Sustainable Growth in India: Study of Converging Regional Incomes

Abhishek Behl,
Junior Research Fellow, Symbiosis Institute of Research and Innovation, Symbiosis International University, Pune

Dr. Manju Singh,
Professor and Head-PhD Program and Research Projects, Symbiosis International University, Pune

Abstract

Increasing economic disparities among both people and regions are always an issue of great concern. Reducing regional economic disparity and ensuring balanced development is crucial in maintaining political stability of countries with federal polity. The findings of studies concerning regional disparities are thus essential in the promotion of balanced regional development. A study of this kind assumes special significance for India as the sustainability of growth momentum of one of the fast growing economies of the world relies on the political stability of Indian federal polity. The research outcome of regional disparity analysis is, however, often ambiguous and is not robust to choice of strategies, namely â and ó convergence analysis. The regression based theoretically appealing â convergence approach has not given adequate attention to spatial effects. This study estimated parameters of Bayesian Spatial Durbin Model using state wise real per capita Gross State Domestic Product (GSDP) data computed from Central Statistical Organization (CSO) during the period 1980 – 2010. The study concludes that the later reform period has witnessed beta convergence due to feedback effect. The debate of convergence of â in Indian scenario is explained using inclusion of spatial effects in this study.

Keywords: *Bayesian Econometrics, Convergence,Spatial Durbin Model*

1. Introduction

Increasing economic disparities among both people and regions are always an issue of grave concern. β Reducing regional economic disparity and ensuring balanced development is crucial in maintaining political stability of countries with federal polity. The findings of studies concerning regional disparities are thus essential in the promotion of balanced regional development. A study of this kind assumes special significance for India as the sustainability of growth momentum of one of the fast growing economies of the world relies on the political stability of Indian federal polity. The regional convergence analysis adopts two approaches namely β & convergence approach. Of the two approaches, convergence approach (Barro & Sala-i-Martin, 1996) is widely preferred for its roots in neoclassical analysis. However, the traditional regression models of convergence strategy have not acknowledged the spatial effects namely spatial dependence and spatial heterogeneity. This second section of this paper reviews the convergence approach in regional convergence analysis. The inclusion of spatial effects in this approach, the empirical issues related to that approach, and the interpretation of the model is discussed in this section.

This study proposes a framework of convergence approach that incorporates the concerns of spatial effects and accounts for the presence of spatial dependence and spatial heterogeneity. The section three explains the data source and methodology used in the study i.e Spatial Durbin Model, a variant of spatial autoregression model using state-wise per capita income data during 1980-2010 is estimated and the results of the same is presented. Section four discusses the obtained result and section five concludes.

2. convergence approach

Conventionally the regional convergence is assessed in convergence and convergence framework (Barro & Sala-i-Martin,1995, Sala-i-Martin, 1996). The ó convergence is bound to exist when the dispersion of real per capita income across regions fall over time. On the other hand, convergence is presumed when there is a negative correlation between growth in income over time and its initial level. Among the two, regression based convergence approach is widely used compared to dispersion measure based convergence approach because of its proximity to neo classical theoretical analysis. In a typical convergence approach, a neo classical growth equation, on cross sectional data is used. The regression model used in this approach may be given as

$$\frac{y_{it} - y_{io}}{y_{io}} = \alpha + \beta y_{io} + u_i$$

where y_{it} is the income of the i^{th} state at time 't'; y_{io} is

the income of the state at the initial year. So, is

the growth of state at time 't'.

In this approach, the coefficient of y_{i0}, is assessed for its statistical significance and for its sign to infer about convergence. The estimation of to be negative and statistically significant, points to confirmation of convergence in this approach. In other words, the lower initial income region has a higher growth rate as compared to regions with a higher initial income. The statistical insignificance or the positive co-efficient and its significance would suggest rejection of β convergence.

