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Spatial spill-overs, structural transformation and economic growth in India

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Abstract Using a panel of highly spatially disaggregated district-level data for the most recent period this paper demonstrates 'how spatial dimension and structural transformation influence convergence in economic growth in India'. Our findings show an absolute convergence in economic growth across districts, a finding contrary to the widely reported evidence of divergence across states. More importantly, we find strong spatial linkages in economic growth, leading to a significant acceleration in its speed of convergence. Further, structural transformation too influences the speed of convergence via its spill-over effects, but different sectors influence it differently. While, services sector does not have any significant influence on the speed of convergence, agricultural sector generates positive spill-overs, enhancing the speed of convergence. These findings suggest a need to harness the potential growth effects of spatial linkages by investing more in infrastructure, agricultural research, technology dissemination and skill development especially in the lagging regions, and dismantling the regulatory barriers to inter-regional trade and free flow of goods and services, to bridge the regional developmental gaps.

Keywords Economic growth, convergence, spatial spill-overs, sectoral composition

JEL codes O11, O13, O47

The process of economic reforms that began in India in 1991 has made a conspicuous impact on its economic landscape. Since then, the economy has been growing at an annual rate of about 7%; almost double the rate of growth realized during the pre-reforms period. Regional patterns of growth, however, have been asymmetrical, leading to an accentuation in inter-regional disparities in economic development (Nagaraj et el. 2000; Sachs et al. 2002; Bhattacharya and Sakthivel 2004; Purfield 2006; Sodwriwiboon and Kalra 2010; Agarwalla and Pangotra 2011; Sofi and Raja Sethu Durai 2017; OECD 2017). Reducing regional disparities is, therefore, a major policy concern, as the regions left behind in economic development could be more prone to social tensions and fissiparous tendencies (Shankar and Shah 2003; Sodwriwiboon and Kalra 2010). The Government of India, of late, has launched a programme for rapid transformation of the districts lagging behind in socio-economic development (NITI Ayog 2018) by improving synergy between schemes of central and state governments, collaboration between citizens and government functionaries, and competition among the districts. In other words, this programme aims at harnessing the potential of spatial linkages and synergies in developmental programmes for reducing regional disparities in socio-economic development.

In recent years, spatial dimension has been recognized as an important factor in socio-economic development (Krugman 1999; Fingleton 1999; Gallup, et al. 1999; López-Bazo et al. 1999; Rey and Montouri 1999; Rey 2001; Henley 2005; Fingleton and Lopez-Bazo 2006). It is contended that although the location of an economic activity in itself is an important factor of its performance, but it can also be influenced by its surrounding locations via transmission of knowledge and information, inter-regional trade, and flow of capital and labour. Likewise, structural transformation that provides information on the dynamics of sectoral composition can explain spatially correlated economic performance (Curran 2012). In the past few decades, Indian economy has undergone a structural transformation exhibiting a significant decline in the share of agriculture in gross domestic product (GDP) but unaccompanied by a commensurate decline in its share of workforce. Agriculture still supports about half of the country's workforce, and therefore, agricultural growth is considered important for bridging gaps in the regional development (Birthal et al. 2009; Ghosh et al. 2013; Binswanger-Mkhize and D'Souza 2015).

Nonetheless, the empirical evidence on spatial effects on economic growth in India is scarce. Only a few studies have assessed the spatial effects on economic growth and convergence (e.g., Shaban 2006; Bandyopadhyay 2012; Ghosh et al. 2013; Banerjee and Banik 2014; Chatterjee 2014); and the evidence is mixed depending on the level of disaggregation of spatial units and the differences in the sectoral composition of growth. Bandyopadhyay (2012) and Ghosh et al. (2013) report no spatial dependence in economic growth; while, Chatterjee (2014) finds evidence of spatial dependence in agricultural growth across Indian states. Importantly, at higher levels of spatial disaggregation (i.e., district level) there is an evidence of strong spatial linkages in economic growth (Shaban 2006; Banerjee and Banik 2014).

Post-reforms, India has made significant progress in physical infrastructure (roads, electricity, banking and markets) and communication and information networks, and also towards dismantling the regulatory barriers to inter-regional trade and free flow of resources, technologies and information. These are presumed to have influenced the regional dynamics of growth at different levels of spatial disaggregation. Several studies that have examined regional dynamics of growth during the post-reforms period (e.g., Nagaraj et al. 2000; Aiyer 2001; Purfield 2006; Birthal et al. 2009; Agarwalla and Pangotra 2011; Binswanger-Mkhize and D'Souza 2015; Sofi and Raja Sethu Durai 2017) show absolute divergence, but conditional convergence in economic growth across states. There are two main limitations of these studies. One, the use of state-level data mask heterogeneity in growth trajectories available at spatial units below the states. Two, most of these studies assume that state economies are isolated and independent of one another. Hence, ignoring heterogeneity and dependence in economic growth at higher level of spatial disaggregation is likely to produce biased and misleading results (Rey and Montouri 1999; Fingleton 1999; López-Bazo et al. 1999; Fingleton and Lopez-Bazo 2006).

