

**Farm Productivity and Nonfarm Employment
for Rural Development in India**

2002

Anit Nath Mukherjee

**Farm Productivity and Nonfarm Employment for
Rural Development in India**

Submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Economics

by

Anit Nath Mukherjee

Doctoral Program in Policy and Planning Sciences

University of Tsukuba

December 2002

Dedicated to the memory of late Professor Yuji Kubo

Acknowledgements

First and foremost, I wish to record my sincerest gratitude to my advisor, Professor Yoshimi Kuroda, for his wholehearted support and guidance during my graduate work. His contribution at every stage of the thesis has been invaluable, and has seen me through the usual bouts of disappointment and despair.

Professor Mamoru Kaneko and Professor Makoto Ohta have provided substantive comments on the thesis and have helped me through the process of the preparation of the manuscript. The dissertation owes much to their guidance, and I express my sincere appreciation for their support.

I have also benefited from insights and critical comments from the participants in the doctoral seminars, especially Professor Masatoshi Yoshida, Professor Atsushi Yoshida, Professor Steve Turnbull, Professor Tatsuyoshi Miyakoshi, Professor Fumikazu Hida and Professor Eizo Akiyama. Special words of appreciation are also due to Dr. Shenggen Fan, Dr. Peter Hazell, Dr. Junichi Ito and Dr. Xiaobo Zhang for making my stay at IFPRI extremely fruitful. I must also thank Professor Yujiro Hayami, Professor Jeffrey Kline, Professor Myung-Jae Lee, Professor Philip McCann and Professor Yoshito Takasaki for their encouragement at various stages of the thesis.

I would like to acknowledge the financial support of the Ministry of Education, Science, Sports and Culture of Japan, which gave me the opportunity to dedicate myself fully to the research leading to this thesis.

During my seven years of stay in Japan, I have been fortunate to have a wide circle of friends and well-wishers. I would like to express my heartiest appreciation to Juan Ernesto Pardinás, Guadalupe Mendoza, Ruth Vanbaelen, Takahiro Hosono, Hector Monges, Bernardo and Lilyan Garduno, Alberto Cabezas, Claudio Puty, Roberta de Carvalho, Mohammed Rahmatullah and Salma Islam, Reena and Suresh Sundaresan,

Paul Austin, Shormila Mukherji, Cristina Melo, Courage Kamusoko, Bernard and Akiko Dupraz, Sumio Hamagata, Radha Balkaransingh, Romeo Teruel and past and present members of the Kuroda Zemi.

Friends from my college and university days in India, especially Priyodarshi Banerjee, Prachi Deshpande, Gouri Seetharam, Debapriya Mitra, Chandrima Sinha, Asmita Kabra, Biswajit Nag, Rupa Dutta Gupta, Arnab and Swati Gupta and Atreyee Sen have also been a constant source of encouragement and support.

I consider myself extremely fortunate to have met Dr. Ana Paula Vidal Bastos, Dr. Mahfuzul Hoque and Dr. Mahmuda Akter at the University of Tsukuba. The bond of friendship that we formed over the course of our stay in Tsukuba is one that I shall treasure for a long time to come. I am also fortunate to have shared the joys and the sorrows of the last few years with my wife, Ana. Her kindness and patience have been crucial for finishing the current work.

A special note of thanks are due to my wonderful parents, Anjali and Amar Nath Mukherjee, who have kept their faith in me and have given me unflinching support throughout my academic career.

Finally, I would like to acknowledge the contribution of two persons without whom this work would not have been possible. Professor Anjan Mukherji and late Professor Yuji Kubo gave me the chance to come to Japan and pursue my doctoral work at the University of Tsukuba. My deepest respects and appreciation are reserved for both of them. Professor Mukherji has helped me understand the value of dedication in the pursuit of knowledge in the broadest sense of the term. Professor Kubo taught me the value of critical analysis for addressing various issues in development economics. This thesis is dedicated to his everlasting memory.

Abstract

We study the role of inter-linkages between total factor productivity (TFP) in agriculture and nonfarm employment for rural development in India. Recent studies have shown that rural nonfarm employment together with public investment in physical and social infrastructure help to alleviate poverty in the rural areas. We show that those states of India that have managed to exploit the inter-linkages between agriculture and nonfarm sector, have attained higher levels of rural development.

We use a dataset comprised of 14 states of India from 1973 to 1993 for our analysis. In Chapter 2, we analyze the issue of convergence in agricultural TFP among the Indian states. Employing recent panel convergence tests, our analysis indicates that conditional convergence holds true for Indian agriculture. After controlling for fixed factors, we find evidence that the late starters (eastern, central and southern states) have caught up with the leaders (northern states) in terms of their TFP growth rates. This indicates that, contrary to earlier studies that reported divergence in agricultural growth among Indian states, productivity growth in Indian agriculture in the post-Green Revolution period has shown signs of convergence in the long run.

Extending the previous analysis, in Chapter 3, we find that the rural development gap among states in India has decreased substantially, through growth in farm productivity and nonfarm employment. Balanced development of the farm and nonfarm sectors have helped states to catch up with Kerala, which was the leading state in India in terms of rural development at the beginning of the period. We construct an indicator of rural development defined as the ratio of TFP growth in agriculture and rural farm-nonfarm employment ratio. Controlling for state-specific fixed factors and

idiosyncratic yearly shocks, we provide evidence of convergence in rural development across India in the long run.

In Chapter 4, we find that inter-state differences in agricultural TFP and rural development can be explained by differences in nonfarm employment and infrastructure among Indian states. Tests of causality indicate that there is a symbiotic relationship between farm and nonfarm sectors in rural India. Therefore, states that have a growing nonfarm sector, together with higher levels of physical and social infrastructure, have attained higher levels of agricultural and rural development.

This thesis supports the need for policies designed to increase nonfarm employment in the rural areas as described in Chapter 5. Exploiting positive linkages between improved public infrastructure, greater rural nonfarm employment and higher productivity growth in agriculture will create the conditions for spatially balanced rural development across states in India.

Contents

<i>List of Tables</i>		viii
<i>List of Figures</i>		ix
Chapter 1	Introduction	1
1.1	Initial Comments	1
1.2	Motivation for the Thesis	2
1.3	Background of the Thesis	3
1.4	Analytical Procedure in the Thesis	6
1.4.1	Research Topics	6
1.4.2	Data and Methodology	7
1.4.3	Results and Contribution	7
1.5	Organization of the Study	8
Chapter 2	Convergence in Agricultural Productivity	10
2.1	Introductory Comments	10
2.2	TFP Growth in Agriculture in Indian states	12
2.2.1	Data Sources and Measurement	13
2.2.2	Performance of Indian Agriculture	16
2.2.3	States-level Agricultural Productivity in India	18
2.3	Tests of Convergence in Productivity across States	21
2.3.1	Basic Model	21
2.3.2	Estimation Procedure	23
2.4	Estimation Results	25
2.4.1	Results from Levin and Lin (LL) Method	25
2.4.2	Further Tests of Convergence	27
2.5	Concluding Comments and Extension	28

Chapter 3	Convergence in Rural Development	30
3.1	Initial Comments	30
3.2	Background Issues	31
3.3	Rural Development in India	34
3.4	Tests of Convergence in Rural Development	40
3.4.1	Convergence in Rural Employment Ratio	41
3.4.2	Convergence in Rural Development Indicator	43
3.5	Concluding Remarks	45
Chapter 4	Effect of Rural Non-farm Employment and Infrastructure on Agricultural Productivity	48
4.1	Initial Comments	48
4.2	Causality between Nonfarm Employment and TFP	49
4.2.1	Method of Analysis	51
4.2.2	Results of the Test of Causality	52
4.3	Infrastructure, TFP and Nonfarm Employment	56
4.3.1	Infrastructure Affecting Farm and Nonfarm Sectors	59
4.3.2	Empirical Method and Results	62
4.4	Summary of the Results	66
Chapter 5	Summary and Conclusion	69
5.1	Main Contribution	69
5.2	Summary of the Thesis	69
5.3	Summary of the Chapters	70
5.4	Policy Implications	72
Appendix I	Dynamic Panel Model for Causality Test	73
Appendix II	Tables	77
Table A.1	Index of TFP Growth, 1973-1993	78
Table A.2	Rural Employment Ratio, 1973-1993	79
Appendix III	Map of India	80
Bibliography		81

List of Tables

2.1	Unit Root Estimates using Levin and Lin (1992)	25
2.2	Unit Root Tests for Levin and Lin (2002)	26
2.3	Other Tests of Convergence	27
3.1	Convergence Tests for Rural Employment Ratio	43
3.2	Convergence Tests for RDI	44
4.1	Test of Causality between TFP and NFARM	54
4.2	Technology, Infrastructure and TFP in Rural India	57
4.3	Annual Compound Growth Rate of Employment for Usual Status Workers by Broad Sector of Production	58
4.4	Estimation Results using 3-Stage Least Squares	65
A.1	Index of TFP Growth, Various States and All India (1970=100)	78
A.2	Statewise Employment Ratio (Agriculture to Nonagriculture), 1973-1993	79

List of Figures

2.1	Total Factor Productivity Growth: States and All India	15
2.2	TFP Growth Rates in Different States	17
2.3	Dispersion in TFP in Agriculture across Indian States	20
3.1	Farm and Nonfarm Employment Growth in India	33
3.2	TFP and Nonfarm-Farm Employment Ratio Growth in India	34
3.3	Rural Development Indicator for Indian States, (1970=100)	38
3.4	Variation in Farm-Nonfarm Employment Ratio	42

Chapter 1

Introduction

1.1 Initial Comments

This thesis studies the linkages between agricultural productivity, nonfarm employment and infrastructure in the overall economic development of rural areas in fourteen states in India. Specifically, it aims to clarify various issues in the debate concerning regional variations in agricultural productivity growth, and to investigate the role of nonfarm employment in rural development in India. It also seeks to analyze the effect of various types of social and physical infrastructure on both farm productivity and nonfarm sector development.

In this chapter, first, in Section 1.2, we outline the motivation for the studies undertaken in this thesis. A link between agricultural and nonfarm sectors is a key idea in this thesis, which is explained in Section 1.2. Second, in Section 1.3, we summarize preceding studies relevant to this thesis. It reveals that in the Indian case, those studies have been concentrating on the problem of poverty but not on linkages in rural areas. Third, in Section 1.4, we describe the formulation of our problem, application of the methods of analysis, and then we summarize our results and the contributions of this thesis. Strong linkages are shown to exist between farm and nonfarm sectors in rural areas in India. Finally, in Section 1.5, we explain the organization of the thesis.

1.2 Motivation for the Thesis

‘Green Revolution’ ushered in an era of significant growth in agriculture in most parts of east and south Asia from the late 1960s. Countries in the region, including India, succeeded in increasing output enough to become self-sufficient in food by the middle of the 1980s. However, the improvement in living conditions of the rural population has been uneven across the region. In India, for example, the gains from improved productivity in agriculture have not been translated into significantly higher levels of economic development, and this is so especially in the rural areas.

Previous studies point to several factors that may be responsible for this unevenness in rural development. Firstly, the gain in agricultural productivity has been concentrated in specific areas, leading to regional imbalances within the country. Secondly, the provision of public infrastructure is inadequate for sustaining a high growth rate in agricultural productivity. Thirdly, high population growth increases pressure on land, and low literacy rates reduce opportunities for off-farm employment. These and other factors combine to restrict faster economic development and poverty alleviation in the rural areas. However, it should be pointed out that increase in agricultural productivity through positive linkages with the rural nonfarm sector has not received adequate attention.

Nonfarm employment generates income for farm households and influences both their consumption and production decisions. Nonfarm income helps to smooth consumption shocks through bad harvest years. It also enables farmers to invest in productive assets and to adopt technologies that entail a higher level of risk and also a higher expected return (Lanjouw and Lanjouw, 2001). The nonfarm sector provides services such as repair and maintenance, transport etc., required for modern commercial

agriculture. Higher farm productivity, in turn, leads to higher demand for nonfarm goods and better supply of inputs for agriculture-based industries. Therefore, the channels of interlinkages are varied, and are of utmost importance for growth in both sectors.

In the Indian context, there has been a debate on rural-urban linkages, which has remained largely inconclusive. Recent studies in rural development have extended this debate and have underlined the importance of linkages within the rural areas¹. However, none of these studies have explicitly investigated the linkages between agricultural productivity, nonfarm employment and infrastructure in the rural areas. The motivation of this thesis is to analyze these linkages in rural India and to explain their impact on rural development.

A survey of previous work in this area is necessary to put this thesis into perspective. In the following Section 1.3, we provide an overview of the existing research relevant to this thesis.

1.3 Background of the Thesis

The first issue that this study addresses is whether agricultural productivity growth rate across various Indian states have tended to converge or not. Previous studies on US, Japan, and OECD countries report that technological change in agriculture has shown signs of convergence over the last four decades.² McCunn and Huffman (2000) has shown that there are significant spillover effects of TFP across US states, leading to

¹ See Fan, Hazell and Thorat (2000); Fan, Hazell and Hoque (2000) for recent studies in this area.

² Various aspects of this issue has been studied in Bernard and Jones (1996); Fulginiti and Perrin (1998); Gutierrez (2000); Martin and Mitra, (2001).

long-run convergence in agricultural productivity. However, no such study has been carried out in India so far.

Until now, most studies on India have focused on the impact of output growth on poverty (Ahluwalia, 1985; Saith, 1981; Bell and Rich, 1994; Datt and Ravallion, 1998). Researchers in this field have reported that some states and regions have done better than others in terms of their poverty performance, mostly due to institutional factors and initial levels of development. Recent studies have even argued that agricultural growth is a major factor in sustaining regional economic inequalities (Das and Barua, 1996). However, these studies use partial measures of productivity, such as land and labor productivity, and not total factor productivity (TFP) in their analysis.

The second research objective is to study regional rural development incorporating both the farm and the nonfarm sectors. Analysis of the importance of the rural nonfarm sector as a contributor to rural development has flourished recently.³ There is increasing realization that agriculture is not the only economic sector in the rural areas, and a large variety of nonfarm activities exist. They include traditional village industries such as handicrafts; agriculture related wage and self-employment such as husking, milling, food processing; and increasingly, wage and self-employment in manufacturing and service sectors, such as small and medium scale industries, transport, trade, repair workshops etc.

In recent papers, strong linkages that exist between the farm and the nonfarm sectors within the rural areas have been emphasized (Fan, Hazell and Thorat, 2000; Ravallion and Datt, 2002). In a study of several Latin American countries conducted recently, the average rural nonfarm income is estimated to be at nearly 40 percent of the

³ For a review article, see Lanjouw and Lanjouw (2001).

total rural household income.⁴ In all the study countries, there is strong expenditure as well as production linkages with agriculture. Nonfarm employment and income thus play an important role in rural economic development.

Turning our attention to India, one of the major structural problems of the Indian economy is the slow rate of diversification of the labor force from agriculture to non-agricultural occupations. In a comprehensive study of Indian agriculture, Bhalla and Singh (2001) notes that there has been “a rapid capitalization in agriculture in response to rising wages (and availability of capital at cheap rates) and this resulted in displacement of labor in certain agricultural occupations.... many areas where new technology had not taken root also continued to absorb labor in agriculture because of increasing population and non-availability of nonagricultural employment” (Bhalla and Singh, 2001, p. 48).

In our analysis, we devise an indicator for rural development that takes into account both agricultural productivity and the transformation of rural labor force. We ascertain whether the gap in the level of rural development across states have shown a tendency to converge or not. Strong farm-nonfarm linkages would enable states to catch up with the leaders and reduce inequalities in rural development.

In the third research objective, we analyze the linkages between agricultural productivity, nonfarm employment and rural infrastructure. In a recent paper, Fan, et.al. (2000) has analyzed the linkages between agricultural productivity, government infrastructure investment and poverty. Lack of basic infrastructure in the rural areas has acted as a brake against improved productivity performance in countries such as India (Rosegrant and Hazell, 2000). Nonfarm development also requires facilitating conditions such as roads, electricity, skilled workforce and financial and

⁴ World Development (2001), Special Issue on Rural Nonfarm Employment and Incomes in Latin America.

social services. In addition to infrastructure, growth in nonfarm sector requires a productive agriculture as we have seen in the case of Latin America. However, this symbiotic relation between agriculture and nonfarm sector has not been incorporated in the study by Fan, et.al. (2000). Therefore, our analysis extends their study for rural India and incorporates linkages with rural infrastructure as well as inter-linkages among agricultural and nonfarm sectors.

In the next section, we explain the framework for analysis to empirically investigate the impact of the different kinds of infrastructure and convergence in agriculture and rural development across states of India. New panel data techniques are especially appropriate in this context, as mentioned in Section 1.4 below.

