar	-2.28	0.23	-7.64	0.01	-0.06	0.91	-4.97	0.01	-3.79	0.02
Gujarat	-1.67	0.51	-2.38	0.19	-4.90	0.01	-4.31	0.01	-3.17	0.06
Haryana	-2.21	0.18	-1.37	0.55	-2.09	0.28	-1.39	0.61	-2.32	0.26
Karnataka	-0.53	0.83	-2.83	0.01	-2.85	0.11	-1.96	0.19	-0.82	0.84
Kerala	-1.85	0.44	-1.49	0.54	-2.79	0.09	-0.56	0.89	-1.09	0.67
Madhya Pradesh	-3.44	0.02	-0.20	0.90	-2.60	0.15	-2.47	0.26	-2.08	0.32
Maharashtra	-1.26	0.61	-1.07	0.69	-1.10	0.12	-4.13	0.01	-1.94	0.23
Orissa	-0.93	0.81	-341.00	0.01	-2.74	0.12	-3.50	0.03	-0.99	0.75
Punjab	-2.27	0.24	-0.83	0.81	-2.93	0.12	-1.72	0.48	-0.85	0.77
Rajasthan	-4.95	0.01	-6.01	0.01	-3.00	0.08	-1.64	0.45	-2.42	0.15
Tamil Nadu	-1.63	0.44	-3.26	0.01	-1.64	0.50	-2.60	0.10	-2.04	0.26
Uttar Pradesh	0.44	1.00	-3.58	0.02	-2.15	0.26	-0.28	0.90	0.58	1.00
West Bengal	-1.69	0.46	-1.45	0.46	-2.80	0.11	-0.67	0.41	-0.73	0.44
LLC Test Statistic	-0.84	0.20	-1.12	0.13	-2.97	0.00	-3.06	0.00	-0.52	0.30
Large Sample IPS Test Statistic	-1.10	0.14	-109.04	0.00	-3.54	0.00	-3.24	0.00	-0.55	0.29
Bootstrapped IPS Test Statistic	-1.13	0.13	-4.69	0.00	-3.60	0.00	-3.55	0.00	-0.89	0.19
Bootstrapped MW-Fisher Test Statistic	37.00	0.18	74.04	0.00	55.06	0.00	55.41	0.00	34.89	0.25

Sources: Indian authorities; and IMF staff estimates.

The results are from LLC, IPS, and MW panel unit root test for long run convergence.

$$\Delta(y_{i,t}-\bar{y}_t)=\delta_i+\rho_i(y_{i,t-1}-\bar{y}_{t-1})+\sum_{k=1}^{p_i}\phi_{i,k}\Delta(y_{i,t-k}-\bar{y}_{t-k})+u_{i,t}$$

For details, see Appendix 1. State real net domestic product per capita is used as a proxy for the state income. Annual data ranges from 1960–2003.

ADF test statistic, ρ_i, and related p-value for each individual together with panel test statistics. The p-values are estimated by Monte Carlo simulation as the ADF test statistics are nonstandard t distribution. Column 1-2 shows results for the whole sample 1960–2003. We then split the sample according to reform period. We report pre-1980 results in columns 3–4, and post-1980 results in columns

