

The Institute for Food Economics and Consumption Studies
of the Christian-Albrechts-Universität Kiel



**Climate-Smart Agriculture in Pakistan: Implications for Climate Risk Management,
Food Security, and Poverty Reduction**

Dissertation

Submitted for Doctoral Degree

awarded by the Faculty of Agricultural and Nutritional Sciences

of the

Christian-Albrechts-Universität Kiel

Submitted by

Muhammad Faisal Shahzad (M.Sc.)

Born in Pakistan

Kiel, 2020

The institute for Food Economics and Consumption Studies
of the Christian-Albrechts-Universität Kiel



**Climate-Smart Agriculture in Pakistan: Implications for Climate Risk Management,
Food Security, and Poverty Reduction**

Dissertation

Submitted for Doctoral Degree

awarded by the Faculty of Agricultural and Nutritional Sciences

of the

Christian-Albrechts-Universität Kiel

Submitted by

Muhammad Faisal Shahzad (M.Sc.)

Born in Pakistan

Kiel, 2020

Examination Board:

Chairman: Prof. Dr. Dr. Christian Henning (Dean)

Examiner: Prof. Dr. Awudu Abdulai

Examiner: Prof. Dr. Martin Schellhorn

Assessor: Prof. Dr. Marie Catherine Riekhof

Date of Oral Examination: 17. 06. 2020.

Gedruckt mit der Genehmigung der Agrar-und Ernährungswissenschaftlichen Facultät der
Christian-Albrechts Universität zu Kiel.

Diese Arbeit kann als pdf-Dokument unter https://macau.uni-kiel.de/receive/macau_mods_0000

[0648](#) dem Internet geladen werden.

Dedication

I dedicate this dissertation to my father Haji Farzand Ali, my mother Shamim Akhter, and the whole family. I hope that this achievement will complete the dream that you had for me all those many years ago when you chose to give me the best education you could. I further dedicate this work to future generations of researchers entering the field of climate change impact assessment and nutritional sciences. May you find a world worthy of your passion, dedication, and talent. If you don't, help us build it.

Acknowledgments

First of all, I am thankful to Almighty Allah (SWT), the sustainer of the Universe, for giving me the strength, good health, and wisdom to complete this milestone successfully. I am thankful to beloved Prophet Hazrat Muhammad (PBUH) for his eminent aphorisms and encouragement about knowledge acquisition that give me full strength to accomplish this program. I want to give thanks to all the persons that have become a big part of this research. To my family, especially to my father, mother, wife, sisters, and brothers for their moral support and prayers in order to complete this study. I am obliged to present my utmost gratitude to my doctoral mentor, a great thinker and generous soul, Prof. Dr. Awudu Abdulai, for guiding and helping me in order to make the study a well-done achievement. His inspiring questions during lab group meetings, the stimulating and engaging discussion has given me the impetus to go further during the memorable hours that I have spent at my computer writing and revising research papers. I further extend the gratitude to all dearests who live in my heart and colleagues, especially at the Institute of Food Economics and Consumption Studies, who helped me to do this study presentable. With gratitude, my special thanks also go to the Higher Education Commission (HEC) of Pakistan, and the German Academic Exchange Service (DAAD) for the financial support granted to me throughout the study period. I am also thankful to Haji Muhammad Hussain (lately deceased) and Manzoor Hussain Lehri for their personal guarantee after securing HEC scholarship. A bundle of thanks to Dr. Muhammad Shakir Aziz and Dr. Asif Naeem for proofreading this document. I am also thankful to the data collection team for their quality work during the field survey. Finally, thanks to all the respondents for their full cooperation that made them a big part of this study.

Kiel, June 2020.