Another variant growth regression involves logarithm differences and more explanatory variables in addition to the principal variable, initial income (Barro & Sala,1992). The presence of β convergence in this framework is taken as the incomes of all regions converge to each of its steady state (conditional β convergence).

where i (i=1, …, n), 0, and T are the indices that denote region, initial period, and final period respectively; y denotes the income; $T^{-1} \times \ln(y_{it}/y_{i0})$ is the growth rate; x_i is a vector of m structural/ control variables of the region ; $\aa_i$'s are i.i.d. errors

2.1 β convergence and spatial effects

The growth is determined by large number of observable and unobservable factors and so parsimonious models are likely to result in specification error. The spatial lag term is likely to imbibe information of those variables. Therefore, the importance of inclusion of spatial effect viz., spatial dependence and spatial heterogeity within the growth equation framework was stressed in convergence analysis (Seya et al., 2012). However, it was pointed out that the spatial dependence issue was handled in an adhoc manner such traditional general econometric analysis (Fingleton &Lopez-Bazo, 2006). A systematic effort was made to include the spatial dependence using economic spillover models (Egger & Pfaffermayr, 2006). It was suggested that various spatial autoregression models(SAR) offer sufficient scope for the inclusion of spatial dependence or spatial spillover effects into growth equation models.

Different spatial auto regression models (SAR) were considered in the literature. The difference was essentially charecterised by the inclusion of spatial lag terms for the different explanatory variables components in the growth regression namely, initial income variable, structural variable and control variables(Lopez-Bazo et al., 2004; Ertur and Koch, 2007; Basile, 2008). Kakamu(2009) has favoured the inclusion of spatial lag for dependend and for all the explanatory variable to address the issue of spatial dependence. This type of models in literature is called Spatial Durbin Models (SDM).

The growth equation model in SDM framework is likely to be afflicted with heteroscedastic error as the growth determinants of spatial units would vary and would be difficult to specify (Seya et al., 2012). In turn, the estimates in the presence of such hertoscedasticity would be inefficient. This is serious in convergence testing as statistical significance of is prime concern in deciding on the issue of convergence. Further, the inclusion of spatial lag variables in SDM would tend to increase the risk of multicollinearity problem in the growth regression (Kakamu, 2009).

Different approaches to address those issues of estimation in this framework were considered. One strategy suggested to address the concerns in the estimation was panel data approach (Lopez-Rodrigues, 2008; Parent and LeSage 2010). But this approach suffers from data availability as preparing a data set of explained and explanatory variables for all the years was not always possible. The second approach to address the issue of spatial heterogeneity in the spatial Durbin framework was using Maximum Likelihood Estimators (MLE) but was found to suffer from loss of degrees of freedom (Seya et al., 2012). The third approach that uses Bayesian Econometrics was found to provide strategy to address the issue of spatial dependence, spatial heteroscedasticity and loss of degrees of freedom at once (Geweke, 1993). This strategy is also found to provide robust estimates in the presence of multicollinearity. For this study, the third approach observed to be appealing. The details of the methodology used in this study are discussed below:

2.2 Bayesian approach to estimation of SDM

The Bayesian approach to estimate Spatial Durbin Model was described by Seya et al.(2012). The SDM model is defined as

$$Y^* = \rho W Y^* + \alpha \iota + \boldsymbol{\beta}\, Y_0 + \theta W Y_0 + X\gamma + WX\xi + \varepsilon,$$

where Y* is an n×1vector whose elements are given by $T^{-1} \times \ln(y_{i,T}/y_{i,0})$; é is an n×1 vector with all elements equal to 1; Y_0 is an n×1 vector whose elements are given by $\ln(y_{i0})$; WY* is an n x 1 vector whose elements are spatial lag for Y*; X is an n×m structural and control variables matrix; WX is an n x m matrix whose elements are the spatial lags of structural and control variables; å is an n×1 vector of i.i.d. errors; W is a row- standardized spatial weight matrix of order n; ñ is the spatial dependence parameter.

In sum, in this framework the issue of spatial dependence is accounted by the spatial lag terms of explained and explanatory variables and the issue of spatial heterogeneity is addressed through employing the Bayesian estimates (LeSage, 1997; Pace and Barry, 1998).

The Bayesian estimation approach would require specification of three components namely, the prior distribution, likelihood function and the posterior distribution. The prior distributions are used to express the prior beliefs of the researcher on the parameters in terms of a probability distribution. Each of the parameters in the model needs to be assigned with a prior. The priors are of two types namely non informative / diffuse / ignorant priors and informative priors. The information about each of the parameters may be defined in terms of appropriate prior distributions, viz., normal, inverse gamma and chi-square distributions.