In this paper, using a panel of district-level data for the period 2001-2015 we assess whether or not the spatial interconnectedness and structural transformation influence convergence in economic growth in India. To the best of our knowledge, ours is one of the few studies that examine spatial effects on convergence in economic growth in India using such a highly spatially disaggregated dataset. Our findings show an absolute convergence in economic growth across districts, a finding contrary to the widely reported evidence of divergence across states. More importantly, our findings show a strong spatial effect on economic growth, leading to a significant acceleration in its speed of convergence. Structural transformation also matters in growth convergence. Services sector, the main driver of India's economic growth, does not influence much the speed of convergence, while agricultural sector generates positive spill-overs on convergence.

Rest of this paper is structured as follows. In the next section, we discuss data sources and provide descriptive statistics on key variables. Section 3 provides empirical strategy, and the results are discussed in section 4. Concluding remarks are made in the last section.

Data and descriptive statistics

In this paper, we use a panel of district-level data on GDP and its components for the period 2001-2015, generated by an economic research and data analytics firm the 'Indicus Analytics' employing a similar methodology as does the Central Statistical Organization (CSO) of the Government of India. The data on GDP and its components are available for 641 districts at 2011 constant prices[1].

[1] To check reliability of the data we collapsed district-level GDP of each state, and compared it with that reported in the National Accounts Statistics. The estimated correlation coefficient between the two series is more than 0.98 for most states.

Besides quantifying spatial linkages in economic growth, we also examine effects of structural transformation and a few facilitators of economic growth. We include shares of agriculture and services sectors in GDP, human capital and banking infrastructure in our analysis. Human capital is proxied by literacy rate, the information on which has been extracted from the Census of India 2001 and 2011.The number of bank branches per thousand population is an indicator of financial outreach. The information on bank branches has been extracted from the EPW Research Foundation (http://www.epwrfits.in/TypesOfBSR.aspx).

To begin with, we analyze changes in the structure of Indian economy and in the per capita income (defined as GDP per person). During 2001-2015, the per capita income increased at an annual rate of 6.3% (Table 1). The economy also underwent a structural transformation *albeit* at a slow pace. Services sector grew at an annual rate of 7.2%, raising its GDP share to 57% in 2013-15 from 52% in 2001-03. Agricultural sector, on the other hand, experienced sluggish growth (3.8%), leading to a decline in its GDP share from 20% in 2001-03 to 15% in 2013-15.

Nonetheless, there exit considerable disparities in the level and growth of per capita income at subnational level, i.e., states and districts. Figure 1 shows association between income growth and initial level of per capita income. Across states, income growth is positively correlated with initial income level (Figure 1a), indicating divergence in income growth across states. The relationship, however, is weak across districts. From Figure 1b we find considerable dispersion in per capita income and its performance

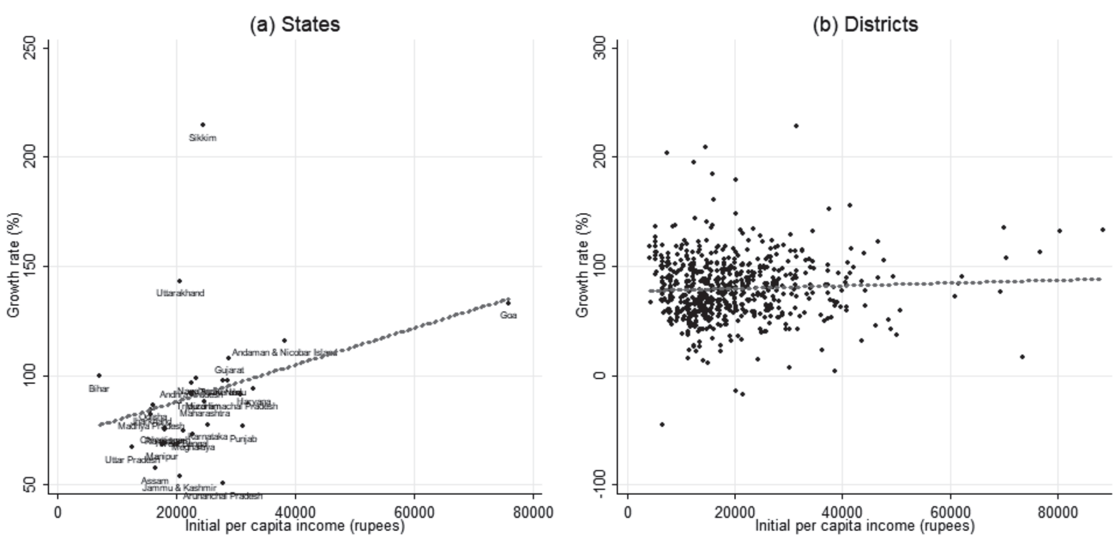

Figure 1 Initial level of per capita income and income growth, 2001-2015

Table 1 Summary statistics of per capita GDP (Rupees at constant 2004-05 prices)

	Agriculture		Industries		Services		Total	
	2001-03	2013-15	2001-03	2013-15	2001-03	2013-15	2001-03	2013-15
Mean	4762	8056	5757	12257	9810	22912	20329	43225
Median	4181	6567	3912	8043	8027	17655	17583	35431
Maximum	28781	66208	46614	180096	65358	236035	94686	305321
Minimum	179	139	308	1212	2269	2651	4148	4442
Standard deviation	2932	6228	5753	13806	6893	20395	12201	31552
Sectoral share (%)	19.6	15.3	28.5	28.1	51.9	56.6	100.0	100.0
% annual growth	3.8		6.2		7.2		6.3	

