High Yielding Variety Adoption, Technical Efficiency and Poverty Reduction for Rural Rice Farming Households under Rainfed Ecosystem: An Example of Eastern India

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TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANOVA	Analysis of variance
DEA	Data envelopment analysis
FYM	Farmyard manure
GIAM	Global Irrigated Area Mapping
HYV	High yielding variety
ICAR	Indian Council of Agricultural Research
IFAD	International Fund for Agricultural Development
IIA	Independence of irrelevant alternatives
IRRI	International Rice Research Institute
ISI	Indian Statistical Institute
MSME	Ministry of Micro, Small & Medium Enterprises
NFHS	National Family Health Survey
NGO	Non-governmental Organization
TC	Technical change
TE	Technical efficiency
TEC	Technical efficiency change
TFP	Total factor productivity
TV	Traditional variety
SC	Scheduled caste
SFA	Stochastic frontier analysis
SFPF	Stochastic frontier production function
ST	Scheduled tribe

ABSTRACT

High Yielding Variety Adoption, Technical Efficiency and Poverty Reduction for Rural Rice Farming Households under Rainfed Ecosystem: An Example of Eastern India

Keywords: HYV adoption, technical efficiency, rural poverty reduction, eastern India

This Ph.D. dissertation covers the regional development in eastern India where the study area— Giridih and Purulia— is located, by focusing on the patterns of agricultural development under rainfed ecosystem and poverty reduction among surveyed rural households. The dataset analyzed is drawn from a panel household survey, collected jointly by the International Rice Research Institute and Indian Statistical Institute in Kolkata during the Kharif seasons in the time period between 1998-1999 and 2004-2006. The study area has been recognized as one of the poorest regions in the country and has drawn upon the long-term interests of development economists.

The agricultural development is investigated from the aspects of farmers' decision making regarding high-yielding variety (HYV) rice adoption, and the technical efficiency of sampled rice farms and plots during the survey periods. In addition, the relationship between agricultural and non-agricultural development is discussed to understand the roles they played in rural poverty reduction. The study provides needed empirical evidence at both plot- and farm-level, allowing for gaps in the existing literature to be filled as well as highlighting the important areas for policy intervention. The three main research areas addressed in this dissertation are:

1. Since rice plays a significant role in the agricultural development of the study area, the use of HYVs plays a key role in increasing rice productivity, enabling food security, and reducing hunger. Therefore, the first part of the study explores the factors that influenced the probability of adopting HYVs by small-scale rice farming households over time.

Applying McFadden's choice model, the empirical results argue that potential high yield served as the main driver for sampled farmers to adopt HYVs, since yield is significant for explaining the farmer's choice. The 'subsistence pressure' is found for these farming households, thus cultivating a higher yielding rice variety becomes essential for their livelihood. The study also identifies the important roles played by education, landholding size, labor availability, the share of production sold in the market, and share of non-agricultural income in affecting farmer's decision of HYV adoption. In addition, the agroecological factors—land types and irrigation availability—also significantly influenced and constrained farmer's adoption choice. To meet their maximum utilities, policymakers should facilitate the farmers to cultivate properly and scientifically, and to lessen the environmental constraints for rice productivity growth.

2. Aiming to improve the agricultural productivity of surveyed small-scale rice farmers and, thus, the income earning from agriculture that would eventually contribute to the living standard improvement, the second part of the study addresses the issue by estimating the degree of technical efficiency at farm-level, and plot-level separated for traditional varieties (TVs) and HYVs. Additionally, at a farm-level, the output growth decomposition analysis has been conducted, where the main driving force for production growth during the survey period is identified.

Applying stochastic frontier analysis, the unknown production structure of sampled farmers has been estimated using the translog production function with a single time-trend presentation of the technical change. The farm-level estimation finds that the sampled rice farms were operated relatively close to the production frontier. Only a small proportion faced the severe issue of technical inefficiency. The estimations at plot-level argue for lower technical efficiency scores for both TV and HYV plots when compared with the farm-level estimation, and the mean technical efficiency of HYV plots was higher than that of TV plots. The farm-specific reasons for technical inefficiency include the effects of the age of household heads, the highest education attainment of household members, the size of landholding, the share of non-agricultural income, the share of plots in lower land types, and the share of plots being irrigated. Another non-neglected factor is the external environment, particularly the sufficiency of rainfall. The study also finds the technical change was the main contributor to the growth of rice production over time. Therefore, how to facilitate the farmers to better implement the adopted new technologies and improve their efficiency of utilizing the technologies are open for discussion by policymakers and researchers.

3. The last part of the study provides empirical evidence to the debate as to whether agricultural development is complementary or a substitute for non-agricultural development and poverty reduction. The roles that agricultural development played in non-agricultural development and in poverty reduction are identified. In addition, the contribution made by the non-agricultural sector is addressed and the specific pathways through which the surveyed households had escaped poverty are highlighted.

The mobility tables and corresponding transition matrix tables are constructed to present the income mobility patterns, focusing on the main income sources households relied upon. To understand the impact that agricultural development had on each type of household income, a set of fixed-effects estimations of yield effects has been examined from the perspective of the relationship between changes in yields and changes in the outcome measures. The finding supports the premise that growth in agricultural productivity and in the non-agricultural sector had a substitute relationship. However, in districts with a more developed non-agricultural sector (such as Giridih), the relationship tended to be more complementary; this supports the findings of the previous studies, suggesting that solely focusing on improving agricultural income, without ensuring a successful non-agricultural sector, was ineffective. Therefore, it is crucial for policymakers to pay attention to the development of non-agricultural sectors as the source of household income expansion and rural poverty reduction in the area.

CHAPTER 1. Introduction

1.1 Research Motivation

Although world poverty has been halved since 1990, there are still 1.2 billion people living in extreme poverty (World Bank, 2012). Approximately 75% of the extreme poor are rurally located and most rely on agriculture for their livelihood, which implies that extreme poverty continues to be a rural phenomenon. A large body of research argues for the importance of increasing agricultural productivity to achieve any pro-poor growth, as it can help rural residents overcome the unfavorable initial conditions and bring direct benefits to them by increasing their income and food security.

With the wide-spreading Green Revolution, new agricultural technologies are diffused to rural farming households in the developing countries, which contributed greatly to improving agricultural productivity and reducing hunger in rural areas. However, as Pingali (2012) argued, "[the] Green Revolution was not always the panacea for solving the myriad of poverty, food security, and nutrition problems facing poor societies" (p.12303). The success of the Green Revolution neglected the rainfed agriculture and left the regions under rainfed ecosystems behind (Devendra, 2016).

Rainfed agriculture is defined as agriculture that depends largely on rain and the rainfed lands account for more than 75% of the world's total croplands, mainly in the arid and semi-arid tropical zones. About 38% of the world's poor population lives in the rainfed regions, among which 75% live in rural areas (Wani, Sreedevi, Rockström, & Ramakrishna, 2009). The rainfed regions are believed to be affected more greatly in terms of climate variability, such as droughts, floods, etc., and this results in the vulnerability of agricultural productivity.

To this day, countries like India still have a substantial proportion of their rural population living below the poverty line. Rainfed agriculture accounts for 60% of the croplands in India, which feeds approximately 82% of the rural poor population (Fan & Hazel, 2000). These poor people are mainly engaged in traditional agriculture and are highly vulnerable to environmental fluctuations under rainfed ecosystems. A lack of rainfall will result in crop failure and, thus, an increase in poverty. Therefore, how to reduce rural poverty in the rainfed regions remains a critical issue for researchers and policymakers.

A large body of previous literature claims that agricultural development (agricultural productivity improvement) plays an important role in rural poverty reduction. To break the environmental constraints of rainfed regions as well as to achieve pro-poor growth, improved agricultural productivity and technological innovations are often advocated strategies. However, there is an ongoing debate on whether agricultural development is a prerequisite to rural poverty reduction while increasing attention has been given to the potential for promoting non-agricultural development as the pathway of rural poverty reduction.

To identify what may contribute to the rural poverty reduction in rainfed regions of India, data collected from eastern India can provide empirical evidence on this issue. Eastern India is the most poverty-stricken region of the country where the rural population is mainly engaged in agricultural activities on rainfed lands.

The panel dataset was drawn from a household survey conducted by the International Rice Research Institute (IRRI) and the Indian Statistical Institute (ISI) in Kolkata between 1998-1999 and 2004-2006. Nearly 600 farming households were surveyed in sixteen villages from the Giridih district of Jharkhand state and Purulia district of West Bengal state. This dataset allows all the proposed research questions in this Ph.D. study to be addressed consistently using the same samples.

Agricultural productivity improvement is the primary focus of this study, which is examined empirically from two aspects: (1) the farmer's choice in adopting technical innovation—High Yielding Variety (HYV) rice, as well as (2) the farmer's potential of utilizing them—farmer's technical efficiency. In addition, an examination of the relationship between agricultural productivity growth and non-agricultural growth to rural poverty reduction becomes another focus of this study, to identify the most promising path out of rural poverty in the region. The study hopes to facilitate eastern Indian policymakers to properly identify their policy priorities in improving agricultural productivity and through this the income and living standards of the impoverished rural households.

1.2 Research Questions and Hypotheses

The main research question examined in this study is: Does the agricultural development in the form of farmer's HYV adoption and technical efficiency contribute to the rural poverty reduction during 1998/99 to 2004/06 in the rainfed agricultural ecosystem of eastern India? To tackle this main research question, three sub-research questions, as well as the corresponding hypotheses, are thus constructed and examined empirically in the following chapters, which are summarized in Table 1.1.

Table 1.1 Summary of the sub-research questions and hypotheses

Research Question 1. Do the varietal characteristics and a set of socioeconomic and agroecological factors affect the sampled farmer's choice among different rice varieties?
● *Hypothesis 1.1* Potential yield is the most important varietal characteristics for

farmers to choose HYVs.

- *Hypothesis 1.2* The socioeconomic factors, such as the age of household head, education attainment, labor availability, farm size, the share of production sold in the market, and share of non-agricultural income, may positively affect a farmer's adoption of HYVs, while the distance to the market may have a significant and negative impact.
- *Hypothesis 1.3* The agroecological characteristics, particularly the elevation of croplands (medium land, lowland) and irrigation availability may have positive impacts on farmer's choice of HYVs.

Research Question 2. Have the estimated technical efficiencies of the sampled farmers increased over time and been influenced by some specific household characteristics? Is the technical efficiency change the main driving force for the output growth during the survey period?

- *Hypothesis 2.1* The estimated technical efficiencies of sampled farmers of which were higher for HYV plots than for TVs generally decreased during the survey period.
- *Hypothesis 2.2* The household characteristics, e.g. the age of household head, education attainment, farm size, the share of HYV plots, the share of non-agricultural income and the share of plots in lower land types (medium land and lowland), may be significantly and negatively associated with the technical inefficiencies, while the distance to market may have a positive relationship with the inefficiencies.
- *Hypothesis 2.3* The growth in rice production during the survey period was mainly contributed by the technical change, rather than technical efficiency change.

Research Question 3. Is the agricultural development a complement or a substitute for the non-agricultural development and for the rural poverty reduction in the study area?

- *Hypothesis 3.1* A substantial proportion of sampled households change their main income source and become increasingly reliant on non-agricultural income for living.

- *Hypothesis 3.2* Agricultural development has positive impacts on the agricultural income, but negative impacts on the non-agricultural income and the total income of the sampled households.
- *Hypothesis 3.3* The share of non-agricultural income significantly and positively influences the household member's income level.

1.3 Significance of the Research

The findings of this study will, in general, contribute to the rural poverty reduction in the developing countries and bring benefits to rural farming households, particularly under the rainfed ecosystems. The case of eastern India has been applied for analysis, where the significance of the research stems from the following aspects:

(1) The dataset used in the study is unique, as it is one of a few datasets that enable all the research questions to be addressed consistently using the same samples. The plot-level agricultural data collected in the survey are applied in the estimations, in addition to the household/farm-level analysis, which contributes to extending the existing knowledge by providing more detailed information and more precise results on crop choice and productivities, and providing the policymakers with a valuable empirical basis for understanding the likely effects of their efforts.

(2) Since adopting HYVs has been regarded as the solution to low productivity in agriculture over the years, policies on promoting HYVs to small-scale rice farmers are necessary to improve productivity and, thus, the farmer's income level. The study analyzes household socioeconomic factors, as well as the agroecological characteristics associated with the rainfed ecosystems constraining the farmer's

adoption of HYVs. The findings contribute to a better understanding of the farmer decision-making process and facilitating the policy design for improving the HYV adoption and implementation.

(3) Improving a farmer's technical efficiency, as another possible way of increasing agricultural productivity, has been thoroughly discussed in the study by estimating the technical efficiencies and factors affecting the technical inefficiencies. The studies on technical efficiency at a disaggregated plot-level and across different rice varieties (TVs vs. HYVs) are still rare in India; this study fills the gap in the literature. The findings can also enlighten the policy-making process and help policymakers deliver appropriate policies that improve the technical efficiencies of the farmers.

(4) The study also answers the question of what the most promising way is for rural farming households to escape poverty. There is still an ongoing debate about whether agricultural growth is a necessity for non-agricultural growth, and for rural poverty reduction. Lacking relevant data is the main reason for a notable scarcity of empirical literature on this topic. This study provides much-needed empirical evidence at the sub-national level, allowing for gaps in the existing literature to be filled, as well as highlighting important fields for policy intervention.

As the low agricultural productivity and the high incidence of poverty among the rural farming households under rainfed ecosystems have been widely argued by the previous literature, this Ph.D. dissertation contributes to the existing literature by providing more empirical evidence based on a unique dataset that can address these issues in a consistent manner and possible solutions generated from eastern India. Broadly speaking, most problems faced by the sampled farmers are commonly faced by rural farmers living in other developing countries under rainfed ecosystems. Therefore, the findings of this study may also enlighten policymakers and researchers across the world and affect the corresponding policy formations.

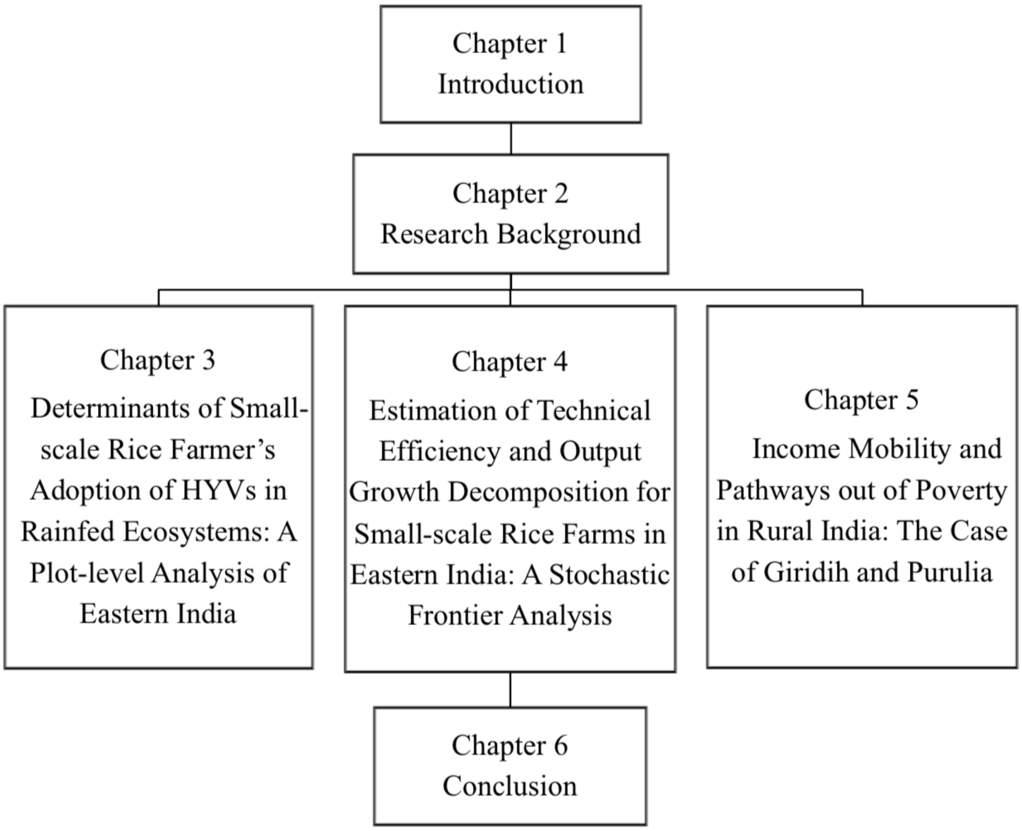
1.4 Research Structure

The main body of this Ph.D. dissertation consists of six chapters, as shown in Figure 1.1. First, Chapter 1—as the main introduction—raises the problems faced by the rural population in eastern India, as well as identifies the author's motivation behind conducting this study. The chapter then proposes the main and sub-research questions with the corresponding hypotheses for each sub-question. The research gap with previous studies is also identified and, thus, the contributions of the study are highlighted.

Chapter 2 provides detailed background information regarding the research questions, where three main features of the study area—unfavorable rainfed ecosystem for rice production, backward agricultural practices and high incidence of rural poverty—are identified. In addition, the study area and dataset applied in the empirical analysis are thoroughly introduced.

Chapters 3, 4, and 5 are constructed as three independent but logically connected empirical studies, each of which attempts to tackle the specific sub-research question proposed in Chapter 1. Chapter 3 examines the factors that affected a farmer's choice of HYVs with a focus on the varietal characteristics of rice, as well as the socioeconomic and agroecological constraints of the sampled farmers. Chapter 4 estimates the technical efficiency at both farm-level and plots-level with TVs and HYVs differed, examines the potential determinants of their technical inefficiency, and identifies the main driving source for rice production growth over time. Chapter 5 discusses the relationship between agricultural development and non-agricultural development—whether complement or substitute—and the role agricultural development plays in the rural poverty reduction within the study area.

Figure 1.1 Structure of the Ph.D. dissertation



The last chapter, Chapter 6, concludes with a summary of all findings in response to the research questions and hypotheses. Policy recommendations are given to solve the problems presented in the introduction of the study. The limitations of the study and future works are also identified in this closing chapter.

CHAPTER 2. Research Background

Regional development depends on ecologically permissible and sustainable agricultural production systems, with people fully involved in the process. In order to facilitate poor farming households with improving their income level, it is important for researchers and policymakers to gain a thorough understanding of the agroecological and socioeconomic constraints faced by farmers. This generalization can also be applied to the rainfed growing areas in eastern India. The agroecological and socioeconomic characteristics of the study area are identified from three aspects in this chapter: the rainfed ecosystem of rice production, backward agricultural practices, and high incidence of rural poverty.

2.1 Rainfed Ecosystem of Rice Production

According to the global irrigated area mapping (GIAM) project, in 2000, the estimated area of global rainfed croplands totaled 1.75 billion hectares, which is 5.5 times the area of the total global irrigated croplands. India ranks first regarding both its extent (86 million hectares) and its production value among all the rainfed agricultural countries. Table 2.1 shows that the rainfed regions in India are quite different from the irrigated regions as rainfed regions which are characterized with higher poverty rate, lower land and labor productivities, less per capita food consumption, lower level of infrastructural and social development when compared with the irrigated regions (Sharma et al., 2006).

In eastern India, rice is the main crop that is grown and consumed by local farming households. Rice production in the region covers 26.8 million hectares, accounts for 63% of the country's total rice croplands and meets 48% of the country's total production needs. Rice demand in India is predicted to exceed the supply and challenge people's food security in the near future due to the rapidly growing population. In the 1980s, the growth of rice production and productivity in eastern India was rapid, with an average annual growth rate of 5.85% and 4.89% respectively. However, in the early 1990s, growth had slowed down to 2.14% and 1.49% in the region, which fell behind the national production goals (Singh & Singh, 2000).

Due to the collaborative efforts of Indian government and the international organizations, e.g. International Fund for Agricultural Development (IFAD) and the International Rice Research Institute (IRRI), along with state agricultural universities, Non-governmental Organizations (NGOs) and farmer's groups in eastern India[1], the annually growth rate of rice productivity had surpassed 2% during 1994-1999, which contributed greatly to the rainfed rice production of the country (Singh & Singh, 2000).

Table 2.1 Comparison of the characteristics of rainfed and irrigated regions in India

Indicators	Rainfed Regions	Irrigated Regions	Country Average
Poverty rate (headcount %)	37	33	35
Land productivity (Rs./ha)	5,716	8,017	6,867
Labor productivity (Rs./ha)	6,842	9,830	8,336
Per capita consumption of food grains (Kg./year)	260	471	365
Infrastructure development index	0.30	0.40	0.35
Social development Index	0.43	0.44	0.43

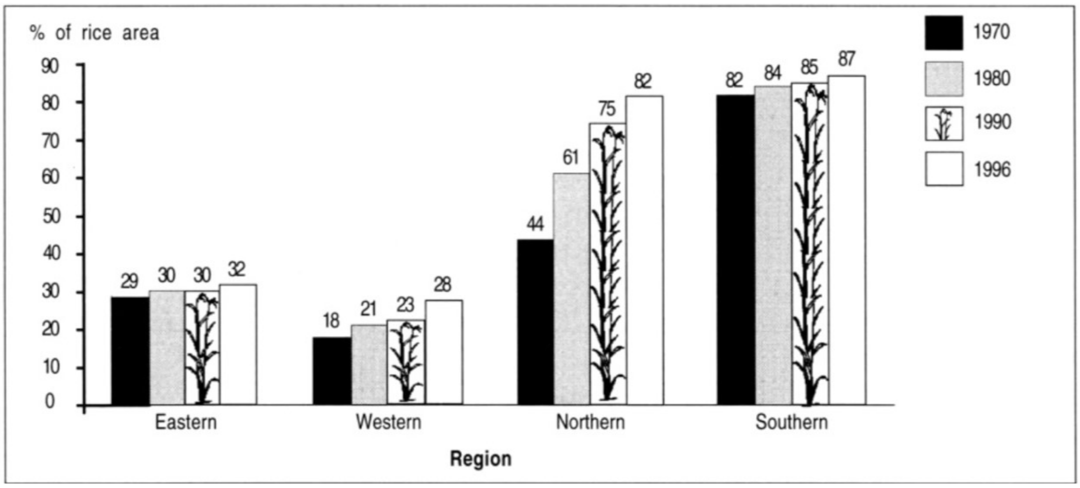
Source: Sharma, B. R., Sharma, B., Rao, K., Vittal, K., & Amarasinghe, U. (2006). *Realizing the potential of rainfed agriculture in India*. draft prepared for the IWMI-CPWF project on strategic analyses of India's national river-linking project.

