Indian Agricultural Growth- A Spatial Perspective

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ABSTRACT

In this paper, we study the role of relative spatial location of states on agricultural growth in India. We use different definitions of neighbourhood and through a Spatial Durbin Model in a dynamic panel framework, we find that district based weighing scheme best explains the spatial dependence. The channels through which spatial spill-over occur are rural literacy, roads, irrigation and income of neighbouring states. The other factors driving agricultural income growth in India are inputs, infrastructural support and agricultural diversification. Identification of these channels of spatial interdependence will have implications for policies aimed at reducing spatial differences across Indian states.

JEL CODES: *O13, O18, R12, R15*

Key words: *Agriculture, spatial growth, spatial weight matrix, spatial dependence, spill over*

1. Introduction

The role of spatial dependence i.e. impact of geographical location of regions with respect to each other on land use, deforestation patterns, farming decisions and land price volatility is gaining popularity in recent years (Irwin and Bockstael, 2002, Nelson and Hellerstein, 1997, Florax et al, 2002 and Schmidtner, 2012). The underlying idea driving the influence of geographic location is that forces driving regional agricultural performance could exhibit significant geographic dependence because of agro-climatic zones being spread over multiple regions, spill-over of information and technology and trade and transportation infrastructure into neighbouring regions etc. Because of the inter-play of these and many other factors, regions act like interacting agents and we therefore need to empirically specify a structure to this spatial dependence which can be modelled on the basis of a number of theoretical frameworks as discussed in Anselin (2002).

This study takes the case of Indian agriculture and tries to understand the role of spatial location on income growth across 17[2] major states of India over the period from 1967-68 to 2010-11. The precise objectives of this paper are one, to identify the spatial structure which incorporates inter-dependence among states in the most appropriate manner, two, to estimate the impact of spatial dependence on growth and channels of spatial spill over in agricultural performance and three, to identify other

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[2] The states are Andhra Pradesh (AP), Assam, Bihar+Jharkhand, Gujarat, Haryana, Himachal Pradesh (HP), Jammu & Kashmir (JK), Karnataka, Kerala, Maharashtra, Madhya Pradesh +Chhattisgarh (MP), Orissa, Punjab, Rajasthan, Tamil Nadu (TN), Uttar Pradesh+ Uttarakhand (UP) and West Bengal (WB). The 17 states that we study contribute more than 96% of the national Net Domestic Product (NDP) from agriculture.

factors driving Indian agricultural growth. Indian agriculture offers a good case to study the issue of spatial spill-over given the presence of huge diversity in agro-climatic conditions, spatial disparity in agricultural performance (Bhide, Kalirajan and Shand, 1998; Chand and Chauhan, 1999; Mukherjee and Koruda, 2003; Ghosh, 2006, Somashekharan, Prasad and Roy, 2011), considerable influence on the rest of the economy through various direct and indirect linkages and geographical concentration of agricultural performance (Bhalla and Singh, 1997). State has been chosen as the unit of analysis owing to paucity of data at a lower level (for example districts) on income from agriculture and its explanatory factors for such a long time span. Studies like Rosegrant and Evenson, 1999, Fan et al, 2000 have documented the importance of infrastructural support like irrigation, markets, roads etc. However, all these studies have considered each region to be an absolute economic unit and role of its relative location with respect to other regions have been ignored. This paper, to our best possible knowledge is the first attempt to identify the role of neighbours in Indian agriculture.

Methodology used in this analysis involves spatial econometric techniques which have been primarily adopted from Anselin (1988), Elhorst (2003) where geographical information like longitudes, latitudes of a region are used in the empirical estimation to weigh the relative spatial relations among regions. One of the first and most important steps towards spatial econometric analysis is specifying the structure of spatial relationship among regions i.e. defining neighbours. Empirically this spatial structure is modelled through Spatial Weight Matrix, W (Anselin, 1988, Elhorst, 2003, 2010). W, as will be discussed later, is a symmetric 'nxn' matrix where 'n' is the number of regions and the numerical values of the elements of the matrix are defined by the definition of neighbourhood. It is necessary that they are specified correctly as eventually these Ws will determine the extent and possibility of spatial spill over across regions. Studies like Elhorst (2010) and Stakhovych and Bijmolt (2009) suggest that information criteria like AIC, BIC and log likelihood values can successfully be used to find out the best possible W for the regional units under study. In this study, we compare different Ws in our estimation strategy and identify the one which best explains spatial relationship across states.