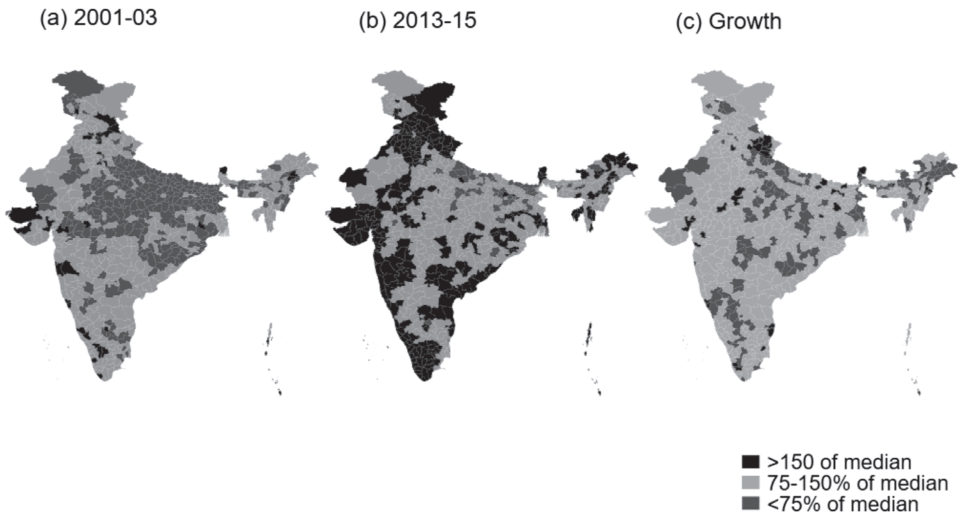

Figure 2 Spatial dispersion of per capita income and growth

across districts. The association between income growth and initial income level, although, is positive but not as strong as in case of states. This is possibly because of greater spatial interactions among districts in a state than among states.

We probe this relationship further by mapping spatial dispersion in per capita income across districts. Based on median value of per capita income at all-India level for the period 2001-2015, we classify districts into: low-income (below 75% of median); middle-income (75-150% of median); and high-income (more than 150% of median) groups. Correspondingly, Figure 2 shows distribution of districts in 2001-03 and 2013-15. Initially, a large number of districts, mostly from the eastern states of Bihar, Jharkhand, Odisha and West Bengal, and the central states of Madhya Pradesh, Chhattisgarh and Maharashtra, were concentrated in the low-income group. Only a few districts along the coast of Arabian Sea and from north-western states of Punjab and Haryana belonged to the high-income group (Figure 2a). Nonetheless, most districts experienced an upward mobility over time. A large number of districts from the coastal states of Gujarat, Maharashtra, Goa, Karnataka, Kerala, Tamil Nadu and Andhra Pradesh, and northern states of Punjab, Haryana, Himachal Pradesh and Jammu & Kashmir moved to the high-income group (Figure 2b). Several low-income districts from the central and eastern regions also improved their position, but a few, mostly from the eastern region, have remained stuck in low-income trap.

These preliminary results are as expected. Punjab and Haryana have been the sheet of green revolution, and experienced substantial improvements in agricultural productivity, farm incomes and rural wages. The hill-states of Himachal Pradesh and Jammu & Kashmir specialize in high-value horticultural crops and have benefitted from their demand-driven growth. The coastal districts, on the other hand, are favoured destinations for export-oriented manufacturing units because of the ease of logistic links with foreign suppliers and customers (Sachs et al. 2002; Andersson et al. 2013).

Empirical strategy

Our empirical strategy is built on β-convergence, a commonly used measure of convergence (Barro and Sala-i-Martin 1992; Islam 1995; Aiyar 2001; Cashin and Sahay 1995; Nagaraj et al. 2000; Ghosh 2006; Purfield 2006). β-convergence occurs if the poor regions grow faster than the rich. Mathematically, β-convergence can be expressed as:

$$y_{it} = \alpha_i + \beta \ln y_{i0} + \delta x_{it} + \varepsilon_{it} \qquad \ldots(1)$$

where, y_{it} is per capita income of district *i* in year *t*, and ln y_{i0} is its initial level (in log). α_i is intercept term that controls for the district-specific time-invariant unobservable factors, and x_{it}, is a vector of spatial characteristics. ε_{it} is an identical, independent and normally distributed error term.

Spatial dependence can be incorporated into β-convergence equation through (i) interaction among dependent variables (endogenous effects) of spatial units, (ii) influence of independent variables of neighbouring units on the dependent variable of spatial unit *i* (exogenous effects), and (iii) interaction among error terms when omitted variables are spatially correlated. For (i) and (ii), spatial dependence has a substantive interpretation, in that growth of a district is jointly determined by growth of other districts. In this case, the standard OLS estimates are not consistent whether or not the error terms are correlated. Conversely, if spatial dependence operates through an error process it is considered to be a nuisance, as the spatial error autocorrelation affects efficiency of the estimates.