Muhammad Faisal Shahzad

Email: faisaluaaf@gmail.com

Table of Contents

List of Tables	xiii
List of figures	xv
Abstract	xvi
Zusammenfassung.....	xviii
Chapter 1	
General Introduction	1
1.1. Background	1
1.2. Problem setting and motivation.....	3
1.3. Climate and geography of Pakistan.....	9
1.4. Review of Pakistan’s agricultural sector and climate change impacts.....	12
1.5. Brief profile of Punjab province (study area).....	14
1.6. Study objectives	17
Future outlook of the study	17
Structure of the dissertation.....	18
References	20
Chapter 2	
Adaptation to Extreme Weather Conditions and Farm Performance in Rural Pakistan ...	27
Abstract	27
2.1. Introduction	28
2.2. Materials and methods	32
2.2.1. Modeling adaptation to extreme weather conditions	32

2.2.2. Selection into adaptation to extreme weather conditions.....	34
2.2.3. Impact assessment of adaptation to extreme weather conditions.....	34
2.2.4. Estimation and identification	36
2.2.5. The empirical specification	39
2.2.6. Study area	42
2.2.7. Data collection and data description	44
2.3. Empirical Results	46
2.3.1. Descriptive statistics and mean differences between adopters and non-adopters.	46
2.3.2. Determinants of adaptation to extreme weather conditions	50
2.3.3. Volatility of farm net returns	51
2.3.4. Downside risk exposure and kurtosis.....	53
2.3.5. Farm net returns	56
2.3.6. Average treatment effects on the treated (ATT)	59
2.4. Discussion	59
2.5. Conclusion and policy implications	62
Acknowledgments.....	63
References	64
Appendix A	72

Chapter 3

Climate Risk Management in Agricultural and Rural Household Welfare: Empirical

Evidence from Pakistan	78
-------------------------------------	-----------

Abstract	78
----------------	----

3.1. Introduction	79
3.2. Data and descriptive statistics	83
3.3. Methodology	89
3.3.1. Conceptual framework	89
3.3.2. Empirical Strategy	91
3.3.3. Counterfactual analysis and average treatment effects on the treated (ATT).....	97
3.4. Results and discussion.....	98
3.4.1. Determinants of climate-smart farm practices	98
3.4.2. Economic implications of climate-smart agricultural practices	101
3.5. Conclusion and policy implications	109
References	112
Appendix B	119

Chapter 4

The Heterogeneous Effects of Adoption of Climate-Smart Agriculture on Household

Welfare in Pakistan	125
Abstract	125
4.1. Introduction	126
4.2. Conceptual framework and estimation.....	129
4.3. Study area, data collection and data description	134
4.3.1. Study area	134
4.3.2. Data collection and data description	134
4.4. Results and discussion.....	140

4.4.1. First stage (selection equation) results	141
4.4.2. Second stage estimation	144
4.4.3. Marginal treatment effects (MTE) results	151
4.4.4. Robustness checks	155
4.4.5. Summary of causal effects of adoption on food security and poverty	157
4.4.6. Simulating policy strategies	159
4.5. Conclusion and policy implications	161
References	164
Appendix C	170
Chapter 5	
Conclusion and policy implications	172
5.1. Summary of empirical methods	174
5.2. Summary of results.....	176
5.3. Policy implications.....	179
Appendix 1: Questionnaire.....	181

List of Tables

Table 1.1 Climate, soil types and crops of agro-ecological zones in Pakistan.....	11
Table 1.2 Agriculture and socio-economic indicators of Pakistan	13
Table 1.3 Climate and characteristics of agro-ecological zones of Punjab province	16
Table 2.1 Definition and descriptive statistics of selected variables.....	47
Table 2.2 Descriptive statistics and mean difference between adopters and non-adopters.....	48
Table 2.3 Determinants of adaptation to extreme weather conditions and its impact on the volatility of farm net returns.....	52
Table 2.4 Determinants of adaptation to extreme weather conditions and its impact on downside risk exposure.	54
Table 2.5 Determinants of adaptation to extreme weather conditions and its impact on Kurtosis.	55
Table 2.6 Determinants of adaptation to extreme weather conditions and its impact on household farm net returns	57
Table 2.7 Impact of adaptation to extreme weather conditions on farm net returns, the volatility of farm net returns, and downside risk exposure.....	59
Table 2.A1 Log-linear farm net returns function estimation.....	73
Table 2.A2 Residuals calculation of potential endogenous variables	74
Table 2.A3 Instrumental variables validation test (Probit model).....	75
Table 2.A4 Instrumental variables validation test non-adopters (OLS).....	76
Table 2.A5 Instrumental variable correlation test	76
Table 3.1 Definition and descriptive statistics of selected variables.....	86
Table 3.2 Summary statistics of the variables used for the CSA adopters and non-adopters	88
Table 3.3 Determinants of CSA practices choices, MNL model estimation	100
Table 3.4 Impact of CSA practices choices on farm net returns, second stage MESR estimation	103