Table 5. Club Convergence

High-Income States	Whole		pre-1980		1980–1992		post-1992	
	ADF	p-value	ADF	p-value	ADF	p-value	ADF	p-value
Gujarat	-2.08	0.23	-6.30	0.01	-3.53	0.04	-4.24	0.02
Haryana	-3.22	0.01	-2.95	0.08	-3.57	0.03	-1.77	0.41
Maharashtra	-2.47	0.03	-3.29	0.04	-2.68	0.08	-5.66	0.02
Punjab	-0.94	0.72	-2.63	0.12	-2.64	0.12	-2.14	0.23
Tamil Nadu	-1.78	0.34	-1.95	0.37	-3.44	0.05	-2.09	0.24
LLC Test Statistic	-0.70	0.24	-3.79	0.00	-3.58	0.00	-2.98	0.00
Large Sample IPS Test Statistic	-1.48	0.07	-5.00	0.00	-4.34	0.00	-4.35	0.00
Bootstrapped IPS Test Statistic	-3.51	0.00	-4.55	0.00	-3.65	0.00	-4.71	0.00
Bootstrapped MW-Fisher Test Statistic	21.98	0.02	26.93	0.00	28.73	0.00	23.22	0.01
Medium-Income States								
Andhra Pradesh	-2.49	0.15	-4.56	0.01	-3.21	0.05	-2.55	0.16
Karnataka	-1.19	0.67	-1.04	0.77	-3.80	0.03	-2.45	0.11
Kerala	-2.56	0.09	-1.80	0.37	-3.13	0.09	-1.84	0.28
Rajasthan	0.09	0.98	-4.28	0.01	-4.21	0.02	-0.72	0.84
West Bengal	-1.62	0.45	-0.75	0.83	-1.68	0.41	-0.58	0.42
LLC Test Statistic	0.18	0.57	-2.32	0.01	-3.61	0.00	0.93	0.82
Large Sample IPS Test Statistic	-0.04	0.48	-2.51	0.01	-4.42	0.00	-0.24	0.40
Bootstrapped IPS Test Statistic	-0.15	0.44	-2.55	0.01	-3.65	0.00	-1.02	0.15
Bootstrapped MW-Fisher Test Statistic	11.05	0.35	21.30	0.02	27.43	0.00	12.71	0.24
Low-Income States								
Assam	-1.26	0.56	-1.49	0.53	-1.95	0.33	-3.18	0.06
Bihar	-6.21	0.01	-1.96	0.31	-2.20	0.23	-5.05	0.02
Madhya Pradesh	-0.78	0.83	-2.46	0.15	-3.19	0.05	-3.32	0.04
Orissa	-1.51	0.47	-3.38	0.05	-4.34	0.01	-3.66	0.02
Uttar Pradesh	-1.64	0.46	-3.93	0.03	-1.13	0.75	-0.47	0.87
LLC Test Statistic	-0.59	0.28	-2.43	0.01	-2.91	0.00	-4.82	0.00
Large Sample IPS Test Statistic	-1.97	0.02	-2.93	0.00	-2.72	0.00	-4.23	0.00
Bootstrapped IPS Test Statistic	-2.10	0.02	-2.49	0.01	-2.29	0.01	-3.36	0.00
Bootstrapped MW-Fisher Test Statistic	13.81	0.18	20.41	0.03	20.93	0.02	27.99	0.00

Sources: Indian authorities; and IMF staff estimates.

The results are from LLC, IPS, and MW panel unit root test for long run convergence.

$$\Delta(y_{i,t}-\bar{y}_t)=\delta_i+\rho_i(y_{i,t-1}-\bar{y}_{t-1})+\sum_{k=1}^{k}\phi_{i,k}\Delta(y_{i,t-k}-\bar{y}_{t-k})+u_{i,t}$$

For details, see Appendix 1. State real net domestic product per capita is used as a proxy for the state income. Annual data ranges from 1960–2003.

States are divided into 3 subgroups based on growth performance, and first ranked using real net states domestic product per capita.

Then Kendall's coefficient of concordance is computed. There is no significant rank change over whole period or in sub-periods.

The data is then split into high, medium, and low income groups and testsed for convergence.

The ADF test statistic, ρ_i, and related p-value for each individual together with panel test statistics are provided.

The p-values are estimated by Monte Carlo simulation as the ADF test statistics are nonstandard t distribution.

Column 1-2 shows results for the whole sample 1960–2003. Then the sample is split according to reform period.