The simplest specification for quantifying spatial dependence in economic is through the Spatial Autoregressive Model (SAR) that allows growth of a district to be directly influenced by the growth of neighbouring districts. This effect is independent of exogenous variables, and can be captured by including a spatial autoregressive parameter, **ρ**, and a spatial weight matrix, **W**, in Eq. (1):

$$y_{it} = \alpha_i + \beta \ln y_{i0} + \delta x_{it} + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \varepsilon_{it} \qquad \ldots(2)$$

where, w_{ij} is an element of a pre-specified non-negative spatial weight matrix **W** of order N that describes spatial arrangement of the districts. It is possible that, apart from being directly influenced by the economic growth of its neighbours, a district's own economic growth is influenced by a complex set of random shocks transmitted from within the district as well as from other districts. Such unexpected shocks do not enter the systematic component of model, but are captured in the error term. This specification is termed as the Spatial Error Model (SEM), and can be written as:

$$y_{it} = \alpha_i + \beta \ln y_{i0} + \delta x_{it} + \upsilon_{it} \qquad \ldots(3)$$

$$\upsilon_{it} = \lambda \sum_{j=1}^{N} w_{ij} \upsilon_{it} + \varepsilon_{it}$$

where, υ_{it} denotes spatially autocorrelated error term, and λ is a parameter associated with spatially lagged error term. The SEM captures residual spatial dependence due to spatially autocorrelated regressors, and transmits spatial dependence in the form of random shocks. If a district has limited number of neighbours, an inverse operator in the transformation defines error covariance structure that diffuses district-specific shocks not to its neighbours alone but throughout the system. In other words, a random shock in a district not only influences economic growth of its own but also of other districts through spatial transformation.

However, transmission of random shocks, as in SEM, is considered inconsequential. Hence, there is a need to identify a spatial model that can accommodate more than one spatial interaction. The Spatial Auto-regressive Model with Autoregressive Disturbances (SARAR) includes spatially lagged dependent variable and spatially autocorrelated error term; and the Spatial Durbin Model (SDM) accommodates spatially lagged dependent variable as well as spatially lagged explanatory variables. Nonetheless, the choice of model should be grounded in theory with explicit economic foundations (Corrado and Fingleton 2012). Based on several specification tests (see table A1 for panel unit root tests, and table A2 for specification tests in the appendix), we choose SDM as our preferred specification:

$$y_{it} = \alpha_i + \beta \ln y_{i0} + \delta x_{it} + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \sum_{j=1}^{N} \gamma w_{ij} z_{ijt} + \varepsilon_{it} \qquad \ldots(4)$$

where, γ denotes (K,1) vector of parameters of spatially lagged regressor.

The spatially lagged dependent variable in Eq. (4) may give rise to the problem of endogeneity because of its correlation with error term, ε; hence the OLS estimates can be biased and inconsistent. Therefore, we estimate Eq.(4) using the maximum likelihood method (see, Anselin 1995; Lesage and Pace 2009).

Most studies identify spatial spill-overs by just looking at the direction and magnitude of regression coefficients. However, the spatial models have a complicated dependence structure due to which a change in an explanatory variable in a district influences not only its own dependent variable but also of all other districts indirectly. For example, a change in per capita income of a district influences per capita incomes of its neighbours (spill-over effect) which in turn impact per capita incomes of their neighbours, including the district itself (feedback effect). Therefore, a partial derivative of the dependent variable with respect to explanatory variables can provide a better interpretation of spatial effects (LeSage and Pace 2009). For this, we denote Eq. (4) in a matrix form without subscripts:

$$y = (1-\rho W)^{-1}(\alpha + \delta x + W\gamma z + \beta y) + (I-\rho W)^{-1}\varepsilon \quad \ldots(5)$$

The matrix of partial derivative of y with respect to k^th^ variable at a point of time can be written as:

$$\frac{\partial y}{\partial x_k} = (I-\rho W)^{-1}(\delta_k I_N + \gamma_K I_N + \gamma_k W) \quad \ldots(6)$$

Eq. (6) provides decomposition of the total effect into: direct (diagonal elements of the matrix) and indirect (off-diagonal elements of the matrix) effect, that enable us to know whether or not the per capita income of a district is influenced more by its neighbours relative to its own.

Spatial dependence in economic growth

Exploratory analysis

Moran's I is a commonly used measure to detect spatial autocorrelation in a data series. It provides whether distribution of a variable is clustered, dispersed, or random. The global form of Moran's I can be written as:

$$Global\,Moran's\ I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \quad \ldots(7)$$

where, is an element of spatially weighting matrix **W** corresponding to districts i and j; ȳ is mean of the variable of interest, and N is the number of districts. Moran's I can be interpreted as a measure of covariance of observations in the neighbouring districts relative to the variance of observations across districts. A value of Moran's I closer to unity indicates clustering of spatial units.

Moran's I provides for global spatial autocorrelation. However, the possibility of spatial clustering around a district cannot be ruled out, which needs to be identified. For the purpose, we estimate local Moran's I:

$$Local\,Moran's\ I = \frac{(y_i-\bar{y})\sum_{j=1}^{n} w_{ij}(y_j-\bar{y})}{\sum_{i=1}^{n}(y_i-\bar{y})^2/n} \quad \ldots(8)$$

In absence of global spatial autocorrelation, local Moran's I identifies districts that exhibit significant deviation from spatial randomness; and in presence of global spatial autocorrelation, it identifies districts that contribute most to overall pattern of spatial clustering.