Our findings provide evidence in favour of spatial dependence and spill over among states. We further find that among the different spatial weight matrices, district based matrix explains state-level spatial spill-over in the best way. This implies that spatial relation at the state level is actually driven by spill-over occurring at the district level. There is a lot of diversity within states in India and hence often one can find more homogeneity between contiguous districts of neighbouring states compared to non-contiguous districts of the same state. The contiguous-district based spatial weight matrix controls for this spatial homogeneity among neighbouring states. We find that channels of spatial spill over are income growth, rural literacy, irrigation and road quality. The other state-level factors which have been driving growth in Indian agriculture are inputs, infrastructure, cropping pattern and rainfall.

The rest of the paper is organized as follows: In section 2 we discuss how we define neighbours for our analysis and discuss the results of spatial dependence detection tests. In section 3 we discuss the methodology adopted for the study and results are discussed in section 4. We finally conclude in section 5.

2. Defining neighbourhood and detecting spatial dependence

Empirically specifying the structure of spatial dependence among regions forms the backbone of spatial econometric analysis. This neighbourhood structure will eventually define the extent of possible spatial relationship among the regional units. A spatial weight matrix (W) is an *nxn* positive matrix (where n is number of regions) which specifies the neighbourhood set for each region/state/cross-sectional observation. In each row, a non-zero element w_{ij} defines j as being a neighbour of i. By convention, an observation is not a neighbour to itself, so that the diagonal elements are zeros (Anselin, 2002). Various different forms of spatial weight matrices have been used in literature (like contiguity based, inverse distance based among many others).

Unfortunately literature does not guide us on how to decide the structure of W. Recent studies like Elhorst (2010) and Stakhovych and Bijmolt (2009), Harris & Kravtsova (2009) among many others have explored this aspect and tried to identify tests which can determine the best possible W for the study. Stetzer (1982) shows that the specification of weight is important for parameter estimation, especially when sample sizes are small and data is auto correlated. Griffith and Lagona (1998) show that incorrectly specified weight matrix can lead to a loss of efficiency of estimators. Monte-Carlo study by Stakhovych and Bijmolt (2009) conclude that a weights matrix selection procedure that is based on 'goodness-of-fit' criteria increases the probability of finding the true specification. This method of selecting spatial weight matrices has however been criticized by Harris & Kravtsova (2009). They claim that it would only find the best among the competing spatial weight matrices and will not be able to identify the true spatial relationship unless one of the competing matrices is actually the true spatial relationship Elhorst (2010) in response states that, 'the Monte Carlo results found by Stakhovych & Bijmolt (2009) partly refute this critique. Although there is a serious probability of selecting wrong spatial weights matrix if spatial dependence is weak, consequences of this poor choice are limited because the coefficient estimates are quite close to the true ones. Conversely, although wrong choice of a spatial weights matrix can distort the coefficient estimates severely, probability that this really happens is small if spatial dependence is strong.' Following Elhorst (2010) and Stakhovych and Bijmolt (2009) we use log-likelihood values and information criteria, viz. AIC and BIC to identify the model which explains spatial dependence and interaction among regions in the best possible manner.

