

Impact Assessment of Farmer Field Schools in Cotton Production in China, India and Pakistan

Piyatat Pananurak

A Publication of the Pesticide Policy Project
Hannover, January 2010
Special Issue Publication Series, No. 14

Pesticide Policy Project Publication Series
Special Issue No. 14, January 2010

Institute of Development and Agricultural Economics
Faculty of Economics and Management
Leibniz University of Hannover, Germany

**Impact Assessment of Farmer Field Schools in Cotton Production
in China, India and Pakistan**

Doctoral Dissertation at the Faculty of Economics and Management
Leibniz University of Hannover, December 2009

Editors of the Pesticide Policy Project Publication Series:

Prof. Dr. H. Waibel
Institute of Development and Agricultural Economics
Faculty of Economics and Management
Leibniz University of Hannover
Königswortherplatz 1
30167 Hannover
Germany
Tel.: +49 (0)511 762-2666
Fax: +49 (0)511 762-2667
E-Mail: waibel@ifgb.uni-hannover.de

All rights reserved by the author.

Publication of the Institute of Development and Agricultural Economics
Königswortherplatz 1, 30167 Hannover, Germany
Printing: Unidruck Hannover, 30419 Hannover, Germany

ISBN: 3-934373-15-1

To
my beloved parents, Sutat and Wipada,
brothers and sister

Preface

Numerous economic studies were carried out for agricultural projects in developing countries. Many of such studies focused on irrigation infrastructures, micro credit institutions, or research and development of genetic improvement technologies. Integrated Pest Management (IPM) projects are popular in the development agenda and many studies were carried out but only few of them apply rigorous economic methodologies.

There are at least three reasons why scientifically-based economic impact assessment studies are needed for IPM. First, funding agencies and research managers are being held accountable for their allocation decisions. Therefore, they demand a notion of the rate of return of the investment. Accountability for the use of scarce public funds is hence, becoming increasingly important. There is a particular scarcity of such studies in the area of knowledge-intensive technologies in the wider context of natural resources management. Second, ex-ante and ex-post impact assessments can stimulate a useful discussion among development experts that can improve the design of agricultural projects. Third, high rates of return have been demonstrated for other investments in agricultural development especially in the field of genetic improvement research in cereal crops. However, it is not known to what extent investments in technologies in the realm of natural resources management are of similar success. Particularly, in IPM projects considerable controversy exists whether or not satisfactory rates of return can be achieved.

The study of Ms. Piyatat Pananurak is unique as it covers the three major cotton producers in Asia, namely China, India and Pakistan. The purpose of this research is to shed some light on the welfare effects of a large scale project that has promoted the Farmer Field School (FFS) concept in IPM in cotton in Asia. Cotton is known as a crop where problems of pests and pesticide overuse are especially distinct. The project was implemented by the Food and Agriculture Organization of the United Nations (FAO), who had first implemented the FFS concept with a large program in Indonesia during the 1980s. The contribution of the study is a rigorous economic analysis for a large scale project making use of secondary data collected by the project teams through internal monitoring.

Results of this study provide information for future investment decisions in IPM extension and can help policy makers to adjust resource allocations for better targeting of extension programs in developing countries. The cost-benefit analysis at farm-level and the welfare analysis at the macro-level were based on conservative assumptions.

The study finds that FFS training in IPM is worth doing but improvements in the design and the implementation of such programs are desirable. For example, targeting of program implementation remains an issue that needs to be given more attention. Also, this research shows that more economic studies are needed that quantify the positive effects of IPM on environment and human health.

Hannover, January 2010

Hermann Waibel

Acknowledgements

I would like to express my gratitude to several persons and organizations who gave assistance during this study. First and foremost I express the deepest appreciation to my supervisor, Prof. Dr. Hermann Waibel, who gave me the opportunity to study for my PhD in Germany and who has supported me throughout my thesis with his patience and knowledge. Without his guidance and persistent help this dissertation would not have been possible. Very special appreciation and sincere thanks are given to my second supervisor, Assist. Prof. Dr. Suwanna Praneetvatakul, who has always encouraged me since my master's degree. She has not only given me advice for my studies but also for everything I have been confronted with.

This study would not have been possible without the data from "FAO-EU IPM Program for Cotton in Asia". I am grateful for the valuable suggestions of Dr. Gerd Walter-Echols and also highly thankful for the work of the impact assessment teams in China, India and Pakistan who organized the field surveys and conducted their impact studies. Thanks go particularly to farmers in the countries who willingly participated in the surveys. Additional thanks are due to International Cotton Advisory Committee (ICAC) and Dr. Ben Shepherd who provided and suggested useful data sources.

In my daily work I have been blessed with friendly and cheerful colleagues and staff at the Institute of Development and Agricultural Economics and the Institute for Environmental Economics and World Trade. I deeply appreciate the kind assistance from Sabine, Theda, Nuinuy, Levison, Rudi and Wu in reading and correcting my draft of the thesis. Moreover, special thanks go to "my lovely and beautiful friends" who share wonderful memories with me in Germany. Thanks for the warm-hearted invitations on every Christmas from the Hardeweg family. My immense thanks go to dear friends, Hippolyte, Hilde, and Pi Noi, who are a part of my success although they could not be here to share my happiness.

I thank Pi Chu and Pi Whan for essentially teaching me how to cook good Thai food and everything else needed to survive in Germany. A note of thanks is expressed to other Thai friends who are always beside me giving strong support beyond words.

Last but not least, sincere appreciation goes to my parents and family for continual strong support throughout the course of this journey, and their unconditional love.

Hannover, December 2009

Piyatat Pananurak

Contents

List of tables	xii
List of figures	xvi
List of abbreviations	xvii
Abstract	xix
Zusammenfassung	xxiii
1 Introduction	1
1.1 Background.....	1
1.2 Objectives	3
1.3 Organization of the thesis.....	4
2 Cotton production in China, India and Pakistan	7
2.1 The importance of the cotton sector in the three countries	7
2.2 Selected trends in cotton production	9
2.3 Transgenic cotton varieties	12
2.4 Why is Bt cotton not a substitute for farmers' training?	14
2.5 The evolution of FFS in IPM extension and its impact	16
2.6 Summary.....	20
3 Conceptual framework and data collection	23
3.1 Theoretical background and methodologies.....	23
3.1.1 Theoretical background	23
3.1.2 Methodologies.....	29
3.2 Survey methodology	39
3.2.1 Study areas.....	39
3.2.2 Survey design	43
3.2.3 Data collection	44
3.3 Summary.....	46
4 Description of farm households and cotton production	49
4.1 Description of study areas.....	49
4.1.1 China	49

4.1.2	India.....	51
4.1.3	Pakistan.....	52
4.2	Comparison of household characteristics, costs and returns of cotton production	53
4.2.1	Country comparison of household characteristics	53
4.2.2	Comparison of household characteristics of farmer groups by country	55
4.2.3	Country comparison of costs and returns of cotton production.....	59
4.2.4	Comparison of costs and returns of farmer groups by country.....	62
4.3	Summary	66
5 Economic impact of training of farmers in cotton production in Asia.....		67
5.1	Statistical comparison of impact indicators	67
5.1.1	Pesticide input and environmental indicators	68
5.1.2	Output indicators	78
5.1.3	Farmers' knowledge, practices, and attitudes.....	84
5.2	Impact assessment model	92
5.2.1	Description of variables used in the models	92
5.2.2	Model tests	95
5.2.3	Results of model tests	97
5.3	Results of econometric models.....	99
5.3.1	Simple regression.....	99
5.3.2	Multivariate models.....	103
5.4	Summary	112
6 Cost-benefit analysis of the FAO-EU IPM program		115
6.1	Cost-benefit analysis at farm-level.....	116
6.1.1	Data.....	116
6.1.2	Results of cost-benefit analysis at farm-level.....	121
6.2	Welfare analysis of FFS training	128
6.2.1	Model assumptions.....	128
6.2.2	Results of welfare analysis	133
6.3	Summary	136
7 Summary, conclusions and recommendations		139

7.1	Summary.....	139
7.2	Conclusions and recommendations	144
	References.....	149
	Appendices.....	167
	Appendix A: Results of econometric models	167
	Appendix B: Simple regressions for combined-model	199
	Appendix C: Benefits and costs of FFS training under FAO-EU IPM Program for Cotton in Asia (Scenario B to D).....	201

List of tables

Table 2.1: Percentage share of major producers of world cotton production, 1970 - 2007.....	10
Table 2.2: Harvested cotton area (million ha) and cotton yield (kg/ha) of the world and three main cotton producer in Asia, 1970 - 2006	11
Table 2.3: Share of Bt cotton area and total cotton production in China between 2000 and 2007	13
Table 2.4: Share of Bt cotton area and total cotton production in India between 2002 and 2007	13
Table 2.5: Outcomes of IPM-FFS program in Asia	19
Table 3.1: The coefficients of treatment and control group between time periods of policy intervention, and differences	31
Table 3.2: Number of FFS villages in three countries in the baseline survey	43
Table 3.3: Numbers of farmers who were interviewed pre- and post-FFS training	46
Table 4.1: Household and farm characteristics before training in China, India and Pakistan, crop years 2000 (China and India), 2001 (Pakistan)	54
Table 4.2: Household and farm characteristics before training by farmer category in China, crop year 2000.....	56
Table 4.3: Household and farm characteristics before training by farmer category in India, crop year 2000	57
Table 4.4: Household and farm characteristics before training by farmer category in Pakistan, crop year 2001	59
Table 4.5: Costs and returns of cotton production before training in China, India and Pakistan, crop years 2000 (China and India), 2001 (Pakistan)	61
Table 4.6: Costs and returns of cotton production before training in China by farmer category, crop year 2000	63
Table 4.7: Costs and returns of cotton production before training in India by farmer category, crop year 2000	64
Table 4.8: Costs and returns of cotton production before training in Pakistan by farmer category, crop year 2001.....	65

Table 5.1: Value, quantity and frequency of total pesticide and insecticide use before and after training by farmer category in China, crop years 2000 and 2002	70
Table 5.2: Value, quantity and frequency of total pesticide and insecticide use before and after training by farmer category in India, crop years 2000 and 2002	72
Table 5.3: Environmental impact quotient by farmer category before and after FFS training in India, crop years 2000 and 2002	73
Table 5.4: Value, quantity and frequency of total pesticide and insecticide use before and after training by farmer category in Pakistan, crop years 2001 and 2003	75
Table 5.5: Environmental impact quotient by farmer category before and after FFS training in Pakistan, crop years 2001 and 2003	77
Table 5.6: Cotton yield, revenue, gross margin and household income before and after training by farmer category in China, crop years 2000 and 2002	79
Table 5.7: Cotton yield, revenue, gross margin and household income before and after training by farmer category in India, crop years 2000 and 2002	81
Table 5.8: Cotton yield, revenue, gross margin and household income before and after training by farmer category in Pakistan, crop years 2001 and 2003	83
Table 5.9: Farmers' knowledge, decision making on pesticide application, and attitudes on cotton pests before and after training by farmer category in China, crop years 2000 and 2002	86
Table 5.10: Farmers' knowledge, pest and crop management practices, and attitudes toward environment and conservation before and after training by farmer category in India, crop years 2000 and 2002	88
Table 5.11: Farmers' knowledge, practices, and attitudes before and after training by farmer category in Pakistan, crop years 2001 and 2003	91
Table 5.12: Description of variables used in the DD-models and combined-countries models	94
Table 5.13: Summary results of econometric problem on DD-models	98
Table 5.14: Comparison of effect of FFS on insecticide expenditure (\$/ha) among three countries (simple regression)	100
Table 5.15: Comparison of effect of FFS on total EIQ scores among three countries (simple regression)	101

Table 5.16: Comparison of effect of FFS on the cotton yield among three countries (simple regression)	102
Table 5.17: Comparison of effect of FFS on the gross margin among three countries (simple regression)	103
Table 5.18: Comparison of effect of FFS on insecticide costs among three countries (multivariate models).....	104
Table 5.19: The effect of FFS on insecticide costs (combined-countries model)	105
Table 5.20: Comparison of effect of FFS on total EIQ scores among three countries (multivariate models).....	106
Table 5.21: The effect of FFS on total EIQ (combined-countries model).....	107
Table 5.22: Comparison of effect of FFS on the cotton yield among three countries (multivariate models).....	109
Table 5.23: The effect of FFS on cotton yield (kg/ha) (combined-countries model)	110
Table 5.24: Comparison of effect of FFS on the gross margin among three countries (multivariate models).....	111
Table 5.25: The effect of FFS on gross margin (\$/ha) (combined-countries model)	112
Table 6.1: Numbers of farmers participating in the FAO-EU IPM Program for Cotton in Asia	117
Table 6.2: Project and opportunity costs of the FFS training program in three countries (US \$)	118
Table 6.3: Comparison of average pesticide costs and value of cotton yield pre- and post-training, for FFS farmers and control group	120
Table 6.4: Total annual benefits per household by cost reduction and crop income.....	121
Table 6.5: Benefits and costs of FFS training with 100% adoption rate in China (\$1,000).....	122
Table 6.6: Benefits and costs of FFS training with 100% adoption rate in India (\$1,000)	123
Table 6.7: Benefits and costs of FFS training with 100% adoption rate in Pakistan (\$1,000)	124
Table 6.8: Assumptions of project's investment analysis.....	124

Table 6.9: Scenario analysis of the financial rate of return in three countries	125
Table 6.10: Major data and assumptions for benefit assessment of FFS training among three countries using the DREAM model	130
Table 6.11: Economic surplus of the FFS training (\$1,000)	134
Table 6.12: Benefits and costs of FFS training based on benefits from economic surplus (\$1,000).....	135
Table B- 1: The effect of FFS on insecticide costs (simple combined-countries model)	199
Table B- 2: The effect of FFS on total EIQ (simple combined-countries model).....	199
Table B- 3: The effect of FFS on cotton yield (kg/ha) (simple combined-countries model)	200
Table B- 4: The effect of FFS on gross margin (\$/ha) (simple combined-countries model)	200
Table C- 1: Benefits and costs of FFS training based on one year benefits and 80% adoption rate in China (\$1,000): Scenario B	201
Table C- 2: Benefits and costs of FFS training based on three years benefits and 100% adoption rate in China (\$1,000): Scenario C.....	201
Table C- 3: Benefits and costs of FFS training based on three years benefits and 80% adoption rate in China (\$1,000): Scenario D.....	202
Table C- 4: Benefits and costs of FFS training based on one year benefits and 80% adoption rate in India (\$1,000): Scenario B	202
Table C- 5: Benefits and costs of FFS training based on three year benefits and 100% adoption rate in India (\$1,000): Scenario C	203
Table C- 6: Benefits and costs of FFS training based on three year benefits and 80% adoption rate in India (\$1,000): Scenario D	203
Table C- 7: Benefits and costs of FFS training based on one year benefits and 80% adoption rate in Pakistan (\$1,000): Scenario B	204
Table C- 8: Benefits and costs of FFS training based on three years benefits and 100% adoption rate in Pakistan (\$1,000): Scenario C	204
Table C- 9: Benefits and costs of FFS training based on three years benefits and 80% adoption rate in Pakistan (\$1,000): Scenario D	205

List of figures

Figure 1.1 Share of the world cotton production, average between 2003 and 2005	3
Figure 3.1: Chain of events in IPM extension	24
Figure 3.2: Economic surplus due to FFS introduction	26
Figure 3.3: Scope of financial and economic analysis	28
Figure 3.4: Chart of survey sampling in China.....	41
Figure 3.5: Chart of survey sampling in India	42
Figure 3.6: Chart of survey sampling in Pakistan	42
Figure 4.1: Map of Shandong, Anhui and Hubei province in China	50
Figure 4.2: Map of Bellary and Raichur districts of Karnataka state in India.....	51
Figure 4.3: Map of Khairpur and Sukkur districts of Sindh province in Pakistan	52
Figure 4.4: Share of pesticide and fertilizer in total variable cash costs before training in China, India and Pakistan, crop years 2000 (China and India), 2001 (Pakistan)	62
Figure 6.1: Impact of FFS adoption on benefit-cost ratio based on a one-year benefit period.....	126
Figure 6.2: Impact of FFS adoption on benefit-cost ratio based on three year benefits' incidence	127

List of abbreviations

APCOM	Agricultural Price Commission
APTMA	All Pakistan Textile Mills Association
BCR	Benefit-Cost Ratio
Bt	Bacillus thuringiensis
CAAS	Chinese Academy of Agricultural Sciences
CBA	Cost-benefit analysis
CCI	Cotton Corporation of India
CGIAR	Consultative Group on International Agricultural Research
COTLOOK	Cotton Outlook
DD	Difference-in-Differences
DREAM	Dynamic Research Evaluation Management
EIQ	Environmental Impact Quotient
EIRR	Economic Internal Rate of Return
EU	European Union
FAO	Food and Agricultural Organization of the United Nations
FFS	Farmer Field Schools
FIRR	Financial Internal Rate of Return
FMA	Financial Markets Association of Pakistan
GDP	Gross Domestic Product
GE	Genetically Engineered
GNI	Gross National Income
ha	Hectare
hh	Household
ICAC	International Cotton Advisory Committee
ICP	Inter-country Program
IFPRI	International Food Policy Research Institute
IMR	Inverse of Mill's ratio
IPC	Development and Application of Integrated Pest Control
IPM	Integrated Pest Management
IRR	Internal Rate of Return
IV	Instrumental Variable
kg	Kilogram
km	Kilometre

I	Liter
LSD	Least Significant Difference
md	Man day
NATESC	National Agro-technical Extension and Service Center
NGOs	Non-government organizations
NIC	National Informatics Centre by Government of India
Non-FFS	Non-participants in Farmer Field Schools village
NPV	Net Present Value
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PAN	Pesticide Action Network UK
PANNA	Pesticide Action Network North America
PI	Pesticide Index
ROW	Rest of the world
R&D	Research and Development
ToF	Training of Facilitators
USDA	United States Department of Agriculture
VIF	Varian Inflation Factor
WTO	World Trade Organization
\$	United States Dollar

Abstract

Recently the demand for impact assessment studies of development programs has been increasing because donors place more importance on accountability for the use of scarce public funds. So the recipients of these funds are challenged to constantly improve their development activities.

The overall aim of this study is to analyze the economic impact of a Farmer Field Schools (FFS) training program in Integrated Pest Management (IPM) in cotton in Asia. The project was financed by official development assistance funds from the European Union (EU) and carried out by the Food and Agriculture Organization of the United Nations (FAO) in three cotton producing countries in Asia, namely China, India and Pakistan. The program was named “FAO-EU IPM Program for Cotton in Asia”. The specific objectives of the study are: (i) to assess the impact of FFS training at farm level on cotton productivity, insecticide use and the environment, (ii) to assess the efficiency of project investment at the country and aggregate levels, and (iii) to evaluate the welfare effects of the project. Results of the study are meant to provide information for future investment decisions in agricultural extension in these countries and help policy makers to adjust resource allocations for better targeting of extension programs.

In this study, panel data were collected before and after the training from a total 808 of farmers in the three countries. The study was designed to compare three groups of farmers, i.e. farmers participating in the training (FFS farmers), those living in the same village but not participating in the training (Non-FFS farmers), and farmers in different villages not included in the training program but with similar socioeconomic and agro ecological conditions (control group).

The impact assessment was carried out in three steps: (i) parametric and non-parametric statistical tests, which allowed the detection of differences between trained and non-trained farmers; (ii) econometric models, including a Difference-in-Differences (DD) model and a fixed-effects model using the pooled data from all countries. The econometric models allowed the detection of causality between project intervention and impact; (iii) calculation of the efficiency of investment in the context of a financial analysis taking the farmers’ point of view, and calculation of the of total economic surplus, using a partial equilibrium model called the “Dynamic

Research Evaluation for Management” (DREAM) model, which further qualified the overall efficiency of the investment made in the program.

Results of the econometric models and statistical comparisons among the three groups of farmers in the countries involved showed that in all three countries the FFS training is effective. On the input and environmental side, FFS farmers use less pesticide and choose those with lower toxicity. On the output side, the effects of FFS training differ among countries. In China, participants performed better in terms of both cotton yield and gross margin. In contrast, the economic impacts of FFS training do not show an effect on cotton productivity in India, and in Pakistan all three groups experienced lower yields because of uncommon pests in the year after training. However, the FFS group still increased productivity and gross margin as compared to the other groups. The econometric models revealed that in Pakistan the knowledge variable, i.e. the recognition of pests and natural enemies, was significantly related to the reduction of pesticides and environmental impact. Furthermore, knowledge advancements positively affected cotton yield and gross margin in India and China. It was also found that there is virtually no diffusion effect from farmers trained in FFS to their neighbours, which agrees with findings reported in the literature.

The cost-benefit analysis at farm-level, and the welfare analysis at the macro-level, were based on conservative assumptions, including only the period of external assistance and excluding any possible diffusion effects. For the financial analysis it was found that investments in farmers’ training pay off in Pakistan and India. However, in China, results suggest that the program has not reached its target due to a low adoption rate relative to the extent of program investment. Sensitivity analysis revealed that the program investment reaches break-even if the benefits of the training program are sustained for at least three years, and at least 90% of trained farmers apply the knowledge taught in FFS. The social cost benefit analysis showed that the consumers in the three countries and in the rest of the world (ROW) gain, while producers in China and in ROW lose. This is due to the downward effect on cotton price stemming from increased productivity in countries that apply integrated pest management technology as taught in FFS. However, on a global level the benefits generated by the FFS program were found to be positive.

The results found in this study suggest that FFS training in IPM should be undertaken, but targeting of program implementation remains an issue that needs to be given more attention. Also, further studies are required to assess the full benefits from IPM technologies, by valuing the positive effects on environment and human health.

Keywords: Cotton, impact assessment, Integrated Pest Management (IPM), Farmer Field Schools (FFS), China, India, Pakistan

Zusammenfassung

Aktuell ist eine steigende Nachfrage für die Evaluierung von Forschungs- und Entwicklungsprojekten zu beobachten, weil die Mittelgeber der Rechenschaftspflicht über den Einsatz knapper öffentlicher Mittel eine zunehmende Bedeutung beimessen, und bestrebt sind, ihre Entwicklungsaktivitäten fortwährend zu verbessern.

Diese Studie zielt darauf ab, die ökonomischen Wirkungen der Ausbildung von Baumwollbauern in so genannten *Farmer Field Schools* (FFS) in den drei bedeutendsten Baumwollproduzierenden Ländern, China, Indien und Pakistan, zu analysieren. Das Training folgt dabei dem Ansatz des integrierten Pflanzenschutzes (IPM). Das Entwicklungsprojekt mit der Bezeichnung „*FAO-EU IPM Program for Cotton in Asia*“ förderte das Schulungsprogramm. Im Einzelnen verfolgt die Studie folgende Ziele: (i) die Bewertung der Auswirkungen des Trainings auf den Einsatz von Insektiziden, die Umwelteffekte und die Produktivität der Baumwollproduktion auf der Ebene der Produzenten, (ii) die Einschätzung der Effizienz der getätigten Investitionen auf der Projektebene und (iii) die Evaluierung der Wohlfahrtseffekte des Gesamtvorhabens. Die Ergebnisse der durchgeführten Analyse sollen dazu beitragen, die Allokation von Ressourcen der Geber besser abzustimmen und die Zielorientierung von Programmen zu optimieren.

Die Analyse beruht auf einem Paneldatensatz, für den die Daten vor und nach dem Schulungsprogramm von insgesamt 808 Baumwollbauern in den drei Ländern erhoben wurden. Die gesamte Stichprobe wurde dabei in drei Vergleichsgruppen unterteilt: (i) Programmteilnehmer und (ii) Nichtteilnehmer, die in den gleichen Schulungsdörfern lebten, und (iii) Bauern aus Dörfern, in denen kein Schulungsprogramm durchgeführt wurde, jedoch ähnliche sozio-ökonomische und agro-ökologische Bedingungen vorherrschten.

Die Wirkungsanalyse wurde in drei Schritten durchgeführt: (1) parametrische und nicht-parametrische Tests dienten zur Messung der Unterschiede zwischen am Projekt teilnehmenden und nicht am Projekt teilnehmenden Bauern, (2) ökonometrische Modelle zur Prüfung der Kausalität zwischen Training als Projektinput und der Wirkung des Projektes auf die teilnehmenden Bauern, und (3) die Verwendung des „*Dynamic Research Evaluation for Management*“ (DREAM)

Modells, zur Berechnung der gesamtwirtschaftlichen Effekte und der gesamtwirtschaftlichen Effizienz des Vorhabens unter Berücksichtigung der Produzenten- und Konsumentenrenten.

Die Ergebnisse der ökonometrischen Modelle und der statistischen Vergleiche der drei Farmergruppen machten deutlich, dass die Teilnahme am Trainingsprogramm in allen drei Ländern Wirkung zeigt. Auf der Inputseite wurden insgesamt weniger Pestizide verwendet und teilnehmende Landwirte wählten insbesondere Pflanzenschutzmittel mit geringerer Toxizität. Auf der Outputseite dagegen sind länderspezifische Unterschiede zu erkennen. So erzielten chinesische Landwirte nach der Schulung geringfügig höhere Erträge und Deckungsbeiträge, während in Indien keine signifikante Produktivitätssteigerung zu verzeichnen war. In Pakistan dagegen verzeichneten alle drei Gruppen von Landwirten geringere Erträge aufgrund eines für die Region ungewöhnlichen Schädlingsbefalles. Im Vergleich zu den Referenzgruppen konnte jedoch die Teilnehmergruppe ihre Produktivität steigern und einen höheren Deckungsbeitrag erzielen. Weiterhin zeigen die Ergebnisse der ökonometrischen Modelle, dass der Einfluss von Wissen über Schädlinge und geeignete Bekämpfungsmaßnahmen signifikant zur Reduktion des Pestizideinsatzes und der negativen externe Effekte in Pakistan beitragen. Es wurde allerdings festgestellt, dass die Diffusionswirkungen des Projektes sehr gering sind. Dieses Ergebnis deckt sich weitgehend mit den Erkenntnissen aus der hierzu verfügbaren Literatur.

Die Kosten- und Nutzenanalyse auf Mikroebene und die Wohlfahrtsanalyse auf Makroebene basierte auf vorsichtigen Annahmen, wobei nur die Jahre der externen Unterstützung durch die Geldgeber einbezogen wurden und mögliche Diffusionseffekte ausgeschlossen wurden. Aus Sicht des Projektes konnte festgestellt werden, dass sich die Investitionen in die Ausbildung von Landwirten in Indien und Pakistan lohnen. In China dagegen konnte dieses Ziel nicht erreicht werden, da die Adoptionsrate in Relation zu den getätigten Investitionen zu gering war. Eine Sensitivitätsanalyse zeigte, dass die Gewinnschwelle nur erreicht wird, wenn der Nutzen mindestens drei Jahre anhält und dabei die Adoptionsrate über 90% liegt. Die Wohlfahrtsanalyse auf volkswirtschaftlicher Ebene verdeutlichte, dass die Nachfrager von Rohbaumwolle von dem Schulungsprojekt profitieren, während Produzenten aufgrund der negativen Preiseffekte kurzfristig Verluste durch das

Projekt zu verzeichnen haben. Insgesamt lässt sich aber feststellen, dass aus globaler Sicht das Projekt positiv zu bewerten ist.

Die Ergebnisse der durchgeführten Untersuchungen erlauben die Schlussfolgerung, dass Ausbildungsprogramme im integrierten Pflanzenschutz nach dem Konzept der Feldschulen sinnvolle Investitionen sein können. Allerdings sollte der Zielorientierung bei der Implementierung solcher Programme mehr Beachtung geschenkt werden. Zudem sollten zukünftige Studien den Nutzen neuer Pflanzenschutztechnologien vollständig abbilden, indem externe Effekte auf die Umwelt und Gesundheit berücksichtigt werden.

Schlagwörter: Baumwolle, Wirkungsmessung, integrierter Pflanzenschutz, Farmer-Feld-Schulen, China, Indien, Pakistan

1 Introduction

This study carries out an economic impact assessment of farmer training in three major cotton producing countries in Asia, namely China, India and Pakistan. The training program, which has become known as Farmer Field Schools (FFS), aims to promote the well-known concept of Integrated Pest Management (IPM). The program was implemented under the “FAO-EU IPM Program for Cotton in Asia”. This chapter first provides some background of the study. Then the objectives of the study are stated, and the third part of the chapter outlines the organization of the thesis.

1.1 Background

The so-called Green Revolution is generally associated with the use of modern, high yielding varieties, irrigation and high levels of chemical inputs, including mineral fertilizers and synthetic pesticides. While this technological package has contributed to remarkable increases in productivity (Evenson and Gollin 2003), the widespread diffusion of Green Revolution technologies has also generated negative externalities.

One of the downsides of input-intensive agriculture as promoted by the Green Revolution has been side-effect on the health and environment associated with chemical pesticides. Besides the increased productivity, one major drawback of this progress is the increase and over-consumption of synthetic fertilizers and pesticides. A recent report on trends in global agriculture shows that pesticide use continues to rise in world agriculture, including in the developing countries, which endangers the sustainability of many agricultural systems (IAASTD 2009). Some studies have established clear evidence that pesticides cause significant negative effects on human health (e.g. Rola and Pingali 1993) and detrimental effects on the environment (Pretty and Waibel 2005).

A response to the pesticide problem has been the promotion of the integrated control concept (Stern et al. 1959), which called for a judicious use of pesticides based on economic need and took into account negative side effects. IPM is a knowledge-based approach to plant protection (Hall and Duncan 1984) that promotes the combination of biological, cultural and chemical control to keep pests below economically acceptable levels (Metcalf and Luckmann 1975; Rabb and Guthrie 1970; Smith and Pimentel 1978).

In developing countries, IPM was first introduced on a large scale in rice production in Indonesia (Oka 1991; Röling and van de Fliert 1994). It is there where a new training concept, the so-called Farmer Field Schools (FFS) was used as a tool to improve farmers' knowledge and empower them to make more informed decisions on pest control. FFS has also been introduced into African agriculture with the expectation that it could raise agricultural productivity and thus contribute to poverty reduction (Spielman and Davis 2008). Numerous studies have been carried out to examine the economic impact of the FFS on pesticide use and yield (e.g. Feder et al. 2003). Other studies looked at the diffusion of the concept and found that without intensive and good quality training the FFS approach will not spread from farmer to farmer by itself (Feder et al. 2003; Rola et al. 2002). On the other hand, it was well established that FFS is successful in improving farmer knowledge (Godtland et al. 2003) and can help farmers to reduce pesticide use (World Bank 2002).

Cotton is a crop that is exposed to a range of damaging insect pests and therefore generally receives particularly high levels of pesticide use. Approximately 25% of the world's insecticides are used on cotton (Allen Woodburn Associates Ltd 1995; PANNA 2008) despite its small share in the total cropping area. The major share of the world's cotton is produced in Asia, with China, India and Pakistan as the three major producers (see Figure 1.1). Based on the average production shares between 2003 and 2005, China was the single largest producer of cotton, followed by the US, India and Pakistan. However, recent reports suggest that India has overtaken China as the world's major producer (Gulati 2009).

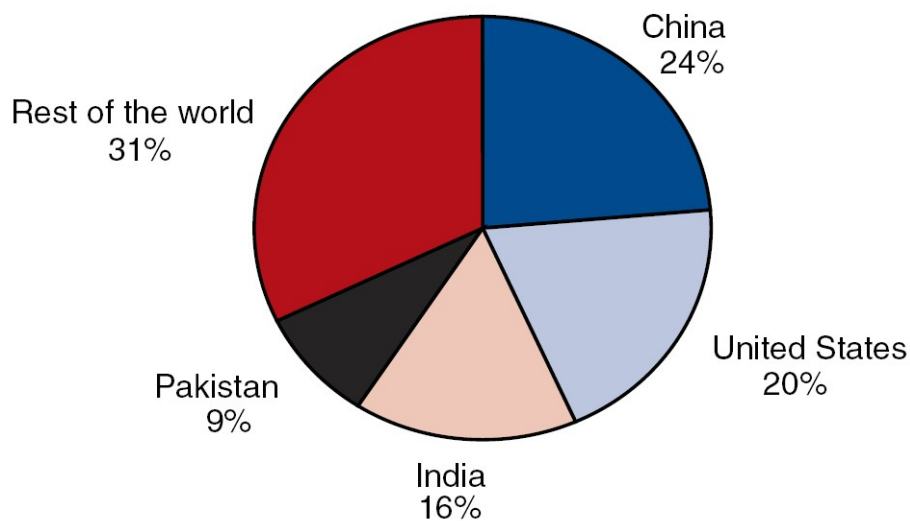


Figure 1.1 Share of the world cotton production, average between 2003 and 2005

Source: Economic Research Service: USDA (2009c)

To overcome the problem of excessive pesticide use the Food and Agricultural Organization (FAO), with financial support from the European Union (EU), launched an IPM-FFS program in 1999 with the objective of improving farmer knowledge in crop and pest management. Up to 2004, the program had conducted a total of 3,660 FFS for 93,700 farmers in six member countries, namely Bangladesh, China, India, Pakistan, Philippines and Vietnam. However, this study is limited to the three major Asian cotton producers.

1.2 Objectives

The overall objective of this study is to analyze the economic impact of the “FAO-EU IPM Program for Cotton in Asia” implemented from 2000 to 2004, both from a farm level and a project level perspective. The specific objectives are:

- To assess the impact of FFS training on insecticide use, environment and cotton productivity at farm level;
- To assess the efficiency of project investment by country and at the aggregate level and
- To evaluate the welfare effects of the project.

The objectives are in line with the need to establish more evidence about the economic benefits of Farmer Field Schools in developing countries. Such information will serve as an important basis for further investments in agricultural extension in those countries. Moreover, such impact assessments can help policy makers to adjust resource allocations and improve the targeting of programs (Maredia et al. 2000).

1.3 Organization of the thesis

The thesis is organized into seven chapters. Chapter 2 provides some background on the development of the cotton production and cotton sector in China, India and Pakistan, and describes some of the institutional settings related to agricultural extension in these countries. The chapter is divided into six parts as follows. In the first part, the cotton sector in each country is introduced. The next part covers trends in cotton area and productivity in the three countries as compared to the rest of the world. In the third part, the emergence of a new technology, i.e. the insect resistant transgenic cotton varieties, is described. This technology has often been called a simple solution to insect pest problems in cotton that would not require much knowledge as “the solution is in the seed”. In the fourth part, a literature review of the importance of farmer knowledge in spite of the new technology is presented. The fifth part describes the rationale in greater detail and looks at the procedure of the FFS approach in IPM and its impact from past studies. The last part sums up the chapter.

In Chapter 3, the methodology and procedure of data collection of this study are explained, including a theoretical framework for impact assessment, and the descriptions of the models, which were developed for measuring the effects of training on pesticide use and cotton productivity. In addition, the study areas, the survey design, and the sampling procedures in the three countries are described.

In Chapter 4, descriptive statistics of cotton farming in the three countries are presented using data from the baseline survey, which had been carried out prior to the implementation of the training. The geographic and the agricultural production

conditions of the five study sites, namely the provinces of Shandong, Anhui and Hubei in China, Karnataka state in India, and Sindh province in Pakistan are provided. The descriptive statistics of household characteristics and the performance parameters of cotton production are grouped by three types of farmers, i.e. those who participated in the training, those who did not participate but live in the same village and farmers randomly selected from a control village.

Chapter 5 shows the results of the economic impact analysis of training at the farmers' level. The chapter consists of two major sections. First, a comparison of the performance of cotton production among the three groups of farmers in the three countries is carried out using parametric statistical tests. A "before and after" and a "with and without" comparison are performed simultaneously.

In the second section, the econometric analysis is presented. Two models, a classic Difference-in-Differences model (DD-model) and a fixed-effects model are presented. A range of econometric tests was carried out to validate the assumptions of the models. The results are shown for the different performance parameters, i.e. cotton yield, gross margin, insecticide costs and environmental effects using the Environmental Impact Quotient (EIQ). The DD-models are used to compare FFS impacts among three countries. In order to evaluate aggregated effects, the sample is pooled and a fixed-effects model is used to control for possible discrepancies in individual country-specific characteristics.

Chapter 6 evaluates the efficiency of investment in the farmers' training program. Here the results of economic impact of the program presented in Chapter 5 are used as the base for the evaluation. The chapter is divided into two major parts. In the first part, a financial analysis of the project investment at farm level is carried out for the three countries separately. In the second part, following the concept of economic surplus, the aggregate impact of FFS training in all three countries is assessed at the aggregate level. The Dynamic Research Evaluation for Management (DREAM) model is applied, which allows the calculation of producer and consumer benefits from FFS training in the three countries and the rest of the world (ROW).

The final chapter summarizes the results of this research and draws some conclusions. In addition, recommendations are provided that could be used for planning similar programs in agricultural extension to improve their cost-effectiveness.

2 Cotton production in China, India and Pakistan

This chapter begins by giving some background on cotton production and the cotton sector in the three countries in this study. Next, trends in cotton production in the three countries are compared to the rest of the world. In the third part of the chapter, the development of insect resistant transgenic Bt cotton varieties is analyzed with regard to their potential contribution to increasing productivity and reducing insecticide use. This analysis provides some arguments for the need for farmer training in IPM, which are presented in the fourth part of the chapter. Thereafter the concepts of IPM and Farmer Field Schools are introduced and a review of past studies on the impact of IPM in developing countries is provided. The chapter concludes with a summary.

2.1 The importance of the cotton sector in the three countries

Cotton is a major cash crop for farmers in developing countries. FAO (2009b) reported that in Asia, cotton cultivation is the main source of income for more than 100 million low-income small-scale farmers. In addition, cotton is a major consumer of agrochemicals, and cotton processing provides jobs for millions of workers in textile and garment factories. Therefore, cotton is an important part of rural development in many Asian countries. In the three countries included in this study, the cotton sector is an important part of the economy. It includes the production sector, mainly operated by small scale farmers, and the input supply industry and especially the textile industry, which are parts of the cotton value chain. The relative importance of the cotton sector differs among the three countries because of the differences in the structure of the economies and the states of development.

Firstly, due to its large population, China is the largest producer of cotton and at the same time the major consumer of cotton-based textile products (Economic Research Service: USDA 2007). In 2005, the export value of clothing accounted for 25% of the world's textile and clothing export value. China is thus the largest textile exporter in the world (MacDonald 2007). In China, cotton accounts for 1% of the Gross Domestic Product (GDP) (Gillson et al. 2004). The textile industry employs more than 10 million workers and in some provinces cotton is the major source of agricultural income for rural areas (UNEP 2002). The cotton sector has been subjected to a major amount of government intervention. For example, until the late

nineties, the domestic cotton price was subsidized. In 1999, China liberalized the cotton market, which made domestic prices for lint to drop although they remained above world market level (FAOSTAT 2009). Domestic cotton policy interventions in China also have an influence on world prices due to stockholding and imports (USTR 2003).

On the input side, the government of China continues to heavily subsidize the production of cotton to around 30% of the production value. In 2007/08, some \$70 million was allocated by the central government for farmers to purchase high-quality seeds (Baffes 2004; ICAC 2006). Not surprisingly, China remains competitive in the international cotton market (UNEP 2002).

Secondly, although India has the largest cotton area in the world, cotton output is lower than that in China because of low productivity (Project Cotton 2008). While during the past India has been a net exporter of cotton, it has recently become a net importer. Since 1999, India has imported about 6% of total world imports. On the other hand, the impressive growth in the textile and garment industry has caused a growth in exports of finished products. Currently, India is the second largest textile producer in the world after China, accounting for about 15% of world production, with export values exceeding \$12 billion (Economic Research Service: USDA 2007).

Also, consumption of raw cotton by India's textile industry grew by around 35% during 1993-2002. Mill consumption of cotton between 1991 and 1998 increased at an average annual rate of 4.3%, which is higher than world consumption growth rate. In the same period, taking advantage of relatively low costs of cotton processing, Indian textile exports to other Asian markets increased faster than to other countries (Guitchounts 2005).

The cotton sector in India generates 4% of its GDP (James 2007). As is the case in China, India is also subsidizing cotton production. One form of subsidy is the writing off of farmers' debts with rural and cooperative banks (ICAC 2008). In addition, minimum support prices for each cotton variety are established by the Cotton Corporation of India (CCI), a government-owned organization (NIC 2008).

Thirdly, cotton is called "white gold" in Pakistan with cotton and cotton products contributing up to 10% to its GDP (Banuri 1998; Gillson et al. 2004) and accounting for around two-thirds of Pakistan's export earnings. Pakistan is the fourth largest

cotton consumer in the world, and cotton is Pakistan's largest industrial sector with hundreds of ginning factories and textile mills. From 30 to 40% of Pakistan's cotton production goes to the domestic textile market while the remainder is exported as raw cotton, yarn, and garment.

Cotton area, with over 3 million ha, covers 15% of the agricultural crop area of the country. Cotton area has increased during the last 30 years (Economic Research Service: USDA 2007).

Unlike in China and India, during the past, Pakistan did not provide support or subsidies to cotton producers for inputs (Pakissan.com 2009). However, in 1981 the Agricultural Price Commission (APCOM) was established mainly to advise the government on price policy for cotton and other agricultural commodities to ensure a minimum price to the growers for their produce when prices in the open market fell below a set level (Government of Pakistan 2006).

2.2 Selected trends in cotton production

In this section, cotton area production and productivity in the three countries are compared to the rest of the world.

Table 2.1 shows the shares of global cotton production between 1970 and 2007 by major cotton producing countries. The data show that the majority of cotton is produced in Asia, with almost 60% of the global cotton harvest. The largest producer of cotton in the world is China, accounting for over a quarter of the world production, followed by the United States. India is the third largest producer but its average annual production growth between 1970 and 2007 is the highest, at 4.6% (see Table 2.1). In India, cotton production has increased steadily over the past thirty years but especially since 2005. Pakistan is the fourth largest major producer in the world and over the same period, the average annual production growth was higher than in China.

Table 2.1: Percentage share of major producers of world cotton production, 1970 - 2007

Period average	China	United State	India	Pakistan	Brazil	Former Soviet Union	Turkey	Others
1970–74	17.3	19.4	8.5	4.8	4.6	18.4	3.9	23.1
1975–79	16.8	19.4	9.3	4.1	4	20.4	3.8	22.2
1980–84	25.7	16.9	9.6	4.9	4.5	16	3.4	18.9
1985–89	23.1	16.5	10.7	8	4.3	15.6	3.3	18.7
1990–94	24.3	19.9	11.8	8.6	3	11.7	3.3	17.4
1995–99	22.4	19.2	14.4	8.4	2.4	8	4.2	21.1
2000–03	24.1	19.6	13.4	8.8	4.8	7.2	4.1	17.9
2004	25.4	19	15.6	9.1	4.8	6.6	3.4	16.1
2005	25.1	20.3	16.2	8.6	4	7.1	3	15.7
2006 ^{1/}	29.1	17.7	17.9	8.1	5.7	6.7	3.2	11.5
2007 ^{2/}	29.7	15.8	19.7	8.2	5.9	6.9	2.8	11
Average growth ^{3/}	3.3	1.7	4.6	3.7	2.6	-0.7	1.6	0.1

Note: ^{1/}Estimates, ^{2/}Forecast, ^{3/}1970-2007 geometric growth of volume of production (%)

Source: Economic Research Service, USDA (2007) cited in Cororaton and Orden (2008)

In Table 2.2, the harvested area and the cotton yield are presented for the whole world and for the three countries included in this study. There are currently about 34 million ha of cotton in the world, with little fluctuation during the past thirty years. Among the three countries included in the study, India has the largest cotton area followed by China. During the recent past (2002-06), cotton areas were constant in Pakistan, increased in China but dropped in India when compared to the period 1995 to 2001. Overall, however, the cotton area has not shown a clear trend over the past thirty years.

There are marked differences in productivity among the three countries, with China clearly having the highest yields, which are almost double of those in Pakistan and almost threefold of those in India. The two latter countries show yields below the world average. As shown in Table 2.2, generally there was a positive trend in cotton yields. Compared to the nineties, average cotton yields have grown markedly. The only exception is India where yields declined during the first two years of this decade but have increased in the last period by some 50% while at the same time cotton area has decreased. However, India's cotton yields remain the lowest among the

three countries and are far below world average. Average cotton yields in China are higher than world average but are below in India and Pakistan.

Table 2.2: Harvested cotton area (million ha) and cotton yield (kg/ha) of the world and three main cotton producer in Asia, 1970 - 2006

Period average	World		China		India		Pakistan	
	Area	Yield	Area	Yield	Area	Yield	Area	Yield
1970–74	33	400	5	459	8	147	2	330
1975–79	32	409	5	451	8	158	2	281
1980–84	32	476	6	680	8	190	2	343
1985–89	31	548	5	797	7	257	3	548
1990–94	33	570	6	773	8	288	3	594
1995–99	34	580	5	966	9	311	3	569
2000–01	33	622	4	1,096	9	292	3	601
2002-06	34	704	5	1,141	8	431	3	666
Average 1970- 2006		532		771		257		480
Average growth ^{1/}		76		149		197		101

Note: ^{1/}Between two periods: 1970-74 and 2002-06 (%), Area is harvested area (million ha)
Source: Economic Research Service, USDA (2007) cited in Cororaton and Orden (2008)

2.3 Transgenic cotton varieties

Biotechnology in the form of transgenic varieties has been introduced in cotton production. In fact, insect-resistant, transgenic Bt cotton¹, after its large scale introduction in US agriculture, has been the first transgenic crop introduced in developing country agriculture (James 2002a). The attractiveness of this technology stems from the expectation of pesticide reduction and high productivity.

China was the first developing country to introduce Bt cotton on a large scale. This was made possible by major public sector investment in biotechnology research of around \$56 million (\$8 million in 1986 and accelerated to \$48 million in 1999) (Huang et al. 2002c). Since the mid-1990s, the Chinese Academy of Agricultural Sciences (CAAS) has collaborated with the Monsanto Company and with the cottonseed company Delta and Pineland from the United States. Meanwhile, numerous varieties from the CAAS and provincial research institutes are available for sale in provinces where the cotton bollworm is a damaging pest. Many Bt varieties were produced by backcrossing local varieties with the varieties from Monsanto and CAAS (Huang et al. 2002b).

Table 2.3 presents the share of Bt cotton area and total cotton production during 2000 - 2007. The results show that in 2000, farmers in China had adopted Bt cotton on 12% of the total area, while two years later, the adoption increased to nearly 50% of the total area and continues to increase (James 2003a; 2003b; 2004; 2006; 2007).

In India, the first genetically modified crop had been approved in 2002 after much controversy. However, there was unauthorized release and cultivation of Bt cotton in some areas. The results of the adoption of Bt cotton in India has been mixed, with both successes and failures (Business & Industrial Research Division 2006).