The joint probability density function of error terms in the growth equation characterizes the likelihood function. The product of likelihood of each sample point would give likelihood of sample. The likelihood function would be a function of regression co-efficients, error variance and the spatial autocorrelation measure. Hence, the log likelihood function of the sample could be written as,

$$L(\beta, \sigma, \rho, Y^*, X) = (2\pi)^{-n/2} \sigma^{-n} |I_n - \rho W| \exp\{\frac{-1}{2\sigma^2}(\varepsilon\varepsilon')\}$$

$$\text{where } \varepsilon = [I_n - \rho W](Y^* - X\beta)$$

The posterior distributions summarize information about different parameters of the model are drawn from the posterior distributions. The estimation and statistical inference in the Bayesian tradition the posterior distributions are derived by multiplying the likelihood function with the prior distribution function. The conditional posterior distribution of each parameter is derived using either Gibbs Sampling Algorithm or Metropolis-Hastings Algorithm.

2.3 Deriving posterior density for the coefficients of growth equation model in SDM

The Spatial Durbin Model could be rewritten as

$$[I_n pW]Y^* = Z\phi + \varepsilon,$$

Where

$$Z = [\iota Y_o WY_o XWX] and\, \phi = [\alpha \beta \theta \gamma \xi],$$

To derive full prior distribution of this model, all the parameters of the model need to be specified. The parameters of interest in this model consists of regression co-efficient , spatial dependence parameter, error variance and relative variance co-variance of stochastic error term(V)

If the prior distributions are assumed to be independent, the joint prior distribution of the parameters used in the model may be given as

$$\pi(\phi\rho, \sigma^2_\varepsilon, V) = \pi(\phi).\pi(\rho).\pi(\sigma^2_\varepsilon).\pi(V)$$

The priors for the above parameters and justifications for the same is given in Seya et al(2012). The following are the priors for the parameters:

(i) $\rho \sim unif(-1,+1)$, a uniform prior

(ii) $\phi \sim$ a diffuse prior

(iii) $\sigma^2\varepsilon \sim$ a standard diffuse prior

iv) $v_i^{-1}|q \sim iid\, x^2(q), v_i$ is the i^{th} element in the diagonal of V, the relative variance covariance matrix.

v) $q \sim T(a_q, b_q)$, a Gamma prior, the parameter q characterizes the distribution of v_i.

Joint posterior distribution function of the parameters may be got from the product of the respective prior and likelihood functions. Full conditional prior for various parameters in the model may be derived as given below:

a)The full conditional prior for ϕ

$\pi(\phi\rho, \sigma^2_\varepsilon, V, q) \alpha N(r, S)$ Normal distribution, where

$$r = [\sigma_\varepsilon^{-2} Z' V^{-1} \overline{Y}]$$

$$S = [\sigma_\varepsilon^{-2} Z' V^{-1} Z]^{-1}; and\, \overline{Y} = (I_{n-\rho} W)Y$$

b) The full conditional prior for σ^2_ε

$$\pi(\sigma^2_\varepsilon|\rho, \sigma^2_\varepsilon, V, q)\, \alpha\, IG[\frac{n}{2}, \frac{ev^{-1}e}{2}],$$

Inverse Gamma Distribution

$$\pi(\sigma^2_\varepsilon|\rho, \sigma^2_\varepsilon, V, q) \propto IG[\frac{n}{2}, \frac{e'V^{-1}e}{2}]$$, Inverse Gamma Distribution

(c) The full conditional posterior for v_i in V

$$\pi\left(\frac{\sigma_\varepsilon^2 e_i^2}{v_i}\middle|, \rho, \sigma_\varepsilon^2, V_{-i} q\right) \alpha \, \text{iid} \, x^2(q+1)$$

Chi square distribution

e_i is the i^{th} element of e & v_{-i} denotes the vector of all diagonal elements except v_i

d) The full condition posterior for ρ

$\pi(\rho \mid \phi, \sigma_\varepsilon^2, V, q) \alpha \mid I - \rho W \mid \exp\{\frac{-1}{2\sigma^2}(eV^{-1}e)\}$ is a kernel of distribution