1.4 Analytical Procedure in the Thesis

In the light of the above discussion, here, we formulate our research plan below. The topics for the discussion are of current interest and relevance to the rural economy of India. The dataset studies the period of high productivity growth in Indian agriculture, and the results indicate several policy options that will contribute to rural development in India.

1.4.1 Research Topics

In the context of the motivation and the background of the study mentioned above, we summarize questions to be addressed in this study as follows:

- i) What has been the pattern of productivity growth in agriculture across the different states of India? Is the diffusion of technology leading to convergence or divergence in productivity across states?
- ii) How has the productivity increase affected rural development? How does structural transformation of the rural labor force influence rural development in this context?
- iii) Are there causal linkages between nonfarm employment and agriculture? How does rural infrastructure affect farm and nonfarm sectors in India?

1.4.2 Data and Methodology

The dataset comprises 14 major agricultural states of India over the period from 1973-1993. This time period covers the post-Green Revolution era in Indian agriculture, and is characterized by a high overall growth in agricultural output. We employ panel data analysis following Bernard and Jones (1996) for testing convergence and a simultaneous equation framework to analyze the linkages in the rural sector. We test our hypothesis on convergence using recent panel convergence tests introduced by Levin and Lin (1992, 2002). For analyzing the impact of infrastructure, we test for causality between farm productivity and nonfarm employment, and then estimate the linkages in the rural areas using a simultaneous equation framework.

1.4.3 Results and Contribution

- i) Controlling for state-specific fixed factors, we find evidence of catch-up by states with lower initial levels of productivity over the study period. This is the first study of its kind for India, and is in line with evidence from state-level U.S. data.
- ii) We find significant distributive impact across regions of both the increase in TFP and structural change in the rural labor force. There has been a substantial improvement in rural development, with most of the states catching up with the leader at the initial period. The experience of West

Bengal shows that a balance can be achieved between farm and nonfarm growth, and it is mutually beneficial. This new approach captures the contribution of intersectoral linkages in rural development in India.

- iii) The analysis provides strong evidence of externalities arising from nonfarm development, with infrastructure also playing an important role. However, different types of infrastructure have varying impact on the development of the two sectors. The specific contribution of this chapter is to extend the earlier study by Fan,et.al.(2000) to take into account the simultaneity between farm productivity and nonfarm employment in rural India, and test for causality between them. Furthermore, we have included credit to the nonfarm sector as one of the variables in the model, which has so far been neglected in previous studies. Therefore, the contribution of physical, social as well as financial infrastructure in rural development has been analyzed in the same econometric framework.

1.5 Organization of the Study

In the present study, Chapter 2 analyzes the question of productivity convergence among the Indian states. Our analysis indicates that conditional or beta-convergence holds true for Indian agriculture. After controlling for fixed factors, we find evidence that the late starters (eastern, central and southern states) have caught up with the leaders (northern states) in terms of their TFP growth rates. This is identical to the findings in McCunn and Hoffman (2000) in their study of US agriculture.

Taking this analysis further in Chapter 3, we find that the indicator of rural development defined as the ratio of farm productivity to rural farm-nonfarm

employment ratio captures the regional rural development scenario in India. Nearly all the states have tended to catch up with Kerala, the leading state in 1973. Therefore, we find that there has been a significant reduction in the rural development gap among states, although some have performed much better than others. This evidence of convergence gives credence to the argument that the contribution of nonfarm employment in rural development has been underestimated until now.

In Chapter 4, the causality between nonfarm employment and agricultural productivity is empirically tested. The finding of bi-directional causality between the two sectors leads us to adopt a simultaneous-equation econometric model to test for the impact of infrastructure on the two sectors. Our results are in line with Fan et.al.(2000) in that we find significant effect of physical infrastructure on TFP in agriculture. We also find that both physical and social infrastructure are important for nonfarm development. Nonfarm employment and income, together with rural infrastructure, improves productivity in agriculture. Agriculture also has positive linkage with the nonfarm sector, although the estimated linkages are weak. This finding is important for policy-making, where until now the issue of interlinkages within the rural sector has not received adequate attention.

Chapter 5 concludes this thesis with a summary of the findings and policy prescriptions. Modern agricultural technology has had a positive effect on productivity in most parts of India. Moreover, the study distinctly shows that there are significant linkages between nonfarm employment and agricultural productivity. These linkages are further enhanced through higher provision of physical and social infrastructure in the rural areas. Greater intervention by the government in such spheres as irrigation, roads, electricity, finance and literacy would provide the conditions for both farm and nonfarm sectors to flourish.

Chapter 2

Convergence in Agricultural Productivity*

2.1 Introductory Comments

Agriculture in India has shown remarkable growth over the last three decades after the introduction of improved seed-fertilizer technology in the late 1960s, the so-called 'Green Revolution'. High production growth due to improvement in yield rates for major food crops has characterized the period from the early 1970s until now. Studies on agricultural growth in India have documented this rise in output across most parts of the country. However, there are significant differences in opinion regarding the impact on rural poverty and variation in regional productivity in the agricultural sector.

A representative cross-section of such studies focusing on poverty (Ahluwalia, 1985; Saith, 1981; Bell and Rich, 1994; and others) suggest that while there has been some reduction in poverty over the years of rapid agricultural growth, the impact of exogenous shocks such as inflation is still large in the determination of wages and income in the rural areas. There is also enough empirical evidence in the literature to suggest that poverty and inequality are still persistent in rural India in spite of substantial gains in land and labor productivity in agriculture.

The overall growth in productivity at the national level masks significant differences between those states that have progressed rapidly, such as Punjab and those

* This chapter is based on Mukherjee and Kuroda (2002), *Agricultural Economics* (Forthcoming).

that have lagged behind. Das and Barua (1996) has shown that substantial income inequalities exist among the states of India from the beginning of the Green Revolution period until the first half of the 1990s. Using maximum entropy method to investigate the determinants of the persistence of regional inequality, the study finds that differences in agriculture and infrastructure are the largest sources of inequality among the various regions of the country. A more recent study by Fan, Hazell and Hoque (2000) shows that in India, governments tend to underinvest in regions that have low level of productivity and infrastructure, that they call 'less-favored areas'. They show that the effect of investment in land and infrastructure on poverty in these areas would be much higher as compared to the 'more-favored areas'. In a separate study, Fan, Hazell and Thorat (2000) also show that gains in total factor productivity (TFP) can result through increases in government spending on physical and social infrastructure in the rural areas. This indicates that TFP plays a significant role in fostering or diminishing regional imbalances.

TFP indices capture the effect of technological change in agriculture. As we shall see in the next section, the period after the Green Revolution has been characterized by an increase in the TFP growth rates across India, with one exception. However, the persistence of regional inequality in agriculture found by Das and Barua (1996) can also be the result of differing rates of TFP growth in the various states under consideration. Therefore, from a policy perspective, it is important to understand the long-run movement in the regional productivity differences and take effective measures (such as higher infrastructure investment, research and development etc.) for correcting such imbalances.

In this chapter, therefore, we focus on the question of whether there has been a tendency towards convergence in agricultural productivity in the last two decades in

India over a representative cross-section of Indian states. Our contribution to the existing literature is to explicitly test for convergence in agricultural TFP across Indian states for a panel dataset of fourteen states from 1973 to 1993, using a variety of tests recently developed for estimating convergence in panel data models.

The plan of the chapter is as follows. In Section 2.2, we outline the TFP data on the different states, and we see that the productivity growth across states has been uneven. In Section 2.3, we formulate and estimate an econometric model for convergence, following Bernard and Jones (1996) study of sectoral convergence in OECD countries. Section 2.4 provides discussion of the results and its relation to earlier studies on convergence, and we see that the Indian experience has been similar to that in the US and OECD countries. Section 2.5 concludes with the implications of the study and its extension in the second chapter of the thesis.

2.2 TFP growth in agriculture in Indian States

In this section, we describe the dataset on TFP used for the analysis in this and the subsequent chapters of the thesis. The data shows that TFP growth rates have generally been positive but varies for different states over the period from 1973-1993. We examine the differences in productivity by comparing the high- and low-productivity states, laying the foundation of the convergence analysis in the subsequent section.

2.1.1 Data Sources and Measurement

The dataset employed is a panel of fourteen major agricultural states for the period 1973 to 1993.¹ This dataset has been compiled by the World Bank and the International Food Policy Research Institute (IFPRI) in collaboration with various agencies of the Government of India.² Productivity in agriculture is measured as total factor productivity (TFP) index, which is the ratio of total output to total input. In several inter-country studies of convergence in TFP, the Malmqvist indices under the frontier production function framework are used (see Fulginiti and Perrin, 1998; Gutierrez, 2000; Thirtle, et.al.,1995). Other studies have used growth accounting techniques using the elasticities of labor and capital to estimate TFP (Bernard and Jones, 1996; Martin and Mitra, 2001). This is due to the fact that the complete and comparable set of prices of input and output are not available for the countries under consideration. In case such data are available (as in our case), the Divisia indices would be the best approximation to capture the effect of unaccounted inputs in agriculture (TFP), such as irrigation, electricity, research and development, etc.

Therefore, Törnqvist-Theil approximation of the Divisia index is used to construct the growth in TFP for each state between time periods t and $t-1$. The state productivity indexes thus created are normalized using the value for the year 1970 as the base year. The expression for the calculation of the index for each state is given by:

$$\ln(TFP_t / TFP_{t-1}) = \sum_i 0.5 * (S_{i,t} + S_{i,t-1}) * \ln(Y_{i,t} / Y_{i,t-1}) - \sum_j 0.5 * (W_{j,t} + W_{j,t-1}) * \ln(X_{j,t} / X_{j,t-1}),$$

¹ The states in alphabetical order are: Andhra Pradesh, Bihar, Gujrat, Haryana, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh and West Bengal.

² For details of the dataset and sources, see Fan, et.al., (1999).

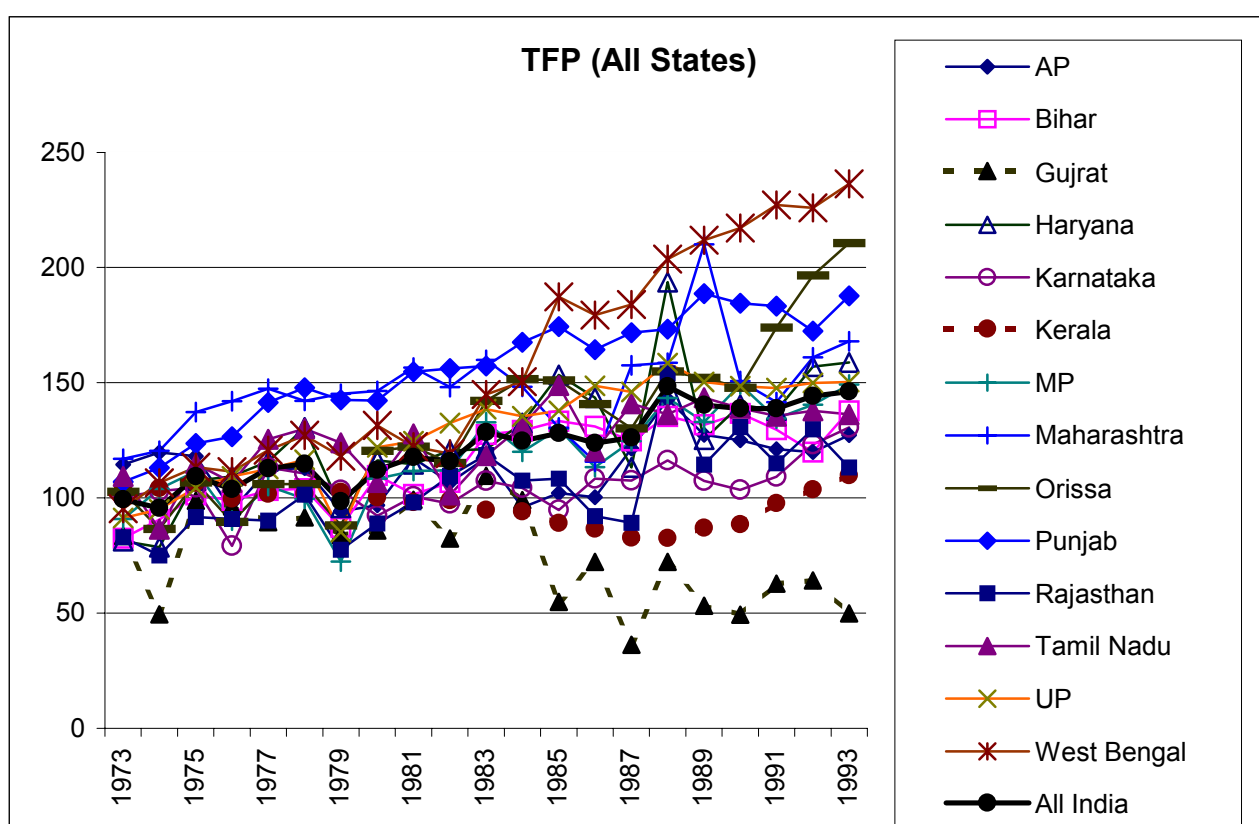
where the left hand side is the log of the total factor productivity index; $S_{i,t}$ and $S_{i,t-1}$ are output i 's share in total production value at time t and $t-1$, respectively; and $Y_{i,t}$ and $Y_{i,t-1}$ are quantities of output i at time t and $t-1$, respectively. Farm prices are used to calculate the weights of each crop in the value of total production. $W_{j,t}$ and $W_{j,t-1}$ are cost shares of input j in total cost at time t and $t-1$, respectively; and $X_{j,t}$ and $X_{j,t-1}$ are quantities of input j at time t and $t-1$, respectively. Thirty crops (rice, wheat, jowar, bajra, maize, ragi, barley, gram, other pulses, groundnut, sesame, linseed, rapeseeds and mustard, castorseed, safflower, nigerseed, coconut, soybeans, sunflower, potato, tapioca, sweet potato, banana, cashewnut, coffee, jute, sugarcane, onion and fruits) and three major livestock products (milk, chicken, and sheep and goat meat) are included in total production. Farm prices are used to calculate the output shares.

Five inputs (labor, land, fertilizer, tractors and animals) are included. Labor input is measured as total female and male labor (including both family and hired) engaged in agricultural production. A conversion ratio of 0.7 has been used to convert female labor to its male labor equivalent.³ Land is measured as net cropped area; fertilizer input is measured as the total amount of nitrogen, phosphate and potassium uses; tractor input is measured by the number of four-wheel tractors (including both private- and government-owned); and animal input is measured as the number of draft animals (total buffalos). Wages of agricultural labor are used as the price of labor; rental rates of tractors and animals are used for their respective prices; and fertilizer price is calculated as a weighted average of the prices of nitrogen, phosphate and potassium. The land price is measured as the residual of total revenue net of measured costs for labor, fertilizer, tractors and bullocks.

³ The ratio 0.7 is calculated on the basis of the ratio of the rural wage rate for male and female labor in India. Previous studies have also used this ratio for India and China (Fan, et.al.,2000), whereas 0.8 has been used for Japan by Kuroda (1995).

Table A.1 provides the data on TFP for the states under consideration and Figure 2.1 plots the data for convenience of exposition. We index the series using the values of 1970 as the base year. Since agricultural production and consequently TFP is prone to fluctuations, the base year is chosen such that it can be considered a ‘normal’ year in terms of absence of any year-specific shock.

Figure 2.1: Total Factor Productivity Growth: States and All-India



2.2.2 Performance of Indian Agriculture

For the whole of India, the rate of TFP growth has accelerated from the early 1970s to the late 1980s. While from 1973 to 1980, the trend growth rate was 1.45 percent, it increased to 2.33 percent in the decade of the eighties. However, from the

late eighties onwards, there has been a discernable decline in the rate of TFP growth, being only 1.21 percent from 1989 to 1993. Recent data coming out of India also shows the same trend.