Figure 3 shows global Moran's I for the level and growth of per capita income, estimated using row-standardized inverse distance spatial weights matrix[2]. The value of global Moran's I for per capita income is positive and highly significant, indicating a strong spatial dependence in per capita income, i.e., the rich districts are located nearer to other rich districts, and the poor districts are in neighbourhood of other poor districts. For income growth, Moran's' I is positive and highly significant, but has a smaller value than for income level, which indicates a stronger spatial dependence in income level than in its growth. Further, we find Moran's I rising between 2001 and 2007, that indicates increasing spatial clustering of districts during this period.

Figure 3 also plots standard deviation of log per capita income, a measure of σ-convergence. The standard deviation rises until 2007, but slows down afterwards. The correlation between Moran's I and standard deviation is positive (0.68) during 2001-2007 and negative (-0.71) during the latter period, that respectively indicate positive and negative co-movements. Rey and Montouri (1999) contend that such a co-movement represents dynamic characteristic of spatial clustering on account of (i) clusters becoming more homogeneous, and (ii) emergence of new clusters during the period of increasing income dispersion. Accordingly, our results show that clusters have become relatively more homogeneous, but at the same time income differences among clusters have also increased.

Global Moran's I ignores potential instability of local units. We, therefore, investigate whether overall distribution of incomes is spatially concentrated; and if it is concentrated, then where — among the rich or the poor districts. Local Moran's I for each observation

[2] To check whether our results are robust to the specification of spatial matrix, we also examine spatial dependence using contiguity matrix. The results are almost similar as from inverse distance matrix.

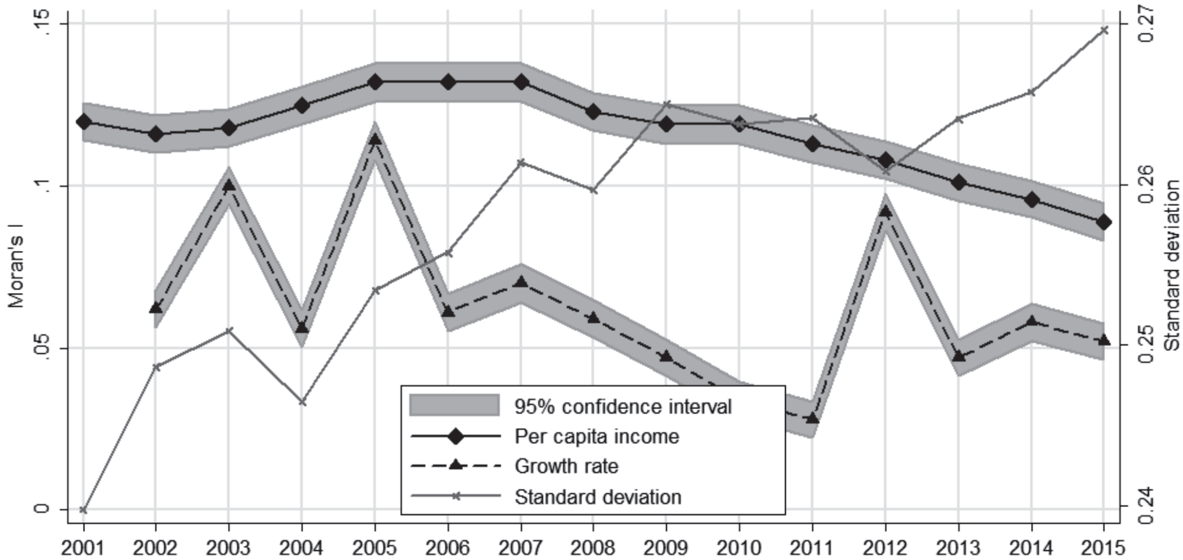

Figure 3 Global Moran's I and standard deviation in per capita income across districts

indicates the extent of spatial clustering of similar values around that observation (Anselin 1995). This helps us to deduce statistical significance of the pattern of spatial association at that location. Figure 4a and 4b respectively show local Moran's I for 2001-03 and 2013-15. We observe four types of local spatial associations: (i) a high-income district having high-income neighbours (HH); (ii) a low-income district having high-income neighbours (LH); (iii) a low-income district having low-income neighbours (LL); and (iv) a high-income district having low-income neighbours (HL). HH and LL exhibit positive local spatial autocorrelation, leading to formation of spatial clusters; and HL and LH show negative local spatial autocorrelation, and therefore these are spatial outliers. From the analysis of local Moran's I, we conclude that the local pattern of spatial association does contribute to the global trend of positive spatial association. A majority of local indicators that are significant fall either in HH or LL cluster, and the remaining that show negative spatial association fall in HL or LH cluster. This suggests that deviations from the global trend are not dominated by any particular form of negative spatial relation. From this analysis, we detect two distinct clusters in our data — one consisting of low-income districts spread over the eastern and central states (West Bengal, Bihar, Jharkhand, Uttar Pradesh, Chhattisgarh and Madhya Pradesh); and another comprising of high-income districts from the coastal states of Kerala, Goa, Maharashtra, Gujarat, Karnataka,