(e) The log of the full condition posterior distribution for q

$$\pi(q \mid \rho, \phi, \sigma_\varepsilon^2, V) = \text{constant} + \frac{nq}{2} \ln(\frac{q}{2}) - n \ln \Gamma(\frac{q}{2}) - (Kq - (a_q - 1) \ln(q)$$

where $K = \frac{1}{2} \sum_{i=1}^{n} \{In(v_i) + \frac{1}{v_1}\} + b_a$

The samples for the distributions [a]-[c] are generated with Gibbs Sampler, and the distributions [d]-[e] are generated with Metropolis – Hastings Algorithm (M-H Algorithm). These samples were used for the further analysis.

2.4 Interpreting the Spatial Durbin Model:

The traditional convergence approach draws its inference solely from the coefficient of initial income variable (Y_0), for spatial Durbin model this interpretation is not valid (LeSage and Fischer 2008; Fischer 2010). In this model there would be two effects; one described by Y_0 and the other described by WY_0, as Y^* is affected directly by any change in Y_0 and is also affected by the feedback effect through Y. Thus, the impact of the initial value varies with location and the neighborhoods described by W. The former effect is the direct effect while the later is the indirect effect. They may be measured using the following:

$M_{direct} = n^{-1} tr(S(W)),\ S(W) = [1 - \rho W]^{-1} [\boldsymbol{\beta} I - \theta W];$

$M_{total} = n^{-1} \iota' S(W) \iota$

$M_{indirect} = M_{total} - M_{direct}$, where, $S(W) = (I - \rho W) - 1(\boldsymbol{\beta} I + \theta W)$.

3. Methodology and data source

This study analyzed the regional disparity among 17 major states viz., Andhra Pradesh, Assam, Bihar, Goa, Gujarat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh and West Bengal, using the state-wise data on Gross State Domestic Product (GSDP) at 2004-05 constant prices, obtained from the Ministry of Statistics and Programme Implementation. The per capita income was calculated using the projected state-wise population data from the report of the Registrar General of Census, Government of India. The spatial weight matrix was computed based on row standardized binary contiguity matrix.

The Bayesian approach to Spatial Durbin Model was estimated with the help of Spatial Econometric Toolbox for MATLAB developed by LeSage and Pace (2009) for the three periods viz., [a] 1980 – 1991 (pre reform period); [b] 1991 – 2000 (early reform period); and [c] 2000 – 2010 (later reform period).

This study used proportion of agriculture in per capita GSDP, proportion of industry in per capita GSDP and tertiary to industrial sector outputs ratio as structural variables, apart from the usual growth equation variables. The marginal likelihood was computed using method developed by Gelfand and Dey (1994).

4. Results and Discussion:

The results are given in the table 1 for all the 3 periods and the t value of the same is given. The statistic values suggest that the samples were successfully converged to the posterior distribution.

Table 1: Results of parameter estimation of Spatial Durbin Model for various time periods

Estimated Parameters of Spatial Durbin Model	Pre Reform period	Early Reform period	Later Reform period
Initial Income	-0.0123	0.0121	0.0078
	(6.2709)	(9.1792)	(9.7654)
Proportion of Agriculture	(0.0514)	(0.0909)	(0.0908)
	(2.1626)	(13.3185)	(6.8347)
Proportion of Industry	0.0016	-0.0135	-0.0319
	(0.0319)	(1.0391)	(1.2785)
Tertiary – Industry Ratio	-0.0054	0.0048	-0.0026
	(1.5013)	(3.4152)	(1.0669)
Spatially lagged initial income	0.0196	0.0336	-0.0184
	(4.7171)	(7.0966)	(7.4311)
Spatially lagged proportion of agriculture	0.0350	-0.0969	-0.1727
	(0.9213)	(3.2758)	(8.4939)
Spatially lagged proportion of industry	-0.1741	-0.1239	-0.3973
	(1.6124)	(2.3915)	(7.0927)
Spatially lagged tertiary industry ratio	-0.0287	0.0066	-0.0402
	(3.6079)	(1.3946)	(7.3162)
Constant	0.0636	-0.3184	0.4222
	(0.6921)	(4.6158)	(6.3473)
Spatial Dependence measure - Rho (ρ)	0.1030	-0.3143	-0.1462
	(14.0658)	(36.4325)	(16.6499)
Error variance σ_ε^2	0.0027	0.0012	0.0015
	(3.0117)	(1.8254)	(2.9036)
R^2	0.7894	0.4583	0.4279