In this study we compute and compare four measures of W, viz. (1) state contiguity based (2) inverse distance based (3) length of shared border based and (4) district[3] contiguity based. State-contiguity based matrices have been constructed in a way such that weight 'one' implies that states are contiguous to one another and 'zero' implies that they are not. Thus in this weighing criterion we assume that states which are non-neighbours will not have any spatial dependence among them and all states which share borders will have a uniform spatial dependence of weight 'one'. This is the most commonly used matrix and one of the reasons behind its frequent usage is its simplicity in both construction and interpretation. However, the assumption of two non-neighbouring states to not have any spatial dependence is rather strong and often erroneous. Therefore, our second matrix which is the inverse distance based matrix gives weights according to the inverse of distance between the centroids of the two states. This way all the states are neighbours with one another in the sense that none of the elements is zero in the matrix. This weighing scheme ensures that higher weight is given to states which are closer to each other and vice-versa. And because higher weights are given to closer states it implies that weights are proportional to the probability of possible spill over or among the neighbours.

The third spatial weight matrix we use is length of border based spatial weight scheme. Here, weights are assigned according to length of border shared between two states. If a state has two neighbours, one with a higher shared border length compared to the other, rather than giving a uniform weight to both the contiguous states, higher weight to the first state with higher shared border length will ensure that incorporated spatial effects are proportional to the possibility of connectivity and therefore spatial spill-over. And the fourth spatial weight matrix we use is contiguous-district based spatial scheme. Here, weight is assigned according to the total number of contiguous districts between two states. The idea behind using districts based spatial weight matrix is that states in India are spread across diverse agro-ecological zones and hence controlling state level contiguity does not guarantee that spatial dependence is completely incorporated. Quite often districts within a state are more homogeneous to contiguous districts in the neighbouring states compared to non-contiguous districts of the same state. This district based matrix will give a higher weight to states with which with more number of contiguous districts with neighbouring state.

Spatial dependence is typically detected using Global and local Moran's I tests. Both these statistics measure the degree of dependence among observations in a geographic space. Global Moran's I test statistics for the presence of global spatial dependence among the spatial units is given by:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (1)$$

[3] Districts in India are lower administrative units compared to states and groups of districts form states.

Where n is the number of regions, w_{ij} is the element of the weight matrix W, x_i is the value of the variable at region i and $\bar{x}$ is the cross-sectional mean of x. Values range from −1 (indicating perfect dispersion) to +1 (perfect correlation). A significant correlation statistic indicates presence of spatial dependence. It is possible that for a given year global spatial detection tests indicate no spatial relation while local spatial tests indicate strong dependence across some regions in the total set of regions. These local Moran's I tests allow for decomposition of global indicators. For each location, these values compute its similarity with its neighbours and test whether the similarity is statistically significant. For each location, local Moran's I test statistic can be computed and this is given by

$$I_i = \frac{(x_i - \bar{x})\sum_j w_{ij}(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2/n} \qquad (2)$$

Under the null hypothesis of no spatial dependence, both the global and Local Moran's I test statistic asymptotically follow a standard normal distribution. Global and Local Moran's I correlation statistics using the four spatial weight matrices indicate significant spatial dependence in terms of income per rural person across states of India are given in Table 1 and 2 respectively.

Table 1 and Table 2

We find that states have significant local spatial dependence in 1966 even when there was no significant global spatial dependence. States which had significant local spatial dependence for almost all the years were Northern states like Punjab, Haryana, Himachal Pradesh and Uttar Pradesh and eastern states like Bihar, West Bengal, Orissa, Assam , western states like Madhya Pradesh, Maharashtra, Rajasthan and Gujarat and Andhra Pradesh in south.

Thus, this preliminary analysis points towards possible spatial dependence across states and it provides an empirical basis to identify the most appropriate W and to analyse the channels through which spatial spill over occurs across states in India.

3. Methodology adopted and data sources

We assume a Cobb-Douglas functional form to empirically estimate the relation between annual growth in income per rural person (our dependent variable) and the explanatory variables like input usage, infrastructural support, cropping pattern and spatially lagged variables for each state. We use a fixed effects panel framework for estimating our models. These are based on the Solow-Swan or Ramsey models of output per worker[4].