The agroecological environment of eastern India is generally characterized as a drought-prone rainfed ecosystem with a large share of crops cultivated on the rainfed

[1] The project is within the context of the IFAD-aided Project Collaborative Research and Development of Sustainable Rice Farming Systems in South Asia. It aims to improve farmers' income and living standards through developing sustainable and economic rice and rice production system by conducting a series of researches and technology verifications in the farmers' croplands under rainfed ecosystem in eastern India.

lands. As shown in Figure 2.1, when compared with other major rice-growing regions, the share of irrigated lands in eastern India was the lowest, and the expansion of irrigated lands was rather limited between the 1970s and 1990s.

Figure 2.1 Change of the share of irrigated lands in India, by regions



Note: Reprinted from Singh, V. P., & Singh, R. K. (Eds.). (2000). *Rainfed rice: A sourcebook of best practices and strategies in eastern India*. Los Baños, Philippines: International Rice Research Institute.

To meet the expected rice demands of India's expanding population in the future, solely relying on higher yields achieved from irrigated rice-growing areas will be insufficient. This is because rainfed areas account for the majority of the total croplands and are responsible for the consumption needs of a larger proportion of the population. Given this, key issues for policymakers are how to manage rice production in rainfed ecosystems and how to identify, deliver and apply appropriate rainfed technologies. Efforts to enhance the production of rainfed lands can substantially contribute to overall rice production. Other major constraints of rainfed agriculture in the region are discussed in the following sections within this chapter.

2.2 Backward Agricultural Practices

Agriculture is the main source of livelihood in eastern India. A large portion of the region's income comes from agricultural sectors. Around 70% of the working population is employed in agricultural works, either as cultivators or as agricultural labors. Besides rice, other crops including wheat, maize, and pulses are also grown to a very limited extent, and sugarcane and potato are cultivated in some limited areas. Drought, flood, low natural resource base, and lack of suitable technologies are the major constraints to higher agricultural productivity for the rainfed lands of the region (Singh & Singh, 2000).

The region's climate is categorized as sub-humid and sub-tropical with annual rainfall ranging from 750 mm to 1,860 mm (Banik et al., 2004). Two main cropping seasons for rice grown in the region are identified, Kharif and Rabi[2], based on the monsoon. Yearly and seasonally fluctuations in rainfall is a notable feature. The region receives a greater share of annual rainfall from the south-west monsoon during the months of June to September, which accounts for 83% of the total annual rainfall. Although there is an adequate amount of rainfall, its seasonal feature is not particularly beneficial for agriculture. The sloping terrain allows for a quick runoff of the rainwater, and the impervious nature of rocks in most parts of the region do not allow water to be stored underground.

In the study area, the diffusion of Green Revolution technological innovations for rice progressed slowly. Rice production featured a low high yielding variety (HYV) adoption rate, low irrigation potential, limited use of market-purchased inputs, and a heavy reliance on traditional farming techniques. The adoption of HYVs seems to lag

[2] The Kharif season designates the crop cultivation during the south-west monsoon between July and October; the Rabi season runs from October to March.

behind other regions in India as HYV seeds suitable for the humid climate of the study area were latecomers. Farmers' lack of awareness of HYVs and a risk management approach also constrained HYV adoption. Additionally, opportunities to purchase HYV seeds were limited by the poor economic conditions of the farming households.

National and international collaborative efforts mattered in the study area, a number of improved site-specific technologies and HYV seeds were introduced and adopted rapidly by the end of the 20th Century. The HYV coverage in the region had reached 60% of the total rice areas but still ranked the lowest when compared with other regions of the country (Singh & Singh, 2000). According to Hossain, Jaim, Paris, and Hardy (2012), the main trait for the households in eastern India to adopt HYVs is the high yield for more grains from limited farm size (dominated), followed by the reasons of higher grain quality, short maturity, lodging resistance, and higher milling recovery. If the farmers are convinced that a varietal performs substantially better than the existing ones, they start to adopt, and small-scale rice farmers follow. It normally takes 2 to 3 years for the varieties to reach site-specific suitability, or even longer if there exists information lag for the farmers (Lakra et al., 2012).

Improved agricultural practices are being gradually practiced, despite traditional agricultural implements still being used in cultivation. The low adoption rate of the modern cultivation practices of intercropping and purchasing modern agricultural inputs (e.g. chemical fertilizer, insecticides/pesticides) demonstrates the traditional nature of agriculture that most sampled farming households engaged in. Subsistence farming in the region is typically conducted on small and marginal lands, and the farmers usually use indigenous tools such as hoes[3], digging sticks, desi ploughs, and so on for rice cultivation.

[3] A hoe is a traditional and multi-functional agricultural hand tool used for shaping soil, clearing land, and harvesting root crops.

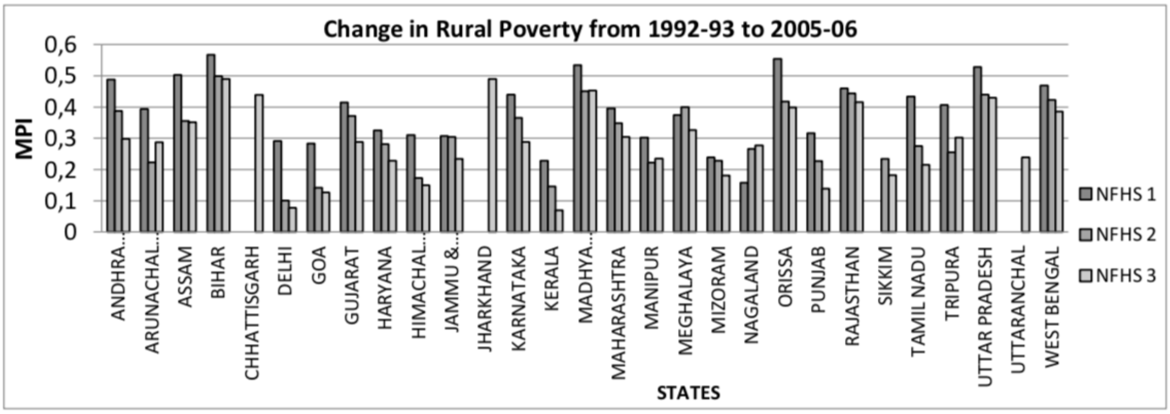
The rice output was primarily used for the farmers' own consumption, and the surplus would be brought to sell in the nearby market.

2.3 High Incidence of Rural Poverty

Another particular concern of researchers and policymakers is the widespread extreme poverty across eastern India. The poverty rate of eastern Indian rural households is among the highest in Asia. Nearly all Indian states have experienced declines in poverty in recent decades. According to the National Family Health Survey (NFHS), the headcount rural poverty ratio has decreased from 37% in 1992-93 to about 29% in 2005-06. However, the states in eastern India have generally remained with high poverty incidence and have been less successful in poverty reduction. Regarding the country's rural poverty ranking (see Figure 2.2), states like Bihar and West Bengal in eastern India ranked first and fifth place in 1998-99, and second and seventh place in 2004-05 among all the states in India.

The rural households in eastern India mainly rely on farming for their livelihood which ties the households' income to natural resources base and agroecological conditions in the region. Opportunities for households to pursue off-farm employment are limited due to the inaccessibility of rural areas to significant labor markets. Even if the non-agricultural working opportunities are available, workers from rural farming households often encounter social barriers or find themselves ethnically and educationally disadvantaged compared to other workers. Other socioeconomic factors causing poverty among these farming households include capital scarcity, the small average size of landholdings, low wages of off-farm employment and marginalization of segments of the population from the mainstream economy.

Figure 2.2 Change in Rural Poverty from 1992-99 to 2005-06



Source: Datasets of NFHS 1(1992-93), NFHS 2(1998-99) and NFHS 3(2005-06)

Note: Reprinted from Roy, A., Banerjee, A., Chaudhuri, B, & Montier, E. (2014). *Multi-dimensional poverty index- a state level analysis of India* (Working Paper No. 5). Brussels: Nopoor Project.

2.4 Sample Districts and the Dataset

The study area proposed in this study lies in the eastern fringe of the Chhotanagpur Plateau, which covers two districts in the adjacent states in eastern India: the Giridih district of Jharkhand and the Purulia district of West Bengal (see Figure 2.3). The study area was covered with dense forests and was largely unsettled before the British colonial era. The small residential population was primarily engaged in the extraction of forest productions, while agricultural activities hardly took place at that time. Under the British colonial domination, large-scale deforestation was conducted in the region, to meet the needs of building national railways. Later on, most of the local residents turned to farming for their livelihood on the available cleared lands. Rice represents the predominant crop in the study area and is the primary focus of agricultural and economic activities in the two districts.

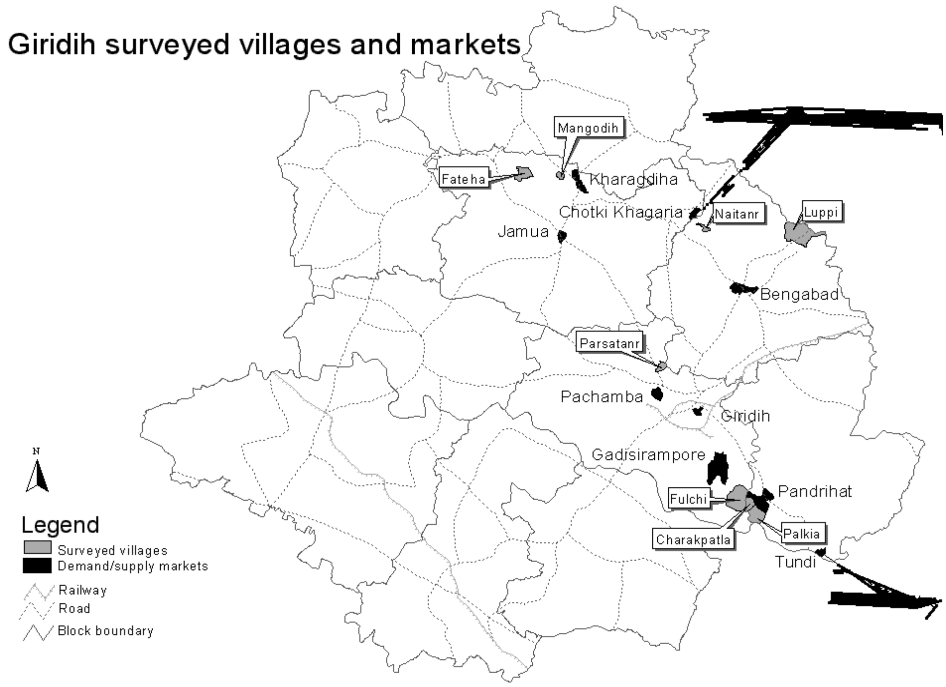
Unfortunately, the natural resource base in the study area is poorly suited to agriculture. The trend of rapid degradation caused by deforestation, monsoon rains and inappropriate land use practices can be observed. The lack of non-agricultural work opportunities and degradation of natural resources make the future of rural farming households that live there a cause for concern.

Figure 2.3 Map of India and the study area

The research project is carried out by the International Rice Research Institute (IRRI) and Indian Statistical Institute (ISI), which aims to identify pathways for small-scale rice farmers to escape poverty and address natural resource degradation, thus improving the incomes earned from drought-prone, rainfed agriculture. The project evaluated promising and appropriate interventions suited to the agroecological and socioeconomic circumstances of the area, as well as the policy environment found in the study area.

The Giridih district has been an administrative district of Jharkhand state since 2000 (formerly part of Bihar state); it covers a total cultivated land of 4,854 km^2. According to the census released by the Directorate of Census Operations in 2011, 2.45 million people lived in the district, 91.49% of which were rural residents.

Figure 2.4 Sample villages and markets in Giridih district

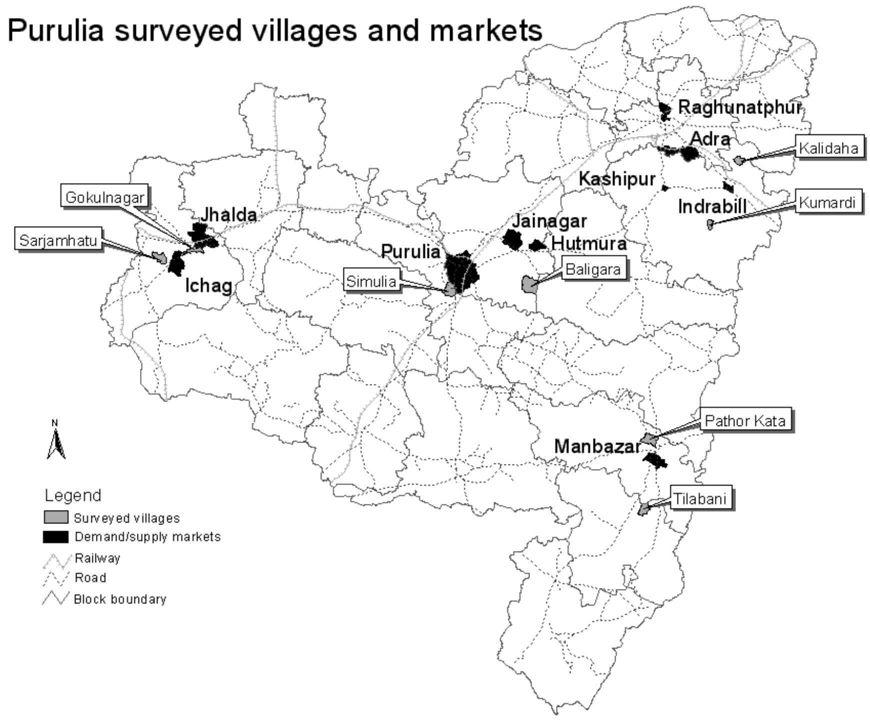


Source: Reprinted from Banik, P., Edmonds, C., & Fuwa, N. (2014) Sustainability Implications of the Evolution of Rice Farming amid Rural Poverty: The Case of the Chhotanagpur Plateau in Eastern India. *Journal of Sustainable Development*. 7(4), 282–297.

The climate of the Giridih district is categorized as sub-tropical, where the monsoon comes between June and September. Geographically, Giridih has a dense forest surrounding and an average altitude of 289 m. The district is bestowed with mineral resources, especially coal and mica. Therefore, a mining industry was established in the district that attracted substantial immigrants from the surrounding areas. The mining industry developed for around 30 years but eventually declined because the demand for mica decreased and other mineral recourses depleted. Consequently, the immigrants turned to agriculture for their livelihood (Banik et al., 2004).

The Purulia district, as part of West Bengal state, covers an area of 6,259 km^2. Approximately 2.93 million people settled in the district, 87.25% of which were a rural population (Census, 2011). Scheduled Castes (SCs) and Schedule Tribes (STs) form a significant part of the population.

Figure 2.5 Sample villages and markets in Purulia district



Source: Reprinted from Banik, P., Edmonds, C., & Fuwa, N. (2014) Sustainability Implications of the Evolution of Rice Farming amid Rural Poverty: The Case of the Chhotanagpur Plateau in Eastern India. *Journal of Sustainable Development*. 7(4), 282–297.

Geographically, Purulia is located in the western-most area of West Bengal and, thus, the district is regarded as a funnel for the monsoon and gateway of the state's developed industrial belts and hinterlands. The general elevation of the district ranges from 150 m to 300 m, which is characterized by an undulating topography with hilly terrain. The climate of Purulia is similar to Giridih. The agriculture sector is the backbone of the district's economy, and a substantial number of the population rely upon agricultural work as their livelihood. No significant industries were established besides in some areas with coal resources. Purulia is among the most backward districts in West Bengal state regarding to economic and social development.

Highly undulated topography is a common feature for the two sampled districts, where the lands ranges from flat land to steep slopes. Four distinct land types can be identified in the study area: upland, mid-upland, medium land, and lowland. There exist largely variations in terms of the terrains, soil textures and water conditions across the different land types. The soil fertility increases along with the decrease of the topography, which gives distinct constraints and opportunities for cropping systems (Banik et al., 2004).

The use of improved technologies in rice production is limited among the sampled households. By 1998-99, the HYV adoption rate was only 29.5% during the Kharif season, which was much lower compared to the regional average. However, the HYV adoption rate increased substantially in the follow-up survey. About 83% of the sampled households reported HYV cultivation during 2004-06. Based on the plot-level data, the HYV adoption rate also differs by land types; the adoption rate is twice as high on medium and lowland as on upper terraces.

The most widely adopted HYVs in the study area during Kharif season are Swarna for lowlands; Lalat, IR-36, and Sita for medium lands. These varieties are introduced to adapt to the rainfed ecosystem across different land types and are resistant to various diseases. Farmers prefer Swarna for its high yield while Lalat, IR-36, and Sita are preferred for their shorter duration (See Table 2.2). In the study of Lakra et al. (2012), farmers reported that it took 2 years for full adoption of IR-36, and 3 years or more for full adoption of Swarna, Lalat, and Sita.

Table 2.2 Characteristics of the popular HYVs in Jharkhand and West Bengal state

Variety	Year of notification	Duration (days)	Yield (tons/ha)	Suitable ecosystem
Swarna	1987	140	5.0-5.5	Rainfed, lowland
Lalat	1989	125-130	4.0	Irrigated medium land
IR-36	1982	112-115	4.0-5.5	Irrigated, rainfed upland or lowland
Sita	1978	130-135	3.0-4.0	Medium lowland

Source: Indian Council of Agricultural Research

The main reasons for the sampled households to not use HYVs are higher risk in production and higher seed costs of HYVs (Banik et al., 2004). Therefore, the invention of new varieties to cope with the risky and unfavorable environment (drought, submergence, flood, etc.) and the policies to subsidize seed purchasing are needed to increase rice productivity substantially.

Giridih and Purulia share similar agroecological characteristics, but different governing institutions. In Purulia, the local governance system—the Panchayat system[4] based on democratic elections of local leaders—is well-developed and actively implemented. In contrast, wealthy large landholders tended to dominate economic and political institutions in Giridih. Inequality between the relatively better-off and impoverished households seemed to be more pronounced in Giridih.

Ethnically, the study area is located at the so-called 'tribal belt', where the population is dominated by the SCs and STs. Participation of SCs and STs in agricultural development and economic activities is limited by institutional arrangements and the characteristics of agroecology and socioeconomics. As such, the poverty ratio is higher among SCs and STs than in other social groups, and the pace of poverty reduction is

[4] An Indian system of democratic local governance based on the political elections.

slower (Das, Hall, Kapoor, & Nikitin, 2012). The social, economic, and political position of lower castes in many rural areas continues to be characterized by a lack of political power and social isolation.

To address the agroecological and socioeconomic factors affecting farmers' agricultural production and poverty conditions, the household survey was carried out in eight villages in each of Giridih district and Purulia district. Applying the stratified random sampling method, data were collected from 541 households (266 households in Giridih and 275 households in Purulia) over two periods of 1998-1999 and 2004-2006. During the follow-up survey, the sampled households were split so that the number of samples increased to 678 households. The attrition rate was very low (about 2.3%) due to death and migration. The panel dataset captured detailed agricultural and socioeconomic information of the farming households, which make it possible to address all the research questions designed by this study.

CHAPTER 3. Determinants of Small-scale Rice Farmer's Adoption of High-yielding Varieties under Rainfed Ecosystems in Eastern India: Using McFadden's Choice Model

3.1 Introduction

As the dominant crop for South Asian countries, including India, rice is of importance in agricultural development and rural poverty reduction. The 'Green Revolution' brought modern agricultural technologies that have benefitted worldwide rice production and contributed significantly to an increase in productivity, particularly in irrigated environments. However, by the end of the 20th Century, there was still low rates of adoption of high-yielding varieties (HYVs), limited use of modern technologies, and low agricultural productivity in rainfed regions (Krishnaiah, 1999).

The study area of the Giridih district of Jharkhand and the Purulia district of West Bengal is located in the Chhotanagpur Plateau of eastern India, which is recognized as largely under the rainfed rice system. Rice cultivation is the main agricultural activity of people living in eastern India where is responsible for 48% of the total rice production of the country. For a long time, a number of challenges existed for rice production in the area, such as poor-quality seeds, a lack of suitable varieties for the unfavorable environment, unavailability of irrigation facilities, a lack of access to markets, among others. Therefore, as Ghimire and Huang (2016) argued, success in the enhancement of the HYVs in the rainfed areas requires an understanding of the constraints affecting farmer's HYV adoption.

The objective of this study is to explore the HYV adoption pattern and the factors that influence the probability of adopting HYVs by small-scale rice farmers using the dataset collected in Giridih and Purulia district where, during the survey period, the adoption rate of HYV rice was relatively low. Categorizing all the reported rice varieties into traditional varieties (TVs), medium-duration HYVs and long-duration HYVs, this chapter applies McFadden's choice model. In doing this, it finds that farmer's choices are impacted significantly by rice yield, education attainment, labor availability, farm size, the share of the products sold in the market, the share of plots in lower land types and irrigation availability.

Since plot-level studies on farmers' decision-making among different rice varieties in India are still rare, this study attempts to fill the gap in research by providing more precise results. McFadden's choice model is utilized and the alternative-specific attributes, as well as the case-specific characteristics, are considered, which provides a comprehensive understanding of the constraints faced by sampled farmers when adopting HYVs.