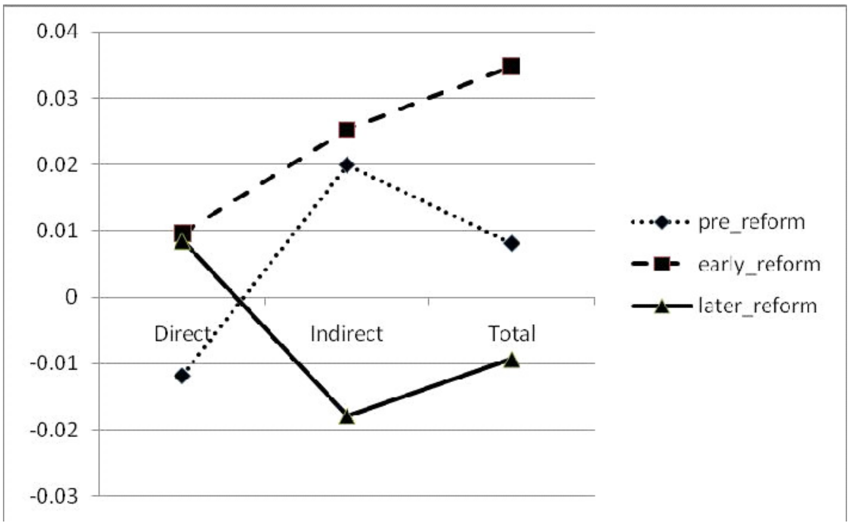
β

Source: Author's calculation based on the methodology
Note: The t-values of the respective coefficients are given in the parenthesis.

The estimation of ñ was positive for the first period. This could mean that the neighboring regions have evolved similarly especially over this period. The estimate for the initial income was negative only for the pre reform period. But for the other two periods the coefficients were positive and significant. However, the convergence hypothesis should not be tested with these estimates. For all the periods the coefficient of agricultural proportion was negative and significant. In the first period coefficient of industrial proportion and of the tertiary-industry ratio the same was positive and negative respectively but not significant. In the early reform period, the coefficient of industrial proportion was found to be negative and insignificant. The tertiary – industry ratio was significantly positive. In the later reform period, the coefficient of proportion of agriculture was found to be negative and statistically significant but for the other two variables, it was not statistically significant.

As mentioned in the methodology, in the spatial Durbin model, convergence hypothesis cannot be tested using the values of in the growth regression. Therefore, the direct, indirect and total effects were derived from results of the analysis.

Figure 1 Decomposition of the overall effect of Y_0 on Y^* into direct and indirect effects (1980–2010)



Source: Authors calculation based on methodology.
Notes: Pre reform period represent the years 1980 to 1991; Early reform period represent the years 1991to 2000; Later reform period represent the years 2000 to 2010

The figure suggests that in the pre reform period direct effect was negative but the indirect effect was found to positive and the overall effect was positive. In the early reform period all the effects (direct / indirect / total) were positive. In the later reform period, though the direct effect was found to be positive, the indirect and overall effect was found to negative and hence a confirmation of beta convergence. In the pre reform and early reform periods the total effect suggesting the negation of beta convergence. The convergence studies of regional income conclude convergence in pre reform and non convergence in post reform periods. The direct effect of the growth equation is observed and interpreted in traditional β convergence studies. However, due to the feedback/ indirect effect, the total effect suggests that the later reform period alone witnessed convergence though the pre reform period witnessed non convergence. The negative indirect effect suggests the non existence of spillover effects. Thus, the result of this paper is able to explain irreconcilable outcomes found in the debate around convergence analysis.