Table 6: Medium-Income States without Andhra Pradesh and Karnataka

States	Whole		post-1992	
	ADF	p-value	ADF	p-value
Kerala	-3.27	0.03	-41.56	0.01
Rajasthan	-2.6	0.13	-0.65	0.82
West Bengal	-2.86	0.01	-1.39	0.12
LLC Test Statistic	-1.92	0.03	0.92	0.82
Large Sample IPS Test Statistic	-2.82	0.00	-26.71	0.00
Bootstrapped IPS Test Statistic	-4.54	0.00	-9.76	0.00
Bootstrapped MW-Fisher Test Statistic	20.30	0.00	13.85	0.03

Sources: Indian authorities; and IMF staff estimates.

The results are from LLC, IPS, and MW panel unit root test for long run convergence.

$$\Delta(y_{i,t} - \bar{y}_t) = \delta_i + \rho_i(y_{i,t-1} - \bar{y}_{t-1}) + \sum_{k=1}^{p_i} \phi_{i,k} \Delta(y_{i,t-k} - \bar{y}_{t-k}) + u_{i,t}$$

For details, see Appendix 1. State real net domestic product per capita is used as a proxy for the state income. Annual data ranges from 1960–2003.

The ADF test statistic, ρi, and related p-value for each individual together with panel test statistics are provide

The p-values are estimated by Monte Carlo simulation as the ADF test statistics are nonstandard t distributic

Table 7. Income Divergence across Indian States: Regression Analysis

	Dependent variable: Difference of Log of Income Per Capita						
Share of service sector (percent)	0.019***	0.018***	0.020***	0.018***	0.020***	0.018***	0.020***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Real credit per capita (percent)	0.521***	0.537***	0.521***	0.528***	0.513***	0.532***	0.501***
	(0.027)	(0.025)	(0.027)	(0.023)	(0.025)	(0.019)	(0.023)
Development expenditure to	0.075***	0.073***	0.074***	0.074***	0.076***	0.073***	0.078***
total expenditure (percent)	(0.008)	(0.008)	(0.009)	(0.005)	(0.006)	(0.006)	(0.006)
Infrastructure	0.019						
(1st principal component)	(0.018)						
-T&D loss ratio (percent)		-0.001		-0.001			
		(0.004)		(0.004)			
-Telephone lines (million)			0.000		0.000		0.000***
			(0.000)		(0.000)		(0.000)
Spillover effect							
-High to High	-0.128	-0.119	-0.105	-0.118	-0.110	-0.112	
	(0.090)	(0.102)	(0.086)	(0.101)	(0.082)	(0.093)	
-High to Medium	0.077	0.074	0.098	0.085	0.109	0.089	
	(0.212)	(0.221)	(0.207)	(0.217)	(0.197)	(0.214)	
-High to Low	0.261	0.295	0.231	0.301	0.230	0.302	
	(0.231)	(0.233)	(0.229)	(0.228)	(0.230)	(0.226)	
-Medium to Medium	0.291	0.281	0.314	0.240	0.300	0.245	
	(0.518)	(0.518)	(0.527)	(0.488)	(0.498)	(0.483)	
-Medium to Low	0.109	0.114	0.109	0.110	0.110	0.112	
	(0.228)	(0.226)	(0.231)	(0.228)	(0.235)	(0.227)	
-Low to Low	0.469***	0.493*	0.417***	0.492***	0.406*	0.485***	
	(0.209)	(0.208)	(0.219)	(0.203)	(0.217)	(0.195)	
Literacy rate (percent)	-0.001	-0.001	-0.001				
	(0.001)	(0.002)	(0.001)				
Private sector employment	0.044	0.043	0.078				
Total employment (percent)	(0.175)	(0.167)	(0.178)				
Constant	-0.022	-0.027	-0.019	-0.028	-0.023	-0.028	0.004
	(0.031)	(0.030)	(0.030)	(0.027)	(0.027)	(0.027)	(0.015)
Adjusted R-squared	0.931	0.931	0.932	0.932	0.933	0.932	0.934

Sources: Indian authorities; and IMF staff estimates.