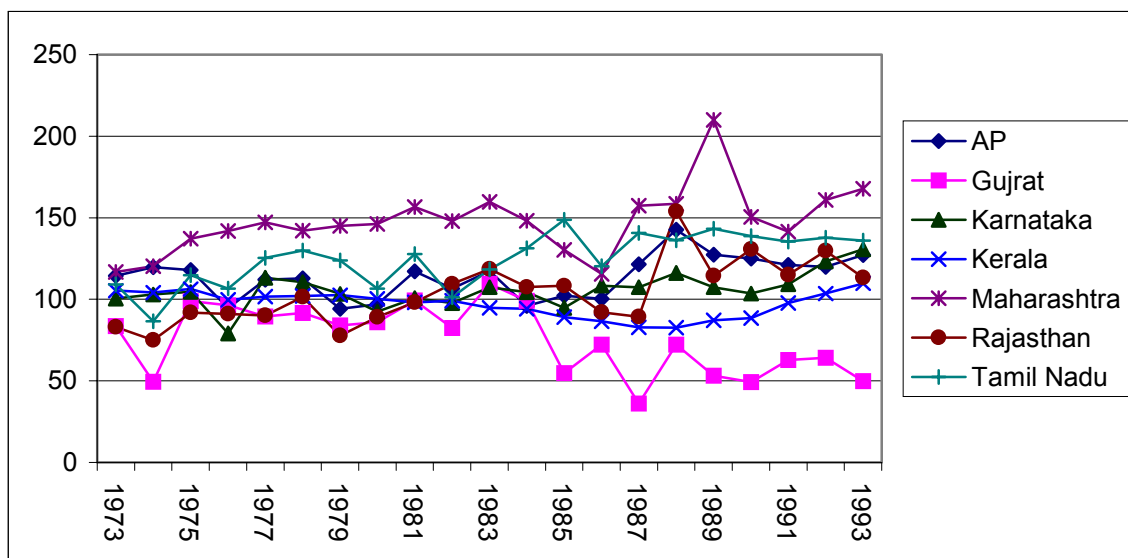
The decade of the seventies was the time when total factor productivity was being affected by the introduction of new technology, which were termed as the Green Revolution. It gathered strength in the first half of the eighties, when the growth in TFP peaked. The experience of the years from the second half of the eighties can be taken as an indication of the fact that the so-called 'Green Revolution' technologies have run their course, and it would be difficult to sustain a high rate of TFP growth in the absence of major technological breakthrough in the field of agricultural science.

We can see from the data in Table A.1 that there has been a wide variation in the rate of TFP growth across regions of India over the period 1973-93. Some states have done better than others in terms of their agricultural performance, with West Bengal and Punjab being the frontrunners. The divergence in productivity is captured by Figure 2.1, which shows the fluctuations in the TFP growth across states over the whole time period.

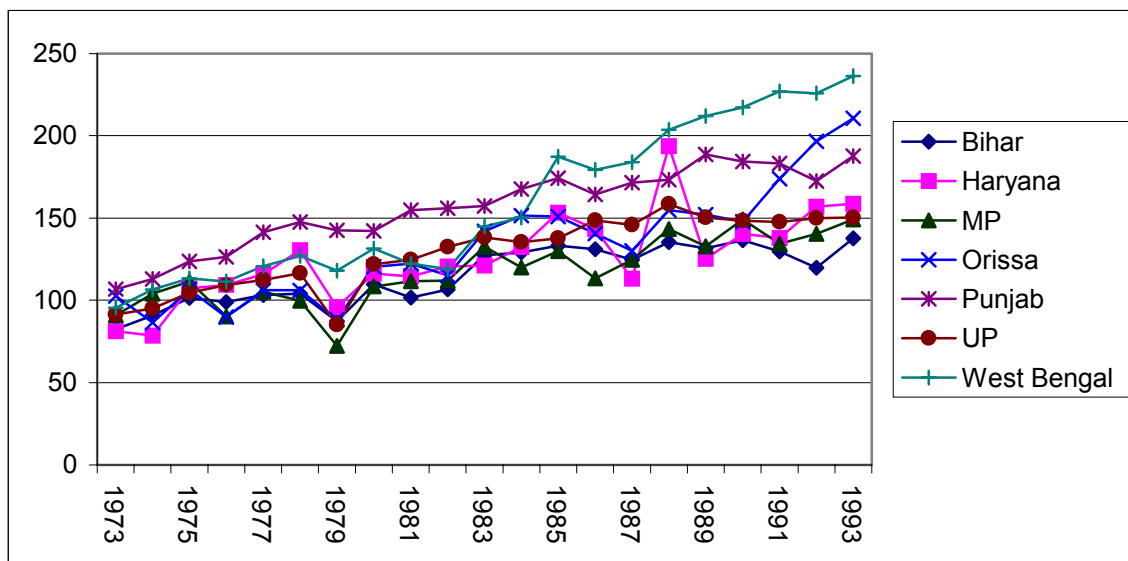
A closer examination reveals that the states can be broadly divided into ones that are 'high-performing' and those that are 'low-performing' on the basis of their performance ranking over the entire period of time (Figure 2.2). In the former case, the states have shown very substantial improvement in agricultural productivity (over 2 percent throughout the period). On the other hand, the 'low-performing' states have managed moderate improvements in TFP, while two states, Gujrat and Kerala, have recorded negative rates of TFP growth for the entire period. Therefore, the All-India data on TFP masks important and widespread regional disparities in agricultural performance across the country.

Figure 2.2: TFP Growth Rates in Different States

(a) Low Performing States



(b) High Performing States



growth rates over the three subperiods across states. In the first period from 1973-80, the two major agricultural states of north India, Punjab and Haryana, had the best performance among all the states. This is mainly because they got a head start regarding the introduction of modern technologies in foodgrain production, which then spread to

other states of the country. The second period from 1980-88 saw better TFP performance in nearly all the states (except Gujrat, Maharashtra and Kerala), but was marked by a slowdown in the TFP growth in Haryana and Punjab, possibly due to diminishing returns to technology in agriculture. Overall, this period saw the fruits of technology being harvested by most major agricultural states in India, and went a long way towards the achievement of self-sufficiency in foodgrain production by the early 1980s.

From the late eighties onwards, there is substantial evidence of an overall slowdown in TFP growth in India, as can be seen from Table A.1. Major agricultural states in north India, such as Bihar, Uttar Pradesh, Punjab and Rajasthan recorded minor or even negative rates of TFP growth in this period. However, Haryana, Karnataka, Kerala, Maharashtra, Orissa and West Bengal all recorded significant productivity gains.

2.2.3 Divergence in Productivity among States

To understand the divergence in productivity experience, we calculate the standard deviation of TFP for each year across states (following Barro and Sala-i-Martin (1995), Bernard and Jones (1996) and others). A few interesting points can be noted from Figure 2.3. It seems apparent that overall, there has been an increase in the cross-regional dispersion of TFP in agriculture over the entire time period. The movement has been very uneven, with sharp increases followed by significant declines in productivity dispersion. The trend, however, has been unambiguously towards greater dispersion, since the trend line has a positive slope.⁴

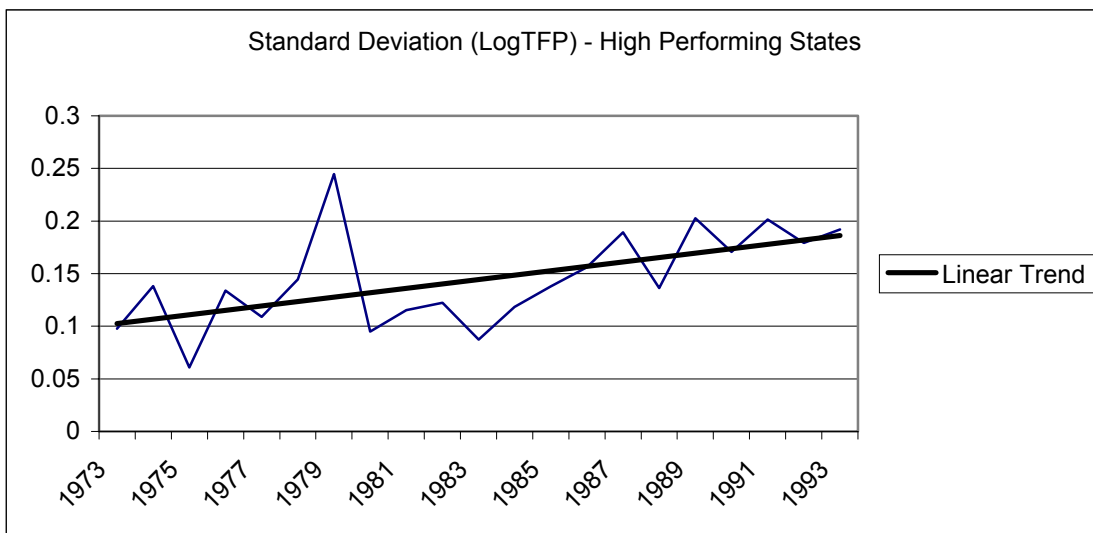
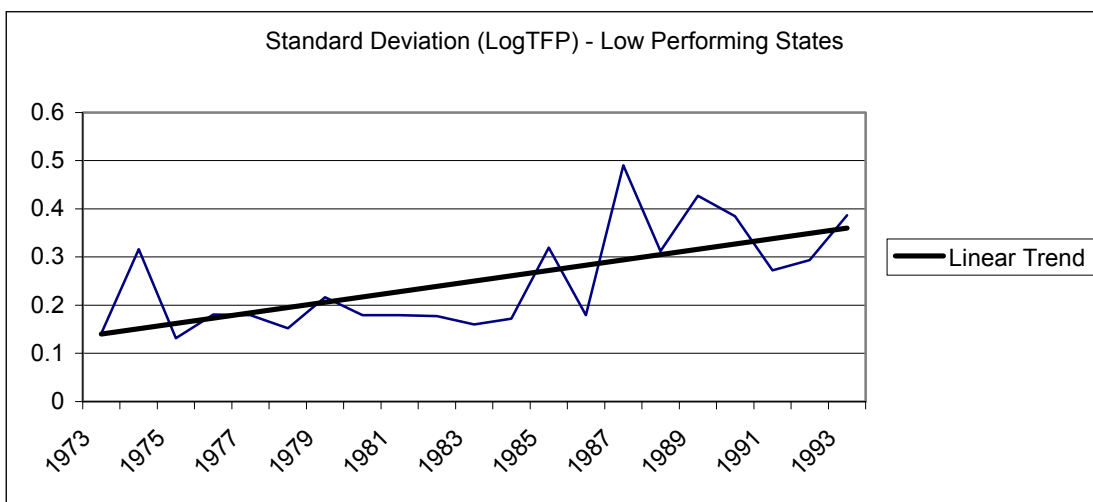
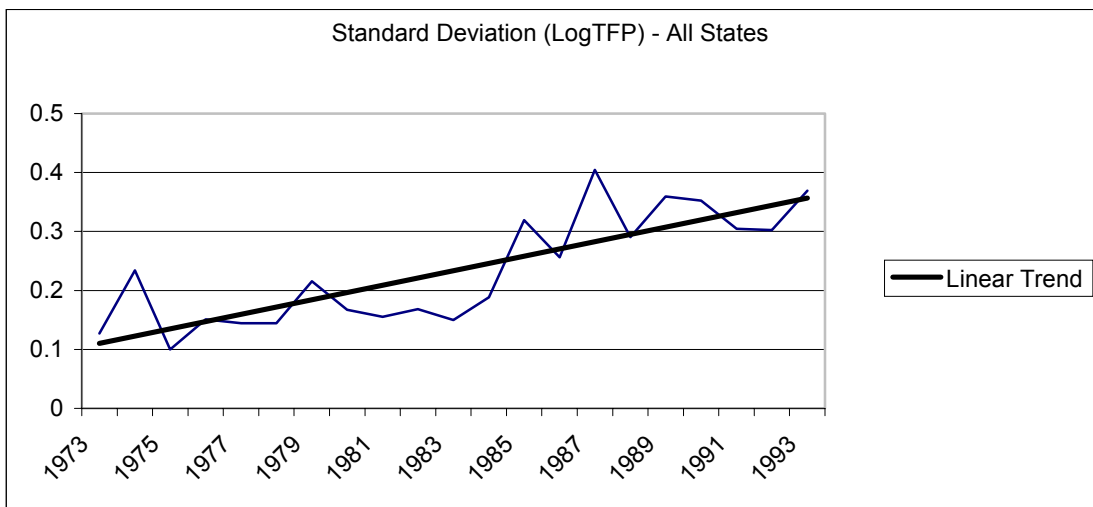
⁴ This might be one of the reasons behind Das and Barua (1996) observation of increasing inequalities in agriculture in Indian states.

However, as we had seen from the aggregate analysis in Table A.1 and Figure 2.1, a distinct pattern emerges when we separate out the ‘low-performing’ and the ‘high-performing’ states taking the average annual rate of TFP growth at the national level as the benchmark. The lower panels of Figure 2.3 show the dispersion according to the performance level of the states. We can see that the aggregate dispersion is more or less identical to that of the movement of the ‘low-performing’ states.

On the contrary, while the ‘high-performing’ states have shown a general increase in dispersion, the magnitude is lower than that of the states that have not had a fast pace of productivity increase. Moreover, the oscillations around the trend line show signs of dampening, which indicates that the long-run dispersion is tending towards a steady state. As pointed out by Datt and Ravallion (1998), this might be due to the initial conditions such as differences in natural endowments, physical and human infrastructure, etc. Therefore, in our empirical section, we set up our null hypothesis taking into account the heterogeneity in TFP performance among states and evaluate the different tests of convergence for their applicability vis-à-vis our data.

In the next section, we set up a test of convergence of state TFP indices by analyzing the panel of 14 major states of India between 1973-1993. The time period is long enough for us to use the asymptotic properties of the estimated convergence coefficients, taking into account the recent developments in panel convergence analysis.

Figure 2.3: Dispersion in TFP in Agriculture across Indian States



2.3 Tests of Convergence in Productivity across States

2.3.1 Basic Model

The neoclassical growth model without technology predicts convergence in output per worker for similar, closed economies based on the accumulation of capital. However, even in the neoclassical model, if the exogenous technology processes follow different long-run paths across countries, there will be no tendency for the output levels to converge. Analogously, in our case, we are interested in finding out whether the different states in India, especially the major agricultural ones considered in this study, have managed to narrow their technology gap. To see this, we construct a simple model of sectoral output in which convergence in output occurs due to the improvement in TFP. The behavior of TFP in this model is such that relatively backward regions can grow more rapidly by efficiently using the same technologies that are available to the leading regions.

Following Bernard and Jones (1996), we assume that the production process can be represented by a simple Cobb-Douglas production function with constant returns to scale.⁵ We can write the log of the output in agriculture in state i at time t , $\ln Y_{it}$, as:

$$\ln Y_{it} = \ln A_{it} + \alpha \ln K_{it} + (1 - \alpha) \ln L_{it}, \quad (2.1)$$

where A_{it} is an exogenous technology process, K_{it} is the capital stock, and L_{it} is the number of workers in the sector. We assume that A_{it} evolves according to:

$$\ln A_{it} = \gamma_i + \lambda \ln D_{it} + \ln A_{it-1} + \varepsilon_{it}, \quad (2.2)$$

⁵ Although it is a restrictive assumption, it simplifies our argument for the use of Divisia index where prices of factors and inputs are taken as the marginal product and marginal cost respectively in calculating TFP.

with γ_i being the asymptotic rate of growth of agriculture in state i , λ parameterizing the speed of the catch-up denoted by D_{it} , and ε_{it} represents the region-specific productivity shock. We allow D_{it} to be a function of the productivity differential in agriculture in region i from that of the national average, A_n :

$$\ln D_{it} = \ln \hat{A}_{it-1}, \quad (2.3)$$

where a hat indicates a ratio of the national average of a variable to the same variable in state i , i.e.,

$$\hat{A}_{it} = A_{it} / A_{nt}$$

This formulation implies that productivity gaps between states are a function of the lagged gap in productivity. We also presume that technological convergence occurs independent of capital deepening. Therefore, the model yields a simple equation for the time path of TFP given as:

$$\ln \hat{A}_{it} = (\gamma_i - \gamma_n) + (1 - \lambda) \ln \hat{A}_{it-1} + \hat{\varepsilon}_{it}, \quad (2.4)$$

where $\hat{\varepsilon}_{it}$ are iid error terms.⁶ If $\lambda > 0$, the difference in the technology levels between the state and the national level will be stationary. Alternatively, if $\lambda = 0$, productivity levels would grow at different rates permanently and show no tendency to converge. In that case, difference between the TFP in state i and the national average will be non-stationary.

⁶ Since our dataset includes cross-section observations, we shall subsequently set up our tests of convergence for serially correlated errors as well.

2.3.2 Estimation Procedure

Tests for convergence in panel data models is a subject of ongoing theoretical investigation.⁷ Earlier studies have tested for unit roots using the methodology proposed by Levin and Lin (1992). Bernard and Jones (1996) further extended this discussion to include non-zero drift terms in the framework.

Levin and Lin (1992) proposed a method of testing for unit roots in a finite sample panel data. For estimation purposes, we consider the general version of equation (2.4):

$$\ln \hat{A}_{it} = \rho \ln \hat{A}_{it-1} + \mu_i + v_{it}, \quad (2.5)$$

where $v_{it} \sim iid(0, \sigma_v^2)$ and $\mu_i \sim iid(\bar{\mu}, \sigma_\mu^2)$ is an individual-specific effect. We also assume following Levin and Lin (1992) that v_{it} has $2+\Delta$ moments for some $\Delta > 0$ and $E\mu_i v_{it} = 0$ for all i and t , and other regularity conditions hold.