¹ Bt (*Bacillus thuringiensis*) cotton is generated by engineering techniques derived from the soil bacterium that gave the plant its name (AGBIOS 2009). The transgenic cotton varieties were developed to be resistant to bollworm, which is the major pest of cotton. The cotton produces a special protein that is toxic only to certain pests (English and Slatin 1992). Bollworms feeding on the leaves of Bt cotton become sleepy and lethargic, causing less damage to the crop (Gandhi and Namboodiri 2006).

Investment in crop biotechnology is increasing. India is investing \$25 million annually, of which \$15 million comes from public sector research and an additional \$10 million from the private sector (James 2002a).

Table 2.3: Share of Bt cotton area and total cotton production in China between 2000 and 2007

Year	Total cotton area (million ha) ^{1/}	Bt cotton area (million ha) ^{2/}	Production (million tons) ^{1/}
2000	4.1	0.5	4.42
2001	4.8	1.5	5.31
2002	4.5	2.1	5.49
2003	5.3	2.8	5.18 ^{3/}
2004	5.9	3.7	6.60
2005	5.4	3.3	6.18
2006	6.0	3.5	7.73
2007	6.2	3.8	8.06

Source: ^{1/}Economic Research Service: USDA (2008), ^{2/} James (2003a; 2003b; 2004; 2006; 2007)

Note: ^{3/}The cotton production in 2003 was dropped due to natural calamities (FAO 2009a).

Table 2.4 presents the share of Bt cotton cultivation area and cotton production in India from 2002 to 2007. Nowadays, India has the largest area under Bt cotton, greater than that in China. In 2005 and 2006, the area under Bt cotton was enlarged by about 15% and over 40%, respectively. Up to 2007, the share of Bt cotton in the total cotton area had reached over 60% of total cotton area in the country.

Table 2.4: Share of Bt cotton area and total cotton production in India between 2002 and 2007

Year	Total cotton area (million ha) ^{1/}	Bt cotton area (million ha) ^{2/}	Production (million tons) ^{1/}
2002	7.7	<0.1	2.31
2003	7.6	0.1	3.05
2004	8.8	0.5	4.14
2005	8.9	1.3	4.15
2006	9.2	3.8	4.75
2007	9.5	6.2	5.36

Source: ^{1/}Economic Research Service: USDA (2008), ^{2/} James (2002b; 2003b; 2006)

Note: The total area which is presented in this table is discrepant with Table 2.2 due to Cororaton and Orden (2008) reported the rough average figure.

In Pakistan, adoption of Bt varieties has been low due to stricter application of bio-safety regulations. In 2005, the Pakistan Atomic Energy Commission (PAEC) provided 40 tons of seed of Bt cotton (insect resistant) varieties; which were grown over 3,238 ha in 2005/06. These early users of Bt cotton have been tightly screened and evaluated by PAEC on the basis of their capacity to follow Bio-safety rules. However, due to uncontrolled release of genetically engineered varieties, there could be illegal use of Bt cotton varieties or fake brands under name of Bt cotton seeds available in the market. However, no reliable information is available about the actual diffusion of this technology in Pakistan.

2.4 Why is Bt cotton not a substitute for farmers' training?

Transgenic Bt cotton varieties were added to the portfolio of pest management technology some ten years ago. Those varieties are believed to be an effective tool against the cotton pests, loosely grouped as cotton bollworms and defoliators with different tolerances to Bt cotton (e.g. Adamczyk et al. 1998). In China, the diffusion of Bt cotton has been rapid and India has recently overtaken China in terms of the proportion of area under Bt cotton (Gulati 2009). Many scientists are very optimistic about the contribution of transgenic varieties to productivity growth in developing countries (e.g. Qaim and Zilberman 2003). Some crop protection scientists see biotechnology as a solution to the problems that pesticide use created (e.g. Naranjo 2005).

Also, numerous impact assessment studies on Bt cotton have been carried out in China (e.g. Huang et al. 2002b) and India (e.g. Qaim 2005). The studies claim that farmers who use Bt cotton have higher yields because of reduced damage from bollworms and will reduce the level of pesticide usage (Huang et al. 2002d). Similarly, in India, a study by Gandhi and Namboodiri (2006) found that under irrigated as well as non-irrigated conditions the yields of Bt cotton were higher than the yields of non-Bt cotton.

Therefore, the question arises: is there still any need for a knowledge-based pest control concept like Farmer Field Schools if all the technology is "in the seed"? Based on a thorough review of the literature, there are good arguments to conclude that Bt cotton may not be the "silver bullet" solution to pest problems. For example, a global review of 47 peer-reviewed economic papers on the farm-level impact of Bt

cotton in developing countries (Smale et al. 2009) found that the results are rather mixed. The authors found that most of the papers focus on China, India and South Africa with economic returns being highly variable over years, farm type, and geographical location. Thus, the study concludes that “the institutional and marketing arrangements for supplying the technology and marketing the product may be the single most important determinant of Bt impact at the farm-level, even when the trait is shown to be effective”. The authors also note that the most obvious limitation to deriving solid evidence of Bt cotton impact is the short time period considered in the studies. While some studies were enthusiastic about the benefits of GM cotton for farmers in China (see for example Huang and Wang 2002a; Huang et al. 2002b; 2002d; Pray et al. 2001; 2002), other case studies were more cautious (e.g. Fok et al. 2005; Keeley 2006; Pemsil and Waibel 2007; Pemsil et al. 2005; 2006; Yang et al. 2005a; 2005b).

Though a considerable number of studies were conducted to assess the farm-level impact of Bt cotton in China, none of them has used panel data. However, monitoring the same farms over time is important in assessing the long-term performance of the technology. There are factors that can question the sustainability of GM crops. The first one is the possibility of the build up of resistance to Bt toxin in the target pests (e.g. Carrière et al. 2001; Tabashnik et al. 2003; Wu et al. 2002), similar to what has been observed with chemical pesticides. Furthermore, secondary pests can develop as a result of broader ecosystem effects and cause additional yield loss (e.g. Wang et al. 2006). Also, in India questions have been raised as to whether Bt varieties produce less yields than the hybrid varieties grown by farmers (Venkateshwarlu 2002).

In a thorough review paper, Glover (2009) examined the basic assumption underlying the many econometric impact assessment studies to determine benefits of transgenic crops. He carefully evaluated the hidden assumptions that have shaped both the pro-poor claims on behalf of GM crops and the methods that have been used to evaluate them. He found that the assumptions have involved a radical simplification of the complex agronomic and livelihood contexts into which GM crops have been inserted, and therefore concludes that there could be a bias towards overestimating the benefits of GM crops in poor countries.

In addition, based on the experience with other production inputs, notably chemical pesticides, the institutional arrangements in the seed delivery systems with a large number of GM cotton varieties released to the market, can lead to a deterioration of the quality of Bt varieties (e.g. Pemsl et al. 2005).

Taking into account the evidence that exists in the literature, it can be concluded that in order to realize the potential of pest resistant transgenic varieties, these should be treated as a component of integrated production and pest management (IPPM) and not as single solutions. To effectively incorporate the Bt technology into an IPPM, a conducive institutional policy environment is first needed. Secondly, it is also important that farmers understand the true properties of Bt varieties and know what questions they should ask the dealers who offer them an array of new varieties. For example, the chances that pesticides will be reduced in cotton but may be increased in other crops. A study from Hubei province, China has shown that farmers who were using Bt cotton and at the same time received IPM training, decreased their pesticide use significantly more than untrained farmers (Yang et al. 2005b). Using an econometric model Wu et al. (2007) found a positive interaction between the adoption of Bt varieties and participation in Farmer Field Schools.

2.5 The evolution of FFS in IPM extension and its impact

Increasing consumer concern about healthy food, and higher priority given to environmental policy by governments, requires more knowledge by farmers regarding management of natural resources. The concept of Integrated Pest Management (IPM), which promotes a combination of environmentally more benign practices to reduce the need for harmful chemical pesticides, fits well into this new paradigm of farming technology. Under IPM farmers are trained to monitor their fields for potential pest outbreaks and use chemical pesticides only if the economic threshold is exceeded (Metcalf and Luckmann 1975; Rabb and Guthrie 1970; Smith and Pimentel 1978).

An important institution for the dissemination of IPM has been the Food and Agricultural Organization (FAO), which since long has provided coordination, leadership and resources to promote IPM, particularly in developing countries. The FAO Inter-country Program (ICP) for the Development and Application of Integrated Pest Control (IPC) in rice in South and South-East Asia in 1980 can be considered

as the starting point. During the period 1987 to 1997, IPM became more of an extension and training program. The Farmer Field Schools (FFS), which promoted participatory experiential learning to help farmers develop their analytical skills, critical thinking and creativity, and helped them learn to make better decisions, soon became the major IPM tool (Kenmore 1997). What made the FFS different from traditional extension and training systems such as the training and visit concept was that the trainer is more of a facilitator than an instructor (Röling and van de Fliert 1994).

The first large-scale implementation of FFS took place in 1989 in rice in Indonesia. Subsequently, 12 other countries in Asia have taken this approach, also in crops other than rice, namely in vegetables, cotton etc. Moreover, the program also spread to other continents such as Africa, Latin America, the Middle East and Eastern Europe (van den Berg and Jiggins 2007). Recently, FFS programs were being implemented in 78 countries and in total it is estimated that more than four million farmers have been trained under this program. The largest share of farmers trained under FFS is in Bangladesh, China, India, Indonesia, the Philippines, and Vietnam (Braun et al. 2006).

The IPM approach was first applied to cotton in 1999, when FAO and the European Union launched a five-year regional program under "FAO-EU IPM Program for Cotton in Asia" covering Bangladesh, China, India, Pakistan, the Philippines and Vietnam. The program adopted the FFS concept tested in other crops to cotton. In particular, the "cotton ecosystem analysis" in which participants meet once a week during the cotton season and, in small groups, make detailed observations by comparing notes and drawings of what they observe, was developed (FAO-EU IPM Program for Cotton in Asia 2004b). The program was terminated at the end of December, 2004 after funding from the EU ended. However, the program continues to be active at the community level in some of the countries, including in China.

FFS projects have been subjected to economic impact assessments. A meta-analysis of 25 short-term impact studies commissioned by the FAO was carried out by van den Berg (2004). In Table 2.5, the studies conducted in Asia are reported. Most of the studies were carried out on rice, one on vegetables and one on cotton. Overall the studies concluded that FFS can help to reduce pesticide use.

Some authors have been critical of the economic efficiency of investments in FFS. For example, Feder et al. (2003) found that the IPM-FFS program in Indonesia had no significant impact on the trained farmers nor on their neighbors. According to their study, expenditures for pesticide increased between 1990-91 and 1998-99 by 81% for trained farmers and 169% for non-trained farmers. During the same period yields declined by 11% and 15%, respectively. The authors attributed these negative results to the complexity of the IPM information, which especially curtails the diffusion process from IPM-trained farmers to others. In another study using the same data set, Yamazaki and Resosudarmo (2007), however found a reduction in pesticides use although their analysis suggests that the performance of FFS farmers was declining over time and the effect of the FFS on rice yield was phasing out.

Table 2.5: Outcomes of IPM-FFS program in Asia

Country	Crop	Outcome	Source
Bangladesh	Egg plant	80% reduction in pesticide applications frequency, from 7.0 to 1.4 per season; 25% increase in yield was also observed	Larsen et al. (2002)
Cambodia	Rice	64% reduction in pesticide volume; 43% reduction in pesticide frequency; participant farmers knew more of beneficial organisms and alternative pest control methods; they were better aware of pesticide health risks than non-participant farmers	van Duuren (2003)
China	Cotton	46% reduction in insecticide application frequency from 6.3 to 3.1 per season; 78% reduction from 7.4 to 1.3 kg/ha; 16% increase in yield and 20% increase in income	National Agro-technical Extension and Service Center (2003)
Indonesia	Rice	Training caused a change from preventative spraying to observation based pest management that results in 60% reduction in the use and expenditure of insecticides.	Monitoring and Evaluation Team (1993)
Sri Lanka	Rice	Insecticide applications reduced 81% from 2.2 to 0.4 applications per season; 23% yield increase and 41% increase in profits. The overall training costs were recovered 7-fold within a single season. Training impact was durable over six years after training.	van den Berg et al. (2002)
Thailand	Rice	60% reduction in the use of insecticides and molluscicides; increase in knowledge about pests and natural enemies	Praneetvatakul and Waibel (2003)
Vietnam	Rice	Insecticide use reduced by 82% from 1.7 to 0.3 applications per season; fungicide use reduced after training in the North but increased in the South, probably due to a combination of factors	Pincus (1999)

Source: van den Berg (2004)

The success of IPM extension programs is ultimately judged by the adoption rate of the IPM systems and the improvements in productivity (Dent 1995). A number of constraints to a more widespread adoption of IPM in developing countries have been identified, including inappropriateness of technology, economic factors, non-availability of appropriate information, the strong influence of the chemical industry in convincing farmers that pesticides are indispensable and the lack of coordination among implementing agencies (Escalada and Heong 1994; Goodell 1984; Malone et al. 2004; Matteson et al. 1994; Peshin 2005; van de Fliert 1993).

2.6 Summary

This chapter has first provided an introduction to cotton production and cotton sector in the three countries included in this study. Secondly, the development of insect resistant transgenic Bt cotton varieties was discussed with regard to their potential contribution to increased productivity and reduced insecticide use. Arguments were provided for the need for farmer training in IPM. The concept of IPM and Farmer Field Schools was introduced and a review of past studies on the impact of IPM in developing countries was provided.

As an important cash crop for farmers, and raw material for the garment and textile industry, cotton is a significant economic sector in the three countries. It is also a major source of foreign exchange through the exporting of raw cotton, yarn, and garments. Therefore, the cotton sector has been subject to various types of government interventions, including subsidies.

Regarding the structure of cotton production, it has been shown that China, India and Pakistan are major cotton producers and the majority of cotton is produced by small-scale farmers. During the recent past the three countries significantly increased their productivity, and especially in China cotton yields are well above the world average. India is the country with the largest cotton area but its productivity is below world average although yields have increased recently. Also, among the three countries included in the study, the adoption share of Bt cotton is highest in India, although causality with observed productivity increases remains doubtful. Pakistan is the third largest cotton producer in Asia with more productivity than India.

Cotton production is marked by the heavy use of external inputs, especially chemical pesticides. Hence, many pests have become resistant to pesticides and therefore

governments are looking for ways to reduce dependency of pesticides and maintain sustainability of cotton production. Among the alternatives available to date, Bt cotton has been actively promoted in China and India. However, in Pakistan the government has been more reluctant. Since available studies regarding the economic benefits of Bt cotton provide mixed results, there is a need to undertake additional efforts to increase productivity and reduce pesticide use. Hence, Bt varieties can be seen as just one component of an Integrated Pest Management system. The IPM approach through the FFS concept with participatory experiential learning can improve the level of knowledge for farmers and allow them to make more informed decisions. Therefore, an assessment of the effects of farmer training in these three major cotton producers is expected to provide useful information for policy makers in China, India and Pakistan, and in other developing countries. In the next chapter, the theoretical framework and research methodology will be presented.

3 Conceptual framework and data collection

This chapter is divided into two major parts. The first part describes the research methodology, including the theoretical background of impact assessment as applied to Integrated Pest Management (IPM) and a description of the econometric models used. The second part describes the survey methodology, including a brief description of the study areas, survey design, and the sampling procedures in the three countries included in this analysis. A summary is provided at the end of the chapter.

3.1 Theoretical background and methodologies

3.1.1 Theoretical background

Impact assessment aims to determine the consequences of an intervention in the development process. These consequences are measures of project outcomes, which are of interest to the decision maker. The analysis can either be ex-ante, i.e. conducted prior to the intervention, or ex-post, i.e. after the project was implemented. In the former case, a foretelling of impact based on some type of prediction model must be made. In the latter case, which is the more frequent type of impact analysis, outcomes are measured at some point in time after the intervention took place.

The need for impact assessment arises for several reasons. One is accountability for the use of scarce public funds. Development projects carried out by international aid agencies and national governments usually entail investments, which require public funds that are competed for by alternative uses. Donors increasingly demand accountability for the funds and evidence of the net social benefits of their investments. Moreover, impact assessment can generate lessons learned, which are useful for improvement of research and development programs (Zilberman and Waibel 2007). Furthermore, impact evaluation can improve targeting of research programs and help to adjust resource allocations across programs (Maredia et al. 2000)

There are two major challenges in impact assessment studies. The first is to establish causality between the project intervention and the final impact, measured by specific impact indicators. It is often difficult to link the intervention with the end result. The second challenge is to establish a realistic counterfactual, i.e. a reference

point for the situation without intervention. This is crucial because impact is defined as the difference between the situation without intervention and the situation after intervention.

As regards the first challenge, which is called the attribution problem, the specific features of the IPM technology must be taken into consideration. Integrated Pest Management (IPM) is a knowledge-intensive technology that involves several steps along an impact pathway. In Figure 3.1, the impact pathway is shown as a staircase model first conceptualized by Bennett (1975). Applying this concept to Farmer Field Schools (FFS), the starting point consists of inputs in terms of planning, organization, material and human resources. These inputs will enable the training activities, which must be performed to a minimum standard in order to be effective. If the latter is the case, it could be assumed that training will result in farmer participation (step 3) and will prompt them for some reaction (step 4), which could be changes in knowledge, attitudes, skills and aspirations. Only if these changes occur is it reasonable to assume that there will be changes in pest and crop management practices, which will finally lead to an impact in terms of increased cotton productivity, farmer income or welfare gain for the society.

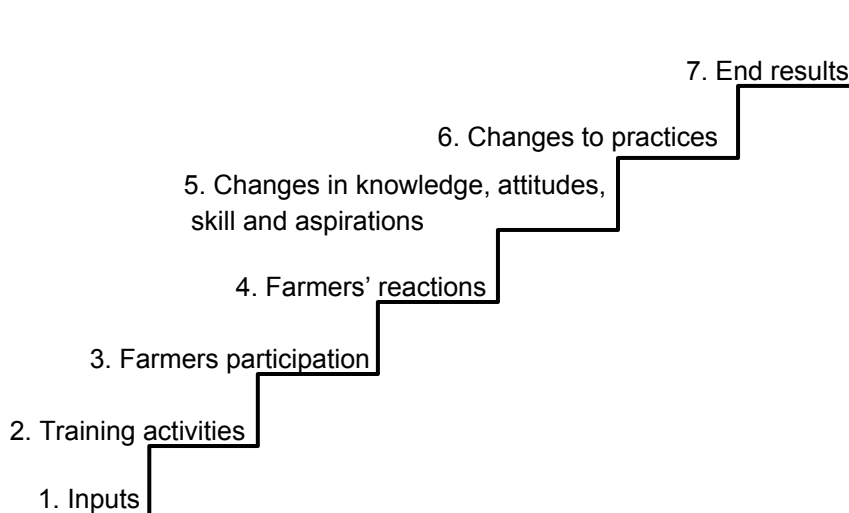


Figure 3.1: Chain of events in IPM extension

Source: Bennett (1975) and Peshin, Jayaratne et al. (2009)

To attribute the observed outcomes to the intervention requires the specification of indicators, which must be measurable in terms of quantity, quality and time. In principle, indicators can be defined for each level of the impact pathway. However, this is rarely done in practice. Many IPM impact studies define indicators at step 5, namely the change in knowledge, which is the immediate outcome expected from an intervention like FFS training. For the next level, i.e. changes in farmer practices, it is necessary to distinguish IPM practices from conventional ones. Due to the multiple definitions of IPM this is not an easy task. However, one frequently used indicator is the change in pesticide practices, both in terms of type of pesticide, the frequency of spraying and the quantity used. Sometimes the monetary value is used as an aggregate measure combining type and quantity.

As pointed out by Norton and Swinton (2009), if many farmers improve their pest management practices to achieve more effective control of pests with less harm for human health and the environment due to reduced spraying of harmful pesticides, there will be positive aggregate market and non-market effects. The market effects are generally expressed as economic surplus. The economic surplus approach is based on the competitive market-clearing model introduced by Edwards and Freebairn (1984). This model can be applied to assess the welfare effects of FFS training in cotton. If many cotton farmers increase their productivity after FFS training, the aggregate market effects result in a shift of the cotton supply curve. This is because higher productivity will lower the marginal costs of production of IPM adopters, which will result in a lower market price depending on the elasticity of supply and demand. This leads to an increased producer and consumer surplus because of higher output and lower prices.

The effect is conceptualized in Figure 3.2. D and S_0 represent the initial demand and supply functions and the initial equilibrium price and equilibrium quantity are P_0 and Q_0 respectively. Producer surplus (PS) is estimated as the area below the price line (P_0) and above the supply curve (S_0), while the consumer surplus (CS) is the area below the demand curve (D) and above the price line (P_0). Total economic surplus (ES) is the sum of the producer and consumer surpluses.

The effects of FFS training can be measured as reduction in pesticide cost and better effectiveness of control, which results in enhanced productivity. Thus, marginal costs of IPM farmers will shift to the right, i.e. they will be lower for a

defined level of output. On the aggregate level, this will shift the supply curve to the right (S_1). Assuming the demand curve remains unchanged, which is reasonable as there is no market bonus for IPM cotton, FFS training will induce a shift in supply leading to an increase in output from Q_0 to Q_1 . Consequently, the cotton market price drops from P_0 to P_1 . Producers who can profit from the FFS knowledge are better off if the reduction in production expenses such as pesticide costs and the increase in productivity outweigh the negative effect associated with the decrease of the cotton price. Consumers are also better off because of the reduced cotton price and increased consumption. The change in producer surplus (ΔPS), which is a measure of the producer gain, is equal to area P_1bcd , while the change in consumer surplus (ΔCS), which is a measure of the consumer benefits, is equal to the area P_0abP_1 . The change in total economic surplus (ΔES), which measures total benefits, is the sum of the change in consumer and producer surpluses and is equal to the shaded area I_0abl_1 .

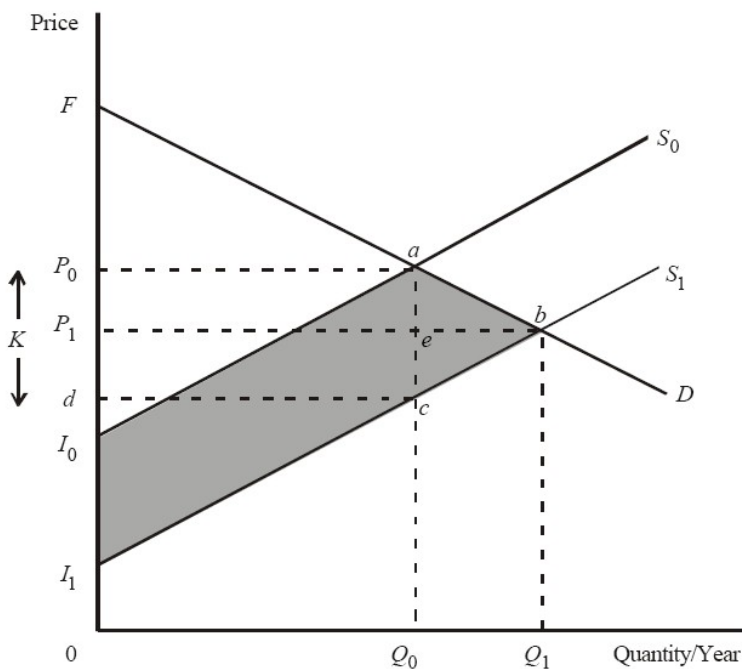


Figure 3.2: Economic surplus due to FFS introduction

Source: Alston, Norton, and Pardey (1995)

In practice, the change of the cost per unit of production multiplied by the initial quantity, $K \times Q_0$, is applied as an approximation for estimating the economic surplus. Thus, the size of the market, indicated by the initial quantity Q_0 , as well as the size of

the productivity gain, indicated by the change of the cost per unit of production, K , are critical factors in estimating the economic benefits (Alston et al. 1995; Norton and Davis 1981).

The economic surplus model is the basis for a cost-benefit analysis (CBA) of a project or program intervention. It allows the comparison of program costs to benefits in order to estimate the program's impact on social welfare. This method also offers information that can be used to improve the quality of public policies, which can contribute to an increase in social welfare. In CBA a major distinction needs to be made between financial and economic analyses. First, financial analysis assesses the efficiency of investment from the point of view of a private economic agent. Hence, actual market prices are used, regardless whether they reflect the actual scarcity of the resources used in the economy. Second, economic analysis takes the point of view of the whole society. Here shadow prices are used and transfer payments are removed (Gittinger 1982). Hence, in economic analysis the effect of the program on producer and consumer welfare, and the effect on government budget is normally estimated. The boundary of the analysis is a national economy. Positive or negative externalities on other economies are not considered, Figure 3.3 shows the basic complements of financial and economic analysis (Perkins 1994).

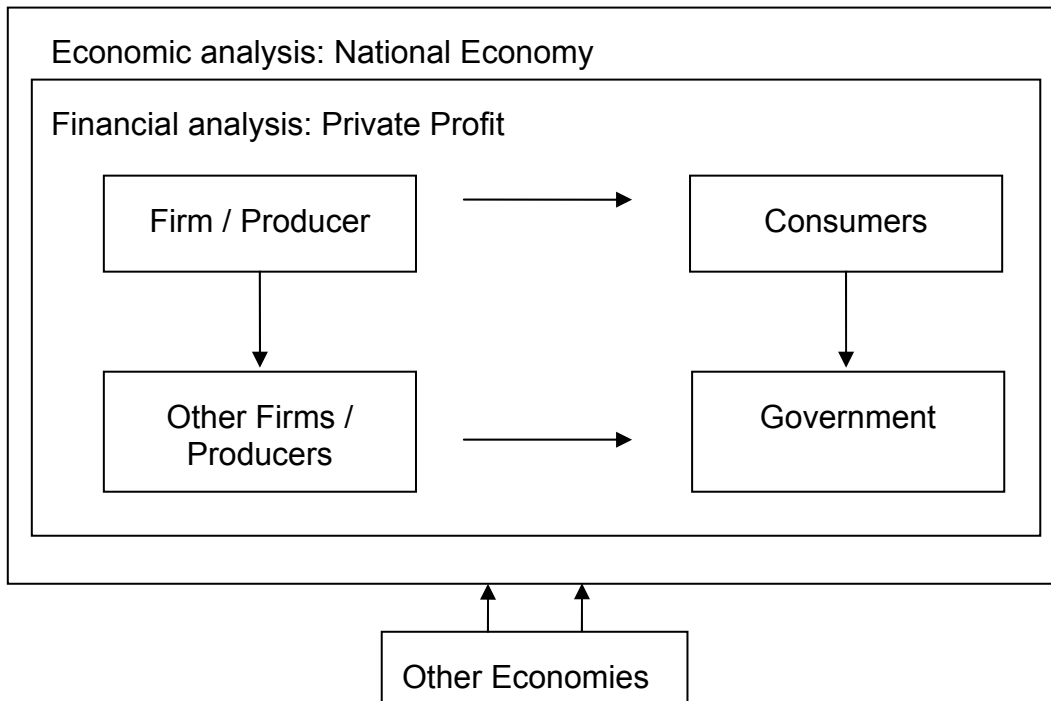


Figure 3.3: Scope of financial and economic analysis

Source: Perkins (1994)

CBA can be extended if environmental effects are included. This may be especially relevant for investments in IPM, where changes in the type of pesticide use and the reduction in the amount of pesticides are major results. More benign pest management practices can generate human health and environmental benefits. Since, it is difficult to put a monetary value on such effects, indexing methods have been developed for assessing health and environmental effects of pesticides. Examples of such indices used in the literature are the Pesticide Index (PI) of Penrose et al. (1994), a multi-attribute toxicity index developed by Benbrook et al. (2002) and the Environmental Impact Quotient (EIQ) developed by Kovach et al (1992). In this study, the EIQ method is selected to assess the environment impact of IPM practices. The EIQ calculation uses active ingredients of pesticides and applies a rating system in ten categories to identify a single value of the environmental impact rating. The ten categories include: (i) action mode of pesticides, (ii) acute toxicity to birds, (iii) fish, (iv) bees, (v) acute dermal toxicity, (vi) long term health effects, (vii) residue half-life in soil and (viii) plant surface, (ix) toxicity to beneficial organisms, and (x) groundwater and runoff potential. Finally, in

the EIQ model pesticides are grouped into three principal components of an agricultural production system, namely farm workers, consumers and ecology. The resulting EIQ value can be used to compare different pesticides and thus to assess the effect of a change in pesticide management practices as introduced by FFS training.

3.1.2 Methodologies

The actual assessment of impact can be carried out in three steps: (i) parametric and non parametric statistical tests, (ii) econometric models and (iii) models of economic surplus. Generally, the analysis of impact starts with statistical methods aimed at detecting differences between trained and non-trained farmers. The econometric models aim to detect causality between project intervention and final result, while the economic surplus models are used to calculate the aggregate benefit of the training. The latter can be used to calculate the efficiency of the investment.

To minimize the attribution problem in impact assessment, it is useful to establish two kinds of differences, namely a “before and after” and a “with and without” difference. This so-called Difference-in-Differences (DD) method has been widely used in many fields of research. For example, Card (1990) applied the idea to the study of the effects of immigration on domestic wages and employment. The study assessed the employment effects of a rise in the minimum wage in the state of New Jersey, using the state of Pennsylvania as control group in order to identify the variation in employment that New Jersey would have experienced in the absence of a rise in the minimum wage (Card and Krueger 1994).

The basic idea of the DD method is that outcomes of an intervention are observed for two groups in two time periods. One of the groups is the treated group (exposed to a treatment, e.g. FFS training) and observations are made prior (pre-treatment) and after the intervention (post-treatment). Another is the control group (not exposed to treatment) during either period. The observed outcomes of both groups are made in each time period and the difference of the control group is subtracted from the difference of the treatment group. The DD procedure removes biases in post-treatment that could result from structural differences between the two groups, as well as biases from comparisons over time in the treated group that could be the result of trends (Ashenfelter and Card 1985; Wooldridge 2002). Thus, a control

group will be defined to allow the removal of confounding factors and to isolate the treatment effect (Abadie 2005; Baker 2000; Ezemenari et al. 1999).

Statistical analysis

The most direct effect of FFS training is expected to be an increase in knowledge of the participants. IPM training includes identification of pests, diseases and beneficial organisms, which enables farmers to better assess their field situation. The training also covers general agronomic and specific pest management practices (Walter-Echols and Ooi 2005). A straightforward method for the detection of differences is to apply parametric statistical tests such as the T-test if only two groups (e.g. before and after) are compared, and the F-Test if more than two groups (trained, exposed, non-trained) are compared.

The same procedure can be applied to compare pest and crop management practices of trained and untrained farmers. This can be carried out either by comparing the use or non-use of specific pest management practices (e.g. pest monitoring, use of biological control methods, plant spacing etc.) or by comparing costs and returns per unit area. Farm-level profits can measure the effect of changes between pre- and post-FFS training in input and output quantities and single out price effects by comparing data from several sites, i.e. FFS villages. The procedure tests for significant differences in mean profitability (Norton and Swinton 2009; Swinton et al. 2002).

While the main purpose of the statistical analysis of differences in profitability of the production enterprise is to assess the economic attractiveness of the technology, such information can also be used to estimate the aggregated market effects of an IPM program (Norton and Mullen 1996).

Econometric models

A major shortcoming of simple statistical comparisons is the fact that effects of other factors that may have changed during and after the time of FFS training cannot be captured. Hence, regression analysis as combination of cross section and time series data with at least two time periods, including a binary intervention indicator, can be formulated as follows (Wooldridge 2002):

$$y = \beta_0 + \beta_1 dG + \beta_2 dT + \beta_3 dG * dT + \varepsilon \quad (3.1)$$

where y is the outcome of the variable of interest, e.g. pesticide use of individual farmers, dT denotes the time period dummy for the post-intervention change (dT equals one and zero otherwise) which is aggregating factors that would cause changes in y over time. The variable dG is a dummy variable, which captures differences between the treatment and control groups prior to the intervention. It equals one for individuals in the treated group and is zero otherwise. The multiplier of interaction term, $dG * dT$, is a dummy variable equal to unity for those observations in the treatment group after the intervention.

The regression coefficients of equation (3.1) shown in Table 3.1 can be applied to the case of FFS training.

Table 3.1: The coefficients of treatment and control group between time periods of policy intervention, and differences

	FFS group	Control group	Difference
Before Training	$\beta_0 + \beta_1$	β_0	β_1
After Training	$\beta_0 + \beta_1 + \beta_2 + \beta_3$	$\beta_0 + \beta_2$	$\beta_1 + \beta_3$
Difference	$\beta_2 + \beta_3$	β_2	β_3

Source: based on Card and Krueger (1994) and Wooldridge (2002)

From Table 3.1, the Ordinary Least Squares (OLS) estimator for the program or evaluation is $\hat{\beta}_3$, which has been labelled the DD estimator. Let $\bar{y}_{CG,B}$ denote the sample average of y for the control group before policy change, and $\bar{y}_{CG,A}$ is the average of y for the control group after policy change. Define $\bar{y}_{TG,B}$ and $\bar{y}_{TG,A}$ similarly for treatment group. Then the $\hat{\beta}_3$ can be expressed as

$$\hat{\beta}_3 = (\bar{y}_{TG,A} - \bar{y}_{TG,B}) - (\bar{y}_{CG,A} - \bar{y}_{CG,B}) \quad (3.2)$$

For estimating intervention effects, to see how effective $\hat{\beta}_3$ is, it can be compared to alternative estimators. One approach is to use only the change in the mean over time for the treatment group and ignore the control group completely, $\bar{y}_{TG,A} - \bar{y}_{TG,B}$. Here the problem is that the mean response can change over time due to other factors or events that are correlated with the outcomes but are not caused by the intervention (Baker 2000). Another approach is to compute the difference in means between the treatment and control groups after policy change and ignore the time period before policy intervention, $\bar{y}_{TG,A} - \bar{y}_{CG,A}$.

In the cross section approach, the problem is that there might be systematic, unmeasured differences between the treatment and control groups before the intervention, i.e. before the FFS training. Therefore, attributing the estimated difference in averages to the training might be misleading. By comparing the time changes in the means for the treatment and control groups, both group-specific and time-specific effects are allowed for. The unbiased DD estimator, however, requires the policy change to not be systematically related to other factors that affect y (and are hidden in ε). In most applications, additional covariates appear in equation (3.1); for example, household characteristics. Thus, it is possible that the random samples within a group have systematically different characteristics in the two time periods.

For the individual-level panel data, the simple case assumes two time periods and an intervention of program indicator, w_{it} , which is unity if unit i participates in the program at time t . The simple model is:

$$y_{it} = \beta_0 + \beta_1 dT_t + \beta_2 w_{it} + s_i + \varepsilon_{it}, \quad t = 1, 2 \quad (3.3)$$

where $dT_t = 1$ if $t = 2$ and zero otherwise, s_i is unobserved effect, and ε_{it} are the idiosyncratic errors. The coefficient β_2 is the treatment effect. A simple estimation procedure is to calculate the difference to remove s_i :

$$(y_{i2} - y_{i1}) = \beta_1 + \beta_2(w_{i2} - w_{i1}) + (\varepsilon_{i2} - \varepsilon_{i1}) \quad (3.4)$$

or:

$$\Delta y_i = \beta_1 + \beta_2 \Delta w_i + \Delta \varepsilon_i \quad (3.5)$$

If $E(\Delta w_i | \Delta \varepsilon_i) = 0$, the change in treatment status is uncorrelated with changes in the idiosyncratic errors, then OLS applied to equation (3.5) is consistent.

When $w_{i1} = 0$ for all i , no exposure to the program existed in the initial time period.

Then the OLS estimator is:

$$\hat{\beta}_2 = \Delta \bar{y}_{treat} - \Delta \bar{y}_{control} \quad (3.6)$$

which is a DD estimate that expresses a difference in the means of the same units over time. This estimate can be derived without introducing heterogeneity by simply writing the equation for y_{it} with a full set of group-time effects. Also, (3.6) is not the same estimate obtained from the regression y_{i2} on 1, y_{i1} , w_{i2} - that is, using y_{i1} as a control in a cross section regression.

In the study of FFS training in China, India and Pakistan, the DD-model takes the form of a logarithmic growth model. Growth in performance, i.e. pesticide use, environmental impact quotient (EIQ) score, cotton yield, and gross margin, is explained by the training intervention and other socio-economic characteristics of the farmers on a country by country basis. The model differentiates among three groups of farmers. The first group comprises farmers participating in the FFS training (FFS group). The second group consists of farmers who were not participating in the training but living in the same village (Non-FFS group). Thus, the Non-FFS farmers may be able to capture some knowledge from FFS group, i.e. there is a spill over effect. The last group is the control group; farmers who were not participating in the

FFS and live in a different village, but with similar socio-economic conditions as the FFS village.

The DD-model is formulated using data collected prior to and after the training when trained farmers had the opportunity to apply this new knowledge and the Non-FFS farmers were likely to be exposed to new information and able to observe the IPM practices of trained farmers.

In this study, the DD-model is specified as follows:

$$\Delta(\ln Y_{ijt}) = \alpha + \beta D_{Nijt} + \mu D_{Gijt} + \gamma \Delta X_{ijt} + \delta \Delta Z_{ijt} + \Delta \varepsilon_{ijt} \quad (3.7)$$

For farmer i in village j and time period t , Y denotes the cotton production performance indicators such as yield or pesticides use. Unobserved determinants are fixed over time, which could affect outcomes at either household or village level. D_N and D_G denote the dummy variable for Non-FFS and FFS farmers respectively. The differencing operator Δ denotes the difference between the time of pre-training and post-training. X and Z are the vectors of household and farmer characteristics that also may affect performance. The corresponding vectors of parameters are γ and δ ; ε is the residual that represents all time-varying components of the error. And e denotes the exponential operator. The growth in performance (α) is identical among all three groups of farmers prior to the training, and the control farmers maintain the original rate of performance growth (α) throughout the period. The growth rate is expected to improve for both FFS and Non-FFS farmers after program exposure. With respect to output indicators (yield and gross margin) after the training, FFS farmers are assumed to switch to higher performance growth (μ). In addition, the improvement among FFS is expected to be greater than among Non-FFS farmers. Therefore, the hypothesis is that the growth rate of FFS exceeds those of Non-FFS and the latter exceeds those of the control group (i.e. $\mu > \beta > \alpha$). Regarding pesticide input and environmental indicators, the hypothesis is the other way around (i.e. $\mu < \beta < \alpha$) (Feder et al. 2003).

To minimize the effects from other factors beyond the program intervention and some unobserved differences between the treatment and control groups in the initial time period, panel data of the same respondents between pre- and post- FFS training for participant and non-participant farmers are used. A full description of the variables used in the model is described in Chapter 5.

Fixed-effects estimator

In order to analyze the total impact of FFS training for large cotton producing countries in Asia, the combined panel data of the three countries were used. Here two different estimation methods can be distinguished, i.e. a fixed-effects model or a random-effects model (Verbeek 2004). The choice between the two models can be made by applying the Hausman test. The idea of the test is to compare the estimation results of the fixed-effects and the random-effects. If these are not statistically different from one another, it is safe to use the random-effects model (Baum 2006; Park 2008a).

For this study, a fixed-effects model was used as by the Hausman test, the hypothesis that the difference in coefficients is not systematic was strongly rejected.

Equation (3.8) shows the general form of a panel data model, which considers the linear unobserved effects model for T time periods, where x_{it} is vector of variables that vary over individual and time, β is vector of coefficients on x_{it} , U_i is the unobserved or individual effect, ε_{it} is the disturbance term, N is the number of individuals and T is the number of time periods.

$$Y_{it} = \beta X_{it} + U_i + \varepsilon_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T \quad (3.8)$$

The structure represented in equation (3.8) might be restricted to allow for heterogeneity across individuals without the full generality (and infeasibility) that this equation implies. In particular, it might be restricted to make the slope coefficients constant over both individuals and times and allow for an intercept coefficient that varies either over individuals or time.

$$\bar{Y}_i = \beta \bar{X}_i + U_i + \bar{\varepsilon}_i, \quad i = 1, \dots, N \quad (3.9)$$

where $\bar{Y}_i = T^{-1} \sum_{t=1}^T Y_{it}$, $\bar{X}_i = T^{-1} \sum_{t=1}^T X_{it}$, $\bar{\varepsilon}_i = T^{-1} \sum_{t=1}^T \varepsilon_{it}$. U_i is called “fixed-effects” when it is treated as a parameter to be estimated for each cross section observation i . The fixed-effects model rests on the assumptions that U_i are uncorrelated with ε_{it} and are allowed to be arbitrarily correlated with X_{it} . The model controls for omitted variables that change over time but are constant between cases. Thus the model allows us to use the variation between cases in order to estimate the effect of omitted independent variables on the dependent variable.

Subtracting equation (3.9) from equation (3.8) for each t gives the fixed-effects transformed equation,

$$Y_{it} - \bar{Y}_i = \beta (X_{it} - \bar{X}_i) + \varepsilon_{it} - \bar{\varepsilon}_i \quad (3.10)$$

or

$$\ddot{Y}_{it} = \beta \ddot{X}_{it} + \ddot{\varepsilon}_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T \quad (3.11)$$

where $\ddot{Y}_{it} \equiv Y_{it} - \bar{Y}_i$, $\ddot{X}_{it} \equiv X_{it} - \bar{X}_i$, and $\ddot{\varepsilon}_{it} \equiv \varepsilon_{it} - \bar{\varepsilon}_i$. The time demeaning of the original equation has removed the individual specific effect U_i .

In this study, the general fixed-effects model can be specified as:

$$\ddot{Y}_{it} = \alpha + \mu D_{Git} + \beta D_{Nit} + \sigma E_t + \gamma \ddot{X}_{it} + \delta \ddot{Z}_{it} + \ddot{\varepsilon}_{it} \quad (3.12)$$

For farmer i and time period t , where \ddot{Y}_{it} are performance indicators of cotton production activities. D_{Git} and D_{Nit} denote the dummy variable for FFS and Non-FFS farmers respectively; μ and β are the vectors of coefficients on D_{Git} and D_{Nit} ; α denotes a vector of coefficient on the control farmers. E_t denotes the time dummy variable, which is pre- and post-training periods; σ is the vectors of coefficients on

E_t . \ddot{X}_{it} and \ddot{Z}_{it} are the variables of household and farmer characteristics; γ and δ are the vectors of coefficients on \ddot{X}_{it} and \ddot{Z}_{it} , respectively., and $\dot{\varepsilon}_{it}$ is the idiosyncratic error. The individual-level effect controls for unobserved factors variation among three countries.

Both DD and fixed-effects models were applied to the data set of the three countries in order to test for the causality between program intervention and practice change. The measured differences then served as a basis for calculating the welfare effects and efficiency of the program investment.

Investment Efficiency

Typically, there are three investment criteria that are used in cost-benefit analysis, i.e. net present value (NPV), internal rate of return (IRR), and benefit-cost ratio (BCR).

The NPV is defined as the sum of the present values of the cumulative cash flow induced by an investment generated over a defined time period. Costs and benefits of the project that occur in future periods are discounted. For a constant discount rate, the difference in the cumulative discounted benefits and costs can be defined as NPV (Kingma 2001; Perkins 1994):

$$NPV = \sum_{t=0}^n \frac{B_t - C_t}{(1+r)^t}$$

where B_t represents benefits of the project, C_t denotes the project costs, r is the discount rate, and n is the number of time periods for which the project will operate. A project is acceptable if the NPV exceeds zero.

The most common measure for assessing the efficiency of the project's investments is the internal rate of return (IRR). The IRR is the discount rate, r^* , at which the project's NPV equals zero. Thus the IRR is a measure of the actual investment efficiency regardless of the discount rate. (Brent 2006; Kingma 2001; Perkins 1994):

$$NPV = \sum_{t=0}^n \frac{B_t - C_t}{(1 + r^*)^t} = 0$$

In financial analysis, the IRR can be interpreted as the maximum interest rate that the project could afford to pay and still recover all investment and operating costs. In this analysis, r^* is called the financial internal rate of return (FIRR); in economic analysis, it is called the economic internal rate of return (EIRR). An investment is efficient from a private point of view if the IRR exceeds the opportunity costs of capital and from the society's point of view if it exceeds the social rate of time preference.

The third investment criterion used to measure the efficiency of investment is the benefit-cost-ratio (BCR). Its computation is similar to that of the NPV but it is expressed as a ratio of the sum of a project's discounted benefits to the sum of the project's discounted costs. With the help of this ratio it is easy to show the impact of a rise in costs or fall in benefits on the project's feasibility (Perkins 1994).

The ratio can be expressed mathematically as:

$$BCR = \frac{\sum_{t=0}^n \frac{B_t}{(1+r)^t}}{\sum_{t=0}^n \frac{C_t}{(1+r)^t}}$$

A program is deemed to be acceptable if the BCR is greater than or equal to one.

In the case of FFS training in cotton in the three countries, the investment efficiency in the context of a financial analysis has been calculated using the three investment criteria outlined above. The assumptions for the programs benefits were derived from the statistical analysis, while the econometric models were used to test the attribution between the program intervention and the outcome, and thus establish evidence of impact. Hence, in this calculation only a partial welfare analysis was applied based on the data available.

As a final step in the methodology applied to assess the impact of the “FAO-EU IPM Program for Cotton in Asia”, the Dynamic Research Evaluation for Management (DREAM) model developed by the International Food Policy Research Institute (IFPRI) was also applied. Based on the conceptual framework of economic surplus as explained above, DREAM is designed to evaluate the economic impacts of agricultural research and development (R&D). It is simulated for market processes, technology adoption, spill over effects, and trade policy scenario based on flexible, multi-market, partial equilibrium model (Alston et al. 1995; Wood et al. 2001). A detailed explanation of the assumptions used is presented in Chapter 6.

3.2 Survey methodology

3.2.1 Study areas

A decision by program organizers to place the FFS program in villages might be to make program management more convenient. Therefore, village selection bias should be taken into concern. The study sites for the impact assessment study were chosen using a multi-stage sampling procedure. First, the provinces and district were selected purposively in cotton growing areas and thereafter in these districts the FFS were selected at random from all the FFS villages.

In China, the provinces of Shandong, Anhui, and Hubei were included (Figure 3.4). In each province, two townships in one county were selected. Shandong province, Lingxian County has the largest agricultural area of the province and is located in the northwestern part of the province. FFS training was conducted in the township of Mi. In Dingzhuang Township, three control villages were included in the survey.

In Anhui province, Dongzhi County located in the southwest of the province with the townships of Dadukow and Xiangyu were selected as the study areas. The townships are about 70 km apart and are both major cotton-growing areas. Again, three FFS and three corresponding control villages were selected in both townships. In Hubei province, Yingcheng County in the centre of the province was selected. Here too, three FFS and three control villages per townships were selected.