Figure 1. Indian States Growth: Explanatory Variables

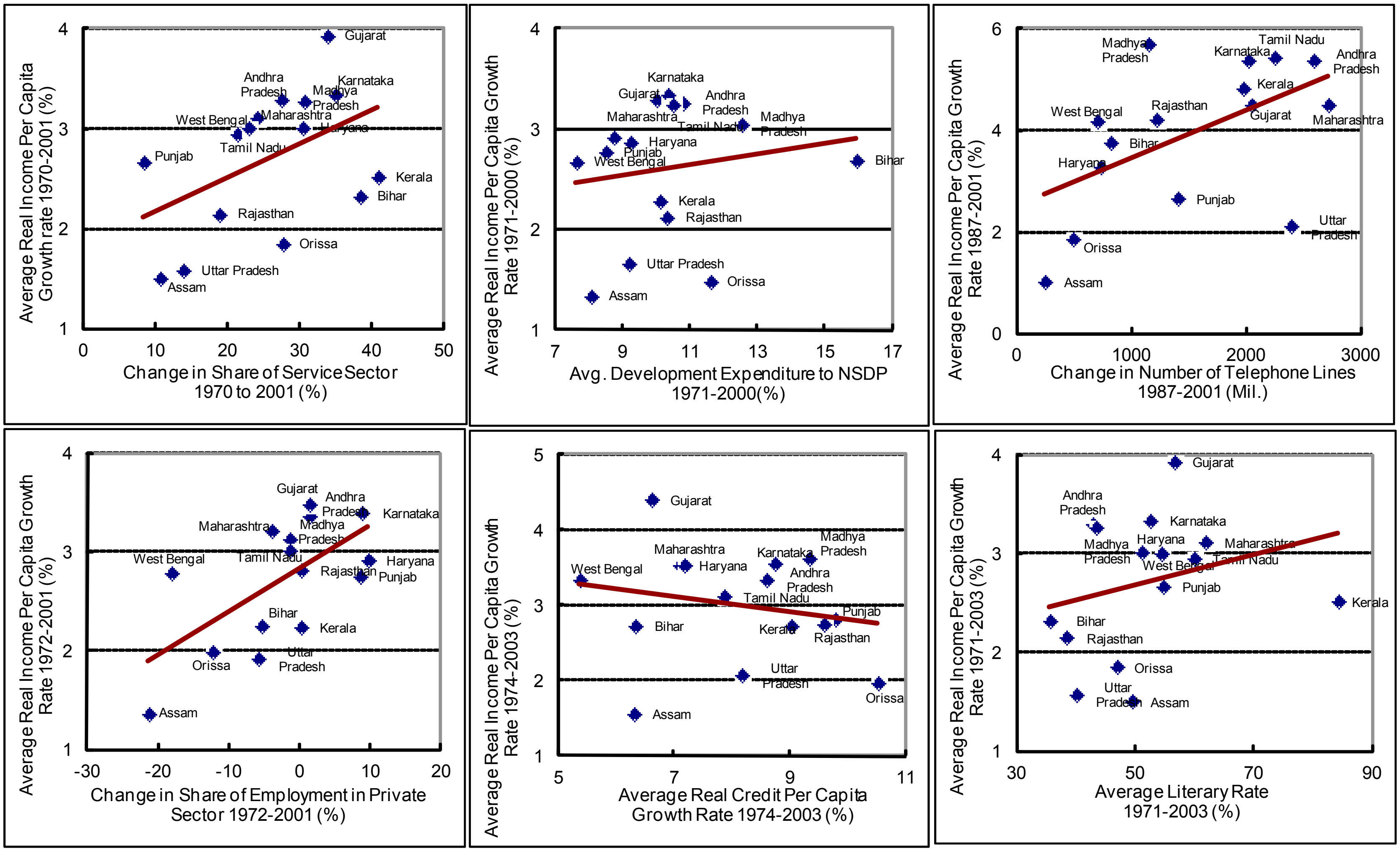

Figure 2. Spillovers among Indian states (full sample)