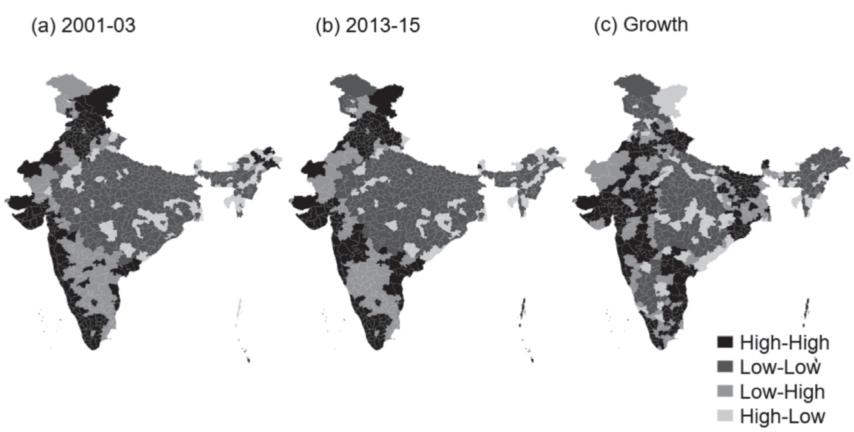

Figure 4 Local Moran's I for level and growth in per capita income

Tamil Nadu and Andhra Pradesh, and the northern states of Punjab, Haryana, Himachal Pradesh and Jammu & Kashmir. And, these clusters have persisted in 2001-03 as well as in 2013-15. This pattern is expected, as most districts in LL cluster lie in the states that are highly populated, less urbanized, poor in human capital and infrastructure, and have low level of agricultural productivity. On the other hand, most districts in HH cluster have high rates of urbanization and are better-endowed in human capital and infrastructure.

Spatial spill-overs, structural transformation and convergence

For selection of a model that best fits to the data at hand, we follow LeSage and Pace (2009) and Elhorst (2010) and proceed from a general to a specific approach. First, we examine whether the SDM as a general specification is more appropriate than nested models viz., SAR and SEM, and for this we conduct LR tests. For the non-nested models we rely on information criteria, i.e. AIC and BIC. This approach allows us to choose a spatial specification that incorporates all three types of interaction effects, i.e., endogenous interaction effects of dependent variable, exogenous interaction effects of explanatory variables, and interaction effects of error terms. Results are presented in Table A2 in the appendix. Hausman test rejects random effects model in favour of fixed effects model. Wald statistics for spatial terms is highly significant and endorses our preference for spatial models over non-spatial fixed effects model. If and , then SDM reduces to SAR; and if , then SDM collapses to SEM. LR tests reject the null hypotheses , and . The information criteria show superiority of SDM over SARAR.

SDM allows us to statistically identify spatial dependence structure that best fits to the data. It provides unbiased estimates even if the true data-generating process is SAR or SEM. Further, the spatially lagged regressors control the bias due to omitted variables if these are first-order spatially correlated with regressors (LeSage and Pace 2009). Further, the spill-overs from SDM are of global nature, i.e., a change in a regressor in a district is transmitted to all other districts irrespective of whether or not these are connected as per the spatial matrix **W**.

Table 2 compares estimates of SDM versus non-spatial fixed effects models. The regression coefficient of per capita income from the non-spatial fixed effects model is negative and highly significant (col. 2), indicating absolute convergence in economic growth. This is contrary to the evidence of divergence reported in several other studies. Further, we proceed to estimate -convergence incorporating spatial dependence, and the results are shown in colum 3 of Table 2. The spatial autoregressive coefficient, , is positive and significant, which confirms presence of spatial linkages in economic growth. The coefficient of per capita income is significantly negative and larger, almost four times of the one estimated from the non-spatial fixed effects model. This clearly reveals presence of strong spatial linkages in India's economic growth.

Spatial correlation could arise due to differences in economic structures, resource endowments, physical infrastructure and institutions across spatial units. Therefore, we estimate SDM incorporating the GDP shares of economic sectors, literacy rate and financial outreach. First, we augment the spatial β-convergence equation by literacy and banking variables. Regression coefficient of literacy is positive, but insignificant (col. 4). Banking variable is significant but negative, which is contrary to our expectation. Banerjee and Banik (2014) also report similar evidence. Nevertheless, these developmental indicators are not found to impact much the speed of convergence.

Further, we augment SDM by incorporating GDP shares of agriculture and services sectors, independent of development indicators. The speed of convergence now rises by about 25% (col. 5). However, the regression coefficients of agriculture and services are opposite — agriculture enhances speed of convergence, while services sector does not. This contradiction can be explained looking at the geographical concentration or spread of these sectors. Agriculture engages about half of India's labour force, and over time it has also undergone a significant technological transformation. On the other hand, services sector has remained concentrated in or around the urban centres. Ghani et al. (2011) and Desmet et al. (2015) also show that in India's services sector agglomeration forces dominate dispersion forces in larger urban centres.