Table 3.5 Overall average treatment effects on the treated	105
Table 3.6 Location-wise average treatment effects on the treated	106
Table 3.7 Quantile-wise average treatment effects on the treated.....	108
Table 3.B1 Impact of CSA practices on risk exposure, second stage MESR estimation	119
Table 3.B2 Test on the validity of selection and potential endogenous variable instruments (Farm net returns).....	120
Table 3.B3 Test on the validity of selection and potential endogenous variable instruments (Skewness)	120
Table 3.B4 Parameters estimates of net returns function	121
Table 3.B5 Parameter estimates of potential endogenous variable credit constraint	122
Table 3.B6 Parameter estimates of of potential endogenous variable extension services	123
Table 3.B7 Suest-based Hausman tests of IIA assumption	123
Table 3.B8 Correlation matrix.....	124
Table 3.B9 Robustness checks	124
Table 4.1 Descriptive Statistics and definition of selected variables.....	139
Table 4.2 Descriptive statistics and mean difference between adopters and non-adopters.....	140
Table 4.3 Selection equation and outcome equations results for HFIAS.....	146
Table 4.4 Selection equation and outcome equations results for HDDS.....	148
Table 4.5 Selection equation and outcome equations results for poverty headcount.....	150
Table 4.6 Selection equation and outcome equations results for poverty gap (severity).....	151
Table 4.8 Impact of different policies on propensity scores and outcome variables.....	160
Table 4.C1 Test on the validity of the selection instruments HFIAS.....	170
Table 4.C2 Test on the validity of the selection instruments HDDS.....	170
Table 4.C3 Test on the validity of the selection instruments poverty headcount index	171
Table 4.C4 Test on the validity of the selection instruments poverty gap index.....	171
Table 4.C5 Matrix of correlations	171

List of figures

Fig. 1.1 Schematic diagram showing the impacts of climate change on water, agriculture, food security, and household welfare	8
Fig. 1.2 Division of agro-ecological zones of Pakistan.....	10
Fig. 1.3 Map of Punjab province divided into agro-ecological zones.....	15
Fig. 2.1 Map of Pakistan showing study area and agro-ecological zones.....	43
Fig. 2.A1 Kernel density plot for adopters and non-adopters (Net Returns).....	77
Fig. 3.1 Map of Pakistan showing study area and data collection sites	85
Fig. 3.2 Unconditional farm net returns distributions by CSA practices	87
Fig. 4.1 Map of Pakistan showing study area and data collection sites.....	135
Fig. 4.2 Common support.....	142
Fig. 4.3 MTE curve for household food insecurity access scale (HFIAS).....	153
Fig. 4.4 MTE curve for household dietary diversity scores (HDDS)	153
Fig. 4.5 MTE curve for poverty headcount index	154
Fig. 4.6 MTE curve for poverty severity	154
Fig. 4.7 MTE curves for HFIAS: functional form robustness checks.....	155
Fig. 4.8 MTE curves for HDDS: functional form robustness checks	156
Fig. 4.9 MTE curves for poverty headcount: functional form robustness checks	156
Fig. 4.10 MTE curves for poverty gap: functional form robustness checks	157