Broadly, there are three forms of spatial relation: (1) spatial dependence in dependent variable i.e. spatial lag model, (2) spatial dependence in error i.e. spatial error model and (3) spatial dependence in explanatory variables i.e. spatial Durbin model. Anselin (1988) and Lesage (2009) and Elhorst (2003) point out that least squares estimators, if used in case of models with spatially lagged dependent

[4] See Barro and Sala-i-Martin (1995) for a detailed description.

variables lead to biased and inconsistent estimates because of the correlation between spatially lagged variables and the residual and therefore we use a maximum likelihood estimation framework for our analysis. Additionally, bias correction procedure adopted by Lee and Yu (2010) was also adopted in the study to obtain unbiased estimators in the presence of spatial and time fixed effects. Panel data also suffers from initial values problem and this is controlled through dynamic panel models where the lagged value of the dependent variable is also used as an additional explanatory variable. This corrects the autocorrelation problem in panel data models (Wooldridge; 2005, Pfaffermayr; 2012).

The Spatial Durbin model we use to estimate the impact of spatial spill-over can be specified as follows:

$$\begin{aligned} growth_{it} &= ln(y_{i,t}) - ln(y_{i,t-1}) \\ &= \alpha_i + \beta\, ln(y_{i,t-1}) \\ &\quad + \delta growth_{i,t-1} + \gamma_1 inputs_{it} \\ &\quad + \gamma_2 infrastructure\ and\ other\ state\ level\ characteristics_{it} \\ &\quad + \gamma_3 human\ capital_{i,t} + \gamma_4 rainfall_{i,t} + \gamma_5 spatial\ variables_{i,t} + \epsilon_{i,t} \end{aligned} \quad (4)$$

Here, coefficient of β gives evidence in favour or against convergence across states α_i is the state specific effects and the impact of the other factors on growth can be obtained from coefficients $\gamma_1 to\ \gamma_5$. Our primary variable of interest is γ_5 which helps us in identifying the channels of spill-over in agriculture.

Spatially weighted variables have been constructed by weighing the neighbouring states using the different spatial weight matrices i.e. these newly created variables are the weighted means of observations of neighbouring states where the weights are in accordance to the spatial weight criteria used

Growth in agricultural income per rural person is our primary variable of interest in this analysis. The only consistent state level data available on income from agriculture for states in India from 1967 onwards is net state domestic product (NSDP) from agriculture at constant (2004-05) prices. Data source for the same is Economic and Political Weekly Research Foundation (EPWRF) database.

Following other studies on Indian agriculture (Fan et al, 2000, Binswanger, 1993), the other control variables in our analysis are inputs and infrastructure, institutional and state level policy related. Table 3 gives details on all explanatory variables and their sources.

Table 3: Explanatory variables and data sources

4. Results

Table 4 gives the results of our analysis. Model 1 is the baseline non-spatial model where we do not include spatially lagged variables while models 2-5 are spatial models with different spatial weight matrices. On the basis of log-likelihood, AIC and BIC, all the spatial models (models 2 – 5) perform better than the non-spatial model (model 1) for the entire period[5] which confirms the presence of significant spatial dependence and spill-over in income growth in Indian agriculture. As literature does not provide much guidance on the spatial weight criteria, the spatial models (models2-5) have been compared on the basis of log-likelihood, AIC and BIC and the contiguous districts based spatial matrix (model 5) performs the best among all other models. This confirms that spatial dependence across states in India is controlled better through contiguous district based spatial weight matrices where higher weight is given to states with more number of contiguous districts. We discuss model 5 in the rest of the paper.

Results show that among all the spatially weighted variables, spatial spill-over in income from Indian agriculture has occurred through income growth, rural literacy, irrigation and road quality. This finding is in line with studies on other countries like Alston (2002) which concludes that knowledge based channels are the primary source of spatial spill-over in agriculture. Tong (2012) found significant spatial spill-over through road infrastructure. Although, we could not find evidence in existing literature in favour of significant impact of spatial irrigation, the reason behind this could be that when neighbouring districts receive irrigation investments, its impact does not suddenly stop at the state boundary and therefore neighbouring states also receive positive benefits from irrigation. Moreover, it can also be explained on the lines that contiguous states with more number of contiguous districts will further have higher chances of over-lap of agro-ecological conditions leading to a higher similarity in irrigation potential and hence higher spatial spill-over.