3.2 Literature Review: HYV Adoption in India

With the spread of the Green Revolution, Substantial resources such as HYV seeds, chemical fertilizers, and insecticides/pesticides, combined with various supportive policies to increase rice farmer's productivity, have been invested to support modern agricultural inputs (Banik et al., 2006; Hazell, 2010; Pingali, 2012). While a large number of studies explore the patterns in Indian farmers' HYV adoption and potential factors affecting their choices, there is still an ongoing debate as to what the key determinants really are.

Previous influential studies have focused primarily on the impacts that social learning has on farmers' decisions to adopt HYVs. As farmers learn more, either through their own experience or the experience of neighbors, the scale of adoption increases. Foster and Rosenzweig (1995) utilized a target-input model, finding that due to imperfect knowledge regarding the management of new varieties, farmers do not initially adopt HYVs. However, after observing neighbors' experiences and having their own experiences, adoption gradually occurs.

The increasing demands in inputs, such as chemical fertilizers and irrigation assets, lead to a large body of studies focusing on the potential importance of inputs in HYV adoption. Kohli and Singh's (1997) study in Punjab found that inputs play a substantial role in faster HYV adoption, arguing that the government enables the easy attainment of HYVs and their necessary inputs by the farmers so that the technology can be rapidly diffused.

More recent studies have emphasized the impact of socioeconomic and agroecological factors, such as landholding size, tenure conditions, risk control, access to credit, labor availability, soil quality, and land type. These studies have identified that these factors impact significantly on farmer's decisions regarding HYV adoption (Hagos & Zemedu, 2015; Tiongco & Hossain, 2015).

It should be noted that across the country, the benefits of the Green Revolution have been felt unequally. Successful experiences can be found in the country's main irrigated lands rather than the rainfed lands, where irrigation development is slow and droughts regularly occur at different stages of rice growth (Evenson & Gollin, 2003; Ward, Ortega, Spielman, & Singh, 2014). Therefore, promoting HYV adoption in the rainfed systems remains to be of particular interest for researchers and policymakers.

This study investigates the socioeconomic constraints faced by small-scale rice farmers to adopt HYVs, with an additional focus on the agroecological effects, since choosing HYVs to fit into different land types and cultivating conditions is important in improving agricultural productivity in eastern India (Krishnaiah, 1999).

3.3 Study Area and Dataset

The study area—the Giridih district of Jharkhand state (formerly part of Bihar state) and the Purulia district of West Bengal state—is located in the Chhotanagpur Plateau in eastern India. This rainfed area has been a long-term area of interest for development economists as it is considered to be an area with particularly low agricultural productivity and high rates of rural poverty (Banik et al., 2004). The data utilized in this study is taken from a household survey jointly carried out by the International Rice Research Institute (IRRI) and Indian Statistical Institute (ISI) in Kolkata during the Kharif seasons between 1998-99 and 2004-06. The main purpose of the survey was to explore the main agroecological and socioeconomic constraints for agricultural productivity and household income in the study area.

Using a stratified random sampling method based on the farm size, data was collected from eight villages in Giridih and Purulia. Approximately 34 households were selected and surveyed in each village. A total of 541 households (266 households in Giridih and 275 households in Purulia) were visited in the initial round. In the follow-up survey, the same households were visited, but as households split over time the number of sampled households increased to 678 (330 households in Giridih and 348 households in Purulia). There was a low attrition rate, with only a 2.3% reduction during the survey period because of death or migration. The agricultural information was collected at plot-level. This allowed the study to gain more precise results from the estimations, thus better facilitating policy development and application.

The Giridih and Purulia districts lie in adjacent states, and share similarities in topographic features and the predominance of rainfed cultivation; they also face similar problems in agricultural production and poverty reduction. In the study area, agricultural production was largely rice based, as more than 90% of the sampled households reported being part of rice production during the Kharif season. It was very difficult to find large commercial farms, and a substantial number of sampled farms are small-scale rice farmers, with an average landholding of only 1.92 acres. Rice production was largely consumption-based. Rice output was primarily used for the farmers' own consumption, with the surplus being brought to sell in the nearby market. In the initial survey, only 24% of the sampled households reported selling the rice they produced in the market, although in the follow-up survey, this proportion increased to approximately 46%.

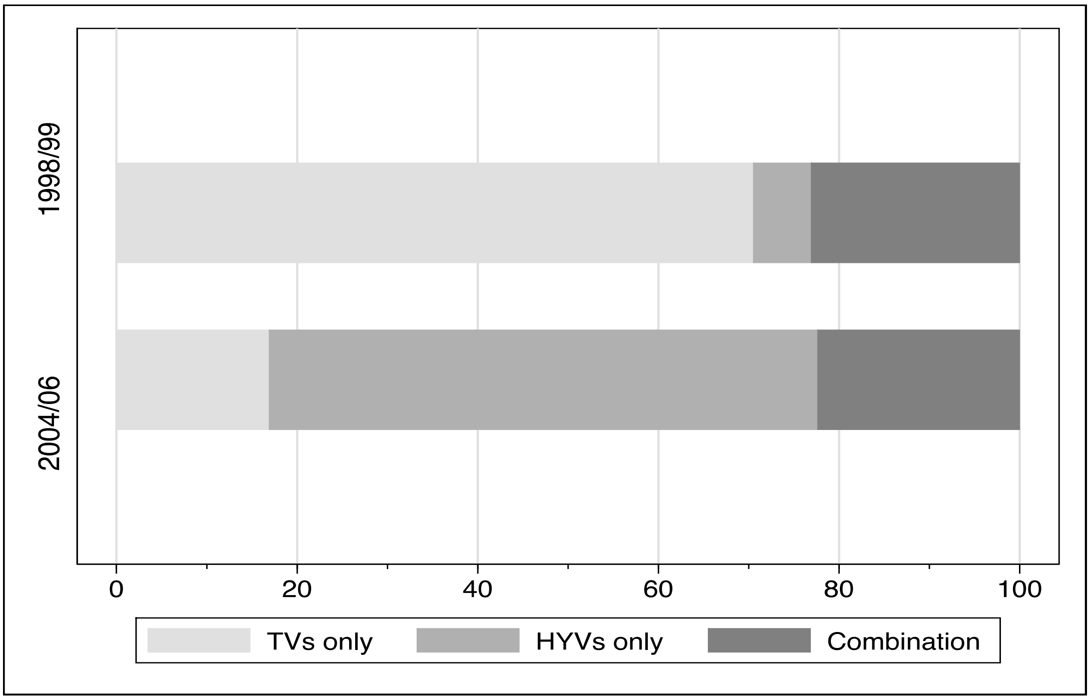
Therefore, rice production served as their main activity, of which the productivity is important for their livelihood. However, the HYV adoption rate was relatively lower in the study area when compared with the national average. Using the data collected for each sampled rice plot, this study aimed to identify key constraints on farmers' adoption of the HYVs in the rainfed area.

3.4 Patterns of HYV Adoption

In terms of the rice varieties adopted, the patterns of rice cultivation changed substantially during the survey period. The main feature reflected in Figure 3.1 is increasing HYV adoption and decreasing TV adoption. The adoption rate of HYVs was quite low in the initial survey. 70.52% of the sampled farming households cultivated only

TVs, while only 6.39% of the households were pure HYV cultivators. Growing a combination of TVs and HYVs was reported by 23.1% of households. However, the proportion of farms solely adopting HYVs increased significantly in the follow-up survey. 60.75% of the sampled households were engaged in the cultivation of only HYVs, while the proportion of pure TV cultivators dropped to 16.89%. 22.37% of the sampled households were still cultivating a combination of TVs and HYVs, a similar proportion to that in the initial survey.

Figure 3.1 Change of rice variety adoption over time



There were 33 different rice varieties (16 TVs and 17 HYVs) reported in the survey in total. Different rice varieties respond differently to the exogenous environment and production risks and are associated with varying yields. To meet different environmental constraints, reduce the possible production risks and maximize their economic returns, the sampled farmers normally plant one or more varieties. The 33 rice varieties are divided into two groups—TVs and HYVs, in order to identify the farmer's decision-making process as well as to simplify the model estimation. Based on the duration[5], the 17 HYVs were further categorized into medium-duration HYVs and long-duration HYVs. In Table 3.1, some of the characteristics of the three varietal groups are summarised by means.

The study area featured an undulated topography where four land types can generally be identified: upland, mid-upland, medium land, and lowland. In the uplands that were covered with light-textured soil, the sampled farmers tended to grow drought-tolerant TVs with relatively low yields. Generally, these TVs are short-duration types that mature within 90 days. The mid-uplands, which remain flooded for a longer period of time than the uplands, are sown mainly with TVs and medium-duration HYVs. In the area, the featured medium-duration HYVs are Lalat, IR36, and Sita, which require about 120 days to reach maturation. The soil conditions at the medium land allow long-duration varieties of rice to grow. Long-duration HYVs become the main cultivars in the lowlands because of the high level of standing water that accumulates there. In the study area, Swarna is the most commonly cultivated variety out of several long-duration HYVs that need more than 140 days to mature (Banik et al., 2004; Pionetti, 1997). The observation meets the general trend of rice cultivation in the area demonstrated in the previous studies (Hossain, Jaim, Paris, & Hardy, 2012).

Not only is the duration of rice an important economic characteristic of rice varieties but it is also an influential indicator of a farmer's varietal choice for different agroecological conditions. According to Table 3.1, the potential yield is ranked in ascending order across TVs, medium-duration HYVs, and long-duration HYVs. Long-

[5] According to the IRRI, the rice varieties were broadly classified as very early (90-105 days), early (105-120 days), medium (120-140 days), and long (beyond 140 days), based on total duration in tropical countries like India.

duration HYVs had the highest average yield (1,750 kg.), followed by medium-duration HYVs (1,446 kg.) and then TVs (1,065 kg.). HYVs also presented a higher average sold price than TVs, where the sold price was about 6 Rs./kg. for both long- and medium-duration HYVs and 4 Rs./kg. for TVs. The summary suggests that the inputs (e.g. labor, seed, farmyard manure, and chemical fertilizer) utilized in the production of TVs, medium-duration HYVs and long-duration HYVs were also different. It shows that long-duration HYVs require greater amounts of labor and chemical fertilizers than medium-duration HYVs, and even more than TVs.

Table 3.1 Summary of the varietal characteristics

Variable	Description	TV	HYV medium	HYV long
Yield	variety yield (kg./acre)	1065.37	1446.31	1750.28
Price	paddy sold price (Rs./kg.)	3.98	6.00	6.05
Labor	no. days of labor working (day/acre)	123.03	136.22	143.81
Seed	quantity of seeds applied (kg. /acre)	56.48	47.12	49.22
FYM	quantity of farmyard manure applied (kg. /acre)	1,116.12	1,296.46	1,206.59
Chemical	quantity of chemical fertilizer applied (kg. /acre)	20.99	48.08	71.83
Upland	share of growing on upland (%)	13.85	2.91	2.84
Mid-upland	share of growing on mid-upland (%)	48.69	47.64	20.21
Middle land	share of growing on middle land (%)	13.85	20.73	33.33
Lowland	share of growing on lowland (%)	23.61	28.73	43.62
Irrigation	Share of being irrigated (%)	4.65	4.00	8.51%

Source: author’s calculation based on the dataset.

In addition, agroecological characteristics such as land type and irrigation availability also vary across the three varietal groups. TV plots were mainly distributed on mid-upland (48.69%) and lowland (23.61%), and a small proportion (13.85%) was also found on upland and middle land. Nearly half of the medium duration HYV plots were located on mid-upland, and the other half were evenly distributed on lower terraces of middle land and lowland. The long duration HYV plots were systematically distributed in ascending order from upland to lowland.

3.5 Methodological Framework

The empirical model applied for analysis should be able to address the trade-off among potential choices in order to identify how small-scale rice farmers in the study area made their decisions when adopting different varieties. When modeling farmers' choices, two theoretical approaches, profit maximization and utility maximization, are widely argued for and applied. The profit maximization approach assumes that the farmer's production aims to maximize profits (Schultz, 1964). However, profit maximization has been criticized as it ignores other important aspects of the farmer's decision-making process (i.e. consumption). The utility maximization approach takes both production and consumption goals into account. When farmers' production and consumption decisions are interdependent, something that is commonly observed in rural areas, utility maximization better meets the estimation purpose (Mendola, 2007). Lin, Dean, and Moore's (1974) study used data collected from six Californian farms and found that utility maximization more accurately predicted farmers' behaviors than profit maximization.

Given this, this study adopts McFadden's (1974) choice model (also known as alternative-specific conditional logit model), which is derived from the utility maximization theoretical approach. This model gained popularity for examining individuals' choice behavior in economics and many other disciplines, such as marketing, transportation, and psychology. The microeconomic theory behind it assumes individuals are rational, and that when facing competing choices, they would attribute a utility level to each of the corresponding choices and then choose the one with the highest utility level (Guimarães & Lindrooth, 2007).

McFadden (1974) believed that unobservable factors associated with the individual or with the choice existed that brought a random element into the individual's decision-making process. McFadden's choice model analyzes the probability of individuals choosing among several alternatives and is developed from the random utility model. These alternatives can be expressed as a set of independent variables of the alternative characteristics subjective to the individuals (Rajbhandary & Basu, 2006). As argued by Mutware and Burger (2014), since "it makes use of wide and detailed information on alternatives, can explain match-specific details, and allows for multiple alternatives" (p. 270), McFadden's choice model is effective for the choice framework of rice variety.

The plot-level data[6] collected from the household survey is organized into the combinations of individuals choosing from various rice varieties. The model then estimates the probability of farming household *i* selecting rice variety *j* as the crop grown on the plot among the other alternatives. The random utility maximization takes the following form (Cameron & Trivedi, 2009):

$$U_{ij} = V_{ij} + \varepsilon_{ij} \qquad (i = 1, \dots, N;\ j = 1, \dots, J) \tag{1}$$

U_{ij} is supposed to be the highest utility for farming household i and alternative j which equals to the sum of a systematic utility V_{ij} and an unobserved random utility ε_{ij}. V_{ij} is a function of observable variables and unknown parameters.

The outcome $y_i = j$ is chosen if alternative *j* has the highest utility among all the

[6] The data applied in estimation are the plot-level data collected in both Giridih and Purulia districts in the initial survey and the data collected in Purulia district only in the follow-up survey, due to lacking information on specific rice varieties in Giridih district.

alternatives, which is specified as:

$$\Pr(y_i = j) = \Pr(U_{ij} \geq U_{ik}),\ \forall\, k$$
$$= \Pr(\varepsilon_{ik} - \varepsilon_{ij} \leq V_{ij} - V_{ik}),\ \forall\, k \qquad (2)$$

Selecting from TVs, medium-duration HYVs and long-duration HYVs, a multinomial choice model specifies that $V_{ij} = x'_{ij}\beta + z'_i\gamma_j$. Thus, McFadden's choice model is expressed as:

$$U_{ij} = x'_{ij}\beta + z'_i\gamma_j + \varepsilon_{ij} \qquad (3)$$

where U_{ij} is the utility that farming household i perceives from alternative j. The independent variables come in two forms: alternative-specific variables x_{ij} and case-specific variables z_i. x_{ij} refers to the varietal attributes varying among the alternatives. z_i refers to the socioeconomic characteristics varying only among farming households. β and γ_j are the parameters to be estimated, and ε_{ij} presents an unobserved random component.

Therefore, p_{ij}, the probability for farming household *i* of selecting choice *j* over the other alternatives is performed as:

$$p_{ij} = \mathrm{P_r}(\mathrm{y}_i = j | x_{ij}) = \frac{\exp(x'_{ij}\beta + z'_i\gamma_j)}{\sum_{k=1}^{J} \exp(x'_{ik}\beta + z'_i\gamma_k)} \qquad (4)$$

McFadden's choice model permits the maximum likelihood estimation (MLE) for the parameters. The density for the *i*th farming household is written as:

$$f(y_i) = p_{i1}^{y_{i1}} \times \cdots \times p_{iJ}^{y_{iJ}} = \prod_{j=1}^{J} p_{ij}^{y_{ij}} \qquad (5)$$

where y_{i1}, …, y_{iJ} are *J* indicator variables. $y_{ij} = 1$ if the farming household i picks rice variety *j*; and $y_{ij} = 0$ otherwise. The maximum likelihood function for *N* independent observations is the product of *N* densities:

$$L = \prod_{i=1}^{N} \prod_{j=1}^{J} p_{ij}^{y_{ij}} \tag{6}$$

The estimation results are also reported in the form of marginal effects, which captures the change in the probability for a unit change in one explanatory variable, keeping all other explanatory variables constant.

To interpret the coefficients, the alternative-specific variable can be denoted by x_m with corresponding coefficient β_m, the effect of a change in x_{mik} which is the value of x_m for farming household *i* and alternative *k*, is:

$$\frac{\partial p_{ij}}{\partial x_{mik}} = \begin{cases} p_{ij}\left(1 - p_{ij}\right)\beta_m & j = k \\ -p_{ij}p_{ik}\beta_m & j \neq k \end{cases} \tag{7}$$

If $\beta_m > 0$, the own-effect is positive as $p_{ij}\left(1 - p_{ij}\right)\beta_m > 0$, but the cross-effect becomes negative since $-p_{ij}p_{ik}\beta_m < 0$. Therefore, taking the positive coefficient as an example, it means increasing the chosen for the specific alternative and decreasing chosen for all the other alternatives.

The coefficient of the case-specific variable for farming household *i* can be treated as the parameters of a binary logit model against the base category, thus the estimated model is equivalent to a set of pairwise logit models. Setting the base category as the alternative 1 ($\gamma_1 = 0$), the estimation can be simplified as

$$\mathrm{P_r}(\mathrm{y}_i = j|\mathrm{y}_i = j \text{ or } 1) = \frac{\mathrm{P_r}(\mathrm{y}_i = j)}{\mathrm{P_r}(\mathrm{y}_i = j) + \mathrm{P_r}(\mathrm{y}_i = 1)} = \frac{\exp(z_i'\gamma_j)}{1 + \exp(z_i'\gamma_j)} \tag{8}$$

Thus, $\hat{\gamma}_j$ is the parameter between alternative *j* and alternative 1. A positive coefficient means that as parameter increases, the farming household is more likely to choose alternative *j* over alternative 1 and vice versa for the negative coefficient.

3.6 Empirical Results

3.6.1 Summary of the determinants for farmer's choice

As stated in Equation 3, the sampled farmers choices from three group, TVs, medium-duration HYVs, and long-duration HYVs, were affected by a set of varietal attributes and various farmers' socioeconomic and agroecological characteristics, which are listed and defined in Table 3.2. The dependent variable 'choice' equals to "1" if the farmer chooses at least one rice variety out of the three alternatives; otherwise 'choice' equals "0".

Aligning with Islam, Sumelius, and Bäckman's (2012) study, the alternative-specific variables specified in the model are yield and sold price, reflecting the farmer's perception of HYVs. Information about the varieties that are not chosen is difficult to find. As such, the estimation applies the multiple regression imputation method to generate these values, following Mutware and Burger's (2014) study. The case-specific variables used in the estimation reflect farmer's socioeconomic characteristics. These include: age of the head of the household as a proxy for farming experience, the highest educational attainment of the household member, labor availability, total landholding size, distance to the nearest local market, the share of rice production sold in the market and the share of non-agricultural income. Selected agroecological features of the farming households are the share of plots on lower land types (medium land and lowland) out of total plots, and the share of plots being irrigated, to explore the exogenous environmental constraints of the farmer's adoption of HYVs. To control for time differences and district differences, the year dummy and district dummy are also applied.

Table 3.2 Definition of the potential determinants of HYV adoption

Variable	Description
Rice variety attributes	
Yield	variety yield (kg/acre)
Price	Variety sold price (Rs./kg.)
Socioeconomic and agroecological characteristics of the farmers	
HH. age	Age of household head (year)
HH. education	Education of household head (year)
Max education	Highest education of household member (year)
Labor availability	No. of agricultural labor (age between 15 and 65)
Farm size	Total landholding size (acre)
Distance	Distance to nearest local market (km)
% Sold production	Share of production sold in the market (%)
% Non-ag. income	Share of non-agricultural income (%)
% Mid-upland	Share of plots on mid-upland (%)
% Middle land	Share of plots on middle land (%)
% Lowland	Share of plots on lowland (%)
% Irrigation availability	Share of plots being irrigated (%)
District	1 = Giridih; 0 = Purulia
Year	1 = 2004/06 (follow-up survey); 0 = 1998/99 (initial survey)

The summary statistics in Table 3.3 report the means of the potential determinants of a farmer's choice among different rice varieties: TVs, medium duration HYVs, and long duration HYVs. An analysis of variance (ANOVA) is used to test the hypothesized differences in means for these potential determinants across adopters of the three rice varieties. The results of ANOVA tests are summarized in Table 3.3, which strongly supports the existence of differences (at 10% significance level) among the varieties.

In Table 3.3, TV, medium-duration HYV, and long-duration HYV adopters are shown in ascending order, in terms of the mean value of the age of the household head and household members' highest educational attainments. It indicates that when compared with the other adopters, those who adopted long-duration HYVs had greater farming experience and higher education levels. On average, the medium-duration HYV adopters used more agricultural laborers and used larger lands for production. Their farms were located closest to the local market, they sold a larger share of their products in the market, and, when compared with those who adopted the other two varieties, a greater proportion of their income came from non-agricultural sources.