Figure 3.5 presents the locations of the sample in India. The districts of Raichur and Bellary in Karnataka State were selected for the investigation. In each of the two

districts, five FFS villages and corresponding control villages, at least 30 km apart, were selected.

In Pakistan, the survey was carried in two areas of Sindh province, namely the districts of Khairpur and Sukkur. Khairpur district is located in northern part of Sindh province where four FFS villages were randomly selected from different clusters of FFS situated in four adjacent Tehsils² (Figure 3.6). For every FFS village, a respective control village was chosen within a 20 km radius in Sukkur district. These were nearly 60 km away from the nearest FFS villages in Khairpur district.

² A tehsil (or tahsil, taluk, taluka, mandal) is an administrative division of Pakistan, India and some countries of South Asia. It consists of a city or town as its headquarters, possibly additional towns, and a number of villages.

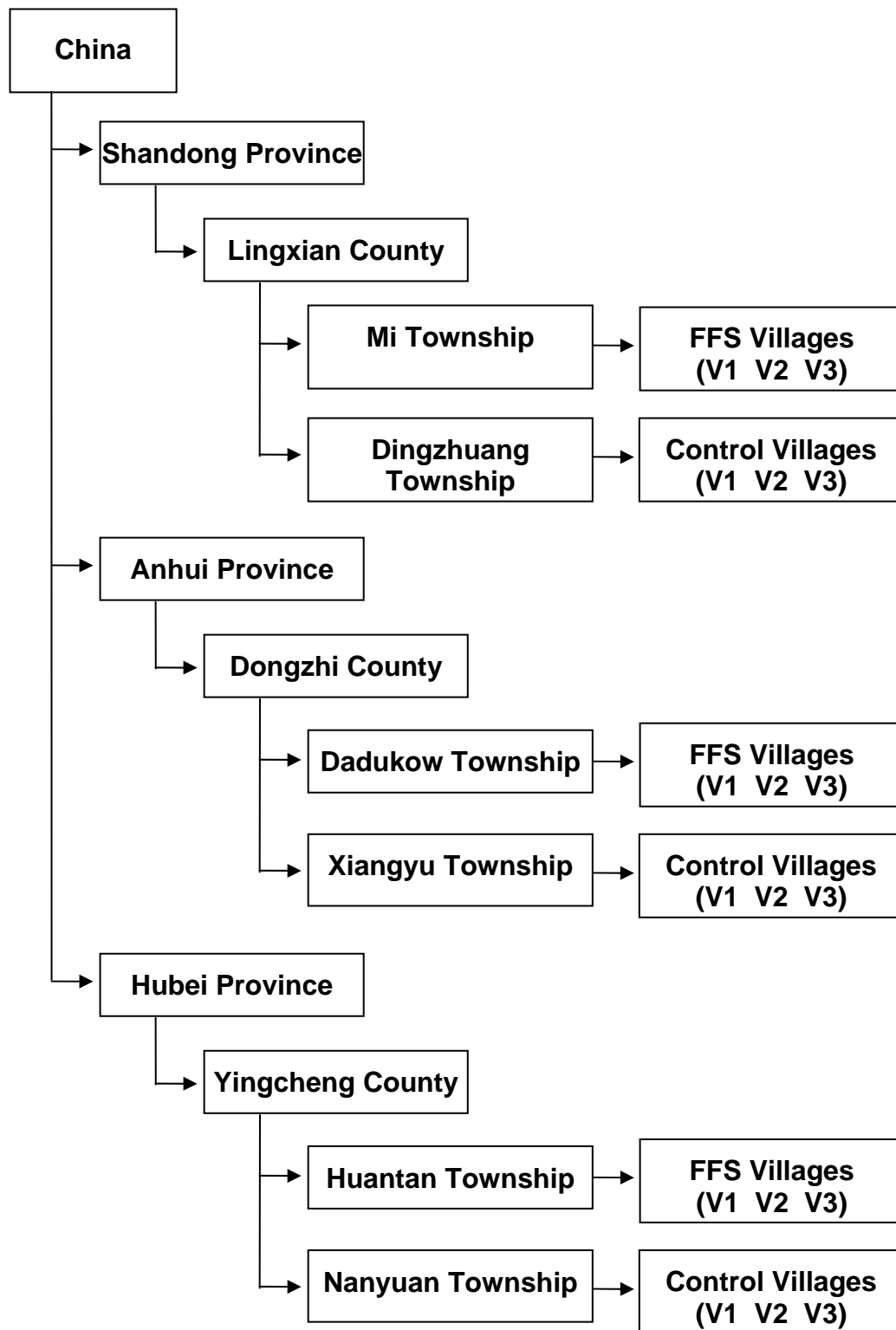


Figure 3.4: Chart of survey sampling in China

Source: FAO-EU IPM Program for Cotton in Asia

Note: V denotes village number.

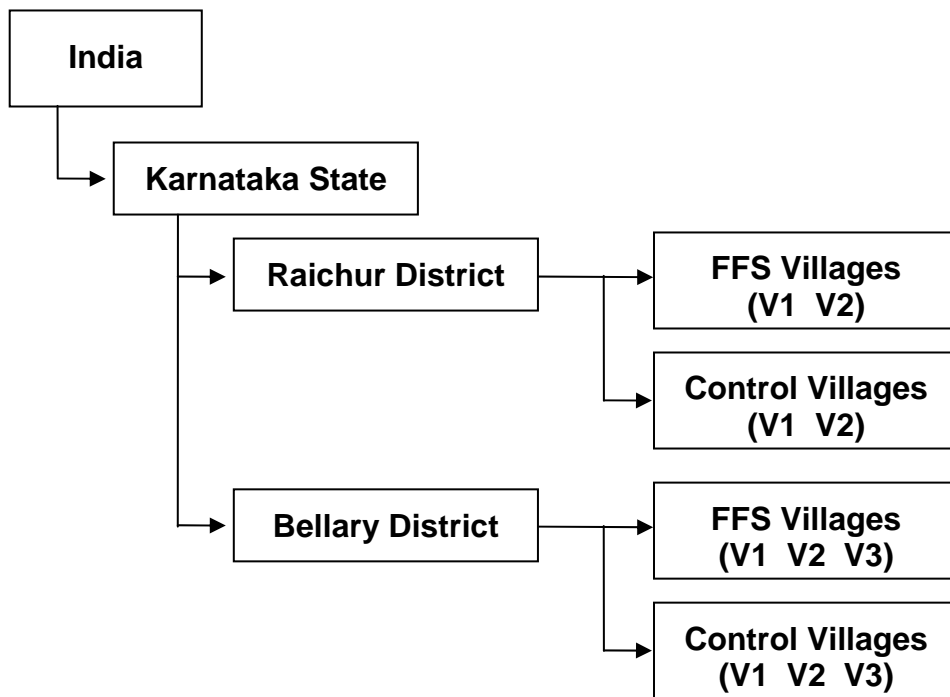


Figure 3.5: Chart of survey sampling in India

Source: FAO-EU IPM Program for Cotton in Asia

Note: V denotes village number.

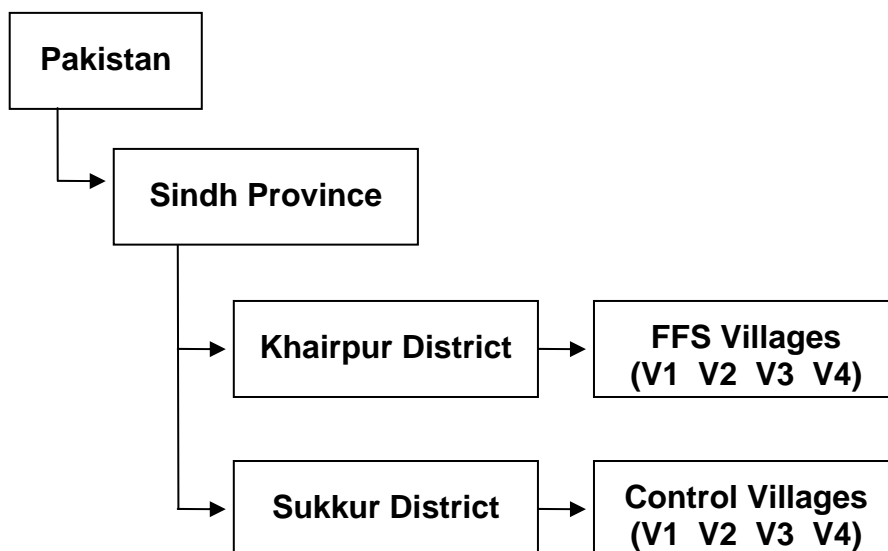


Figure 3.6: Chart of survey sampling in Pakistan

Source: FAO-EU IPM Program for Cotton in Asia

Note: V denotes village number.

Table 3.2 provides an overview of the samples in the three countries for the baseline survey. The largest sample was from China, but it also had the largest variation, as three provinces were included. The smallest village sample is from Pakistan with only four FFS villages. Here the training started one year later than in the other two countries.

Table 3.2: Number of FFS villages in three countries in the baseline survey

Country	Province /State	District /County	Control Village	FFS Village	Training year
China	3	3	9	9	2001
India	1	2	5	5	2001
Pakistan	1	1	4	4	2002

Source: FAO-EU IPM Program for Cotton in Asia

Note: Figures are same for control villages

3.2.2 Survey design

The data collection procedure included two surveys. First, a baseline survey prior to training was carried out, and secondly a follow-up survey in the cotton season after the training. Hence, a two-year panel database was established.

In the sample, a differentiation was made among three different groups of farmers. These groups were: (i) farmers who participated in the FFS training, i.e. the FFS graduates. These farmers were normally selected by the extension workers and village leaders on the basis of their willingness to participate, but no definite rules were established, so that the possibility of selection bias cannot be excluded; (ii) a random sample of farmers who live in the FFS villages but who did not attend the training. Again, it is not known if farmers who actually wanted to participate in the training but were denied were included in this group. The third group of farmers from whom data were collected were farmers from a so-called control village. For the selection of these villages, the program had established clear criteria, which assured that the control villages have similar agro ecological and socio-economic conditions to the FFS villages. At the same time, these villages were sufficiently distant in order to minimize the likelihood of information exchange between control and FFS villages. The control village was located at least 30 km apart from the nearest FFS village. It was ascertained that the control village was not targeted for inclusion in FFS training

at a later point in time in order that the counterfactual would remain for the follow-up survey.

3.2.3 Data collection

The data used in this study were collected by survey teams of the FAO-EU IPM Program for Cotton in Asia. In each country, the program contracted an institution that was entrusted with data collection following a common methodology. In China, the National Agro-technical Extension and Service Center (NATESC), which was also the main partner of the program, was entrusted with the data collection. In India, a team of private consultants headed by a former university professor in agricultural extension and concurrently head of a NGO called “Participatory Rural Development Initiatives Society” was contracted. Finally, the Social Sciences Institute of the National Agricultural Research Centre in Pakistan was given the task of collecting the data.

The questionnaire included sections on village and household characteristics, household income, agricultural production activities especially cotton, pesticide use and its influence on health. Particular emphasis was given to knowledge, perception and practices in pest management for cotton as this was the main content of the FFS training. The questionnaire of the baseline survey was applied as a recall survey asking farmers about the previous season. In the impact survey, farmers had been monitored throughout the season.

All survey teams were trained in the survey methodology and in the concept of impact assessment in a workshop in 2001. The teams were also instructed on the concept of FFS, survey design and methodology; and were provided with the methodology of statistical and econometric analysis for the data that they collected. The training workshop encouraged the country teams to carry out their own data analysis on special aspects of the program. For example, an impact study using an econometric approach was carried out by Wu et al. (2005) using data from one of the three provinces in China. In India, a study using descriptive statistics as methodology analysed the effects of FFS on farmers’ knowledge (Reddy and Suryamani 2005). In Pakistan, the effect of FFS on rural poverty was investigated using parametric statistical tests to compare different income groups before and after FFS training

(Khan and Ahmad 2005). However, only this study undertakes a comparison among the three countries.

Table 3.3 provides an overview of the total number of farmers included in the samples for both years. A large variation in attrition is observed between the baseline and the follow-up survey. In China, attrition rates were low at 1%. In Pakistan, it was 14%, which is acceptable. However, attrition was high in India where 29 % of the farmers could be retained. This is due to the decision of farmers to refrain from cotton production in the second year.

Since the study was on cotton, only farmers who grew cotton in both survey years were included in the sample. On the other hand, in the FFS villages no limit was set on training participation, i.e. regardless how often farmers attended the training sessions, they were retained in the sample.

The reason for the high rate of attrition in India was late arrival of the monsoon, which prompted many respondents to shift to other crops. In addition, one control village was excluded because of unreliable information on yield and pesticide use. Nevertheless, India was retained in the sample for comparison and for use in the pooled sample.

In total, 808 respondents were included in the analysis of the impact of FFS training, which can be considered as one of the largest samples in contrast to many of the other studies on FFS (see van den Berg 2004).

Table 3.3: Numbers of farmers who were interviewed pre- and post-FFS training

Country	Pre-FFS training				Post-FFS training				% remaining
	FFS	Non-FFS	Control	Total	FFS	Non-FFS	Control	Total	
China	180	180	180	540	177	178	180	535	99%
India	97	97	97	291	37	30	16	83	29%
Pakistan	90	70	60	220	78	59	53	190	86%
Total	367	347	337	1,051	292	267	249	808	77%

Source: FAO-EU IPM Program for Cotton in Asia

Note: FFS = farmers who participated in FFS training

Non-FFS = farmers who did not participate in FFS training but live in the same village as FFS farmers

Control = farmers who did not participate in FFS training and live in another village

3.3 Summary

This chapter first described the theoretical background of impact assessment and outlined the research methodologies, including the econometric models that are used in the analysis of the impact of Farmer Field Schools in cotton in China, India and Pakistan. Second, the data collection procedure including the survey designs, the sampling methods and a brief description of the study areas were provided.

In the first section of the chapter, it was pointed out that the demand for impact assessment is increasing because of the greater importance donors place on: (i) accountability for the use of scarce public funds, (ii) evidence of the net social benefits of investments, and (iii) improvements to a research and development program.

The construction of an impact pathway first applied to IPM by Bennett (1975) illustrates the process of impact assessment by analogy to the steps of a staircase. The starting point or first step consists of inputs, and the final step is the increase in income of the target group or welfare gain to the society.

In this study, the concept of economic surplus as a basis for cost benefit was used. In addition, non-market effects of pesticides were included through an indexing method, i.e. the environmental impact quotient.

The analytical methods used in this study are statistical tests (T-test and F-test), and econometric models. The latter are Difference-in-Differences and fixed-effects models.

The farm level panel data were collected before and after the FFS training was conducted, with the same households being interviewed in each case. Farmers were classified into a participant group (FFS group) and two non-participant groups (Non-FFS and control group). The Non-FFS farmers are living in the same village as the participating farmers, and hence comparison between them can be used to assess the degree of diffusion. The control group consists of non-participants, who live in different villages to farmers in the first two groups.

Based on the methodology of IPM assessment, and the theoretical aspects that have been discussed before, the following hypotheses of this study are established:

- (1) In different socio-economic conditions in the three countries, FFS training based on IPM practices could help farmers to reduce over-usage of pesticide, increase cotton yield and gain more profit. Consequently, negative externalities will be reduced due to a decrease in pesticide usage.
- (2) The benefits of FFS training occur primarily at the national level, but positive externalities can be achieved by an increase in production and a decrease in cotton price at international cotton markets. Therefore, both cotton producers and consumers can benefit from public investments in FFS.

In the next chapter, a descriptive analysis of baseline data of farm household and cotton production in the three countries are presented.

4 Description of farm households and cotton production

In this chapter, the study areas for the impact assessment in the three countries are introduced in some detail. This will give a better understanding of the natural and socio-economic conditions that affect cotton production and productivity.

The first part of the chapter introduces the geographic location and some demographic, socioeconomic and administrative features of the study sites in the three countries separately. The locations are the provinces of Shandong, Anhui and Hubei in China, the state of Karnataka in India and Sindh province in Pakistan.

In the second part of the chapter, comparisons of farm household characteristics, the input structure, and productivity are shown, as well as costs and returns of cotton production. Here a distinction is made among three farmer groups, as introduced in chapter 3, namely farmers trained in Farmer Field Schools (FFS), non-trained but exposed farmers living in the same village (Non-FFS group), and non-trained and non-exposed farmers from a neighboring village, where no FFS training was conducted (control group). The data used for the descriptive analysis are those collected from the baseline survey before start of FFS training. In China and India, the baseline surveys were carried out in 2000, while in Pakistan it was one year later.

4.1 Description of study areas

4.1.1 China

Field surveys in China were conducted in Shandong, Anhui and Hubei provinces. The provinces are located on the eastern edge of the north, east, and central part of China, respectively (see Figure 4.1).



Figure 4.1: Map of Shandong, Anhui and Hubei province in China

Source: Applied from Economic Research Service: USDA (2009a)

Shandong is one of the major agricultural areas in China with a variety of crops, including cotton, wheat, sorghum and maize. Anhui is more mountainous and cotton is less important.

In Shandong province, data were collected in Lingxian County, located in the northwestern part of the province. The area is predominantly rural with a comparatively low population density. Over 90% of the population are engaged in agriculture (UNESCAP 2006b).

In Anhui province, which is located between the basins of the Yangtze River and the Yellow River, data were collected in Dongzhi County. The area is predominantly agricultural with a large variety of annual and perennial crops. Among the cash crops cotton is important but farmers can also switch to other crops such as tobacco and medicinal plants (Anhui Agriculture Information Net 2006).

The third area where data was collected is in Hubei province, which is host to the “Three Gorges Dam”, the largest hydroelectric dam in the world. Hubei province ranks first in crop production in China with a range of crops, including cotton. The study area is located in Yingcheng County, in the centre of Hubei province. Agriculture is the main source of livelihood for about 90% of the population (UNESCAP 2006a).

4.1.2 India

In India, data were collected in Karnataka state (Figure 4.2), which is located in the western part of the country, with a coastline on the Arabian Sea in the west. The state capital is Bangalore, a rapidly growing city with a concentration of IT industries. However, over three fourths of the provincial population is rural and around 71% of the work force is engaged in agriculture, which contributes about half of the total income of the state.

The study areas are located in the Bellary and Raichur districts. Bellary district is located in the eastern part of the state. It is mainly agricultural with about one third of its cultivable area irrigated. The district of Raichur is also predominantly rural but the share of irrigated land is lower with 22% of the cultivable area. In both districts cotton is an important cash crops but farmers can also grow other crops such as maize, wheat, pulses and ground nuts (National Information Centre of Karnataka State 2006).

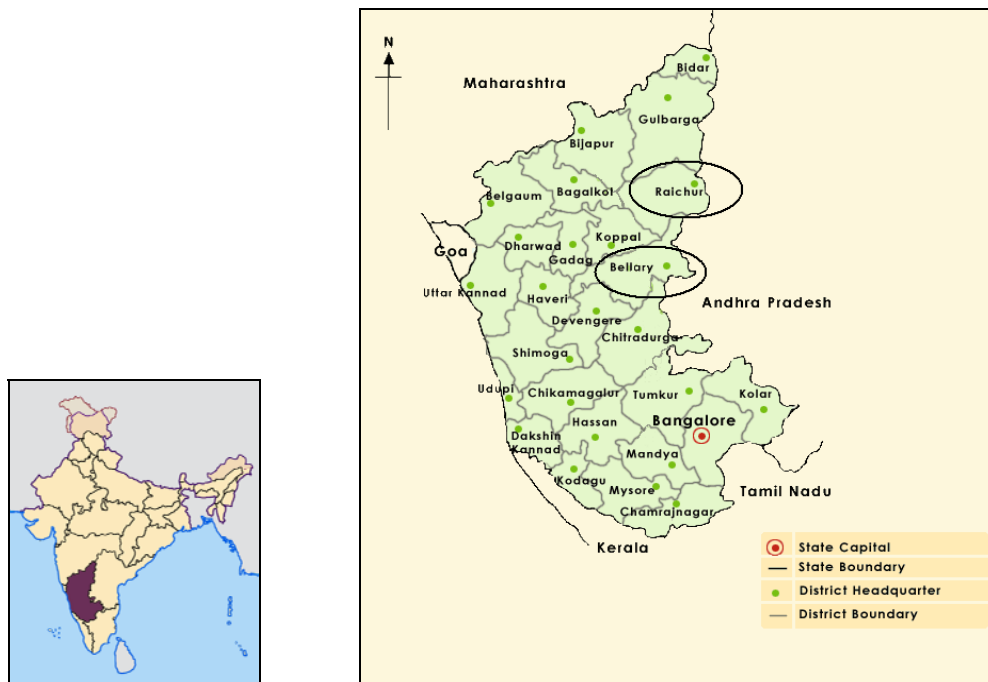


Figure 4.2: Map of Bellary and Raichur districts of Karnataka state in India

Source: Map of India (2006)

4.1.3 Pakistan

The study site in Pakistan was located in the districts of Khairpur and Sukkur in the province of Sindh (Figure 4.3). It is the third largest province in Pakistan, situated in the southeastern part of the country with a population of over 30 million, equivalent to about one fourth of the total population of Pakistan. The two districts are located along the fertile plain of the Indus River. They are dominated by a rural population that continues to grow at a rate close to 3% per year. In terms of livelihood activities in both districts, cotton is a major crop but others such as sugarcane, rice and maize are also important, among others. In Sukkur district the fishing industry is important in addition to agriculture (Development Statistics of Sindh 2006).



Figure 4.3: Map of Khairpur and Sukkur districts of Sindh province in Pakistan

Source: Pickatrail (2006)

Comparing the economic conditions in the three countries shows that all study areas are dominated by agricultural activities. However, production conditions differ with regard to cropping system and infrastructure. The most advanced agricultural infrastructure in terms of irrigation exists in China, while in India rain-fed cotton is dominant. In all the study areas farmers grow cotton along with a range of other crops.

4.2 Comparison of household characteristics, costs and returns of cotton production

4.2.1 Country comparison of household characteristics

This section shows the profiles of the agricultural households included in the samples of all the three countries. Table 4.1 gives an overview of some household characteristics such as family size, educational level, gender, age of household head, cropping pattern and annual income. The data in Table 4.1 are country averages for all three groups of farmers derived from the baseline surveys.

It is shown that when comparing the three countries there are both differences and similarities. Differences exist in household size, which is lowest in China and highest in Pakistan, thus reflecting differences in population policy among the three countries.

Pakistan has the highest average annual income per capita, while in China farmers' income is \$50/year less than those in Pakistan. On average, the sampled farmers in all three countries are rather poor in comparison to the World Bank's official statistic³ (The World Bank 2002b, 2003).

Education, as measured by the number of years schooling of the respective household heads, is highest in Pakistan and lowest in India. Hence cotton farmers in Pakistan are among the better educated as compared to the overall education level in Pakistan. With regard to gender, male-headed households are dominant, and only in China was there a considerable share of female-headed households.

In all the three countries, the majority of farmers in the sample are comparatively young, with most of the household heads below 45 years of age. In China, the proportion of household heads that are older than 45 years is highest.

Cropping area per household differs greatly among the countries. As expected it is smallest in China and highest in Pakistan, although India is almost level with Pakistan. Compared to the average farm size in the respective countries, the farmers

³ In China and India, the Gross National Income (GNI) per capita in 2000 amounts to 780 \$ and 450\$, respectively. In Pakistan, the GNI per capita in 2001 accounts for 470 \$.

included in the sample are among the larger farmers in India and Pakistan. Little differences exist in the share of cotton in the cropping area, which indicates the degree of specialization in this crop. In Pakistan and China, the share is over one third, while it is below 30% in India. This difference is also reflected in the share of cotton in the total household cash income. This is over 40% in China and Pakistan, but only 20 % in India.

Table 4.1: Household and farm characteristics before training in China, India and Pakistan, crop years 2000 (China and India), 2001 (Pakistan)

Parameters	Countries		
	China	India	Pakistan
Number of observation (N=808)	535	83	190
Household size (persons)	4.32 (1.17)	6.31 (2.05)	12.17 (6.58)
Household income (\$/capita/year)	259.64 (126.31)	299.61 (297.52)	308.24 (236.17)
Household head's educational level (years of schooling)	6.80 (2.39)	4.51 (4.38)	7.50 (5.64)
Household head: Male (%)	69.72	99.80	100.00
Average age of household head (years)	_ ^{1/}	34.31 (8.37)	38.54 (13.96)
Age: ≤ 45 years (%) ^{2/}	57.01	90.36	71.79
Age: > 45 years (%) ^{2/}	42.99	9.64	28.21
Crop area (ha) ^{3/}	0.82 ^{4/} (0.32)	5.28 (4.61)	5.60 (5.09)
Cotton area (ha)	0.29 (0.19)	1.57 (1.45)	2.18 (1.97)
Other crops area (%)	73.17 ^{4/}	70.08	61.07
Cotton income (\$/household/year)	460.54 (320.11)	369.73 (295.28)	1,524.50 (1,527.89)
Cotton income (%)	43.35	21.25	43.99

Note: Standard deviation is shown in parentheses.

^{1/} China's data is not available.

^{2/} Range of age was set because data in China was not specified in more detail.

^{3/} The crop area means cultivated area in a whole year.

^{4/} Because Hubei's data are not available, it is estimated by Shandong and Anhui's data

Source: own calculations

4.2.2 Comparison of household characteristics of farmer groups by country

In this section, a comparison of the three groups of farmers on a country-by-country basis is presented. The purpose of the analysis is to identify similarities and differences between farmers who participated in the FFS training, those who did not participate in the training but live in the same village and those who live in control villages. The parameters include household characteristics, household income and cropping pattern. Since the data refer to the situation before the training, comparison of the parameters allows some conclusions about the role that factors other than training will play in differences in cotton productivity observed before and after FFS training.

Table 4.2 shows household and farm characteristics in China before FFS training for the three farmer groups. The results show that household size is constant, with about four members across the three groups. The small household size is a reflection of the family planning policy in China. On a per capita basis, average household income is below the international poverty line, but with very little differences among the three groups.

Education, as measured in the average years of schooling of the household head, shows little difference and is remarkably high, ranging between 6.5 and 7.2 years. The difference between FFS and Non-FFS farmers is minimal, suggesting that either education is fairly uniform in the villages in China or that education was not a criterion for selecting farmers to participate in the training.

For the criterion “age of household head”, only the age category was known. Accordingly, the proportions below and above 45 are close to unity. In terms of gender, overall there is a dominance of male-headed households, which is least pronounced in the FFS villages, where over 40% of the household heads are women.

Farm size is below 1 ha for all three groups and cotton area amounts to about 25% to 30%. Hence the degree of specialization in cotton is low, which is also reflected in the share of cotton in household income. Summarizing the comparisons made above it is safe to say that the three farmer groups are fairly similar in China even though the sample in China was drawn from three provinces.

Table 4.2: Household and farm characteristics before training by farmer category in China, crop year 2000

Parameters	Farmer Category		
	FFS	Non-FFS	Control
Number of observation (N = 535)	177	178	180
Household size (persons)	4.40 (1.12)	4.27 (1.29)	4.29 (1.11)
Household income (\$/capita/year)	234.95 (101.60)	257.58 (132.21)	285.67 (137.21)
Household head's Educational level (years of schooling)	7.20 (2.19)	6.71 (2.35)	6.50 (2.58)
Household head: Male (%)	57.63	62.92	88.33
Age: ≤ 45 years (%) ^{1/}	62.71	53.93	54.44
Age: > 45 years (%) ^{1/}	37.29	46.07	45.56
Crop area (ha) ^{2/3/}	0.78 (0.31)	0.78 (0.30)	0.91 (0.34)
Cotton area (ha)	0.26 (0.12)	0.25 (0.10)	0.35 (0.28)
Other crops area (%) ^{3/}	69.23	69.23	79.12
Cotton income (\$/household/year)	417.14 (215.17)	402.27 (183.81)	560.84 (459.80)
Cotton income (%)	42.55	39.41	47.42

Note: Standard deviation is shown in parentheses.

^{1/} Range of age was set because data in China was not specified in more detail.

^{2/} The crop area means cultivated area in a whole year.

^{3/} Because Hubei's data are not available, it is estimated by Shandong and Anhui's data

Source: own calculations

Table 4.3 presents features household and farm characteristics of the three groups of Indian farmers before FFS training. The results show that household size is fairly similar among the three groups, although FFS households are somewhat larger. For household income, FFS farmers earn the most, while the incomes of the Non-FFS group and farmers in control village are only 55% and 77% of the income of FFS farmers respectively. Considering the education level of farmers, the average years of schooling range from just over four to almost five years, with the highest level in the FFS group. Most household heads in the three farmer groups are young males aged below 40 years. Cotton is not the major source of income, as only 18% to 32% of the household incomes are from cotton. FFS farmers have the highest crop area

among the three groups but are least specialized in cotton as their proportion of cotton corresponds to only around 20% of total crop area. It is higher among the control farmers, with around 50%. The results demonstrate that Non-FFS and control farmers have smaller cropping areas and are poorer than FFS farmers. However, for all the three groups per capita income shows that the average household is below the international poverty line. Hence the differences in income in favor of the FFS group may not matter that much, as all farmers in the sample belong to the poorer segment of the rural population.

Table 4.3: Household and farm characteristics before training by farmer category in India, crop year 2000

Parameters	Farmer Category		
	FFS	Non-FFS	Control
Number of observation (N = 83)	37	30	16
Household size (persons)	6.70 (2.28)	5.97 (1.85)	6.06 (1.77)
Household income (\$/capita/year)	377.57 (379.59)	207.69 (147.09)	291.71 (253.60)
Household head's educational level (years of schooling)	4.97 (4.87)	4.13 (4.38)	4.13 (3.16)
Household head: Male (%)	100.00	100.00	93.75
Average age of household head (years)	32.27 (7.77)	36.70 (9.67)	34.56 (5.94)
Age: ≤ 45 years (%)	97.29	80.00	83.33
Age: > 45 years (%)	2.70	20.00	16.67
Crop area (ha) ^{1/}	6.27 (4.63)	4.25 (4.56)	4.91 (4.49)
Cotton area (ha)	1.65 (1.55)	1.32 (1.21)	2.33 (2.22)
Other crops area (%)	76.87	68.94	52.75
Cotton income (\$/household/year)	405.29 (236.32)	255.56 (188.54)	501.55 (475.51)
Cotton income (%)	17.98	21.50	31.66

Note: Standard deviation is shown in parentheses.

^{1/} The crop area means cultivated area in a whole year.

Source: own calculations

It is shown in Table 4.4 that cotton producers in Pakistan have large households with around 12 members, which is generally the case among all three farmer groups. The same is true for household income, which does not differ much among the three groups. It is also shown that on a per capita basis household income in the Pakistan sample is below \$330 per year, which is below the international poverty line of \$1.25 per capita per day.

A marked difference exists in the education level of the farmers in the three groups. As becomes clear from Table 4.4, the average education level of household heads in the FFS farmer group is almost twice that of farmers in the FFS village who did not participate in the training. This indicates that farmers participating in the training tend to be more educated than other farmers, which suggests that there could be a selection bias, considering that the Non-FFS farmers were chosen at random from the village population. More importantly, farmers in the control village also have a lower education level, with about three years less in schooling. To some extent the difference in education is also reflected in the ages of the heads of households. While the average ages of FFS and farmers in the control villages are similar, Non-FFS farmers are about 10 years older on average. However, in general the majority of the farmers in all groups are fairly young. In Table 4.4, it is shown that 60% to 85% of the farmers are below 45 years of age.

Regarding the scale of cotton production and the degree of specialization in cotton, it is shown that farmers in the control village have larger cotton areas and a higher share of cotton than farmers in the FFS village. However, the share of cotton is below 50%, which means that other crops also play an important role. This is reflected in the share of income from cotton, which is around 50% on average but is highest in the control villages.

In conclusion, the comparison of the three groups shows that in most parameters, farmers are similar. The only exception is the years of formal schooling, which is highest in the FFS village. Hence the knowledge effect of FFS training could be influenced by these differences in initial conditions.

Table 4.4: Household and farm characteristics before training by farmer category in Pakistan, crop year 2001

Parameters	Farmer Category		
	FFS	Non-FFS	Control
Number of observation (N = 190)	78	59	53
Household size (persons)	12.44 (6.25)	11.95 (7.67)	12.04 (5.81)
Household income (\$/capita/year)	302.73 (198.83)	328.20 (303.49)	294.12 (201.86)
Household head's educational level (years of schooling)	7.5 (5.64)	3.95 (4.37)	4.36 (4.37)
Household head: Male (%)	100.00	100.00	100.00
Average age of household head (years)	36.51 (13.93)	44.62 (13.66)	34.83 (12.33)
Age: ≤ 45 years (%) ^{1/}	71.79	61.02	84.91
Age: > 45 years (%) ^{1/}	28.21	38.98	15.10
Crop area (ha) ^{2/}	5.25 (6.22)	5.32 (4.30)	6.44 (3.88)
Cotton area (ha)	1.95 (2.23)	1.91 (1.72)	2.82 (1.68)
Other crops area (%)	62.86	63.91	56.21
Cotton income (\$/household/year)	1,470.42 (1,819.49)	1,293.90 (1,296.67)	1,860.79 (1,235.87)
Cotton income (%)	40.66	37.48	57.14

Note: Standard deviation is shown in parentheses.

^{1/} Range of age was set because data in China was not specified in more detail.

^{2/} The crop area means cultivated area in a whole year.

Source: own calculations

4.2.3 Country comparison of costs and returns of cotton production

This part presents costs and returns of cotton production in the three countries. A breakdown of the major production inputs is provided, including material inputs and their costs as well as for hired and family labor. The detailed information allows calculation of the gross margins per ha of cotton, which can be compared across the three countries and among the three farmer groups. As in the presentation of the farm and household characteristics, the data are taken from the baseline survey. Hence the comparisons among the three farmer groups give an indication of the differences in productivity prior to FFS training.

Table 4.5 presents the costs and returns of cotton production before FFS training in the three countries. Comparing cotton yields, China clearly stands out with an average yield of more than 3 tons per ha. In the two other countries cotton productivity is some 30% lower than in China. Farm gate prices of cotton are similar in the three countries, with Pakistan having the lowest prices, which is reflected in the low revenues and low gross margins. As expected, the gross margin is highest in China. However, it needs to be mentioned that there are differences in technology, as China, with its very small farm and plot sizes, is relying on manual labor, which is not factored into the gross margin. In fact, input of family labor in China is very high, which still results in considerable returns to labor of around \$2.70 per man day. There are marked differences in the input structure among the three countries. As expected, fertilizer expenditures are highest in China but pesticides are some 25% higher in India than in China despite the marked differences in productivity. Seeds costs stand out in China, which could be related to the widespread use of transgenic cotton varieties that initially included a technology fee. In Pakistan, where cotton farms are larger, costs for fuel, land preparation and irrigation are highest, indicating a higher degree of mechanization.

Overall the comparison of costs and revenues among the three countries shows that there could be differences in productivity and efficiency of cotton production. For example, the high amount of pesticide use in India and the relatively high labor costs with only moderate cotton yields suggest the existence of efficiency gaps. This also suggests that FFS has the potential to make improvements in inputs use efficiency and in yield.

Table 4.5: Costs and returns of cotton production before training in China, India and Pakistan, crop years 2000 (China and India), 2001 (Pakistan)

Parameters	Countries		
	China	India	Pakistan
Number of observation (N = 808)	535	83	190
Cotton yield (kg/ha)	3,218.76 (609.32)	2,254.80 (792.38)	2,082.55 (711.72)
Cotton revenues (\$/ha)	1,602.91 (318.65)	938.79 (343.08)	692.59 (244.62)
Seed costs (\$/ha)	34.53 (26.97)	29.15 (20.73)	12.13 (4.28)
Fertilizer costs (\$/ha)	204.98 (85.54)	112.15 (47.66)	101.84 (38.93)
Pesticide costs (\$/ha)	120.57 (81.09)	169.37 (60.73)	93.01 (116.73)
Fuel and irrigation costs (\$/ha)	8.49 (13.46)	3.54 (5.38)	34.38 (43.60)
Costs of land preparation (\$/ha)	0.00 (0.00)	8.97 (14.60)	65.41 (22.41)
Hired labor (\$/ha)	0.00 (0.00)	106.29 (52.77)	73.09 (45.54)
Family labor (md/ha)	461.33 (222.59)	152.28 (60.56)	32.32 (28.93)
Variable costs (\$/ha)	871.22 (243.62)	663.48 (158.40)	431.85 (155.17)
Variable cash costs (\$/ha)	368.57 (133.62)	429.48 (128.34)	379.87 (156.40)
Cotton gross margin (\$/ha)	1,233.71 (346.49)	484.62 (282.49)	312.72 (248.43)

Note: Standard deviation is shown in parentheses.

Gross margin means the revenues above variable cash costs.

Source: own calculations

Comparing the shares of material inputs shows that pesticides make up a considerable proportion of the material costs, which provides some opportunities for reduction and such reduction is one of the main objectives of the FFS concept. As shown in Figure 4.4 the biggest potential for pesticide reduction seems to exist in India. However, also in China where Bt cotton is widespread, pesticide reduction seems a legitimate target and can be expected to be in the interests of the farmers. Nearly half of the farmers in the Chinese sample were growing Bt cotton.

Nevertheless, they still intensively apply pesticides, which is consistent with the studies of Huang et al. (2003) and Pemsl (2005). Hence diffusion of the Bt technology does not render FFS training useless. In Pakistan, the potential for pesticide reduction seems more limited as the item “other material inputs” occupies the major share of the costs.

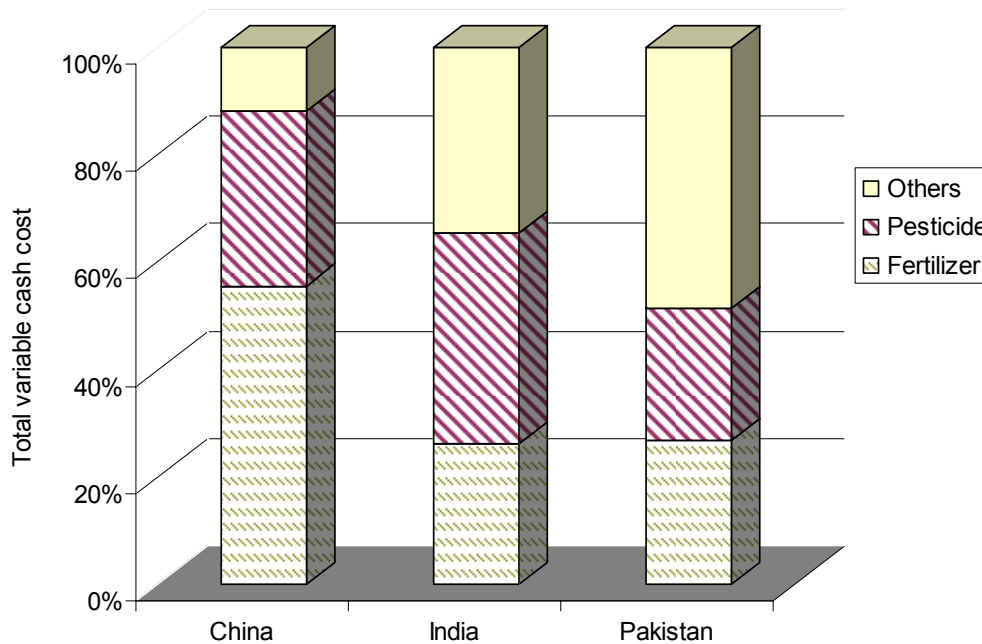


Figure 4.4: Share of pesticide and fertilizer in total variable cash costs before training in China, India and Pakistan, crop years 2000 (China and India), 2001 (Pakistan)

Source: own presentation

4.2.4 Comparison of costs and returns of farmer groups by country

Comparing costs and returns among the three groups of farmers shows that in China they are very similar in terms of productivity, gross margin and input use. This not only refers to the average values but also to the standard deviations given in parentheses in Table 4.6. As indicated by the yields and inputs, as well as the high amount of family labor⁴, the three groups apply the same cotton production

⁴ In China, only family labor was used in cotton production. Therefore, there is no cost of land preparation and hired labor.

technology. Hence the initial conditions for impact assessment are suitable, as few confounding factors are to be expected in the assessment of the post-training situation.

Table 4.6: Costs and returns of cotton production before training in China by farmer category, crop year 2000

Parameters	Farmer Category		
	FFS	Non-FFS	Control
Number of observation (N = 535)	177	178	180
Cotton yield (kg/ha)	3,239.55 (687.58)	3,220.11 (597.13)	3,196.97 (537.82)
Cotton revenues (\$/ha)	1,627.26 (354.40)	1,604.58 (310.41)	1,577.30 (287.92)
Seed costs (\$/ha)	34.30 (30.01)	32.29 (26.80)	36.96 (23.73)
Fertilizer costs (\$/ha)	199.99 (82.68)	207.03 (85.80)	207.87 (88.26)
Pesticide costs (\$/ha)	123.44 (76.72)	127.28 (85.35)	111.11 (80.53)
Fuel and irrigation costs (\$/ha)	8.78 (14.16)	8.27 (13.09)	8.42 (13.19)
Family labor (md/ha)	467.07 (272.00)	448.97 (158.75)	467.90 (223.44)
Variable costs (\$/ha)	875.43 (288.99)	864.06 (198.35)	874.17 (236.56)
Variable cash costs (\$/ha)	366.52 (124.82)	374.87 (140.26)	364.35 (135.74)
Cotton gross margin (\$/ha)	1,260.08 (373.39)	1,229.17 (344.44)	1,212.25 (320.28)

Note: Standard deviations are shown in parentheses.

Gross margin means the revenues above variable cash costs.

No cost for land preparation was included. No hired labor, all labor was family labor.

Source: own calculations

The initial conditions in the Indian sample are rather heterogeneous. Also, the sample suffers from a small number of control farmers. This is reflected in the high standard deviations as shown in Table 4.7. While yields and revenues are rather similar, differences exist in input use. In particular, average pesticide expenditures among FFS farmers are twice more than those of control farmers. They are also somewhat higher as compared to the non-participant farmers in the same village. Interestingly, the gross margin of the control farmers is higher than those of the two

other groups due to lower input use, suggesting that production efficiency in FFS villages is low, which leaves room for improvement through FFS training. On the other hand, the impact analysis needs to be interpreted with care as confounding factors may affect differences in productivity after training.

Table 4.7: Costs and returns of cotton production before training in India by farmer category, crop year 2000

Parameters	Farmer Category		
	FFS	Non-FFS	Control
Number of observation (N = 83)	37	30	13
Cotton yield (kg/ha)	2,279.76 (595.74)	2,212.46 (623.79)	2,276.50 (1,350.07)
Cotton revenues (\$/ha)	939.45 (258.90)	954.11 (279.79)	908.56 (574.28)
Seed costs (\$/ha)	24.64 (11.52)	40.91 (27.27)	17.55 (11.07)
Fertilizer costs (\$/ha)	122.67 (43.92)	115.47 (34.76)	81.63 (64.54)
Pesticide costs (\$/ha)	190.52 (42.33)	180.33 (51.72)	99.91 (64.83)
Fuel and irrigation costs (\$/ha)	3.66 (5.20)	3.14 (4.55)	4.03 (7.27)
Costs of land preparation (\$/ha)	9.03 (16.54)	8.03 (10.80)	10.59 (16.71)
Hired labor (\$/ha)	96.83 (31.86)	131.73 (67.43)	80.46 (42.06)
Family labor (md/ha)	169.41 (56.55)	144.69 (50.24)	126.88 (77.27)
Variable costs (\$/ha)	704.45 (99.27)	709.04 (105.48)	483.32 (221.58)
Variable cash costs (\$/ha)	447.35 (82.08)	479.61 (105.95)	294.16 (163.77)
Cotton gross margin (\$/ha)	459.15 (235.43)	477.10 (268.96)	557.61 (394.91)

Note: Standard deviation is shown in parentheses.

Gross margin means the revenues above variable cash costs.

Source: own calculations

The conditions in the sample from Pakistan are better than in India as the sample is more balanced among the three groups. Also, productivity is quite similar and the variations around the mean values are small. However, input costs differ. While expenditures for fertilizer vary only little, pesticide costs are much higher in the

control village, albeit with a high variation, which indicates a considerable heterogeneity in production technology or knowledge. Technology difference may also be demonstrated by a lower level of family labor. On the other hand, it is remarkable that the standard deviation of the yield is only moderate. In conclusion, while the efficiency gaps in India may be in the FFS villages, in Pakistan they are perhaps more pronounced in the control villages. For the impact assessment this means that the knowledge and productivity effects of FFS training may be overestimated (Table 4.8).

Table 4.8: Costs and returns of cotton production before training in Pakistan by farmer category, crop year 2001

Parameters	Farmer Category		
	FFS	Non-FFS	Control
Number of observation (N = 190)	78	59	53
Cotton yield (kg/ha)	2,136.68 (696.73)	1,985.48 (754.42)	2,110.95 (686.72)
Cotton revenues (\$/ha)	707.94 (237.36)	671.22 (260.01)	693.78 (240.39)
Seed costs (\$/ha)	11.91 (4.88)	12.58 (4.61)	11.94 (2.68)
Fertilizer costs (\$/ha)	94.44 (38.33)	94.59 (33.81)	120.81 (39.36)
Pesticide costs (\$/ha)	74.35 (30.81)	72.13 (37.41)	143.73 (207.18)
Fuel and irrigation costs (\$/ha)	33.27 (49.74)	35.89 (46.89)	34.34 (28.07)
Costs of land preparation (\$/ha)	60.17 (18.10)	63.74 (23.18)	75.00 (24.53)
Hired labor (\$/ha)	77.63 (48.68)	64.63 (50.86)	75.83 (31.98)
Family labor (md/ha)	35.35 (29.52)	37.43 (33.35)	22.17 (19.08)
Variable costs (\$/ha)	408.25 (113.94)	401.70 (106.62)	500.13 (221.34)
Variable cash costs (\$/ha)	351.77 (110.38)	343.55 (116.83)	461.65 (214.81)
Cotton gross margin (\$/ha)	356.18 (217.56)	327.67 (236.30)	232.13 (286.77)

Note: Standard deviation is shown in parentheses.

Gross margin means the revenues above variable cash costs.

Source: own calculations

4.3 Summary

The data used for the descriptive analysis presented in this chapter refer to the baseline survey collected before the start of FFS training. The time of data collection differed by one year between China and India on the one hand and Pakistan on the other hand. By presenting a geographic description of the study sites in the three countries, a better judgment of the plausibility of the differences in farm characteristics and cotton productivity is facilitated. Furthermore, in the second part of the chapter, the analysis of farm household characteristics, input structure and productivity provides a better understanding of the welfare position of the cotton farmers in the sample. This information allows interpretation of the results of the impact assessment in the context of the general development objectives of the country. Results have shown that the cotton farmers in all the three countries belong to the poorer segment of the rural population, which renders potentially positive poverty impacts of the FFS program.