The null hypothesis that we test is $H_0 : \rho = 1$ for all i against the alternative hypothesis $H_A : \rho < 1$ for all i . This means that we are testing whether the group of states as a whole are converging or not. Under this alternative hypothesis, the states are taken as homogenous, controlling for state-specific fixed effects. The t-values are asymptotically centered and normal, and therefore we can test for convergence using the significance level of the t-statistics.

In case a deterministic element such as a time-trend is present in the data, we can include a state-specific parameter $\eta_i \cdot t$ in (2.5) to control for idiosyncratic yearly shocks to the agricultural sector. Moreover, we also specify the model to take into account the

⁷ For a review article, see Banerjee (1999).

persistence in the error terms likely to result from presence of cross-sectional elements in the panel dataset.

The assumption of homogeneity in the panel convergence test has been criticized by several papers (Im, Pesaran and Shin (IPS), 1997; Harris and Tzavalis, 1999; Hadri, 2000). Recently, Levin and Lin (2002) has improved the earlier model to allow for the degree of persistence in individual panel to vary freely. Extending (2.5) and taking into account the individual and trend variations, the following equation tests for unit root in panel data:

$$\Delta y_{it} = \delta_{it} y_{i,t-1} + \sum_{L=1}^{p_i} \theta_{iL} \Delta y_{i,t-L} + \alpha_{0i} + \alpha_{01} \cdot t + \zeta_{it}, \quad (2.6)$$

where the error term is distributed independently across individuals and follows a stationary invertible ARIMA process for each individual. The procedure involves performing augmented Dickey-Fuller (ADF) regressions with the lag order permitted to vary across individuals. For reasons of simplification, we test for the same lag-length across all panels, choosing p_i in accordance with the method proposed by Levin and Lin (2002). These estimations have been carried out using NPT1.2 and Coint 2.0 on GAUSS⁸.

⁸ The GAUSS code for NPT 1.2 can be downloaded from <http://web.syr.edu/~cdkao>.

2.4 Estimation Results

2.4.1 Results from Levin and Lin (LL) method

Tables 2.1 and 2.2 present the results of the tests for convergence using the two methodologies described above. From the results of Table 2.1, we observe that all specifications reject the null of non-stationarity. LL1 is specified without intercept and time-trend but with individual-specific effects. LL2 includes all three, while LL3 is estimated without intercept and time-trend but considering serial correlation across time periods.

Table 2.1: Unit Root Estimates using Levin and Lin (1992)

Model	Coefficient (ρ)	t-value	Critical Probability
LL1	0.543	-5.031	0.000
LL2	0.117	-9.816	0.000
LL3	0.872	-8.091	0.000

Note:

LL1: Individual-specific effect only.

LL2: Individual-specific effect and individual time-trend.

LL3: Serially correlated errors, without intercept and time trend.

A closer look at the results indicates that among the three, LL2 has the lowest coefficient but the highest t-statistic. LL3 shows a significant improvement in the estimated coefficient when serial correlation is taken care of. Therefore, these preliminary results indicate that there is a tendency for the levels of TFP across states in

India to converge. The rejection of the null hypothesis implies that all the states are converging at the same rate towards a steady state.

Table 2.2: Unit Root Tests for Levin and Lin (2002)

Model	Lag Length	Coefficient (ρ)	t_{δ} value	Critical Probability
LL4	1	0.559	17.868	0.000
	2	0.818	26.066	0.000
LL5	1	0.898	40.874	0.000
	2	0.985	51.354	0.000

Note:

LL4: With individual-specific effect.

LL5: With individual-specific effect and individual time trend.

Table 2.2 provides the estimation results for LL4 and LL5 based on the improved model of Levin and Lin (2002). We estimate the two models with one and two-period lags in the ADF regressions. LL4 includes an individual-specific effect only whereas LL5 includes individual time trend as well. The results point to a rejection of the null hypothesis and a substantial improvement in the estimated coefficients. The test statistic t_{δ} is obtained from pooling the individual test statistics in the final stage of the estimation. Therefore, for LL5 with one lag, the rate of convergence is 11 percent, decreasing to 4 percent when both lags are included in the ADF regression.

2.4.2 Further Tests of Convergence

Although Levin and Lin (2002) is a substantial improvement over the previous series of tests, the question still remains whether pooling has any effect on the outcome of the convergence tests. IPS97 and Hadri (2000) provide two instances where the independence assumption across cross-sections is utilized to test for unit roots. On the other hand, in small-sample estimations with the time dimension limited, the asymptotic distributions of the test statistics can be different from LL results (Harris and Tzavalis, 1999). Therefore, it is necessary to carry out these additional tests to determine whether panel heterogeneity and sample-selection have any effect on the outcome of the LL tests.

Table 2.3: Other Tests of Convergence

Model	Test Statistic	Critical Probability
IPS97	-2.696	0.043
HT1	3.609	0.000
HT2	24.018	0.000
Hadri	362.896	0.000

IPS97: With time trend; HT1: With intercept; HT2: With intercept and time trend; Hadri: With time trend.

Table 2.3 outlines the result of IPS97, Hadri and Harris and Tzavalis (HT) tests for the specifications using time trend for IPS97 and Hadri, and both intercept and time trend for HT. As is evident, the test statistic in all the three cases rejects the null of non-stationarity. Therefore, we can say that the LL test results are robust to alternative

specifications of panel independence and small-sample bias. The above results unambiguously point to a rejection of the hypothesis of a unit root, indicating long-run convergence in TFP levels taking into account individual-specific variations.

Recently, McCunn and Huffman (2000) investigated the convergence in TFP for agriculture in forty-two U.S. states. They found no evidence of σ - convergence but characteristics of conditional β - convergence in the data. In our study, we use panel unit-root tests under various specifications to test for β - convergence, and come to exactly the same conclusions. Although due to data limitations we cannot decompose the convergence rates into its components, our conjecture is that in the long run, elimination of differences in infrastructure, R&D, social services etc. would have a significant impact on the rate of convergence across states in India, which is consistent with McCunn and Huffman (2000).

2.5 Concluding Comments and Extension

This chapter analyses convergence in TFP growth in Indian agriculture across states over the last two decades. The agricultural sector has performed admirably after the introduction of modern technology and high-yielding varieties since the late-1960s, the so-called ‘Green Revolution’. However, an analysis of the disaggregated data at the state level underscores the variation in the rate of TFP growth across the different states of the country. We find that broadly, the states can be categorized according to their growth in TFP in agriculture between ‘high-performing’ and ‘low-performing’ groups. There is no evidence of a reduction in the productivity gap between these groups of

states over time, leading us to conclude that until now, the rates of productivity growth have not been homogeneous in all states under consideration.

The convergence analysis, on the other hand, shows evidence of long-run convergence. After controlling for fixed factors, the TFP gap measured by the distance of each state's productivity level from the all-India average is found to be stationary. This result is robust to specifications that take into account the cross-sectional variations across states and idiosyncratic yearly shocks in the panel dataset under consideration. In the context of the previous studies on agricultural performance in India, this result challenges the prevailing consensus of divergence in productivity and poverty impact of technological change.

The results also suggest that state-specific factors are important in convergence among states. Until now, agroclimatic factors have been regarded as the major factor in explaining the variation in TFP across states. However, in the subsequent chapters, we introduce nonfarm sector and infrastructure to explain the difference in productivity performance. Interlinkages between agriculture, nonfarm employment and physical and social infrastructure will help to explain the difference in regional TFP growth.

Chapter 3 extends the analysis in this chapter and looks at convergence in rural development that includes both agriculture and nonfarm sectors. Our results would show that strong linkages between them contribute to convergence in rural development in the fourteen states of India under consideration.

Chapter 3

Convergence in Rural Development*

3.1 Initial Comments

In the previous chapter, we analyzed convergence in agricultural productivity in Indian states from 1973 to 1993. After controlling for fixed effects, we found evidence of long-run convergence in TFP among them. However, as discussed in Chapter 1, recent work emphasizes on the potential role of nonfarm employment and income in rural development. In Section 3.2 of this chapter, we put this study in the perspective of previous work in rural development. There is a consensus that nonfarm employment plays an important role in rural development. However, a synthesis of agricultural productivity and the nonfarm employment in explaining the change in rural development has not been attempted so far.

In Section 3.3, we investigate the regional diversity in rural development in India from 1973 to 1993. There are significant differences between the states, and it has to be explained both in terms of agricultural growth as well as structural change in employment in the rural areas. Section 3.4 presents an analysis of the measure of rural development defined in Section 3.3. We find that a combined measure of rural development including both TFP in agriculture and nonfarm employment growth shows

* This chapter is based on Mukherjee and Kuroda (2002), *Journal of Asian Economics* 13: 385-398.

strong evidence of convergence in the long run. Section 3.5 concludes with a discussion of policy measures for rural development.

3.2 Background Issues

Previous studies have noted that the rural nonfarm sector in developing countries experienced a decline in the colonial period (Ranis and Stewart, 1993). However, country-specific surveys over a representative sample of developing countries have shown the persistence and propagation of a wide variety of nonfarm employment and output (Chuta and Lieldholm, 1979; Reardon, Crawford and Kelly, 1994). The importance of the rural nonfarm sector in economic development was further underlined by the success of the township and village enterprises (TVEs) in rural China. Studies have shown that the TVEs play an integral part of the growth in the Chinese economy (Byrd and Lin, 1990; Findlay, Watson and Wu, 1994).

The rural nonfarm sector has been the focus of recent studies on rural development in various parts of the world. Nonfarm employment reduces absolute poverty and relative inequality within the rural areas (Lanjouw, 1999; van de Walle 2000). It is also recognized that the nonfarm sector plays a positive role in improving productivity in agriculture. Farmers with off-farm sources of income are more willing to invest in land and technology. This is especially true of cash crops, where the risk and returns to new technology are both high.¹ A study of North Arcot district in south India found that a 1% increase in nonfarm employment is associated with a more than proportionate increase in agricultural production (Hazell and Ramasamy, 1991).

¹ See Lewis and Thorbecke (1992) for a case study of coffee production in Kenya.

On the other hand, higher rural nonfarm employment generation and better poverty-alleviation occurs in regions that have a dynamic agricultural sector as well (Reardon, Berdegue and Escobar, 2001). Consumption and production linkages feed both the farm and nonfarm sectors, leading to higher growth in off-farm employment generation and agriculture.

Particularly in the case of India, an additional aspect about the importance of the nonfarm sector employment may be set out as follows. The rural working population can be divided into agricultural labor, nonagricultural labor and the residual, which we term as unemployed for convenience of exposition. Now, over time, if opportunities for employment in agriculture remain constant (as has been the case of India), with population growth, the nonfarm employment needs to be increased if unemployment is to be contained and eventually reduced.

Formalizing this argument, let us suppose that in the first period, the distribution of the population in the rural sector can be expressed as follows:

$$L_1^R = L_1^A + L_1^N + U_1, \quad (3.1)$$

where L_1^R is the total population in the rural sector in the first period, and L_1^A , L_1^N and U_1 are agricultural employment, rural nonfarm employment and rural unemployment respectively. Similarly, in the second period, we denote the distribution of rural workforce as:

$$L_2^R = L_2^A + L_2^N + U_2, \quad (3.2)$$

where the components are defined as above. Now, subtracting (3.1) from (3.2), we get,

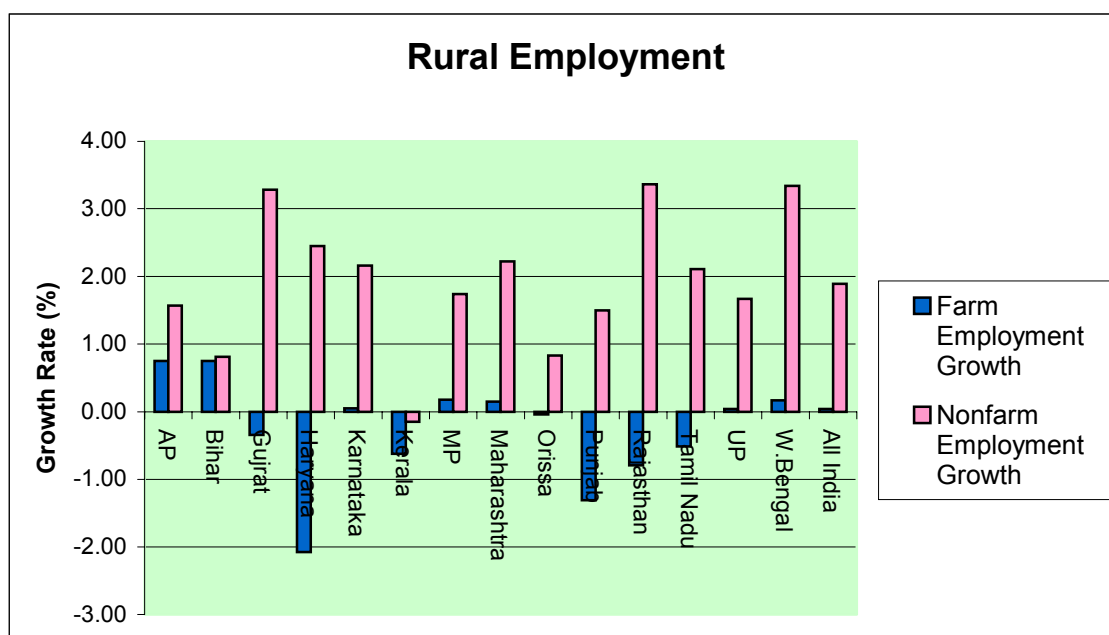
$$L_2^R - L_1^R = (L_2^A - L_1^A) + (L_2^N - L_1^N) + (U_2 - U_1). \quad (3.3)$$

The left hand side of equation (3.3) denotes the growth in rural population, which we know is positive in the case of India. Now, the first term on the right hand side denotes the growth in agricultural employment, while the second term denotes the growth in

rural nonfarm employment. Since the policy objective is to have $(U_2 - U_1) \leq 0$, increase in farm and nonfarm employment must account for the growth in rural population for equation (3.3) to hold.

Rural employment growth in India across states in farm and nonfarm sectors is presented in Figure 3.1, for the period from 1973 to 1993. It shows that almost all the states have had positive growth in nonfarm employment, although the growth rates over the period vary considerably. On the other hand, farm employment has declined in six of the fourteen states, increased substantially in two, and has remained stagnant in the rest. For the whole of India (including the states not included in this study), the agricultural workforce has remained remarkably stable in spite of substantial gains in agricultural productivity over the study period, as we have seen in Chapter 2. This implies that the ratio of farm to nonfarm employment has decreased from the levels at the beginning of the period, leading to a change in the structure of the laborforce. Therefore, from (3.3), growth in nonfarm employment can be seen as a means to absorb the rural population growth and reduce rural unemployment in India.

Figure 3.1: Farm and Nonfarm Employment Growth in India

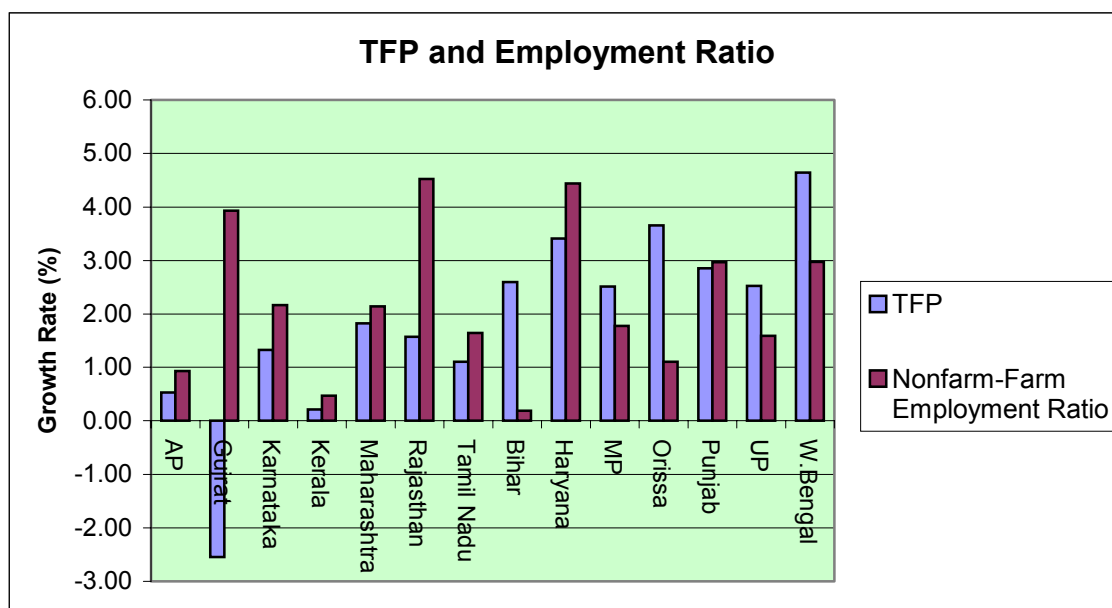


We now have a strong case for studying the rural nonfarm sector in conjunction with agricultural productivity to investigate the levels of rural development in India. Growth in both these sectors holds the key for improving the livelihood of the rural population, and the linkages between them have to be exploited in the process of development, as we shall see in the case of Indian states below.