A change in an explanatory variable in a district influences not only the growth of the district itself but

Table 2 Estimates of non-spatial fixed effects regression and spatial Durbin model

	Non-spatial	Spatial Durbin Model			
		Absolute convergence	Conditional convergence	Conditional convergence	Conditional convergence
Ln GDP per capita$_{t-1}$	-0.02992***	-0.1125***	-0.1150***	-0.13995***	-0.1442***
	(0.0025)	(0.0052)	(0.0052)	(0.0052)	(0.0052)
% share of agriculture in GDP				0.18226***	0.1864***
				(0.0195)	(0.0195)
% share of services in GDP				-0.21964***	-0.2193***
				(-0.0194)	(0.0194)
Literacy rate (%)			0.0001		2.72E-05
			(0.0000)		(2.98E-05)
No of bank offices per thousand population			-0.00001**		-5.86E-07***
			(0.00001)		(1.19E-07)
Constant	0.36052***				
	(0.02491)				
Rho		1.27571***	1.28296***	1.29786***	1.28753***
		(0.0215)	(0.0218)	(0.0238)	(0.0239)
Spatial lag of regressors					
Ln GDP per capita$_{t-1}$		0.11867***	0.11543***	0.13142***	0.0215
		(0.0059)	(0.0068)	(0.0078)	(0.0163)
% share of agriculture in GDP				-0.83184***	-0.95747***
				(0.0958)	(0.1178)
% share of services in GDP				-0.23378*	-0.68527***
				(0.0930)	(0.1253)
Literacy rate (%)			-0.0002		0.00072*
			(0.0003)		(0.0003)
No. of bank offices per thousand population			0.0000		-0.00001***
			(0.0000)		(0.0000)
Number of observations	8960	8960	8960	8960	8960
BIC	-25292.7	-25576.2	-25556.2	-26129.7	-26136.8
AIC	-25306.9	-25604.6	-25613.1	-26186.5	-26207.8

All regressions include district fixed effects. Figures in parentheses are standard errors robust to heteroscedasticity and within-district serial correlation.
***, ** and * indicate significance at the 1%, 5% and 10%, respectively.

of the neighbouring districts also. The total effect of an explanatory variable is, therefore, sum of its coefficient in the upper panel of Table 2 and coefficient on its spatial lag in the lower panel (Atella et al. 2014). The decomposition of total effect into direct effect (partial derivative) and indirect effect (cross-partial derivative or spatial spill-over effect) is a straightforward way to analyse economic growth across district boundaries, that is, whether the per capita income of a district is influenced more by its neighbours relative to its own. Direct effect provides impact of a change in an independent variable of a district on its own dependent variable. It also generates feedback effect due to its impact passing through neighbouring districts and back to the district of its origin. Indirect effect captures impact of a change in an independent variable on the dependent variable of neighbouring districts, that is, the spill-over effects.

Table 3 presents estimates of direct, indirect and total effects. The direct as well as indirect effects of literacy

Table 3 Marginal effects

	SDM with lagged GDP			SDM with development indicators			SDM with sectoral share			SDM with all regressors		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Lag GDP	-0.113***	0.062***	-0.051***	-0.11515***	0.0.078***	-0.038***	-0.140***	0.112***	-0.028**	-0.144***	0.118***	-0.026**
	(0.005)	(0.007)	(0.006)	(0.005205)	(0.010)	(0.010)	(0.005)	(0.011)	(0.011)	(0.005)	(0.011)	(0.011)
% share of agriculture							0.181***	1.333***	1.513***	0.185***	1.394***	1.580***
							(0.019)	(0.240)	(0.244)	(0.019)	(0.247)	(0.251)
% share of services							-0.221***	1.161***	0.941***	-0.220***	1.290***	1.070***
							(0.019)	(0.244)	(0.247)	(0.019)	(0.257)	(0.260)
Literacy rate				0.00004	0.00003	0.000031				0.00003	0.00064	0.00068
				(0.00003)	(0.0007)	(0.00070)				(0.00003)	(0.00066)	(0.00067)
No. of offices per thousand population				-3.73E-07**	0.00003	2.36E-06**				-5.04e-07***	5.03e-06***	4.52e-06**
				(1.29E-07)	(0.00002)	(1.12E-06)				(1.24e-07)	(1.43e-06)	(1.44e-06)

Standard errors in brackets. ***, ** and * indicate significance at the 1%, 5% and 10%, respectively.

are positive, but negligible. These are also negligible for banking variable, but go in opposite direction — direct effect is negative, while indirect effect is positive and dominates the direct effect. The direct and indirect effects of agriculture are positive and significant, implying that a positive change in agriculture in a district not only contributes its own economic growth but also to the economic growth of other districts through global spill-overs. Interestingly, its indirect effect dominates the direct effect, and its feedback effect (i.e., difference in regression coefficient and direct effect) is also quite large. This indicates that there are considerable spatial spill-overs of agricultural growth on Indian economy. On the other hand, the direct as well as indirect effects of services sector are significant, and also go in opposite direction — direct effect is negative and indirect effect is positive. This indicates that a positive change in services sector in a district reduces its own growth, but creates positive global spill-overs. Its feedback effect, however, is negligible. These results are as expected. There is considerable heterogeneity in India's services sector, in terms of activities, locations, and requirements of capital and skills; and therefore it is possible that the growth of an economic activity in a district is constrained by shortage of resources and skilled manpower, and also by regulations and policies regarding investment, employment, wage rates, fiscal incentives, etc.