The last section of the chapter analyzed the yield and cost structure of cotton in the three countries and also among the three farmer groups. Results show that there are differences in productivity among the three countries, with China clearly showing the highest productivity levels. Also, the data show that the level of pesticide use is a significant factor among the production inputs. This suggests that there is the potential to reduce pesticide use through Farmer Field Schools and thereby increase the economics of cotton production and serve the environment at the same time.

Overall, the information presented in this chapter is believed to be useful in the interpretation of the more formal impact assessment using statistical methods and by means of econometric models presented in Chapter 5.

5 Economic impact of training of farmers in cotton production in Asia

This chapter has two purposes: The first is to conduct a comparative analysis of the impact of Farmer Field Schools (FFS) on pesticide use, cotton output, farmers' knowledge on ecosystem analysis and other indicators. The results are expected to show differences in the performance amongst three groups of farmers: those who participated in the training (FFS group), those who did not participate but who were exposed to information on Integrated Pest Management (IPM) (Non-FFS group) and the control group, i.e. farmers who were not exposed to any IPM-related information (see Chapter 3). The analysis is conducted separately for the three countries.

The second purpose is to conduct an inter-country comparison. The analysis is based on a Difference-in-Differences (DD) model. Additionally, a fixed-effects model is used to analyse the total impact of the combined three countries as described in Chapter 3.

The chapter proceeds as follows. Section 5.1 presents a statistical comparison of a number of impact indicators for each country by applying statistical tests. Sections 5.2 and 5.3 present the specification and the results of the DD-model. Section 5.4 is a summary.

5.1 Statistical comparison of impact indicators

The comparative analysis of the impact of FFS is carried out by use of a wide range of indicators, which are assumed to be affected by IPM-FFS training. These include: (1) pesticide input and environmental indicators such as quantity, quality and frequency of pesticides used in cotton production, and the Environmental Impact Quotient (EIQ); (2) output indicators such as cotton yield, and monetary returns (revenue, gross margin, household income); and (3) human capital indicators, including farmers' knowledge of ecosystem analysis, pest application practices and attitudes. T-test, F-test, and Chi-square test were used to statistically compare the impact (Park 2008b). Group means of pertinent parameters were compared by using an F-test for the among-groups comparison and using a T-test for the pre- and post-training comparison. In the same way, the Chi-square test was used to analyze proportions of binary variables. If the among-group means are significantly different,

the multiple comparison, i.e. the Least Significant Difference (LSD) method of post-hoc test, is applied at the second stage to identify differences among groups. Results of these tests indicate differences in group means in the pre- and post training stages. Non-significant differences in the pre-training stage indicate similar base conditions. Significant differences in the post-training period provide a first indication of the training impact. This has to be confirmed by significant differences between the pre- and post-FFS participants and opposite results for control farmers. Moreover, diffusion effects from FFS would be evident for the non-participant group in FFS villages if the means are significantly different from the control group.

The results on the comparison of group means before and after FFS training by farmer category for three countries are presented in Table 5.1 to Table 5.11.

5.1.1 Pesticide input and environmental indicators

IPM is a pest management approach based on the principles of ecological balance and sustainable management of natural resources by applying control measures that are cost-effective and safe for farmers and consumers. The emphasis of IPM-FFS training is on pest control to reduce pesticide use (PAN 1998; PAN (Pesticide Action Network UK)). Negative external effects of pesticides on the environment are measured by the environmental impact quotient (EIQ). The EIQ is calculated by taking into account the toxicity of active pesticide ingredients to natural enemies, wildlife, and humans, degree of exposure, aquatic and terrestrial effects, soil chemistry, etc. (see Chapter 3), and can be used as an indicator to compare and evaluate different pesticides and pest management programs (Kovach et al. 1992).

China

In pre- and post-FFS training, the pesticide use for cotton farmers in China is shown in Table 5.1. The results show that all three groups of farmers spend more money on insecticides than on any other types of pesticides both before and after the FFS training. In the year before FFS training, the use of all pesticides among the three groups was not significantly different. If we consider insecticide application only, significant differences are found between FFS farmers and farmers in the control villages, with the latter group using less. In terms of spraying frequency for all pesticides and insecticides, the frequency is the same for all the three groups.

After FFS training, the results show that there are significant changes in pesticide expenditure. All three groups of farmers reduced the costs of all pesticides and insecticides after training. The cost reduction is more than 50% by farmers in the FFS villages and around 30% by farmers in the control villages. Although the control group reduced costs of all pesticides after the FFS training, the quantities of all pesticides and insecticides they applied increased significantly. This implies that control farmers possibly switched to less expensive pesticides.

In summary, the results from multiple comparisons show that the participant farmers significantly reduced their pesticide costs, quantities and frequency of applications more than Non-FFS and control farmers. And the non-participants in the FFS villages also reduce pesticide use more than farmers in the control villages.

Hence, these results suggest that in the short term FFS training can help participant farmers reduce their pesticide usage, and some information about IPM knowledge and practices could be transferred from FFS participants to their friends who are non-participating farmers in the same village.

Due to lack of information about pesticide compounds in China, the EIQ scores for China were not calculated. This is because only sales names were known and these cannot be readily related to the chemical compounds.

Table 5.1: Value, quantity and frequency of total pesticide and insecticide use before and after training by farmer category in China, crop years 2000 and 2002

Parameters	Farmer Category			F-test
	FFS	Non-FFS	Control	
Number of observation (N=535)	177	178	180	
Pesticide cost (\$/ha)				
-Pre-training	123.44	127.28	111.11	1.952 ^{ns}
-Post-training	49.14 ^a	60.69 ^b	80.19 ^c	20.293 ^{***}
t-test	-14.686 ^{***}	-12.615 ^{***}	-6.393 ^{***}	
Insecticide cost (\$/ha)				
-Pre-training	114.65 ^a	118.95 ^a	100.98 ^b	2.703 [*]
-Post-training	42.60 ^a	54.40 ^b	72.38 ^c	21.781 ^{***}
t-test	-15.687 ^{***}	-13.088 ^{***}	-6.404 ^{***}	
Pesticide quantity (kg/ha)				
-Pre-training	17.63	19.19	17.05	1.985 ^{ns}
-Post-training	10.44 ^a	15.42 ^b	19.35 ^c	35.839 ^{***}
t-test	-11.686 ^{***}	-5.174 ^{***}	3.304 ^{***}	
Insecticide quantity (kg/ha)				
-Pre-training	16.12 ^a	17.86 ^b	15.22 ^a	3.299 ^{**}
-Post-training	8.79 ^a	13.57 ^b	17.40 ^c	34.705 ^{***}
t-test	-12.825 ^{***}	-5.969 ^{***}	3.034 ^{***}	
Frequency of pesticide application (no./season)				
-Pre-training	17.13	17.05	16.64	0.221 ^{ns}
-Post-training	8.46 ^a	11.13 ^b	13.29 ^c	28.668 ^{***}
t-test	-15.159 ^{***}	-12.380 ^{***}	-8.888 ^{***}	
Frequency of insecticide application (no./season)				
-Pre-training	14.54	14.62	14.13	0.239 ^{ns}
-Post-training	6.56 ^a	9.30 ^b	11.22 ^c	33.110 ^{***}
t-test	-17.541 ^{***}	-13.267 ^{***}	-9.603 ^{***}	

Note: *** Significant at 1%, ** Significant at 5%, * Significant at 10%, ^{ns} Non-significant difference
Means in rows followed by different superscript letters are significantly different.

Source: Own calculations

India

Table 5.2 presents pesticide use for farmers in India in pre- and post-training years (2000 and 2002). As is typical for cotton production, all three groups of farmers generally apply insecticides more than other types of pesticides. In the year before FFS training, the results show that different groups of farmers use pesticides and insecticides differently. Based on the LSD test, the farmers in the FFS villages spent more on pesticides, most of which is on insecticides, than farmers in the control villages by around 46%. The same results are found for the quantities and frequencies of all pesticides and insecticides.

After FFS training the results show significant changes in pesticide use between different groups. Firstly, both FFS and Non-FFS farmers reduce their costs and quantity of pesticides, and also spray less often than before the training. After participant farmers attended the program, their pesticide costs were reduced by approximately 70%. Non-FFS farmers reduced their pesticide use by a remarkable 55%, while the pesticide use by the control group is not significantly different between the two years. Secondly, LSD test results show that in the post-training year, FFS farmers expended the least amount of money for all pesticides and insecticides than the other groups. In terms of quantity of all pesticides and insecticides, both FFS and Non-FFS farmers applied at the same rate. This suggests that some information on IPM knowledge from FFS farmers would have spilled over to Non-FFS farmers.

These results imply that the FFS training has helped participants to reduce their pesticide use in the short term and some spill over effect on IPM knowledge to the non-participants in the same village exists in India. And the results raise some question as to whether the ecological conditions in the control village are identical to those in the FFS village.

Table 5.2: Value, quantity and frequency of total pesticide and insecticide use before and after training by farmer category in India, crop years 2000 and 2002

Parameters	Farmer Category			F-test
	FFS	Non-FFS	Control	
Number of observation (N=83)	37	30	16	
Pesticide cost (\$/ha)				
-Pre-training	190.52 ^a	180.33 ^a	99.91 ^b	18.982 ^{***}
-Post-training	57.73 ^a	81.15 ^b	70.38 ^b	3.079 ^{**}
t-test	-14.837 ^{***}	-9.101 ^{***}	-1.361 ^{ns}	
Insecticide cost (\$/ha)				
-Pre-training	187.87 ^a	177.40 ^a	98.92 ^b	18.609 ^{***}
-Post-training	52.99 ^a	79.57 ^b	77.49 ^b	4.053 ^{**}
t-test	-12.951 ^{***}	-9.177 ^{***}	-1.461 ^{ns}	
Pesticide quantity (kg/ha)				
-Pre-training	22.17 ^a	20.25 ^a	12.54 ^b	17.259 ^{***}
-Post-training	9.91 ^a	9.82 ^a	17.90 ^b	4.244 ^{**}
t-test	-8.083 ^{***}	-9.477 ^{***}	1.210 ^{ns}	
Insecticide quantity (kg/ha)				
-Pre-training	21.86 ^a	19.93 ^a	12.43 ^b	16.826 ^{***}
-Post-training	9.27 ^a	9.55 ^a	17.72 ^b	4.624 ^{***}
t-test	-8.518 ^{***}	-9.373 ^{***}	1.192 ^{ns}	
Frequency of pesticide application (no./season)				
-Pre-training	21.41 ^a	19.63 ^b	11.81 ^c	31.258 ^{***}
-Post-training	10.11	11.40	11.44	0.918 ^{ns}
t-test	-10.597 ^{***}	-8.992 ^{***}	-0.206 ^{ns}	
Frequency of insecticide application (no./season)				
-Pre-training	21.38 ^a	19.63 ^b	11.81 ^c	31.116 ^{***}
-Post-training	9.32	10.83	10.81	1.370 ^{ns}
t-test	-11.618 ^{***}	-9.805 ^{***}	-0.580 ^{ns}	

Note: *** Significant at 1%, ** Significant at 5%, ^{ns} Non-significant difference

Means in rows followed by different superscript letters are significantly different.

Source: Own calculations

In Table 5.3, the EIQ scores identify environmental effects from the use of pesticide as show in Table 5.2. It is consistent that in the pre-training year, farmers in the FFS villages spray more often and with higher quantities than farmers in the control villages. Thus, there are significant differences for the three groups of farmers in all

the EIQ categories. The farmers in the FFS villages have to face more negative environmental impacts than farmers in the control villages. Comparing the scores in the year after training, there are significant differences among the three groups of farmers but they are contrary to the situation in the pre-training year. After the training, the farmers in the FFS villages had significantly lower EIQ scores, which suggests they have switched to pesticides that are better in terms of farm worker health, consumer and ecology safety. Thus, the result suggests that the FFS training in India not only helps farmers reduce pesticide use but also generates environmental benefits.

Table 5.3: Environmental impact quotient by farmer category before and after FFS training in India, crop years 2000 and 2002

Parameters	Farmer Category			F-test
	FFS	Non-FFS	Control	
Number of observation (N=83)	37	30	16	
Total EIQ (score)				
-Pre-training	256.85 ^a	234.38 ^a	141.96 ^b	18.004 ^{***}
-Post-training	105.36 ^a	127.75 ^a	236.13 ^b	5.957 ^{***}
t-test	-8.666 ^{***}	-6.833 ^{***}	1.546 ^{ns}	
EIQ: Farm worker (score)				
-Pre-training	253.81 ^a	231.91 ^a	145.47 ^b	14.100 ^{***}
-Post-training	84.15 ^a	137.26 ^a	243.23 ^b	8.193 ^{***}
t-test	-10.724 ^{***}	-5.572 ^{***}	1.426 ^{ns}	
EIQ: Consumer (score)				
-Pre-training	79.91 ^a	72.81 ^a	41.01 ^b	15.573 ^{***}
-Post-training	29.03 ^a	35.98 ^a	69.05 ^b	5.741 ^{***}
t-test	-8.832 ^{***}	-6.554 ^{***}	1.468 ^{ns}	
EIQ: Ecology (score)				
-Pre-training	436.82 ^a	398.42 ^a	239.40 ^b	18.604 ^{***}
-Post-training	203.01 ^a	210.12 ^a	396.23 ^b	4.892 ^{***}
t-test	-7.354 ^{***}	-7.370 ^{***}	1.631 ^{ns}	

Note: ^{***} Significant at 1%, ^{ns} Non-significant difference

Means in rows followed by different superscript letters are significantly different.

Source: Own calculations

Pakistan

Table 5.4 shows pesticide use for cotton farmers in Pakistan before and after IPM training. As indicated by the quantities and frequencies, the results show that most of

the pesticides used by FFS farmers are insecticides, since the differences between the aggregate values and the values for insecticides are marginal. The same is true for the Non-FFS farmers, and the farmers in the control villages did not use other types of pesticides apart from insecticides. Comparing pesticide use in general and insecticide use in particular in the year before the training (2001), the results show that there are significant differences among the three groups using an F-test. Farmers in the control villages spent almost twice the amount of money, used large quantities and sprayed more often than the farmers in the two other groups. However, the difference in quantity and frequency of spraying is less pronounced, which suggests that the farmers in control villages on average use more expensive pesticides.

Comparing the three groups after the FFS training (2003) shows that some important changes took place. First, based on the t-tests, farmers who were trained in FFS significantly reduced the amount of money and the quantity of all pesticides including insecticides and reduced their spraying frequency by about 15%. Second, the result for the Non-FFS farmers is mixed, as there was no significant reduction in the costs of all pesticides and in the number of all pesticides and insecticides applications. On the other hand, the differences in the quantity of all pesticides in general and insecticides in particular, as well as in the costs of insecticides, were significant. This suggests that at least some information provided to FFS participants may have reached the non-participating farmers in the same village through various intra-village communication channels.

The comparison between the pre- and post training status of the control villages shows a more complex picture. The costs of pesticide and insecticide use were not significantly lower but the quantities were significantly reduced. At the same time the spraying frequency was significantly higher in the post training year. This suggests that some changes in external factors took place. For example, the pest conditions may have changed and the farmers in the control villages have adjusted their pesticide use strategies by using cheaper pesticides and have reduced the dose per application.

Overall these results suggest that the FFS training has led to a reduction of pesticide use by trained farmers in the short term and there could have been some diffusion of pest management knowledge to the non-participating farmers in the same village.

The results also indicate that when analysing the situation before the FFS training, the ecological conditions in FFS and control villages may be different.

Table 5.4: Value, quantity and frequency of total pesticide and insecticide use before and after training by farmer category in Pakistan, crop years 2001 and 2003

Parameters	Farmer Category			F-test
	FFS	Non-FFS	Control	
Number of observation (N=190)	78	59	53	
Pesticide cost (\$/ha)				
-Pre-training	74.35 ^a	72.13 ^a	143.73 ^b	7.414 ^{***}
-Post-training	48.06 ^a	61.22 ^a	122.64 ^b	37.540 ^{***}
t-test	-5.727 ^{***}	-1.533 ^{ns}	-0.691 ^{ns}	
Insecticide cost (\$/ha)				
-Pre-training	71.00 ^a	69.84 ^a	143.73 ^b	8.059 ^{***}
-Post-training	43.66 ^a	57.05 ^a	122.64 ^b	43.051 ^{***}
t-test	-6.070 ^{***}	-1.822 [*]	-0.691 ^{ns}	
Pesticide quantity (l/ha)				
-Pre-training	8.37 ^a	7.48 ^b	6.99 ^b	4.685 ^{**}
-Post-training	4.93 ^a	6.12 ^b	9.30 ^c	21.859 ^{***}
t-test	-8.234 ^{***}	-2.375 ^{**}	4.634 ^{***}	
Insecticide quantity (l/ha)				
-Pre-training	7.98 ^a	7.23 ^b	6.99 ^b	2.818 [*]
-Post-training	4.48 ^a	5.71 ^b	9.30 ^c	28.023 ^{***}
t-test	-8.474 ^{***}	-2.722 ^{***}	4.634 ^{***}	
Frequency of pesticide application (no./season)				
-Pre-training	4.33 ^a	3.85 ^b	5.15 ^c	11.750 ^{***}
-Post-training	3.76 ^a	4.22 ^a	6.21 ^b	26.868 ^{***}
t-test	-2.630 ^{***}	1.636 ^{ns}	3.895 ^{***}	
Frequency of insecticide application (no./season)				
-Pre-training	4.13 ^a	3.71 ^b	5.15 ^c	16.232 ^{***}
-Post-training	3.53 ^a	4.00 ^a	6.21 ^b	34.296 ^{***}
t-test	-2.748 ^{***}	1.300 ^{ns}	3.895 ^{***}	

Note: *** Significant at 1%, ** Significant at 5%, * Significant at 10%, ^{ns} Non-significant difference
Means in rows followed by different superscript letters are significantly different.

Source: Own calculations

In Table 5.5, the environmental effects of pesticide use are compared for different farmers groups before and after the FFS training. It is shown that prior to the training no significant difference existed in any of the EIQ categories. At first glance this is surprising because of the significantly higher amount spent on pesticides by the control farmers (see Table 5.4). However, it should be noted that the EIQ depends greatly on the type and frequency of the pesticides used. While as shown in Table 5.4 the differences in the frequencies and types among the three groups are sometimes significant, the absolute differences are less pronounced. On the other hand, the comparisons of EIQ scores after training show that using an F-test there are significant differences among the three categories of farmers. In addition, using the T-test it is shown that the FFS farmers had significantly lower EIQ scores after they had received training on the subjects of occupational health (farm worker), consumer safety and environmental safety. This suggests that the FFS training has not only helped cotton farmers in Pakistan to reduce their presumably uneconomical pesticide use but has also generated environmental benefits through a switch to safer types of pesticides.

Table 5.5: Environmental impact quotient by farmer category before and after FFS training in Pakistan, crop years 2001 and 2003

Parameters	Farmer Category			F-test
	FFS	Non-FFS	Control	
Number of observation (N=190)	78	59	53	
Total EIQ (score)				
-Pre-training	194.39	156.94	196.47	1.165 ^{ns}
-Post-training	98.26 ^a	156.92 ^a	336.95 ^b	15.314 ^{***}
t-test	-4.356 ^{***}	-0.001 ^{ns}	2.504 ^{**}	
EIQ: Farm worker (score)				
-Pre-training	176.44	128.46	178.63	1.749 ^{ns}
-Post-training	82.90 ^a	135.41 ^a	266.88 ^b	8.934 ^{***}
t-test	-4.116 ^{***}	0.209 ^{ns}	1.457 ^{ns}	
EIQ: Consumer (score)				
-Pre-training	40.74	30.42	39.57	1.535 ^{ns}
-Post-training	20.02 ^a	31.56 ^a	62.41 ^b	9.927 ^{***}
t-test	-4.177 ^{***}	0.152 ^{ns}	1.733 [*]	
EIQ: Ecology (score)				
-Pre-training	365.99	311.93	371.21	0.691 ^{ns}
-Post-training	191.86 ^a	303.78 ^a	681.57 ^b	18.334 ^{***}
t-test	-4.204 ^{***}	-0.112 ^{ns}	3.060 ^{***}	

Note: *** Significant at 1%, ** Significant at 5%, * Significant at 10%, ^{ns} Non-significant difference
Means in rows followed by different superscript letters are significantly different.

Source: Own calculations

5.1.2 Output indicators

The FFS training utilizes participatory methods that help farmers to learn to make better decisions (Kenmore 1997) and become better managers of their fields (van den Berg 2004). Generally, some of the expected benefits of IPM are higher yields and lower yield variance due to more effective pest management carried out as a combination of tactics, with the use of chemical pesticides as a measure of last resort (Fleischer et al. 1999). Thus, increases in yield and profit are the immediate impacts of IPM (van den Berg 2004). In this section, cotton yield, revenue, gross margin, and household income are used as the output indicators of benefits from FFS training.

China

Table 5.6 presents cotton yield, revenue, gross margin, and household income before and after FFS training for cotton farmers in China. In the year before the training, the results show that cotton production, revenue from cotton sales and the revenue above variable cash cost (gross margin) were not significantly different among the three farmer groups. For annual household income, the results from the F-test and LSD test show that the farmers in the control villages have significantly higher incomes than the farmers in the FFS villages. The difference is about 15%. This suggests that in the pre-training year the ability to produce cotton is similar for all three groups of farmers but those in control the villages can earn more income from other sources than farmers in the FFS villages.

Distinguishing the mean outputs of the three farmer groups after the FFS training, the results show that some changes took place. In the post-training year, the participant farmers produced more cotton and earned more income than the Non-FFS farmers and farmers in the control villages. The results also show that all the farmer groups obtained more cotton yield and earn more income in the post-training year than in the pre-training year, due to other agricultural technologies that help farmers to improve their productivity, such as the introduction of *Bacillus thuringiensis*-cotton (Bt cotton) in China. In the post-training year more farmers in China adopted Bt cotton than in the pre-training year (see Chapter 2). When we consider total household income after the FFS training, the results show that FFS farmers earned a total annual income similar to that of the control farmers and Non-

FFS farmers. However, the amount of income earned by Non-FFS farmers is significantly lower than that for farmers from the control villages.

Table 5.6: Cotton yield, revenue, gross margin and household income before and after training by farmer category in China, crop years 2000 and 2002

Parameters	Farmer Category			F-test
	FFS	Non-FFS	Control	
Number of observation (N=535)	177	178	180	
Yield (kg/ha)				
-Pre-training	3,239.55	3,220.11	3,196.97	0.218 ^{ns}
-Post-training	3,943.43 ^a	3,648.75 ^b	3,488.07 ^c	126.572 ^{***}
t-test	14.347 ^{***}	8.815 ^{***}	6.614 ^{***}	
Revenue (\$/ha)				
-Pre-training	1,627.26	1,604.58	1,577.30	1.101 ^{ns}
-Post-training	2,027.40 ^a	1,840.19 ^b	1,761.80 ^c	109.526 ^{***}
t-test	14.730 ^{***}	8.371 ^{***}	7.409 ^{***}	
Gross Margin (\$/ha)				
-Pre-training	1,260.08	1,229.17	1,212.25	0.873 ^{ns}
-Post-training	1,698.19 ^a	1,489.80 ^b	1,367.60 ^c	110.008 ^{***}
t-test	16.020 ^{***}	8.591 ^{***}	5.296 ^{***}	
Household Income (\$/year)				
-Pre-training	980.34 ^a	1,020.79 ^a	1,182.69 ^b	9.685 ^{***}
-Post-training	1,388.45 ^{ab}	1,303.12 ^a	1,462.99 ^b	4.504 ^{**}
t-test	9.336 ^{***}	5.938 ^{***}	5.861 ^{***}	

Note: *** Significant at 1%, ** Significant at 5%, ^{ns} Non-significant difference

Means in rows followed by different superscript letters are significantly different.

Source: Own calculations

India

Table 5.7 presents cotton yield, revenue, gross margin, and household income before and after FFS training for cotton farmers in India. In the year before FFS training, the results shows cotton yield and revenue from cotton production are not significantly different among the three farmer groups. Although the control farmers spent less cash on pesticides than farmers in the FFS villages in the pre-training year (see Table 5.2), their gross margins are not significantly different for all the three farmer groups. For the annual household income, the LSD test shows that the FFS farmers earn more household income than Non-FFS farmers, but the income of control farmers is not different to that of FFS farmers.

The comparison in the post-training year shows that the effects of FFS training on cotton yield and income are not distinct. Even though the FFS farmers experienced higher yields and revenues after the FFS training, the non-participants also performed better in that year. Additionally, using the F-test and LSD test, the cotton yield and revenue of the FFS group are not significantly different from that of the Non-FFS group. Additionally, the control farmers experienced higher yield and more revenue than farmers in the FFS village. The reason for the increase in yield of the control group might be less pest incidence during the post-training year (Reddy and Suryamani 2004). Although there was a reduction in input costs, especially for pesticides by participant farmers (see Table 5.2) and higher yield after the FFS training, the gross margin of the FFS group is not significantly different from the gross margin of the control group. For the household income after FFS training, there are also no significant differences among the three groups.

In general, this analysis suggests that the FFS program in India did not significantly increase cotton productivity.

Table 5.7: Cotton yield, revenue, gross margin and household income before and after training by farmer category in India, crop years 2000 and 2002

Parameters	Farmer Category			F-test
	FFS	Non-FFS	Control	
Number of observation (N=83)	37	30	16	
Yield (kg/ha)				
-Pre-training	2,279.76	2,212.46	2,276.50	0.066 ^{ns}
-Post-training	2,540.03 ^a	2,463.50 ^a	3,234.81 ^b	8.380 ^{***}
t-test	1.933 [*]	1.592 ^{ns}	2.570 ^{**}	
Revenue (\$/ha)				
-Pre-training	939.45	954.11	908.56	0.090 ^{ns}
-Post-training	1,079.81 ^a	1,056.92 ^a	1,259.58 ^b	3.114 ^{**}
t-test	2.290 ^{**}	1.368 ^{ns}	2.348 ^{**}	
Gross Margin (\$/ha)				
-Pre-training	459.15	477.10	557.61	0.690 ^{ns}
-Post-training	790.70 ^a	679.98 ^b	903.12 ^a	3.763 ^{**}
t-test	5.431 ^{***}	3.057 ^{***}	3.176 ^{***}	
Household Income (\$/year)				
-Pre-training	2,203.83 ^a	1,188.89 ^b	1,584.38 ^{ab}	4.645 ^{***}
-Post-training	2,727.39	1,859.01	2,236.46	0.702 ^{ns}
t-test	0.895 ^{ns}	1.859 [*]	1.951 [*]	

Note: *** Significant at 1%, ** Significant at 5%, * Significant at 10%, ^{ns} Non-significant difference
Means in rows followed by different superscript letters are significantly different.

Source: Own calculations

Pakistan

Table 5.8 shows cotton yield, revenue and gross margin from cotton production, and total household income for cotton farmers in Pakistan before and after FFS training. Using the F-test to compare the cotton yield and revenue before FFS training (2000), the result shows that the differences among the three groups are non-significant. The cotton revenue depends on the yield and price. The non-significant differences among the three groups of farmers in yield and revenue suggest that all the farmer groups earn similar product prices, which is consistent with the policy of the Pakistan government, which supports a minimum guaranteed price for cotton (Salam 2008). If

we consider the gross margin, defined as revenue above variable cash cost⁵ from cotton production, before FFS training, the results show that the farmers in the FFS villages have significantly higher gross margins than farmers in the control villages. This result is the consequence of higher pesticide expenditure by the control group, as shown in Table 5.4. The annual household income in the pre-training year is not significantly different among the three groups of farmers.

Comparing the three groups after training, the results show that all three groups experienced low yields in this year, approximately 60% lower than the yields in the pre-training year, due to unusual pest infestation and excessive vegetative growth in that year (Azeem Khan et al. 2005). Although yields for all of groups declined, the LSD test shows that FFS farmers experienced higher yields than the other groups of farmers, while the control farmers had average yields higher than the Non-FFS group. Comparing the means of the revenue and gross margins between pre- and post-training for the three farmer groups, the results show that the revenue and gross margin for FFS farmers increased significantly, because FFS farmers experienced relatively lower reduction in cotton yield while they decreased other inputs such as pesticide and fertilizer. After FFS training, the non-FFS farmers and those from the control villages obtained cotton revenues and gross margins that are not significantly different from the ones obtained in the pre-training year. This observation also correlates with household income.

In general, these results suggest that in the short term, the IPM practices from the FFS training have increased productivity for farmers who participated in the training but not for non-participants. This is different from pesticides use practices, where indeed some diffusion can be found. The result suggests that measures to increase crop productivity, like agronomic practices and the correct timing and application rate of pesticides, are not easily picked up by neighbours and friends as they require in-depth knowledge, understanding and skills.

⁵ The calculation of gross margin used variable cash cost only because the information on non-cash cost is not complete.

Table 5.8: Cotton yield, revenue, gross margin and household income before and after training by farmer category in Pakistan, crop years 2001 and 2003

Parameters	Farmer Category			F-test
	FFS	Non-FFS	Control	
Number of observation (N=190)	78	59	53	
Yield (kg/ha)				
-Pre-training	2,136.68	1,985.48	2,110.95	0.815 ^{ns}
-Post-training	1,479.42 ^a	1,079.23 ^b	1,241.75 ^c	14.062 ^{***}
t-test	-7.368 ^{***}	-7.972 ^{***}	-8.613 ^{***}	
Revenue (\$/ha)				
-Pre-training	707.94	671.22	693.78	0.377 ^{ns}
-Post-training	925.31 ^a	659.79 ^b	688.32 ^b	20.493 ^{***}
t-test	5.698 ^{***}	-0.247 ^{ns}	-0.118 ^{ns}	
Gross margin (\$/ha)				
-Pre-training	356.18 ^a	327.67 ^a	232.13 ^b	4.229 ^{**}
-Post-training	605.27 ^a	351.53 ^b	208.07 ^c	36.486 ^{***}
t-test	6.522 ^{***}	0.544 ^{ns}	-0.470 ^{ns}	
Household income (\$/year)				
-Pre-training	3,616.67	3,452.25	3,256.77	0.231 ^{ns}
-Post-training	5,170.45 ^a	3,483.80 ^b	3,615.95 ^b	2.682 [*]
t-test	2.815 ^{***}	0.096 ^{ns}	0.910 ^{ns}	

Note: *** Significant at 1%, ** Significant at 5%, * Significant at 10%, ^{ns} Non-significant difference
Means in rows followed by different superscript letters are significantly different.

Source: Own calculations

5.1.3 Farmers' knowledge, practices, and attitudes

One of the objectives of the Farmer Field Schools training is to augment farmers' knowledge and skills as a foundation for behavioral change in decision-making abilities so that they can cope with pests and crop management problems on their own (Reddy and Suryamani 2005; Rola et al. 2002). Hence, this part of the analysis aimed at examining the extent of knowledge gains, changes of farm management practices, ability to identify pests and their natural enemies, and attitudes toward pests and environment.

The scores of changes in behaviors and attitudes of Pakistan and India were examined and codified by local experts in both countries. Since this method was uncommon in China, the results were presented as percentage of frequency of farmer practices.

China

Table 5.9 presents the farmers' knowledge of pest recognition, decision making on pesticide application, and attitudes to cotton pests in China before and after FFS training. The knowledge of pests is determined from the number of pests and beneficial insect types that farmers can recognize. The method for deciding on pesticide application given precedence by farmers, i.e. using own feelings, using calendar spraying, following neighbors and doing fields surveys, is shown as a percentage of total farmers in each group. The attitudes to cotton pests, for instance on whether farmers will spray pesticide immediately when they see pests or will survey on the cotton field and compare population between pests and natural enemies first, are presented as percentages of total farmers in each group.

The results show that before the training all farmer groups could identify pests similarly. But the LSD test shows that the FFS group knows more about the natural enemies in cotton fields than other groups. When asked how they made decisions about spraying pesticide in the pre-training year, all groups mostly decide by their own feelings. Control farmers use calendar spraying and tend to follow their neighbors rather than relying on their own observations more than farmers in FFS villages. Around 16% of the three farmer groups decided to spray pesticides by doing field surveys. For attitude on cotton pests, the majority of the farmers in each

group spray pesticides immediately when they see pests and in Non-FFS and control groups, farmers have this attitude more than in the FFS group by around 10%. Moreover, more farmers in the FFS group than in the Non-FFS and control groups do surveys and compare populations of pests and natural enemies.

After the FFS training, comparison between the pre- and post-training show that the FFS farmers could remember more types of insects in post-training and were able to distinguish between pests and natural enemies. Non-FFS and control farmers could also recognize pests slightly better in post-training. FFS farmers could make decisions on applying pesticides more effectively in post-training, such that the majority of FFS farmers (90%) preferred surveying in cotton fields and then deciding either to use pesticides or not by comparison of populations of pests and natural enemies. But control farmers still had a tendency to immediately spray pesticides when they discovered pests in the field. Moreover, around 67% and 33% of control farmers used their own judgement and calendar spraying respectively for making a decision on pesticides usage. For Non-FFS farmers in post-training, some farmers changed to doing surveys and comparisons between pests and natural enemies population.

These results suggest that the FFS training helped farmers by increasing their knowledge on pest management and helped them to make better decisions for using pesticides in their cotton fields.

Table 5.9: Farmers' knowledge, decision making on pesticide application, and attitudes on cotton pests before and after training by farmer category in China, crop years 2000 and 2002

Parameters	Farmer Category			Chi-square ^{1/} / F-test
	FFS	Non-FFS	Control	
Number of observation (N=535)	177	178	180	
Pests recognition (no.)				
-Pre-training	3.97	3.70	3.84	1.651 ^{ns}
-Post-training	6.95 ^a	4.20 ^b	4.17 ^b	155.552 ^{***}
t-test	15.717 ^{***}	6.721 ^{***}	6.307 ^{***}	
Natural enemies recognition (no.)				
-Pre-training	1.76 ^a	1.47 ^b	1.39 ^b	6.892 ^{***}
-Post-training	4.97 ^a	2.76 ^b	1.91 ^c	279.502 ^{***}
t-test	23.950 ^{***}	12.544 ^{***}	9.140 ^{***}	
Spraying pesticide by using own feelings (%)				
-Pre-training	65.00	61.20	60.00	1.013 ^{ns}
-Post-training	28.20	57.90	66.70	57.700 ^{***}
Chi-square test	47.961 ^{***}	0.420 ^{ns}	1.722 ^{ns}	
Spraying pesticide by using calendar (%)				
-Pre-training	10.70	9.00	18.90	8.910 ^{***}
-Post-training	4.00	7.90	33.30	70.941 ^{***}
Chi-square test	5.977 ^{***}	0.146 ^{ns}	9.733 ^{***}	
Spraying pesticide following neighbours (%)				
-Pre-training	14.70	10.10	30.60	27.356 ^{***}
-Post-training	9.00	18.50	34.40	35.820 ^{***}
Chi-square test	2.701 [*]	5.149 ^{**}	0.620 ^{ns}	
Spraying pesticide using field surveys (%)				
-Pre-training	17.50	15.20	16.70	0.365 ^{ns}
-Post-training	89.80	36.50	16.10	206.991 ^{***}
Chi-square test	186.134 ^{***}	21.165 ^{***}	0.365 ^{ns}	
Attitude: immediate spraying (%)				
-Pre-training	76.30	86.00	85.00	6.984 ^{**}
-Post-training	1.10	45.50	82.20	239.788 ^{***}
Chi-square test	210.633 ^{***}	64.646 ^{***}	0.507 ^{ns}	
Attitude: comparison of pests and natural enemies' population (%)				
-Pre-training	8.50	2.20	0.00	20.037 ^{***}
-Post-training	82.50	32.80	1.10	253.171 ^{***}
Chi-square test	195.507 ^{***}	57.354 ^{***}	2.011 ^{ns}	

Note: *** Significant at 1%, ** Significant at 5%, * Significant at 10%, ^{ns} Non-significant difference
Means in rows followed by different superscript letters are significantly different.

^{1/} testing the percentages of parameters among three farmer groups

Source: Own calculations

India

In India, the knowledge and practices scores were calculated from comprehension in pests, diseases, natural enemies, pesticides, ecosystem information, pest management and other crop management practices. The score for skill in pest and other crop management practices was assessed by pest diagnostics and the performance of other crop management practices such as alternative methods (without pesticides), agro-ecosystem analysis, experiments, communication and facilitation skills. Diagnostic skills were tested by observing the diagnostic capacity and confidence after farmers were shown pictures of particular damage symptoms, pests or natural enemies. The score of attitude for environment and conservation was deduced from questions related to environmental pollution from pesticides, safety measures for pesticides usage, saving natural enemies, environmentally friendly technologies from IPM, etc. (Reddy and Suryamani 2005).

Table 5.10 shows (1) number of pests recognized, (2) number of beneficial insects recognized, (3) score of knowledge on pest and disease, natural enemies and ecosystem, (4) score of pest management practices, (5) score of other crop management practices, (6) score of skill on pest and other crop management practices, and (7) score of attitude on environment and conservation of farmers before and after FFS training. In the year before training, farmers' knowledge on pests, natural enemies, disease, ecosystem, and pest and crop management were similar for both FFS farmers and control farmers. But in the FFS villages, participant farmers had rather more knowledge than non-participant farmers on pests, disease, natural enemies and ecosystem.

In the post-training year, the results show that FFS farmers remembered natural enemies better than the other two farmer groups, while the numbers of pest recognitions of the three groups are similar. Moreover, after training the FFS farmers' knowledge increased substantially. Also, for pest management and other crop management practices, FFS farmers obtained scores higher than those of Non-FFS and control farmers. Regarding skill for pest and other crop management practices, FFS farmers had more confidence after training than Non-FFS and control farmers. For attitude towards environment and conservation after training, FFS farmers were also more likely to use environmentally friendly methods.

The results from Table 5.10 suggest that the FFS training has increased farmers' knowledge and skills on pest and plant management based on IPM practices, and changed their attitudes on the environment and conservation.

Table 5.10: Farmers' knowledge, pest and crop management practices, and attitudes toward environment and conservation before and after training by farmer category in India, crop years 2000 and 2002

Parameters	Farmer Category			F-test
	FFS	Non-FFS	Control	
Number of observation (N=83)	37	30	16	
Pests recognition (no.)				
-Pre-training	4.70	4.43	4.63	0.607 ^{ns}
-Post-training	3.19	3.53	3.31	1.396 ^{ns}
t-test	-7.058 ^{***}	-4.382 ^{***}	-3.085 ^{***}	
Natural enemies recognition (no.)				
-Pre-training	0.51 ^a	0.00 ^b	0.38 ^a	5.427 ^{***}
-Post-training	1.57 ^a	0.40 ^b	0.19 ^b	25.298 ^{***}
t-test	5.446 ^{***}	3.247 ^{***}	-0.613 ^{ns}	
Knowledge: Pest & disease, natural enemies and ecosystem (score)				
-Pre-training	35.97 ^a	31.47 ^b	32.13 ^{ab}	2.889 [*]
-Post-training	47.73 ^a	32.60 ^b	29.06 ^b	44.637 ^{***}
t-test	6.600 ^{***}	0.619 ^{ns}	-1.059 ^{ns}	
Pest management practices (score)				
-Pre-training	4.46	3.77	3.19	1.455 ^{ns}
-Post-training	12.62 ^a	6.13 ^b	5.31 ^b	56.967 ^{***}
t-test	13.203 ^{***}	3.814 ^{***}	1.698 ^{ns}	
Other crop management practices (score)				
-Pre-training	9.57	11.20	9.81	1.226 ^{ns}
-Post-training	23.30 ^a	21.67 ^{ab}	19.19 ^b	2.699 [*]
t-test	15.499 ^{***}	7.899 ^{***}	7.788 ^{***}	
Skill: Pest & other crop managements (score)				
-Pre-training	4.05 ^a	0.20 ^b	0.00 ^b	12.841 ^{***}
-Post-training	14.30 ^a	8.13 ^b	4.44 ^c	38.022 ^{***}
t-test	9.033 ^{***}	13.043 ^{***}	6.743 ^{***}	
Attitude: Environment & conservation (score)				
-Pre-training	15.54 ^a	13.03 ^b	12.44 ^b	16.121 ^{***}
-Post-training	26.43 ^a	18.73 ^b	17.88 ^b	20.528 ^{***}
t-test	2.977 ^{***}	7.624 ^{***}	10.881 ^{***}	

Note: *** Significant at 1%, * Significant at 10%, ^{ns} Non-significant difference

Means in rows followed by different superscript letters are significantly different.

Source: Own calculations

Pakistan

Table 5.11 presents farmers' knowledge and capacities for practice changes, skills, and attitude scores in Pakistan before and after the FFS training. The decision-making empowerment score was determined by using different decision aids such as self-conducted ecosystem analysis including pest scouting, consulting fellow farmers, relying on own knowledge, reading labels on pesticides, accessing agricultural programs on TV and radio, and understanding health problems and pesticide use. Scoring on field experimentation was assessed by giving weights to experimentation initiatives undertaken by farmers, such as early or late planting, trap crops, change in variety, physically controlling pests, and experimentation on pesticide chemical alternatives. The land improvement score was taken from farmers using organic or natural materials. The biodiversity score was derived from responses to questions on crop losses estimated by farmers. Score of the attitude towards the environment was deduced from questions that included belief in cultural and biological methods of crop protection on biodiversity losses, understanding of pesticide threat to natural environment, know-how on pesticide hazards to all living organisms, and beliefs about health risks of spraying. Social recognition of the farmers was assessed through assigning different scores for the amount of contact with other farmers for discussion on social and technical matters (Azeem Khan et al. 2005).

Comparing the number of pest recognitions before training shows that the three groups of farmers had similar knowledge of the different types of pest. In the case of natural enemies, the FFS farmers knew more about beneficial insects than other groups. Concerning the skill for decision-making in the pre-training year, the FFS group and the control group have equal scores and the Non-FFS group has the lower scores. In the scores for field experimentation, land improvement and observed biodiversity, the results show that the farmers in the FFS villages and control villages have quite different skills in field practices. The farmers in the FFS village have better skills than the farmers in the control village. For the attitude towards environment, the three farmer groups have similar scores on natural environment and biological methods. It is worth noting that FFS farmers are more likely to discuss and exchange their information with neighbours than Non-FFS and control farmers.

After the FFS training, i.e. crop year 2003, the comparison between pre- and post-training shows considerable changes. FFS farmers significantly increased their knowledge of pest management after training such that they could recognize more pests and natural enemies than Non-FFS and control farmers. And participant farmers were more confident in decision-making and relied more on their knowledge. Moreover, they changed to use more natural materials and had more confidence in biological methods. They also had more discussion with fellow farmers. On the other hand, the majority of control farmers showed no significant difference between pre- and post-training. For the Non-FFS group, the change was in the same direction as for the FFS group.

These results suggest that the farmers who attend the IPM training have better skills in field decision-making and prefer to discuss social and technical matters with others. In addition, the farmers in FFS villages have more knowledge than farmers in control villages on the use of organic materials for land improvement and on crop losses estimation. After the FFS training, the participant farmers gained more knowledge, skills and attitude on pest and plant management, which led to changes in their practices and adoption to IPM technology.

Table 5.11: Farmers' knowledge, practices, and attitudes before and after training by farmer category in Pakistan, crop years 2001 and 2003

Parameters	Farmer Category			F-test
	FFS	Non-FFS	Control	
Number of observation (N=190)	78	59	53	
Pests recognition (no.)				
-Pre-training	2.12	2.07	2.04	0.073 ^{ns}
-Post-training	5.04 ^a	2.75 ^b	1.81 ^c	116.261 ^{***}
t-test	13.406 ^{***}	3.733 ^{***}	-1.148 ^{ns}	
Natural enemies recognition (no.)				
-Pre-training	0.17 ^a	0.03 ^b	0.04 ^b	2.571 [*]
-Post-training	3.06 ^a	0.71 ^b	0.13 ^c	140.815 ^{***}
t-test	19.034 ^{***}	4.583 ^{***}	2.327 ^{**}	
Skill: Decision making (score)				
-Pre-training	16.03 ^a	10.34 ^b	14.91 ^a	5.682 ^{***}
-Post-training	34.49 ^a	9.49 ^b	9.43 ^b	41.478 ^{***}
t-test	6.111 ^{***}	-0.485 ^{ns}	-3.009 ^{***}	
Field experimentation (score)				
-Pre-training	11.03 ^a	7.80 ^{ab}	5.28 ^b	3.038 ^{**}
-Post-training	15.26 ^a	11.19 ^{ab}	6.79 ^b	5.335 ^{***}
t-test	2.037 ^{**}	1.272 ^{ns}	0.621 ^{ns}	
Land improvement (score)				
-Pre-training	20.19 ^a	23.73 ^a	2.83 ^b	14.368 ^{***}
-Post-training	52.56 ^a	11.86 ^b	5.66 ^b	82.257 ^{***}
t-test	7.394 ^{***}	-2.739 ^{***}	1.030 ^{ns}	
Observed biodiversity (score)				
-Pre-training	52.44 ^a	51.19 ^a	45.66 ^b	2.808 [*]
-Post-training	72.05 ^a	54.75 ^b	46.32 ^c	40.770 ^{***}
t-test	8.852 ^{***}	1.062 ^{ns}	0.224 ^{ns}	
Attitude: Towards environment (score)				
-Pre-training	37.95	36.10	33.77	0.604 ^{ns}
-Post-training	75.90 ^a	39.15 ^b	29.81 ^b	44.815 ^{***}
t-test	9.735 ^{***}	0.731 ^{ns}	-1.274 ^{ns}	
Social recognition (score)				
-Pre-training	13.72 ^a	8.98 ^b	6.60 ^b	6.617 ^{***}
-Post-training	27.44 ^a	7.63 ^b	8.11 ^b	17.582 ^{***}
t-test	4.608 ^{***}	-0.600 ^{ns}	0.509 ^{ns}	

Note: *** Significant at 1%, ** Significant at 5%, * Significant at 10%, ^{ns} Non-significant difference
Means in rows followed by different superscript letters are significantly different.

Source: Own calculations

5.2 Impact assessment model

The core of the impact analysis of the FFS program is a DD-model and the fixed-effects method (see Chapter 3). In this section, a description is presented of variables that are used in the DD-model, and the econometric tests used to ensure the efficiency and reliability of estimations.

5.2.1 Description of variables used in the models

Following the conceptual framework described in Chapter 3, the DD-models help to establish causality between the FFS training and pest management practices and cotton productivity of training participants. The model has been applied to capture the changes after training for insecticide costs, EIQ score, cotton yield, and gross margin over time (pre- and post-training) and among the three farmer groups.