Table 3.3 Summary statistics and mean comparison of the potential determinants

Variable	TVs	Medium duration HYVs	Long duration HYVs	F	*p*-value
No. of observation	881	275	282		
Yield	1065.4	1446.3	1750.3	115.45	0.0000***
Price	3.98	6.00	6.05	574.30	0.0000***
HH. age	48.6	52.12	53.06	15.36	0.0000***
HH. education	4.02	5.49	5.50	19.92	0.0000***
Max education	7.13	8.55	8.83	5.30	0.0000***
Labor availability	4.16	5.07	5.04	28.73	0.0000***
Farm size	2.37	2.68	1.96	4.19	0.0154**
Distance	2.76	2.38	2.93	4.26	0.0144**
% Sold production	0.06	0.15	0.15	57.88	0.0000***
% Non-ag. income	32.39	37.32	32.74	2.49	0.0837*
% Mid-upland	44.56	45.61	32.44	25.62	0.0000***
% Middle land	15.07	22.47	27.63	39.52	0.0000***
% Lowland	26.92	27.57	35.93	14.59	0.0000***
% Irrigation availability	4.69	4.12	8.67	3.35	0.0355**
District	0.47	0.14	0.05	137.06	0.0000***
Year	0.05	0.68	0.68	586.02	0.0000***

Note: (1) author's calculation based on the dataset.

(2) *, $p< 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

(3) Means of farmer's characteristics reported in each category refers to the farmer cultivated at least one plot with the corresponding variety. The characteristics are not exclusive for the three varieties as the farmers can be a cultivator for a single or a combination of varieties.

Regarding land types, sampled farmers tended to cultivate more long-duration HYVs in both medium land and lowland than both medium-duration HYVs and TVs. The share of plots being irrigated is greater for plots where long-duration HYVs were being grown than it is for the TVs and medium-duration HYVs. In the next section, McFadden's choice model is used to further estimate the impacts of these variables on a farmer's choice of different rice varieties.

3.6.2 Empirical results of McFadden's choice model

To guarantee the validity of the model choice, two pre-tests have been conducted. Firstly, the likelihood-ration test is applied for the null hypothesis that the multinomial logit model ($\beta_{yield} = 0$ and $\beta_{price} = 0$) is preferred over McFadden's choice model. The result strongly rejected the null hypothesis, showing that McFadden's choice model is the more suitable option. Secondly, Hausman-McFadden tests are applied to check the validity of the independence of irrelevant alternatives (IIA). The results indicate that the null hypothesis of the existing IIA cannot be rejected at common significance levels, justifying the choice of the model. As such, the model has been specified using McFadden's choice model and analyzed with the MLE.

The estimation of McFadden's choice model turns out to be highly significant at 1%, with the results being summarized in Table 3.4. Keeping TVs as the base alternative ($\hat{\gamma}_{TVs} = 0$), the estimates on the top column of the table report the coefficients $\hat{\beta}$ of the alternative-specific variables yield and price. The estimates in the bottom column report the coefficients of the case-specific variables, $\hat{\gamma}_{MHYVs}$ and $\hat{\gamma}_{LHYVs}$.

The results show that the potential rice yield (kg./acre) is significantly and positively associated with farmers' decision making among TVs, medium-duration HYVs and long-duration HYVs. According to Equation 7, when treating TVs as the base alternative, if the yield of TVs increases, farmers' demands for TVs would increase in tandem and, thus, decrease their demands for the other two alternatives. This finding aligns with previous studies, which argue that differences in yield are the main incentive for farmers to adopt HYVs (Dewi & Istriningsih, 2018; Pionetti, 1997). However, since the estimated coefficient for price is not significant, the price failed to show any apparent influence on farmers' choice out of the three varieties.

Table 3.4 suggest that the sampled farmers' decision-making processes were likely to be affected by a set of their socioeconomic and agroecological characteristics. Regarding the human capital attributes, contrary to previous studies finding significant and positive impacts of household head's age in HYV adoption (Akudugu, Guo, & Dadzie, 2012; Ghimire, Huang, & Shrestha, 2015), there is no evidence to support such arguments. According to the estimation results, age of household heads is not an important factor in explaining farmers' choice among different varieties, implying that sampled farmers did not choose rice varieties relying on their farming experience.

The results indicate that education is significant for famer's choice, although the coefficient signs of the two education variables are opposite to each other. An increase in the highest educational attainment of the household members leads to a decrease in the probability of choosing HYVs, relative to the probability of choosing TVs. This is consistent with Rosenzweig's (1982) view on education's different influence on new technology adoption. He claimed that education may encourage adoption by lowering the learning cost, but it may also discourage adoption, as growing HYVs increases the opportunity cost of the farmer being employed in a more profitable, non-agricultural sector. According to previous empirical evidence, there is no single answer to the correlations between education and adoption (Akudugu et al., 2012; Ghimire et al., 2015;

Holloway, Shankar, & Rahman, 2002).

Table 3.4 McFadden's Choice Model Estimates (TVs based)

Rice variety attributes				
Yield			0.00030 (0.00009) ***	
Price			0.2076 (0.1365)	
Farmer's socioeconomic &agroecological attributes				
	Medium duration HYVs		Long duration HYVs	
HH. age	0.0005	(0.0077)	0.0058	(0.0077)
HH. education	0.0648	(0.0291)**	0.0511	(0.0287)*
Max education	-0.0705	(0.0285)**	-0.0688	(0.0274)**
Labor availability	0.1231	(0.0486) **	0.1231	(0.0506)**
Farm size	0.0192	(0.0346)	-0.1124	(0.0581)*
Distance to market	-0.0573	(0.0421)	0.0420	(0.0400)
% Sold in market	1.2673	(0.6482)*	1.5235	(0.6562)**
% Nonag. income	-0.0026	(0.0036)	-0.0031	(0.0035)
% Nonag. inc×district	0.0144	(0.0072)**	0.0120	(0.0105)
% Mid-upland	0.0152	(0.0065)**	0.0009	(0.0070)
% Medium land	0.0141	(0.0076)*	0.0128	(0.0078)
% Lowland	0.0124	(0.0067)*	0.0141	(0.0070)**
% irrigation	-0.1896	(0.4700)	0.7085	(0.3350)**
District	-0.6426	(0.4346)	-1.8459	(0.6184)***
Year	3.5871	(0.2582)***	3.0966	(0.2499)***
Constant	-3.6869	(0.7551)***	-3.0685	(0.7803)***

Note: (1) ***, **, * represent significance at 1%,5% and 10% level respectively;
(2) standard errors in parentheses.

As expected, households with more available agricultural laborers tended to choose long-duration HYVs, rather than the TVs. On the one hand, when compared to TVs, HYVs essentially require greater labor inputs in production and management. On the other hand, more agricultural laborers could facilitate the timely availability of labor in order to learn the technical skills necessary for HYV production (Islam, Sumelius, &

Bäckman, 2012). Another perspective proposed by Holloway et al. (2002) argues that higher subsistence pressure within larger households could lead to increased adoption of HYVs for consumption-based farming households.

The results also show that farm size has negative and significant impacts on the farmer's HYV adoption. Smaller farms are more likely to adopt long-duration HYVs over TVs than larger farms. This is consistent with the argument that when the potential benefits are clear, smaller farmers are rapid HYV adopters (Mutware & Burger, 2014). A higher yield is crucial to guarantee the food consumption of farming households with limited land. This finding again highlights the 'subsistence pressure' argument: higher subsistence pressure leads to faster adoption of new technologies. This is supported by Chayanov's (1966) theory and aligns with the findings of Holloway et al. (2002) in Bangladesh.

Two market attributes are captured. These are the distance between farms and the nearest local market, as the proxy for ease of buying inputs and selling products; and the share of rice products sold in the market, as a control for the extent of market involvement. The results indicate that distance to the nearest local market does not significantly explain farmers' choices. However, the share of rice products sold in the market shows significant and positive impacts on the probability of adopting HYVs. Increasing market involvement encourages farmers to choose HYVs as HYVs are able to bring better economic returns.

As no significant results are reported, the influence of non-agricultural income share on farmers' HYV adoption is not obvious. Income earned from non-agricultural activities could help farmers afford the input costs, such as seed and chemical fertilizer costs related to HYV production (Hailu, Abrha, & Weldegiorgis, 2014). However, as observed in the study area, the increasing engagement in non-agricultural employment may also cause competition, with family labor choosing between farm and off-farm work. This then reduces the labor availability for farming and decreases HYV adoption (Ghimire & Huang, 2016).

In the study area, farmers' agroecological differences played an important role in the adoption of HYVs. Results indicate that there is a greater likelihood of farmers growing long-duration HYVs if they possess more plots in medium and lowlands when compared with TVs. Irrigation availability is also crucial to a farmer's decision (Gauchan et al., 2012). Relative to TVs, if the coverage of the irrigation system expands, the farmers are more likely to grow long-duration HYVs. These results reflect the fact that, in the study area, unfavorable environments on upper lands and a lack of irrigation constrain HYV adoption.

Considering the time difference, in the follow-up survey period, the probability of HYV adoption is significantly higher than the initial survey period. Farmers in Purulia show a significantly higher possibility of choosing long duration HYVs than farmers in Giridih which could be explained by the scheme entitled "Manikit" under which the HYVs are systematically distributed through the Panchayat system (Banik et al., 2004).

3.6.3 Marginal effects of the estimation

The marginal effects are also estimated to capture the extent to which changes in explanatory variables affect the probabilities of farmer's choice. The estimates are summarized and reported in Table 3.5. The predicted probability of choosing a particular rice variety (among the three options) is generated from the McFadden's conditional logit estimation, which indicates 61% probability of choosing TVs, 19% probability of choosing medium duration HYVs, and 20% probability of choosing long duration HYVs.

Table 3.5 Marginal effects of the influential factors of variety adoption

	TVs		Medium duration HYVs		Long duration HYVs	
Rice variety attributes						
Yield	0.00007	(0.00002)***	0.00005	(0.00001)***	0.00004	(0.00001)***
Price	0.0472	(0.0310)	0.0321	(0.0211)	0.0276	(0.0182)
Farmer's socioeconomic &agroecological attributes						
HH. age	-0.0007	(0.0015)	-0.0001	(0.0011)	0.0008	(0.0009)
HH. education	-0.0133	(0.0058)**	0.0085	(0.0041)**	0.0048	(0.0035)
Max education	0.0159	(0.0055)***	-0.0088	(0.0041)**	-0.0070	(0.0033)**
Labor availability	-0.0252	(0.0099)**	0.0119	(0.0068)*	0.0133	(0.0061)**
Farm size	0.0092	(0.0083)	0.0064	(0.0051)	-0.0155	(0.0074)**
Distance to market	0.0028	(0.0080)	-0.0101	(0.0060)*	0.0073	(0.0049)
% Sold in market	-0.3143	(0.1325)**	0.1499	(0.0900)*	0.1645	(0.0776)**
% Nonag. income	0.0006	(0.0007)	-0.0003	(0.0005)	-0.0003	(0.0004)
% Nonag. inc×district	-0.0030	(0.0015)**	0.0019	(0.0011)*	0.0012	(0.0014)
% Mid-upland	-0.0020	(0.0012)	0.0023	(0.0010)**	-0.0004	(0.0009)
% Medium land	-0.0031	(0.0014)**	0.0018	(0.0011)	0.0013	(0.0010)
% Lowland	-0.0030	(0.0013)**	0.0015	(0.0010)	0.0015	(0.0009)***
% irrigation	-0.0493	(0.0781)	-0.0507	(0.0695)	0.1000	(0.0419)**
District	0.2698	(0.0849)***	-0.0436	(0.0671)	-0.2262	(0.0760)***
Year	-0.7646	(0.058)***	0.4608	(0.0436)***	0.3038	(0.0383)***
Predicted Probability	61.21%		19.00%		19.80%	

Note: (1) ***, **, * represent significance at 1%,5% and 10% level respectively;
(2) standard errors in parentheses.

Taking the marginal effects of yield as example, the estimates show that an additional 1 kg in rice yield would increase the choice probability by 0.007 percentage points for TVs, 0.005 percentage points for medium duration HYVs and 0.004 percentage points for long duration HYVs, respectively. Therefore, the marginal effect of yield is the highest for the TVs, than the other two alternatives.

It should be highlighted that the marginal effects for irrigation availability is relatively high. One unit increase in the share of plots being irrigated would results in 10 percentage point increase in choice probability of long duration HYVs, which reflects the importance of expanding irrigation coverage in the study area.

The estimates of marginal effects are consistent with most of the findings in the previous section. However, the correlations between the household head's education level and farmer's adoption of long duration HYV becomes unobvious. The marginal effect suggests that distance to the nearest local market has negative impacts on farmer's probability of choosing medium duration HYVs. This complies with the previous studies arguing that farms located nearer to local markets were more likely to adopt HYVs (Ghimire et al., 2015; Hagos & Zemedu, 2015). Unlike estimated by the McFadden's choice model, the marginal effects estimation indicates only larger share of plots in mid-upland can significantly increase the probability of choosing medium-duration HYVs for the sampled farmers.

3.7 Conclusion

As HYVs have been considered the solution to agricultural development, agricultural policies, particularly those focused on increasing farmer's HYV adoption, are necessary in order to improve agricultural productivity and thus farmers' earning potential from the agricultural sector. As such, understanding the determinants of farmers' choice among different rice varieties is important in policy development and application. This study provides an original insight into this area by applying McFadden's choice model, categorizing 33 reported rice varieties into three groups (TVs, medium-duration HYVs, and long-duration HYVs) and incorporating both the alternative-specific variables and case-specific variables in the analysis. The empirical estimation attempts to fill the literature gap by identifying the socioeconomic and agroecological factors associated with rice farmers' HYV adoption under the rainfed ecosystem in eastern India.

As observed, the adoption rate of HYVs increased substantially between the two survey periods. Empirical results show that potentially high yields serve as the main driver in farmers adoption of HYVs, as yield is significant at explaining the farmer's choice, aligning with Saha's (2004) findings. When making adoption decisions, sampled farmers relied on education more than farming experience. The subsistence pressure of the farming households with smaller landholdings and/or with more household members to feed are obvious. Cultivating a higher-yielding rice variety became essential for their livelihood, contributing to their adoption of HYVs.

The role that the market plays in affecting a farmer's choice of HYVs cannot be ignored, despite the rice produced by sampled farmers largely being for consumption. For the better-off households who sell their products at markets, the larger the proportion of rice products they sell in the market, the more they tend to choose to grow HYVs. The study also finds that the highest education levels of household members negatively impacts adoption. This implies that increasing off-farm employment opportunities resulted in farmers working in non-agricultural sectors instead of learning new agricultural technologies, thus depressing the likelihood of HYV adoption. The determinants of farmer's HYV adoption found in this study are in line with previous studies conducted by Husain, Hossain, and Janaiah (2001), Hollaway et al. (2002), Asfaw and Admassie (2004), and Foster and Rosenzweig (2010).

In addition, agroecological factors (land types and irrigation availability), also significantly influenced and constrained farmers' adoption choice, something that is also supported by Rola and Alejandrino (1993), and Fuwa, Edmonds and Banik (2007). To achieve higher utilities, policymakers should facilitate farmers ability to cultivate properly and scientifically. Additionally, they should lessen the existing environmental constraints (e.g., improve irrigation coverage, introduce better suitable HYVs for upper lands) for rice productivity growth.

CHAPTER 4. Estimation of Technical Efficiency and Output Growth Decomposition for Small-scale Rice Farms in Eastern India: A Stochastic Frontier Analysis

4.1 Introduction

Rice has long been the dominant crop and staple food for rural farming households in eastern India, which has been recognized as one of the regions with the highest incidence of poverty in the country. Rice production in eastern India covers 26.8 million hectares, accounts for 63% of the country's total rice croplands and produces 48% of the country's total production needs (Singh & Singh, 2000). By the end of the twentieth century, the Green Revolution had brought new agricultural technologies that contributed greatly to improving agricultural productivity and reducing hunger in India. However, as pointed out by Walker and Ryan (1990), the Green Revolution technologies are diffused at a particularly slow rate in the rice-growing areas of eastern India, which constrains the agricultural productivity of rice farmers in the region.

This chapter focuses on estimating the degree of technical efficiency of the sampled small-scale rice farmers over time. As Fuwa et al. (2007) argued, it is important for policymakers to understand the technical efficiency of farmers which enables them to properly allocate policy priorities for the improvement of farmers' agricultural productivity and thus agricultural incomes. The panel data analyzed in this chapter were collected during the Kharif season[7] over two time periods—1998-1999 and 2004-2006—

[7] i.e., the monsoon season, which generally runs from June to November/December.

in the districts of Giridih and Purulia in eastern India. The estimations of technical efficiency are carried out at both aggregated farm-level, and disaggregated plot-levels where traditional varieties (TVs) and high-yielding varieties (HYVs) are differentiated. An empirical model of stochastic frontier production function (SFPF) with a sub-model of inefficiency effects is applied in order to assess the degree of technical efficiency and the determinants of technical inefficiency of the sampled rice farms. Additionally, the output growth decomposition analysis at farm-level identifies the contributions made by aggregated input growth, technical change and technical efficiency change to the total rice production growth during the survey period.

The study finds the sampled farms in eastern India operated at a moderate level of efficiency with the average technical efficiency score equals to 81% during the survey period. The plot-level empirical evidence suggests that plots cultivating HYVs are more technically efficient than the plots cultivating TVs. According to the output growth decomposition analysis, technical change, rather than technical efficiency change, was the main driving force of the rice production growth during the study time. As plot-level study of technical efficiency are still rare in India, this study aims to fill the literature gap in the domain. Knowledge obtained from the degree of technical efficiency and the driving forces of output growth can provide a better understanding of the structure of rice production among sampled farms as well as assist policymakers to allocate their priority in investment, to achieve the goal of enhanced economic performance and growth.

The remainder of the chapter is organized as follows. Section II reviews the previous literature on technical efficiency estimation of rice farms in developing countries, while the following section builds the methodological framework on a set of estimations on technical efficiency and output growth decomposition. Section IV provides background information to the study area and the panel dataset, while Section V presents the empirical results and discussion on estimated technical efficiency, changes to technical efficiency over time, the determinants of technical inefficiency and the driving forces behind output growth. The final section is a discussion of the study's conclusions.

4.2 Previous Studies on Technical Efficiency of Rice Farms

Estimations of the degree of technical efficiency have been widely carried out by researchers over the previous decades (Battese & Coelli, 1992; Wu, 1995; Latruffe, Balcombe, Davidova, & Zawalinska, 2004), with a large proportion finding significant technical inefficiency among rice farmers in India and other developing countries. The average technical efficiency score of twenty-eight farm-level studies of rice farms reviewed by Bravo-Ureta et al. (2007) is 72.4%, suggesting that these farms are operated relatively far from being efficient.

However, farm-level estimations that do not control for environmental factors tend to generate lower technical efficiency. Using plot-level data in the states of Jharkhand and West Bengal in India, the study of Fuwa et al. (2007) argues that not controlling for the differences in the topographic characteristics will result in an overestimation of technical inefficiency. Sherlund, Barrett and Adesina (2002) also conclude similar findings in their research on rice farmers in Cote d'Ivoire. After controlling for the heterogeneous environmental factors affecting rice production (e.g. pests, plot slopes, soil quality, etc.), the estimated technical efficiency significantly increased, especially among small-scale rice farmers.

Another concern in estimating the technical efficiency of rice farmers is that a single estimation strategy that does not account for variation may produce unrepresentative results. Bhattacharya and Mandal (2016) criticize previous studies that use either a single variety of rice, or the aggregated output of different rice varieties that fail to capture significant differences in technical efficiency. Their study considers rainy and non-rainy rice varieties cultivated in the Assam state of India and finds that a decrease in the production of non-rainy varieties results in an increase in rainy varieties. Islam et al. (2012) estimate the technical efficiency of TVs and HYVs[8] rice farmers in Bangladesh and find that the HYV production is associated with lower technical efficiency scores and has a larger variation in yield in comparison to TVs. Sharif and Dar (1996) find similar results in their analysis of one hundred households in a Bengali village.

Previous studies differentiating technical efficiency of TVs and HYVs are mainly conducted at aggregated farm-level by identifying rice crops grown in different seasons such as "Aus", "Aman" and "Boro". However, not all farmers (but a majority does) cultivate same rice crops in a specific season, which weakens the confidence of the estimation results. Furthermore, such farm-level analysis is hard to apply to an area without clear cropping patterns of TVs and HYVs by seasons. Estimations of technical efficiency that account for subtle differences in adopted rice varieties are still rare in India and may report different findings from the significant technical inefficiencies presented in the previous studies.

Therefore, this empirical study is designed to fill the literature gap by: (1) carrying out an empirical analysis at both farm- and plot-level; (2) including the environmental control variables in the stochastic frontier production function; (3) considering the differences between the technical efficiencies of TVs and HYVs and (4) conducting

[8] TVs refer to the rainfed rice crops grown in "Aus" (spring) and "Aman" (summer) seasons. HYVs refer to the irrigated "Boro" (winter) crops in their study.

output growth decomposition analysis. This study is unique as previous research has not addressed these four aspects in a consistent manner within an Indian context. Moreover, using the plot-level data of the sampled farms enables this study to identify the technical efficiency of different rice varieties in a single growing season. Contrary to the findings of Sharif and Dar (1996) and Islam et al. (2012) in Bangladesh, this study found higher technical efficiency scores for HYV over TV plots during the Kharif season in eastern India.

4.3 Methodological Framework

4.3.1 Technical efficiency

The concept of relative technical efficiency is first defined and developed by Farrell (1957) which compares a farm's real production with an efficient farm's ideal production by using the same inputs. To estimate the technical efficiency, the production function frontier is usually estimated by using a non-parametric approach (data envelopment analysis - DEA) or a parametric approach (stochastic frontier analysis - SFA).

The choice of using DEA or SFA as a measure of technical efficiency has been widely debated and, according to Wadud and White (2000), is dependent on the purpose of the research. The main advantage of using DEA is that, as a non-parametric approach, it does not require a specific functional form defining the technology, so that the mis-specification issue can be avoided. However, a concern raised is that the DEA approach neglects the error term and interprets the inefficiency effects as the sole account of deviations from the frontier, which is not always the case in reality. Therefore, the technical efficiency scores estimated by the DEA are generally lower than those estimated by the SFA (Kumbhakar & Lovell, 2003).