We find that lagged per capita income (β) is significant and negative in all the models, indicating statistically significant evidence in favour of catching up effect within Indian states over the entire period 1967-68 to 2010-11 i.e. states which had a lower income in the previous year were catching up with higher income states owing to a higher growth rate. Among inputs, tractors, land and livestock play a statistically significant impact in all the models[6]. Both tractor and land ownership have a positive impact on growth indicating the importance of asset ownership in growth of income. Among livestock, only buffaloes and sheep play a significant role in growth. Interestingly, buffaloes have a negative impact on growth in spatial models (insignificant in non-spatial model) while sheep have a positive impact. Although the reason driving the negative relation between buffaloes and growth and

[5] Data for state level agricultural expenditure is available only from 1972. So these set of results in table 4 are for the time period 1972-73 to 2010-11.

[6] Fertilizer consumed per unit of cropped area is not significant in any of the models and hence has been dropped from the analysis.

insignificant relation between cattle and goats and growth is not very clear, it is possible that these results point towards a non-optimal mix of different types of livestock dominated by bovines[7].

Results show that infrastructural support in a state has statistically significant impact on its income growth. Key infrastructure like gross area irrigated, villages electrified, road quality and state expenditure on agriculture are significant and positive drivers of growth of income in all the models. Results suggest that higher the infrastructural support in the state more is the income generated from agriculture. These findings are in line with other studies on Indian agriculture like Fan et al, 2000 and Binswanger and Khandker, 1993. Cropping pattern has been controlled through share of total cropped area under different groups of crops like cereals, pulses, sugar, oil seeds, fibre etc. Share of area under fibre, sugar and oil-seeds are all significant and positively influence the growth of income from agriculture[8]. These results in favour of significant impact of fibre, sugar and oil-seeds support findings from studies like Joshi, Birthal and Minot (2006) which concludes that diversification has been a dominant source of growth since the 1980s in Indian agriculture. Human capital has been controlled through rural literacy rate and as expected it has a positive impact on growth of income from agriculture. Deviation of actual rainfall from its normal level greater than 10 per cent significantly reduces growth of income from agriculture in all the models and the impact on income growth is proportional to the level of deviation of actual rainfall from normal

5. Conclusion

Growth in income from agriculture has been very different across states in India because of differentials in agro-ecological conditions, cropping pattern, input usage, infrastructural support, yield levels, etc. This pattern of persistent inter-state disparity with a significant spatial pattern provides an empirical basis to analyse the reasons behind the spatial dependence and hence the source of spatial spill-over in Indian agriculture. Existing literature on growth in Indian agriculture has assumed each state to be an independent and isolated unit. But in reality the performance of neighbouring states can depend on each other due to spatial spill-over. Using spatial econometric techniques (Anselin, 1988 Elhorst, 2003), we find that apart from other state level factors, growth in Indian agriculture is greatly influenced by relative spatial location of states. Spatial weight matrices form the core of the spatial analysis and therefore, it is very important that they are correctly specified. It is these matrices, which eventually defines neighbours for each regional unit (state in our case) and subsequent identification of the channels of spill-over is based on these matrices.

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[7] At the all India level, from 1966 to 2007, on an average bovines account for approximately 65% of all livestock, and within bovines, animals in milk constitute only approximately 35%.