Table 5.12 presents the description of variables used in the DD-models and combined-countries models. All continuous variables in the DD-models reflect differences between pre- and post-training. The dependent variables used in the models are based on the common IPM impact targets like economic well-being, pesticide reduction, and environmental conservation (Walter-Echols and Ooi 2005). In this analysis the indicators are categorized as farmer level effects both on the input side, i.e. insecticide expenditures and on the output side, i.e. cotton yield and gross margin. Moreover, the EIQ score indicates environmental effects (see Chapter 3).

The explanatory variables included in the models can be grouped into four categories: (i) farmer group (ii) knowledge and skills, (iii) input used, and (iv) farm resources. The first category of variables refers to the three farmer groups, as explained in Chapter 3. They allow for the assessment of the direct impact of the FFS training as well as the diffusion effect of the program. The second type of variables measures the effect of improved farmers' knowledge and skills in cotton cultivation and in pest management. It is hypothesized that these variables are negatively related with insecticide cost and EIQ score, because IPM practices have led to appropriate and efficient use of agricultural inputs. On the other hand, a positive relation with yield and gross margin is expected.

The third category of variables measures external production inputs, including nitrogen fertilizer and insecticides. For the model with insecticide cost as the dependent variable, nitrogen fertilizer is expected to have a positive effect because of its stimulating effect on pests (Cisneros and Godfrey 2001; Letourneau 1988; Zehnder 2009). For the model with cotton yield as dependent variable, the independent variable “insecticide cost” is expected to show a positive relationship. The last category is farm resources, which includes family labor for field management, total family labor, and the area planted to cotton. Family labor, including the time for field monitoring, is expected to have a negative association with insecticide use and EIQ score because IPM practices will help to minimize pesticide usage and but tend to be more labor-intensive. Total family labor is expected to have a positive relationship with cotton production and gross margin due to the probability that increasing family labor could imply more intensive farm management. The cotton area is expected to have a positive relationship with the gross margin per ha because farmers with a larger cotton area will tend to be more professional due to their large-scale production.

Table 5.12: Description of variables used in the DD-models and combined-countries models^{1/}

Group	Name	Type	Description
<i>Dependent variables</i>			
	Insecticide expenditure	Continuous	Cash cost of insecticide (\$/ha)
	EIQ	Continuous	Environmental impact quotient (score)
	Cotton yield	Continuous	Cotton production (kg/ha)
	Gross margin	Continuous	Revenue above variable cash cost (\$/ha)
<i>Independent variables</i>			
Farmer group	FFS group	Dummy	1 = participant farmers; 0 = otherwise
	Non-FFS group	Dummy	1 = non-participant farmers, who live in the same village as participant farmers; 0 = otherwise
	Control group ^{2/}	Dummy	1 = non-participant farmers, who live in another village; 0 = otherwise
Time ^{3/}		Dummy	1 = after FFS training; 0 = before FFS training
Knowledge and skill	Knowledge	Continuous	Number of type of pest or natural enemy that farmers know
	Skill and field practices	Continuous	Score of skill and field practices
Input resource	Nitrogen fertilizer	Continuous	Quantity of nitrogen fertilizer (kg/ha)
	Insecticide expenditure	Continuous	Cash cost of insecticide (\$/ha)
Farm resource	Family labor for field management	Continuous	Family labor of field management activities (md/ha)
	Family labor	Continuous	Total family labor (md/ha)
	Cotton area	Continuous	Cultivation area of cotton (ha)

Source: Own presentation

Note: ^{1/} The variables are used same in DD-models and combined-countries models

^{2/} The variable appears as a constant term in the model.

^{3/} The variable is only used in combined-countries models.

5.2.2 Model tests

In order to carefully investigate and ameliorate important econometric problems, this study applies five types of tests. Collinearity, multicollinearity, heteroskedasticity, endogeneity and selectivity bias tests⁶ are required to produce dependable and efficient estimations (Gujarati 1995; Pindyck and Rubinfeld 1998).

To investigate collinearity a correlation coefficient between any pair of explanatory variables is calculated. An absolute value close to one means that strong correlation exists. Additionally, Hill et al. (2001) mentions that the strong linear relationship could be biased if the coefficient in absolute value is greater than 0.9.

The multicollinearity problem can be detected by the Variance Inflation Factor (VIF). More precisely, the VIF is an index that measures how much the variance of a coefficient is increased because of collinearity. A VIF value greater than 10 is an indication of potential serious multicollinearity (Hair et al. 2005; Kutner et al. 2004).

The Breusch-Pagan-Godfrey test is capable of detecting heteroskedasticity (Greene 2000). In the presence of heteroskedasticity, robust standard errors can alternatively be calculated, which permits correct testing of hypotheses (Schmidt 2005).

Since one of the objectives of FFS training is to build human capacity, especially with regard to farmers' knowledge and skills, the change in knowledge could be endogenously influenced by the decision to participate in training. The Hausman test is popularly used to check whether there is such a problem (Davidson and MacKinnon 1993; Hausman 1978). In this study, age, gender and education are used as appropriate instrumental variables (IV)⁷ for farmers' plant and pest management abilities in its regression on FFS training. The residuals from this regression are then computed and included as an additional independent variable in the DD-models. If the coefficient of the residual is significantly different from zero,

⁶ This study omits a test for serial correlation due to the fact that first-differencing the data in the model already removes the individual-level effect and the term based on the time-invariant covariates. The test is neither necessary, nor available, for data of two periods of time (see Wooldridge 2002).

⁷ IV methods allow consistent estimation when the explanatory variables (covariates) are correlated with the error terms. For detailed discussion on the properties of the identifying instrument, see Maddala (1983), Wooldridge (2002), and Greene (2003).

then endogeneity is present and Ordinary Least Squares (OLS) does not produce consistent results.

The last statistical problem concerns the purposive assignment of villages with FFS training. Some villages were intuitively chosen by program organizers when characteristics in infrastructure and crop production coincide. In addition, farmers decided by themselves to participate in the training. Therefore, it is possible that participants with higher learning capacity or higher education prefer to join the program more than less educated farmers (Willis and Rosen 1979). In order to control selective placement both of villages and participants, the Heckman procedure is applied to each case (Heckman 1976, 1979).

For the village selection process, a probit model is firstly estimated, whereby the dependent variable is a dummy, assigning 1 if the farmer lives in one of the FFS villages and 0 for those in the control villages. Explanatory variables⁸ used in this binary response model comprise village and farmer characteristics. In the first stage of the farmers' self-selection test, the probability of participation in the training within the FFS villages is estimated by using a dummy variable (assigning 1 if the farmer attends the training and zero otherwise) as the dependent variable and farmer characteristics like age, gender, education, farm size and family size are included as explanatory variables. Then, the Inverse of Mill's Ratio⁹ (IMR) or hazard rate is estimated in both first steps of each test and then treated as a new variable in a substantive equation, which is the DD-model. The ratio captures the expected value of the disturbances in the substantive equation after the non-random selection has occurred. If the IMR is non-significant it can be assumed that no selective bias exists.

⁸ By reason of incomplete and non-identical data of village characteristics for all three countries, the explanatory variables, added in the first stage of the village selection process, are not the same.

⁹ The inverse of Mill's ratio is the ratio of the probability density function over the cumulative distribution function of a distribution (Berk 1983; Heckman 1976).

5.2.3 Results of model tests

Table 5.13 shows the summary results of econometric tests on both DD-models, i.e. simple and multivariate regressions. In general, there is no serious problem.

The maximum correlation coefficient of 0.67 is reached in India, and values of VIF are low. Therefore, there is no correlation problem within the explanatory variables. The 14 models in which heteroskedasticity has been detected were corrected by obtaining robust standard errors. These models comprise insecticide expenditure from all countries, EIQ score from Pakistan and India, and gross margin from China and India. Moreover, the Hausman test for all regressions reveals that there is no endogeneity of change in knowledge after the program intervention. Hence, it is convenient to use OLS.

For the both selectivity tests, the result between FFS and control villages apparently shows no selection bias for village characteristics among those villages in three countries. Additionally, in FFS villages, there is no self-selection for participant farmers. Therefore, this study can concentrate on the OLS estimation.

Table 5.13: Summary results of econometric problem on DD-models

Country / Indicators	^{2/}	Collinearity test ^{3/}	Multicollini- nearity test ^{4/}	Hetero- skedasticity test ^{5/}	Endoge- neity test ^{6/}	Selection bias ^{7/} :	
						between villages	in FFS village
China							
Insecticide cost	S	0.50	1.33	***	-	ns	ns
	M	0.60	1.48	***	ns	ns	ns
Cotton yield	S	0.50	1.33	ns	-	ns	ns
	M	0.60	1.57	ns	ns	ns	ns
Gross margin	S	0.50	1.33	*	-	ns	ns
	M	0.60	1.63	ns	ns	ns	ns
India							
Insecticide cost	S	0.67	1.84	***	-	ns	ns
	M	0.67	1.45	***	ns	ns	ns
EIQ score	S	0.67	1.84	***	-	ns	ns
	M	0.67	1.49	***	ns	ns	ns
Cotton yield	S	0.67	1.84	***	-	ns	ns
	M	0.67	1.88	ns	ns	ns	ns
Gross margin	S	0.67	1.84	***	-	ns	ns
	M	0.67	1.40	***	ns	ns	ns
Pakistan							
Insecticide cost	S	0.56	1.46	***	-	ns	ns
	M	0.56	1.29	***	ns	ns	ns
EIQ score	S	0.56	1.46	***	-	ns	ns
	M	0.56	1.27	***	ns	ns	ns
Cotton yield	S	0.56	1.46	ns	-	ns	ns
	M	0.62	1.56	ns	ns	ns	ns
Gross margin	S	0.56	1.47	ns	-	ns	ns
	M	0.62	1.57	ns	ns	ns	ns

Note: ^{1/} *** Significant at 1%, * Significant at 10%, ns: Non-significance

^{2/} Model type: S means simple regression and M means multivariate regression

^{3/} Maximum correlation coefficient in absolute value

^{4/} Mean value of Variance Inflation Factor

^{5/} Chi²-test of Breusch-Pagan / Cook-Weisberg test

^{6/} T-test of coefficient to the residual variable

^{7/} T-test of coefficients to the Inverse Mill ratio

Due to lack of information concerning scientific name of pesticides, the EIQ score of China can not be calculated.

Source: Own calculations

5.3 Results of econometric models

This section of the study focuses on input and output performances presented in simple and multivariate regression models, whereby in the latter models additional variables accounting for farm and household characteristics are included. Changes in insecticide costs and EIQ scores are used as indicators for the effect of training on input use. The output indicators for FFS effects are captured by cotton yield and gross margin values.

It is hypothesized that after training the highest growth rate in output parameters will be achieved by the FFS group and the upward shift of the Non-FFS group will be greater than that of the control group ($\mu > \beta > \alpha$). With respect to the training effect on the input side, it should be the other way around ($\mu < \beta < \alpha$). The Wald-test was applied as a tool to test the regression coefficients¹⁰.

5.3.1 Simple regression

In the simple regressions, only the dummy variables of the three groups, i.e. farmers from FFS, Non-FFS, and control villages are included. The coefficient of the control group (α) represents the pre-training growth rate of all three farmer groups. The difference in growth rates between the FFS group and the control group is shown by the coefficient of the FFS group (μ). Finally, the coefficient of the Non-FFS group (β) reflects the diffusion effect of the training¹¹.

Effect on inputs

Table 5.14 and Table 5.15 present the impact of FFS on insecticide cost and EIQ score, respectively. According to the results of the insecticide cost analysis (Table 5.14), the coefficients for the farmer group dummy variables were negative in all three countries. However, only for the FFS group were the coefficients significant. This result was expected and is consistent with the results found in other similar analyses (e.g. Praneetvatakul and Waibel 2008). Moreover, in India the variable that

¹⁰ The results of econometric models from STATA program can be seen in Appendix A.

¹¹ The results of combined-countries from fixed-effects model are shown in Appendix B.

measures the diffusion effect was found to be significant. However, the effect on pesticides is more than 30% lower than for the FFS farmers, which suggests that not all skills that participants learn in field schools are observable by their neighbours, and effective diffusion requires intensive training. The overall fit of the models is not very good, with rather low R^2 , but the models are significant. The hypothesis tests are consistent with the study's assumption, i.e. after the training, the FFS group switched to lower insecticide use. In all three countries the trend in insecticide use of FFS farmers is lower than that of the control and Non-FFS farmers.

Table 5.14: Comparison of effect of FFS on insecticide expenditure (\$/ha) among three countries (simple regression)

Countries/ Dependent variable/ Variables	China Insecticide expenditure (\$/ha)		India Insecticide expenditure (\$/ha)		Pakistan Insecticide expenditure (\$/ha)	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
FFS group (μ)	-0.962 ^{***}	0.109	-2.400 ^{**}	0.985	-1.647 ^{***}	0.471
Non-FFS group (β)	-0.043 ^{ns}	0.239	-1.767 [*]	0.969	-0.489 ^{ns}	0.469
Control group (α)	-0.078 ^{ns}	0.054	0.840 ^{ns}	0.964	-0.090 ^{ns}	0.099
R^2	0.0478		0.1807		0.0452	
F-statistics	39.11 ^{***}		5.81 ^{***}		6.51 ^{***}	
N	535		83		190	
Hypothesis test: (p-values)						
$\mu < \alpha$	0.000		0.017		0.001	
$\mu < \beta$	0.000		0.007		0.076	
$\beta < \alpha$	0.856		0.072		0.298	

Note: ^{***} Significant at 1%, ^{**} Significant at 5%, ^{*} Significant at 10%, ^{ns} Non-significant difference

Source: Own calculations

Table 5.15 shows the environmental and human health impact of FFS training for Pakistan and India¹². The results indicate that FFS farmers in both countries switched to less toxic pesticides as compared to the control groups, as shown by significant coefficient of FFS group variable and hypothesis test. Some within-village

¹² Since the pesticide compound names were not known in China, it was not possible to calculate EIQ.

diffusion effect was observed in Pakistan as indicated by the negative, significant regression coefficient beta and the p-value of hypothesis test ($\beta < \alpha$). Results for the control groups differ between the two countries. While in Pakistan the pesticides used by control farmers were even more harmful than in the year of the baseline, the effect in India was not significant.

Table 5.15: Comparison of effect of FFS on total EIQ scores among three countries (simple regression)

Countries Dependent variable/ Variables	India Total EIQ scores		Pakistan Total EIQ scores	
	coefficient	Robust Std. Err.	coefficient	Robust Std. Err.
FFS group (μ)	-2.503 ^{***}	1.000	-2.274 ^{***}	0.534
Non-FFS group (β)	-1.036 ^{ns}	1.141	-0.922 [*]	0.517
Control group (α)	1.253 ^{ns}	0.981	0.328 ^{**}	0.156

R ²	0.1204		0.0649	
F-statistics	5.64 ^{***}		10.06 ^{***}	
N	83		190	
Hypothesis test: (p-values)				
$\mu < \alpha$	0.014		0.000	
$\mu < \beta$	0.019		0.058	
$\beta < \alpha$	0.366		0.076	

Note: ^{***} Significant at 1%, ^{**} Significant at 5%, ^{*} Significant at 10%, ^{ns} Non-significant difference
Due to lack of information concerning scientific name of pesticides, the EIQ score of China can not be calculated.

Source: Own calculations

Effect on outputs

The effect of FFS on cotton yield and gross margin is demonstrated in Table 5.16 and Table 5.17, respectively. The FFS group in China and Pakistan reached high growth rates in both cotton yield and gross margin. In China, it can be seen that the growth rates of both the Non-FFS and the control group were not as high as that of FFS group. Therefore, the hypothesis that FFS and Non-FFS would perform better than the control group can be confirmed in this country. In Pakistan, control farmers achieved a significantly negative growth rate, indicating that they could not plant as well during the study period. In India, the results were opposite to expectations. The control farmers significantly increased their yield while for both FFS and Non-FFS

farmers the effect was negative. A similar effect was found for the gross margin (Table 5.16) although the coefficients for the farmer groups were not significant. But both models, i.e. yield and gross margin, are non-significant. The reasons for the negative effect are not obvious, but may be due to unobserved factors (i.e. not pests and pest management) that were different between the FFS and control villages. It is unlikely however that the training caused these effects unless the wrong messages were relayed by the trainers, such as an emphasis purely on pesticide reduction and neglect of productivity aspects.

Table 5.16: Comparison of effect of FFS on the cotton yield among three countries (simple regression)

Countries/ Dependent variable/ Variables	China Cotton yield (kg/ha)		India Cotton yield (kg/ha)		Pakistan Cotton yield (kg/ha)	
	Coefficient	Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Std. Err.
FFS group (μ)	0.117 ^{***}	0.020	-0.360 ^{**}	0.176	0.210 ^{**}	0.087
Non-FFS group (β)	0.040 ^{**}	0.020	-0.368 ^{**}	0.177	-0.019 ^{ns}	0.092
Control group (α)	0.099 ^{***}	0.014	0.492 ^{***}	0.163	-0.567 ^{***}	0.067
R ²	0.0594		0.0915		0.0477	
F-statistics	16.79 ^{***}		2.30 ^{ns}		4.68 ^{***}	
N	535		83		190	
Hypothesis test: (p-values)						
$\mu > \alpha$	0.000		0.044		0.017	
$\mu > \beta$	0.000		0.934		0.007	
$\beta > \alpha$	0.051		0.041		0.837	

Note: ^{***} Significant at 1%, ^{**} Significant at 5%, ^{ns} Non-significant difference

Source: Own calculations

Table 5.17: Comparison of effect of FFS on the gross margin among three countries (simple regression)

Countries/ Dependent variable/ Variables	China Gross margin (\$/ha)		India Gross margin (\$/ha)		Pakistan Gross margin (\$/ha)	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Std. Err.
FFS group (μ)	0.197 ^{***}	0.033	0.130 ^{ns}	0.255	0.195 ^{***}	0.050
Non-FFS group (β)	0.073 ^{**}	0.035	-0.034 ^{ns}	0.178	0.091 [*]	0.053
Control group (α)	0.141 ^{***}	0.024	0.451 ^{***}	0.143	-0.083 ^{**}	0.039
R ²	0.062		0.0065		0.0775	
F-statistics	19.14 ^{***}		0.24 ^{ns}		7.81 ^{***}	
N	535		83		189	
Hypothesis test: (p-values)						
$\mu > \alpha$	0.000		0.611		0.000	
$\mu > \beta$	0.000		0.492		0.031	
$\beta > \alpha$	0.038		0.852		0.089	

Note: ^{***} Significant at 1%, ^{**} Significant at 5%, ^{*} Significant at 10%, ^{ns} Non-significant difference

Source: Own calculations

5.3.2 Multivariate models

In this section the simple models are complemented by explanatory variables of farmers' knowledge about pests and natural enemies, nitrogen fertilizer and family labor for field management. Additional variables of farmer and household characteristics are included in the models. Results are first presented for each country separately, followed by the pooled data for all the three countries.

Effect on inputs

Table 5.18 presents the results of the training impact on insecticide costs. In all three countries, the FFS training significantly reduces insecticide use. The non-significant coefficient on the Non-FFS group indicates that there is no diffusion effect. These results confirm the findings from the simple model analysis. With respect to farmers' knowledge about pests and natural enemies, only in Pakistan can a significant impact on insecticide reduction be detected.

In China, nitrogen fertilizer applied in cotton fields was positively related to insecticide use, meaning that more intensive fertilizer use triggers more insecticide application (see Cisneros and Godfrey 2001; Zehnder 2009). Additionally, family labor for field management, such as field monitoring and irrigation, reduced

insecticide use in China. In harmony with a study on effects of IPM on labor organization, the FFS farms reduced time spent on pesticide application in post-training and increased time spent on IPM tasks (Mancini 2006). The results of the hypothesis tests confirm that the FFS group significantly reduces insecticide use after the training as compared to the control group ($\mu < \alpha$) for all three countries. The F-statistics show that the models are highly significant.

Table 5.18: Comparison of effect of FFS on insecticide costs among three countries (multivariate models)

Countries/ Dependent variable/ Variables	China Insecticide expenditure (\$/ha)		India Insecticide expenditure (\$/ha)		Pakistan Insecticide expenditure (\$/ha)	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
FFS group (μ)	-0.775 ^{***}	0.241	-2.456 ^{**}	1.091	-1.156 ^{***}	0.427
Non-FFS group (β)	0.106 ^{ns}	0.242	-1.883 ^{ns}	1.18	-0.341 ^{ns}	0.447
Control group (α)	-0.090 ^{ns}	0.068	1.154 ^{ns}	1.526	-0.338 ^{ns}	0.208
Knowledge (score)	-0.029 ^{ns}	0.073	0.153 ^{ns}	0.178	-0.230 ^{**}	0.100
Nitrogen fertilizers (kg/ha)	0.002 ^{***}	3x10 ⁻⁴	-0.001 ^{ns}	0.002	0.004 ^{ns}	0.003
Family labor for field management (md/ha)	-0.004 ^{***}	0.002	6x10 ^{-5ns}	0.001	-0.003 ^{ns}	0.003
R ²	0.1356		0.1922		0.0693	
F-statistics	51.82 ^{***}		4.47 ^{***}		3.21 ^{***}	
N	535		83		190	
Hypothesis test: (p-values)						
$\mu < \alpha$	0.001		0.027		0.007	
$\mu < \beta$	0.012		0.025		0.147	
$\beta < \alpha$	0.663		0.115		0.447	

Note: ^{***} Significant at 1%, ^{**} Significant at 5%, ^{ns} Non-significant difference

Source: Own calculations

Table 5.19 shows the impact on insecticide expenditures of the pooled data. After compensating for the effect of heterogeneity across panel units, i.e. countries, it is shown that the FFS group significantly reduced insecticide applications. After FFS training, farmers reduced insecticide use, which is reflected in the significantly negative coefficient of the time variable. The Non-FFS group also reduced

insecticide use, while in villages without any FFS training at all, the expenditures for this input increased. Knowledge has a non-significant effect on insecticide use probably because knowledge had different effects in the three countries (see Table 5.18). Consistent with expectations, the application of nitrogen fertilizer is positively related to insecticide expenditures. Additionally, the result shows that improvements in field management lead to a decrease in insecticide use.

Table 5.19: The effect of FFS on insecticide costs (combined-countries model)

Countries/ Dependent variable/ Variables	Three countries Insecticide expenditure (\$/ha)	
	Coefficient	Robust Std. Err.
FFS group (μ)	-11.503 ^{***}	4.123
Non-FFS group (β)	-8.164 [*]	4.406
Control group (α)	76.624 ^{***}	7.318
Time	-43.014 ^{***}	2.974
Knowledge (score)	0.166 ^{ns}	0.946
Nitrogen fertilizers (kg/ha)	0.184 ^{***}	0.008
Family labor for field management (md/ha)	-0.129 ^{***}	0.018
<hr/>		
R ²	0.27	
F-statistics	160.97 ^{***}	
N	1616	
Hypothesis test: (p-values)		
$\mu < \alpha$	0.005	
$\mu < \beta$	0.310	
$\beta < \alpha$	0.064	

Note: ^{***} Significant at 1%, ^{*} Significant at 10%, ^{ns} Non-significant difference
Source: Own calculations

The effects of FFS training on environmental issues are presented in Table 5.20. The results of the simple models for both Pakistan and India can be confirmed, since significantly negative growth rates of the FFS groups are obtained. According to the Wald tests, the pesticide use of the FFS group has a lower EIQ score than the control and Non-FFS group, while Non-FFS farmers show a non-significantly

different trend from the control group. In Pakistan, both the knowledge and the skills effect are significantly helping farmers, consumers' health, and the environment. Likewise, the coefficient on scores from skill and field practices is also negatively correlated with EIQ scores. Moreover, the variable of labor for field management also contributes significantly to a reduction of environmental harm in Pakistan.

Table 5.20: Comparison of effect of FFS on total EIQ scores among three countries (multivariate models)

Countries/ Dependent variable/ Variables	India Total EIQ (scores)		Pakistan Total EIQ (scores)	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
FFS group (μ)	-2.575 ^{***}	0.986	-1.681 ^{***}	0.437
Non-FFS group (β)	-1.318 ^{ns}	1.095	-0.832 ^{ns}	0.515
Control group (α)	1.731 ^{ns}	1.396	0.296 ^{ns}	0.188
Knowledge (score)	0.259 ^{ns}	0.224	-0.289 ^{***}	0.106
Skill and field practices (scores)	0.026 ^{ns}	0.075	-0.029 ^{**}	0.014
Family labor for field management (md/ha)	-0.002 ^{ns}	0.003	-0.006 ^{**}	0.003
<hr/>				
R ²	0.1451		0.1186	
F-statistics	4.20 ^{***}		4.84 ^{***}	
N	83		190	
Hypothesis test: (p-values)				
$\mu < \alpha$	0.011		0.000	
$\mu < \beta$	0.050		0.176	
$\beta < \alpha$	0.232		0.108	

Note: ^{***} Significant at 1%, ^{**} Significant at 5%, ^{ns} Non-significant difference

Due to lack of information concerning scientific name of pesticides, the EIQ score of China can not be calculated.

Source: Own calculations

In accordance with these findings, the combined-country model in Table 5.21 shows that FFS training significantly helps farmers to decrease the use of toxic pesticides, as can be seen from the hypothesis tests and the significant coefficient on FFS variable. Moreover, the significant variable of Non-FFS indicates that non-participant farmers in FFS villages also use pesticides with lower EIQ scores. In contrast, the

control group applies more harmful pesticides. The time variable has no significant effect on EIQ scores in Pakistan and India, which means that there is no clear trend in the toxicity of pesticides used over time. The significantly negative sign of the knowledge coefficient explains that extensive knowledge about pests or natural enemies results in farmers' selection less toxic pesticides. Skills in cotton cultivation and family labor also contribute to an improvement in the rational use of pesticides.

Table 5.21: The effect of FFS on total EIQ (combined-countries model)

Countries/ Dependent variable/ Variables	Two countries EIQ (score)	
	Coefficient	Robust Std. Err.
FFS group (μ)	-60.188 ^{***}	24.158
Non-FFS group (β)	-81.965 ^{***}	26.142
Control group (α)	307.597 ^{***}	29.745
Time	2.113 ^{ns}	19.161
Knowledge (score)	-19.127 ^{***}	6.015
Skill and field practices (score)	-0.777 ^{ns}	0.713
Family labor (md/ha)	-0.101 ^{**}	0.043
<hr/>		
R ²	0.06	
F-statistics	6.36 ^{***}	
N	546	
Hypothesis test: (p-values)		
$\mu < \alpha$	0.013	
$\mu < \beta$	0.201	
$\beta < \alpha$	0.002	

Note: ^{***} Significant at 1%, ^{**} Significant at 5%, ^{ns} Non-significant difference

Due to lack of information concerning scientific name of pesticides, the dependent variable is summarized from EIQ scores of Pakistan and India.

Source: Own calculations

Effect on outputs

The effects of FFS training on cotton yield comparing all three countries are shown in Table 5.22. Again, the FFS groups from Pakistan and China achieved significant higher growth rates in comparison to the control and Non-FFS groups. In Pakistan, plots with more family labor input also produced a higher output (Ghorbani et al. 2008; Yilmaz and Ozkan 2004). This can be explained by more efficient labor use for different farm activities. In China, the result shows that farmers who applied more insecticide obtained lower yields. Although this analysis expects a positive sign for the relationship between insecticide cost and cotton yield, it is possible that the inappropriate use of insecticides will lead to lower yield. One reason could be that the spray of chemicals during the early growth period of cotton can induce resurgence of cotton aphids and other pests late in the season. However, it has been recommended that insecticide application should be delayed as long as possible (Wu and Guo 2005).

With regard to the knowledge variable, only India shows a positive significant effect on cotton productivity, although the FFS group could not perform better than the control group. From a recent IPM analysis around the world (van den Berg 2004), it is known that in the most intensive cropping systems IPM will normally lead to pesticide reduction. There can be an indirect effect of the training on yield either due to better targeting of pest control measures or because farmers might have become more efficient in their use of other inputs. Then, some previous studies could not discover the benefit from IPM on increasing yield (Praneetvatakul and Waibel 2003; van Duuren 2003).

Table 5.22: Comparison of effect of FFS on the cotton yield among three countries (multivariate models)

Countries / Parameters	China Cotton yield (kg/ha)		India Cotton yield (kg/ha)		Pakistan Cotton yield (kg/ha)	
	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
FFS group (μ)	0.086 ^{***}	0.024	-0.283 ^{ns}	0.175	0.218 ^{**}	0.108
Non-FFS group (β)	0.022 ^{ns}	0.021	-0.303 ^{**}	0.155	0.034 ^{ns}	0.095
Control group (α)	0.085 ^{***}	0.015	0.620 ^{***}	0.123	-0.592 ^{***}	0.067
Knowledge (score)	0.004 ^{ns}	0.006	0.098 ^{**}	0.048	0.013 ^{ns}	0.021
Family labor (md/ha)	9x10 ^{-6ns}	3x10 ⁻⁵	-2x10 ^{-4ns}	1x10 ⁻⁴	0.003 ^{***}	0.001
Insecticide expenditure (\$/ha)	-4x10 ^{-4***}	1x10 ⁻⁴	0.002 ^{**}	0.001	3x10 ^{-4ns}	2x10 ⁻⁴
R ²	0.0869		0.203		0.1095	
F-statistics	10.07 ^{***}		3.92 ^{***}		4.52 ^{***}	
N	535		83		190	
Hypothesis test: (p-values)						
$\mu > \alpha$	0.000		0.109		0.045	
$\mu > \beta$	0.011		0.87		0.055	
$\beta > \alpha$	0.288		0.054		0.718	

Note: ^{***} Significant at 1%, ^{**} Significant at 5%, ^{ns} Non-significant difference

Source: Own calculations

Table 5.23 presents the results of the combined-model for three countries on cotton yield. According to the previous results, the model shows significant positive coefficients for FFS group and control group, and a negative coefficient for insecticide cost. The result can be interpreted as showing that FFS and control farmers increased the cotton yield. However, regarding the hypothesis tests, the FFS group produced higher yields than the control group, while there is a non-significant coefficient for the Non-FFS group. After the FFS training was conducted one year later, the cotton yield was higher than the year before. As more insecticide application leads to lower production that is consistent with the results from the DD-model (Table 5.22).

Table 5.23: The effect of FFS on cotton yield (kg/ha) (combined-countries model)

Countries/ Dependent variable/ Variables	Three countries Cotton yield (kg/ha)	
	Coefficient	Robust Std. Err.
FFS group (μ)	140.855 ^{***}	44.164
Non-FFS group (β)	-11.853 ^{ns}	37.473
Control group (α)	2892.980 ^{***}	109.123
Time	96.296 ^{**}	46.309
Knowledge (score)	4.892 ^{ns}	8.667
Family labor (md/ha)	0.134 ^{ns}	0.158
Insecticide cost (\$/ha)	-1.323 ^{**}	0.683
<hr/>		
R ²	0.07	
F-statistics	11.66 ^{***}	
N	1616	
Hypothesis test: (p-values)		
$\mu > \alpha$	0.001	
$\mu > \beta$	0.000	
$\beta > \alpha$	0.752	

Note: ^{***} Significant at 1%, ^{**} Significant at 5%, ^{ns} Non-significant difference

Source: Own calculations

The effects of FFS training on gross-margin becomes evident for Pakistan and China when applying a multivariate model as shown in Table 5.24. Moreover, the diffusion effect of FFS is shown by the significant positive coefficients on the Non-FFS groups in these two countries. This confirms again the results from simple models. In Pakistan, the result is consistent with the yield model, since more efficient labor input generally achieves higher productivity and more profit (Kabwe and Tschirley 2007). In China, the knowledge and cotton area had positive significant effects on the gross margin. The gross margin model from India has a poor goodness of fit. A very low value of the R² (0.039) shows that the gross margin function does not explain much of the relationship between the dependent and the independent variables, as most of the variables had a non-significant effect on the increase in return.

Table 5.24: Comparison of effect of FFS on the gross margin among three countries (multivariate models)

Countries / Parameters	China Gross margin (\$/ha)		India Gross margin (\$/ha)		Pakistan Gross margin (\$/ha)	
	Coefficient	Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Std. Err.
FFS group (μ)	0.155 ^{***}	0.041	0.062 ^{ns}	0.228	0.211 ^{***}	0.064
Non-FFS group (β)	0.069 ^{**}	0.033	-0.074 ^{ns}	0.189	0.121 ^{**}	0.056
Control group (α)	0.146 ^{***}	0.025	0.538 ^{***}	0.178	-0.100 ^{***}	0.039
Knowledge (score)	0.017 ^{**}	0.009	-0.057 ^{ns}	0.082	0.002 ^{ns}	0.012
Family labor (md/ha)	7x10 ^{-5ns}	6x10 ⁻⁵	-4x10 ^{-4*}	3x10 ⁻⁴	0.002 ^{**}	0.001
Cotton area (ha)	0.292 ^{**}	0.118	0.038 ^{ns}	0.055	0.002 ^{ns}	0.008
R ²	0.0838		0.0392		0.105	
F-statistics	9.68 ^{***}		0.89 ^{ns}		4.30 ^{***}	
N	535		83		189	
Hypothesis test: (p-values)						
$\mu > \alpha$	0.000		0.788		0.001	
$\mu > \beta$	0.032		0.534		0.111	
$\beta > \alpha$	0.039		0.698		0.030	

Note: ^{***} Significant at 1%, ^{**} Significant at 5%, ^{*} Significant at 10%, ^{ns} Non-significant difference
Source: Own calculations

In Table 5.25, the result of combined-model again confirms that FFS training helps farmers obtain higher gross margin because of the reduction in input expenditures and increasing cotton yield. The non-participant farmers from FFS villages and control villages also obtain more profit. According to the Wald-test the result follows the hypothesis of the study that the FFS farmers perform better than the Non-FFS and the Non-FFS farmers perform better than the control. The significantly positive sign on the time variable indicates that the gross margin increased in the year after the FFS-training. Finally, more family labor contributes to higher profit.

Table 5.25: The effect of FFS on gross margin (\$/ha) (combined-countries model)

Countries/ Dependent variable/ Variables	Three countries Gross margin (\$/ha)	
	Coefficient	Robust Std. Err.
FFS group (μ)	159.645 ^{***}	20.320
Non-FFS group (β)	62.219 ^{***}	18.522
Control group (α)	1053.196 ^{***}	26.999
Time	226.427 ^{***}	15.827
Knowledge (score)	6.814 ^{ns}	4.509
Family labor (md/ha)	0.099 [*]	0.054
Cotton area (ha)	-3.524 ^{ns}	6.130
<hr/>		
R ²		0.14
F-statistics		67.86 ^{***}
N		1616
Hypothesis test: (p-values)		
	$\mu > \alpha$	0.000
	$\mu > \beta$	0.000
	$\beta > \alpha$	0.001

Note: ^{***} Significant at 1%, ^{*} Significant at 10%, ^{ns} Non-significant difference

Source: Own calculations

5.4 Summary

To sum up the results of both statistical comparison of the economic performances and econometric models, in all the three countries the impact of FFS training can be perceived. On the input side, FFS farmers use less pesticide and choose those with lower toxicity. On the output side, the effects are different from country to country. In Pakistan, all three groups experienced lower yields because of uncommon blight in the year after training. However, the FFS group still increased productivity and gross margin. In China, participants performed better in terms of both cotton yield and gross margin as compared to the control farmers. In contrast, the economic impacts of FFS training do not show an effect on cotton productivity in India. Moreover, the results show that the knowledge variable, i.e. the recognition of pests and natural enemies, was significantly related to the reduction of pesticides and environmental impact in Pakistan. Furthermore, knowledge advancements positively affected cotton yield and gross margin in India and China, respectively.

The indirect impact from the training, i.e. the gain in IPM information of Non-FFS farmers, is inconsistent. The diffusion effect from FFS training is not robust and varies across the models. The coefficients of Non-FFS in insecticide regression of India, EIQ score of Pakistan, and cotton yield of China, became non-significant after other variables were added in multivariate models. While the results indicate that pest management information could spread from participants to their neighbours, this effect is limited to some elements of knowledge and may not apply to skills at all. Hence, the probability of adoption of FFS technology is low (Schultz 1975; Wozniak 1984; 1987). For farmers who did not attend practical skills training and do field experiments, the adoption of knowledge-intensive technology cannot be expected (Rahm and Huffman 1984; Sunding and Zilberman 2001). Moreover, the post-training data were collected one year later after the training. Non-FFS farmers did not realize what could be achieved and therefore did not experience the benefits. Accordingly, diffusion may occur but may be rather limited to a short-term impact. This is also confirmed by previous studies (Feder et al. 2003; Rola et al. 2002).

To assess the results under different conditions, multivariate regressions were also used in addition to the simple regressions. These were carried out as a robustness check by itemizing alternative specifications that take into account other variables such as farm and household characteristics that could influence performances. After controlling for other variables, the dummy variables of FFS group, however, are still highly significant. Thus, the results support the conclusions from simple models. Moreover, results from the combined-model also confirm the effect of FFS training, which harmonize with the results of DD-models.

In the next chapter, the evaluation of investment in farmers' training programs will be taken into account. In addition, the benefit of FFS training in the three countries at the macro-level will be assessed by estimating the economic surpluses.

6 Cost-benefit analysis of the FAO-EU IPM program

The FAO-EU project on Integrated Pest Management (IPM) for cotton in Asia implemented Farmer Field Schools (FFS) training in three main cotton producing countries: China, India and Pakistan, between 2000 and 2004.

Cotton is an important traded commodity and its production and processing are an important source of employment. Globally, more than 100 million farming units are engaged in cotton production (FAO 2003). In the three countries studied, cotton production and trade play an important role, as explained in Chapter 2. Therefore, the international cotton price can be easily influenced by a reduction in supply by one of these countries. For instance, a significant drop in cotton stocks in China resulted in a sharp increase in the international cotton price in 2003 (Cororaton and Orden 2008). The FFS project on IPM organized by the “FAO-EU IPM Program for Cotton in Asia” has the primary aim of reducing pesticide use and improving the cotton production system by training farmers. Therefore, benefits of the project in these three major cotton-producing countries should be able to affect the national economy and also have an influence on the international market.

Economically, development projects such as the FFS training are considered to be investments. Hence, the known investment criteria can be applied to ascertain the desirability of a project with respect to its economic efficiency (Silva and Pagiola 2003).

This chapter presents the methodology and results of a cost-benefit analysis of the IPM-FFS program in the three countries. A previous study by Praneetvatakul et al. (2005) investigated the impact of the “FAO-EU IPM Program for cotton in Asia” by applying cost-benefit analysis with a specific focus on financial analysis, based on the benefits from income increase and improved health. Results showed that the project did pay off even under conservative assumptions. In this chapter the analysis is taken further to also assess the macro-level impact of the program.

The chapter is divided into two parts. The first part has the objective to investigate the efficiency of the project investment at the farm-level in China, India and Pakistan. Based on the results in Chapter 5, the benefits of FFS training at the household level were assessed by statistical comparative analysis and Difference-in-Differences (DD) models. Under the application of a robustness check, the results show that the

project produces benefits in terms of pesticide reduction in all three countries, as well as yield increases in China and Pakistan.

Based on the conceptual framework of economic surplus that is described in Chapter 3, in the second part, the benefits of FFS training at the macro-level, i.e. the welfare analysis, are investigated using the Dynamic Research Evaluation for Management (DREAM) model. The purpose is to estimate the aggregate level of social benefits from FFS training in cotton production and cotton trade. A competitive market-clearing model is employed to assess the overall benefits and their distribution. The model estimates the social benefits in the three countries and the rest of the world (ROW) that result from the FFS training.

6.1 Cost-benefit analysis at farm-level

In this part, the indicators used in the cost-benefit analysis on farm-level are described in Chapter 3, i.e. Net present value (NPV), Internal rate of return (IRR) and Benefit-cost ratio (BCR).

6.1.1 Data

The data used here comprises project costs, including direct expenditures and opportunity costs of participants, and project benefits that are gained from cost reduction in pesticide application and increasing yield.

Project costs

Table 6.1 presents the number of graduated farmers from FFS training between 2000 and 2004. In total there were 72,187 farmers from the three countries who took part in the training, which corresponds to around 36% of participants from China, 46% from India and 17% from Pakistan. In China, the program started in 2000 with around 1,100 participants and increased threefold in 2001 and 2002. In 2003, over 12,000 farmers participated in the training program, but participation sharply decreased in the last year. In India, the program started in the same year as in China, with a very small number of farmers. The number of participants in India increased every year up to 21,600 in 2004. In Pakistan the training started in 2001 with a relatively small number of participants, which sextupled in 2002 and increased up to 4,800 in 2004.

Table 6.1: Numbers of farmers participating in the FAO-EU IPM Program for Cotton in Asia

Year	China	India	Pakistan
2000	1,099	150	0
2001	3,424	1,569	575
2002	9,206	4,306	3,062
2003	12,030	5,728	4,144
2004	500	21,600	4,794
Total	26,259	33,353	12,575

Note: The training started in Pakistan in 2001.

Source: FAO-EU IPM Programme for Cotton in Asia (2004a).

The project costs were calculated as the sum of operational costs from 2000 to 2004 and the opportunity costs of participating farmers. The project operational costs consist of direct costs for carrying out farmers' training, the overall technical assistance by the project management unit, the planning and evaluation workshops, traveling costs, equipment, the costs for management and administration in the three countries and the program management unit at the regional FAO office in Bangkok (FAO-EU IPM Program for Cotton in Asia 2004a). The opportunity costs of farmers have been calculated as foregone earnings for the time spent in participating in the FFS program during season-long training of approximately 14-20 weeks (depending on the country). Based on the average hired-labor wage, the opportunity cost amounted to \$22.75, \$18.52 and \$13.29 per participant for Pakistan, China and India, respectively. The annual opportunity cost is calculated by multiplying the number of participant farmers by the individual opportunity cost per farmer in each year.

Table 6.2 shows total costs during the project implementation phase. The total project operational costs for all three countries amounted to about \$8.3 million, out of which 45% was spent in China, 35% in India and 20% in Pakistan. The relatively small budget for Pakistan can be attributed to the comparatively smaller number of cotton farmers in that country. In addition, synergy effects could be achieved because the Asian Development Bank and the Arab Gulf Fund funded two complementary cotton IPM projects in Pakistan during that time. The projects were

implemented as one under the National IPM Program (FAO-EU IPM Program for Cotton in Asia 2004b).

The total costs for all three countries were estimated as approximately \$9.5 million, where the total annual cost per participant is \$160.94 in China, \$100.25 in India and \$151.56 in Pakistan.

Table 6.2: Project and opportunity costs of the FFS training program in three countries (US \$)

Year	China		India		Pakistan	
	Project costs	Opportunity costs	Project costs	Opportunity costs	Project costs	Opportunity costs
2000	492,148	20,353	212,209	1,994	97,966	-
2001	831,181	63,412	634,469	20,852	312,310	13,081
2002	1,147,657	170,495	577,310	57,227	394,766	69,661
2003	1,109,465	222,796	955,957	76,125	586,499	94,276
2004	159,346	9,260	520,534	287,064	228,298	109,064
Sum	3,739,796	486,317	2,900,478	443,261	1,619,839	286,081
Total	4,226,113		3,343,740		1,905,920	

Note: The opportunity cost is calculated as the number of FFS farmers multiplied by \$22.75 for Pakistan, \$18.52 for China and \$13.29 for India.

Source: FAO-EU IPM Programme for Cotton in Asia (2004a) and own calculations

Project benefits

The benefits of the project correspond to savings due to pesticide reduction on the input side and income earnings from yield increase on the output side. The measurement is based on impact study results from the previous chapters (statistical comparative analysis and DD-models). Table 6.3 presents the benefits of the FFS training on pesticide cost reduction and the value of cotton yield, which are evaluated by the difference between post- and pre-training of FFS farmers minus that of control farmers (DD-method¹³). The result shows that FFS training accounts for benefits from pesticide reduction of up to \$103 per ha in India, which amounts to around 40% of cost compensation. Cost reductions in China are second, where the FFS farmers can reduce costs by \$43 per ha. In Pakistan, the FFS group reduces pesticide expenditures by around \$5 per ha as compared to control farmers.

On the output side, the benefits from FFS training are related to an enhancement in cotton productivity. In China and Pakistan, yield increases through FFS training generated increases in cotton revenue by \$216 and \$223 per ha. However, in India, the economic impact on cotton productivity could not be observed due to the efficient use of other input factors (see Chapter 5). The total benefits from the FFS program are calculated as the value of pesticide reduction and yield increases for China and Pakistan.

¹³ The DD-method is $\Delta \text{FFS} - \Delta \text{Control}$.

$\Delta \text{FFS} = [\text{after training} - \text{before training}]$ of FFS group, $\Delta \text{Control} = [\text{after training} - \text{before training}]$ of control group

Table 6.3: Comparison of average pesticide costs and value of cotton yield pre- and post-training, for FFS farmers and control group

	China		India		Pakistan	
	FFS	Control	FFS	Control	FFS	Control
Pesticide cost (\$/ha)						
Pre-training	123.44	111.11	190.52	99.91	74.35	143.73
Post-training	49.14	80.19	57.73	70.38	48.06	122.64
t-test	-14.686 ^{***}	-6.393 ^{***}	-14.837 ^{***}	-1.361 ^{ns}	-5.727 ^{***}	-0.691 ^{ns}
Change (Post-Pre)	-74.3	-30.92	-132.79	-29.53	-26.29	-21.09
Change (FFS-Control)	-43.38		-103.26		-5.2	
%Change (FFS-Control)	-32.36		-40.14		-20.69	
Yield value(\$/ha)						
Pre-training	1,627.26	1,577.30	-	-	707.94	693.78
Post-training	2,027.40	1,761.80	-	-	925.31	688.32
t-test	14.730 ^{***}	7.409 ^{***}	-	-	5.698 ^{***}	-0.118 ^{ns}
Change (Post-Pre)	400.14	184.5	-	-	217.37	-5.46
Change (FFS-Control)	215.64		-		222.83	
%Change (FFS-Control)	12.89				31.49	

Note: ^{***} Significant at 1%, ^{ns} Non-significant difference, FFS: farmers who participated in the FFS training, Control: non-participants in control village

Source: Own calculations

Table 6.4 shows the total annual benefits per household, calculated as the average cotton area per household multiplied by total benefits per ha. Because Chinese farmers grow cotton on comparatively small plots, the total benefit per household (hh) of FFS training in China is smallest (\$75 per hh). On the other hand, the total benefits in Pakistan amount to \$497 per household due to the large cotton production area.

Table 6.4: Total annual benefits per household by cost reduction and crop income

	China	India	Pakistan
Total benefits (\$/ha)	259.02	103.26	228.83
Pesticide reduction	43.38	103.26	5.20
Yield increase	215.64	-	222.83
Average cotton area (ha/household)	0.29	1.57	2.18
Total benefits (\$/hh)	75.12	162.12	497.11

Source: Own calculations

Based on these calculations, the total annual benefits from FFS training can be calculated as benefits per household multiplied by the number of trained farmers in each year.