Abstract

Climate-smart agriculture (CSA) has emerged as a framework for developing and implementing robust agricultural systems, which simultaneously improve food security, living conditions in rural areas, facilitate adaptation to climate change, provide mitigation benefits and improve household welfare. In recent decades, climate variability has made the world agricultural systems more uncertain, causing reproductive failure and severe yield reductions in many crops. At the same time, a growing population with increasing food demand and poverty appeal to adopt CSA at the household level. As adoption rates in developing countries like Pakistan are low, the adverse impacts of climate change such as temperature increases, erratic rainfall patterns, extreme weather conditions significantly undermine agricultural production and food systems in such countries, where hunger, malnutrition, and poverty are already predominant. Climate-smart agricultural (CSA) practices appear to be useful tools in the form of adaption strategies to manage agricultural farms that reduce climate risks and increase farm productivity in the developing world. This study, therefore, contributes to the growing literature on the impact of CSA practices on farm performance, and rural household welfare by exploring climate risk management, the contribution of single or joint adaptation strategies in enhancing farm net returns, food and nutrition security, as well as poverty reduction in rural Pakistan. In particular, the study first examines adaptation to extreme weather conditions impact on farm net returns, and risk measures of this outcome variable (volatility, downside risk exposure, and kurtosis) by using endogenous switching regression (ESR) model to account for selection bias. Secondly, the study employs multinomial endogenous switching regression (MESR) to explore climate risk management through multiple adaptation practices and their impact on household welfare. The study also inspects factors influencing farmers' decisions to adopt these practices. Finally, the marginal treatment effect approach is employed in analyzing the food and nutrition security as well as the poverty status of rural farm households. The empirical results reveal that adoption of CSA practices exerts a positive and significant impact on reducing volatility, downside risk exposure, and kurtosis of farm net returns.

The results further reveal that farmers who adopted CSA practices obtain higher farm net returns. The collective findings from the study show that farmers' decisions to adopt CSA practices are mainly influenced by temperature and rainfall shocks, education of household head, extension services, the experience of past climate-related shocks (such as floods, droughts, and pest infestation, etc.), climate change information, climate change perception and climate-resilient trainings. Credit constraint is the major barrier faced by the farmers in adopting CSA practices, causing low adoption rates. In the multiple CSA practices' adoption analysis, the results reveal that soil and water conservation coupled with crop rotation as soil and water conservation exerts the maximum impact on farm net returns earned from adapted plots followed by input mix, diversifying seed variety, and changing cropping calendar, respectively. The findings also show that all of the CSA practices significantly reduce downside risk exposure and crop failure of farm households. Besides, controlling household and farm-level characteristics, climate variability, and regional dummies, the empirical results confirm that observable and unobservable heterogeneity significantly varies across farm households. The results further reveal that adoption of CSA practices significantly reduces household food insecurity and increases household dietary diversity at the lower level of unobserved resistance to adoption and vice versa. The findings also show that farmers who adopted CSA practices experience a lower level of poverty than traditional farmers. These findings call for development policy measures to promote CSA practices across the country through climate change awareness, climate-resilient trainings, and access to extension as well as formal and informal credit sources to enhance adoption rates for increasing agricultural productivity and expanding food systems for a growing population.

Keywords: Climate-smart agriculture, climate change, impact assessment, risk management, food security, poverty reduction, household welfare, Pakistan.