Unlike DEA, the parametric SFA approach incorporates the error term with a component exhibiting inefficiency effects and other components indicating the random effects and exogenous factors that are beyond the control of the farmers. As Coelli (1998) argued, SFA might be the more appropriate choice for such analysis, especially in agricultural settings, since the random errors caused by weather, pest infestation, etc. tend to be important.

Therefore, a stochastic frontier production function (SFPF) proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977) is applied in this study, which is expressed as:

$$Y_{it} = f(X_{jit}, \alpha, t)\exp(\varepsilon_{it}) \tag{1}$$

where the dependent variable Y_{it} is the rice production of the farm i in year t., $f(\cdot)$ represents the specific functional form, such as the translog function or the Cobb-Douglas function, X_{jit} is the amount of inputs j used in the production of the farm i in year t, t is a time index, α referred to a set of parameters to be estimated, and ε_{it} is the error term that can be decomposed as $\varepsilon_{it} \equiv V_{it} - U_{it}$. V_{it} is a symmetric random error caused by weather, pests, etc., which is normally distributed with a mean of zero and a constant variance σ_v^2 to capture the stochastic effects. U_{it} is an asymmetric random error caused by technical inefficiency factors, which is under the truncated normal distribution with a mean of μ and a variance σ_u^2.

The cross-farm variation in technical inefficiency can be estimated simultaneously with the stochastic frontier specification by a maximum likelihood procedure. Battese and Coelli (1995) specify that the technical inefficiency component U_{it} is a linear function of a set of farm characteristics to capture technical inefficiency effects. The technical inefficiency effects model is specified as:

$$U_{it} = Z_{it}\theta + \omega_{it} \tag{2}$$

where Z_{it} is a vector of variables, including time and farm-specific factors, θ refers to the parameters to be estimated, and ω_{it} is a vector of unobservable random variables. Given the model specification, the prediction of technical efficiency depends on its conditional expectation. Therefore, the technical efficiency for the farm *i* in year *t*. is identified by:

$$TE_{it} = \exp(-U_{it}) \tag{3}$$

4.3.2 Stochastic frontier production function

In this study, the production structure of sampled rice farmers is estimated by SFA in a form of the translog production function with single-output, multiple-input and a time variable that represents technical change. The translog form is conceptually simple since it does not restrict the structure of technology, which takes the following form:

$$\ln Y_{it} = \alpha_0 + \sum_{j=1}^{5} \alpha_j \ln X_{jit} + \frac{1}{2}\sum_{j=1}^{5}\sum_{k=1}^{5} \alpha_{jk} \ln X_{jit} \ln X_{kit} + \alpha_t t + \frac{1}{2}\alpha_{tt} t^2$$

$$+ \sum_{j=1}^{5} \beta_j \ln X_{jit} t + \sum_{m=1}^{7} \delta_m EE_{mit} + V_{it} - U_{it} \tag{4}$$

Y_{it} represents the total amount of rice (in kilograms) produced by the farm *i* in year *t*. X_{jit} is a set of the amount of production input (labor, land, seed, farmyard manure and chemical fertilizer) *j* of the farm *i* in year *t*, EE_{mit} refers to a vector of control variables of exogenous environmental factor *m* (e.g., land type, soil quality, etc.), where the technical inefficiency effects U_{it} is specified as:

$$U_{it} = \theta_0 + \sum_{n=1}^{13} \theta_n Z_{nit} + \omega_{it} \tag{5}$$

Where Z_{nit} are the socioeconomic characteristics of the sampled farming household (e.g. the age of household head, education attainment, farm size, and etc.) that have potential impacts on farm's technical inefficiency. The parameters of Equation (4) and (5) are estimated simultaneously by the maximum likelihood estimation (MLE), where the variance is parameterized as:

$$\sigma^2 = \sigma_v^2 + \sigma_u^2,\ \gamma = \sigma_u^2/\sigma^2\ \ (0 \leq \gamma \leq 1) \tag{6}$$

Here, σ^2 is assumed to be an aggregation of random events and technical inefficiency. The parameter γ explains the impact of technical inefficiency on rice production, ranging from zero to one. A γ result near zero indicates that variation of the real output from frontier output primarily derives from stochastic effects; whereas a γ result close to one implies that most of the random variations are caused by the effects of inefficiency.

Developed from Equation (4), the translog production function applied for the sampled plots (with TVs and HYVs differentiated) utilizes plot-level inputs and output information and can be expressed as:

$$\begin{aligned} \ln Y_{pit} = {} & \alpha_0 + \sum_{j=1}^{5} \alpha_j \ln X_{jpit} + \frac{1}{2}\sum_{j=1}^{5}\sum_{k=1}^{5} \alpha_{jk} \ln X_{jpit} \ln X_{kpit} + \alpha_t t + \frac{1}{2}\alpha_{tt} t^2 \\ & + \sum_{j=1}^{5} \beta_j \ln X_{jpit} t + \sum_{m=1}^{7} \delta_m EE_{mpit} + V_{pit} - U_{it} \end{aligned} \tag{7}$$

The error caused by the inefficiency effects in Equation (7) is also attributed to the household characteristics which at the same time control for the farm fix-effects of the plot-level stochastic frontier estimation of the technical efficiency[9].

4.3.3 Output growth decomposition

Aiming to evaluate the contributors to a farmer's agricultural development over time, the decomposition of output growth is also estimated. Based on the study of Fan (1991), the rice production growth can be seen as a change along with or beneath the production frontier (size effects), a shift in the production frontier (technical change), and a change of deviations from the production frontier (technical efficiency change).

According to Ahmad and Bravo-Ureta (1995) and Giannakas, Schoney and Tzouvelekas (2001), using the SFPF specified in Equation (1) and (4), the output growth decomposition function is defined as:

$$\ln\hat{Y}_{it} = \hat{f}(X_i, \alpha, t) + \ln T\hat{E}_{it} + \sum_J \varepsilon_{ji}\left(X_{ji}, \alpha, t\right) \ln\hat{X}_{jit} \qquad (8)$$

$\hat{f}(X_i, \alpha, t)$ represents the technological change of the farm i, $\ln T\hat{E}_{it}$ is the technical efficiency component, and the last component $\sum_J \varepsilon_{ji}\left(X_{ji}, \alpha, t\right) \ln\hat{X}_{jit}$ refers to the size effects. The deviation of Equation (7) with respect to time is expressed as follows:

$$\ln\dot{Y}_i = \dot{f}(X_i, \alpha, t) + \ln T\dot{E}_i + \sum_J \varepsilon_{ji}\left(X_{ji}, \alpha, t\right) \ln\dot{X}_{ji} \qquad (9)$$

where the dot above the variable represents its growth rate over time, which can be approximated as:

$$\ln\hat{Y}_{it} - ln\hat{Y}_{it-1} = \hat{\alpha}_t + \left(lnT\hat{E}_{it} - lnT\hat{E}_{it-1}\right) + \sum_J \varepsilon_{ji}\left(X_{ji}, \alpha, t\right)\left(ln\hat{X}_{jit} - ln\hat{X}_{jit-1}\right) \qquad (10)$$

9 Limited by the dataset, the inefficiency effects cannot be captured for each plot.

$\ln\hat{Y}_{it} - ln\hat{Y}_{it-1}$ represents the rice production growth of the farm i over time, $\hat{\alpha}_t$ is the effects of technical change, $lnT\hat{E}_{it} - lnT\hat{E}_{it-1}$ refers to the impact of technical efficiency change on rice production growth and $\sum_J \varepsilon_{ji}\left(X_{ji}, \alpha, t\right)\left(ln\hat{X}_{jit} - ln\hat{X}_{jit-1}\right)$ estimates the influence of aggregated inputs growth rate applied to output growth weighted by production elasticity, ε_{ji}.

Starting from farm-level and extending to plot-level estimates, this chapter analyzes the technical efficiency with inefficiency effects (environmental influences considered), the pattern of technical efficiency over time and the main source of production growth for the sampled small-scale rice farms. Specifically, the estimation is carried out at two levels: farm-level, where the output and inputs are aggregated for all plots; and plot-level, where the estimations are carried out separately for plots cultivated with HYVs and TVs.

4.4 Study Area and Dataset

This empirical study analyzes a panel dataset collected from a two-round survey that was conducted jointly by the International Rice Research Institute (IRRI) and the Indian Statistical Institute (ISI) in Kolkata in 1998-1999 and 2004-2006 to capture the agroecological and socioeconomic factors constraining agricultural productivity and farmers' income in the study area. The study areas cover the Giridih district of Jharkhand state[10] and the Purulia districts of West Bengal state, which are adjacent to one another and share similar agroecological characteristics. Applying the stratified random sampling method, eight villages in each of the Giridih and Purulia districts were selected and surveyed. The production data applied in the analysis were drawn from 1,035 rice plots operated by 452 households in the initial survey, and 1,144 rice plots run by the same

[10] Giridih district is formerly part of Bihar state before 2000.

households in the follow-up survey.

The climate of the study area is categorized as sub-humid and sub-tropical, with hot humid summers and cool dry winters. The rainfall ranges from 750 mm to 1,860 mm/year, and the historical annual average rainfall is about 1,370 mm according to available rainfall records in the region. Highly undulated topography is a common feature for the two sampled districts. Four distinct land types are identified: upland, mid-upland, medium land, and lowland. There exist large variations in terms of the terrains, soil textures and water conditions across the different land types. The soil fertility decreases along with the decrease of the altitude which affects varieties of rice cultivated and patterns of cropping (Banik et al., 2004).

The study area is located on the eastern India "tribal belt", where the population is dominated by the Scheduled Castes (SCs) and Schedule Tribes (STs). A substantial proportion of the population is primarily engaged in farming activities for livelihood, and their agricultural production features a low HYV adoption rate, low irrigation potential, limited use of market-purchased inputs, and a heavy reliance on traditional farming techniques during the survey period. Other socioeconomic and institutional arrangements also tend to limit the participation of SCs and STs in agricultural development and economic activities so that the poverty ratio is higher, and the pace of poverty reduction is slower among the SCs and STs than for other social groups. According to the National Family Health Survey (NFHS), the headcount rural poverty ratio in Bihar and West Bengal state ranked first and fifth place in 1998-99, and second and seventh place in 2005-06 among all the states in India. Therefore, the needs of improving agricultural productivity and reducing rural poverty in the study area are urgent which draws longtime attention of policymakers and researchers.

Table 4.1 presents a summary of the key input/output and environmental control variables used in the SFPF estimation. The output variable (*Y)* is the total rice production measured in kilograms. The inputs included in the model as explanatory variables are:

- Total labor (L) consists of both hired and family labor involved in work that is related to rice production, measured in person days;
- Total landholdings *(K*) used for rice cultivation, measured in acres;
- Total amount of farmyard manure (*FYM*) applied to rice production, measured in kilograms;
- Total amount of chemical fertilizer (*FC*) applied to rice production, measured in kilograms;
- Total amount of seeds (*S*) used for rice production, measured in kilograms.

A substantial number of the sampled farms are small-scale rice farms, as larger commercial farms are rarely found in the area due to previous land reforms. The reforms placed limits on the size of farms that could be owned or inherited. The average size of the sampled rice farm is 1.93 acres, and the average rice production is 2,113 kg with an average input of 95 kg of seeds, 1,534 kg of farmyard manure, 58 kg of chemical fertilizer and 232 days of total labor working.

Given that the study area is largely rainfed, only 7.99% of rice plots (9% of TVs and 7% of HYVs) are irrigated. The use of modern agricultural machinery is seldom found. The adoption rate of HYVs during the Kharif season in the study area is relatively low—approximately 18.99% in the initial survey—which substantially increased later. Up to the point of the follow-up survey, the adoption rate of HYVs has reached 67.61%.

The highly dissected nature of the landscape serves as another constraint of rice production. As Fuwa et al. (2007) argued, any estimation will be biased if topographic differences are not considered. Therefore, potential topographic effects are considered by the inclusion of land type dummy variables in the estimation. According to Sherlund et al. (2002), irrigation and soil quality are also influential environmental control variables. In addition, the district dummy variable is added to capture the variation across the two districts.

Table 4.1 Summary statistics of main in/output variables in SFPF

1998/99 ~ 2004/06	Per Farm		Per TV plot		Per HYV plot	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Sample size	*(902)*		*(1,210)*		*(969)*	
Production (kg.)	2113.06	2071.57	872.75	1026.98	877.52	1032.94
Labor (person day)	232.30	222.72	97.15	106.76	96.52	112.90
Land (acre)	1.93	1.84	0.85	0.92	0.73	0.94
Farmyard manure (kg.)	1533.66	1792.54	621.10	767.73	650.17	961.75
Chemical fertilizer (kg.)	57.98	113.35	19.61	40.74	28.90	71.16
Seed (kg.)	95.39	108.48	42.79	48.69	35.55	57.62
Time (1=04/06; 0=98/99)	1.50	0.50	1.31	0.46	1.80	0.40
Dist. (1=Giridih; 0=Purulia)	0.50	0.50	0.61	0.49	0.46	0.50
Irrigation (1=yes; 0=no)	0.14	0.35	0.09	0.28	0.07	0.26
Normal soil (1=yes; 0=no)	0.45	0.50	0.27	0.44	0.27	0.44
Good soil (1=yes; 0=no)	0.79	0.41	0.68	0.47	0.68	0.47
Mid-upland (1=yes; 0=no)	0.85	0.35	0.48	0.50	0.39	0.49
Medium land (1=yes; 0=no)	0.32	0.47	0.12	0.32	0.18	0.39
Lowland (1=yes; 0=no)	0.62	0.49	0.29	0.46	0.38	0.49

Source: author's calculation based on the survey data collected.

Table 4.2 presents the farming household characteristic variables used in the inefficiency effects model, including the time variable t, the age of the head of the household, the number of years in education of the household member with the highest educational level, the total land area operated by the household, the share of non-agricultural income from the total household income, the share of HYV rice plots adopted the share of rice plots relating to each land type owned by the farming households, the share of plots being irrigated during the Kharif season, and a district dummy to capture the district difference.

Table 4.2 Summary statistics of household characteristics in inefficiency model

	Mean	Std. Dev.	Min	Max
Time	0.50	0.50	0	1
Age of household head (year)	49.45	13.05	16	95
Educational attainment (year)	7.39	4.35	0	21
Size of landholding (acre)	1.93	1.85	0.02	15
Distance (km.)	2.55	2.23	0.5	7
HYV adoption (%)	45.35	44.18	0	100
Nonag. income (%)	38.68	32.69	0	100
Nonag. income×district	23.73	31.85	0	100
Land in mid-upland (%)	47.82	30.35	0	100
Land in middle land (%)	14.28	23.26	0	100
Land in lowland (%)	29.93	27.80	0	100
Irrigation (%)	8.33	23.63	0	100
District	0.50	0.50	0	1

Source: author's calculation based on the survey data collected.

4.5 Empirical Results

According to Equation (4), the estimated value of the variance parameter σ_u^2 amounts to 0.0851, 0.1307 and 0.0944, and the value of σ_v^2 equals to 0.0581, 0.0660 and 0.0861 for farms, TV plots and HYV plots, respectively. The variance ratio parameter $\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$ is significant for all estimations, which indicates that the technical inefficiency has an effect on the output. Its corresponding parameter γ^*[11] is estimated to be 0.3472 for farms, which indicates that 34.72% of the variability between observed

[11] The contribution of the variance of technical inefficiency effects to the total variance (γ^*) is expressed as $\gamma^* = \gamma / [\gamma + (1-\gamma)\pi/(\pi - 2)]$ (Greene, 1999).

and frontier production can be explained by the corresponding variation in technical inefficiencies of the sampled farms. The value of γ^* is 0.4184 and 0.2849 for TVs and HYVs, respectively.

4.5.1 Generalized Likelihood-ratio Tests of Hypotheses

The SFPF with the sub-model of inefficiency effects is carried out for the sampled rice farms at both aggregated farm-level and disaggregated plot-level of TVs and HYVs. However, prior to the estimation, the preferred model needs to be specified after several hypothesis tests, which are presented in Table 4.3. The hypothesis tests are performed using generalized likelihood-ratio (LR) test. The test statistic λ is defined as $\lambda = -2[\lambda(H_0) - \lambda(H_1)]$ and follows a chi-squared or a mixed chi-squared distribution, the critical value of which can be obtained from Table 1 in Kodde and Palm (1986, p. 1246).

As shown in Table 4.3, the null hypothesis that Cobb-Douglas is an adequate and preferable specification of the production frontier (α_{jk}= 0, α_{tt}= 0 and β_j= 0, $\forall j$) is strongly rejected by the data. The second null hypothesis that there is no technical change (α_t= α_{tt}= 0 and β_j= 0, $\forall j$) and that the time variable can be dropped, is rejected. The third null hypothesis that inefficiency effects are not present in the model (γ= θ_0= θ_n= 0, $\forall n$) is also strongly rejected.

Given the specifications of the translog frontier with inefficiency effects, the above hypothesis tests show that the joint effects of the chosen explanatory variables on technical inefficiency are statistically significant. These tests indicate that the preferred frontier model for the study is the translog function form with technical change, and with the sub-model of the inefficiency effects. In addition, the presence of technical inefficiency is important for explaining the difference between the real and frontier productions of the sampled rice farms.

Table 4.3 Generalized likelihood-ratio tests of null hypotheses for parameters

Hypothesis	Calculated LR- statistic λ			Decision
	Farm	TVs	HYVs	
Cobb-Douglas α_{jk}= 0, ∀j, α_{tt}= 0, β_j= 0, $\forall j$	54.42	117.08	102.13	Rejected H_0
Zero technical change α_t= α_{tt}= 0, β_j= 0, $\forall j$	58.30	48.43	35.00	Rejected H_0
No Inefficiency effects γ= θ_0= θ_n= 0, $\forall n$	8.56	25.69	9.03	Rejected H_0

Note: The critical values are obtained from Table 1 in Kodde and Palm (1986).

4.5.2 Technical efficiencies

The mean and range of the estimated technical efficiency score and the sample size based on the estimation of SFPF are reported in Table 4.4[12]. The results indicate that technical efficiency estimates at the farm-level differ from estimates at a more disaggregated plot-level. During the survey period, the sampled rice farms are operating moderately from the efficient frontier. The mean farm-level technical efficiency over time is 80.49%, which implies that, with the current level of technology and input quantity, a 19.51% increase in rice production is possible.

The plot-level analysis indicates that the plots cultivated with HYVs are, on average, more efficient than those cultivated with TVs. The technical efficiency for plots growing HYVs is 79.70% during the survey period. When compared with the farm-level efficiency, these HYV plots operate further away from the production frontier. However, plots planted with TVs display a higher degree of technical inefficiency, with a mean estimated technical efficiency score of 76.82%. The variation in confidence intervals of the efficiency estimates is found across the sampled farms and plots. The difference between the mean lower- and upper-efficiency bounds is 38.37% at the farm-level. Larger

[12] See Appendix Table 1 for the full estimation results of SFPF.

variability is found in the TV and HYV plots, which are reported as 42.36% and 41.60%, respectively.

Table 4.4 Mean technical efficiency score (%) and its range

	Farm			Plot with TVs			Plot with HYVs		
%	1st	2nd	Avg.	1st	2nd	Avg.	1st	2nd	Avg.
Sample size	452	450	902	840	370	1,210	195	774	969
Technical efficiency	81.15	76.93	80.49	80.85	71.15	76.82	99.99	75.75	79.70
minimum	41.97	35.10	43.33	43.39	13.94	23.15	99.99	15.15	26.03
maximum	94.75	95.43	94.77	95.31	93.85	95.71	99.99	96.59	96.16
Range	36.77	38.04	38.37	39.53	36.17	42.36	0.03	42.64	41.60
lower bounds	60.71	56.72	59.16	58.53	52.91	53.93	99.97	53.00	56.33
upper bounds	97.48	94.76	97.53	98.06	89.08	96.29	100	95.64	97.93

Source: author's calculation based on the survey data collected.