[8] Share of cereals, pulses and rest of the crops was not significant and therefore have been dropped from the estimation models

We compared four different types of spatial matrices in our analysis viz. (1) state-contiguity based (2) inverse distance based, (3) length of border based and (4) district-contiguity based. The district-contiguity based and length of border based matrices differentiate the impact of two contiguous neighbours as the one with higher number of contiguous districts or length of border shared gets a higher weight in the matrix. This weighing scheme ensures that the incorporated spatial effects are proportional to the possibility of spatial spill-over. Global and local Moran's I tests using these weights found statistically significant spatial dependence across states.

From our results we find that the contiguous district based spatial weight matrices perform the best in terms of AIC, BIC and log-likelihood criteria compared to the other spatial weight matrices thereby confirming our hypothesis that districts explain spatial dependence better than states in Indian agriculture as latter is hugely heterogeneous owing to the existence of more than one agro-ecological zone in a state. This shows that use of spatial weight matrices must be done in a cautious manner i.e. the spatial weight matrix must be such which explains the inherent spatial process. Here, spatially lagged dependent and explanatory variables were computed using spatial weight matrices. A dynamic fixed effect model was used to correct the autocorrelation problem in panel data.

We find that the primary channels of spatial spill-over in Indian agriculture in the entire time-period were growth, rural literacy, roads and irrigation. Therefore, economic policy measures targeting improvement and expansion of infrastructural support and literacy can have an important impact in promoting long run agriculture growth and help in reducing disparity across Indian states.

Some of the limitations of the present study have to be kept in mind while drawing conclusions. Data is not available on an annual basis for some variables like livestock, tractor etc. and hence we interpolated them to obtain a continuous time series. This might have introduced some errors in out estimated models. Nevertheless, the results confirm the spatial dependence in Indian agriculture and point towards the channels of intervention which can potentially reduce inter-state disparity.

TABLES

Table 1: Results of global Moran's test

year	contiguous states	inverse distance	shared-border	contiguous districts
1966	-0.036	-0.030	0.090	0.062
2010	0.192**	0.066**	0.317**	0.283**

Note: *: p<0.10;**: p<0.05;***: p<0.01 Source: author's estimations. Note: results of other years can be shared on request

Table 2-Results of Local Moran's test

Year	State	Moran's I	Year	State	Moran's I
	Contiguity			District	
1966	West Bengal	0.735**	1966	Bihar+Jharkhand	0.925**
1966	Bihar+Jharkhand	0.72**	1966	West Bengal	2.198***
2010	Punjab	0.747**	2010	Haryana	0.606*
2010	Bihar+Jharkhand	1.389***	2010	Bihar+Jharkhand	1.202**
			2010	Punjab	1.667***
	Inverse Distance			Border	
1966	West Bengal	0.393**	1966	Bihar+Jharkhand	1.087**
2010	Assam	0.164**	1966	West Bengal	2.446***
2010	Orissa	0.152**	2010	Haryana	0.855**
2010	Punjab	0.367**	2010	Bihar+Jharkhand	1.211***
2010	Haryana	0.399**	2010	Punjab	1.885***

Note: *: p<0.10;**: p<0.05;***: P<0.01 Source: Author's Estimations. Note: Results of other years can be shared on request

Table3: Data sources and definitions

Dependent & Explanatory variables	Data source
Dep var: Net State domestic product (NSDP)per rural person	NSDP from Economic and Political Weekly Research foundation (EPWRF) &population from CENSUS
gross cropped area per rural person	Land use statistics, ministry of agriculture
tractors per rural person	quinquennial livestock Census, Government of India
livestock per unit geo area	quinquennial livestock Census , Government of India
fertilizer per gross crop area	Fertilizer Statistics
irrigation: share of gross area irrigated in total cropped area	Land use statistics, Department of Economics and Statistics, Ministry of Agriculture
roadquality:surfaced road to total road	Basic Road Statistics and Statistical abstracts of India
villages electrified=1 if <100 % elec and 0 if =100 %	Economic and Political Weekly Research foundation (EPWRF)
agri exp per unit geo area	Finances of state government" published by RBI
diversification: share of area under diff crop groups	Area, Yield, Production of Principle Crops" by Ministry of Agriculture
rural literacy rate	CENSUS, various years
rain deviation dummy,=1 if b/w 5 to 10, =2 if b/w 10 to 20, =3 if >20, =0 if<5	statistical abstract of india

Source: Author

Table 4: Results of spatial and non-spatial regressions

Dependent variable is growth rate defined as annual growth rate i.e. $\ln(y_t)-\ln(y_{(t-1)})$ where y_{it} is the income per rural person in i-th state and t-th year.