5. Conclusions

The study reviewed various growth models and contends that Spatial Durbin Model of Fingleton and Lopez-Bazo(2006) was empirically suitable. In this framework the regional income disparity using real percapita GSDP data in India during the pre early and later reform periods is analysed. The study estimated parameters of Bayesian Spatial Durbin Model for the three periods viz., pre reform (1980-1991), early reform (1991-2000) and later reform (2000-2010) periods. The convergence hypothesis is tested in the light of LeSage and Fischer (2008) formulation. The results suggest that the convergence does not hold from the pre-reform and early reform periods. But the later reform period indicate regional convergence. The later reform period witnessed beta convergence due to feedback effect. The contemporary debate was only involving direct effect, and overlooked the indirect and total effects. The inclusion of spatial effects in convergence analysis helped to address the econometric issues such as violation of sphericity assumption and to resolve the raging debate in convergence analysis.

References :

1. Barro R.J. and X. Sala-I-Martin, 1992. Convergence. Journal of Political Economy 100(2), 223-251p
2. Barro R.J. and X. Sala-i-Martin, 1995. Economic Growth. MIT Press:Cambridge
3. Basile, R., 2008. Regional economic growth in Europe: A semiparametric spatial dependence approach. Papers in Regional Science 87 (4), 527–544p
4. Egger P. and M. Pfaffermayr, 2006. Spatial convergence. Papers in Regional Science 85 (2), 199–215p
5. Ertur C. and W. Koch, 2007. Growth, technological interdependence and spatial externalities: theory and evidence. Journal of Applied Econometrics 22, 1023–1062p
6. Fingleton B. and E. López-Bazo, 2006. Empirical growth models with spatial effects. Papers in Regional Science 85 (2), 177–198p
7. Fischer M.M., 2010. A spatial Mankiw–Romer–Weil model: The Annals of Regional Science. Published online, DOI.doi:10.1007/s00168-010-0384-6

8. Gelfand A.E. and D. Dey, 1994. Bayesian model choice: asymptotic and exact calculations. Journal of the Royal Statistical Society B 56, 501–514p

9. Geweke J., 1993. Bayesian treatment of the independent Student-t linear model. Journal of Applied Econometrics 8, 19–40p

10. Kakamu K., 2009. Small sample properties and model choice in spatial models: a Bayesian approach. Far East Journal of Applied Mathematics 34 (1), 31– 56p

11. LeSage J.P., 1997. Bayesian estimation of spatial autoregressive models. International Regional Science Review 20, 113–129p

12. LeSage J.P., and M.M. Fischer, 2008. *Spatial growth regressions: model specification, estimation and interpretation*. Spatial Economic Analysis 3 (3), 275–304p

13. LeSage J.P., and R.K. Pace, 2009. *Spatial Econometric Toolbox for MATLAB*, Retrieved http://www.Spatial-Econometrics.com/html/jplv7.zip

14. López-Bazo E., Vayá E., and M. Artís, 2004. *Regional externalities and growth: evidence from European regions*. Journal of Regional Science 44 (1), 43– 73p

15. Lopez-Rodriguez J., 2008. *Regional convergence in the European Union: results from a panel data model*. Economics Bulletin 18 (2), 1–7p

16. Mankiw N.G., Romer D. and D.N. Weil, 1992. *A contribution to the empirics of economics growth*. Quarterly Journal of Economics 107 (2), 407–437p

17. Ministry of Statistics and Programme Implementation. State Domestic Product. (2012). Gross State Domestic Product at factor cost, 1980-2013 [Data file]. Retrieved from http://mospi.nic.in/Mospi_New/upload/SDPmain_04-05.htm

18. Pace R.K., R. Barry, J.M. Clapp, and M. Rodriquez, 1998. *Spatiotemporal autoregressive models of neighborhood effects*. The Journal of Real Estate Finance and Economics 17 (1), 15–33p

19. Parent O. and J.P. LeSage, 2010. *Spatial dynamic panel data models with random effects*. Presented at the Fourth World Conference of the Spatial Econometrics Association, Chicago, 9–12 June, 2010

20. Sala-i-Martin X., 1996. *Regional cohesion: Evidence and theories of regional growth and convergence*. European Economic Review 40, 1325-1352p

21. Seya H., M.Tsutsumi, and Y. Yamagata, 2012. *Income convergence in Japan: A Bayesian spatial Durbin model approach.* Economic Modeling 29(1), 60-71p

22. Watanabe T., 2001. *On sampling the degree-of-freedom of Student's-t disturbances*. Statistics & Probability Letters 52, 177–181p