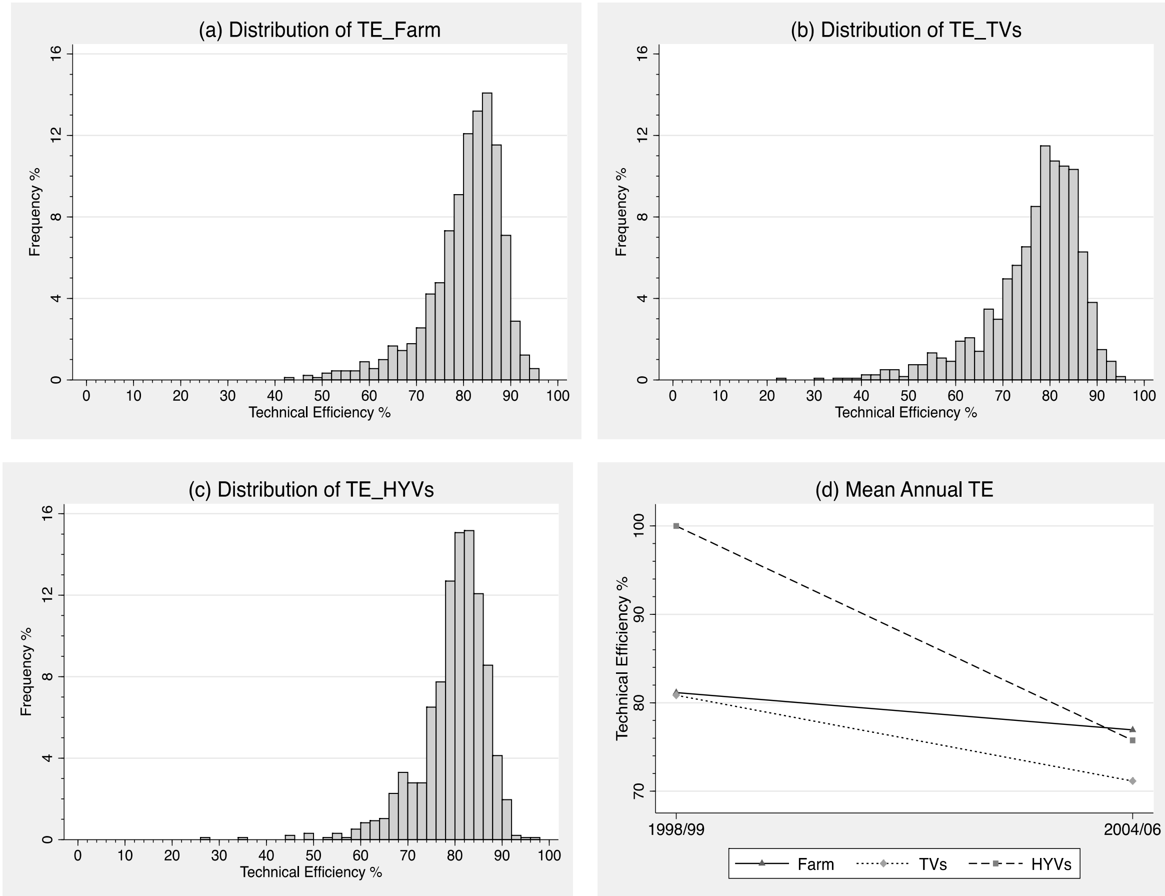
Figure 4.1 displays the distribution and movement of technical efficiencies over time[13]. In relation to the distribution of farm-level technical efficiency (as presented in Figure 4.1a), more than half of the farms (57.98%) fell into the range between 80% and 90%, while 4.66% reached above 90%. Only 9.42% of the farmers with technical efficiency under 70% indicate that a small proportion of the farms are operated with significant technical inefficiency.

The technical efficiency at plot-level presents mixed results. Figure 4.1 (b) shows that the technical efficiency of the TV plots is skewed to the left in terms of frequency compared with the distribution of the farm-level estimates. Therefore, a larger proportion of TV plots are technically inefficient. However, in relation to the HYV plots, Figure 4.1 (c) displays a greater distribution of technical efficiency on the right side. Approximately 57.38% of the HYV plots and 44.21% of the TV plots achieve technical efficiency above

[13] See Appendix Table 2 for the full estimation results of TE score, distribution and movement.

80%, implying that the HYV plots are generally operated more efficiently than the TV plots.

Figure 4.1 Distribution and change of technical efficiencies (TE), 1998-99~2004-06



Source: author's calculation based on the dataset.

In addition, the technical efficiencies of the two survey time periods are estimated separately to show the movement of technical efficiency over time. Figure 4.1 (d) indicates that the annual mean technical efficiency of the sampled farms decreases during the survey period, from 81.15% in 1998-99 to 76.93% in 2004-06. At plot-level, the annual technical efficiency decreases for both TVs and HYVs. The efficiency of the TV plots decreases from 80.85% to 71.15%. However, even with a substantial increase in HYV adoption, the annual technical efficiency of the HYVs reduce significantly from

99.99% to 75.75%. The HYV plots surveyed in 1998/99 have no technical inefficiency effects ($\gamma = 0$), which explains the high technical efficiency score (99.99%) achieved during that time. Fuwa et al. (2007) argue that, in the early stage of HYV adoption, technically efficient farms are more willing than the less efficient farms to implement new rice varieties. Technically efficient farms shift to HYVs cultivation prior to less efficient farms.

Figure 4.1 (d) shows that, with the diffusion of the Green Revolution, farms' mean efficiencies of utilizing the new agricultural technologies reduce over time. On one hand, the process of keeping up with and implementing technical advances becomes increasingly complex. On the other hand, farmers normally lack sufficient information and knowledge about new varieties in the early stages of HYV adoption (Saha, 2004). External climate shocks, such as the drought that occurred at the beginning of the planting season during the follow-up survey, is another unpredictable factor that could have influenced technical efficiency, which reveals the instability of rainfed rice production in the area. The production of HYVs tends to fluctuate more widely suggesting that they are more vulnerable to negative weather events. This reflects the arguments presented in previous studies, which indicate that HYV cultivation involved higher risks (Sharif & Dar, 1996; Islam et al., 2012). Other factors that can potentially contribute to a farm's technical inefficiency are discussed in the inefficiency effects model.

4.5.3 Input elasticities and returns to scale

In Table 4.5, the parameter estimates are reported in the form of input elasticities and returns to scale that are evaluated at means. The results indicate that land and seeds have the highest contribution to rice production, the elasticity scores of which are 0.4948 and 0.3689 respectively for the farms over time. Therefore, for example, a 1% increase in land size would increase rice production by 0.4948%. The elasticity estimates for labor and fertilizer inputs (fym and chemical fertilizer) are significantly lower at 0.0266, 0.0553 and 0.0416 respectively. When compared with the farm-level analysis, the estimations at a disaggregate plot-level shows that the land is a more important resource than seeds, labor, and fertilizer for both TVs and HYVs, as they are less scarce resources in rice production.

Table 4.5 Input elasticities and returns to scale from SFPF estimation

Year: 199/99-2004/06		Plots pooled	
Inputs	Farm level	TVs only	HYVs only
Labor	0.0266 (0.054)	0.0294 (0.065)	0.0474 (0.054)
Land	0.4948 (0.138)	0.5490 (0.165)	0.5060 (0.152)
Farmyard manure	0.0553 (0.023)	0.0513 (0.030)	0.0388 (0.029)
Chemical fertilizer	0.0416 (0.031)	0.0355 (0.017)	0.0297 (0.031)
Seed	0.3689 (0.162)	0.3388 (0.125)	0.3381 (0.152)
Return to Scale	0.9872 (0.031)	1.0041 (0.041)	0.9600 (0.048)

Note: corresponding standard deviations are in the parentheses.

The estimated returns to scale over time are 0.9872 for farms, 1.0041 for TVs and 0.9600 for HYVs, which implies that the returns to scale are more or less constant. For the farms, an increase of 1% of all inputs would result in an output increase of 0.9872%. Overall, increasing the inputs would improve rice production of the sampled rice plots. However, the increase would not be significant, as the marginal increase in the output of rice production would be more or less equivalent to the average increase in the inputs. Therefore, to facilitate the growth of rice production, it is more important to improve the farm's technical efficiency, rather than increasing the number of inputs used.

4.5.4 Inefficiency effects model parameters

To identify the reasons for the differentials of technical efficiency among the sampled rice farms and plots, the estimates of the inefficiency effects model can provide more insights. Rather than only reporting the parameter estimates, the results are summarized in Table 4.6 in the form of marginal effects, which indicate both the direction and magnitude of the explanatory variables' influence on technical inefficiency.

Hadley, Shankar, Thirtle, and Coelli (2001) argue that including the time variable in the SFPF exposes the change of the frontier over time, while including the time variable in the inefficiency effects model reveals the extent to which the farm is catching up with the frontier. The significant time variable reported in Table 4.6 indicates that the sampled farms and TV plots have kept up with the shifting production frontier.

The age of the household head (as a proxy for farming experience) is found to have a negative impact on the technical inefficiency of the HYVs, which indicates that experience on the farm is crucial for the cultivation of HYVs. As observed, the HYV adoption rate increased substantially during the survey period. Following experienced farmers, those who are less experienced also began to cultivate new rice varieties that may have led to a decrease in their technical efficiency. This result is consistent with the findings of Kuppannan, Ramarao, Samiappan, and Malik (2017).

Instead of the household head's education level, the highest educational achievement among household members matters in the survey area. For all the estimations, the highest educational attainment has a significant negative correlation on a farm's technical inefficiency. Farmers with higher education levels are found to be more technically efficient, which is consistent with research on Indian rice farmers by Bhattacharyya and Mandal (2016) and Samarpitha, Vasudev and Suhasini (2016). Extended schooling can increase learning capacity and improve a farm's technical efficiency through the acquisition of agricultural knowledge. The mean highest educational attainment is only 7.38 years of the sampled farms, which serves as a significant drawback to technical efficiency improvement.

Table 4.6 Marginal effects of variables in the inefficiency effects models

Parameters		Marginal Effects		
		Farm	TVs	HYVs
Time	θ_1	0.0673 (0.051)**	0.0642 (0.041)**	-0.0051 (0.686)
Age of household head	θ_2	-0.00002 (0.977)	-0.0002 (0.733)	-0.0017 (0.033)**
Educational attainment	θ_3	-0.0043 (0.037)**	-0.0049 (0.033)**	-0.0082 (0.001)***
Size of landholding	θ_4	-0.0035 (0.664)	0.0052 (0.354)	0.0172 (0.004)***
Distance	θ_5	-0.0006 (0.895)	0.0039 (0.368)	-0.0042 (0.350)
% HYV adoption	θ_6	0.0002 (0.287)	-0.0004 (0.352)	-0.00008 (0.902)
% Nonag. income	θ_7	0.0054 (0.000)***	0.0012 (0.016)**	0.0010 (0.001)***
% Nonag. inc×district	θ_8	-0.0047 (0.002)***	-0.0012 (0.072)*	0.0053 (0.324)
% Land in mid-upland	θ_9	-0.0013 (0.011)**	-0.0020 (0.001)***	0.0017 (0.309)
% Land in middle land	θ_{10}	-0.0013 (0.030)**	-0.0020 (0.024)**	0.0029 (0.095)*
% Land in lowland	θ_{11}	-0.0016 (0.002)***	-0.0011 (0.062)*	0.0022 (0.188)
% Irrigation	θ_{12}	-0.0005 (0.460)	-0.0018 (0.024)**	-0.0009 (0.171)
District	θ_{13}	0.3767 (0.006)***	0.1289 (0.007)***	-0.8792 (0.086)*

Note: *P-value* in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The parameter of farm size is also estimated. In contrast with certain studies (Adesina & Djato, 1996; Coelli, Rahman & Thirtle, 2002), the results at the farm-level indicate that farm size does not have a significant influence on technical efficiency. Larger farms in the sample are not the ones with higher technical efficiencies. However, statistical significances are found for the HYVs, which implies that larger farms tended to have less technically efficient HYV plots. As stated, large commercial farms are absent in the area and the use of inputs and modern agricultural appliances is rather limited. For the relatively large farms, factors such as a lack of inputs, machinery and management investment constrain their ability to efficiently utilize new technologies. This is similar to studies carried out by Ali, Parikh and Shah (1994) and Samarpitha et al. (2016).

According to the results, farms with a larger share of HYVs failed to show higher technical efficiencies. The share of non-agricultural income (out of a total household income) has positive and significant impacts on technical inefficiency for farms and HYV plots. A substantial number of sampled households shift their main income source from agricultural to non-agricultural work that is independent of their own farms for their livelihood. However, focusing on non-agricultural work results in less attention being paid to the crops relative to other farms (Coelli et al., 2005) and thus a decrease in technical efficiency. The finding complies with Abdulai and Huffman (2000).

In relation to the topographic effects for sampled farms and TV plots, a larger proportion of plots operating on the lower terraces tends to be more technically efficient, which conforms with the findings of Rola and Alejandrino (1993) and Fuwa et al. (2007). However, for HYV plots, a larger proportion of plots on the middle ground has a positive impact on technical inefficiency. Only 14% of the sampled farming households reported owning one or more irrigated plots. The share of Irrigated plots shows no significant impacts on technical inefficiency for farms and for HYV plots, while larger share of irrigated plots leads to lower technical inefficiency for the TV plots.

Examining the interaction term of non-agricultural income share and district dummy reveals that non-agricultural share negatively affects the technical inefficiency of farms and TV plots in the Giridih district, but the correlation remains positive in the Purulia district. This reflects the non-agricultural development could facilitate the agricultural development in Giridih, rather than in Purulia. Giridih district is suited with a better developed non-agricultural sector than in Purulia district, where the relationship between agricultural development and non-agricultural development tends to be complementary (Wu, 2018). According to Table 4.6, farms and TV plots in Giridih are significantly more technical inefficient in comparison to Purulia. Although the HYV adoption rate is higher and the adoption pace is faster in Purulia, farmers are less efficient at utilizing new technology than in Giridih.

4.5.5 Production growth decomposition

Production growth and its decomposition have been a subject of investigation in the study. Limited by the nature of the data, the decomposition is only conducted at the farm-level. The analysis focuses on the output change by examining how much of it is driven by input changes, total factor productivity (TFP) and unexplained output changes respectively (Kumbhakar, Wang & Horncastle, 2015). The TFP is further decomposed into technical change (TC) and technical efficiency change (TEC), which makes it possible to understand whether the sampled farms have improved their production levels simply through technical progress or through the more efficient use of existing technology.

Table 4.7 reports that rice production is stable on sampled farms, with a growth rate of only 0.28% over the survey periods. This growth stems from a 23.15% increase in TFP, a 4.56% decrease in input usage and an 18.31% decrease in other unexplained factors. The results imply that a reduction in input usage reduces production growth. The use of seeds is the main driving force for the total input growth, which increases production by 16.72%. The effects of labor and the input of chemical fertilizer are also positive, but marginal. However, the decreased input of land greatly reduces production growth by 27.82%. A possible explanation for this might be that, as the cropping pattern changed during the survey period, the land is shifted to cultivate other crops with better economic returns than rice.

Production growth is driven by TC and TEC, which are 20.14% and 3.01% respectively. Technological progress causes the production frontier to shift outward, while improvements in technical efficiency have only a slight impact on narrowing the gap between the real and ideal productions. There is still an 18.31% reduction in output change that remains unexplained, which is associated with other unobserved factors, such as 'learning-by-doing' issues. The difficulties encountered by the sampled farmers due to their lack of relevant knowledge in the early stages of HYV adoption are likely to have negatively impacted on their rice production. It takes time to learn and adapt to new standard practices following the introduction of HYVs. The results indicate that TFP growth is the main driving force behind the slight output growth during the period. The contribution of TFP to output growth comes largely from the TC, more specifically the introduction and utilization of new technological innovations to seed, fertilizer, labor, etc.

Table 4.7 Production growth decomposition of rice farms

Output growth %			00.28
Input driven growth %	*-4.56*	*Total Factor Productivity %*	*23.15*
Labor	0.41	Technical change	20.14
Land	-27.82	Technical efficiency change	3.01
Farmyard manure	-01.00		
Chemical fertilizer	7.13		
Seed	16.72		
Explained output change %			18.59
Unexplained output change %			-18.31

Source: author's calculation based on the survey data collected.

4.6 Conclusion

This study aims to estimate the technical efficiency of rice production among small-scale rice farmers in the Giridih and Purulia districts of eastern India and the determinants of their technical inefficiencies. Data collected on the outputs and inputs of individual farms and plots during the periods between 1998-1999 and 2004-2006 is estimated using the SFPF. During the survey period, new technological innovations of HYV have been introduced and implemented by most of the sampled farmers, which potentially advanced their production frontier.

The estimation at an aggregated farm-level finds that the sampled rice farms are moderately technically efficient and operated relatively close to the production frontier. Only a small proportion faces the severe issue of technical inefficiency. The estimations at a more disaggregated plot-level specify lower technical efficiency scores for both TV and HYV plots when compared with farm-level estimations. A difference in technical efficiency between TVs and HYVs is found in the study. The mean technical efficiency for HYV plots is higher than for TV plots, even though previous studies have found contrary results (Islam et al., 2012; Sharif & Dar, 1996).

The results indicate that the diffusion of technological innovation in rice production is not accompanied by an improvement in a farmer's ability to fully utilize them. Although a plausible increase in adopting HYVs is observed, the mean annual technical efficiency experiences a general decrease over time. The farm-specific reasons for technical inefficiency include the age of household heads, the highest educational attainment of household members, the size of landholding, the share of HYV plots, the share of non-agricultural income, the share of plots in various land types and the differences between the districts. Another non-negligible factor is the external environment, particularly the sufficiency of rainfall. Any unexpected environmental factor could put the production at risk, thus substantially decrease the technical efficiency. The production growth found that technical change (TC) plays a key role in increasing rice production, implying the importance of technological innovations. Therefore, how to facilitate the farmers to better implement the adopted new technologies, as well as increase their efficiency of utilizing the technologies, are open to discussion by policymakers and researchers.

CHAPTER 5. Income Mobility and Pathways out of Poverty in Rural India: The Case of Giridih and Purulia

5.1 Introduction

The Chhotanagpur Plateau in India —where Giridih and Purulia are located— has long drawn attention of researchers due to its low agricultural productivity and high incidence of poverty. This study covers regional development in the area, focusing on economic mobility patterns over almost a decade. The question of whether agricultural growth and non-agricultural growth are complementary or a substitute to poverty reduction has been examined carefully. While some researchers argue that increasing agricultural productivity has helped to raise rural incomes and reduce rural poverty, others argue that growth in the non-agricultural sector has had an even more substantial impact on rural poverty reduction (Foster & Rosenzweig, 2004). Concrete empirical evidence of such debate has been relatively few and far between due to a lack of proper data, making it difficult to draw conclusions (Fuwa & Marciano, 2017).

The analysis in this chapter is based on the household-level panel dataset collected by the International Rice Research Institute (IRRI) between 1998-99 and 2004-06, covering the survey areas of Giridih and Purulia in the Eastern Indian 'tribal belt', regarded as the poorest region of the country. The study is conducted under the theoretical framework of structural transformation. It empirically estimates the correlation between agricultural growth and non-agricultural growth and the roles they played in poverty reduction and also identifies the patterns of household income mobility and specific pathways through which the households escaped poverty. The findings indicate that agricultural growth in general was a substitute to non-agricultural development and failed to contribute to poverty reduction in the study area. However, when taking district-specific effects into account, this relationship becomes reversed in Giridih district. The importance of non-agricultural sector development in facilitating agricultural growth and raising household income has been found in Giridih district.

The question is tackled based on the following steps: Section 2 reviews the previous literature on the ongoing debate. After the literature review, Section 3 describes the study area and the panel dataset and identifies the trend of rice yield across the districts. Section 4 presents empirical evidence on the household income mobility patterns, the relationship among agricultural growth, non-agricultural growth and poverty reduction, and the specific non-agricultural pathways (occupations of household members) for escaping poverty. Section 5 provides interpretations of all the empirical evidences found in previous sections, which is followed by the conclusions in the final section.

5.2 Literature Review: Structural Transformation and Rural Poverty Reduction

History has shown that poverty reduction is often achieved through a structural transformation in a society (Foster & Rosenzweig, 2004). Structural transformation is considered synonymous with a reduction in poverty, with societies escaping poverty as a result of economic growth in both the agricultural sector and other forms of production. As Timmer and Akkus (2008) argued, the more successful the transformation, the faster the pace of poverty reduction.

At a global level, it is widely acknowledged that an increase in agricultural productivity is considered vital for economic growth across all sectors, contributing greatly towards poverty reduction (Eswaran & Kotwal, 1993). However, focusing only on enhancing agricultural productivity growth as a way to improve income in rural areas can be counterproductive. This is because an increase in global food productivity tends to cause global prices to decrease, meaning that farmers receive lower returns. At the same time, it will be particularly problematic if the households are unable to increase their yield due to the poorly suited climates or topography reasons (Foster & Rosenzweig, 2004). Therefore, it is vital that trying to reduce poverty with agricultural growth is assessed to see if it will be effective and that attention is paid to expanding the non-agricultural sector in order to prevent the problem worsening.

At the national or subnational level, however, the results appear to be more mixed. This can be seen in the assessments of 'growth elasticity' within poverty reduction. China, for example, follows the global trend, with income growth in the agricultural sector being over three times higher than growth in the non-agricultural sector (Ravallion & Chen, 2007). Meanwhile, in India, the service sector has grown more than the agricultural sector, with both of these sectors contributing to poverty reduction. This is in contrast with manufacturing sector growth, which has been found to increase poverty levels (Ravallion & Datt, 1996).

Disagreement remains over the main driver of poverty reduction. In contrast to Fuwa, Balisacan, and Bresciani (2015)'s findings, small-scale studies of Filipino villages suggest poverty reduction is in fact primarily due to growth in the non-agricultural sector (Hayami & Kikuchi, 2000). Similarly, McCulloch, Weisbrod, & Timmer's study (2007) of rural Indonesia concludes that poverty reduction is achieved by non-agricultural growth, as opposed to agricultural growth. Even studies conducted within the same country tend to have conflicting results. When looking at the example of India, Foster and Rosenzweig (2004) argued that agricultural productivity growth is a substitute for non-agricultural income growth, whereas Ravallion and Datt (2002) suggested that agricultural growth and non-agricultural growth complement one another, with higher agricultural productivity being associated with higher levels of poverty reduction.

Thus, there remains a debate as to whether agricultural growth is necessary for poverty reduction and general economic growth at a national and subnational level. This has only been further highlighted by the lack of relevant data, resulting in a notable scarcity of empirical literature on this topic. Through the assessment of income sources and occupations of specific households, this study will be able to explore the income mobility patterns of certain households across a decade. It also analyses panel data to estimate the relationship between agricultural and non-agricultural growth, and the roles they play in poverty reduction in the area. This provides much-needed empirical evidence at the subnational level, allowing for the gaps in the existing literature to be filled, as well as highlighting important areas for policy intervention.

5.3 Description of the Study Area and Dataset

The dataset analyzed are drawn from a household-level panel survey, collected jointly by the IRRI and Indian Statistical Institute (ISI) in Kolkata during the 1998-1999 and 2004-2006 crop seasons, ‘to examine the biophysical and socioeconomic factors constraining agricultural activity and household income in the region’ (Banik et al., 2004, p.1). The survey was conducted in 8 villages in each of the Giridih and Purulia district. Being in the adjacent states of Jharkhand[1] and West Bengal, the two districts share similar

[1] Jharkhand was separated from Bihar in the year of 2000.

biophysical characteristics and are identified as having particularly low agricultural productivity with severe poverty conditions.