6.1.2 Results of cost-benefit analysis at farm-level

For the cost-benefit analysis it is assumed that all participant farmers adopt the IPM technology that they have acquired during FFS training for one year. Hence, benefits are assumed to accrue for one year after participation in the program. This cautious assumption is based on the fact that farmers may abandon the technology, and follow-up activities may be uncertain after the program was terminated.

Based on these assumptions, the basic benefits from FFS training for year t are evaluated as the benefits per household multiplied by the number of FFS attendances in year $t-1$. To define present values of project costs and benefits, a discount rate of 12% for Pakistan and India, and 8% for China¹⁴ is assumed.

Table 6.5, Table 6.6 and Table 6.7 show the results of the cost-benefit analysis for China, India and Pakistan, respectively, based on the assumptions described above.

Evaluation results of the program investment in China are presented in Table 6.5. The results show a negative NPV of \$0.7 million after the program was terminated in year 2004, and the BCR is less than one. Although the benefits of FFS training per

¹⁴ Based on a working paper from the Asian Development Bank, which reports social discount rates in countries for cost-benefit analysis (Zhuang et al. 2007).

ha were higher in China than in Pakistan, the project costs per farmer were substantially greater. In addition, the small plot sizes in China had a negative effect on the total project benefits. Thus, the benefit per household was too small (\$75.12 per hh) to cover the costs of the project. However, this result is based on one-year benefits, and farmers might continue to use IPM technology for some few years more, which would improve the results of the cost-benefit analysis.

Table 6.5: Benefits and costs of FFS training with 100% adoption rate in China (\$1,000)

Year	Benefits	Costs	Net benefits	Discounted cumulative cash flow
2000	-	512.50	-512.50	-474.54
2001	82.55	894.59	-812.04	-1,170.73
2002	257.20	1,318.15	-1,060.96	-2,012.95
2003	691.52	1,332.26	-640.74	-2,483.92
2004	903.64	168.61	735.04	-1,983.67
2005	37.56	-	37.56	-1,960.00
Total	1,972.47	4,226.11	-2,253.65	
NPV	-1,960.00			
BCR	0.42			
FIRR	-			

Note: Used discount rate at 8%, NPV: Net present value, BCR: Benefit-cost ratio, FIRR: Financial internal rate of return

Source: Own calculations

Although, the results of the econometric analysis for India were ambiguous due to the small sample size using the mean difference of the statistical analysis as assumption for benefit estimation (see Chapter 5), the results of the cost-benefit analysis presented here show a positive NPV of about \$0.7 million and a BCR of 1.29 (Table 6.6). The FIRR is 27%. The discounted cumulative cash flow shows that the pay-off period of the training program in India was reached after the project terminated in 2005. The analysis confirms that the FFS training project in India can

be economically justified even under the conservative assumption that the benefits of FFS training accrue for only one year.

Table 6.6: Benefits and costs of FFS training with 100% adoption rate in India (\$1,000)

Year	Benefits	Costs	Net benefits	Discounted cumulative cash flow
2000	-	214.20	-214.20	-191.25
2001	24.32	655.32	-631.00	-694.28
2002	254.36	634.54	-380.17	-964.88
2003	698.08	1,032.08	-334.00	-1,177.15
2004	928.61	807.60	121.02	-1,108.48
2005	3,501.75	-	3,501.75	665.62
Total	5,407.13	3,343.74	2,063.39	
NPV	665.62			
BCR	1.29			
FIRR	26.89%			

Note: Used discount rate at 12%, NPV: Net present value, BCR: Benefit-cost ratio, FIRR: Financial internal rate of return

Source: Own calculations

The results for Pakistan show a positive NPV of \$2.2 million and BCR of 2.7. The FIRR is 96%. As shown by the positive discounted cash flow, the pay-off period had been reached in 2003, which was the second phase of FFS training. The analysis indicates that the project investment on farmers' training in Pakistan was efficient. Although the analysis uses rather conservative assumptions, the break-even point was reached quickly (Table 6.7).

Table 6.7: Benefits and costs of FFS training with 100% adoption rate in Pakistan (\$1,000)

Year	Benefits	Costs	Net benefits	Discounted cumulative cash flow
2000	-	97.97	-97.97	-87.47
2001	-	325.39	-325.39	-346.87
2002	285.84	464.43	-178.59	-473.99
2003	1,522.14	680.78	841.36	60.71
2004	2,060.00	337.36	1,722.64	1,038.19
2005	2,383.12		2,383.12	2,245.55
Total	6,251.10	1,905.92	4,345.18	
NPV	2,245.55			
BCR	2.73			
FIRR	96.08%			

Note: Used discount rate at 12%, NPV: Net present value, BCR: Benefit-cost ratio, FIRR: Financial internal rate of return

Source: Own calculations

In order to analyse the sensitivity of the cost-benefit analysis to the underlying assumptions, a scenario analysis was conducted, by applying three different scenarios (B, C and D) as compared to the initial scenario A.

Table 6.8: Assumptions of project's investment analysis

Scenario	Incidence of benefits (years)	Adoption rate (%)
A	1	100
B	1	80
C	3	100
D	3	80

Note: Scenario A is the base scenario.

Source: Own presentation

The results of the different scenarios are presented in Table 6.9. For scenario B, the FIRR decreases by 18% in Pakistan and by around 13% in India. The benefits of the FFS project in China do not cover the expenses under the assumptions of scenario A and B.

An assumption that FFS farmers retain IPM practices for three years after the training (scenario C) results in an increase of the FIRR to 16% for China, 72% for India and 147% for Pakistan. Hence, it can be concluded that the training program in China will pay off if all participant farmers adopt this technology for at least three years.

In the last scenario D, with an adoption rate of 80%, and a three-year benefit period, the FIRR remains sufficiently high to still exceed the applicable discount rate in Pakistan and India. However, the FIRR of China is found to be as low as 5%, rendering the project inefficient in China.

Table 6.9: Scenario analysis of the financial rate of return in three countries

Scenario	FIRR		
	China	India	Pakistan
A	-	26.89%	96.08%
B	-	13.85%	74.25%
C	15.60%	72.05%	146.83%
D	4.98%	59.09%	125.52%

Note: The details of result are shown in Appendix C, FIRR: Financial internal rate of return
Source: Own calculations

These results lead to the question: at which minimum rate of adoption would the efficiency of investment be assured in each single country? If the project can generate benefits for the duration of one year after training, Figure 6.1 shows that Pakistan performs better than India¹⁵. For every \$1 invested by the project in FFS training, the benefits obtained in Pakistan are greater than those in India. The

¹⁵ Because the benefits of FFS training in China could not cover the total cost even at a 100% adoption rate, China is not presented in Figure 6.1.

minimum adoption rate for economic efficiency of investment is approximately 40% in Pakistan, and 80% in India (where BCR exceeds 1).

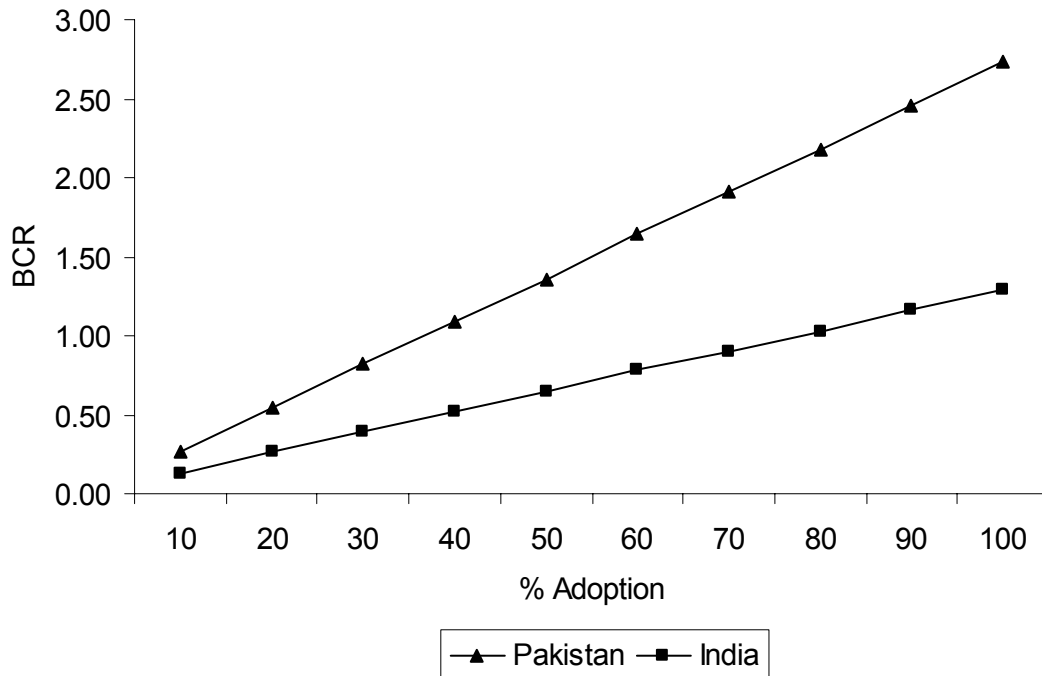


Figure 6.1: Impact of FFS adoption on benefit-cost ratio based on a one-year benefit period

Source: Own presentation

Figure 6.2 presents the impact of FFS adoption on BCR, given that benefits accrue for three years after training. The results show that the minimum adoption rates are 15% in Pakistan, 30% in India and 90% in China.

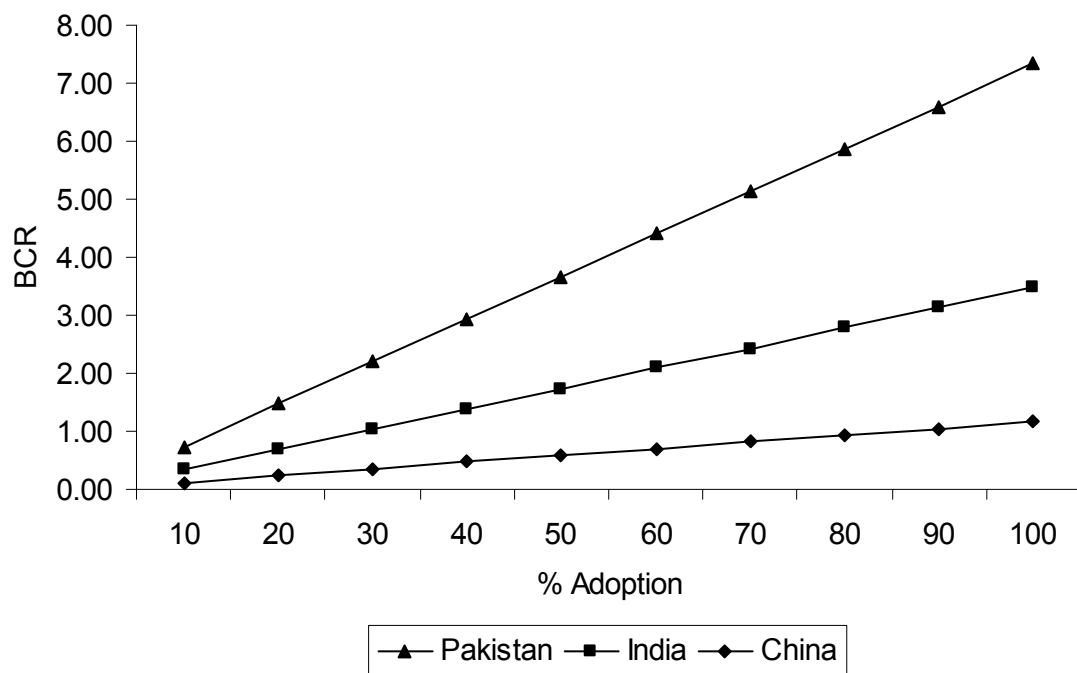


Figure 6.2: Impact of FFS adoption on benefit-cost ratio based on three year benefits' incidence

Source: Own presentation

6.2 Welfare analysis of FFS training

As described in Chapter 3, the welfare effects of FFS in the three countries were calculated using a simulation model called “Dynamic Research Evaluation Management” (DREAM). This is a partial equilibrium model, which allows the evaluation of the economic impact of agricultural research and development (R&D) interventions by making assumptions about the market mechanism, the technology adoption process and spill over effects (Wood et al. 2001)¹⁶. The model uses a scenario approach, whereby a scenario is defined as a specific combination of market conditions, commodities and regions where the impacts of an intervention are being measured. The model then calculates the discounted cumulative producer and consumer surpluses for the duration of the project. These can be compared to the total costs of project implementation accruing to the implementing agency (FAO-EU IPM program) and the costs that occur at farmer level, which are the opportunity costs of labor. As discount rate the figure applied by the Asian Development Bank was used (Zhuang et al. 2007).

6.2.1 Model assumptions

For the assessment of the welfare effects of the FFS training, three types of data are required: (i) cotton quantity and price, (ii) the shift in supply due to improved farmer practices as a result of improved knowledge and better management skills and (iii) the rate of adoption, i.e. how many farmers are able to apply the knowledge they have acquired and how long they retain it. For the latter, the adoption pattern used has a constant rate of diffusion after an initial time lag until adoption reaches a maximum and then declines also at a constant rate until the innovation has depreciated. In addition, the model is calculated for a homogenous product, i.e. no quality differences in cotton with market differentiation are considered. The supply and demand curves are linear, expressing exponential exogenous growth. A parallel supply shift is introduced as a result of the adoption of the innovation induced by the FFS intervention. The model includes multiple regions with a spill over effect on

¹⁶ The windows version 3.0 of DREAM has been used. The software can be downloaded from the home page of the International Food Policy Research Institute (IFPRI): <http://www.ifpri.org/dream.htm>

regions not included in the intervention, i.e. consumers in the other countries (“Rest of the World”) who benefit through the effect on world market prices. Table 6.10 summarizes the major assumptions used in the DREAM model for the three countries separately.

Table 6.10: Major data and assumptions for benefit assessment of FFS training among three countries using the DREAM model

Parameters	China	India	Pakistan	ROW
Market data				
Quantity of cotton production (1,000 tons) ⁽¹⁾				
2000	4,419.16	2,384.13	-	18,674.09
2001	5,311.64	2,680.11	1,804.16	16,958.61
2002	5,485.50	2,307.77	1,735.07	18,354.62
2003	5,183.40	3,044.37	1,706.72	18,442.48
2004	6,596.20	4,138.21	2,425.92	17,865.43
Quantity of cotton consumption (1,000 tons) ⁽¹⁾				
2000	5,115.78	2,954.04	-	17,407.56
2001	5,714.37	2,892.56	1,850.76	16,296.84
2002	6,508.59	2,895.59	2,045.87	16,432.91
2003	6,969.28	2,935.64	2,088.53	16,383.52
2004	8,381.31	3,223.44	2,286.96	17,134.04
Price of cotton (\$/tons) ⁽²⁾				
2000	1,250.23	1,332.71	-	1,232.16
2001	914.82	1,340.76	464.97	941.59
2002	1,155.98	1,348.52	491.68	1,250.90
2003	1,235.47	1,474.77	508.47	1,502.01
2004	1,291.38	1,310.98	503.00	1,159.41
Price elasticity of cotton supply ⁽³⁾	0.144	0.307	0.115	0.182
Price elasticity of cotton demand ⁽⁴⁾	-0.26	-0.20	-0.24	-0.10
Production: growth rate (%/year) ⁽⁵⁾	4.17	2.64	4.03	1.39
Consumption: growth rate (%/year) ⁽⁵⁾	4.35	2.34	6.43	1.28
Technology				
Percentage of supply shift (k-shift) ⁽⁶⁾	32.36	40.14	20.69	-
Adoption				
Maximum adoption level (%) ⁽⁷⁾				
2000	0.005	0.003	-	-
2001	0.016	0.032	0.053	-
2002	0.042	0.088	0.282	-
2003	0.055	0.117	0.382	-
2004	0.002	0.440	0.442	-

Note: ROW: rest of the world. Conversion Factors: 480-lb bales = 217.72 kg (Economic Research Service: USDA 2009b)

- (1) Calculation based on data of Meyer et al (2008).
- (2) Producer price of cotton as found in FAOSTAT (2009). The analysis assumes that the international price of COTLOOK A¹⁷ index represents ROW price. Data of C.I.F. North Europe Quotation of COTLOOK A index, quoted from APTMA (2008). Original source is Cotton Outlook Limited (2009b)
- (3) Quoted from Shepherd (2006) and assumed that the world price elasticity of cotton supply represent ROW price elasticity.
- (4) The price elasticities of three countries are quoted from Sumner (2003). The analysis assumes that the world price elasticity of cotton demand represents ROW price elasticity. Quoted from Gillson et al. (2004), Goreux (2004), Sumner (2005), and Pan et al. (2006).
- (5) Growth rates calculated using $\ln Y = a + bt$, where Y is cotton production/consumption and t is the year between 1940 and 2008. Calculated based on data of ICAC (2009).
- (6) The difference in pesticide use between post- and pre-training of FFS farmer minus that of control farmer Table 6.3.
- (7) Maximum adoption level is calculated from the annual proportion of cotton area of FFS farmers (number of FFS farmers multiplied by average cotton plot size) and total cotton areas in each country (FAO-EU IPM Program for Cotton in Asia 2004b).

The effect on world market prices occurs because in all the three countries cotton is produced in a horizontal market, i.e. production is significant relative to the volume of the world market. For example, China is the largest producer of cotton. Since 2003, China has also been the largest importer, while India and Pakistan are the third and fourth largest cotton producers respectively. The three countries included in the study are among the top four major users and are among the top ten exporters of cotton (Meyer et al. 2008). Therefore, when the marginal costs of production are lowered in large cotton-producing countries this, in principle, will have positive effects on the international cotton price (Cororaton and Orden 2008). Such effects can be

¹⁷ Indicators of international cotton prices are the COTLOOK A and COTLOOK B indexes, and U.S. price. The COTLOOK A index is for cotton classed as Middling 1-3/32" and calculated by the average of the five lowest offering prices of 19 styles of cotton traded in North European ports. The COTLOOK B index is the average of the three lowest offering prices of 8 styles of coarser grades of cotton traders (Cotton Outlook Limited 2009a). Cotton from Pakistan is grouped within the COTLOOK B index (Cororaton and Orden 2008). From China and India, cotton is grouped within the COTLOOK A index (Cotton Outlook Limited 2009a).

reasonably attributed to FFS training as it helps cotton producers towards a more efficient use of inputs and more effective pest management, with effects on the marginal costs of production.

The market conditions of the model (Table 6.10) are defined as variables of cotton prices and quantities, whereby total production and consumption are assumed to be in equilibrium across all regions. Furthermore, it is assumed that the international price equals the ROW price. Price elasticities of cotton supply are taken from a study by Shepherd (2006), which estimates price elasticities of supply for cotton using time-series data from 1961 till 2004 for a set of 30 countries. Moreover, it is assumed that the world price elasticity of cotton supply represents the ROW price elasticity. The price elasticities of cotton demand are taken from the study of Sumner (2003). This analysis assumes an elasticity of cotton demand of -0.1, which agrees with the results found by Gillson et al.(2004), as well as those by Goreux (2004), Sumner (2005), and Pan et al. (2006). The model assumes that the world price elasticity represents the price elasticity of cotton demand of ROW. Production and consumption growth rates are calculated using growth functions of cotton production/consumption and time between 1940 and 2008, based on ICAC data (2009).

For the assumptions of the technology conditions (see Table 6.10), data related to potential impacts from the FFS training are needed. Assumptions have to be made about technological time lags, the percentage change in production costs, represented as a shift of supply curve, and the probability of adoption of IPM practices (project success). The shift in the supply curve is mainly the result of a reduction in the costs of pesticides (Table 6.3). The model expresses this effect by a vertical shift in the supply curve, called the k-shift¹⁸. In the absence of other information it is assumed that the benefits from FFS training remain constant over time, i.e. over the adoption period.

In Table 6.3 the percentage change in pesticide costs between post- and pre-training of FFS farmer less the change that occurred in the counterfactual case, i.e. the

¹⁸ k shift = (change in yield/elasticity of supply) – (change in cost/[1+change in yield/100])

farmers in control villages, is presented. In other words the percentage changes of pesticide use is the basis for calculating the k-shift. As regards the lag period it was assumed that the benefits from FFS occur one year after the FFS training, i.e. when farmers have the opportunity to apply their knowledge in their own fields for the first time. Furthermore, the model assumes a probability of 100% of success, i.e. all adopters achieve the same unitary benefits. The maximum adoption level was expressed as the percentage of the cotton area of farmers participating in the FFS program. Due to the nature of the FFS concept, no technological spill over effects on other cotton producing regions are included.

6.2.2 Results of welfare analysis

The competitive market-clearing model includes all benefits from the three countries, and the Rest of the World (ROW) calculated from a base scenario. Table 6.11 presents the annual economic surplus generated by the project with a breakdown for producer and consumer surpluses. Total economic surplus is derived by summing the surpluses of China India and Pakistan plus the ROW. Results show that highest producer gains can be reached in India, due to its large cotton area, followed by Pakistan with a relatively modest producer gain of some \$1.5 million (see Table 6.11). For China, the model suggests that no benefit accrues to producers on the aggregate level. The model even calculates a loss for Chinese cotton producers of some \$200 000, although the k-shift is rather high (32%). This result is related to the fact that in the last phase (2004) of farmers' training, the number of graduated farmers was very small (2%¹⁹ of total graduated farmers in 2004). Therefore, Chinese producers had disadvantages compared to those in the other countries and their surplus became negative (\$1.7 million) in 2005.

As shown in Table 6.11 producers in other countries (ROW) lose as a result of supply shifts in three major cotton-producing countries under the condition of a competitive world market. On the other hand, consumers in ROW benefit from lower cotton prices. Therefore, even consumers in China gain in spite of the poor performance of the FFS program. In fact due to its large textile industry, Chinese consumers gain more than those in the other two countries.

¹⁹ see Table 6.1

Table 6.11: Economic surplus of the FFS training (\$1,000)

	2001	2002	2003	2004	2005	Total
Producers	59.10	365.40	937.80	1337.70	2,852.30	5,552.30
China	80.20	167.40	574.90	678.00	-1,734.70	-234.20
India	32.50	430.00	1,003.10	1,886.90	8,809.00	12,161.50
Pakistan	0.00	63.50	418.20	547.10	504.50	1,533.30
ROW	-53.60	-295.50	-1,058.40	-1,774.30	-4,726.50	-7,908.30
Consumers	73.50	470.00	1,620.70	2,752.10	8,287.00	13,203.30
China	15.10	102.20	385.00	687.40	2,276.10	3,465.80
India	8.50	50.80	168.00	284.20	858.80	1,370.30
Pakistan	0.00	33.70	123.10	209.50	632.20	998.50
ROW	49.90	283.30	944.60	1,571.00	4,519.90	7,368.70
Total	132.60	835.40	2,558.50	4,089.80	11,139.30	18,755.60

Note: ROW: Rest of the world

Source: Own calculations from DREAM model

Summing the cumulative benefits for all three countries and discounting them at an average discount rate of 10%²⁰, and factoring in the project costs, allows the calculation of the overall efficiency of the project's investments. It can be seen in Table 6.12 that the Net Present Value (NPV) of the project is positive. A comparison of the Benefit Cost Ratio (CBR) and the Internal Rate of Return (IRR) with the results of the financial analysis presented in section 6.1 shows that from a welfare economics point of view, investment in Farmer Field Schools in the three countries was even more efficient. It can be interpreted that if farmers maintained the IPM technology for just one more year after the program had ended (in 2004) the break-even point would be reached.

²⁰ Discount rates in individual countries are based on an ADB working paper (Zhuang et al. 2007) and the Guidelines for the Economic Analysis of Projects (ADB 1997)

Table 6.12: Benefits and costs of FFS training based on benefits from economic surplus (\$1,000)

Year	Benefits	Costs	Net benefits	Discounted cumulative cash flow
2000	-	824.67	-824.67	-749.70
2001	132.60	1,875.31	-1,742.71	-2,189.95
2002	835.40	2,417.12	-1,581.72	-3,378.32
2003	2,558.50	3,045.12	-486.62	-3,710.68
2004	4,089.80	1,313.56	2,776.24	-1,986.86
2005	11,139.30	-	11,139.30	4,300.98
Total	18,755.60	9,475.77	9,279.83	
NPV	4,300.98			
BCR	1.61			
FIRR	36.61%			

Note: Used discount rate at 10%, NPV: Net present value, BCR: Benefit-cost ratio, FIRR: Financial internal rate of return

Source: Own calculations

6.3 Summary

In this chapter, a financial investment analysis was undertaken, using statistical comparative analysis and econometric models based on the results of Chapter 5, where the impact of FFS training was calculated. Thereafter an economic analysis of the program investment was performed using a partial equilibrium model.

For the financial analysis, the estimated annual benefits of FFS from pesticide reduction and yield increase were used to calculate the Internal Rate of Return for the Investment (IRR). The total costs of the program included the project operational costs of the implementing agency and the opportunity costs of labor of farmers participating in the program. Conservative assumptions were made in order to account for the uncertainty of a continued application of IPM practices after external support was terminated. Hence it was assumed that the program's benefits would last at longest for three years. Moreover, no diffusion effect of the IPM practices to non-program farmers in the FFS villages was considered, as results are ambiguous.

Results of the financial analysis show that under the different scenarios the investments in farmers' training by the FAO-EU IPM Program for Cotton in Asia do pay off in Pakistan and India. However in China, results suggest that the program has not reached its target, mainly due to a low adoption rate relative to the program investment.

In the second part of the chapter a welfare analysis was performed using a simulation model. The purpose of this analysis was to examine social benefits that have arisen from the FFS program in the three countries included in the study, and in addition the effects on other countries that produce or use cotton, through the market effects generated by the FFS program.

By establishing assumptions that in part were derived from the statistical and econometric analysis and taken from the literature, the total economic surplus of the program was calculated. Essentially the impact of the FFS program on cotton production and prices was driven by the shift in the supply curve, mainly resulting from cost reduction in pesticide applications. The social benefits indicate that consumers in the three countries and in ROW gain from the FFS project, while producers in China and in the ROW lose due to low adoption and negative price

effects. On a global level the benefits generated by the “FAO-EU IPM Program for Cotton in Asia” are positive.

Calculation of the Economic Internal Rate of Return and related investment measures shows that the net social benefits of the program exceed those of the financial analysis. This suggests that use of public funds from official development assistance budgets is justified. The value calculated can even be considered to be a minimum, as the benefits for farmer health and the environment were not factored in. However, the analysis cannot give a clear answer on the question of program sustainability. It is possible, especially in view of countervailing forces such as the efforts of the pesticide industry to push pesticide sales, that the “shelf-life” of FFS programs may be low, especially if external support is withdrawn at an early stage.

In the next chapter, the results of this study are summarized, some conclusions are drawn and recommendations are provided.

7 Summary, conclusions and recommendations

7.1 Summary

This study performed an economic impact analysis of the Farmer Field Schools (FFS) training program in three major cotton producing countries in Asia; namely China, India and Pakistan. The training program is based on the Integrated Pest Management (IPM) approach launched by the “FAO-EU IPM Program for Cotton in Asia”.

In the three countries, cotton is predominantly a cash crop for small-scale and poor farmers. Cotton is important for the economies of these countries because of its contribution to agriculture’s value added component. Raw cotton is both an important export commodity and an input to the domestic textile industry. Therefore, the cotton sector has been subject to various types of government interventions, including subsidies. The largest cotton producer in the world is China, accounting for a quarter of the world’s total cotton production. India is the second largest producer in Asia and has the largest cultivation area in the world. Pakistan is the third largest in Asia. The three countries together account for about half of the world’s production of raw cotton.

As shown by this study, the production of cotton in the three countries is characterized by intensive use of chemical inputs, especially insecticides. Often these chemicals are used above their economic optimum level from both the society’s and a private economic point of view. Current pest management practices in cotton are a cause of lower profits for farmers, and negative externalities due to negative impacts on human health and environmental effects (Khan et al. 2002; PANNA 2008). Around one quarter of the world’s insecticide use is in cotton, although in terms of cropping area, cotton represents less than 5%. The concept of IPM was developed in the 1950s as an attempt to reduce farmers’ dependency on chemical pesticides. However, the IPM approach is knowledge-intensive and therefore has not been widely adopted. The FFS approach was then developed in the 1980s as an adult education method based on the principles of participation and experiential learning. Its aim was to raise farmers’ knowledge and understanding of the functioning of a crop ecosystem and to enable them to make more benign pest management decisions. Since the 1980s, the FFS approach has been applied in

many countries in Asia, Africa and Latin America on a large variety of crops. In 1999, the European Union commissioned the FAO to undertake a large-scale FFS program to on IPM for cotton in Asia. As described in Chapter 2, some controversy exists in the literature about the efficiency of the investment, and about the fiscal sustainability of the FFS model.

Against this background the objectives of this study were threefold: (1) to assess the impact of FFS training on insecticide use, environment and cotton productivity at farm level, (2) to assess the efficiency of project investment on the country as well as on the aggregate level, and (3) to evaluate the welfare effects of the project.

In the study, a cost benefit analysis based on the concept of economic surplus was carried out. The analytical methods used in this study to generate the data for the cost benefit analysis are statistical tests (T-test and F-test), and econometric models, including a Difference-in-Differences (DD) and a fixed-effects model. In addition, non-market effects of pesticides were measured by using the environmental impact quotient (EIQ) method.

In Chapter 3, it was indicated that the data were collected from field surveys in cotton growing areas in China, India and Pakistan. The study areas were defined as follows: In China, the provinces of Shandong, Anhui and Hubei, the state of Karnataka in India, and Sindh province in Pakistan. A panel data set of 808 farmers was collected by interviewing the same respondents before and after the training. For the impact analysis, the farmers were categorized into three groups: (1) participant (FFS) group, (2) non-participant (Non-FFS) group, i.e. farmers who were living in the same villages where the FFS training had been implemented, and (3) the control group, which consists of non-participants who are living in different villages than the first two groups.

Based on the problem analysis and the theoretical background, the research developed the following hypotheses:

- (1) In different socio-economic conditions in the three countries, FFS training based on IPM practices could help farmers to reduce over-usage of pesticide, increase cotton yield and gain more profit. Consequently, negative externalities would be reduced due to a decrease in pesticide usage.

- (2) The benefits of FFS training occur primarily at the national level, but positive externalities can be achieved by an increase in production and a decrease in cotton price at international cotton markets. Therefore, both cotton producers and consumers can benefit from public investments in FFS.

The analytical procedure was implemented in four steps: (i) parametric and non-parametric statistical tests, which detect differences between trained and non-trained farmers, (ii) econometric models, i.e. DD-model and fixed-effects model, which detect causality between project intervention and outcomes, (iii) the calculation of the financial internal rate of return of the program taking only the effects on farmer income into account and (iv) a partial equilibrium model using a specific software application, the Dynamic Research Evaluation for Management (DREAM) model, to calculate the economic surplus generated by the FFS program and to calculate the efficiency of the project's investments.

Chapter 4 presented the results of a descriptive statistical analysis comparing farm household characteristics, input structure, productivity and costs and returns of cotton production among the three farmer groups as explained in Chapter 3. The data used for the descriptive analysis are those collected from the baseline survey before the start of FFS training. The year of data collection was the same for China and India but was one year later for Pakistan. Results of this analysis showed that there are differences in productivity among the three countries, with China clearly showing the highest productivity levels. Also, the data show that the level of pesticide use is a significant factor among the production inputs. This suggests that there is the potential to reduce pesticide use through Farmer Field Schools and thereby increase the economics of cotton production and serve the environment at the same time. The descriptive analysis of farm household characteristics also illustrated the welfare position of the cotton farmers in the sample, showing that the cotton farmers in all three countries belong to the poorer segment of the rural population. Hence it was concluded that the FFS program has the potential to contribute to poverty reduction in rural areas.

In Chapter 5, a comparative analysis of the impact of FFS on pesticide use, cotton output, farmers' knowledge of ecosystem analysis and other indicators was carried out. By summing the results of both statistical comparison of the economic performances and econometric models in all three countries, the impact of FFS

training can be perceived. On the input side, FFS farmers use less pesticide and choose those with lower toxicity. On the output side, the effects are different from country to country. In Pakistan, all the three groups experienced lower yields because of uncommon blight in the year after training. However, the FFS group still increased productivity and gross margin as compared to the control farmers. In China, participants performed significantly better in terms of both cotton yield and gross margin.

In the DD-model, the country analysis provided quite interesting results. First, the knowledge variable, i.e. the recognition of pests and natural enemies, was significantly related to the reduction in pesticide usage and environmental impact in Pakistan. Furthermore, knowledge advancements positively affected cotton yield and gross margin in India and China. However, the effect of knowledge on pesticide reduction in India was ambiguous.

The diffusion impact of FFS training, i.e. the gain in IPM information of Non-FFS farmers, was inconsistent and varied across the models. The coefficients of Non-FFS in insecticide regression of India, EIQ score of Pakistan, and cotton yield of China, became non-significant after other variables were added in multivariate models. While the results indicate that pest management information could spread from participants to their neighbours, this effect is limited to some elements of knowledge and may not apply to skills at all. Hence, the probability of adoption of FFS technology by other farmers without training is low. Accordingly, diffusion may occur but may be limited to a short-term impact. Here the results of this study confirmed those found in similar research, (e.g. Feder et al. 2003; Rola et al. 2002).

To assess the results under different conditions, multivariate regressions were also used in addition to the simple regressions. After controlling for other variables, the dummy variable of the FFS group was still significant, which confirms the results of the simple models. Moreover, results from the combined-model using pooled data of the three countries also confirm the effect of FFS training, which harmonizes with the results of DD-models.

The analysis of the efficiency of the program investment was performed in Chapter 6. The analysis proceeded in two steps: Firstly a financial analysis which only included the direct effects of the program at farm level, and secondly a welfare

analysis calculating the total economic surplus generated by the program for the economy of each of the three countries, including spill over effects on the world market.

For the financial analysis, the estimated annual benefits of FFS from pesticide reduction and yield increase were used to calculate the Internal Rate of Return for the Investment (IRR). The total costs of the program included the project operational costs of the implementing agency and the opportunity costs of labor of farmers participating in the program. Conservative assumptions were made in order to account for the uncertainty of a continued application of IPM practices after external support was terminated. Hence it was assumed that the program's benefits would last at longest for three years. Moreover, no diffusion effect of the IPM practices to non-program farmers in the FFS villages was considered, as results are ambiguous.

Results of the financial analysis show that under the different scenarios the investments in farmers' training by the FAO-EU IPM Program for Cotton in Asia do pay off in Pakistan and India. However, in China results suggest that the program has not reached its target, mainly due to a low adoption rate relative to the program investment. Although the benefits of FFS training on a per ha basis were higher in China compared to Pakistan, the project costs per farmer were substantially greater, due to the small plot sizes, which increase the unit costs of the training. However, this result is based on the conservative assumption that farmers will switch back to their old practice. Sensitivity analysis showed that the program investment only reaches break-even if the benefits of the training program are sustained for at least three years and the adoption rate must be above 90%.

A welfare analysis using a simulation model was added in order to examine the social benefits that have arisen from the FFS program in the three countries included in the study, and in addition the effects on other countries that produce or use cotton, through the market effects generated by the FFS program.

By establishing assumptions that in part were derived from the statistical and econometric analysis as well as from the literature, the total economic surplus of the program was calculated. The social benefits indicate that consumers in the three countries and in the rest of the world (ROW) gain from the FFS project, while producers in China and in the ROW lose due to low adoption and negative price

effects. On a global level the benefits generated by the FFS program were found to be positive.

Calculation of the Economic Internal Rate of Return and related investment measures shows that the net social benefits of the program exceed those of the financial analysis. This suggests that use of public funds from official development assistance budgets is justified. The value calculated is only a minimum since the benefits for farmer health and the environment were not included. However, no statement can be made regarding the sustainability of the program. Factors such as the efforts of the pesticide industry to push pesticide sales question the long-term benefits of investments in FFS training.

7.2 Conclusions and recommendations

This study has underlined the need for conducting economic impact assessments of public investments in farmers' training in developing countries. To carry out such studies is a challenge because of the difficulty in collecting good data that are required for such analysis, and in applying sophisticated methodologies that are based on sound economic theory. For a large-scale development program that operates in several countries, as is the case for the "FAO-EU IPM Program for Cotton in Asia" analyzed in this study, the organization of data collection is a challenge. In the case at hand, data were collected by country impact assessment teams. While this approach has positively contributed to capacity building for impact assessment studies, it also comes at the expense of rigor and consistency. This is particularly relevant for knowledge-intensive technologies in which cultural differences require well-coordinated data collection protocols. Hence, in defining variables related to knowledge, compromises had to be made that may have weakened the level of significance in the econometric models. The other problem with a decentralized data collection approach is that the sampling suffers from inconsistency. As shown by this study, the sample varies greatly across countries. In India in particular, sample size was below 100 households, which limits the value of advanced econometric methods.

There is also a problem of representativeness in sample selection in nationwide FFS programs. The locations that were chosen are representative for cotton production in these countries but it is not known how well those locations represent the average

conditions under which the training program was implemented. As found in a study on FFS in Senegal (Witt et al. 2008), there is often political pressure for program up-scaling and program placement in order to achieve an even spread of project activities for equity reasons. However, such a strategy may come at the expense of training quality, which is likely to reduce the impact. As also noted by Davis (2006), the FFS approach should not be understood as an overall extension strategy, which however was an indirect program objective and has thus added to the difficulties of ensuring a representative measurement of the program impact. It is therefore possible that the positive direct farm level effects that could be demonstrated by statistical comparisons and the econometric models could be more toward the upper range. Nevertheless, the direct program benefits, i.e. those enjoyed by the FFS farmers, are quite certain provided the training was done well. This conclusion is also supported by the fact that the knowledge diffusion effect is somewhat ambiguous. Low diffusion of FFS instruction was also shown by earlier studies (Feder et al. 2003; Rola et al. 2002; Witt et al. 2008). This fact is related to the intensity of knowledge that is required for improving pest management decision making, of which not all is observable or can be acquired by self-learning by non-participants. As suggested by the study of Witt et al. (2008) a low level of diffusion could also be related to the number of farmers trained relative to the population of farmers in the village. For example, if a higher proportion of farmers – not exceeding a certain maximum – is trained, diffusion of IPM-related information to non-participants will be more likely. Hence there is a lesson for the implementation of FFS programs with considerable implications for impact, which is that the strategy of having a small number of farmers trained per village and maximizing the number of locations per country or region may not lead to maximum impact. Also, a small proportion of trained farmers per village might affect the knowledge-retention period, which is a critical assumption for project benefits. In fact, an agglomeration of FFS farmers may have added benefits such as the formation of local markets for pesticide-reduced, pesticide free or even organic products, commercialization of bio-pesticides, and may lower the costs of introducing other institutional and technical innovations.

In conclusion, while the data collected for this study have generated results that generally have passed statistical testing, care must be taken in drawing conclusions about the efficiency of investments in large-scale, nationwide Farmer Field Schools

Programs. Therefore, in the financial and economic analysis, conservative assumptions were made with regard to the retention period of knowledge transmitted and generated by the Farmer Field Schools training sessions. In view of these limitations, and considering that results were interpreted carefully, it is still safe to say that investment in FFS is likely to pay off in a crop like cotton. This conclusion is reinforced by the results of the descriptive analysis of the baseline situation, which has once more revealed the drastic overuse of chemical pesticides, especially insecticides in cotton. This is even more the case in China where at the time of program implementation genetically modified cotton, which is believed to reduce insecticide use, had already been adopted by many cotton farmers (Huang and Wang 2002a; Huang et al. 2002b; Huang et al. 2002c).

The welfare analysis has shown that at both farm and global level the FAO-EU IPM Program for Cotton in Asia has paid off. FFS training has the potential to generate high net social benefits to the producers and consumers in program countries through lower production costs, and has positive spill over effects on the buyers of raw cotton in the world market due to price effects. Hence, the program has shown that even under conservative assumptions the investments for FFS can pay off. Also, as shown in a study by Yang et al. (2005b) FFS may be complementary to the effectiveness of transgenic cotton varieties. Largely, this study confirms earlier research indicating that farmer education through FFS is effective in changing farmer behavior (van den Berg 2004). Furthermore, the findings of this analysis confirm the results of an economic analysis of a similar IPM program in Pakistan (Erickson 2004).

Overall, this study has also shown that in order to conduct meaningful benefit cost analysis, a well-designed impact assessment scheme is a necessity.

In addition, to sustain the benefits from FFS programs, it is crucial that enabling policy conditions are in place in order to create incentives for farmers to continue IPM practices. Moreover, institutional models need to be developed for placement of FFS projects and policies for up-scaling of IPM.

Since evaluation is an integral part of any development program, it is recommended that it should be planned at the program design stage in order to ensure that the evaluation will be useful for program management, improvement and accountability.

Scientific feedback needs to be utilized by decision makers of development programs for further improvement of development interventions. Governments should support IPM by removing perverse incentives such as subsidies or dole-out programs for chemical pesticides. A conducive policy environment could help to sustain the benefit from the program over a longer time period. Governments should also be more serious in implementing the FAO Code of Conduct for chemical pesticides, especially with regard to the regulation of aggressive advertisement of these products by pesticide companies in developing countries.

Moreover, the socio-economic benefits of IPM technologies certainly go beyond what has been measured in this study. In order to complete the picture of benefits, all aspects related to socio-economic development, health, sustainability, environment conservation etc. that represent the true value of IPM programs should be considered in further studies (Peshin et al. 2009).

References

- Abadie, A. (2005). "Semiparametric Difference-in-Differences Estimators". *Review of Economic Studies*, 72: 1-19.
- Adamczyk, J. J. Jr., V. J. Mascarenhas, G. E. Church, B. R. Leonard and J. B. Graves (1998). "Susceptibility of Conventional and Transgenic Cotton Bolls Expressing the *Bacillus Thuringiensis* CryIA(c) Delta-endotoxin to Fall Armyworm (Lepidoptera: Noctuidae) and Beet Armyworm (Lepidoptera: Noctuidae) Injury". *Journal of Agricultural Entomology*, 15(3): 163-171.
- ADB (Asian Development Bank) (1997). Guidelines for the Economic Analysis of Projects. Economics and Development Resource Center, Asian Development Bank, Metro Manila.
- AGBIOS (2009). GM Database. Accessed on July 30th, 2009. <<http://www.agbios.com/dbase.php>>.
- Allen Woodburn Associates Ltd (1995). Cotton: The Crop and its Agrochemicals Market. Pesticides News No. 30, December 1995.
- Alston, J. M., G. W. Norton and P. G. Pardey (1995). Science under Scarcity: Principles and Practice for Agricultural Research Evaluation and Priority Setting. CAB International (CABI), Wallingford.
- Anhui Agriculture Information Net (2006). Accessed on September 17th, 2006. <<http://www.ahnw.gov.cn/>>.
- APTMA (All Pakistan Textile Mills Association) (2008). Cotton Price. Accessed on May 25th, 2009. <<http://www.apmta.org.pk/cotton%20prices.asp>>.
- Ashenfelter, O. and D. Card (1985). "Using the Longitudinal Structure of Earnings to Estimate the Effects of Training Programs". *The Review of Economics and Statistics*, 67(4): 648-660.
- Azeem Khan, M., I. Ahmad and G. Walter-Echols (2005). Impact of an FFS-based IPM Approach on Farmer Capacity, Production and Income: Evidence from Pakistan. In: P. A. C. Ooi, S. Praneetvatakul, H. Waibel, and G. Walter- Echols: The Impact of the FAO-EU IPM Programme for Cotton in Asia. Pesticide Policy Project Publication Series, Special Issue no.9, Hannover: 123.
- Baffes, J. (2004). Cotton: Market Setting, Trade Policies, and Issues. World Bank Policy Research Working Paper 3218. The World Bank. Washington, D.C.

- Baker, J. L. (2000). Evaluating the Impact of Development Projects on Poverty, A Handbook for Practitioners. The World Bank, Washington, D.C.
- Banuri, T. (1998). Cotton and Textiles in Pakistan. Global Product Chains: Northern Consumers, Southern Producers, and Sustainability, Prepared for United Nations Environment Programme.
- Baum, C. F. (2006). An Introduction to Modern Econometrics Using Stata, A Stata Press Publication. Stata Press, College Station, Texas.
- Benbrook, C. M., D. L. Sexson, J. A. Wyman, W. R. Stevenson, S. Lynch, J. Wallendal, S. Diercks, R. V. Haren and C. A. Granadino (2002). "Developing a Pesticide Risk Assessment Tool to Monitor Progress in Reducing Reliance on High-Risk Pesticides". *American Journal of Potato Research*, 79: 183-199.
- Bennett, C. (1975). "Up to Hierarchy". *Journal of Extension*, 75(2): 7-12.
- Berk, R. A. (1983). "An Introduction to Sample Selection Bias in Sociological Data". *American Sociological Review*, 48(3): 386-398.
- Braun, A., J. Jiggins, N. Röling, H. van den Berg and P. Snijders (2006). A Global Survey and Review of Farmer Field School Experiences. Final Report. Report Prepared for ILRI. Endelea. Wageningen.
- Brent, R. J. (2006). Applied Cost–Benefit Analysis, Second Edition. Edward Elgar Publishing Limited, Cheltenham and Northampton.
- Business & Industrial Research Division (2006). Bt Cotton Cultivation in India. A Report to Understand the Awareness, Perception and Acceptability of Bt Cotton Seeds among Cotton Growing Farmers. Business and Industrial Research Division, IMRB International. Mumbai.
- Card, D. (1990). "The Impact of the Mariel Boatlift on the Miami Labour Market". *Industrial and Labour Relations Review*, 43(2): 245-257.
- Card, D. and A. B. Krueger (1994). "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania". *American Economic Review*, 84(4): 772-793.
- Carrière, Y., T. J. Dennehy, B. Pedersen, S. Haller, C. Eilers-Kirk, L. Antilla, Y.-B. Liu, E. Willott and B. E. Tabashnik (2001). "Large-Scale Management of Insect Resistance to Transgenic Cotton in Arizona - Can Transgenic Insecticidal Crops be Sustained?" *Journal of Economic Entomology*, 94: 315-325.