Variable	non-spatial	contiguity	inverse-distance	shared border	Districts
	[1]	[2]	[3]	[4]	[5]
lagged income	-0.623***(0.094)	-0.627***(0.074)	-0.625***(0.083)	-0.625***(0.071)	-0.624***(0.069)
lagged growth	-0.197***(0.032)	-0.162***(0.028)	-0.167***(0.027)	-0.163***(0.028)	-0.160***(0.028)
per capita tractor	0.959** (0.340)	1.304***(0.398)	1.241***(0.296)	1.378***(0.361)	1.359***(0.377)
per capita land	2.060*** (0.380)	2.034***(0.343)	1.991***(0.358)	2.052***(0.370)	2.046***(0.362)
buffaloes per sq. km.		-0.167**(0.076)	-0.123*(0.063)	-0.183**(0.085)	-0.178**(0.085)
sheep per sq. km.	0.153*** (0.038)	0.122***(0.041)	0.106***(0.036)	0.139***(0.039)	0.134***(0.032)
irrigation	0.121*** (0.030)	0.113***(0.023)	0.119***(0.029)	0.126***(0.023)	0.127***(0.023)
Villageelectricity dummy	-0.053** (0.020)	-0.058***(0.021)	-0.034*(0.021)	-0.054***(0.020)	-0.055***(0.019)
road quality	0.154* (0.084)	0.110*(0.064)	0.135**(0.065)	0.126**(0.052)	0.122**(0.052)
agri exp per area	0.003** (0.001)	0.003***(0.001)	0.002**(0.001)	0.003***(0.001)	0.003***(0.001)
share of oil	1.105***(0.168)	1.107***(0.186)	0.999***(0.188)	1.041***(0.172)	1.033***(0.173)
share of fibre		0.915***(0.322)	0.846**(0.383)	0.923***(0.335)	0.906***(0.328)
share of sugar	2.948* (1.469)	3.139**(1.274)	2.989**(1.262)	2.835**(1.255)	2.926**(1.221)
rural literacy	0.009*** (0.002)	0.004*(0.002)	0.006***(0.002)	0.004*(0.002)	0.004*(0.002)
rain dummy 2	-0.014** (0.006)	-0.014**(0.007)	-0.014**(0.006)	-0.012*(0.007)	-0.012*(0.007)
rain dummy 3	-0.042***(0.013)	-0.040***(0.012)	-0.040***(0.012)	-0.039***(0.012)	-0.039***(0.012)
spatial rural literacy		0.006***(0.001)		0.003**(0.002)	0.003**(0.002)
spatial irrigation				0.101***(0.037)	0.094***(0.036)
Spatial road quality			0.685***(0.215)	0.164**(0.071)	0.160**(0.072)
spatial growth		0.267***(0.044)	0.319***(0.062)	0.258***(0.044)	0.273***(0.047)
STATISTICS					
No. of observation	663	646	646	646	646
log-likelihood	587.857	607.532	602.566	612.487	615.42
AIC	-1147.713	-1183.065	-1173.131	-1192.973	-1198.84
BIC	-1084.758	-1111.532	-1101.599	-1121.44	-1127.307
R-square	0.525	0.567	0.565	0.571	0.573

Note: *:p<0.10;**:p<0.05;***:p<0.01 Source: author's estimations, se within parenthesis

References

Alston, J. M., 2002. Spillovers. *Australian Journal of Agricultural and Resource Economics*. 46, 315–346.

Anselin, L., 1988. Spatial Econometrics: Methods and Models. Kluwer Academic, Dordrecht.