3.3 Rural Development in India

In India, different regions have their own geographic, agroclimatic, social and political characteristics that result in diverse development patterns. In Table 2.1 in the previous chapter, we have seen that the growth rate in TFP in agriculture has shown substantial variation among the different states under consideration. Overall, we found that the rate of technical progress in agriculture is converging across the country. While this is a significant observation, the impact of this technological change on wider rural development is yet to be fully understood.

Figure 3.2: TFP and Nonfarm-Farm Employment Ratio Growth in India



This is because agricultural growth and nonfarm employment generation have so far been studied separately, without considering the substantial interlinkages that exist between them.

Figures 3.1 and 3.2 clearly bring out the diversity in the growth rates in TFP, farm and nonfarm employment across states of India. Most of the states have experienced positive TFP growth over the period after the Green Revolution, with Gujrat being the only exception. In Gujrat, agriculture has been hit by persistent drought from the middle of the 1980s. Being a region with low groundwater sources, irrigation has not proved to be very effective in raising productivity. At the same time, rural nonfarm employment has expanded very rapidly, thereby raising wages in the farm sector.

The southern state of Kerala has been a model of development for the rest of the country, with very high levels of social and physical infrastructure at the beginning of the period. Agriculture is based on plantation crops for export, such as spices and coconut that are traditionally grown in the region. A highly educated workforce in the rural areas migrate mostly to urban centers for skilled jobs, hence the decline in rural nonfarm employment that we see in Figure 3.1. In terms of overall level of development, other states have tried to emulate Kerala's example in following policies for regional economic growth. In the empirical analysis of Section 3.4, we would test for convergence in rural development across India taking Kerala as the reference state. In other parts of the country, however, TFP and nonfarm growth rates have both been positive, although their magnitudes vary widely.

Higher levels of development require a transformation of the structure of employment in the economy (Lewis, 1954; Ranis and Fei, 1961). This is true of the rural areas as well. As discussed in Chapter 1, application of modern production

methods in agriculture entails greater use of mechanical and chemical inputs, such as tractors, threshers, pumpsets and fertilizers. Historically, this increased use of modern inputs has been the source of productivity increase and has helped in freeing up labor for employment outside agriculture. In the classical development theory, this acts as the source of labor supply for the urban-based manufacturing sector, which was thought to be the engine of economic growth. However, the experience of developing countries over the years has not fitted into this neat characterization of the process of development. It is now accepted that nonfarm employment in rural areas would be better able to absorb the increase in rural population and the surplus labor available in the rural areas. Creation of nonfarm employment is thus a necessary corollary to technological change in agriculture in the process of rural development (Rosegrant and Hazell, 2000).

Table A.2 calculates the farm-nonfarm employment ratio for each state over the study period. The ratio has declined from its initial levels in every state, but the rates of decline have not been uniform. It ranges from a high of 5.89% in the case of Rajasthan, to a low of 0.79% in the case of Bihar. Most of the states have experienced a decline in the farm-nonfarm employment ratio between 2 and 4 percent annually over the entire period.

In Figure 3.2, we plot the change in TFP along with the increase in the nonfarm-farm employment ratio for the benefit of exposition. We see quite clearly that with one exception, the growth rates of both TFP and the nonfarm-farm employment ratio have been positive across all the major states of India. This observation is important for the following reasons. Firstly, as we have noted in Section 3.2 above, previous studies have reported that part of the income from increased nonfarm employment is invested in the farm sector to improve the quality of labor, capital and intermediate inputs, which has a

positive effect on TFP. This channel of farm-nonfarm linkage seems to be true in the Indian case as well.

Secondly, from the employment perspective, higher growth in the employment ratio is beneficial for absorbing both the increase in working population and surplus labor in agriculture in the rural areas. In the case of Haryana, for example, increased mechanization of agriculture has led to a fall in farm employment, which is compensated for by rapid nonfarm employment growth of nearly 2.5 percent over the study period. This increase in nonfarm employment may have had a positive effect on TFP in agriculture, which has also risen at a rapid rate. On the contrary, Bihar has experienced a moderately high TFP growth in agriculture, whereas the employment ratio has not changed much. This indicates that farm-nonfarm linkages in Bihar are not as strong as in other states that have created more nonfarm employment opportunities. Indeed, compared to other states of India, Bihar has one of the lowest levels of development, with high levels of rural unemployment and migration from the rural areas.

Thirdly, productivity growth in agriculture generates surpluses for investment in the nonfarm sector. Demand linkages with several service occupations such as repair services and transport encourage entrepreneurship in these sectors. Most of the nonfarm growth can be seen in areas of high agricultural productivity (Reardon, Berdegue and Escobar, 2001). From the supply side, agriculture-based industries such as food processing and packaging also generate nonfarm employment in low-skill occupations. The growth in nonfarm employment generated through such linkages with agriculture act as an important source of income generation to be invested back into agriculture, as we have noted above.

Therefore, higher TFP and nonfarm employment growth are essential elements of a virtuous circle that lead to economic development in the rural areas. However, it is difficult to point to the direction of the causality between the two sectors as well as the impact of farm productivity on rural nonfarm employment and vice versa. This empirical question will be explored in Chapter 4.

On the basis of the previous discussion, following Mukherjee and Kuroda (2002), we compute an indicator of rural development (RDI) that reflects the growth in TFP in agriculture and the structural change in rural employment in each state.

$$RDI \equiv (\text{Index of TFP}) / (\text{Farm-Nonfarm Employment ratio})$$

The numerator is a measure of technological change in agriculture that leads to an increase in agricultural productivity, while the denominator is a measure of the structural transformation in rural employment. The ideal case is that of an increase in the numerator and a fall in the denominator, such that both agricultural productivity and nonfarm activities grow simultaneously.

Figure 3.3: Rural Development Indicator for Indian States (1970=100)

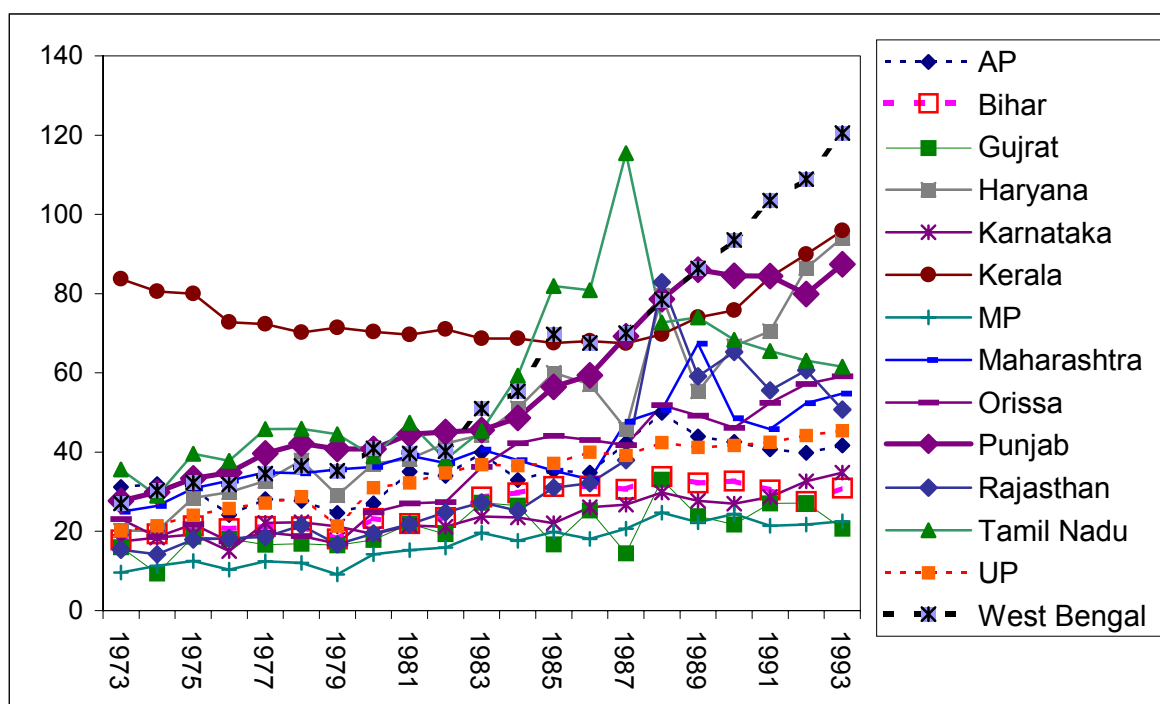


Figure 3.3 shows the plotted values of the RDI from 1973 to 1993 for each state. In the beginning of the period, Kerala had the highest RDI compared to the other states. However, as is evident from the figure, the other states have caught up with Kerala over the whole period. In 1993, West Bengal had the highest RDI among all the states combined, followed by Kerala, Haryana and Punjab. West Bengal has experienced a very substantial increase in the TFP growth rate in agriculture as well as a decline in the farm-nonfarm employment ratio, while the agricultural TFP growth in Kerala improved only in the last period. Thus, it is no surprise that West Bengal has surpassed Kerala in recent years according to our measure.

The observations above concerning geographical variations in rural development are remarkably similar to several studies conducted recently. Gutierrez (2000) finds that migration from the farm to nonfarm sector employment leads to higher speed of convergence in agriculture for OECD countries. In the case of India, Ravallion and Datt (2002) reports that the overall reduction in poverty in rural India has been higher in states that have a higher per capita rural nonfarm output. In their measure, West Bengal comes first followed by Kerala, while Bihar is the worst performer among the states under consideration. This finding is consistent with our measure of RDI as well.

The data also catches the effect of the decline in rural nonfarm employment generation from the late 1980s to the mid-1990s witnessed in some states. Looking at Tamil Nadu, the RDI fell drastically from 1987 to 1993 due to a slowdown both in TFP growth in agriculture and an increase in the farm-nonfarm ratio. Other states such as Rajasthan and Madhya Pradesh also experienced a decline in RDI in the last period. Our measure is sensitive to changes in both TFP and farm-nonfarm ratio, and states that undertake policies to improve both agriculture and create nonfarm employment at the

same time will attain higher level of rural development. The RDI thus provides a simple measure of rural development for policy formulation as well.

Figure 3.3 also gives support to the hypothesis that the different states of India, although following different economic and social policies, are in fact converging towards the level achieved by Kerala. In the next section, we analyze the convergence hypothesis of rural development in the context of Indian states, using the value of RDI calculated above. The results indicate that the levels of rural development are converging across states, pointing towards positive linkages between farm and nonfarm sectors in the rural areas.

3.4 Tests of Convergence in Rural Development

In the previous section, we have explained the construction of the rural development indicator. In Chapter 2, we have seen that there is significant evidence that the TFP in agriculture in India is converging in the period after the Green Revolution. However, we also need to examine the behavior of the denominator, that is, the farm-nonfarm employment ratio before we analyze the convergence properties of the RDI. In this section, first, we investigate whether the employment ratio has tended to converge across states. As noted above, some states have experienced a sharp decline, while in others, the change has not been significant. Next, we check for evidence of convergence in RDI. Taking Kerala as the reference state, we find that there is evidence that other states have caught up with Kerala in rural development. West Bengal, Haryana and Punjab have either surpassed it or have closed the gap considerably in the period after the Green Revolution.

The choice of Kerala as the reference state needs further elaboration. As we have seen from Figure 3.3, the RDI for Kerala was far above any other state at the beginning of the study period. This is because it had followed progressive policies that enabled it to achieve higher levels of development than any other state (Sen, 1999). Although in 1973 it was far ahead in rural development levels compared to the rest of the country, over the years, other states have followed its example and have formulated policies similar to Kerala. Figure 3.3 provides evidence of this catch-up over the study period. Therefore, in order to test for convergence in RDI, Kerala is the best candidate to act as the reference state, because the rest of the states in the sample have followed its example in setting their own development goals. Moreover, being part of the same country, the legal and constitutional boundaries to formulating policies for development are the same in Kerala as in other states of India. This characteristic is different from outliers in cross-country studies where the individual countries have their own political and social characteristics, which make the choice of reference state a matter of contention.

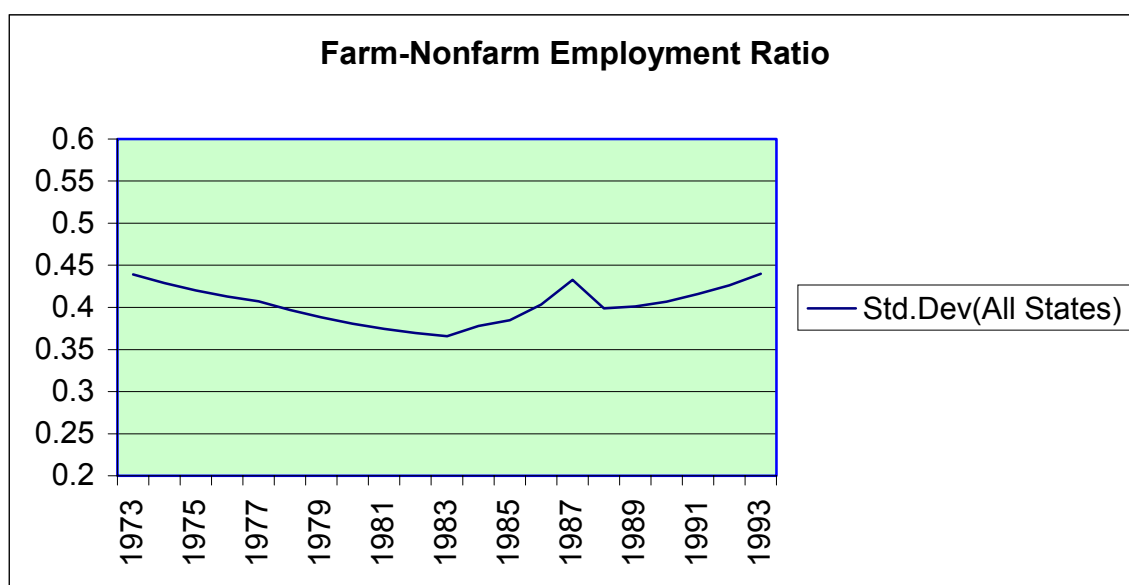
3.4.1 Convergence in Rural Employment Ratio

As evident from Table A.2 and Figure 3.2, the change in the structure of the rural workforce has not been uniform across states. However, it is fair to say that the states that have performed best in terms of RDI, namely West Bengal, Haryana and Punjab, have shown a concurrent increase in both agricultural productivity and nonfarm employment generation in the rural areas. However, it is noticeable that over the entire period, there is substantial variation in the employment ratio across states. It is also

evident from Table 3.1 that six states have shown a reversal in the employment ratio in the period from the late 1980s.

Figure 3.4 provides a graphical representation of the variation in the farm-nonfarm employment ratio across states over the entire period. What is surprising is that after declining significantly from 1973 until the middle of the 80s, there has been an increase in variation in the employment ratio in the period after that.² Therefore, we employ the techniques used in the previous chapter to analyze the long-run convergence in the employment ratio in the rural sector.

Figure 3.4: Variation in Farm-Nonfarm Employment Ratio



The results of the convergence analysis are given in Table 3.1. Under the null hypothesis of no convergence following Levin and Lin (1992), we evaluate the test statistic using LL1 (common intercept and time trend), LL2 (with individual-specific effect) and LL3 (with individual- and time-specific effect). We find that in all the cases,

² A simple regression of the logarithm of the employment ratio against time remains inconclusive.

Table 3.1 Convergence Tests for Rural Employment Ratio

Test Procedure	Coefficient	t-statistic	Critical Probability
LL1	0.969	-3.514	0.000
LL2	0.883	-3.493	0.000
LL3	0.881	-3.727	0.000

Note:

LL1: With intercept and time trend.

LL2: With individual-specific effect.

LL3: With individual-specific effect and individual time trend.

the null hypothesis can be rejected, implying that there is evidence of convergence across states in the employment ratio. The results do not change even if we specify the alternative hypothesis following Levin and Lin (2002) as we have done for convergence in agriculture in Chapter 2.