- Cisneros, J. J. and L. D. Godfrey (2001). "Midseason Pest Status of the Cotton Aphid (Homoptera: Aphididae) in California Cotton: Is Nitrogen a Key Factor?" *Environmental Entomology*, 30(3): 501-510.
- Cororaton, C. B. and D. Orden (2008). Pakistan's Cotton and Textile Economy, Intersectoral Linkages and Effects on Rural and Urban Poverty. Research Report 158. International Food Policy Research Institute. Washington, D.C.
- Cotton Outlook Limited (2009a). The Cotlook Indices - An Explanation. Accessed on February 18th, 2009. <http://www.cotlook.com/information/cotlook_indices.php>.
- (2009b). C.I.F. North Europe Quotation of COTLOOK A and B Index. Accessed on February 18th, 2009. <<http://www.cotlook.com/>>.
- Davidson, R. and J. G. MacKinnon (1993). Estimation and Inference in Econometrics. Oxford University Press, New York.
- Davis, K. (2006). "Farmer Field Schools: A Boon or Bust for Extension in Africa?" *Journal of International Agricultural and Extension Education*, 13(1): 91-97.
- Dent, D. (1995). Integrated Pest Management. Chapman and Hall, London.
- Development Statistics of Sindh (2006). Government of Sindh. Accessed on July 7th, 2006. <<http://www.sbos.sdnpc.org/>>.
- Economic Research Service: USDA (United States Department of Agriculture) (2007). Cotton and Wool Situation and Outlook Yearbook. Market and Trade Economics Division. Washington, D.C.
- (2008). Cotton and Wool Situation and Outlook Yearbook. Market and Trade Economics Division. Washington, D.C.
- (2009a). China Maps. Provincial Map. Accessed on October 13th, 2009. <<http://www.fas.usda.gov/remote/china/chinamap.gif>>.
- (2009b). World Agricultural Supply and Demand Estimates. World Agricultural Outlook Board. Washington, D.C.
- (2009c). World Cotton Production, 2003-05. Production, Supply, and Distribution Database. Foreign Agricultural Service. Accessed on May 15th, 2009. <<http://www.ers.usda.gov/>>.
- Edwards, G. W. and J. W. Freebairn (1984). "The Gains from Research into Tradable Commodities". *American Journal of Agricultural Economics*, 66(1): 41-49.

- English, L. and S. L. Slatin (1992). "Mode of Action of Delta-endotoxin from *Bacillus Thuringiensis*: A Comparison with Other Bacterial Toxins". *Insect Biochemistry and Molecular Biology*, 22(1): 1-7.
- Erickson, R. (2004). Review and Evaluation Technical Assistance No. 3383-PAK: Integrated Pest Management. Asian Development Bank. Philippines.
- Escalada, M. M. and K. L. Heong (1994). New Developments and Need for Training in IPM. Proceedings of the 16th Session of FAO/UNEP Panel of Experts on Integrated Pest Control, FAO, Rome, April 25-29, 1994.
- Evenson, R. E. and D. Gollin (2003). "Assessing the Impact of the Green Revolution, 1960 to 2000". *Science*, 300(5620): 758-762.
- Ezemenari, K., A. Rudqvist and K. Subbarao (1999). Impact Evaluation: A Note on Concepts and Methods. Poverty Reduction and Economic Management Network, The World Bank. Washington, D.C.
- FAO (Food and Agriculture Organization of the United Nations) (2003). FAO Fact Sheets: Input for the WTO Ministerial Meeting in Cancún. Important Commodities in Agricultural Trade: Cotton. FAO. Rome.
- (2009a). Cotton Commodity Notes. Accessed on August 1st, 2009.
<http://www.fao.org/es/ESC/en/15/304/highlight_307.html>.
- (2009b). Less Pesticide, More Income from Cotton. International Year of Natural Fibres-2009, FAO. Accessed on July 31st, 2009.
<<http://www.naturalfibres2009.org/en/stories/cotton.html>>.
- FAO-EU IPM Program for Cotton in Asia (2004a). Proceedings: Policy Seminar on IPM-FFS Impact, FAO Regional Office for Asia and the Pacific, Bangkok, Thailand.
- (2004b). Environmental Education for Poor Farmers. FAO Regional Office for Asia and the Pacific. Bangkok.
- FAOSTAT (2009). Annual Producer Prices of Cotton Lint. Accessed on February 9th, 2009.
<<http://faostat.fao.org/site/570/DesktopDefault.aspx?PageID=570#ancor>>.
- Feder, G., R. Murgai and J. B. Quizon (2003). "Sending Farmers Back to School: The Impact of Farmer Field Schools in Indonesia". *Review of Agricultural Economics*, 26(1): 45-62.
- Fleischer, G., F. Jungbluth, H. Waibel and J. C. Zadaks (1999). A Field Practitioner's Guide to Economic Evaluation of IPM, Pesticide Policy Project Publication Series No.9. Institute for Economics in Horticulture, Hannover.

- Fok, A. C. M., W. Liang, G. Wang and Y. Wu (2005). "Diffusion du Coton Génétiquement Modifié en Chine: Lecons sur les Facteurs et Limites d'un Succes". *Economie Rurale*, 285: 5-32.
- Gandhi, V. P. and N. V. Namboodiri (2006). The Adoption and Economics of Bt Cotton in India: Preliminary Results from a Study. Indian Institution of Management. Ahmedabad.
- Ghorbani, M., A. R. Koocheki and H. Z. Mirakabad (2008). "A Model for Pre-Estimation of Production of Organic Cotton in Iran; Case Study of Khorasan Province". *Asian Journal of Plant Sciences*, 7(1): 13-17.
- Gillson, I., C. Poulton, K. Balcombe and S. Page (2004). Understanding the Impact of Cotton Subsidies on Developing Countries. Working Paper (Unpublished Report).
- Gittinger, J. P. (1982). Economic Analysis of Agricultural Projects, Completely Revised and Expanded. Second Edition. The Johns Hopkins University Press, Baltimore and London.
- Glover, D. (2009). Undying Promise: Agricultural Biotechnology's Pro-poor Narrative, Ten Years on Bt Cotton. STEPS Working Paper 15. STEPS Centre. Brighton.
- Godtland, E., E. Sadoulet, A. de Janvry, R. Murgai and O. Ortiz (2003). The Impact of Farmer Field Schools on Knowledge and Productivity: A Study of Potato Farmers in the Peruvian Andes. Working paper 963. CUDARE, University of California. Berkeley.
- Goodell, G. E. (1984). "Challenges to Integrated Pest Management Research and Extension in the Third World: Do We Really Want IPM to Work?" *Bulletin Entomological Society of America*, 30: 18-26.
- Goreux, L. (2004). Prejudice Caused by Industrialised Countries' Subsidies to Cotton Sectors in West and Central Africa. Background Document to the Submission Made by Benin, Burkina Faso, Chad and Mali to the WTO, Document TN/AG/GEN4. World Trade Organisation (WTO). Geneva.
- Government of Pakistan (2006). Agricultural Policy Institute (API) Formerly (APCom). Food, Agriculture and Livestock Division. Accessed on September 3rd, 2009. <http://www.pakistan.gov.pk/divisions/ContentInfo.jsp?DivID=10&cPath=91_97_785&ContentID=4143>.
- Greene, W. H. (2000). Econometric Analysis, Fourth Edition. Prentice Hall, New Jersey.
- (2003). Econometric Analysis, Fifth Edition. Prentice Hall, New Jersey.

- Guitchounts, A. (2005). Outlook for World Cotton and Textile Trade. ICAC (International Cotton Advisory Committee). Washington, D.C.
- Gujarati, D. N. (1995). Basic Econometrics, Third Edition. McGraw-Hill, Inc., New York.
- Gulati, A. (2009). Indian Agriculture: Changing Landscape. Keynote Papers Presented in Plenary Sessions. 27th Conference of the International Association of Agricultural Economists, Beijing, China, August 16-20, 2009.
- Hair, J. F., B. Black, B. Babin, R. E. Anderson and R. L. Tatham (2005). Multivariate Data Analysis, Sixth Edition. Prentice Hall, New Jersey.
- Hall, D. C. and G. M. Duncan (1984). "Econometric Evaluation of New Technology with an Application to Integrated Pest-Management". *American Journal of Agricultural Economics*, 66: 624-633.
- Hausman, J. A. (1978). "Specification tests in econometrics". *Econometrica*, 46(6): 1251-1271.
- Heckman, J. J. (1976). "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models". *Annals of Economic Social Measurement*, 5(4): 475-492.
- (1979). "Sample Selection Bias as a Specification Error". *Econometrica*, 47(1): 153-161.
- Hill, R. C., W. E. Griffiths and G. G. Judge (2001). Undergraduate Econometrics, Second Edition. John Wiley and Sons Inc., New Jersey.
- Huang, J. and Q. Wang (2002a). "Agricultural Biotechnology Development and Policy in China". *AgBioForum*, 5(4): 122-135.
- Huang, J., R. Hu and C. Fan (2002b). "Bt Cotton Benefits, Costs, and Impacts in China". *AgBioForum*, 5(4): 153-166.
- Huang, J., S. Rozelle, C. Pray and Q. Wang (2002c). "Plant Biotechnology in China". *Science*, 295(25): 674-677.
- Huang, J., R. Hu, S. Rozelle, F. Qiao and C. E. Pray (2002d). "Transgenic Varieties and Productivity of Smallholder Cotton Farmers in China". *The Australian Journal of Agricultural and Resource Economics*, 46(3): 367-387.
- Huang, J., R. Hu, C. Pray, F. Qiao and S. Rozelle (2003). "Biotechnology as an Alternative to Chemical Pesticides: A Case Study of Bt Cotton in China". *Agricultural Economics*, 29(1): 55-67.

- IAASTD (International Assessment of Agricultural Knowledge Science and Technology for Development) (2009). Global Report. B. D. McIntyre, H. R. Herren, J. Wakhungu and R. T. Watson (eds.). Island Press, Washington, D.C.
- ICAC (International Cotton Advisory Committee) (2006). Production and Trade Policies Affecting the Cotton Industry. Accessed on February 6th, 2009.
- (2008). Government Support to the Cotton Industry (Revised). ICAC. Washington, D.C.
- (2009). Cotton Supply and Use. Accessed on February 6th, 2009.
- James, C. (2002a). Global Review of Commercialized Transgenic Crops: 2001 Feature: Bt Cotton, ISAAA Briefs No. 26. ISAAA (International Service for the Acquisition of Agri-biotech Applications), Ithaca, New York.
- (2002b). Preview: Global Status of Commercialized Transgenic Crops: 2002, ISAAA Briefs No. 27. ISAAA (International Service for the Acquisition of Agri-biotech Applications), Ithaca, New York.
- (2003a). "Global Review of Commercialized Transgenic Crops". *Current Science*, 84(10): 303-309.
- (2003b). Preview: Global Status of Commercialized Transgenic Crops: 2003, ISAAA Briefs No. 30. ISAAA (International Service for the Acquisition of Agri-biotech Applications), Ithaca, New York.
- (2004). Global Status of Commercialized Biotech/GM Crops: 2004, ISAAA Briefs No. 32. ISAAA (International Service for the Acquisition of Agri-biotech Applications), Ithaca, New York.
- (2006). Global Status of Commercialized Biotech/GM Crops: 2006, ISAAA Brief No. 35. ISAAA (International Service for the Acquisition of Agri-biotech Applications), Ithaca, New York.
- (2007). Global Status of Commercialized Biotech/GM Crops: 2007, ISAAA Brief No. 37. ISAAA (International Service for the Acquisition of Agri-biotech Applications), Ithaca, NY.
- Kabwe, S. and D. Tschirley (2007). Farmer Yields and Returns to Farmers from Seed Cotton: Does Zambia Measure up? Policy Synthesis. Food Security Research Project, Ministry of Agriculture & Cooperatives, Agricultural Consultative Forum, Michigan State University. Lusaka Zambia.

- Keeley, J. (2006). "Balancing Technological Innovation and Environmental Regulation: An Analysis of Chinese Agricultural Biotechnology Governance". *Environmental Politics*, 15(2): 293 - 309.
- Kenmore, P. (1997). "A Perspective on IPM". *Center for Information on Low External-input and Sustainable Agriculture (ILEIA) Newsletter*, 13(4): 8.
- Khan, M. A., M. Iqbal, I. Ahmad and M. H. Soomro (2002). "Economic Evaluation of Pesticide Use Externalities in the Cotton Zones of Punjab, Pakistan". *The Pakistan Development Review*, 41(4): 683-698.
- Khan, M. A. and I. Ahmad (2005). Impact of an FFS-based IPM Knowledge and Practices on Rural Poverty Reduction: Evidence from Pakistan. In: P. A. C. Ooi, S. Praneetvatakul, H. Waibel and G. Walter-Echols (eds.): *The Impact of the FAO-EU IPM Programme for Cotton in Asia*. Pesticide Policy Project Publication Series, Special Issue no.9, Hannover: 110-123.
- Kingma, B. R. (2001). *Economics of Information: A Guide to Economic and Cost-Benefit Analysis for Information Professionals*, Second Edition. Libraries Unlimited, Inc., Englewood, Colorado.
- Kovach, J., C. Petzoldt, J. Degnil and J. Tette (1992). *A Method to Measure the Environmental Impact of Pesticides*. New York's Food and Life Sciences Bulletin. Cornell University, New York State Agricultural Experiment Station. New York.
- Kutner, M. H., C. J. Nachtsheim, J. Neter and W. Li (2004). *Applied Linear Statistical Models*, Fourth Edition. McGraw-Hill/Irwin, Boston.
- Larsen, E. W., M. L. Haider, M. Roy and F. Ahamed (2002). *Impact, Sustainability and Lateral Spread of Integrated Pest Management in Vegetables in Bangladesh*. Document SPPS 74. Department of Agricultural Extension and DANIDA.
- Letourneau, D. (1988). *Nitrogen Fertilizer's Effects on Pests and Predators*. Ecological Agriculture Projects, Faculty of Agricultural and Environmental Sciences, McGill University. Montreal, Quebec.
- MacDonald, S. (2007). *China's Cotton Supply and Demand: Issues and Impact on the World Market*. A Report from the Economic Research Service. USDA (United States Department of Agriculture). Washington, D.C.
- Maddala, G. S. (1983). *Limited-Dependent and Qualitative Variables in Econometrics*. Econometric Society Monographs. Cambridge University Press, Cambridge.

- Malone, S., D. A. Herbert, Jr. and S. Pheasant (2004). "Determining Adoption of Integrated Pest Management Practices by Grains Farmers in Virginia". *Journal of Extension*, 42(4): 1-7.
- Mancini, F. (2006). Impact of Integrated Pest Management Farmer Field Schools on Health, Farming Systems, the Environment, and Livelihoods of Cotton Growers in Southern India. Ph.D. Thesis; Biological Farming Systems Group, Wageningen University, Wageningen.
- Map of India (2006). Accessed on August 2nd, 2006. <<http://www.maps-india.com/>>.
- Maredia, M., D. Byerlee and J. Anderson (2000). Ex Post Evaluation of Economic Impacts of Agricultural Research Programs: A Tour of Good Practice. Paper presented to the Workshop on "The Future of Impact Assessment in CGIAR: Needs, Constraints, and Options", Standing Panel on Impact Assessment (SPIA) of the Technical Advisory Committee. Rome.
- Matteson, P. C., K. D. Gallagher and P. E. Kenmore (1994). Extension of Integrated Pest Management for Pant Hoppers in Asian Irrigated Rice: Empowering the User. In: R. F. Denno and T. J. Perfect (eds.): Ecology and Management of Plant hoppers. Chapman and Hall, London.
- Metcalf, R. L. and W. H. Luckmann (eds.) (1975). Introduction to Insect Pest Management. John Wiley & Sons, New York.
- Meyer, L., S. MacDonald and J. Kiawu (2008). Cotton and Wool Situation and Outlook Yearbook. Market and Trade Economic Research Service, United States Department of Agriculture. Washington, D.C.
- Monitoring and Evaluation Team (1993). The Impact of IPM Training on Farmers Behavior: A Summary of Results from the Second Field School Cycle. IPM National Program, Indonesia.
- Naranjo, S. E. (2005). "Long-Term Assessment of the Effects of Transgenic Bt Cotton on the Abundance of Non-Target Arthropod Natural Enemies". *Environmental Entomology*, 34(5): 1193-1210.
- National Agro-technical Extension and Service Center (2003). Report on Impact Assessment of China/EU/FAO Cotton IPM Program in Shandong Province, P.R. China. (Unpublished Report). Ministry of Agriculture. Beijing.
- National Information Centre of Karnataka State (2006). Accessed on July 6th, 2006. <<http://www.kar.nic.in/>>.

- NIC (National Informatics Centre) by Government of India (2008). Crop-wise, Market-wise and Minimum Support Prices. Accessed on March 16th, 2009.
<http://india.gov.in/citizen/agriculture/crop_market.php>.
- Norton, G. W. and J. S. Davis (1981). "Evaluating Returns to Agricultural Research: A Review". *American Journal of Agricultural Economics*, 63(4): 685-699.
- Norton, G. W. and J. Mullen (1996). A Primer on Economic Assessment of Integrated Pest Management. In: S. Lynch, C. Greene and C. Kramer-LeBlanc (eds.): Proceedings of the Third National IPM Symposium/Workshop: Broadening Support for 21st Century IPM. U.S. Department of Agriculture, Economic Research Service, Natural Resources and Environment Division, Washington, D.C.
- Norton, G. W. and S. M. Swinton (2009). Protocol for Economic Impact Evaluation of IPM Programs. In: R. Peshin and A. K. Dhawan (eds.): Integrated Pest Management: Dissemination and Impact, Volume 2. Springer Netherlands: 79-101.
- Oka, I. N. (1991). "Success and Challenges of the Indonesian National Integrated Pest Management Programme in the Rice Based Cropping System". *Crop Protection*, 10: 163-165.
- Pakissan.com (2009). First Bt Cotton Grown in Pakistan. Accessed on July 30th, 2009.
<<http://www.pakissan.com/english/advisory/biotechnology/first.bt.cotton.grown.in.pakistan.shtml>>.
- PAN (Pesticide Action Network UK) (1998). Success with Cotton IPM. Pest Management. No.10. November.
- (1998). Success with Cotton IPM. Pest Management. 10. November.
- Pan, S., M. Fadiga, S. Mohanty and M. Welch (2006). "Cotton in a Free Trade World". *Economic Inquiry*, 45(1): 188-197.
- PANNA (Pesticide Action Network North America) (2008). Problems with Conventional Cotton Production. Accessed on September 3rd, 2009.
<<http://www.panna.org/files/conventionalCotton.dv.html>>.
- Park, H. M. (2008a). Linear Regression Models for Panel Data Using SAS, Stata, LIMDEP, and SPSS. Indiana University. Indiana.
- (2008b). Comparing Group Means: T-tests and One-way ANOVA Using Stata, SAS, and SPSS. Indiana University. Indiana.

- Pemsl, D. and H. Waibel (2007). "Assessing the Profitability of Different Crop Protection Strategies in Cotton: Case Study Results from Shandong Province, China". *Agricultural Systems*, 95(1-3): 28-36.
- Pemsl, D. E. (2005). Economics of Agricultural Biotechnology in Crop Protection in Developing Countries the Case of Bt-Cotton in Shandong Province, China. Ph.D. Thesis; Institute for Development and Agricultural Economics, Faculty of Economics and Management, Gottfried Wilhelm Leibniz Universitaet Hannover, Hannover.
- Pemsl, D. E., H. Waibel and A. P. Gutierrez (2005). "Why Do Some Bt-Cotton Farmers in China Continue to Use High Levels of Pesticides?" *International Journal of Agricultural Sustainability*, 3(1): 44-56.
- (2006). The Economics of Biotechnology under Ecosystem Disruption. Contributed Paper Presented at the International Association of Agricultural Economists Conference Gold Coast, Australia, August 12-18, 2006.
- Penrose, L. J., W. G. Thwaite and C. C. Bower (1994). "Rating Index as a Basis for Decision Making on Pesticide Use Reduction and for Accreditation of Fruit Produced Under Integrated Pest Management". *Crop Protection*, 13: 146-152.
- Perkins, F. (1994). Practical Cost Benefit Analysis. Macmillan Education Australia, South Melbourne.
- Peshin, R. (2005). Evaluation of the Dissemination of Insecticide Resistance Management Programme in Cotton in Punjab. Ph.D. Thesis; Punjab Agricultural University, Ludhiana.
- Peshin, R., K. S. U. Jayaratne and G. Singh (2009). Evaluation Research: Methodologies for Evaluation of IPM Programs. In: R. Peshin and A. K. Dhawan (eds.): Integrated Pest Management: Dissemination and Impact, Volume 2. Springer Netherlands: 31-78.
- Pickatrail (2006). Map of Pakistan. Accessed on June 15th, 2006.
<<http://www.pickatrail.com/jupiter/map/pakistan.gif>>.
- Pincus, J. (1999). The Impact of IPM Farmer Field Schools on Farmers Cultivation Practices in Their Own Fields. (Unpublished Report). FAO Programme for Community IPM in Asia.
- Pindyck, R. S. and D. L. Rubinfeld (1998). Econometric Models and Economic Forecasts, Fourth Edition. Irwin/McGraw-Hill, New York.

- Praneetvatakul, S. and H. Waibel (2003). A Socio-economic Analysis of Farmer Field Schools (FFS) Implemented by the National Program on Integrated Pest Management of Thailand. Paper Presented at the CYMMIT Impact Assessment Conference, San Jose, Costa Rica, February 4-7, 2002.
- Praneetvatakul, S., G. Walter-Echols and H. Waibel (2005). The Costs and Benefits of the FAO-EU IPM Programme for Cotton in Asia. In: P. A. C. Ooi, S. Praneetvatakul, H. Waibel and G. Walter-Echols (eds.): The Impact of the FAO-EU IPM Programme for Cotton in Asia. Pesticide Policy Project Publication Series, Special Issue no.9, Hannover: 19-32.
- Praneetvatakul, S. and H. Waibel (2008). A Panel Data Model for the Assessment of Farmer Field School in Thailand. In: K. Otsuka and K. Kalirajan (eds.): Agriculture in Developing Countries-Technology Issues. Sage Publishers, London: 137-151.
- Pray, C. E., D. Ma, J. Huang and F. Qiao (2001). "Impact of Bt Cotton in China". *World Development*, 29(5): 813-825.
- Pray, C. E., J. Huang, R. Hu and S. Rozelle (2002). "Five Years of Bt Cotton in China – the Benefits Continue". *The Plant Journal*, 31(4): 423-430.
- Pretty, J. N. and H. Waibel (2005). Paying the Price: The Full Cost of Pesticides. In: J. N. Pretty (eds.): The Pesticide Detox: Towards a More Sustainable Agriculture. Earthscan Publications Ltd., London: 39-54.
- Project Cotton (2008). Cotton Producers around the World. Department of Textile and Apparel Management, The University of Missouri. Accessed on July 31st, 2009. <<http://cotton.missouri.edu/InOurLives-ProducersWorld.html>>.
- Qaim, M. and D. Zilberman (2003). "Yield Effects of Genetically Modified Crops in Developing Countries". *Science*, 299: 900-902.
- Qaim, M. (2005). "Agricultural Biotechnology Adoption in Developing Countries". *American Journal of Agricultural Economics*, 87(5): 1317-1324.
- Rabb, R. L. and F. E. Guthrie (1970). Concepts of Pest Management. North Carolina State University Press, North Carolina.
- Rahm, M. and W. Huffman (1984). "The Adoption of Reduced Tillage: The Role of Human Capital and Other Variables". *American Journal of Agricultural Economics*, 66: 405-413.

- Reddy, S. V. and M. Suryamani (2004). Higher Gross Margins on Cotton to FFS Farmers. Paper Presented at Regional Workshop on IPM-FFS Impact Analysis, Bangkok, Thailand, June, 2004.
- (2005). Impact of Farmer Field School Approach on Acquisition of Knowledge and Skills by Farmers about Cotton Pests and Other Crop Management Practices - Evidence from India. In: P. A. C. Ooi, S. Praneetvatakul, H. Waibel and G. Walter-Echols (eds.): The Impact of the FAO-EU IPM Programme for Cotton in Asia. Pesticide Policy Project Publication Series, Special Issue no.9, Hannover: 61-73.
- Rola, A. C. and P. L. Pingali (1993). Pesticides, Rice Productivity, and Farmers' Health: An Economic Assessment. International Rice Research Institute (IRRI) and World Resources Institute (WRI), Manila.
- Rola, A. C., S. B. Jamias and J. B. Quizon (2002). "Do Farmer Field School Graduates Retain and Share What They Learn? An Investigation in Iloilo, Philippines". *Journal of International Agricultural and Extension Education*, 9(1): 65-76.
- Röling, N. and E. van de Fliert (1994). "Transforming Extension for Sustainable Agriculture: The Case of Integrated Pest Management in Rice in Indonesia". *Agriculture and Human Values*, 11: 96-108.
- Salam, A. (2008). Production, Prices, and Emerging Challenges in the Pakistan Cotton Sector. Cotton-Textile-Apparel Sectors of Pakistan, Situations and Challenges Faced, IFPRI Discussion Paper 00800. International Food Policy Research Institute.
- Schmidt, S. J. (2005). *Econometrics*. McGraw-Hill, New York.
- Schultz, T. W. (1975). "The Value of the Ability to Deal with Disequilibria". *Journal of Economic Literature*, 13(3): 827-846.
- Shepherd, B. (2006). Estimating Price Elasticities of Supply for Cotton: A Structural Time-series Approach. FAO Commodity and Trade Policy Research Working Paper No. 21. Commodities and Trade Division of the Food and Agriculture Organization of the United Nation. Rome.
- Silva, P. and S. Pagiola (2003). A Review of the Valuation of Environmental Costs and Benefits in World Bank Projects. Environmental Economics Series, Paper No. 94. The World Bank. Washington, D.C.

- Smale, M., P. Zambrano, G. Gruere, J. Falck-Zepeda, I. Matuschke, D. Horna, L. Nagarajan, I. Yerramareddy and H. Jones (2009). Measuring the Economic Impacts of Transgenic Crops in Developing Agriculture during the First Decade: Approaches, Findings, and Future Directions. Food Policy Review No. 10. International Food Policy Research Institute (IFPRI). Washington, D.C.
- Smith, E. H. and D. Pimentel (eds.) (1978). Pest Control Strategies. Academic Press, New York.
- Spielman, D. J. and K. E. Davis (2008). Innovation-Based Solutions for Increasing Agricultural Productivity and Ending Poverty. Advancing Agriculture in Developing Countries through Knowledge and Innovation: A Forum to Bring Together Researchers, Practitioners, and Policymakers, Addis Ababa, Ethiopia, April 7-9, 2008.
- Stern, V. M., R. F. Smith, R. van den Bosch and K. S. Hagen (1959). "The Integrated Control Concept". *Hilgardia*, 29: 81-101.
- Sumner, D. A. (2003). A Quantitative Simulation Analysis of the Impacts of U.S. Cotton Subsidies on Cotton Prices and Quantities. Department of Agricultural and Resource Economics, University of California. Mimeo.
- (2005). Reducing Cotton Subsidies: The DDA Cotton Initiative. In: K. Anderson and W. Martin (eds.): Agricultural Trade Reform and the Doha Development Agenda. A Cobublication of Palgrave Macmillan and the World Bank, Washington. D.C.: 271-292.
- Sunding, D. and D. Zilberman (2001). The Agricultural Innovation Process: Research and Technology Adoption in a Changing Agricultural Sector. In: G. C. Rausser and B. L. Gardner (eds.): Handbook of Agricultural Economics. North-Holland in press, Amsterdam: 207-262.
- Swinton, S. M., K. A. Renner and J. J. Kells (2002). "On-Farm Comparison of Three Postemergence Weed Management Decision Aids in Michigan". *Weed Technology*, 16(3): 691-698.
- Tabashnik, B. E., Y. Carrière, T. J. Dennehy, S. Morin, M. S. Sisterson, R. T. Roush, A. M. Shelton and J.-Z. Zhao (2003). "Insect Resistance to Transgenic Bt Crops: Lessons from the Laboratory and Field". *Journal of Economic Entomology*, 96: 1031-1038.
- The World Bank (2002b). World Development Report 2002. Building Institutions for Markets. The World Bank. Washington, D.C.

- (2003). World Development Report 2003. Sustainable Development in a Dynamic World: Transforming Institutions, Growth, and Quality of Life. The World Bank. Washington, D.C.
- UNEP (United Nations Environment Programme) (2002). The Cotton Sector in China. In: H. Abaza and V. Jha (eds.): Integrated Assessment of Trade Liberalization and Trade-Related Policies, Country Studies - Round II. United Nations, New York and Geneva: 57-76.
- UNESCAP (United Nations Economic and Social Commission for Asia and Pacific) (2006a). Hubei. Accessed on July 9th, 2006.
<<http://www.unescap.org/esid/psis/population/database/chinadata/hubei.htm>>.
- (2006b). Shandong. Accessed on July 9th, 2006.
<<http://www.unescap.org/esid/psis/population/database/chinadata/shandong.htm#pop>>.
- USTR (Office of the United States Trade Representative) (2003). Major Factors Affecting World Cotton Price Behavior, Prepared in Response to Brazil's WTO Challenge of the U.S. Cotton Program. Excerpted from United State - Subsidies on Upland Cotton (WT/DS267). Washington, D.C.
- van de Fliert, E. (1993). Integrated Pest Management: Farmer Field School Generate Sustainable Practices. Wageningen Agricultural University. Wageningen.
- van den Berg, H., H. Senerath and L. Amarasinghe (2002). Participatory IPM in Sri Lanka: A Broad-scale and an In-depth Impact Analysis. Summary Published as: Farmer Field Schools in Sri Lanka: Assessing the Impact. Pesticide News 61 (2003).
FAO Programme for Community IPM in Asia.
- van den Berg, H. (2004). IPM Farmer Field Schools: A Synthesis of 25 Impact Evaluations. Prepared for the Global IPM Facility. Wageningen University. Wageningen.
- van den Berg, H. and J. Jiggins (2007). "Investing in Farmers--The Impacts of Farmer Field Schools in Relation to Integrated Pest Management". *World Development*, 35: 663-686.
- van Duuren, B. (2003). Report of a Consultancy on the Assessment of the Impact of the IPM Programme at Field Level. Integrated Pest Management Farmer Training Project (Unpublished Report). DANIDA, Cambodia.

- Venkateshwarlu, K. (2002). Yield from Bt Cotton Less: Study. The Hindu. Accessed on August 3rd, 2006.
<<http://www.hindu.com/thehindu/2002/12/08/stories/2002120802660600.htm>>.
- Verbeek, M. (2004). A Guide to Modern Econometrics, Second edition. Wiley, Chichester.
- Walter-Echols, G. and P. A. C. Ooi (2005). Concept of Impact Assessment in the FAO-EU IPM Programme for Cotton in Asia. In: P. A. C. Ooi, S. Praneetvatakul, H. Waibel and G. Walter-Echols (eds.): The Impact of the FAO-EU IPM Programme for Cotton in Asia. Pesticide Policy Project Publication Series, Special Issue no.9, Hannover: 1-18.
- (2005). Concept of Impact Assessment in the FAO-EU IPM Programme for Cotton in Asia. In: P. A. C. Ooi, S. Praneetvatakul, H. Waibel, and G. Walter- Echols: The Impact of the FAO-EU IPM Programme for Cotton in Asia. Pesticide Policy Project Publication Series, Special Issue no.9, Hannover: 123.
- Wang, S., D. R. Just and P. Pinstrip-Andersen (2006). Tarnishing Silver Bullets: Bt Technology Adoption, Bounded Rationality and the Outbreak of Secondary Pest Infestations in China. American Agricultural Economics Association Annual Meeting, Long Beach, California, July 22-26, 2006.
- Willis, R. J. and S. Rosen (1979). "Education and Self-Selection". *Political Economy*, 87(5): S7-S36.
- Witt, R., D. E. Pemsil and H. Waibel (2008). "The Farmer Field School in Senegal: Does Training Intensity Affect Diffusion of Information?" *Journal of International Agricultural and Extension Education*, 15(2): 47-60.
- Wood, S., L. You and W. Baitx (2001). DREAM Version 3: User Manual. International Food Policy Research Institute, Washington, D.C.
- Wooldridge, J. M. (2002). Econometric Analysis of Cross Section and Panel Data. MIT Press, London.
- World Bank (2002). Using Indigenous Knowledge to Raise Agricultural Productivity: An Example from India. IK Notes No.45, June 2002.
- Wozniak, G. D. (1984). "The Adoption of Interrelated Innovations: A Human Capital Approach". *The Review of Economics and Statistics*, 66(1): 70-79.
- (1987). "Human Capital, Information, and the Early Adoption of New Technology". *The Journal of Human Resources*, 22(1): 101-112.

- Wu, K., Y. Guo, N. Lu, J. T. Greenplate and R. Deaton (2002). "Resistance Monitoring of *Helicoverpa Armiga* (Lepidoptera: Noctuidae) to *Bacillus Thuringiensis* Insecticidal Protein in China". *Journal of Economic Entomology*, 95: 826-831.
- Wu, K. M. and Y. Y. Guo (2005). "The Evolution of Cotton Pest Management Practices in China". *The Annual Review of Entomology*, 50: 31-52.
- Wu, L., S. Praneetvatakul, H. Waibel and L. Wang (2005). The Impact of FFS on Yield, Pesticide Cost and Gross Margin in Shandong Province, P. R. China: an Econometric Approach. In: P. A. C. Ooi, S. Praneetvatakul, H. Waibel and G. Walter-Echols (eds.): The Impact of the FAO-EU IPM Programme for Cotton in Asia. Pesticide Policy Project Publication Series, Special Issue no.9, Hannover: 33-44.
- Wu, L., D. Pemsil and H. Waibel (2007). The Role of Farmer Training and the Diffusion of Biotechnology in Cotton in China: A Multi-period Analysis. In Tropentag 2007 - Conference on International Agricultural Research for Development, Kassel-Witzenhausen, October 9-11, 2007.
- Yamazaki, S. and B. P. Resosudarmo (2007). Does Sending Farmers Back in School Have an Impact? A Spatial Econometric Approach. Working Paper in Trade and Development No. 2007/03. Division of Economics, Research School of Pacific and Asian Economics, The Australian National University. Canberra.
- Yang, P., M. Iles, S. Yan and F. Jolliffe (2005a). "Farmers' Knowledge, Perceptions and Practices in Transgenic Bt Cotton in Small Producer Systems in Northern China". *Crop Protection*, 24(3): 229-239.
- Yang, P., K. Li, S. Shi, J. Xia, R. Guo, S. Li and L. Wang (2005b). "Impacts of Transgenic Bt Cotton and Integrated Pest Management Education on Smallholder Cotton Farmers". *International Journal of Pest Management*, 51: 231-244.
- Yilmaz, I. and B. Ozkan (2004). "Econometric Analysis of Land Tenure Systems in Cotton Production in Turkey". *International Journal of Agriculture & Biology*, 6(6): 1023-1025.
- Zehnder, G. (2009). Managing the Soil to Reduce Insect Pests. The Cooperative Extension System and Your Local Institution. Accessed on May 2nd, 2009. <<http://www.extension.org/article/18574>>.
- Zhuang, J., Z. Liang, T. Lin and F. D. Guzman (2007). Theory and Practice in the Choice of Social Discount Rate for Cost-benefit Analysis: A Survey. ERE Working Paper

No. 94. Economic and Research Department, Asian Development Bank.
Mandaluyong.

Zilberman, D. and H. Waibel (2007). "Advances in Impact Assessment of Natural Resources Management Research". *Quarterly Journal of International Agriculture*, 47(4): 395-420.

Appendices

Appendix A: Results of econometric models

Simple model of insecticide expenditure: China

reg lnins dg dn, robust

Linear regression	Number of obs =	535
	F(2, 532) =	39.11
	Prob > F =	0.0000
	R-squared =	0.0478
	Root MSE =	1.9815

		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
lnins							
dg		-.9618005	.1092081	-8.81	0.000	-1.176332	-.7472685
dn		-.0433262	.239471	-0.18	0.856	-.5137509	.4270985
_cons		-.0779879	.0542015	-1.44	0.151	-.1844631	.0284872

Wald test: $\mu < \beta$

char status [omit] 2

xi: regress lnins i.status, robust

i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

Linear regression	Number of obs =	535
	F(2, 532) =	39.11
	Prob > F =	0.0000
	R-squared =	0.0478
	Root MSE =	1.9815

		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
_Istatus_1		-.9184742	.2517879	-3.65	0.000	-1.413095	-.4238537
_Istatus_3		.0433262	.239471	0.18	0.856	-.4270985	.5137509
_cons		-.1213141	.2332564	-0.52	0.603	-.5795307	.3369024

Note: The Wald tests: $\mu < \alpha$ and $\beta < \alpha$ show at the P>|t| of dg and dn in the model above.

Simple model of insecticide expenditure: India

```
reg lnins dg dn if id < 10223 | id > 10240 & id != 10293, robust
```

Linear regression

```
Number of obs =      83
F( 2,      80) =      5.81
Prob > F       =      0.0044
R-squared      =      0.1807
Root MSE      =      1.912
```

		Robust				[95% Conf. Interval]	
lnins	Coef.	Std. Err.	t	P> t			
dg	-2.400407	.9849671	-2.44	0.017	-4.360554	-.4402604	
dn	-1.767287	.9690734	-1.82	0.072	-3.695805	.1612302	
_cons	.8402744	.9638061	0.87	0.386	-1.077761	2.75831	

Wald test: $\mu < \beta$

```
char status [omit] 2
```

```
xi: regress lnins i.status if id < 10223 | id > 10240 & id != 10293, robust
i.status      _Istatus_1-3      (naturally coded; _Istatus_2 omitted)
```

Linear regression

```
Number of obs =      83
F( 2,      80) =      5.81
Prob > F       =      0.0044
R-squared      =      0.1807
Root MSE      =      1.912
```

		Robust				[95% Conf. Interval]	
lnins	Coef.	Std. Err.	t	P> t			
_Istatus_1	-.63312	.2267579	-2.79	0.007	-1.084383	-.1818574	
_Istatus_3	1.767287	.9690734	1.82	0.072	-.1612302	3.695805	
_cons	-.927013	.1009017	-9.19	0.000	-1.127814	-.7262121	

Note: The Wald tests: $\mu < \alpha$ and $\beta < \alpha$ show at the P>|t| of dg and dn in the model above.

Simple model of insecticide expenditure: Pakistan

reg lnins dg dn, robust

Linear regression Number of obs = 190
F(2, 187) = 6.51
Prob > F = 0.0018
R-squared = 0.0452
Root MSE = 3.2835

		Robust				
lnins	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dg	-1.64691	.4707643	-3.50	0.001	-2.575601	-.7182185
dn	-.4891338	.4690602	-1.04	0.298	-1.414463	.4361957
_cons	-.0897574	.098647	-0.91	0.364	-.2843613	.1048466

Wald test: $\mu < \beta$

char status [omit] 2

xi : regress lnins i.status, robust

i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

Linear regression Number of obs = 190
F(2, 187) = 6.51
Prob > F = 0.0018
R-squared = 0.0452
Root MSE = 3.2835

		Robust				
lnins	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_Istatus_1	-1.157776	.6497492	-1.78	0.076	-2.439556	.1240045
_Istatus_3	.4891338	.4690602	1.04	0.298	-.4361957	1.414463
_cons	-.5788912	.4585698	-1.26	0.208	-1.483526	.3257436

Note: The Wald tests: $\mu < \alpha$ and $\beta < \alpha$ show at the P>|t| of dg and dn in the model above.

Simple model of total EIQ scores: India

```
reg lneiq_t dg dn if id < 10223 | id > 10240 & id != 10293, robust
```

Linear regression

Number of obs = 83
 F(2, 80) = 5.64
 Prob > F = 0.0051
 R-squared = 0.1204
 Root MSE = 2.6963

		Robust				[95% Conf. Interval]	
lneiq_t	Coef.	Std. Err.	t	P> t			
dg	-2.502768	.9999542	-2.50	0.014	-4.49274	-.5127955	
dn	-1.036462	1.140612	-0.91	0.366	-3.306352	1.233428	
_cons	1.253038	.9807819	1.28	0.205	-.6987801	3.204856	

Wald test: $\mu < \beta$

char status [omit] 2

```
xi: regress lneiq_t i.status if id < 10223 | id > 10240 & id != 10293, robust
i.status      _Istatus_1-3      (naturally coded; _Istatus_2 omitted)
```

Linear regression

Number of obs = 83
 F(2, 80) = 5.64
 Prob > F = 0.0051
 R-squared = 0.1204
 Root MSE = 2.6963

		Robust				[95% Conf. Interval]	
lneiq_t	Coef.	Std. Err.	t	P> t			
_Istatus_1	-1.466306	.614034	-2.39	0.019	-2.688272	-.2443391	
_Istatus_3	1.036462	1.140612	0.91	0.366	-1.233428	3.306352	
_cons	.216576	.5822908	0.37	0.711	-.9422196	1.375372	

Note: The Wald tests: $\mu < \alpha$ and $\beta < \alpha$ show at the P>|t| of dg and dn in the model above.

Simple model of total EIQ scores: India

reg lneiq_t dg dn if id < 10223 | id > 10240 & id != 10293, robust

Linear regression Number of obs = 83
F(2, 80) = 5.64
Prob > F = 0.0051
R-squared = 0.1204
Root MSE = 2.6963

		Robust				
lneiq_t	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dg	-2.502768	.9999542	-2.50	0.014	-4.49274	-.5127955
dn	-1.036462	1.140612	-0.91	0.366	-3.306352	1.233428
_cons	1.253038	.9807819	1.28	0.205	-.6987801	3.204856

Wald test: $\mu < \beta$

char status [omit] 2

xi: regress lneiq_t i.status if id < 10223 | id > 10240 & id != 10293, robust
i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

Linear regression Number of obs = 83
F(2, 80) = 5.64
Prob > F = 0.0051
R-squared = 0.1204
Root MSE = 2.6963

		Robust				
lneiq_t	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_Istatus_1	-1.466306	.614034	-2.39	0.019	-2.688272	-.2443391
_Istatus_3	1.036462	1.140612	0.91	0.366	-1.233428	3.306352
_cons	.216576	.5822908	0.37	0.711	-.9422196	1.375372

Note: The Wald tests: $\mu < \alpha$ and $\beta < \alpha$ show at the P>|t| of dg and dn in the model above.