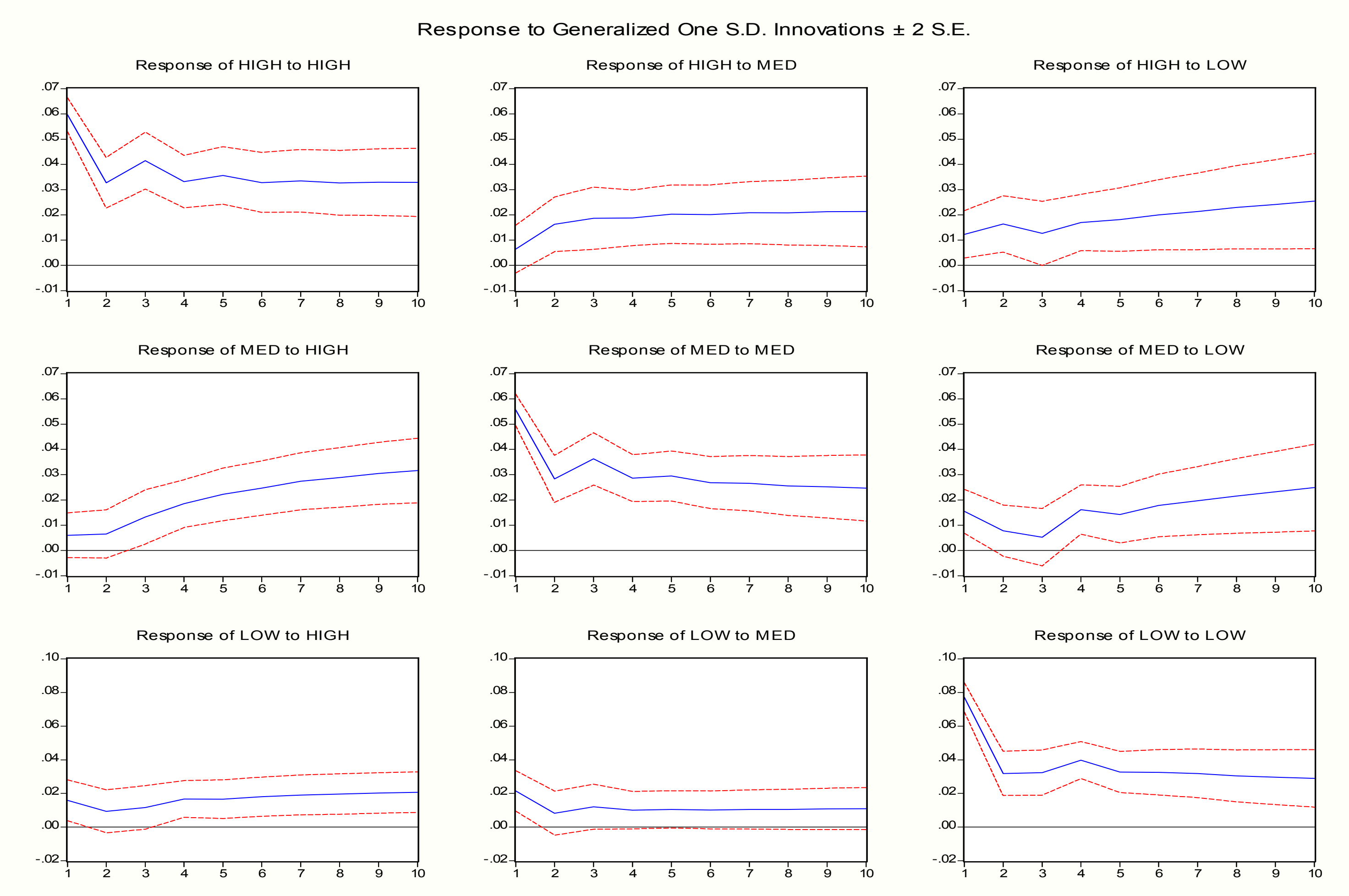

Figure 3. Spillovers among Indian states (pre-1980)