3.4.2 Convergence in RDI

We are now ready to analyze the question of convergence in rural development. In the measure of RDI described in Section 3.2 above, rural development combines both increases in agricultural productivity as well as the change in the structure of the labor force in the rural areas. As noted by Bhalla and Singh (2001), the slow transformation of labor from farm to nonfarm sector jobs acts as a brake against faster rural development in some states, for example, Bihar. On the other hand, the states that have had the fastest reductions in poverty in the period from 1973 to 1993, namely, West Bengal, Haryana and Punjab, have been able to increase the numerator and decrease the denominator in our measure.

Therefore, convergence in RDI can take place through two channels that are interlinked. This linkage has not been exploited in earlier studies, and this is the main contribution of this chapter.

The results of the test for convergence in RDI are given in Table 3.2. In LL1, we specify a common time trend and intercept for all the states. The test statistic rejects the null of non-convergence in this case. As we have discussed above, the initial conditions and other state-specific characteristics lead to substantial variation in the level of rural development. To control for these variations, we need to specify LL2 with individual-specific fixed effects. In this case, the test statistic cannot reject the null of no convergence. However, we also need to take into account idiosyncratic variations due to unforeseen factors, such as rainfall, that affect both agriculture and the nonfarm sectors. In LL3, we specify the test of convergence taking into account both individual fixed effects and idiosyncratic shocks over time. In this case, we reject the null hypothesis at the 5% level of significance. The convergence result also holds true for other specifications of the null hypothesis under the Levin-Lin framework.

Table 3.2 Convergence Tests for RDI

Test Procedure	Coefficient	t-statistic	Critical Probability
LL1	0.924	-2.481	0.006
LL2	0.813	-1.387	0.082
LL3	0.525	-1.674	0.046

Note:

LL1: With intercept and time trend.

LL2: With individual-specific effect.

LL3: With individual-specific effect and individual time trend.

Convergence in RDI thus depends on the specification of the test procedure. Controlling for both fixed factors and idiosyncratic variations, our results indicate that the levels of rural development across states of India are converging. This conforms to the visual representation given in Figure 3.3, from which it is evident that several states have caught up with Kerala that was the leader in the beginning of the period.

Another interesting point to note about the results in Table 3.2 is that idiosyncratic year-specific variations play an important role in regional convergence in RDI. Contrary to the convergence result for farm-nonfarm ratio, we cannot reject the null hypothesis of no convergence when we include only state-specific individual effects only in the LL2 test. This implies that there is substantial variation in the distance between the reference state, Kerala, and other states catching up with it over time. When we control for time-specific variations (due to weather patterns, policy changes, inflation etc.), we get the convergence result as reported in Table 3.3 using the panel characteristic of the data. This may indicate that stable, regionally balanced rural development is not taking place among Indian states, and substantial fluctuations in RDI levels occur due to year-specific conditions prevailing in the economy. In the next chapter, we shall analyze the factors behind this unevenness in development across states.

3.5 Concluding Remarks

In this chapter, we have extended the discussion on rural development to include both farm productivity and nonfarm employment growth as determinants of rural development. States that have higher productivity in the farm sector and have increased

nonfarm employment in rural areas benefit from the interlinkages, and these linkages lead to a higher level of development in the rural areas.

We test the hypothesis that the regions at the lower end of the development spectrum would catch up with the leaders over time. Our results indicate that there is evidence of convergence in rural development across states of India, after we control for both state-specific characteristics and time-specific variations. Compared to the cases of convergence in TFP and farm-nonfarm employment ratio, we found that in RDI, controlling state-specific factors alone does not lead to convergence. The year-specific shocks to the rural sector are also important in states catching up with the leaders. This result is important for policy implications from this analysis.

The question whether the different states in India are converging towards the level of rural development of the leaders is therefore contingent on how the various states manage to reduce the gap in initial inequalities in agricultural productivity and the structure of the labor force in the rural areas. It also depends on smoothing the disruptions due to variations in weather patterns and seasonality in employment opportunities. This observation conforms to the reality on the ground in India.

Agricultural production in many parts of India is still dependent largely on good monsoon rains. Irrigation is deficient in these rain fed parts, which leads to lower productivity growth in agriculture (Fan, Hazell and Hoque, 2000). It is also found that government investment in infrastructure in the low-productivity areas is lower than in areas of higher productivity. Therefore, productivity differences are magnified in years of droughts and floods. On the other hand, year-specific shocks also have an effect on growth of nonfarm sector jobs, especially due to changes in government policies. Temporary, low-skilled sectors such as construction and trade can be affected in ways

similar to agriculture. States that have better social and physical infrastructure as well as a stable agriculture will be less affected by such idiosyncratic yearly variations.

Therefore, the convergence analysis above puts the importance of rural infrastructure into perspective. Infrastructure plays an important role in reducing variations in agricultural productivity and creates conditions for higher nonfarm employment and income. Strong linkages between agriculture and nonfarm activities lead to higher rural development and help states catch up with the leaders. In the next chapter, therefore, we investigate the effect of various types of infrastructure on both TFP and nonfarm employment generation. This will help us explain the differences in the development of the two sectors in India, and to pinpoint the policy measures that should be taken to alleviate regional imbalances in rural development within the country.

Chapter 4

Effect of Rural Non-farm Employment and Infrastructure on Agricultural Productivity

4.1 Initial Comments

The previous chapter provides the basis for analyzing rural development taking into account the increase in agricultural productivity and the change in the structure of employment from farm to nonfarm-based employment in the rural sector. We have seen that in India, both TFP in agriculture and rural development as measured in Chapter 3 show signs of convergence across states in the long run, after controlling for state-specific fixed effects and year-specific idiosyncratic disturbances. The states with comparatively higher growth in agricultural productivity and comparatively faster change in the rural employment structure in favor of nonfarm activities have been able to attain higher levels of development.

The previous analysis therefore raises two important questions that we investigate in this chapter. One, do causal linkages exist between the farm and the nonfarm sectors in rural India? Second, how do different types of infrastructure affect TFP and nonfarm employment in the rural areas?

An answer to the first question is set out in Section 4.2, where we find that causal linkages do exist between the two sectors in rural India, taking into account the

initial conditions at the beginning of the study period, and that this causality is bi-directional. Using the results of the causality test, in Section 4.3, we specify a structural model of the rural sector with infrastructure, where farm productivity and nonfarm employment are endogenous. Our results indicate that social infrastructure is important for generating higher nonfarm employment, and agriculture-specific provisions of infrastructure, such as irrigation and research and extension, have positive effects on agricultural productivity. Strong linkages between the two sectors, especially from nonfarm to farm sector, also emerge from the analysis.

In the next section, therefore, we investigate causal linkages between agricultural productivity and nonfarm employment. Panel data techniques are employed to test for the hypothesis of causality, taking into account the initial conditions in the various states at the beginning of the period.

4.2 Causality between TFP and Nonfarm Employment in India

As we have seen in Chapters 2 and 3 above, recent studies have focused on the role of agriculture and nonfarm sector employment for rural development. We have seen that rural development across states in India can be explained in terms of both TFP and nonfarm employment growth. However, no study has so far examined this causal relation explicitly for India, and there are substantial disagreements regarding the nature and direction of causality between the two sectors in previous studies using partial measures of productivity, such as per-capita output or value added in agriculture (Datt and Ravallion, 1998).

At the beginning of the Green Revolution in India, it was stated that improvement in agricultural productivity would lead to a virtuous cycle in the rural areas. Higher farm output and income would lead to greater investment in the nonfarm sector, which used agricultural inputs in their production.¹ Later studies used this premise to calculate the multiplier effect of an increase in agricultural production on nonagricultural output, the so-called rural-urban linkage (Hazell and Haggblade, 1990). However, little or no attention was paid to the linkages that existed within the rural areas between farm and nonfarm activities, and the productivity enhancing effect of nonfarm employment in the rural areas.

The contribution of the nonfarm sector to economic growth, rural employment generation, poverty alleviation and migration reduction is increasingly being recognized (Lanjouw and Lanjouw, 2001). It has been seen that non-farm sector income accounts for nearly one-third of the total income for rural households in parts of Africa and Asia, including those areas where agriculture has not shown substantial growth (Chuta and Lieldholm, 1979; Lieldholm and Kilby, 1989). In areas of where a competitive labor market is absent, farmers' production and consumption decisions are not independent. In other words, output supply (or profit) and factor demand functions include the effect of exogenous variables such as off-farm income, that enter into their income constraint. (Lopez, 1984; Haggblade, et.al., 1989; Jorgenson and Lau, 2000).

Moreover, the increase in income from nonfarm activities offset idiosyncratic risks in agricultural production. It provides farmers the opportunity to diversify into methods of production that entail a high risk but a higher return, such as multicropping and high-yielding varieties of seeds (Evans and Ngau, 1991; Kochar, 1999). Consequently, nonfarm employment as a proxy for nonfarm income acts as a stabilizing

¹ This line of research was started by Mellor and Lele (1972) and extended by Johnston and Kilby (1975).

force for farm income and indirectly as a source of productivity improvement in agriculture.

Therefore, it is worthwhile to examine the nature and direction of causality between the farm and the nonfarm sector in rural India. Until now, the emphasis in policy making has been on developing the traditional farm to nonfarm linkage, and substantial investments have been made in the area of agro-based industries. Insufficient attention has so far been paid to the other direction, and specific policies for the rural nonfarm sector have not been designed. This is true of most of the developing world, including India (Lanjouw and Lanjouw, 2001; Reardon, et.al., 2001).

In the following subsection, we discuss the method employed in our analysis. We explain the different approaches to causality testing in panel data, and state the reason for choosing our method of analysis.

4.2.1 Method of Analysis

As is evident from the discussion above, the direction of the causality between farm productivity and nonfarm employment is also open to question and as yet not addressed specifically by any study. Moreover, the aggregate data in levels of agricultural production and non-farm sector suffer from the familiar problems of endogeneity, common trends, measurement errors etc. A common way to deal with this kind of problem is to use some form of first differencing. However, as the previous studies on the relation between public capital and productivity have shown, differencing actually destroys the long-run relation and the estimates reflect the short-run effects (Hsiao, 1986; Aschauer, 1989; Holtz-Eakin, 1994; Evans and Karras, 1994).

We address the question of causality between non-farm sector development and total factor productivity in agriculture, using the methods recently proposed by Arellano and Bond (1991) and Blundell and Bond (1998). This uses the properties of dynamic models in a panel framework to estimate the causality relation (Arellano and Bond, 1998). Initial conditions and previous information also play a vital role both in causality tests and in the model estimation. Lagged values of the dependent variable uncorrelated with the error term are used as instruments in the estimation process. Thus the dynamic generalized method of moments (GMM) approach will be used in this paper for causality tests and estimation. This method uses all the information contained in previous lags and levels of dependent variables as instruments. A detailed description of the dynamic panel causality test is provided in the appendix to this chapter.

4.2.2 Results of the Test of Causality

Using the methodology described in Section 4.2.1, we test for causality between farm productivity and nonfarm employment in India over twenty-one years from 1973 to 1993 for fourteen major states. Therefore, the total number of observations is 294.

We estimate the following system of equations in order to perform our test of causality between TFP growth and nonfarm employment in rural India.

$$\ln TFP_{i,t} = \sum_{j=1}^m \alpha_j \ln TFP_{i,t-j} + \sum_{j=1}^m \beta_j \ln NFARM_{i,t-j} + \eta_i + v_{i,t} \quad (4.1)$$

$$\ln NFARM_{i,t} = \sum_{j=1}^m \alpha_j \ln NFARM_{i,t-j} + \sum_{j=1}^m \beta_j \ln TFP_{i,t-j} + \eta_i + v_{i,t} \quad (4.2)$$

where $TFP_{i,t}$ is the total factor productivity of state i at time t , $NFARM_{i,t}$ denotes the nonfarm employment in state i for the year t . To control for variations due to different geographical and meteorological characteristics, we include region (state) specific fixed effects, η_i . However, there might be residual noise arising from the presence of cross-sectional characteristic of the panel data. To correct for such heterogeneity problems, we use the standard errors from the robust two-step estimates including corrections for heteroskedasticity. We also test for serial correlation of the error term for the null hypothesis of presence of autocorrelation in the series.

We include six lags of both the TFP and the NFARM variables for estimation. Although in most of the analysis of standard time-series models lag lengths of less than four are considered, ideally we should test for causality using an arbitrarily long lag length. However, as noted by Holtz-Eakin et.al (1994), the optimal lag-length should be less than one-third of the total time period to avoid overidentification problems.

From our results in Table 4.1, we find that the NFARM variable is significant in the third and fourth lag for the TFP equation. For the NFARM equation, only the fifth lag of the TFP variable is significant. We perform a Wald test under the null hypothesis of all coefficients of the explanatory variables are jointly zero in each equation.

We can see that in both cases, the hypothesis is rejected at one percent level, indicating the existence of bi-directional causality in the two variables. For a sensitivity analysis, we tested for shorter lags as well, but did not find any evidence of causality for lags of the order of less than five. Therefore, we can say that farm productivity and nonfarm employment in rural India have significant interlinkages between them. Moreover, we do not find any evidence of first-order serial correlation in the error term in both cases.

Table 4.1 Tests of Causality between TFP and NFARM

<i>Variable</i>	Dependent Variable: TFP		Dependent Variable: NFARM	
	<i>Coefficient</i>	<i>P-value</i>	<i>Coefficient</i>	<i>P-value</i>
TFP1	0.311**	0.000	-0.028	0.232
TFP2	0.291**	0.000	0.014	0.441
TFP3	0.124**	0.003	0.028	0.124
TFP4	-0.042	0.649	0.014	0.175
TFP5	0.193**	0.000	-0.037**	0.002
TFP6	0.209**	0.000	0.005	0.659
NFARM1	0.799	0.251	1.449**	0.000
NFARM 2	-0.629	0.499	-0.391**	0.000
NFARM 3	1.236**	0.011	-0.013	0.780
NFARM 4	2.131*	0.042	-0.373**	0.000
NFARM 5	-1.439	0.263	0.168	0.211
NFARM 6	0.368	0.698	0.154*	0.031
Wald Test	NFARM1-NFARM6	0.000	TFP1-TFP6	0.002
Test for Serial Correlation	-2.159*	0.031	-2.391*	0.017

Note: ** and * indicate significance at 1% and 5% respectively.

Comparing our results with that of Zhang and Fan (2001), we find that our results closely correspond to their finding of bi-directional causality between agricultural TFP and road investment in rural India using the same dataset at the district level. In our case, we have found evidence of bi-directional causality between the farm and nonfarm sectors at the state level, which is a bigger geographical unit than the districts. This point is noteworthy because it indicates that the linkages between farm and nonfarm activities that exist at the household level that have been reported in earlier studies are carried over to intersectoral linkages over a wide geographical area (Parikh and Thorbecke, 1996). Therefore, our causality result is in line with evidence from micro-level studies on the rural sector using survey data.

This leads us to the next section of the chapter, where we formulate a model of the rural sector, which includes infrastructure. It has been pointed out that an infrastructure provision in the rural areas has a direct influence on the development of the nonfarm sector, as well as on agricultural productivity. We have also seen from this section that the farm-nonfarm linkage also has to be incorporated in a model of the rural sector. Therefore, in Section 4.3, we estimate a simultaneous-equation model with two structural equations, and treat TFP and nonfarm employment as endogenous. Our results below would indicate that infrastructure is crucial for development of both the sectors, but there are varying effects of infrastructure depending on the respective sector. This also helps to explain the differences in TFP and nonfarm employment growth across the states of India, which we have analyzed in the previous chapters.

4.3 Infrastructure, TFP and Nonfarm Employment

A large number of studies about the impact of infrastructure on TFP have agreed that in general, public infrastructure has a positive effect on productivity growth.² These studies have mostly been conducted for advanced OECD countries, using growth-accounting methods to calculate TFP for the whole economy. It is widely believed that direct public investment in physical and social infrastructure, such as roads and education, is essential to sustain and improve the current level of productivity in advanced economies. However, few such studies have been conducted for developing countries, a shortcoming which we shall address in this section.

The debate about the provision of public infrastructure in developing countries is fundamentally different than the debate about the marginal impact of additional infrastructure in developed economies. Developing countries including India suffer from a lack of basic infrastructure such as roads, electricity and schools and hospitals that are essential for both productive activities in the economy and the well being of the population. However, the demand for such infrastructure far exceeds its supply, which is provided wholly by the government. Therefore, in many sectors of the economy, infrastructure is rationed and additional investment depends on the state of public finance and budgetary allocations, and therefore can be taken to be exogenous to the specific sector of the economy.

² See Aschauer (1989); Munnell (1992); Evans and Karras (1994) for pioneering work in this area.