Simple model of cotton yield: China

reg lny dg dn

Source	SS	df	MS	Number of obs =	535
Model	1.25488275	2	.627441375	F(2, 532) =	16.79
Residual	19.8848313	532	.037377502	Prob > F =	0.0000
				R-squared =	0.0594
				Adj R-squared =	0.0558
Total	21.1397141	534	.03958748	Root MSE =	.19333

lny	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dg	.1167757	.0204652	5.71	0.000	.0765732	.1569783
dn	.0400331	.0204362	1.96	0.051	-.0001124	.0801787
_cons	.0988223	.0144102	6.86	0.000	.0705145	.1271301

Wald test: $\mu > \beta$

char status [omit] 2

xi: regress lny i.status

i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

Source	SS	df	MS	Number of obs =	535
Model	1.25488275	2	.627441375	F(2, 532) =	16.79
Residual	19.8848313	532	.037377502	Prob > F =	0.0000
				R-squared =	0.0594
				Adj R-squared =	0.0558
Total	21.1397141	534	.03958748	Root MSE =	.19333

lny	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_Istatus_1	.0767426	.0205221	3.74	0.000	.0364282	.117057
_Istatus_3	-.0400331	.0204362	-1.96	0.051	-.0801787	.0001124
_cons	.1388554	.0144909	9.58	0.000	.110389	.1673218

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Simple model of cotton yield: India

```
reg lny dg dn if id < 10223 | id > 10240 & id != 10293, robust
```

```
Linear regression                                Number of obs =      83
                                                F( 2,      80) =     2.30
                                                Prob > F       =    0.1069
                                                R-squared     =    0.0915
                                                Root MSE     =    .46039
```

	lny	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
	dg	-.3598124	.1762333	-2.04	0.044	-.7105279 -.0090969
	dn	-.367953	.177139	-2.08	0.041	-.7204708 -.0154352
	_cons	.4920905	.1625166	3.03	0.003	.1686721 .8155089

Wald test: $\mu > \beta$

```
char status [omit] 2
```

```
xi: regress lny i.status if id < 10223 | id > 10240 & id != 10293, robust
```

```
i.status          _Istatus_1-3          (naturally coded; _Istatus_2 omitted)
```

```
Linear regression                                Number of obs =      83
                                                F( 2,      80) =     2.30
                                                Prob > F       =    0.1069
                                                R-squared     =    0.0915
                                                Root MSE     =    .46039
```

	lny	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
	_Istatus_1	.0081406	.0980464	0.08	0.934	-.1869778 .2032591
	_Istatus_3	.367953	.177139	2.08	0.041	.0154352 .7204708
	_cons	.1241375	.0704738	1.76	0.082	-.0161099 .2643849

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Simple model of cotton yield: Pakistan

reg lny dg dn

Source	SS	df	MS	Number of obs =	190
Model	2.23654539	2	1.1182727	F(2, 187) =	4.68
Residual	44.6484168	187	.238761587	Prob > F =	0.0104
-----+-----				R-squared =	0.0477
Total	46.8849622	189	.248068583	Adj R-squared =	0.0375
-----+-----				Root MSE =	.48863

lny	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dg	.2100459	.0869827	2.41	0.017	.0384525	.3816392
dn	-.018998	.0924756	-0.21	0.837	-.2014276	.1634315
_cons	-.566569	.0671188	-8.44	0.000	-.6989763	-.4341616

Wald test: $\mu > \beta$

char status [omit] 2

xi : regress lny i.status

i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

Source	SS	df	MS	Number of obs =	190
Model	2.23654539	2	1.1182727	F(2, 187) =	4.68
Residual	44.6484168	187	.238761587	Prob > F =	0.0104
-----+-----				R-squared =	0.0477
Total	46.8849622	189	.248068583	Adj R-squared =	0.0375
-----+-----				Root MSE =	.48863

lny	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_Istatus_1	.2290439	.0843081	2.72	0.007	.0627267	.3953611
_Istatus_3	.018998	.0924756	0.21	0.837	-.1634315	.2014276
_cons	-.585567	.0636145	-9.20	0.000	-.7110613	-.4600727

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Simple model of gross margin: China

reg lngm dg dn, robust

Linear regression Number of obs = 535
F(2, 532) = 19.14
Prob > F = 0.0000
R-squared = 0.0620
Root MSE = .3173

		Robust				[95% Conf. Interval]	
	lngm	Coef.	Std. Err.	t	P> t		
	dg	.1970596	.0325249	6.06	0.000	.1331667	.2609525
	dn	.072777	.0350068	2.08	0.038	.0040084	.1415456
	_cons	.1412174	.024321	5.81	0.000	.0934405	.1889944

Wald test: $\mu > \beta$

char status [omit] 2

xi: regress lngm i.status, robust

i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

Linear regression Number of obs = 535
F(2, 532) = 19.14
Prob > F = 0.0000
R-squared = 0.0620
Root MSE = .3173

		Robust				[95% Conf. Interval]	
	lngm	Coef.	Std. Err.	t	P> t		
	_Istatus_1	.1242826	.0331711	3.75	0.000	.0591202	.1894451
	_Istatus_3	-.072777	.0350068	-2.08	0.038	-.1415456	-.0040084
	_cons	.2139944	.0251787	8.50	0.000	.1645326	.2634563

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Simple model of gross margin: India

```
reg lngm_shor dg dn if id < 10223 | id > 10240 & id != 10293, robust
```

Linear regression

Number of obs = 83
 F(2, 80) = 0.24
 Prob > F = 0.7886
 R-squared = 0.0065
 Root MSE = .95967

		Robust				[95% Conf. Interval]	
lngm_shor	Coef.	Std. Err.	t	P> t			
dg	.1297955	.2545188	0.51	0.611	-.3767131	.6363041	
dn	-.0335149	.1784519	-0.19	0.852	-.3886454	.3216156	
_cons	.4505992	.1425492	3.16	0.002	.1669174	.7342811	

Wald test: $\mu > \beta$

char status [omit] 2

```
xi: regress lngm_shor i.status if id < 10223 | id > 10240 & id != 10293, robust
i.status          _Istatus_1-3          (naturally coded; _Istatus_2 omitted)
```

Linear regression

Number of obs = 83
 F(2, 80) = 0.24
 Prob > F = 0.7886
 R-squared = 0.0065
 Root MSE = .95967

		Robust				[95% Conf. Interval]	
lngm_shor	Coef.	Std. Err.	t	P> t			
_Istatus_1	.1633104	.2366102	0.69	0.492	-.3075588	.6341797	
_Istatus_3	.0335149	.1784519	0.19	0.852	-.3216156	.3886454	
_cons	.4170843	.1073536	3.89	0.000	.2034438	.6307249	

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Simple model of gross margin: Pakistan

reg lngm_shor dg dn

Source	SS	df	MS	Number of obs =	189
Model	1.22005898	2	.610029488	F(2, 186) =	7.81
Residual	14.5247668	186	.078090144	Prob > F =	0.0006
				R-squared =	0.0775
				Adj R-squared =	0.0676
Total	15.7448258	188	.083749074	Root MSE =	.27945

lngm_shor	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dg	.1954336	.0500289	3.91	0.000	.0967366 .2941306
dn	.0908076	.0531535	1.71	0.089	-.0140537 .1956688
_cons	-.0825642	.0387522	-2.13	0.034	-.1590146 -.0061139

Wald test: $\mu > \beta$

char status [omit] 2

xi: reg lngm_shor i.status

i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

Source	SS	df	MS	Number of obs =	189
Model	1.22005898	2	.610029488	F(2, 186) =	7.81
Residual	14.5247668	186	.078090144	Prob > F =	0.0006
				R-squared =	0.0775
				Adj R-squared =	0.0676
Total	15.7448258	188	.083749074	Root MSE =	.27945

lngm_shor	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
_Istatus_1	.104626	.0482153	2.17	0.031	.0095068 .1997452
_Istatus_3	-.0908076	.0531535	-1.71	0.089	-.1956688 .0140537
_cons	.0082434	.0363808	0.23	0.821	-.0635287 .0800154

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Multivariate model of insecticide expenditure: China

reg lnins dg dn rec_pes n_kg flb_fman, robust

Linear regression

Number of obs = 535
 F(5, 529) = 51.82
 Prob > F = 0.0000
 R-squared = 0.1356
 Root MSE = 1.8933

		Robust				[95% Conf. Interval]	
lnins	Coef.	Std. Err.	t	P> t			
dg	-.7751234	.2413957	-3.21	0.001	-1.249335	-.3009115	
dn	.1058501	.2424679	0.44	0.663	-.370468	.5821681	
rec_pes	-.0285884	.0727949	-0.39	0.695	-.1715909	.114414	
n_kg	.0017189	.0003746	4.59	0.000	.000983	.0024547	
flb_fman	-.0038936	.0015326	-2.54	0.011	-.0069043	-.0008829	
_cons	-.0897013	.0684591	-1.31	0.191	-.2241864	.0447838	

Wald test: $\mu < \beta$

char status [omit] 2

xi: regress lnins i.status rec_pes n_kg flb_fman, robust

i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

Linear regression

Number of obs = 535
 F(5, 529) = 51.82
 Prob > F = 0.0000
 R-squared = 0.1356
 Root MSE = 1.8933

		Robust				[95% Conf. Interval]	
lnins	Coef.	Std. Err.	t	P> t			
_Istatus_1	-.8809735	.3488372	-2.53	0.012	-1.56625	-.1956972	
_Istatus_3	-.1058501	.2424679	-0.44	0.663	-.5821681	.370468	
rec_pes	-.0285884	.0727949	-0.39	0.695	-.1715909	.114414	
n_kg	.0017189	.0003746	4.59	0.000	.000983	.0024547	
flb_fman	-.0038936	.0015326	-2.54	0.011	-.0069043	-.0008829	
_cons	.0161488	.2133309	0.08	0.940	-.4029309	.4352285	

Note: The Wald tests: $\mu < \alpha$ and $\beta < \alpha$ show at the P>|t| of dg and dn in the model above.

Multivariate model of insecticide expenditure: India

```
reg lnins dg dn Rec_pes n_kg flbinc if id < 10223 | id > 10240 & id != 10293,
robust
```

```
Linear regression                                Number of obs =      83
                                                F( 5, 77) =      4.47
                                                Prob > F      = 0.0013
                                                R-squared     = 0.1922
                                                Root MSE     = 1.9352
```

```
-----+-----
```

		Robust				[95% Conf. Interval]	
lnins	Coef.	Std. Err.	t	P> t			
dg	-2.455778	1.091218	-2.25	0.027	-4.628669	-.2828862	
dn	-1.882738	1.179977	-1.60	0.115	-4.232371	.4668958	
Rec_pes	.1532637	.1784023	0.86	0.393	-.2019808	.5085081	
n_kg	-.000843	.0016926	-0.50	0.620	-.0042134	.0025274	
flbinc	.0000691	.0011796	0.06	0.953	-.0022798	.0024179	
_cons	1.154497	1.525526	0.76	0.451	-1.883213	4.192207	

```
-----+-----
```

Wald test: $\mu < \beta$

char status [omit] 2

```
xi: regress lnins i.status Rec_pes n_kg flbinc if id < 10223 | id > 10240 & id !=
10293, robust
```

```
i.status      _Istatus_1-3      (naturally coded; _Istatus_2 omitted)
```

```
Linear regression                                Number of obs =      83
                                                F( 5, 77) =      4.47
                                                Prob > F      = 0.0013
                                                R-squared     = 0.1922
                                                Root MSE     = 1.9352
```

```
-----+-----
```

		Robust				[95% Conf. Interval]	
lnins	Coef.	Std. Err.	t	P> t			
_Istatus_1	-.5730401	.2504929	-2.29	0.025	-1.071835	-.0742451	
_Istatus_3	1.882738	1.179977	1.60	0.115	-.4668958	4.232371	
Rec_pes	.1532637	.1784023	0.86	0.393	-.2019808	.5085081	
n_kg	-.000843	.0016926	-0.50	0.620	-.0042134	.0025274	
flbinc	.0000691	.0011796	0.06	0.953	-.0022798	.0024179	
_cons	-.7282406	.3777685	-1.93	0.058	-1.480474	.0239926	

```
-----+-----
```

Note: The Wald tests: $\mu < \alpha$ and $\beta < \alpha$ show at the P>|t| of dg and dn in the model above.

Multivariate model of insecticide expenditure: Pakistan

reg lnins dg dn rec_imsta n_kg fdsur, robust

Linear regression

Number of obs = 190
 F(5, 184) = 3.21
 Prob > F = 0.0084
 R-squared = 0.0693
 Root MSE = 3.268

		Robust				[95% Conf. Interval]	
lnins	Coef.	Std. Err.	t	P> t			
dg	-1.156203	.4266599	-2.71	0.007	-1.997978	-.3144286	
dn	-.3406722	.4466469	-0.76	0.447	-1.22188	.5405355	
rec_imsta	-.2301417	.0999945	-2.30	0.022	-.4274248	-.0328585	
n_kg	.0036755	.0029785	1.23	0.219	-.0022009	.0095519	
fdsur	-.0034202	.0026074	-1.31	0.191	-.0085643	.001724	
_cons	-.3382596	.2077226	-1.63	0.105	-.7480839	.0715648	

Wald test: $\mu < \beta$

char status [omit] 2

xi: regress lnins i.status rec_imsta n_kg fdsur, robust

i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

Linear regression

Number of obs = 190
 F(5, 184) = 3.21
 Prob > F = 0.0084
 R-squared = 0.0693
 Root MSE = 3.268

		Robust				[95% Conf. Interval]	
lnins	Coef.	Std. Err.	t	P> t			
_Istatus_1	-.8155309	.5604491	-1.46	0.147	-1.921264	.2902018	
_Istatus_3	.3406722	.4466469	0.76	0.447	-.5405355	1.22188	
rec_imsta	-.2301417	.0999945	-2.30	0.022	-.4274248	-.0328585	
n_kg	.0036755	.0029785	1.23	0.219	-.0022009	.0095519	
fdsur	-.0034202	.0026074	-1.31	0.191	-.0085643	.001724	
_cons	-.6789318	.4599623	-1.48	0.142	-1.58641	.2285465	

Note: The Wald tests: $\mu < \alpha$ and $\beta < \alpha$ show at the P>|t| of dg and dn in the model above.

Multivariate model of cotton yield: China

reg lny dg dn rec_pes flb ins

Source	SS	df	MS	Number of obs =	535
Model	1.83693025	5	.36738605	F(5, 529) =	10.07
Residual	19.3027838	529	.036489194	Prob > F =	0.0000
				R-squared =	0.0869
				Adj R-squared =	0.0783
Total	21.1397141	534	.03958748	Root MSE =	.19102

lny	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dg	.0856163	.0244216	3.51	0.000	.037641	.1335917
dn	.0221899	.0208422	1.06	0.288	-.0187538	.0631337
rec_pes	.0040015	.0058932	0.68	0.497	-.0075755	.0155785
flb	9.08e-06	.0000352	0.26	0.796	-.00006	.0000782
ins	-.0004683	.000151	-3.10	0.002	-.0007649	-.0001718
_cons	.0848814	.0151322	5.61	0.000	.0551548	.1146079

Wald test: $\mu > \beta$

char status [omit] 2

xi: regress lny i.status rec_pes flb ins

i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

Source	SS	df	MS	Number of obs =	535
Model	1.83693025	5	.36738605	F(5, 529) =	10.07
Residual	19.3027838	529	.036489194	Prob > F =	0.0000
				R-squared =	0.0869
				Adj R-squared =	0.0783
Total	21.1397141	534	.03958748	Root MSE =	.19102

lny	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_Istatus_1	.0634264	.0247671	2.56	0.011	.0147725	.1120803
_Istatus_3	-.0221899	.0208422	-1.06	0.288	-.0631337	.0187538
rec_pes	.0040015	.0058932	0.68	0.497	-.0075755	.0155785
flb	9.08e-06	.0000352	0.26	0.796	-.00006	.0000782
ins	-.0004683	.000151	-3.10	0.002	-.0007649	-.0001718
_cons	.1070713	.0169424	6.32	0.000	.0737887	.140354

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Multivariate model of cotton yield: India

```
reg lny dg dn Rec_bepes flb ins if id < 10223 | id > 10240 & id != 10293
```

Source	SS	df	MS	Number of obs =	83
Model	3.78946222	5	.757892444	F(5, 77) =	3.92
Residual	14.8743277	77	.193173088	Prob > F =	0.0032
				R-squared =	0.2030
				Adj R-squared =	0.1513
Total	18.66379	82	.227607195	Root MSE =	.43951

lny	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dg	-.2833645	.1749536	-1.62	0.109	-.6317416	.0650126
dn	-.3025918	.1547938	-1.95	0.054	-.6108257	.005642
Rec_bepes	.0976607	.0475254	2.05	0.043	.0030255	.192296
flb	-.0002232	.0001701	-1.31	0.193	-.0005619	.0001156
ins	.0018846	.0008642	2.18	0.032	.0001638	.0036054
_cons	.6195765	.1233571	5.02	0.000	.3739411	.8652119

Wald test: $\mu > \beta$

```
char status [omit] 2
```

```
xi: regress lny i.status Rec_bepes flb ins if id < 10223 | id > 10240 & id != 10293
```

```
i.status      _Istatus_1-3      (naturally coded; _Istatus_2 omitted)
```

Source	SS	df	MS	Number of obs =	83
Model	3.78946222	5	.757892444	F(5, 77) =	3.92
Residual	14.8743277	77	.193173088	Prob > F =	0.0032
				R-squared =	0.2030
				Adj R-squared =	0.1513
Total	18.66379	82	.227607195	Root MSE =	.43951

lny	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_Istatus_1	.0192274	.1168944	0.16	0.870	-.2135392	.2519939
_Istatus_3	.3025918	.1547938	1.95	0.054	-.005642	.6108257
Rec_bepes	.0976607	.0475254	2.05	0.043	.0030255	.192296
flb	-.0002232	.0001701	-1.31	0.193	-.0005619	.0001156
ins	.0018846	.0008642	2.18	0.032	.0001638	.0036054
_cons	.3169846	.123087	2.58	0.012	.0718871	.5620822

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Multivariate model of cotton yield: Pakistan

reg lny dg dn rec_pes flb ins

Source	SS	df	MS	Number of obs =	190
Model	5.1332254	5	1.02664508	F(5, 184) =	4.52
Residual	41.7517368	184	.226911613	Prob > F =	0.0006
				R-squared =	0.1095
				Adj R-squared =	0.0853
Total	46.8849622	189	.248068583	Root MSE =	.47635

lny	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dg	.2183813	.1084417	2.01	0.045	.0044323 .4323304
dn	.0341507	.0945856	0.36	0.718	-.152461 .2207624
rec_pes	.0129847	.0212237	0.61	0.541	-.0288884 .0548578
flb	.0033833	.0010937	3.09	0.002	.0012254 .0055412
ins	.0003917	.0002835	1.38	0.169	-.0001677 .0009511
_cons	-.5921801	.0670143	-8.84	0.000	-.7243954 -.4599649

Wald test: $\mu > \beta$

char status [omit] 2

xi: regress lny i.status rec_pes flb ins

i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

Source	SS	df	MS	Number of obs =	190
Model	5.1332254	5	1.02664508	F(5, 184) =	4.52
Residual	41.7517368	184	.226911613	Prob > F =	0.0006
				R-squared =	0.1095
				Adj R-squared =	0.0853
Total	46.8849622	189	.248068583	Root MSE =	.47635

lny	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
_Istatus_1	.1842306	.0955836	1.93	0.055	-.0043501 .3728114
_Istatus_3	-.0341507	.0945856	-0.36	0.718	-.2207624 .152461
rec_pes	.0129847	.0212237	0.61	0.541	-.0288884 .0548578
flb	.0033833	.0010937	3.09	0.002	.0012254 .0055412
ins	.0003917	.0002835	1.38	0.169	-.0001677 .0009511
_cons	-.5580295	.0643608	-8.67	0.000	-.6850095 -.4310494

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Multivariate model of gross margin: China

reg lngm dg dn rec_pes flb cotarea

Source	SS	df	MS	Number of obs =	535
Model	4.7871223	5	.95742446	F(5, 529) =	9.68
Residual	52.3122408	529	.098888924	Prob > F =	0.0000
				R-squared =	0.0838
				Adj R-squared =	0.0752
Total	57.0993631	534	.106927646	Root MSE =	.31447

lngm	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dg	.1554082	.0406468	3.82	0.000	.0755591 .2352572
dn	.0690752	.0333326	2.07	0.039	.0035947 .1345557
rec_pes	.0174652	.0087323	2.00	0.046	.000311 .0346193
flb	.0000739	.0000634	1.17	0.244	-.0000507 .0001985
cotarea	.2915227	.1181288	2.47	0.014	.0594635 .5235819
_cons	.1456432	.0246202	5.92	0.000	.0972778 .1940087

Wald test: $\mu > \beta$

char status [omit] 2

xi: regress lngm i.status rec_pes flb cotarea

i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

Source	SS	df	MS	Number of obs =	535
Model	4.7871223	5	.95742446	F(5, 529) =	9.68
Residual	52.3122408	529	.098888924	Prob > F =	0.0000
				R-squared =	0.0838
				Adj R-squared =	0.0752
Total	57.0993631	534	.106927646	Root MSE =	.31447

lngm	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
_Istatus_1	.086333	.0401532	2.15	0.032	.0074537 .1652123
_Istatus_3	-.0690752	.0333326	-2.07	0.039	-.1345557 -.0035947
rec_pes	.0174652	.0087323	2.00	0.046	.000311 .0346193
flb	.0000739	.0000634	1.17	0.244	-.0000507 .0001985
cotarea	.2915227	.1181288	2.47	0.014	.0594635 .5235819
_cons	.2147184	.024576	8.74	0.000	.1664399 .2629969

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Multivariate model of gross margin: India

```
reg lngm_shor dg dn Rec_pes flb cotarea if id < 10223 | id > 10240 & id != 10293, robust
```

```
Linear regression                                Number of obs =      83
                                                F( 5, 77) =      0.89
                                                Prob > F      = 0.4896
                                                R-squared    = 0.0392
                                                Root MSE    = .96196
```

```
-----+-----
```

		Robust				
lngm_shor	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dg	.0616319	.2280558	0.27	0.788	-.3924852	.515749
dn	-.0735703	.1889565	-0.39	0.698	-.4498308	.3026902
Rec_pes	-.0566133	.0819718	-0.69	0.492	-.21984	.1066133
flb	-.0004418	.0002397	-1.84	0.069	-.0009191	.0000355
cotarea	.0381861	.055427	0.69	0.493	-.0721832	.1485554
_cons	.5380735	.1775733	3.03	0.003	.1844799	.8916672

```
-----+-----
```

Wald test: $\mu > \beta$

char status [omit] 2

```
xi: regress lngm_shor i.status Rec_pes flb cotarea if id < 10223 | id > 10240 & id != 10293, robust
```

```
i.status          _Istatus_1-3          (naturally coded; _Istatus_2 omitted)
```

```
Linear regression                                Number of obs =      83
                                                F( 5, 77) =      0.89
                                                Prob > F      = 0.4896
                                                R-squared    = 0.0392
                                                Root MSE    = .96196
```

```
-----+-----
```

		Robust				
lngm_shor	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_Istatus_1	.1352022	.2164406	0.62	0.534	-.2957861	.5661905
_Istatus_3	.0735703	.1889565	0.39	0.698	-.3026902	.4498308
Rec_pes	-.0566133	.0819718	-0.69	0.492	-.21984	.1066133
flb	-.0004418	.0002397	-1.84	0.069	-.0009191	.0000355
cotarea	.0381861	.055427	0.69	0.493	-.0721832	.1485554
_cons	.4645032	.1321501	3.51	0.001	.2013588	.7276476

```
-----+-----
```

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Multivariate model of gross margin: Pakistan

reg lngm_shor dg dn rec_pes flb cotarea

Source	SS	df	MS	Number of obs =	189
Model	1.65394307	5	.330788615	F(5, 183) =	4.30
Residual	14.0908827	183	.076999359	Prob > F =	0.0010
				R-squared =	0.1050
				Adj R-squared =	0.0806
Total	15.7448258	188	.083749074	Root MSE =	.27749

lngm_shor	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dg	.2107759	.0635397	3.32	0.001	.0854114	.3361404
dn	.1212903	.0555344	2.18	0.030	.0117203	.2308602
rec_pes	.0019241	.0123675	0.16	0.877	-.0224772	.0263253
flb	.0015149	.0006382	2.37	0.019	.0002557	.0027741
cotarea	.0016621	.0084402	0.20	0.844	-.0149905	.0183147
_cons	-.1004716	.0394289	-2.55	0.012	-.1782652	-.0226779

Wald test: $\mu > \beta$

char status [omit] 2

xi: regress lngm_shor i.status rec_pes flb cotarea

i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

Source	SS	df	MS	Number of obs =	189
Model	1.65394307	5	.330788615	F(5, 183) =	4.30
Residual	14.0908827	183	.076999359	Prob > F =	0.0010
				R-squared =	0.1050
				Adj R-squared =	0.0806
Total	15.7448258	188	.083749074	Root MSE =	.27749

lngm_shor	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_Istatus_1	.0894856	.0559307	1.60	0.111	-.0208663	.1998375
_Istatus_3	-.1212903	.0555344	-2.18	0.030	-.2308602	-.0117203
rec_pes	.0019241	.0123675	0.16	0.877	-.0224772	.0263253
flb	.0015149	.0006382	2.37	0.019	.0002557	.0027741
cotarea	.0016621	.0084402	0.20	0.844	-.0149905	.0183147
_cons	.0208187	.0374701	0.56	0.579	-.0531103	.0947476

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Simple combined-countries model of insecticide expenditure

```
xtreg ins dg dn time, i(Dc) fe robust
Fixed-effects (within) regression      Number of obs      =      1616
Group variable (i): Dc                 Number of groups   =           3

R-sq:  within = 0.1296                  Obs per group: min =      166
      between = 0.6637                    avg =      538.7
      overall = 0.1248                    max =      1070
                                          F(3,1610)         =      73.74
corr(u_i, Xb) = -0.0245                 Prob > F           =      0.0000
```

		Robust				
ins	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dg	-20.55946	4.915478	-4.18	0.000	-30.20087	-10.91805
dn	-12.14414	5.005494	-2.43	0.015	-21.96211	-2.326173
time	-51.56264	3.50037	-14.73	0.000	-58.4284	-44.69688
_cons	123.7858	5.284357	23.42	0.000	113.4208	134.1507
sigma_u	21.366759					
sigma_e	70.356569					
rho	.08444117	(fraction of variance due to u_i)				

Wald test: $\mu < \beta$

```
char status [omit] 2
xi: xtreg ins i.status time, i(Dc) fe robust
i.status      _Istatus_1-3      (naturally coded; _Istatus_2 omitted)
Fixed-effects (within) regression      Number of obs      =      1616
Group variable (i): Dc                 Number of groups   =           3

R-sq:  within = 0.1296                  Obs per group: min =      166
      between = 0.6637                    avg =      538.7
      overall = 0.1248                    max =      1070
                                          F(3,1610)         =      73.74
corr(u_i, Xb) = -0.0245                 Prob > F           =      0.0000
```

		Robust				
ins	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_Istatus_1	-8.415316	3.465559	-2.43	0.015	-15.2128	-1.617835
_Istatus_3	12.14414	5.005494	2.43	0.015	2.326173	21.96211
time	-51.56264	3.50037	-14.73	0.000	-58.4284	-44.69688
_cons	111.6416	3.501202	31.89	0.000	104.7742	118.509
sigma_u	21.366759					
sigma_e	70.356569					
rho	.08444117	(fraction of variance due to u_i)				

Note: The Wald tests: $\mu < \alpha$ and $\beta < \alpha$ show at the P>|t| of dg and dn in the model above.

Simple combined-countries model of cotton yield

```
xtreg y dg dn time, i(Dc) fe robust
Fixed-effects (within) regression      Number of obs      =      1616
Group variable (i): Dc                 Number of groups   =           3

R-sq:  within = 0.0366                  Obs per group: min =      166
      between = 0.5255                      avg =      538.7
      overall = 0.0058                      max =      1070
                                           F(3,1610)         =      20.76
corr(u_i, Xb) = -0.0575                  Prob > F           =      0.0000
```

		Robust				[95% Conf. Interval]	
	y	Coef.	Std. Err.	t	P> t		
dg		176.045	39.47197	4.46	0.000	98.62315	253.4668
dn		4.567813	38.06879	0.12	0.905	-70.10177	79.2374
time		167.049	30.13709	5.54	0.000	107.937	226.1611
_cons		2787.429	34.69286	80.35	0.000	2719.381	2855.477
sigma_u		895.16853					
sigma_e		605.74804					
rho		.68591623	(fraction of variance due to u_i)				

Wald test: $\mu > \beta$
char status [omit] 2
xi: xtreg y i.status time, i(Dc) fe robust
i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

```
Fixed-effects (within) regression      Number of obs      =      1616
Group variable (i): Dc                 Number of groups   =           3

R-sq:  within = 0.0366                  Obs per group: min =      166
      between = 0.5255                      avg =      538.7
      overall = 0.0058                      max =      1070
                                           F(3,1610)         =      20.76
corr(u_i, Xb) = -0.0575                  Prob > F           =      0.0000
```

		Robust				[95% Conf. Interval]	
	y	Coef.	Std. Err.	t	P> t		
_Istatus_1		171.4772	36.20496	4.74	0.000	100.4634	242.491
_Istatus_3		-4.567813	38.06879	-0.12	0.905	-79.2374	70.10177
time		167.049	30.13709	5.54	0.000	107.937	226.1611
_cons		2791.997	31.78398	87.84	0.000	2729.655	2854.339
sigma_u		895.16853					
sigma_e		605.74804					
rho		.68591623	(fraction of variance due to u_i)				

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Multivariate combined-countries model of insecticide expenditure

xtreg ins dg dn time Rec_pes n_kg flb_fman, i(Dc) fe robust

```

Fixed-effects (within) regression      Number of obs      =      1616
Group variable (i): Dc                 Number of groups   =           3

R-sq:  within = 0.3249                  Obs per group: min =      166
      between = 0.8166                      avg =      538.7
      overall = 0.2716                      max =     1070

corr(u_i, Xb) = -0.2293                  F(6,1607)          =     160.97
                                          Prob > F            =      0.0000
    
```

		Robust				[95% Conf. Interval]	
	ins	Coef.	Std. Err.	t	P> t		
dg		-11.50264	4.12263	-2.79	0.005	-19.58893	-3.41634
dn		-8.163551	4.406251	-1.85	0.064	-16.80615	.4790515
time		-43.01373	2.973509	-14.47	0.000	-48.84609	-37.18137
Rec_pes		.1656468	.9458096	0.18	0.861	-1.689503	2.020797
n_kg		.1838027	.0083212	22.09	0.000	.1674811	.2001242
flb_fman		-.1285167	.0177835	-7.23	0.000	-.1633981	-.0936353
_cons		76.62438	7.318154	10.47	0.000	62.27025	90.97851
sigma_u		36.663923					
sigma_e		62.021483					
rho		.25896112	(fraction of variance due to u_i)				

Wald test: $\mu < \beta$

char status [omit] 2

xi: xtreg ins i.status time Rec_pes n_kg flb_fman, i(Dc) fe robust

i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

```

Fixed-effects (within) regression      Number of obs      =      1616
Group variable (i): Dc                 Number of groups   =           3

R-sq:  within = 0.3249                  Obs per group: min =      166
      between = 0.8166                      avg =      538.7
      overall = 0.2716                      max =     1070

corr(u_i, Xb) = -0.2293                  F(6,1607)          =     160.97
                                          Prob > F            =      0.0000
    
```

		Robust				[95% Conf. Interval]	
ins	Coef.	Std. Err.	t	P> t			
_Istatus_1	-3.339085	3.288756	-1.02	0.310	-9.789786	3.111616	
_Istatus_3	8.163551	4.406251	1.85	0.064	-.4790515	16.80615	
time	-43.01373	2.973509	-14.47	0.000	-48.84609	-37.18137	
Rec_pes	.1656468	.9458096	0.18	0.861	-1.689503	2.020797	
n_kg	.1838027	.0083212	22.09	0.000	.1674811	.2001242	
flb_fman	-.1285167	.0177835	-7.23	0.000	-.1633981	-.0936353	
_cons	68.46083	5.251582	13.04	0.000	58.16016	78.7615	
sigma_u	36.663923						
sigma_e	62.021483						
rho	.25896112	(fraction of variance due to u_i)					

Note: The Wald tests: $\mu < \alpha$ and $\beta < \alpha$ show at the P>|t| of dg and dn in the model above.

Multivariate combined-countries model of total EIQ scores

xtreg Eiq dg dn time Rec_pes sk_cropman flb, i(Dc) fe robust

```

Fixed-effects (within) regression      Number of obs      =      546
Group variable (i): Dc                 Number of groups   =        2

R-sq:  within = 0.0685                  Obs per group: min =      166
      between = 1.0000                    avg =                273.0
      overall = 0.0625                    max =                380

corr(u_i, Xb) = -0.4195                  F(6,538)           =        6.36
                                          Prob > F            =        0.0000
    
```

		Robust				[95% Conf. Interval]	
Eiq	Coef.	Std. Err.	t	P> t			
dg	-60.1881	24.15835	-2.49	0.013	-107.6444	-12.73184	
dn	-81.96544	26.14191	-3.14	0.002	-133.3182	-30.61271	
time	2.11261	19.16087	0.11	0.912	-35.52667	39.75189	
Rec_pes	-19.12711	6.015415	-3.18	0.002	-30.94369	-7.310529	
sk_cropman	-.7772212	.7128739	-1.09	0.276	-2.177579	.6231363	
flb	-.1014779	.0427036	-2.38	0.018	-.1853641	-.0175918	
_cons	307.5969	29.74471	10.34	0.000	249.1669	366.0269	
sigma_u	27.035951						
sigma_e	187.9864						
rho	.02026466	(fraction of variance due to u_i)					

Wald test: $\mu < \beta$

char status [omit] 2

xi: xtreg Eiq i.status time Rec_pes sk_cropman flb, i(Dc) fe robust

i.status _1status_1-3 (naturally coded; _1status_2 omitted)

```

Fixed-effects (within) regression      Number of obs      =      546
Group variable (i): Dc                 Number of groups   =        2

R-sq:  within = 0.0685                  Obs per group: min =      166
      between = 1.0000                    avg =                273.0
      overall = 0.0625                    max =                380

corr(u_i, Xb) = -0.4195                  F(6,538)           =        6.36
                                          Prob > F            =        0.0000
    
```

	Robust					
Eiq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_Istatus_1	21.77734	17.00091	1.28	0.201	-11.61897	55.17364
_Istatus_3	81.96544	26.14191	3.14	0.002	30.61271	133.3182
time	2.11261	19.16087	0.11	0.912	-35.52667	39.75189
Rec_pes	-19.12711	6.015415	-3.18	0.002	-30.94369	-7.310529
sk_cropman	-.7772212	.7128739	-1.09	0.276	-2.177579	.6231363
flb	-.1014779	.0427036	-2.38	0.018	-.1853641	-.0175918
_cons	225.6315	21.36258	10.56	0.000	183.6672	267.5957
sigma_u	27.035951					
sigma_e	187.9864					
rho	.02026466	(fraction of variance due to u_i)				

Note: The Wald tests: $\mu < \alpha$ and $\beta < \alpha$ show at the P>|t| of dg and dn in the model above.

Multivariate combined-countries model of cotton yield

xtreg y dg dn time Rec_pes flb ins, i(Dc) fe robust

```

Fixed-effects (within) regression      Number of obs      =      1616
Group variable (i): Dc                 Number of groups   =           3

R-sq:  within = 0.0623                 Obs per group: min =      166
      between = 0.7254                   avg =              538.7
      overall = 0.0682                   max =             1070

                                          F(6,1607)         =      11.66
corr(u_i, Xb) = 0.1350                 Prob > F           =      0.0000
    
```

	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
dg	140.8552	44.16432	3.19	0.001	54.22944	227.4809
dn	-11.85298	37.47349	-0.32	0.752	-85.35504	61.64907
time	96.29608	46.30851	2.08	0.038	5.464652	187.1275
Rec_pes	4.891962	8.666818	0.56	0.573	-12.10749	21.89142
flb	.1341582	.158098	0.85	0.396	-.1759418	.4442582
ins	-1.323026	.6833066	-1.94	0.053	-2.663292	.0172397
_cons	2892.98	109.1226	26.51	0.000	2678.942	3107.017
sigma_u	863.80738					
sigma_e	598.16085					
rho	.67589719	(fraction of variance due to u_i)				

Wald test: $\mu > \beta$
char status [omit] 2
xi: xtreg y i.status time Rec_pes flb ins, i(Dc) fe robust
i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

```

Fixed-effects (within) regression      Number of obs      =      1616
Group variable (i): Dc                 Number of groups   =           3

R-sq:  within = 0.0623                 Obs per group: min =      166
      between = 0.7254                   avg =              538.7
      overall = 0.0682                   max =             1070

                                          F(6,1607)         =      11.66
corr(u_i, Xb) = 0.1350                 Prob > F           =      0.0000
    
```

		Robust				[95% Conf. Interval]	
y	Coef.	Std. Err.	t	P> t			
_Istatus_1	152.7081	39.90932	3.83	0.000	74.42835	230.9879	
_Istatus_3	11.85298	37.47349	0.32	0.752	-61.64907	85.35504	
time	96.29608	46.30851	2.08	0.038	5.464652	187.1275	
Rec_pes	4.891962	8.666818	0.56	0.573	-12.10749	21.89142	
flb	.1341582	.158098	0.85	0.396	-.1759418	.4442582	
ins	-1.323026	.6833066	-1.94	0.053	-2.663292	.0172397	
_cons	2881.127	108.2744	26.61	0.000	2668.753	3093.501	
sigma_u	863.80738						
sigma_e	598.16085						
rho	.67589719	(fraction of variance due to u_i)					

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Multivariate combined-countries model of gross margin

xtreg gm dg dn time Rec_pes flb cotarea, i(Dc) fe robust

```

Fixed-effects (within) regression      Number of obs      =      1616
Group variable (i): Dc                 Number of groups   =           3

R-sq:  within = 0.1802                  Obs per group: min =      166
      between = 0.1027                    avg =      538.7
      overall = 0.1442                    max =     1070

corr(u_i, Xb) = -0.0077                  F(6,1607)          =      67.86
                                          Prob > F           =      0.0000
    
```

		Robust				[95% Conf. Interval]	
gm	Coef.	Std. Err.	t	P> t			
dg	159.6448	20.32024	7.86	0.000	119.7879	199.5018	
dn	62.21869	18.52219	3.36	0.001	25.88849	98.54889	
time	226.4267	15.82722	14.31	0.000	195.3825	257.4708	
Rec_pes	6.814405	4.508904	1.51	0.131	-2.029546	15.65836	
flb	.098906	.0541219	1.83	0.068	-.007251	.205063	
cotarea	-3.524079	6.129805	-0.57	0.565	-15.54733	8.499174	
_cons	1053.196	26.99903	39.01	0.000	1000.239	1106.153	
sigma_u	302.4589						
sigma_e	292.64625						
rho	.51648444	(fraction of variance due to u_i)					

Wald test: $\mu > \beta$
char status [omit] 2
xi: xtreg gm i.status time Rec_pes flb cotarea, i(Dc) fe robust
i.status _Istatus_1-3 (naturally coded; _Istatus_2 omitted)

```

Fixed-effects (within) regression      Number of obs      =      1616
Group variable (i): Dc                 Number of groups   =           3

R-sq:  within = 0.1802                  Obs per group: min =      166
      between = 0.1027                    avg =      538.7
      overall = 0.1442                    max =     1070

corr(u_i, Xb) = -0.0077                  F(6,1607)          =      67.86
                                          Prob > F           =      0.0000
    
```

		Robust				[95% Conf. Interval]	
gm	Coef.	Std. Err.	t	P> t			
_Istatus_1	97.42615	19.00605	5.13	0.000	60.14691	134.7054	
_Istatus_3	-62.21869	18.52219	-3.36	0.001	-98.54889	-25.88849	
time	226.4267	15.82722	14.31	0.000	195.3825	257.4708	
Rec_pes	6.814405	4.508904	1.51	0.131	-2.029546	15.65836	
flb	.098906	.0541219	1.83	0.068	-.007251	.205063	
cotarea	-3.524079	6.129805	-0.57	0.565	-15.54733	8.499174	
_cons	1115.414	26.36936	42.30	0.000	1063.693	1167.136	
sigma_u	302.4589						
sigma_e	292.64625						
rho	.51648444	(fraction of variance due to u_i)					

Note: The Wald tests: $\mu > \alpha$ and $\beta > \alpha$ show at the P>|t| of dg and dn in the model above.

Appendix B: Simple regressions for combined-model

Table B- 1: The effect of FFS on insecticide costs (simple combined-countries model)

Countries/ Dependent variable/ Variables	Three countries Insecticide expenditure (\$/ha)	
	Coefficient	Robust Std. Err.
FFS group (μ)	-20.559 ^{***}	4.915
Non-FFS group (β)	-12.144 ^{**}	5.005
Control group (α)	123.786 ^{***}	5.284
Time	-51.563 ^{***}	3.500
<hr/>		
R ²		0.12
F-statistics		73.74 ^{***}
N		1616
Hypothesis test: (p-values)		
$\mu < \alpha$		0.000
$\mu < \beta$		0.015
$\beta < \alpha$		0.015

Note: ^{***} Significant at 1%, ^{**} Significant at 5%

Source: Own calculations

Table B- 2: The effect of FFS on total EIQ (simple combined-countries model)

Countries/ Dependent variable/ Variables	Two countries EIQ (score)	
	Coefficient	Robust Std. Err.
FFS group (μ)	-89.303 ^{***}	25.079
Non-FFS group (β)	-91.776 ^{***}	26.948
Control group (α)	256.711 ^{***}	20.820
Time	-19.614 ^{ns}	16.259
<hr/>		
R ²		0.04
F-statistics		8.42 ^{***}
N		546
Hypothesis test: (p-values)		
$\mu < \alpha$		0.000
$\mu < \beta$		0.872
$\beta < \alpha$		0.001

Note: ^{***} Significant at 1%, ^{ns} Non-significant difference

Due to lack of information concerning scientific name of pesticides, the dependent variable is summarized from EIQ scores of Pakistan and India.

Source: Own calculations

Table B- 3: The effect of FFS on cotton yield (kg/ha) (simple combined-countries model)

Countries/ Dependent variable/ Variables	Three countries Cotton yield (kg/ha)	
	Coefficient	Robust Std. Err.
FFS group (μ)	176.045 ^{***}	39.472
Non-FFS group (β)	4.568 ^{ns}	38.069
Control group (α)	2787.429 ^{***}	34.693
Time	167.049 ^{***}	30.137
<hr/>		
R ²	0.01	
F-statistics	20.76 ^{***}	
N	1616	
Hypothesis test: (p-values)		
$\mu > \alpha$	0.000	
$\mu > \beta$	0.000	
$\beta > \alpha$	0.905	

Note: ^{***} Significant at 1%, ^{ns} Non-significant difference

Source: Own calculations

Table B- 4: The effect of FFS on gross margin (\$/ha) (simple combined-countries model)

Countries/ Dependent variable/ Variables	Three countries Gross margin (\$/ha)	
	Coefficient	Robust Std. Err.
FFS group (μ)	170.761 ^{***}	18.748
Non-FFS group (β)	64.091 ^{***}	18.787
Control group (α)	1101.881 ^{***}	16.349
Time	231.285 ^{***}	14.579
<hr/>		
R ²	0.12	
F-statistics	123.81 ^{***}	
N	1616	
Hypothesis test: (p-values)		
$\mu > \alpha$	0.000	
$\mu > \beta$	0.000	
$\beta > \alpha$	0.001	

Note: ^{***} Significant at 1%

Source: Own calculations

Appendix C: Benefits and costs of FFS training under FAO-EU IPM Program for Cotton in Asia (Scenario B to D)

Table C- 1: Benefits and costs of FFS training based on one year benefits and 80% adoption rate in China (\$1,000): Scenario B

Year	Benefits	Costs	Net benefits	Discounted cumulative cash flow
2000	-	512.50	-512.50	-474.54
2001	66.04	894.59	-828.55	-1,184.89
2002	205.76	1,318.15	-1,112.39	-2,067.94
2003	553.21	1,332.26	-779.05	-2,640.57
2004	722.91	168.61	554.31	-2,263.31
2005	30.05	-	30.05	-2,244.38
Total	1,577.97	4,226.11	-2,648.14	
NPV	-2,244.38			
BCR	0.34			
FIRR	-			

Note: Used discount rate at 8%, NPV: Net present value, BCR: Benefit-cost ratio, FIRR: Financial internal rate of return

Table C- 2: Benefits and costs of FFS training based on three years benefits and 100% adoption rate in China (\$1,000): Scenario C

Year	Benefits	Costs	Net benefits	Discounted cumulative cash flow
2000	-	512.50	-512.50	-474.54
2001	82.55	894.59	-812.04	-1,170.73
2002	339.75	1,318.15	-978.40	-1,947.42
2003	1,031.26	1,332.26	-301.00	-2,168.66
2004	1,852.36	168.61	1,683.75	-1,022.73
2005	1,632.72	-	1,632.72	6.16
2006	941.20	-	941.20	555.34
2007	37.56	-	37.56	575.63
Total	5,917.40	4,226.11	1,691.28	
NPV	575.63			
BCR	1.17			
FIRR	15.60%			

Note: Used discount rate at 8%, NPV: Net present value, BCR: Benefit-cost ratio, FIRR: Financial internal rate of return

Table C- 3: Benefits and costs of FFS training based on three years benefits and 80% adoption rate in China (\$1,000): Scenario D

Year	Benefits	Costs	Net benefits	Discounted cumulative cash flow
2000	-	512.50	-512.50	-474.54
2001	66.04	894.59	-828.55	-1,184.89
2002	271.80	1,318.15	-1,046.35	-2,015.52
2003	825.01	1,332.26	-507.25	-2,388.36
2004	1481.88	168.61	1,313.28	-1,494.56
2005	1306.17	-	1,306.17	-671.45
2006	752.96	-	752.96	-232.11
2007	30.05	-	30.05	-215.87
Total	4,733.92	4,226.11	507.80	
NPV	-215.87			
BCR	0.94			
FIRR	4.98%			

Note: Used discount rate at 8%, NPV: Net present value, BCR: Benefit-cost ratio, FIRR: Financial internal rate of return

Table C- 4: Benefits and costs of FFS training based on one year benefits and 80% adoption rate in India (\$1,000): Scenario B

Year	Benefits	Costs	Net benefits	Discounted cumulative cash flow
2000	-	214.20	-214.20	-191.25
2001	19.45	655.32	-635.87	-698.16
2002	203.49	634.54	-431.05	-1004.97
2003	558.46	1,032.08	-473.62	-1305.96
2004	742.89	807.60	-64.71	-1342.68
2005	2,801.40	-	2,801.40	76.60
Total	4,325.70	3,343.74	981.96	
NPV	76.60			
BCR	1.03			
FIRR	13.85%			

Table C- 5: Benefits and costs of FFS training based on three year benefits and 100% adoption rate in India (\$1,000): Scenario C

Year	Benefits	Costs	Net benefits	Discounted cumulative cash flow
2000	-	214.20	-214.20	-191.25
2001	24.32	655.32	-631.00	-694.28
2002	278.68	634.54	-355.86	-947.58
2003	976.76	1,032.08	-55.32	-982.73
2004	1,881.06	807.60	1,073.46	-373.62
2005	5,128.45	-	5,128.45	2,224.61
2006	4,430.37	-	4,430.37	4,228.68
2007	3,501.75	-	3,501.75	5,642.98
Total	16,221.38	3,343.74	12,877.65	
NPV	5,642.98			
BCR	3.48			
FIRR	72.05%			

Note: Used discount rate at 12%, NPV: Net present value, BCR: Benefit-cost ratio, FIRR: Financial internal rate of return

Source: Own calculations

Table C- 6: Benefits and costs of FFS training based on three year benefits and 80% adoption rate in India (\$1,000): Scenario D

Year	Benefits	Costs	Net benefits	Discounted cumulative cash flow
2000	-	214.20	-214.20	-191.25
2001	19.45	655.32	-635.87	-698.16
2002	222.94	634.54	-411.59	-991.12
2003	781.41	1,032.08	-250.67	-1,150.43
2004	1,504.85	807.60	697.25	-754.79
2005	4,102.76	-	4,102.76	1,323.79
2006	3,544.29	-	3,544.29	2,927.05
2007	2,801.40	-	2,801.40	4,058.49
Total	12,977.11	3,343.74	9,633.37	
NPV	4,058.49			
BCR	2.78			
FIRR	59.09%			

Note: Used discount rate at 12%, NPV: Net present value, BCR: Benefit-cost ratio, FIRR: Financial internal rate of return

Source: Own calculations

Table C- 7: Benefits and costs of FFS training based on one year benefits and 80% adoption rate in Pakistan (\$1,000): Scenario B

Year	Benefits	Costs	Net benefits	Discounted cumulative cash flow
2000	-	97.97	-97.97	-87.47
2001	-	325.39	-325.39	-346.87
2002	228.67	464.43	-235.76	-514.68
2003	1,217.71	680.78	536.93	-173.45
2004	1,648.00	337.36	1,310.64	570.25
2005	1,906.50	-	1,906.50	1,536.14
Total	5,000.88	1,905.92	3,094.96	
NPV	1,536.14			
BCR	2.18			
FIRR	74.25%			

Note: Used discount rate at 12%, NPV: Net present value, BCR: Benefit-cost ratio, FIRR: Financial internal rate of return

Table C- 8: Benefits and costs of FFS training based on three years benefits and 100% adoption rate in Pakistan (\$1,000): Scenario C

Year	Benefits	Costs	Net benefits	Discounted cumulative cash flow
2000	-	97.97	-97.97	-87.47
2001	-	325.39	-325.39	-346.87
2002	285.84	464.43	-178.59	-473.99
2003	1,807.97	680.78	1,127.20	242.37
2004	3,867.98	337.36	3,530.62	2,245.73
2005	5,965.26	-	5,965.26	5,267.92
2006	4,443.13	-	4,443.13	7,277.77
2007	2,383.12	-	2,383.12	8,240.27
Total	18,753.30	1,905.92	16,847.38	
NPV	8,240.27			
BCR	7.33			
FIRR	146.83%			

Note: Used discount rate at 12%, NPV: Net present value, BCR: Benefit-cost ratio, FIRR: Financial internal rate of return

Table C- 9: Benefits and costs of FFS training based on three years benefits and 80% adoption rate in Pakistan (\$1,000): Scenario D

Year	Benefits	Costs	Net benefits	Discounted cumulative cash flow
2000	-	97.97	-97.97	-87.47
2001	-	325.39	-325.39	-346.87
2002	228.67	464.43	-235.76	-514.68
2003	1,446.38	680.78	765.60	-28.12
2004	3,094.38	337.36	2,757.02	1,536.28
2005	4,772.21	-	4,772.21	3,954.04
2006	3,554.50	-	3,554.50	5,561.91
2007	1,906.50	-	1,906.50	6,331.91
Total	15,002.64	1,905.92	13,096.72	
NPV	6,331.91			
BCR	5.87			
FIRR	125.52%			

Note: Used discount rate at 12%, NPV: Net present value, BCR: Benefit-cost ratio, FIRR: Financial internal rate of return