Zusammenfassung

Die Entwicklung und Implementierung von robusten Landwirtschaftssystemen, die darauf abzielen Ernährungssicherheit, rurale Lebensbedingungen und Haushaltswohlfahrt zu verbessern, zeitgleich den Klimawandel abzuschwächen und die Anpassung an diesen zu erleichtern, wird unter dem Rahmenbegriff climate-smarte Landwirtschaft (CSA) zusammengefasst. Innerhalb der letzten Jahrzehnte, haben Klimaschwankungen weltweit zu Unsicherheiten in der landwirtschaftlichen Produktion geführt, die bei diversen Feldfrüchten Unfruchtbarkeit und Ernteauffälle zur Folge hatten. Gleichzeitig stellt die wachsende Bevölkerung mit ihrer gesteigerten Nachfrage nach Lebensmitteln, sowie zunehmende Armut einen Anreiz dar, CSA vermehrt auf Haushaltsebene anzuwenden. Vor allem Entwicklungsländer wie Pakistan, wo Hunger, Unterernährung und Armut bereits vorherrschend sind, sind stark von den Auswirkungen des Klimawandels betroffen. Steigende Temperaturen, unregelmäßige Niederschläge und eine Zunahme an extremen Wetterereignissen schwächen die landwirtschaftliche Produktion in diesen Ländern signifikant, während CSA wenig verbreitet ist. Climate-smarte Landwirtschaftliche (CSA) Praktiken erscheinen als nützliche Strategien zur Adaption, um vom Klimawandel verursachte Risiken zu senken (Climate Risk Management) und die landwirtschaftliche Produktivität in diesen Ländern zu steigern. Diese Arbeit analysiert Climate Risk Management, die Auswirkung von einzelnen oder mehreren Adaptionstrategien auf Netto-Betriebserträge, Ernährungssicherheit, sowie Armutsreduzierung im ländlichen Pakistan und leistet somit einen wichtigen Beitrag zur wachsenden Literatur über die Auswirkungen von CSA Praktiken auf die Landwirtschaft und ländliche Haushaltswohlfahrt. Im Speziellen, untersucht die Arbeit zuerst, wie sich eine Anpassung an Extremwetterereignisse auf die Netto-Betriebserträge und dessen Risikomaße (Volatilität, Downside Risk Exposition und Kurtosis) auswirkt. Dabei wird das endogenous switching regression (ESR) Modell angewandt, um Selektionseffekte zu berücksichtigen. Zweitens, wird Climate Risk Management in Form von multiplen Adaptionstrategien und dessen Auswirkung auf Haushaltswohlfahrt mit Hilfe der multinomial

endogenous switching regression (MESR) Methode analysiert. Diese Studie prüft zudem, welche Faktoren Landwirte dazu bewegen, Adaptionsstrategien umzusetzen. Schließlich wird der Ansatz des marginal treatment effect angewandt, um Ernährungssicherheit und Armut in ländlichen Farmhaushalten zu untersuchen. Die empirischen Ergebnisse zeigen einen positiven und signifikanten Einfluss von CSA Praktiken auf die Reduzierung von Volatilität, Downside Risk Exposition und Kurtosis der Netto-Betriebserträge. Außerdem erzielen Landwirte, die CSA Praktiken anwenden, höhere Netto-Betriebserträge. Die Entscheidung eines Landwirts CSA Praktiken einzuführen, wird von Niederschlags- und Temperaturschocks, Bildungsgrad des Haushaltsvorstands, landwirtschaftlichen Beratungsdiensten und Trainingsprogrammen, die Erfahrung vergangener Klimaschocks (wie Überschwemmungen, Dürren, Krankheitsbefälle, etc.), sowie Informationen über und die Wahrnehmung vom Klimawandel signifikant beeinflusst. Die größte Hürde der Landwirte, um CSA Praktiken umsetzen zu können, ist die Kreditrestriktion, welche in geringen Adoptionsraten resultiert. Der Vergleich verschiedener CSA Praktiken ergab, dass die Kombination von Boden- und Wasserschutz mit Fruchtwechsel den größten Einfluss auf den Netto-Betriebsertrag aufzeigt, gefolgt von Input-Mischung, Diversifizierung von angebauten Feldfrüchten und geänderte Fruchtfolge. Die Ergebnisse zeigen zudem, dass alle CSA Praktiken signifikant die Downside Risk Exposition und Ernteausfälle reduzieren. Außerdem, bei Berücksichtigung von Farm- und Haushaltsmerkmalen, Klimavariabilität und Standort, bestätigen die empirischen Ergebnisse, dass beobachtbare und unbeobachtbare Heterogenität signifikant zwischen Haushalten variiert. Weitere Ergebnisse zeigen, dass die Umsetzung von CSA Praktiken bei geringerem unbeobachtbaren Widerstand gegenüber einer Adoption die Ernährungssicherheit und tägliche Ernährungsvielfalt signifikant erhöht. Zudem erfahren Landwirte, die CSA Praktiken anwenden, geringe Armut als traditionelle Landwirte. All diese Ergebnisse unterstützen die Forderung, CSA Praktiken als Entwicklungsmaßnahme in ganz Pakistan voranzutreiben. Mit einem gesteigerten Bewusstsein hinsichtlich des Klimawandels, entsprechenden Trainingsprogrammen und Zugang zu Beratungsdiensten, sowie zu formellen und informellen