Figure 5 shows 'how direct and indirect effects of structural transformation have evolved? The direct effect of agriculture remains positive and almost constant throughout 2001-2015. This could be attributed to stagnation in adoption rates of technologies or lack of a technological breakthrough. On the other hand, its spill-over effects have slowed down probably on account of poor flow of information, lack of market integration, financial constraints, etc. Nonetheless, these findings suggest a need for greater investment in agricultural research, and strengthening its linkages with extension systems. On the other hand, the direct effects of services have remained negative throughout, but have weakened over time. Its spill-over effects too have diminished. These findings conform to those reported in Ghani et al. (2011) that show that India's services sector has remained concentrated in and around urban centres, depriving rural populations of the benefits of its rapid growth.

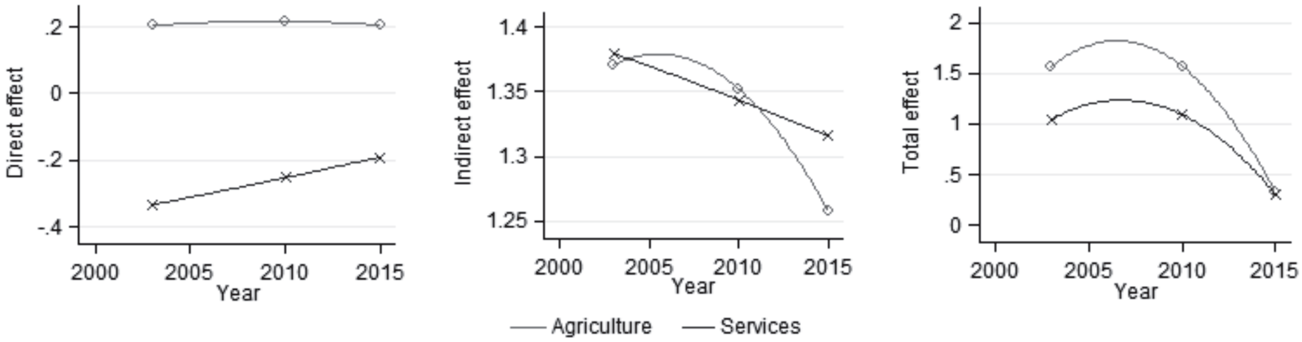

Figure 5 Trends in direct and indirect effects of agriculture and services sectors

Conclusions

Using a panel of district-level data for 2001-2015 this paper has demonstrated 'how spatial dimension influences regional dynamics of economic growth in India'. Three important conclusions emerge from this study. One, contrary to the evidence of divergence in income growth across states as reported in several studies, we find an evidence of absolute convergence in per capita income across districts even without considering spatial effects. But, there are significant spatial effects on economic growth, leading to a significant acceleration in its speed of convergence. Two, driven by technological change, agriculture generates positive spill-overs on economic growth, but these have remained constant over time. Three, services sector does not influence much the speed of convergence in economic growth.

These findings have some important policy implications for reducing regional disparities in economic development. First, policies and strategies should target improving spatial interconnectedness by investing more in infrastructure, markets and communication networks; and it should be accompanied by dismantling of regulatory barriers allowing inter-regional trade and free flow of capital and labour, and diffusion of technologies or knowledge. Second, agriculture has potential to accelerate economic growth of poor regions through its spill-over effects. In these regions, agriculture is subsistence-oriented and faces several technological, informational, financial, infrastructural and market constraints, that need to be addressed to accelerate agricultural growth. Three, services sector has remained concentrated in few pockets in and around metropolitan cities, perhaps due to better logistics and availability of skilled manpower, depriving rural areas of benefits of its rapid growth. This implies a need to identify skill requirements of different activities in the sector, and accordingly to invest in human capital and infrastructure to attract private investment for broadening the base of services sector beyond urban centres. Finally, although human capital and financial outreach are not found to impact much the speed of convergence, their importance as facilitators of economic growth should not be undermined.

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Appendix table 1 Panel unit root tests

	H0: All panels contain unit roots H1: Some panels are stationary (lags chosen to minimize AIC)		H0: Panels contain unit roots H1: Panels are stationary (lags chosen to minimize AIC)		H0: All panels contain unit roots H1: At least one panel is stationary (lags 2)	
	IPS (z-t-tilde-bar)	p-value	HT (rho)	p-value	Fisher (modified inverse chi2 Pm)	p-value
GDP growth	-44.02	0.00	-0.22	0.00	59.52	0.00
Proportion of agriculture in GDP	-27.84	0.00	0.40	0.00	28.58	0.00
Proportion of services in GDP	-19.95	0.00	0.52	0.00	25.23	0.00
Literacy rate (%)	-3.2	0.00	2.46	0.00	136.53	0.00
No. of bank offices per thousand population	-	-	3.97	0.00	6.10	0.00

Appendix table 2 Specification tests

	Chi^2	p value	AIC	BIC
Wald test for inclusion of spatial terms (7)	9032.7	0.00		
Hausman specification test: Fixed effects vs Random effects (9)	189.20	0.00		
Modified Wald test: SDM vs SAR ($\gamma = 0$ and $\rho \neq 0$)	721.47	0.00		
Modified Wald test: SDM vs SEM ($\gamma = -\delta\rho$)	54.59	0.00		
Information criteria for SDM			-27466.1	-27419.5
Information criteria for SARAR			-27395.1	-27369.8