Five hundred and forty-one households, (approximately 34 per village), were surveyed initially, using stratified random sampling, based on the size of the household's landholding. The socioeconomic characteristics of households were captured, including household demographics, plot-level information on agricultural input and output, the allocation of agricultural output, livestock holdings and household capital. However, due to household divisions over time, the number of sampled households increased substantially. In the follow-up survey, the number rose from 266 to 330 between 1997 and 2004 in Giridih; and from 275 to 348 between 1998 and 2006 in Purulia. In the study, the attrition rate from the survey sample was quite low, reducing by only 6 households (2.3%) in each district from the original 541 households, due to the death or migration of household members.

Table 5.1 Change of per capita net income and poverty incidence

		Per capita net income (Rs)	Poverty incidence (%)			Per capita net income (Rs)	Poverty incidence (%)
Giridih District	1998	3,208	68	Purulia district	1999	3,152	80
	2004	4,687	42		2006	3,205	64
Growth rate		46	-26			2	-16

Note: the per capita net income has been expressed as a constant 1998 price; poverty incidences are applied using the official poverty line, published by the Indian Planning Commission in 1999 and 2004.

Source: author's calculation based on the household survey data collected.

The Chhotanagpur Plateau where Giridih and Purulia are lying on is recognized as a part of the 'tribal belt'. There were a substantial proportion of individuals from scheduled tribes and scheduled castes in the population. Poverty incidence was higher, and the pace of poverty reduction was slower than among non-scheduled tribes and castes (Das, Hall, Kapoor, & Nikitin, 2012). According to the Government of India Planning Commission (2014), the statewise headcount of poverty ratios in Bihar and West Bengal were second and fifth highest in 1999-2000, and second and third highest in 2004-05, respectively. Indicators such as estimated per capita net income, land holdings, the value of assets, and access to public services (education and drinking water), also suggested that living standard in the study area was quite low.

The estimated average annual household net income for the baseline data was Rs. 21,830 in Giridih and Rs. 21,843 in Purulia (equivalent to $546 based on the exchange rate at the time of the survey), while per capita net income was only Rs. 3,208 in Giridih and Rs. 3,152 in Purulia (approximately $80). However, due to the higher cost of living, there was a higher local rural poverty line in West Bengal (Banik et al., 2004). Thus, the estimated poverty incidence was higher in Purulia (80%) than in Giridih (68%).

Table 5.1 indicates that, with the development of the local economy, the number of poor households declined in the area during the subsequent decade. In the follow-up survey, the per capita net income in Giridih increased substantially, by about 46%, while the poverty incidence in the district declined by 26%. The income growth in Purulia was not as fast as in Giridih. Per capita net income increased by only 2%, and a smaller proportion (16%) of rural households were lifted above the poverty line in Purulia compared to Giridih.

As mentioned above, agriculture played a predominant role in the sampled area, and most rural households were engaged primarily in farming and/or other agricultural activities. Since agriculture in Giridih and Purulia was largely rice-based (90% of households reported rice production), the growth of rice yield generally represented the development of agriculture in the area. Table 5.2 summarizes the change of per acre rice yield between 1998-99 and 2004-06, of the different rice varieties — Traditional Variety (TV) and High Yield Variety (HYV). The agricultural productivity enjoyed a general growth in the area and it increased by 10% during the survey period, from 1,110 kg to 1,225 kg per acre. In Purulia, the per acre yield of TV rice increased from 1,007 kg to 1,264 kg (26%), and that of HYV rice increased from 1,322 kg to 1,550 kg (17%) during the survey period. However, in Giridih, generally rice yields stagnated and even declined in some cases. The per acre yield of TV rice in Giridih grew from 1,096 kg to 1,127 kg (only 3%), while that of HYV declined from 1,556 kg to 973 kg (38%).

Table 5.2 Change of average rice yield (kg/acre) by variety

	Giridih		Purulia		
	Traditional Variety	High Yield Variety	Traditional Variety	High Yield Variety	Total
97/-98	1,096 (520)	1,556 (61)	1,007 (450)	1,322 (130)	1,110 (1,161)
04/-06	1,127 (334)	973 (393)	1,264 (52)	1,550 (399)	1,225 (1,178)
Change %	3	-38	26	17	10

Note: *number of plots in parentheses.

Source: author's calculation based on the household survey data collected.

The rice yields in Giridih in 1997 exceeded the average level of rice yield between 1992 and 2000. In 2004, however, it was found to be below the district average. Compared to this, in Purulia, the yield in 1998 was below the average between 1991 and 2007 and was higher in 2006. These two opposite trends can be explained by environmental conditions. It was found that in Giridih, 1997 was classed as a 'good year', with good weather for growing crops, leading to a higher yield. In contrast, the weather in Giridih in 2004 was not conducive to growing crops, with low rainfall creating a shorter growing season (Banik, Edmonds, & Fuwa, 2014). In Purulia, the low yields reported in 1998 could be due to a delay in the monsoon, which caused seasonal drought. In 2006, on the other hand, when yields were high, there were high levels of rainfall in May, encouraging crops to grow. From this, it can be seen that environmental factors can have an impact on rice yields and could explain some of the differences between the data.

5.4 Empirical Findings and Discussions

5.4.1 Household income mobility patterns

Given that many households had been lifted above the poverty line during the survey period, in this section, the study follows the methodology used by Fuwa and Marciano 's study (2017) in which the mobility table and corresponding transition matrix table are conducted. These enable to identify income mobility patterns among sampled households, focusing on the main income sources households relied upon, and whether they were in agricultural or non-agricultural sectors. Table 5.3 summarizes the distribution among different categories of household classified, based on whether they were poor or non-poor, and whether agricultural or non-agricultural income was their main source of income.[2]

For the income mobility patterns among the non-poor, not surprisingly in Giridih, the 'most stable category'[3] of the households was the non-poor, with non-agriculture as their main source of income. 57% of households in this category remained in the same status during 1998-2004. In Purulia, however, the same proportion was relatively lower at 43%, and a larger proportion (46%) of non-poor households, with non-agriculture as

[2] The transition matrix is presented in respond to the mobility tables but expressed in the share form and each row totals 100%.
[3] The most stable category refers to the households that experienced no mobility during the survey periods.

their main income source in 1998, fell into poverty in 2004.

Furthermore, in Giridih, a relatively large proportion (30%) of non-poor households, with agriculture as their main income source, stayed stable in the same category, while a proportion changed their main income source from agriculture and remained non-poor during 1998-2004. Only 22% of non-poor households, relying mainly on agricultural income, remained non-poor during 1999-2006 in Purulia. An even smaller proportion (11%) of non-poor households in 1999 remained non-poor by changing their main income source from agriculture to non-agriculture in 2006. Among the non-poor households, downward mobility was more likely to happen in Purulia than in Giridih, and mainly among households that had not changed their main income source.

Focusing on income mobility patterns among the poor households, in both districts, more households moved from relying mainly on agricultural income to non-agricultural income than vice versa. This tendency was more pronounced in Giridih than in Purulia (79% vs.15% in Giridih, and 43% vs.26% in Purulia). In Purulia, the proportion of poor households relying mainly on non-agricultural income (about 58%) was the largest among all categories. This indicated it was the most stable category during the survey period.

Table 5.3 Household mobility table, by poverty status and main income source

Mobility table: 1998-2004 Giridih			2004			
			Poor		Non-poor	
			ag.>nonag.	nonag.>ag.	ag.>nonag.	nonag.>ag.
1998	Poor	ag.>nonag.	9	27	9	38
		nonag.>ag.	5	35	9	44
	Nonpoor	ag.>nonag.	7	9	12	12
		nonag.>ag.	5	13	1	25

Transition matrix: 1998-2004 Giridih			2004				
			Poor		Non-poor		
			ag.>nonag.	nonag.>ag.	ag.>nonag.	nonag.>ag.	Total
1998	Poor	ag.>nonag.	**10.83%**	32.53%	10.83%	45.78%	100%
		nonag.>ag.	5.38%	**37.63%**	9.68%	47.31%	100%
	Nonpoor	ag.>nonag.	17.50%	22.50%	**30.00%**	30.00%	100%
		nonag.>ag.	11.36%	29.55%	2.27%	**56.82%**	100%

Mobility table: 1999-2006 Purulia			2006			
			Poor		Non-poor	
			ag.>nonag.	nonag.>ag.	ag.>nonag.	nonag.>ag.
1999	Poor	ag.>nonag.	49	39	36	23
		nonag.>ag.	15	38	2	11
	Nonpoor	ag.>nonag.	10	2	4	2
		nonag.>ag.	2	16	2	15

Transition matrix: 1999-2006 Purulia			2006				
			Poor		Nonpoor		
			ag.>nonag.	nonag.>ag.	ag.>nonag.	nonag.>ag.	Total
1999	Poor	ag.>nonag.	**33.33%**	26.53%	24.49%	15.65%	100%
		nonag.>ag.	22.73%	**57.58%**	3.03%	16.67%	100%
	Nonpoor	ag.>nonag.	55.56%	11.11%	**22.22%**	11.11%	100%
		nonag.>ag.	5.71%	45.71%	5.71%	**42.86%**	100%

Source: author's calculation based on the household survey data collected.

In addition, the possibility of poverty escape was higher among poor agricultural households than in poor non-agricultural households in Purulia (41% vs. 20% between agricultural vs. non-agricultural routes). However, the possibility of poverty escape did not appear to differ much between poor agricultural and poor non-agricultural households in Giridih (both around 57%). Table 5.3 also indicates that in both districts, poor households tended to escape poverty via non-agricultural routes, except for poor agricultural households in Purulia, which were more likely to be lifted above the poverty line through agricultural rather than non-agricultural routes.

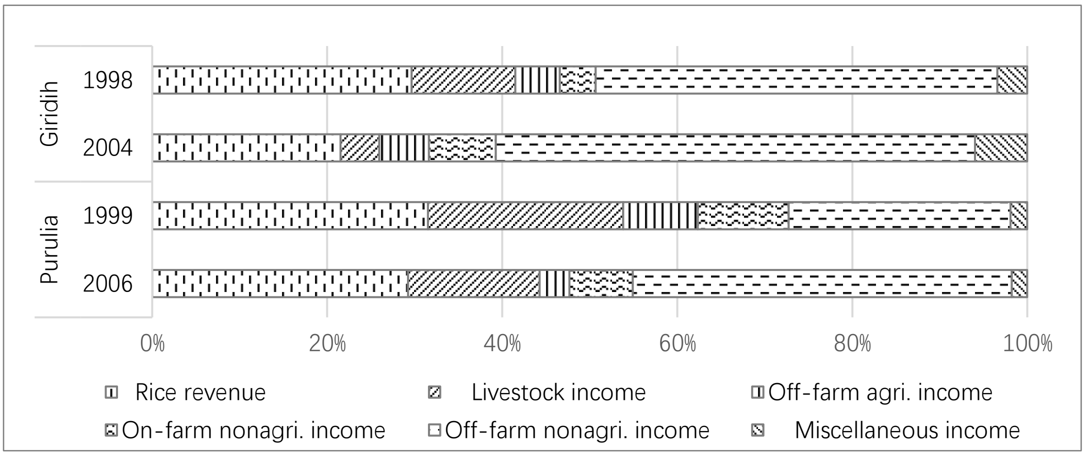
In sum, income mobility patterns across the sampled districts shared similarities and differences. In Giridih and Purulia, among households (100 in Giridih and 72 in Purulia) which escaped poverty during the observation years, 1998-2000 and 2004-06, more shifted their main income source from agriculture to non-agriculture than vice versa. However, the trend for an increasingly larger proportion of households to rely mainly on non-agriculture as their primary income source, in addition to the trend for poor agricultural households to escape poverty via non-agricultural routes, was more apparent in Giridih than in Purulia. Agricultural income was more predominant for households in Purulia. This will be analyzed further in respect to the change in household income composition during the period, focusing on the role of non-agricultural income as a contribution to rural poverty reduction.

5.4.2 Empirical analysis and the importance of non-agricultural development

In the dataset, the average total household income was the sum of two groups of income: agricultural income (rice revenue, livestock income, and off-farm agricultural earnings); and non-agricultural income (on-farm and off-farm non-agricultural earnings together with miscellaneous income).

During the survey period, a general decreasing trend in the share of agricultural income, and an increasing trend in the share of non-agricultural income is observed in the area. Figure 5.1 shows the change of each income composition over time. In the initial round of data, 53% of a household's income came from non-agricultural sources in Giridih, while this share was only 38% in Purulia. The share of non-agricultural income showed a marked growth across the districts during the second survey, with a 15% growth in Giridih and 14% in Purulia. Between 2004-06, non-agricultural income had contributed to more than half of the total household income and was more predominant in Giridih (69%) than in Purulia (52%).

Figure 5.1 Change of total household income compositions



Source: author's calculation based on the household survey data collected.

To understand the impact that agricultural growth had on each type of household income as well as the possible role that non-agricultural growth played in the study area, a set of estimations has been calculated. Firstly, the correlation between yield growth and change in household income was examined. The estimation equation is presented as follows:

$$y_{it} = \beta_1 yield_{it} + \beta_2 (year = 2004) + \beta_3 yield * dist_{it} + \gamma_i + \varepsilon_i \quad (1)$$

where y is the outcome variable for household i in year t, $yield$ is the log of per acre rice yields. $year = 2004$ is a dummy variable indicating whether the survey was taken in 2004 or 2006. $yield * dist$ is an interaction term of rice yields and the district dummy which takes the value of 1 if the households are located in Giridih or takes the value of 0 if in Purulia, β_2 captures period effects common to all households, β_3 reflects the district-specific influence on incomes, γ_i is the unknown intercept for each entity, and ε_i is the error term.

Since the households initially differed in their level of development, households with initially higher yields tended to have higher incomes. This meant that OLS would induce an upward bias in the coefficient β_1. To eliminate the bias, the equations are estimated using fixed effects. Thus, all fixed-effects estimates of yield effects are identified from the relationships between changes in yields and changes in the outcome measures.

Table 5.4 Estimates of the determinants of log of total household income, log of agricultural income, and log of non-agricultural income

DEPENDENT VARIABLE	LOG OF TOTAL HH. INCOME	LOG OF AGRI. INCOME	LOG OF NON-AG. INCOME
Log of yields	0.015	0.310	-0.261
	(0.874)	(0.002) **	(0.047) *
Year=2004/06	0.665	0.284	0.946
	(0.000) ***	(0.000) ***	(0.000) ***
District interactions	0.521	0.533	0.559
	(0.001) ***	(0.001) ***	(0.008) **
No. of observations	938	938	938

Note: *p*-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.4 reports the fixed-effect estimates of (1) for the log of total household income, agricultural income, and non-agricultural income. The estimates show that higher yields are associated with higher agricultural income, but with lower non-agricultural income. A doubling of yields would increase agricultural income by 31%, but decrease non-agricultural income by 26%. They also indicate that yield growth has no significant effect on total household income. All the incomes are higher, given rice yields, in 2004/06 compared to 1998/99. District influence can be found for all the outcomes. The positive effect of yield growth on increasing agricultural income is more pronounced in Giridih than in Purulia. Although the estimations of β_1 indicate that enhancing agricultural productivity will not raise the total income of rural households and even decrease their non-agricultural income in general, after considering the district-specific effects, the positive and significant correlation between yields and total household income becomes clear in Giridih, as well as the positive relationship between yields and non-agricultural income in the district.

Table 5.5 Estimates of the determinants of total household income

DEPENDENT VARIABLE	LOG OF TOTAL HH. INCOME
Non-agricultural share	.009 (0.000) ***
Year=2004/06	.522 (0.000) ***
District interactions	-.003 (0.139)
No. of observations	1,064

Note: *p*-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As there is no evidence showing higher agricultural productivity leads to higher total household income, attention is shifted to the role that non-agricultural growth plays in improving the income level of rural households. Applying fixed-effect estimates and replacing yield by non-agricultural share out of total household income for (1), the results (see Table 5.4) shows that a larger share of non-agricultural income is associated with a higher total household income. This impact is not significantly different in Giridih from Purulia.

As mentioned earlier, focusing only on improving agricultural productivity to eradicate rural poverty is likely to be ineffective. In general, this analysis tells a similar story. The increase in rice yields tended to be a substitute for local non-agricultural growth and failed to contribute to the total household income growth in the study area. In contrast, the share of non-agricultural income played an important role in enhancing the total income of rural households. Therefore, it is no surprise that, in recent years, increased attention has been given to the potential for expanding the non-agricultural sector in rural areas as a way of income growth and poverty reduction (Foster & Rosenzweig, 2004).

However, when taking district differences into account, a more mixed picture is presented through the empirical results. For the rural households in Giridih, the higher yields obtained contributed to the incomes they earned, indicating a ‘complementary' relationship between agricultural growth, non-agricultural growth, and poverty reduction. However, in Purulia, higher yields were associated with lower non-agricultural income and have ambiguous impacts on total household income, which implies ‘substitutive’ relations. The unbalanced development of non-agricultural sectors between the two districts could be the reason for this. Mining industry was established in Giridih after it gained independence as a way to increase industrial development, which attracted investments and migrants, as well as a variety of other industry types. The same cannot be said for Purulia, no important industry has grown here, and due to high frequencies of natural disasters such as floods and droughts, industrial development is even less likely (Ministry of MSME, Government of India, 2012).

In Giridih, the more developed non-agricultural sector provides better employment opportunities for the low-skilled rural household members, freeing them from farming and agricultural productivity. This is consistent with the traditional view on how agricultural growth facilitates non-agricultural growth and poverty reduction. The surveyed household members in Purulia were more likely to stick to agricultural activities because of lack of non-agricultural job opportunities. Relatively small shares of non-agricultural income results in a slower pace of poverty reduction in the district. This means that focusing on the development of the non-agricultural sector may be a better approach to meet the goal of enhancing welfare for rural households.

Combining these results together, it suggests that to increase total household income, the development of the non-agricultural sector is critical (substitution effect dominates), especially in the low levels of non-agricultural sector development. At the same time, the results suggest that there may be an inflection point where the relationship between agricultural productivity growth is complemented by non-agricultural activities if they exist. It would be important to look at both agricultural and non-agricultural activities to determine the relationship they have to poverty reduction and to further explore whether there is a minimum level of non-agricultural activity for such relationship to be complementary.

5.4.3 Identifying the specific non-agricultural pathways (occupations)

By focusing on the households that were lifted above the poverty line via non-agricultural routes, the specific occupations of those household members are identified. In Giridih, for example, the study concentrates on all the working-age members of 82 households that were defined as poor in 1998 but were lifted above the poverty line by 2004 through non-agricultural routes. Table 5.6 summarizes the distribution of primary and secondary occupations of sampled household members, which suggests that their economic activities were predominately unpaid family labor and in agriculture-related jobs. It also argues the diversity of non-agricultural occupational activities of surveyed households.

A substantial proportion of household members (44% in Giridih, and 39% in Purulia) were engaged primarily in unpaid agricultural work at their own family farm. For those household members whose main job was non-agricultural related, the principal occupation was reported as casual daily labor (jobs such as rickshaw driver, construction laborer, soil cutter, manning tea stalls, or shop employee), and self-employment in small-scale manufacturing. Common features of these activities were that they were highly labor intensive with relatively low labor productivity, and low earnings. Only a small proportion of household members (8.45% in Giridih and 9.82% in Purulia) had full-time, stable, non-agricultural work, such as an extension of agricultural tasks, railway employment, school teaching and employment in mining companies (in Giridih). These jobs provided higher levels of pay.

Table 5.6 Specific pathways out of poverty via non-agricultural routes

Giridih: 1998-2004	Occupation1	Share%	Occupation2	Share%
Unpaid family agricultural labor	99	44.00	76	41.76
Permanent part-time agri. labor			17	9.34
Temporary full-time agri. labor			3	1.65
Temporary full-time agri. labor			7	3.85
Full-time worker in industry/ manufacturing	8	3.56		
Full-time service worker in private sector	5	2.22		
Part-time service worker in private sector	1	0.44	1	0.55
Full-time service worker in public sector	6	2.67		
Artisan/craftsperson	3	1.33	1	0.55
Self-employment in small scale manufacturing	26	11.56	1	0.55
Construction workers	5	2.22		
Housekeeper/domestic help			1	0.55
Homemaker			3	1.65
Merchant	4	1.78	1	0.55
Transport worker	3	1.33		
Student			1	0.55
Other (Pvt. Tutor)	2	0.89		
Daily labor	59	26.22	45	24.73
Grocery shop	1	0.44		

Both unpaid agri. labor& p.t. public sec. worker	1	0.44	1	0.55
Both unpaid agri. labor & merchant	2	0.89		
Total	225	100	158	100
Purulia: 1999-2006	Occupation1	Share%	Occupation2	Share%
Unpaid family agricultural labor	44	39.29	33	51.56
Temporary full-time agri. labor			1	1.56
Full-time service worker in private sector	8	7.14	1	1.56
Part-time service worker in private sector	1	0.89		
Full-time service worker in public sector	3	2.68		
Self-employment in small scale manufacturing	27	24.11	9	14.06
Construction workers	3	2.68		
Housekeeper/domestic help			5	7.81
Transport worker	1	0.89		
Daily labor	20	17.86	15	23.44
Grocery shop	3	2.68		
Both Temporary full-time agri. labor& Self-employment in small scale manufacturing	2	1.79		
Total	112	100	64	100

Source: author's calculation based on the household survey data collected.

73% of household members reported that they had a secondary occupation. Household members whose primary occupation was unpaid family agricultural labor (93% in Giridih and 97% in Purulia), also had secondary jobs in one of the non-agricultural sectors. Household members (76% in Giridih and 46% in Purulia) employed mainly in non-agricultural occupations, worked in the agricultural sector as their secondary occupation. The remainder (24% in Giridih and 54% in Purulia) had secondary non-agricultural jobs. The distribution of secondary occupations was similar to that of primary occupations.