Kreditgebern kann die Adoptionsrate von CSA Praktiken erhöht, die landwirtschaftliche Produktivität gesteigert und somit das Ernährungssystem auf die wachsende Bevölkerung angepasst werden.

Chapter 1

General Introduction

1.1. Background

Severe climate change is making the world weather uncertain and has a devastating direct effect on agriculture (Foresight, 2011; Parry et al., 2004; Shannon and Motha, 2015). The average global increase in temperature has risen about 2-degree Fahrenheit (1 °C) during the last decades and probable to continue at a rapid rate (World Bank, 2013), while combined greenhouse gas emissions from agriculture, forestry, and other land use account for 22% of global emissions (FAO, 2010). As such, warm atmosphere, decrease in snowfall, rising sea level, unpredicted changes in precipitation, and greenhouse gas emissions are causing extreme weather events (IPCC, 2013), which as a consequence, adversely affects agriculture, food production and distribution, and rural household welfare. Thus, these adverse extreme weather conditions affect the economic performance of a country (Economic Survey of Pakistan, 2016).

Likewise, extreme climate conditions have a significant effect on soil moisture interaction, land erosion, and earth's temperature. Global warming is causing seasonal variations in crop sowing and harvest patterns due to which production tends to decrease in the future. As a primary source of income in developing countries, agriculture is still a significant contributor to the welfare and socio-economic development (World Bank, 2008). In developing countries, small losses in agriculture production cause greater loss of income because agriculture accounts for a more significant share of GDP compared with an industrial country. Nevertheless, these abrupt and extreme changes in weather conditions are adversely affecting agriculture crop yields (Chmielewski and Muller, 2004; Sharma and Dobriyal, 2014).

Deterioration in agriculture productivity is causing persistent poverty in the farming community and food insecurity as a whole. Yield losses of agriculture crops range between 5 to 25 percent, which is alarming to feeding the enormously growing population (Schwartz and Randall, 2003). The decrease in agricultural productivity results in several adversities, where food security and

poverty are the leading ones. Food security includes four major components: food availability; food accessibility; food utilization; and food affordability (FAO, 2008). Unfortunately, climate change has a considerable effect on all four dimensions (Vogel and Smith, 2002; Clover, 2003). Climate-related food insecurity has a considerable direct and indirect effect on human health (McMichael, et al., 2006). Declining food availability and accessibility are associated with hazardous health problems, malnourishment, and stunt growth in children, serious health problems in pregnancy for both mother and child. It also causes different diseases in children that undermine child educational performance (UNICEF, 2014). In the future, the number of malnourished children would become higher due to climate change (Nelson et al., 2010).

Furthermore, predictions indicate that variations in rainfall would drive 12 million people into absolute poverty by damaging existing water resources. Mainly, monsoon variations cause a disparity in water availability for irrigation. Projections indicate that North West areas of the south Asian region are getting drier. The increase in temperature is leading dry regions towards droughts. Pakistan is highly vulnerable and at high risk due to vague precipitation predictions. Loss of snow cover results in river flow reductions, which are a reliable and stable source of irrigation. Due to the rapid melting of snow water runoff in summers causes floods and creates considerable reductions in dry season flow. Risks become severe if warming reaches 4°C (IPCC, 2013; National Climate Change Policy, 2011). However, it has been predicted that the local vulnerability of climate change adverse impacts would remain persistent (Planning Commission of Pakistan, 2010).