Table 4.2 Technology, Infrastructure and Agricultural Production in India

	Irrigation	Villages Electrified	Road Density	TFP (1970=100)
	%	%	Km/1000km ²	
All India Average				
1973	23.5	39.5	2941	100.04
1980	28.4	57.6	3926	112.15
1990	33.8	84.5	5392	138.64
1993	33.5	87.2	5622	146.16
Annual Growth Rate (%)				
1973-79	1.86	5.46	4.37	1.73
1980-89	1.64	4.36	3.39	2.51
1990-93	-0.88	0.97	1.06	1.34
1973-93	1.74	5.75	4.34	2.19

Source: Author's calculations from Fan, Hazell and Thorat (1999).

Table 4.2 gives the example of the growth of infrastructure in rural India between 1973 and 1993. From the late 1980s, it emerges that there has been a slowdown in the growth of irrigation and road infrastructure as a result of a decline in investment by the government. The slowdown in infrastructure also seems to have affected productivity in agriculture (Table 4.2) and that of the growth in nonfarm employment as can be seen in Table 4.3. Therefore, the data indicates that there are substantial linkages between public infrastructure spending, agricultural TFP and nonfarm employment.

Table 4.3 Annual Compound Growth Rate of Employment for Usual Status Workers by Broad Sector of Production

<i>Production Sectors</i>	Rural Male			Rural Female		
	77-78 to 87-88	87-88 to 93-94	93-94 to 97	77-78 to 87-88	87-88 to 93-94	93-94 to 97
Agriculture	0.30	1.37	2.92	3.41	1.49	1.90
Mining and Quarrying	4.18	1.46	-3.46	9.51	1.20	-23.81
Manufacture	2.78	0.53	1.68	4.91	1.48	-5.05
Utilities	5.55	1.47	1.40	-	-	-
Construction	0.19	-1.00	3.66	18.06	-15.74	-30.85
Trade	3.50	2.74	0.54	3.00	1.21	-26.53
Transport-Communications	5.98	3.09	2.20	14.6	1.20	-
Finance, Real Estate, etc.	8.43	1.45	-5.64	-	-	-
Community and Personal Services	2.30	3.66	2.49	1.47	2.83	-14.37
Total Non-agriculture	3.83	1.52	1.60	5.17	0.17	-16.54
All Sectors	1.48	1.92	2.60	3.65	1.24	-1.25

Source: G.K.Chadha (2001).

In most developing countries, rural infrastructure is often neglected. Although more than half of the population resides in the rural areas, infrastructure provisions are concentrated mostly in the cities. Moreover, within the rural areas, agriculture gets most of the share of the infrastructure outlay, such as irrigation and research and development. Other types of infrastructure such as roads, communications, education

and health do not get adequate attention. This leads to inefficiencies in the distribution of the restricted amounts of infrastructure investment that are actually implemented in the rural areas.

In our analysis above, we have provided evidence of the significant role played by the nonfarm sector in rural development, as also the existence of linkages between agriculture and the nonfarm sectors in the rural areas. In providing important inputs and services for agriculture, the nonfarm sector can be thought of as another kind of infrastructure that is essential for higher productivity growth in agriculture. However, the difference between the nonfarm sector and other infrastructure is that the development of the nonfarm sector itself is dependent on factors such as literacy, power, communications and also productive agriculture. Therefore, in the rest of the chapter, we analyze the impact of nonfarm employment and infrastructure on improving productivity in the farm sector. The causality result leads us to consider a model with nonfarm employment and TFP being endogenous. Before we go to the analytical part of the model, in Section 4.3.1 below, we shall outline the importance of the different types of infrastructure for agricultural and nonfarm development in India.

4.3.1 Infrastructure affecting Farm and Nonfarm Sectors in Rural India

Irrigation:

One of the most important factors affecting TFP in agriculture is access to water resources via irrigation. There is substantial evidence that shows the difference in productivity of irrigated areas as compared to rainfed zones (Fan, Hazell and Hoque, 2000). Irrigated areas suffer less from shocks due to adverse rainfall, and technology adoption is higher due to lesser risk of crop failure.

Research, Development and Extension:

Introduction of modern technology into agriculture necessitates research into better varieties of seeds, optimum use of fertilizer and support to farmers to adopt the new techniques. Therefore, research and development (R&D) institutions contribute to higher productivity in agriculture through improvement in the stock of technological knowledge in agriculture. In India, R&D is carried out in public research institutions and agricultural universities. Therefore, public investment in R&D is one of the major determinants of productivity growth in agriculture.

Physical Infrastructure:

Physical infrastructure in the form of roads, communications and power affects both farm and nonfarm sectors in the rural areas. The marketable surplus in agricultural production has to be transported to the procurement centers, or delivered to processing units. Mechanical threshers and tillers require electricity, which is also used by the nonfarm sector. Road infrastructure is particularly important for the nonfarm sector, where the distance between location of production and that of the market can be large. Therefore, provision of physical infrastructure affect both farm and nonfarm sectors, and their impacts will be estimated in the model in the next section.

Social Infrastructure:

One of the major problems in the rural areas is low level of literacy of the rural population. Except in a few states such as Kerala and West Bengal, the levels of rural illiteracy is as high as forty percent in some regions. This implies fewer employment opportunities in high-skilled jobs for the rural population. It also restricts the development of a dynamic nonfarm sector, and results in lower levels of development.

Therefore, public investment in education would affect rural nonfarm employment and by extension, TFP in agriculture.

Financial Infrastructure:

Previous studies have identified a lack of basic financial infrastructure as one of the causes of rural backwardness (Binswanger, Khandker and Rosenzweig, 1993; Ravallion and Wodon, 2000). Although in rural India, agricultural credit cooperatives have been relatively successful, the nonfarm sector has been adversely affected by a lack of borrowing opportunities from banking institutions. In most of the states, the credit to deposit ratio of commercial banks in the rural areas is less than one. Therefore, the rural areas in India are significantly credit constrained. This affects nonfarm income generation, as well as agricultural productivity.

Our objective in this chapter is to estimate a model of the rural sector that takes into account the dynamics of the linkages between farm productivity and nonfarm sector employment on the one hand and the stock of infrastructure on the other. Differences in infrastructure described above leads to differing levels of agricultural and rural development across India. The empirical analysis in Section 4.3.2 would indicate that policies designed to increase certain types of infrastructure would have beneficial effects on both farm and nonfarm sectors either directly or indirectly. Therefore, in the next section, we first formulate our empirical model and then discuss the results of our analysis.

4.3.2 Empirical Method and Results

To model the impact of infrastructure and nonfarm sector on TFP in agriculture, it is necessary to formulate a simultaneous equation model that takes into account the endogeneity between the two sectors. The following equation outlines the factors responsible for the productivity growth in agriculture (the subscripts are suppressed):

$$TFP = f(R \& D, R \& D_{-1}, \dots, R \& D_{-i}, IRRI, NFARM, ROAD, ELEC) \quad (4.3)$$

In equation 4.3, we hypothesize that the increase in TFP in agriculture is due current and lagged research and development expenditure by the government (R&D), and the availability of irrigation (IRRI). It also depends on the development of the nonfarm sector, proxied by the non-agricultural employment in rural areas (NFARM). We have also included the ROAD variable that measures road density per 1000 square kilometers of geographical space and ELEC that denotes the percentage of villages electrified in each state to take into account the effect of physical infrastructure on TFP growth in agriculture.

$$NFARM = f(TFP, LITER, LENDRAT, ROAD, ELEC) \quad (4.4)$$

Equation (4.4) determines the variables for the development of the rural nonfarm sector. The increase in nonfarm employment opportunities would depend on other physical and social infrastructure variables, such as road density (ROAD) and literacy (LITER), apart from productivity growth in agriculture. It would also depend on the support of financial infrastructure and the availability of credit facilities. Since

agriculture and the nonfarm sector compete for credit in the rural credit market, the farm-nonfarm lending ratio (LENDRAT) would capture the relative importance attached to nonfarm sector employment generation in the disbursement of credit across the states.

We employ the three-stage least squares (3SLS) method for estimating the model. The 3SLS method is consistent and it satisfies the requirements of an instrumental variables estimator. It is also asymptotically efficient and in case the errors are normally distributed, its asymptotic distribution is the same as that of the Full Information Maximum Likelihood (FIML) estimator (Greene, 2000, pg.693).

The estimation results with all variables in their logarithmic form are given in Table 4.4. To control for geographic variations among states, we have estimated all the system equations using dummy variables for each state. Estimations were carried out using STATA 7.

In Model 1 and Model 2, we specify the system equations using either ROAD or ELEC to account for the physical infrastructure effect. We have encountered multicollinearity problems when including both the variables in the same structural equation. Model 3 and Model 4 have included a dummy variable to account for the policy changes that took place in India from the middle of the 1980s. The data shows a significant change in the behavior of the variables, especially NAEMPLY, ROAD, IRRI and ELEC from the mid 1980s. Hence we expect that the dummy variable Dum1985 would capture the break in the data series. Model 5 and Model 6 include dummies for all the 21 years to account for year-specific variations in the cross-sections. This is particularly true when we are trying to estimate structural equations using TFP in agriculture that is prone to fluctuations due to weather patterns in each agricultural season.

An examination of Table 4.4 brings to light several interesting characteristics of the data. For equation (4.3) explaining TFP, we find that for all the six models considered, the NFARM is highly significant and the elasticity with respect to TFP is positive and a high order. The coefficients for R&D and IRRI are also positive and significant in all the models considered, although their estimated values are not as high as expected. However, ROAD is not significant in either Model 1 or Model 3, and neither is ELEC for Model 2 and Model 4.

On the other hand, including year-specific dummies for equation (4.3) gives us a positively significant coefficient for ELEC in Model 6, although ROAD is not significant even in this specification. Moreover, among all the models estimated for Equation 4.3, Model 6 provides the best fit for the data. All the other independent variables are also significant and the coefficients are of positive order in this specification.

Coming to equation (4.4), the effect of TFP on NFARM is unclear. In Models 1, 2 and 4, TFP has a positive and significant effect on the level of NFARM, justifying our causality test results in Section 4.2. However, for Models 3, 5 and 6, we cannot confirm that TFP has a positive and significant effect on nonfarm employment. However, in all the six models under consideration, LITER is positive and significant of a high order of magnitude, and LENDRAT (which is the ratio of farm to nonfarm credit in the rural areas) is negative and significant.

Table 4.4 Estimation Results using 3-stage Least Squares

(I) Dependent Variable: lnTFP

Variables	Model 1	Model 2	Model 3	Model 4	Model 5 (Incl. year dummies)	Model 6 (Incl. year dummies)
Constant	-0.176 (0.929)	0.611 (1.118)	-2.155 (1.479)	-1.221 (1.701)	-3.147 (2.493)	-1.155 (2.459)
Ln NFARM	0.427*** (0.173)	0.362** (0.161)	0.693*** (0.226)	0.573*** (0.224)	0.737*** (0.291)	0.528* (0.289)
Ln R&D	0.057*** (0.021)	0.052*** (0.021)	0.063*** (0.022)	0.059*** (0.022)	0.077*** (0.028)	0.078*** (0.028)
Ln IRRI	0.083* (0.047)	0.085** (0.039)	0.086* (0.047)	0.094** (0.043)	0.097* (0.057)	0.107** (0.053)
Ln ROAD	0.017 (0.098)		0.022 (0.100)		0.078 (0.104)	
Ln ELEC		0.075 (0.053)		0.066 (0.055)		0.108* (0.055)
Dum1985			-0.083** (0.041)	-0.074* (0.041)		
R-square	0.639	0.658	0.602	0.628	0.631	0.674

***p<0.01 **p<0.05 *p<0.10

(II) Dependent Variable: lnNFARM

Variables	Model 1	Model 2	Model 3	Model 4	Model 5 (Incl. year dummies)	Model 6 (Incl. year dummies)
Constant	3.999*** (0.359)	4.206*** (0.516)	4.795*** (0.408)	5.268*** (0.485)	5.822*** (0.649)	6.613*** (0.635)
Ln TFP	0.312* (0.186)	0.479** (0.195)	0.224 (0.163)	0.304* (0.163)	0.033 (0.162)	0.026 (0.159)
Ln LITER	0.632*** (0.131)	0.702*** (0.147)	0.551*** (0.132)	0.593*** (0.142)	0.554*** (0.133)	0.592*** (0.136)
Ln LENDRAT	-0.096*** (0.024)	-0.073*** (0.022)	-0.084*** (0.023)	-0.063*** (0.021)	-0.121*** (0.029)	-0.110*** (0.031)
Ln ROAD	0.138** (0.063)		0.120* (0.061)		0.102** (0.056)	
Ln ELEC		-0.009 (0.046)		0.009 (0.039)		-0.008 (0.035)
Dum1985			0.055*** (0.021)	0.066*** (0.022)		
R-square	0.963	0.952	0.968	0.964	0.975	0.974

***p<0.01 **p<0.05 *p<0.10

This implies that a high literacy rate and a balanced flow of credit to the nonfarm sector would increase nonfarm employment significantly. Contrary to our observations in equation (4.3), ROAD is significant with a positive sign in all the three models where it is included, whereas ELEC does not have any significant effect where it is used as an explanatory variable for equation (4.4). The dummy variable, however, has a positive and significant value for both Model 3 and Model 4, indicating that there is a justification to control for the variation in the data due to the policy changes from the mid-1980s.

4.4 Summary of the Results

To summarize our results, we first note that there is evidence of bi-directional causality between farm and nonfarm sectors in rural India. The hypothesis of a positive effect of the nonfarm employment on agricultural productivity is confirmed for all the models under consideration. This is one of the major contributions of the paper, clarifying the causality analysis that we undertook in Section 4.1.

Also, the results indicate that there are significant productivity gains in agriculture due to higher investment in research and development (which corroborates Fan, et.al., 2000, for India; Kuroda, 1997, for Japan).³ The same can be said of irrigation, since this would reduce the dependence of the farm sector on weather patterns and stabilize income and output. The interesting finding relates to the fact that electricity rather than roads have a significant impact in improving productivity, which might

³ For an international comparison, see Hayami and Ruttan (1970) and Craig, Pardey and Roseboom (1998).

indicate the intensive use of mechanical equipment for agricultural production after the Green Revolution period in India.

Coming to the determinants for increase in nonfarm employment, we note that the effect of TFP is ambiguous. If we take Model 6 as our choice of the final model for equation (4.4) in the system, then we find that controlling for idiosyncratic variation for each year, the effect of TFP on nonfarm employment is not significant. This is another interesting point to be noted from this analysis, that is contrary to the report of Fan, et.al., (2000).

Therefore, rather than finding forward linkage from TFP to NFARM, we can confirm a backward linkage going the other way, the estimates of which is robust across all the specifications tested in this chapter. Moreover, ROAD rather than ELEC seems to have a higher impact on nonfarm employment, which corroborates earlier studies by Ranis, et.al. (1990) for the Philippines.

The final contribution of the analysis is to show that the a more balanced lending policy with respect to both the farm and the nonfarm sectors would result in a higher level of nonfarm employment, which in turn would lead to higher productivity in agriculture through the mechanism described earlier. Credit policies have long been a subject of intensive debate in the political economy literature (Bardhan, 1984; Eswaran and Kotwal, 1986) where it has been pointed out that rural credit markets squeeze out the small farmer or entrepreneur in the competition for capital. This leads to the persistence of poverty in the rural areas of most developing countries, particularly India. A higher credit supply from formal sources, such as commercial banks, co-operative lending institutions and microfinance organizations (for example, the Grameen Bank in Bangladesh) would lead to a rationalization of the cost of credit, which includes the

negative costs due to lack of transparency in rural credit markets (Bayes, 2001). This in turn would help to stimulate nonfarm activities in the rural areas.

Chapter 5

Summary and Conclusion

5.1 Main Contribution

This thesis has documented the symbiotic relationship between farm and nonfarm sectors in rural India. The inter-linkages between agricultural productivity, nonfarm employment and infrastructure have to be exploited in order to achieve the goal of rural development.

5.2 Summary of the Thesis

Rural development has long been synonymous with growth in agricultural sector only. However, recent research has focused on the role of nonfarm sector in reducing poverty and inequality in the rural areas of developing countries. Diversification in rural employment reduces dependence on agriculture and helps the rural population overcome adverse income shocks. It also provides additional resources to invest in better technology in the farm sector, which helps to improve productivity in agriculture.

Development of the nonfarm sector itself requires a productive agriculture and the facilitating infrastructure in the rural areas. The provision of rural infrastructure until

now has focused on improving productivity in the farm sector. Inadequate attention has been paid to the contribution of education, roads and credit in the generating rural nonfarm employment. States that have invested in social and physical infrastructure generally have an expanding nonfarm sector, and higher levels of productivity in agriculture. Therefore, the regional differences in rural development in India arise due to the differences in both farm and nonfarm development.