In sum, many household workers reported that they worked on the family farm as their primary (or secondary) occupation. This indicated that most households worked outside their farms on a part-time or seasonal basis. Table 5.6 indicates that agricultural work was very important for those households that escaped poverty via non-agricultural routes since half of the household members were still engaged primarily in unpaid farming on their own farms. For household members, whose income came mainly through non-agricultural work, more than half of them did an agricultural secondary job (mainly unpaid). For the non-agricultural income source, a substantial proportion of household members worked in unstable jobs. Self-employment in small scale manufacturing was an important income source for both districts. There was a relatively better-developed industrial sector in Giridih, compared to Purulia. A small number of household members in Giridih reported that they worked in factories or industries, whereas none reported that they did so in Purulia.

5.5 Interpreting the Empirical Evidence

In this section, the pathways that enable rural households to escape poverty are interpreted, based on observations and empirical analysis from the panel dataset. The aim of the research was to address whether there is a relationship between agricultural and non-agricultural growth and whether growth in one or the other might contribute more to poverty reduction in the districts. This research was an initial attempt as it was limited by a small sample size.

A general growth trend in rice yields is observed in the study area during the survey period. At the same time, as the household income increased, the poverty incidence of rural households decreased in the study area. Besides the general trends, district differences can be found in the areas. The yield growth is believed to be more pronounced in Purulia, while it was stagnant in Giridih due to the unfavorable climatic conditions. Despite this, the income growth and pace of poverty reduction seemed to be faster in

Giridih than in Purulia.

Income mobility patterns over the survey period were clearly evident, comparing the change of household main income source for living with that of poverty status. In both districts, more sampled households shifted their main earnings from the agricultural sector to the non-agricultural sector, than vice versa. Unsurprisingly, more poor households in the initial survey escaped poverty, relying mainly on non-agricultural income. This was most evident in Giridih compared to Purulia. In Purulia, a substantial proportion of households were lifted above the poverty line by keeping agriculture as their main source of income.

This chapter uses a fixed-effects estimation to examine the correlations between yield growth and household income by sources. The results indicate that for all the surveyed households, growth in yields failed to contribute to total household income growth, and even decreased the local non-agricultural income. In contrast, larger non-agricultural incomes helped households to increase their total income and eventually lifted them above the poverty line. District-specific effects are also found in the analysis. The agricultural productivity improvement of Giridih complemented the development of its non-agricultural sector, while this relationship tended to be substitutive in Purulia. The different development statuses of the non-agricultural sectors in the two districts can be seen to be crucial for understanding the issue.

The details of non-agricultural pathways out of rural poverty were examined by summarizing the occupation distribution of all working-age household members who had escaped poverty through non-agricultural routes. Despite a relatively large number of household members engaged primarily in unpaid farming at their own farms, household members who reported having non-agricultural jobs worked mainly in the service sector in part-time jobs with low pay. A small number of workers had full-time stable jobs. However, in Giridih, there were household members working full-time in industry or manufacturing, which implied the existence of a better developed non-agricultural sector in the district.

For all the surveyed households in the study area, the relationship between agricultural growth and non-agricultural growth tended to be a substitute rather than complementarity. When considering the district differences, it can be seen that whether the household could benefit from agricultural growth also depends on the development level of the local non-agricultural sector. When agricultural productivity increased, a better developed non-agricultural sector could take on more workers who had been freed from agricultural activity. The wage earned from non-agricultural productivities will eventually lift them above the poverty line.

5.6 Conclusions

In recent years it has been questioned whether the expansion of non-agricultural work is reliant on agricultural productivity and whether this can be used to help reduce poverty and increase household income (Johnson, 2000). The absence of proper data has made it difficult to bring empirical insight to this issue, and thus the question has remained largely unresolved.

This empirical study uses a household panel dataset collected from Giridih and Purulia, located in the least developed region of India. The income mobility patterns of rural households were identified, focusing on the relationship between agricultural growth and non-agricultural growth, and whether it was the development of the non-agricultural sector which helped rural households escape poverty. The chapter found that growth in agricultural productivity and in the non-agricultural sector had a substitute relationship in the study area. In districts with a more developed non-agricultural sector (such as Giridih), the relationship was more complimentary. This ties in with previous research, with Foster and Rosenzweig (2004) suggesting that solely focusing on improving agricultural income with ensuring a successful non-agricultural sector was ineffective.

In the study area, sampled household members relied increasingly on non-agricultural income as the main route for escaping poverty. The pro-poor natural of non-agricultural development has been also emphasized by previous studies, as rural industries are able to employ the unskilled rural households and bring benefit to even the poorest members while the agricultural productivity growth is more likely to expand the returns to better-off households with larger lands. Farming was still important in the areas studied and sampled household members were engaged mostly in farming during the cropping season, however, any policies aimed at improving rice productivity needs to consider the opportunity cost of non-agricultural development. According to this study, agricultural productivity growth alone is unlikely to contribute greatly to poverty reduction.

CHAPTER 6. Conclusion

6.1 Summary of the Research

Through analyzing the plot- and farm-level data collected from the Giridih and Purulia districts in eastern India between 1998-1999 and 2004-2006, this Ph.D. dissertation attempts to tackle the issue of rural poverty reduction in this region. Agricultural productivity growth, as a crucial engine of agricultural income improvement for sampled households, became the primary focus of this study. Two possible pathways to improve agricultural productivity—promoting the high-yielding variety (HYV) adoption among farmers under rainfed ecosystem and increasing the farmer's technical efficiency—are empirically examined. In addition, the relationship between agricultural productivity growth and non-agricultural development to poverty reduction serves as the other focus of the study to identify possible pathways out of rural poverty.

Regarding the plot-level data, Chapter 3 uses McFadden's choice model to analyze the factors associated with HYV adoption for the sampled rice farmers. The results reveal that potential yield is an important varietal attribute for farmers when choosing HYVs, as rice with higher yields could alleviate the 'subsistence pressure' of households and bring better economic returns. For the impoverished farming households whose rice production is largely consumption-based, cultivating a higher yielding rice variety become essential for their livelihood. For the better-off farming households whose production was significantly higher, the market behavior of selling a product significantly encourages their adoption of higher-yielding rice varieties to earn a better income. The results also argue for the significant impacts of education, labor availability, farm size, distance to the market on farmer's HYV adoption. The agroecological characteristics of the upper lands, and irrigation unavailability are found to constrain the HYV adoption by sampled farming households.

Chapter 4 utilizes the stochastic frontier analysis (SFA) to estimate the technical efficiencies of the sampled rice farmers and the factors associated with their technical inefficiencies. The estimations at both farm- and plot-level find that the sample farms are operated moderately close to the production frontier, which indicates with current technologies that there is still room for improvement in terms of the efficiencies, to obtain better production performance. The estimated mean efficiency of HYVs is found to be higher than of TVs. The findings also identify the general increase in HYV adoption, as well as the decrease in mean technical efficiencies experienced by the sampled farmers during the survey period, meaning that the diffusion of technological innovation is not accompanied by a farmer's increasing ability to use them. The increasing technical inefficiency was associated with household socioeconomic characteristics, such as age, education, farm size, the share of non-agricultural income, the share of plots in lower lands, and the share of plots being irrigated. In addition, the study argues for the importance of unexpected environmental shocks (e.g., shortage of rainfall), which may decrease the technical efficiency substantially.

Organizing the data as a panel, Chapter 5 discusses the relationship between agricultural and non-agricultural development and the roles they play in rural poverty reduction in the study area. Although agricultural productivity has increased during the survey period, the mobility tables indicate that the sampled households relied increasingly on non-agricultural income as their main income source. Using the fixed-effects model, the estimation pooling two districts' data shows that the growth of agricultural productivity negatively affected the non-agricultural income in the study area, suggesting a substitute relationship between growth in agricultural productivity and in the non-agricultural sector. However, the results differ when considering the two districts separately.

In Giridih, a district with a more developed non-agricultural sector, the relationship between agricultural and non-agricultural growth tends to be complementary. This finding is also consistent with those seen in Chapters 3 and 4, which argues that a higher share of non-agricultural income encourages the farmer's HYV adoption and is associated with lower farm technical inefficiencies in the Giridih district. However, the evidence in the previous chapters argues that the relationship between agricultural and non-agricultural development remains a substitute for each other in the Purulia district, where the non-agricultural sector is less developed. The goal of rural poverty reduction is hard to achieve without considering the impact of non-agricultural growth, since the positive impacts of non-agricultural income shares on a farmer's income are also identified in the estimations. Therefore, solely depending on improving agricultural productivity for rural poverty reduction without developing well-suited non-agricultural sectors is unlikely to occur in the study area.

6.2 Responses to the Research Questions

Combining the results of all three independent estimations, the dissertation attempts to respond to the main research question—Does the agricultural development in the form of farmer's HYV adoption and technical efficiency contribute to the rural poverty reduction during 1998/99 to 2004/06 in the rainfed agricultural ecosystem of eastern India?—and the three sub-research questions proposed in Chapter 1.

Regarding agricultural development, the study observes a general increasing trend in rice productivity and in farmers' HYV adoption, but a decreasing trend in technical efficiency for the sampled farming households during the survey period. Empirical results show the increasing HYV adoption is mainly driven by the consumption needs as well as the economic interests of the sampled households. The process of adoption is accompanied by risks and difficulties, which leads to a decrease in their technical efficiency. According to a decomposition analysis, the technical change (TC) of HYV adoption is the primary contributor to the rice production growth during the survey period, while the importance of technical efficiency change is relatively small.

For the factors affecting the agricultural productivity growth, the study finds that higher education attainment is important in increasing farmers' HYV adoption, as well as decreasing their technical inefficiency; this is in line with previous studies' findings (Asfaw & Admassie, 2004; Foster & Rosenzweig, 2010; Rosenzweig, 1982; Uaiene, Arndt, & Masters, 2009). The smaller farms are found to be faster HYVs adopters and had higher technical efficiencies than larger farms. The studies of Husain et al. (2001) and Hollaway et al. (2002) come to similar conclusions, although opposite deductions are argued by Feder and O'Mara (1981). Larger proportion of rice plots cultivated in the lower land terrace where the soils are more fertile compared to others has significant impacts in increasing HYV adoption and technical efficiency when compared with plots in the upper lands, which is similar to the findings of Rola and Alejandrino (1993), and Fuwa et al. (2007).

It also needs to be noted that more involvement in the non-agricultural employment of the sampled farmers decreases their agricultural productivity, but also reduces their poverty. A larger share of non-agricultural income depresses the farm's technical efficiency, but significantly improved farmer's income level in the study area. In addition, more direct analysis confirms that agricultural productivity growth significantly increases the agricultural incomes, but it is a substitute to the non-agricultural growth and has no obvious impact on rural poverty reduction. This substitute relationship has also been argued by Foster and Rosenzweig (2004), and McCulloch et al. (2007).

When taking the district differences into account, the empirical findings present a mixed picture. In the district with a higher level of non-agricultural development—Giridih—the growth in the agricultural and non-agricultural sectors tend to be complementary. On one hand, the larger share of the non-agricultural income out of total household income increases agricultural productivity by encouraging farmers' HYV adoption and improving the farms' technical efficiency. On the other hand, higher agricultural productivity is found to have positive impacts on farmers' non-agricultural income. Higher agricultural productivity releases the farmers to work in non-agricultural sectors. With the wage earned, the farmers can purchase modern agricultural appliances to further improve their agricultural productivity. However, in the district without well-suited non-agricultural sectors—Purulia—the agricultural development becomes a substitute to the non-agricultural development. Farmers had a lack of choice outside of their farms, and by relying mainly on agricultural income, the pace of rural poverty in Purulia was relatively slow when compared to Giridih.

6.3 Policy Recommendation

For the policymakers, how to facilitate the farmers to better implement the adopted new technologies, as well as increasing their efficiency in utilizing the technologies and eventually reducing rural poverty in the rainfed ecological system, can be drawn from this study.

As the data presented, the education attainment of the sampled households was low in the study area, which constrains agricultural development. Policies targeted at improving education are important since higher education is found to be important in adopting new technological innovation and increasing overall technical efficiency.

The topographic features of the area suggest distinct correspondence to the HYV adoption patterns and technical efficiency of the rice plots. Rather than pooling all farms for a single-policy intervention, the policies targeted to each land type could better maximize farmers' returns. In addition, as the rice production in the area was exposed to the risky external environment, any unexpected natural shocks (e.g., a lack of rainfall) would decrease the production substantially. To maximize utilities, policymakers should facilitate the farmers to cultivate properly and scientifically, as well as to lessen the environmental contains (e.g., improve irrigation coverage, introduce better suitable HYVs for upper land) for rice productivity growth.

The estimations find that agricultural productivity improvement could benefit non-agricultural growth and then reduce poverty. Therefore, the investment in non-agricultural development should also be prioritized by the policymakers, since simply relying on agricultural productivity growth make it difficult to significantly reduce rural poverty.

6.4 Limitations and Future Work

It is notable that this Ph.D. dissertation is an initial attempt to explore the issues of agricultural development and poverty reduction in one of the world's poorest regions under the rainfed ecosystem. Several factors may undermine the impacts of this study.

The obvious limitation of the study is the dataset itself. The data collection was confined to about 600 households in two districts in eastern India. The small sample size will result in insufficient representativeness of the study area. Additionally, the agroecological and socioeconomic information of the households collected in the survey and applied in the analysis are unable to meet all the research purposes. For instance, a lack of information on farmers receiving extension services makes it difficult to capture the learning impacts on farmers' choice among different rice varieties.

Also constrained by the dataset, the plot-level analysis applied in the study can be carried out only under the pooled cross-sectional framework, rather than the panel framework; this makes it difficult to follow the same plot for its changes (e.g., rice variety cultivated, technical efficiency, etc.) over time. Therefore, a more comprehensive dataset is needed for deeper analysis of the yet-to-be-solved issues in the future. Replicating the research with a larger sample size in multiple regions in India or other developing countries could enable better generalizations of the findings of the study.

Another limitation of the study is the additional focus on agricultural development, but less emphasis on non-agricultural development. Although the study argues for the importance of the non-agricultural development in poverty reduction, how the non-agricultural sector affects the work and life of the rural households is still unclear. For future studies, additional data of non-agricultural sector will be required to further analyze the issue of rural poverty reduction from a broader perspective.

In addition, the study is largely quantitatively based, and qualitative methods are rarely used. Therefore, future research could provide more qualitative evidence, such as case studies and interviews, to support the existing quantitative findings and give a more comprehensive picture of the current study.

Lastly, other pressing policy issues can be addressed in future studies to improve the welfare of rainfed rice farmers, such as the maintenance of fertilizer subsidies, levels of national and state import tariffs and other trade barriers, and the government allocation of scarce development resources across competing projects, approaches, and programs.

Appendix

Appendix A Parameter estimates from SFPF estimation

Parameters		Coefficient (*p-value*)		
		Farm	TVs	HYVs
Constant	α_0	6.7190 (0.000)***	5.2692 (0.000)***	4.4071 (0.000)***
Labor	α_1	-0.0504 (0.816)	0.1506 (0.318)	0.0901 (0.653)
Land	α_2	1.4886 (0.000)***	1.1086 (0.000)***	0.2060 (0.423)
Farmyard manure	α_3	0.0726 (0.463)	0.2116 (0.001)***	-0.1557 (0.031)**
Chemical fertilizer	α_4	0.1146 (0.237)	-0.0160 (0.849)	0.0239 (0.848)
Seed	α_5	-0.6736 (0.020)**	-0.3437 (0.089)*	0.5701 (0.002)***
Labor2	α_{11}	-0.0507 (0.194)	-0.0033 (0.910)	-0.0546 (0.097)*
Land2	α_{22}	0.3166 (0.000)***	0.2636 (0.000)***	0.0523 (0.403)*
Farmyard manure2	α_{33}	0.0131 (0.003)***	0.0110 (0.028)**	0.0109 (0.042)**
Chemical fertilizer2	α_{44}	0.0128 (0.122)	0.0031 (0.789)	0.0063 (0.606)
Seed2	α_{55}	0.2818 (0.000)***	0.2194 (0.000)***	0.0974 (0.000)***
Labor×Land	α_{12}	-0.0651 (0.148)	-0.0227 (0.445)	0.0119 (0.750)
Labor×Farmyard	α_{13}	-0.0050 (0.626)	-0.0288 (0.002)***	0.0128 (0.117)
Labor×Chemical	α_{14}	0.0200 (0.158)	-0.0072 (0.604)	0.0286 (0.048)**
Labor×Seed	α_{15}	0.0765 (0.078)*	0.0146 (0.636)	-0.0049 (0.887)
Land×Farmyard	α_{23}	0.0173 (0.443)	0.0378 (0.003)***	-0.0218 (0.184)
Land×Chemical	α_{24}	0.0078 (0.713)	-0.0226 (0.203)	-0.0090 (0.736)
Land×Seed	α_{25}	-0.2635 (0.000)***	-0.2141 (0.000)***	-0.0664 (0.071)*
Farmyard×Chemical	α_{34}	-0.0035 (0.555)	0.0021 (0.657)	0.0048 (0.454)
Farmyard×Seed	α_{35}	-0.0173 (0.419)	-0.0227 (0.063)*	0.0189 (0.209)
Chemical×Seed	α_{45}	-0.0439 (0.020)**	0.0132 (0.417)	-0.0281 (0.256)
Time	α_t	0.6738 (0.028)**	0.6040 (0.053)*	1.2461 (0.000)***
Time×Labor	β_1	0.0048 (0.915)	0.0006 (0.989)	0.0348 (0.533)
Time×Land	β_2	0.1361 (0.055)*	0.1837 (0.010)**	0.3545 (0.000)***
Time×Farmyard	β_3	-0.0004 (0.977)	-0.0048 (0.693)	-0.0028 (0.853)
Time×Chemical	β_4	-0.0066 (0.667)	0.0050 (0.784)	-0.0422 (0.047)**
Time×Seed	β_5	-0.1297 (0.048)**	-0.1037 (0.143)	-0.3294 (0.000)***
Environmental Control Variables				
District	δ_1	-0.3224 (0.000)***	-0.1680 (0.000)***	-0.4538 (0.000)***
Irrigation	δ_2	0.0031 (0.919)	0.0036 (0.918)	0.0298 (0.519)

Normal soil	δ_3	-0.0395 (0.127)	0.0546 (0.284)	-0.0681 (0.218)
Good soil	δ_4	0.0017 (0.958)	0.0820 (0.108)	-0.0375 (0.505)
Mid-upland	δ_5	-0.0507 (0.128)	0.1100 (0.003)***	0.0057 (0.928)
Medium land	δ_6	0.0432 (0.090)*	0.3187 (0.000)***	0.1643 (0.016)**
Lowland	δ_7	0.0862 (0.000)**	0.4178 (0.000)***	0.2765 (0.000)***
Variance Parameters				
$\ln\sigma_u^2$		-2.4638 (0.000)***	-2.0348 (0.000)***	-2.3603 (0.000)***
$\ln\sigma_v^2$		-2.8449 (0.000)***	-2.7176 (0.000)***	-2.4525 (0.000)***
σ_u		0.2917	0.3615	0.3072
σ_v		0.2411	0.2570	0.2934
$\sigma^2 = \sigma_v^2 + \sigma_u^2$		0.1432	0.1967	0.1804
$\gamma = \sigma_u^2/\sigma^2$		0.5941	0.6644	0.5230
Loglikelihood Function		-186.2500	-393.2710	-347.3102

Note: Time2 is omitted due to collinearity. *P-value* in the parentheses. * p<0.10, ** p<0.05, *** p <0.01.

Appendix B Frequency distribution of technical efficiency

	Farm			TVs			HYVs		
%	Average	1998/99	2004/06	Average	1998/99	2004/06	Average	1998/99	2004/06
< 20	0	0	0	0	0	1 (0.27)	0	0	1 (0.13)
20-30	0	0	0	1(0.08)	0	6 (1.62)	1 (0.10)	0	2 (0.26)
30-40	0	0	1 (0.22)	4 (0.33)	0	11 (2.97)	1 (0.10)	0	3 (0.39)
40-50	4 (0.44)	3 (0.66)	15 (3.33)	20 (1.65)	2 (0.24)	21 (5.68)	5 (0.52)	0	14 (1.81)
50-60	23 (2.55)	7 (1.55)	29 (6.44)	58 (4.79)	9 (1.07)	45 (12.16)	10 (1.03)	0	49 (6.33)
60-70	58 (6.43)	23 (5.09)	51 (11.33)	143 (11.82)	57 (6.79)	60 (16.22)	81 (8.36)	0	107 (13.82)
70-80	252 (27.94)	125 (27.65)	136 (30.22)	449 (37.11)	227 (27.02)	108 (29.19)	315 (32.51)	0	282 (36.43)
80-90	523 (57.98)	268 (59.29)	193 (42.89)	504 (41.65)	518 (61.67)	97 (26.22)	533 (55.01)	0	295 (38.11)
> 90	42 (4.66)	26 (5.75)	25 (5.56)	31 (2.56)	27 (3.21)	21 (5.68)	23 (2.37)	195 (100)	21 (2.71)
Sample size	902 (100)	452 (100)	450 (100)	1,210 (100)	840 (100)	3703 (100)	969 (100)	195 (100)	774 (100)
Technical efficiency	80.49	81.15	76.93	76.82	80.85	71.15	79.70	99.99	75.75
minimum	43.33	41.97	35.10	23.15	43.39	13.94	26.03	99.99	15.15
maximum	94.77	94.75	95.43	95.71	95.31	93.85	96.16	99.99	96.59
Range	38.37	36.77	38.04	42.36	39.53	36.17	41.60	0.03	42.64
lower bounds	59.16	60.71	56.72	53.93	58.53	52.91	56.33	99.97	53.00
upper bounds	97.53	97.48	94.76	96.29	98.06	89.08	97.93	100	95.64

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