From the above discussion, it can be concluded that the agriculture sector should overcome three challenges i) sustainably increase agricultural production to meet global food demand, ii) adapt to the impacts of climate change, iii) and reduce greenhouse gas emissions. The concept of climate-smart agriculture (CSA) has been developed and promoted to overcome these challenges by FAO (2010). CSA is an innovative approach projecting development pathway by buffering climate change adverse effects so that agriculture sectors remain more productive and sustainable. CSA

builds resilience to climate risks, which is essential for rural households and communities to cope with the uncertainty created by climate change and extreme weather conditions. Agricultural production systems and food systems must endure substantial changes to achieve sustainability.

To buffer the adverse calamities and their impacts, CSA has emerged as a framework for developing and implementing robust agricultural systems, which simultaneously improve food security, living conditions in rural areas, facilitate adaptation to climate change, provide mitigation benefits and improve household welfare (FAO, 2013). The global community has recommended the incorporation of climate-smart farm practices (CSA practices) into national development plans to mitigate the adverse impacts of climate change on agriculture (IPCC, 2007; World Bank, 2010). Climate-smart farm practice is a practice on the farm, which sustainably increases agricultural productivity, adapts and builds the resilience of agricultural and food systems to climate change, and reduces greenhouse gas emissions from agriculture (FAO, 2013). The CSA practices such as changing input mix and cropping calendar, crop diversification, diversifying seed variety, crop rotation, soil and water conservation, using improved seed variety, income diversification, crop, and livestock integration and improving irrigation efficiency are the strategies generally used to reduce climate change adverse effects (Tubiello et al., 2008; Soglo and Nonvide, 2019).

1.2. Problem setting and motivation

Climate change and extreme weather conditions directly or indirectly affect agricultural productivity and food production. Several studies have been addressed in recent decades on adoption, climate change, food security and poverty, e.g., Hassan and Nhemachena, 2008; Di Falco et al., 2011; Ali and Erenstein, 2017; Javed et al. 2014; Nelson et al., 2014; Issahaku and Abdulai, 2020, etc. The study by Hassan and Nhemachena (2008) revealed that better access to markets, extension and credit services, technology, and farm assets tend to increase the probability of climate change adoption. They further investigated that mono-cropping is more vulnerable to climate change in Africa. In drier areas, farmers would be benefited from increased rainfall. Di

Falco et al. (2011) conducted a study on climate change analysis by using endogenous switching regression analysis. They analyzed farmers' decision to adapt to climate change and the impact of this adaptation on agricultural productivity. They found that access to extension services and credit were the main drivers to climate change adaptation. They also found that adaptation increased farm productivity. Javed et al. (2014) carried out a study on climate change impact on agriculture in Pakistan. They used the fixed effect and instrumental variables for analyzing district-level panel data. They concluded that an increase in temperature was harmful to agriculture. Their findings revealed that agriculture production of the current year was dependent on previous year production. Abid et al., 2016a and Di Falco and Veronesi (2014) explored climate risks, adaptation strategies, and impact on household welfare. Abid et al. (2016a) conducted a study on climate change vulnerability, adaptation, and risk perception at farm level in Punjab Pakistan. They investigated various climate-related risks perceived by farm households. Extreme temperature, insect attack, animal diseases, and crop pests were the main climate-related risks to the farmers, while limited water for irrigation, proper infrastructure availability and poverty were the other risks to the farmers. Di Falco and Veronesi (2014) calculated environmental risk in the presence of climate change considering the role of adaptation in the Nile Basin of Ethiopia. They found that past climate adaptation reduced current downside risk exposure ensuring reduction in crop failure risk. They also found that adaptation to climate change was a successful risk management strategy. It was also concluded that adaptation to climate change for non-adopters was more beneficial in reducing downside risk.