Our objective in this thesis has been to analyze state-level data in the post-Green Revolution period and determine the historical pattern of the changes in rural development, and also the long-run trend towards convergence across states. Our analysis indicates that significant differences in the level of agricultural and rural development exist presently across the different states. However, controlling for fixed differences between them, there is evidence of long-run convergence in both agricultural productivity and rural development. Higher provision of social and physical infrastructure in less-developed states would help close the gap between the different regions of the country.

5.3 Summary of the Chapters

In Chapter 1, we outline our research topics in the context of previous studies in this field. Recent studies have highlighted the linkages between agriculture, nonfarm sector and rural infrastructure. Most studies on India, however, have focused on the link between poverty and agricultural productivity, but few have tackled the issue of inter-linkages described above.

Chapter 2 analyzes the question of productivity convergence among the Indian states. Our analysis indicates that conditional or beta-convergence holds true for Indian agriculture. After controlling for fixed factors, we find evidence that the late starters (eastern, central and southern states) have caught up with the leaders (northern states) in terms of their TFP growth rates.

In Chapter 3, we find that the indicator of rural development, defined as the ratio of farm productivity to rural farm-nonfarm employment ratio, captures the regional rural development scenario in India. Nearly all the states have tended to catch up with Kerala, the leading state in 1973. Therefore, we find that there has been a significant reduction in the rural development gap among states, although some have performed much better than others. This evidence of convergence gives credence to the argument that the contribution of nonfarm employment in rural development has been underestimated until now.

In Chapter 4, the causality between nonfarm employment and agricultural productivity is empirically tested. The finding of bi-directional causality indicates a symbiotic relationship between the farm and the nonfarm sectors in rural India. This leads us to adopt a simultaneous-equation econometric model to test for the impact of infrastructure on the two sectors. We find that physical and social infrastructure are important for nonfarm development. Furthermore, nonfarm employment together with rural infrastructure helps to improve productivity in agriculture. Agriculture also has positive linkage with the nonfarm sector. Thus, our hypothesis of positive linkages between agriculture, nonfarm employment and infrastructure is confirmed in this analysis. This finding is important for policy-making, where until now the issue of interlinkages within the rural sector has not received adequate attention.

5.4 Policy Implications

The findings of this thesis emphasize the role of public policy in rural development, both at the national and the regional level. The major recommendation for policy is to put more emphasis on the development of the rural nonfarm sector to promote rural development.

Policies designed to improve the quantity and the quality of rural infrastructure in the rural areas would have a positive effect on both farm productivity and nonfarm employment generation. However, there is also a need to correct for past imbalances in rural policy, such as favoring agriculture over nonfarm sector in the allocation of rural credit. Investment in R&D, roads and most importantly, literacy, would help to exploit the substantial inter-linkages between farm and nonfarm sectors in the rural areas and would lead to balanced regional development across India.

Appendix I

Dynamic Panel Model for Causality Test

A1. A Simple AR1 Process in Dynamic Panel Estimation

Let us start with the assumption that there are N cross-sectional units observed over T periods. Let i index the cross-sectional observations and t the time periods. We also take into account an individual effect η_i for the i^{th} cross-sectional unit.

$$y_{it} = \alpha y_{it-1} + \eta_i + v_{it} \quad (\text{A1})$$

We will also assume that η_i and v_{it} are independently and identically distributed across i and have the error component structure:

$$E(\eta_i) = 0; E(v_{it}) = 0; E(v_{it}\eta_i) = 0 \quad \text{for } i = 1, \dots, N \text{ and } t = 2, \dots, T \quad (\text{A2})$$

$$E(v_{it}v_{is}) = 0 \quad \text{for } i = 1, \dots, N \text{ and } \forall t \neq s \quad (\text{A3})$$

In addition, we have the standard assumption concerning the initial conditions y_{i1} :

$$E(y_{i1}v_{it}) = 0 \quad \text{for } i = 1, \dots, N \text{ and } t = 2, \dots, T \quad (\text{A4})$$

For estimation in first differences, in the absence of any further restrictions on the process of generating the initial conditions, the autoregressive error components model (A1) – (A4) implies the following $j = 0.5 (T-1)(T-2)$ orthogonality conditions that are linear in α :

$$E(y_{it-s}\Delta v_{it}) = 0 \quad \text{for } t = 3, \dots, T \text{ and } s \geq 2 \quad (\text{A5})$$

where $\Delta v_{it} = v_{it} - v_{i,t-1}$.

The available instruments satisfy the moment restriction in (A5) and can be compactly written as $E(\mathbf{Z}_i' \bar{\mathbf{v}}_i) = \mathbf{0}$, where \mathbf{Z}_i is the $(T-2) \times j$ matrix given by:

$$\mathbf{Z}_i = \mathbf{Z}_i^D = \begin{pmatrix} y_{i1} & 0 & 0 & \dots & 0 & 0 & \dots & 0 \\ 0 & y_{i1} & y_{i2} & \dots & 0 & 0 & \dots & 0 \\ \cdot & \cdot & \cdot & & \cdot & \cdot & & \cdot \\ \cdot & \cdot & \cdot & & \cdot & \cdot & & \cdot \\ 0 & 0 & 0 & \dots & y_{i1} & y_{i2} & \dots & y_{i(T-2)} \end{pmatrix} \quad (\text{A6})$$

and $\bar{\mathbf{v}}_i$ is the $(T-2) \times j$ vector $(\Delta v_{i3}, \Delta v_{i4}, \dots, \Delta v_{i(T-2)})'$.

A2. AR1 Process Including Exogenous Regressor

In models with explanatory variables, Z_i may consist of submatrices with the above block diagonal form along with one-column instruments. Suppose there exists a predetermined regressor that is correlated with the individual effect η_i exhibiting the following property:

$$E(x_{it} v_{is}) = 0 \quad \text{for } s \geq t \\ \neq 0 \quad \text{otherwise}$$

$$\text{and } E(x_{it} \eta_i) \neq 0$$

then the corresponding Z_i^E matrix is given by

$$\mathbf{Z}_i^E = \begin{pmatrix} y_{i1} & x_{i1} & x_{i2} & 0 & 0 & 0 & 0 & 0 & \dots & 0 & \dots & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & y_{i1} & y_{i2} & x_{i1} & x_{i2} & x_{i3} & \dots & 0 & \dots & 0 & 0 & \dots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & & \cdot & \cdot & \cdot & \cdot & & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & & \cdot & \cdot & \cdot & \cdot & & \cdot \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & y_{i1} & \dots & y_{i(T-2)} & x_{i1} & \dots & x_{i(T-1)} \end{pmatrix}$$

As stated in Arellano and Bond (1998), where the number of columns in Z_i^E are very large, using the whole history of the instruments in later cross-sections may lead to overfitting bias in small sample empirical study. We would fix a maximum and minimum lag on the instrument set of the dependent variable and the regressor in our analysis.¹

A3. Combining Differences and Levels

To get the full set of instruments combining the levels and differences, we note that the error term in our panel data model consists of v_{it} and η_i . Where there are instruments available that are uncorrelated with the individual effects η_i , we can use these variables as instruments for the equation in levels (Arellano and Bond, 1998). Under the assumption of mean-stationarity of the model in (2), since Δy_{it} will be uncorrelated with η_i , $\Delta y_{i(T-1)}$ can be used as instruments in the levels equations. In this case, the instrument matrix can be stated as:

$$Z_i^S = \begin{pmatrix} Z_i & 0 & \dots & 0 \\ 0 & \Delta y_{i2} & \dots & 0 \\ \cdot & \cdot & & \cdot \\ 0 & 0 & \dots & \Delta y_{i(T-1)} \end{pmatrix} \quad (\text{A7})$$

which is a block diagonal matrix combining the elements of both (A6) and the instruments for the level equations in their diagonal elements.

¹ For a full explanation of the estimation process using dynamic panel data, refer to Blundell and Bond (1998) and Arellano and Bond (1998).

In the case that exogenous regressors are also present in the model, the optimal instrument matrix can be set up combining the matrices for the regressors and the lagged dependent variables.

One-step estimations using a known weighting matrix are efficient when the error term v_{it} is known to be homoskedastic. In the case of heteroskedastic v_{it} , two-step estimators that use the variance matrix from the estimated error terms in the first step as weights in the regression perform better. However, as stated in Arellano and Bond (1998), for hypothesis testing purposes, it is better to use standard errors from the first step while using the two-step weighting matrix. Since the errors in our case are likely to be heteroskedastic, we would report the robust one-step estimates unless otherwise stated.

Appendix II

Tables

Table A.1: Index of TFP growth, Various States and All India (1970=100)

YEAR	Andhra Pradesh	Bihar	Gujrat	Haryana	Karnataka	Kerala	Madhya Pradesh	Maha-rashtra	Orissa	Punjab	Rajasthan	Tamil Nadu	Uttar Pradesh	West Bengal	All India
1973	114.52	82.44	83.53	81.22	100.41	105.2	90.84	116.95	102.61	106.92	82.9	109.3	91.23	95.35	99.38
1974	119.75	90.63	49.38	78.54	102.92	104.16	103.98	120.48	86.49	113.13	74.96	86.46	95	106.51	95.59
1975	118.05	101.32	98.76	107.49	104.43	106.37	111.57	137.16	106.7	123.74	91.69	114.83	104.51	113.45	109.28
1976	94.57	98.97	96.24	109.29	79.11	99.57	90.15	141.92	89.65	126.55	90.89	106.68	109.32	111.41	103.74
1977	112.21	103.24	89.43	115.95	113.28	101.63	105.16	147.31	106.07	141.37	90.09	125.55	112.48	120.8	112.82
1978	113.01	104.01	91.48	130.53	110.61	101.87	99.59	142.08	105.97	147.68	101.42	130.02	116.57	127.11	114.82
1979	94.16	87.19	83.94	95.74	103.31	102.56	72.34	145.11	88.12	142.5	77.55	123.99	85.13	118.16	98.48
1980	96.77	109.78	85.85	116.29	92.3	100.11	108.39	146.35	120.51	142.16	88.95	106.69	121.98	131.45	112.08
1981	117.34	101.55	99.17	114.67	100.53	98.12	111.68	156.57	122.34	154.75	98.09	127.82	124.72	122.34	117.71
1982	106.69	106.66	82.39	120.63	97.57	98.98	112.05	147.96	115.13	156.04	109.62	101.22	132.42	119.16	115.85
1983	117.41	127.52	109.59	121.21	107.41	94.8	132.76	159.9	142.02	157.25	118.61	118.36	138.39	144.82	128.48
1984	95.85	129.18	99.08	132.45	104.31	94.06	120.09	148.19	151.51	167.57	107.56	131.31	135.34	150.38	124.83
1985	102.14	133.32	54.8	153.36	94.74	89.1	130.03	130.43	150.99	174.27	108.43	148.78	137.69	187.19	128.07
1986	100.29	131.08	72.22	143.44	108.39	86.51	113.43	115.78	140.71	164.27	92.03	120.37	148.55	179.37	123.85
1987	121.52	124.75	36.11	113.28	107.5	82.66	124.68	157.54	130.2	171.62	89.15	140.75	145.97	183.9	126.23
1988	142.77	135.43	72.22	193.67	116.26	82.53	143.3	158.6	154.8	173.25	154.01	136.24	158.48	203.64	148.25
1989	127.49	131.79	53.11	125.35	107.38	86.98	132.92	210.08	152.03	188.69	114.5	143.37	150.27	211.95	140.18
1990	125.08	136.62	49.28	140.42	103.49	88.45	149.17	150.64	147.79	184.41	130.71	138.83	148.46	217.13	138.64
1991	121.16	129.67	62.78	137.89	109.24	97.62	134.4	141.52	173.87	183.25	115.03	135.49	147.55	227.14	138.75
1992	119.97	119.94	64.18	156.95	123.32	103.6	140.42	161.02	196.51	182.41	129.74	137.75	149.9	225.91	144.11
1993	127.27	137.71	49.86	158.78	130.69	109.78	149.19	167.91	210.58	189.73	113.27	136.13	150.26	236.36	146.10
Trend Growth Rate (percent)															
1973-80	-2.71	2.31	3.02	4.93	-0.04	-0.63	-0.91	3.14	1.62	4.51	1.13	2.58	2.19	3.79	1.45
1981-88	1.92	3.46	-9.74	4.76	1.71	-2.91	2.24	-0.82	2.65	1.71	1.16	2.71	2.85	7.85	2.33
1989-93	-0.45	-0.43	1.37	5.84	5.68	6.23	1.71	4.54	9.36	0.32	-0.29	-1.11	0.01	2.58	1.21
1973-93	0.77	2.25	-2.64	2.74	1.01	0.61	2.41	1.14	3.73	2.49	1.07	1.56	2.63	4.62	2.02

Table A.2: Statewise Employment Ratio (Agriculture to Nonagriculture), 1973-93.

YEAR	Andhra Pradesh	Bihar	Gujrat	Haryana	Karnataka	Kerala	Madhya Pradesh	Maharashtra	Orissa	Punjab	Rajasthan	Tamil Nadu	Uttar Pradesh	West Bengal
1973	3.67	4.62	5.21	4.02	5.76	1.26	9.42	4.68	4.43	3.86	5.41	3.06	4.54	3.53
1974	3.75	4.68	5.25	3.90	5.59	1.29	9.17	4.56	4.65	3.78	5.26	2.98	4.43	3.52
1975	3.83	4.73	5.29	3.78	5.43	1.33	8.94	4.44	4.89	3.71	5.12	2.90	4.34	3.51
1976	3.91	4.79	5.33	3.66	5.27	1.37	8.70	4.33	5.13	3.64	4.98	2.82	4.24	3.50
1977	3.99	4.85	5.37	3.55	5.12	1.41	8.48	4.22	5.39	3.57	4.84	2.74	4.14	3.49
1978	4.08	4.92	5.41	3.44	4.95	1.45	8.26	4.10	5.62	3.50	4.71	2.83	4.05	3.48
1979	3.82	4.82	5.10	3.29	4.86	1.44	7.94	4.07	5.23	3.49	4.64	2.79	3.99	3.35
1980	3.58	4.72	4.81	3.14	4.77	1.42	7.63	4.04	4.86	3.48	4.56	2.74	3.93	3.21
1981	3.35	4.63	4.53	3.00	4.69	1.41	7.33	4.00	4.52	3.47	4.49	2.70	3.87	3.08
1982	3.14	4.53	4.27	2.86	4.60	1.39	7.04	3.97	4.21	3.46	4.42	2.65	3.81	2.96
1983	2.94	4.44	4.02	2.73	4.52	1.38	6.77	3.94	3.91	3.45	4.35	2.61	3.76	2.84
1984	2.91	4.35	3.74	2.60	4.44	1.37	6.81	3.90	3.59	3.44	4.26	2.22	3.69	2.72
1985	2.89	4.26	3.27	2.55	4.29	1.32	6.54	3.69	3.42	3.09	3.49	1.82	3.71	2.69
1986	2.88	4.17	2.86	2.51	4.16	1.27	6.28	3.49	3.27	2.77	2.86	1.49	3.72	2.66
1987	2.87	4.08	2.50	2.47	4.02	1.23	6.03	3.30	3.12	2.48	2.35	1.22	3.73	2.63
1988	2.86	4.00	2.18	2.44	3.90	1.18	5.80	3.13	2.98	2.20	1.87	1.87	3.74	2.60
1989	2.90	4.09	2.23	2.26	3.87	1.18	5.96	3.12	3.09	2.19	1.94	1.94	3.65	2.46
1990	2.94	4.17	2.27	2.10	3.84	1.17	6.12	3.10	3.20	2.18	2.00	2.03	3.56	2.32
1991	2.97	4.26	2.32	1.95	3.81	1.16	6.28	3.09	3.32	2.17	2.07	2.07	3.47	2.19
1992	3.01	4.35	2.36	1.82	3.78	1.15	6.45	3.08	3.44	2.16	2.14	2.18	3.39	2.07
1993	3.05	4.45	2.41	1.69	3.75	1.14	6.63	3.06	3.56	2.15	2.23	2.21	3.31	1.96
Trend Rates of Growth(Percent)														
1973-80	0.13	0.51	-0.76	-3.45	-2.75	2.01	-2.93	-2.23	2.02	-1.54	-2.49	-1.45	-2.09	-1.11
1981-88	-1.91	-2.11	-10.64	-2.91	-2.66	-2.55	-3.18	-3.19	-5.95	-6.74	-12.77	-9.89	-0.45	-2.41
1989-93	1.28	2.12	1.96	-7.34	-0.78	-0.66	2.65	-0.44	3.53	-0.53	3.31	3.31	-2.44	-5.62
1973-93	-1.77	-0.79	-5.51	-4.07	-2.22	-0.95	-2.31	-2.28	-2.83	-3.41	-5.89	-2.81	-1.33	-2.95

Source: Author's calculation from National Sample Survey data

Appendix III: Map of India