Anselin, L., 2002. Under the hood: issues in the specification and interpretation of spatial regression models. *Agricultural Economics* **27**, 247-267.

Barro, Robert J., and Xavier Sala-I-Martin., 1995. *Economic Growth*. New York: McGraw Hill.

Binswanger, H.P., Khandker, S., 1993, How infrastructure and financial institutions affect agricultural output and investment in India. *Journal of Development Economics*, **41(2)**, 337-366.

Bhalla, G.S. and Singh, G., 1997. Recent Developments in Indian Agriculture: A State Level Analysis. *Economic and Political Weekly,* **32(13)**, A2-A18

Elhorst, J.P., 2003.Specification and estimation of spatial panel data models. *International Regional Science Review,* **26(3)**, 244-268

Elhorst, J. P. (2010). Applied spatial econometrics: raising the bar. *Spatial Economic Analysis*, *5*(1), 9-28.

Fan, S., Hazell, P. and Haque, T., 2000. Targeting public investments by agro-ecological zone to achieve growth and poverty alleviation goals in rural India. *Food Policy*, **25(4)**, 411-428

Florax, R.J.G.M., Voortman, R.L., Brouwer, J. 2002, Spatial dimensions of precision agriculture: a spatial econometric analysis of millet yield on Sahelian coversands, Agricultural Economics, **27**,425-443

Griffith, D. A., & Lagona, F. (1998). On the quality of likelihood-based estimators in spatial autoregressive models when the data dependence structure is misspecified. *Journal of Statistical Planning and Inference*, *69*(1), 153-174.

Harris, R., Moffat, J., & Kravtsova, V. (2011). In search of 'W'. *Spatial Economic Analysis*, *6*(3), 249-270.

Irwin, E.G., Bockstael, N.E., 2002. Interacting agents, spatial externalities and the evolution of residential land use patterns. Journal of Economic Geography. 2, 31–54

Joshi, P.K., Birthal, P.S. and Minot, N., 2006. Sources of agricultural growth in India: Role of diversification towards high-value crops, IFPRI, MTID Discussion paper No. **98**

Lee L.F. and Yu J., 2010. Estimation of spatial autoregressive panel data models with fixed effects, *Journal of Econometrics* **154(2)**, 165-185

Lesage, *J.P.,* and Pace, R.K., 2009. *Introduction to Spatial Econometrics. New York: Taylor & Francis/CRC Press, 2009.*

Nelson, G.C., Hellerstein, D., 1997. Do roads cause deforestation? Using satellite images in econometric analysis of land use. *American Journal of Agricultural Economics,* **79**, 80–88.

Patton, M. and McErlean, S., 2003. Spatial Effects within the Agricultural Land Market in Northern Ireland. Journal of Agricultural Economics, **54**, 35–54.

Pfaffermayr, M., 2012. Spatial convergence of regions revisited: a spatial maximum likelihood panel approach. *Journal of Regional Science,* **52**, 857–873

Rosegrant, M., Evenson, R, 1999. Agricultural research and productivity growth in India*, IFPRI research report, 109*

Schmidtner, E., Lippert, C., Engler, B., Ha¨ring, A., Aurbacher, J. and Dabbert, S., 2012. Spatial distribution of organic farming in Germany: does neighbourhood matter? *European Review of Agricultural Economics,* **39(4)**, 661–683.

Stakhovych, S., & Bijmolt, T. H. (2009). Specification of spatial models: A simulation study on weights matrices. *Papers in Regional Science*, *88*(2), 389-408.

Tong, Tingting, 2012. "Evaluating the Contribution of Infrastructure to U.S. Agri−Food Sector Output." Master's Thesis, University of Tennessee.

Wooldridge, J. M., 2005. Simple Solutions to the Initial Conditions Problem in Dynamic, Nonlinear Panel Data Models with Unobserved Heterogeneity. *Journal of Applied Econometrics,* **20(1)**, 39–54.