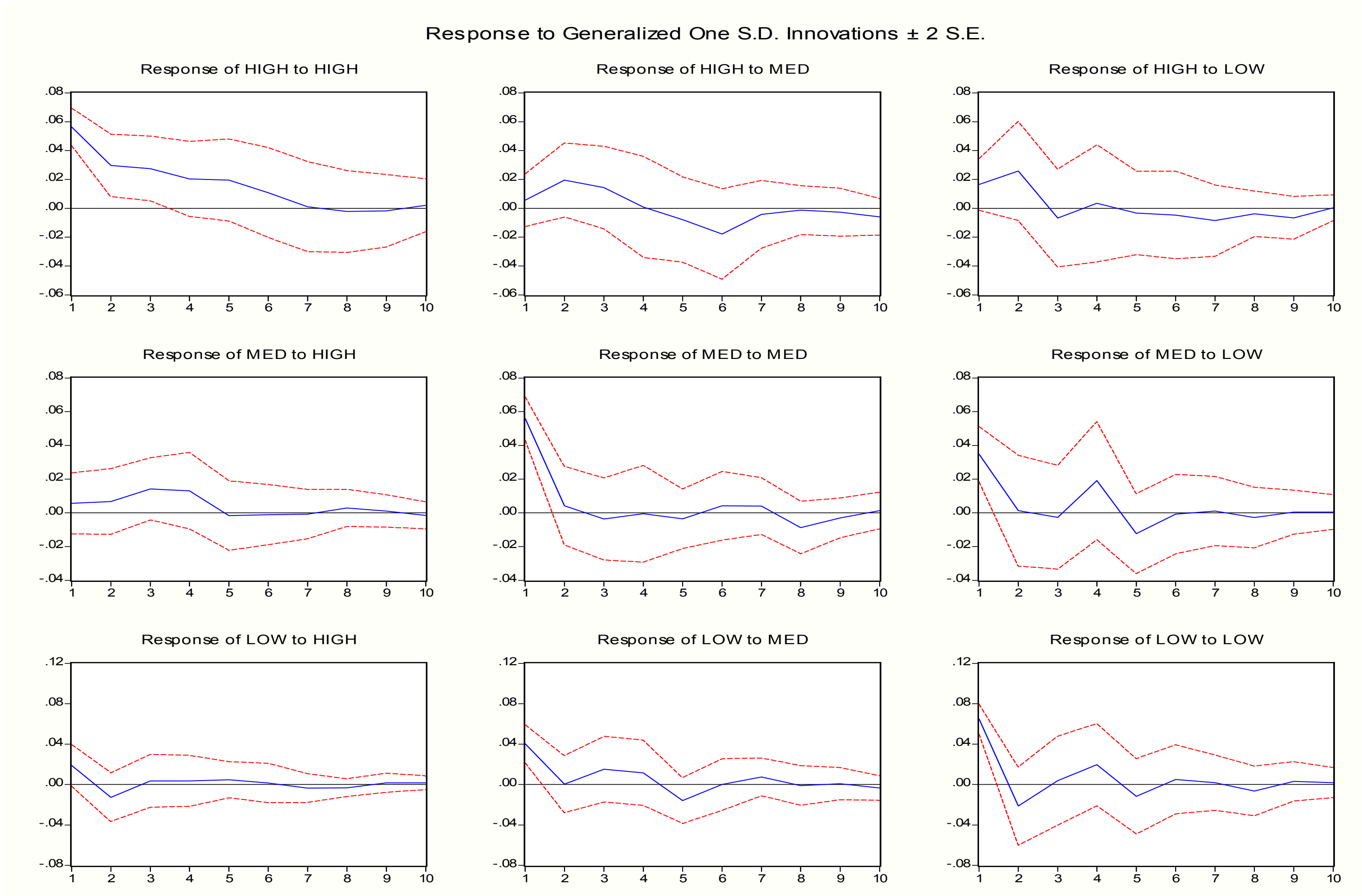

Figure 4. Spillovers among Indian states (1980-92)

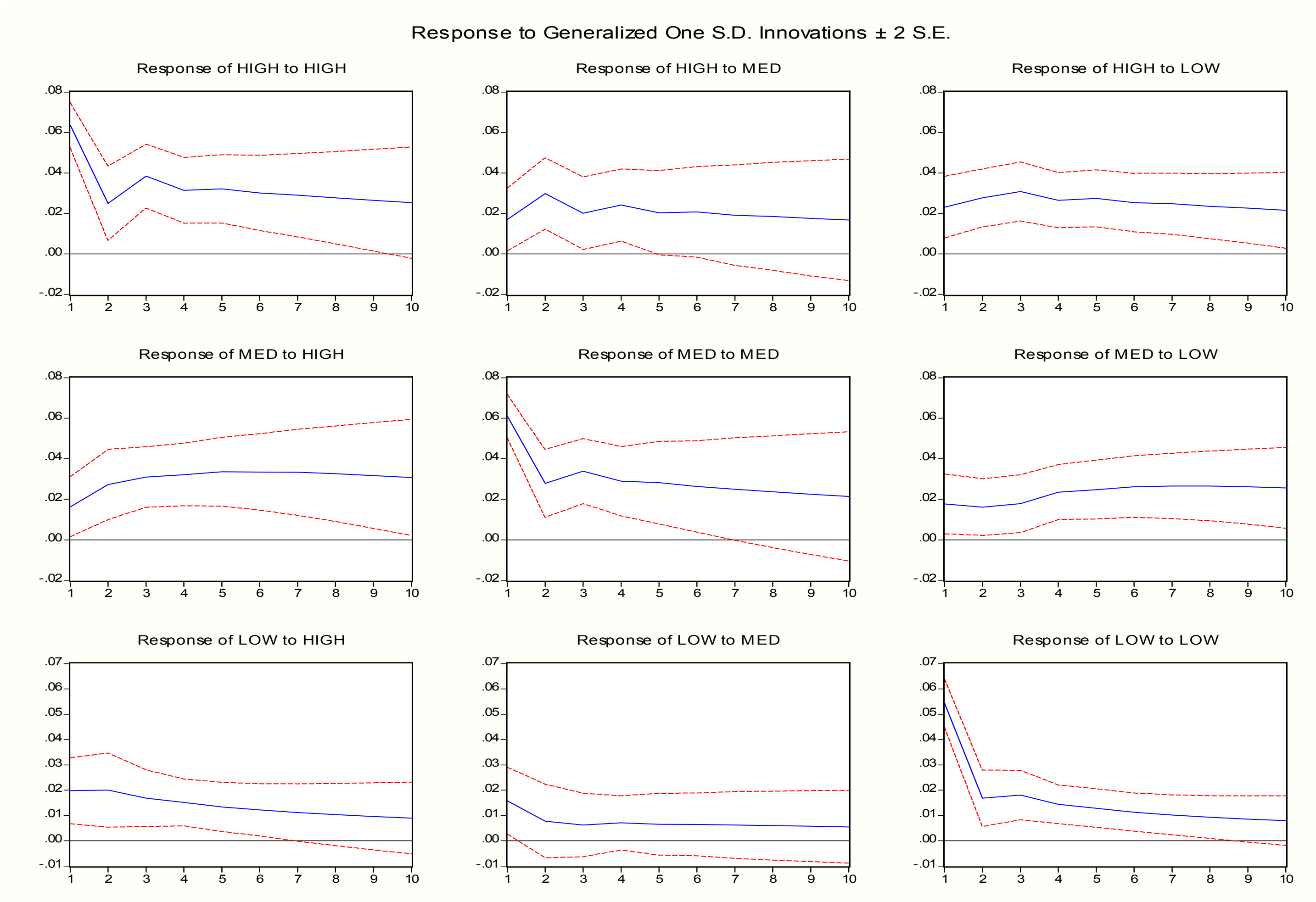

Figure 5. Spillovers among Indian states (post-1992)