Several studies explored the climate change impacts on food security and poverty (McMichael et al., 2006; Deressa et al., 2008; Patz et al., 2002, 2005; Kovats and Hajat, 2008; Azeem et al., 2016; Ahmad et al., 2015; Iqbal and Arif, 2010). Climate change, extreme weather conditions, heat stress, future food yields, and hunger are strengthening infectious diseases and pose considerable health risks, McMichael et al. (2006) investigated studying climate change impacts. They found that social, economic, and demographic disruptions discourse health risks. They suggested planned

preventive and adaptive strategies to cope with climate change adverse effects that were harmful to human health. By using the vulnerability assessment approach, Deressa et al. (2008) found that Afar and Somali regions were most vulnerable to climate change. They concluded that vulnerability to climate change was extremely related to poverty (loss of adaptive capacity). They recommended investment in irrigation techniques for the insurance of irrigation potential to enhance agricultural production and food supply. They also suggested that early warning of extreme weather events to the farmers as preventive measures.

Patz et al. (2005) explored that many human diseases were associated with climate variations. Cardiovascular and respiratory diseases became dominant due to starvation from crop failure and changed the way of disease transmission. Climate change's impact on human health remained uncertain, as there was a lack of long-term data set, the extent of socio-economic variables, varied immunity levels, and resistance to drugs. Projections revealed that health risks would increase due to climate change, while Kovats and Hajat (2008) found that climate change would increase the intensity and frequency of heatwaves that might increase heat-related mortality. Khan and Salman (2012) investigated the relationship between human vulnerability index and climate-induced disasters (floods). By employing logistic regression analysis, they indicated that ownership of livestock, literacy rate, and access to electricity play a decisive role in the recovery of affected households after floods. Patz and Kovats (2002) stated that climate change would suffer a low-income population. Climate change impacts depend on access to health care, age, living region, and public health care infrastructure. Energy consuming countries were responsible for global warming while developing nations were at extreme risk.

However, the literature on the impact assessment of adoption of new emerging climate-smart technologies, mainly on climate risk management, food, and nutrition security and poverty reduction in Pakistani perspective, is scanty. Studies have shown that adaptation of adoption strategies can minimize the adverse impacts of climate change. The study mentioned above by Abid et al. (2016a) explained the climate-related risk and perceptions in graphical form, and some

studies just rely on studying wheat crops for food security in the country (Ahmed et al., 2014; Abid et al., 2016b). Azeem et al. (2016) conducted a study on household vulnerability to food insecurity in Punjab Pakistan by using a multilevel model. They found that the share of a household that was at the risk of becoming food insecure was higher than the share of current food-insecure households. People were not vulnerable due to poor resource endowments but due to household level idiosyncratic risk. Abid et al. (2016b) conducted a study on climate change adaptation and the impact on food security by using propensity score matching technique (PSM). They considered wheat productivity and crop income as food security indicators. They found that farmers used changing planting dates, crop varieties, and different fertilizer types as adaptation strategies to cope with climate change adverse impacts. Furthermore, they confirmed that education, farming experience, weather forecasting, access to agriculture extension, and marketing information had a significant effect on the adaptation decision of farmers. They also found that adaptation to climate change increased wheat productivity and crop income enhancing farmer's welfare and food security.

Ahmad et al. (2015) compiled their results studying farm household's adaptation to climate change on food security, taking into account different agro-ecologies of Pakistan. They employed the potential outcome treatment effects model for analysis. Adaptation strategies were grouped into four categories. Results from the study showed that climate change adapters were more food secure than non-adopters. They further concluded that the education of male and female heads, the structure of the house, crop diversification, livestock ownership, and non-farm income improved food security significantly. Age of household head, small land holding, and food expenditure management were negatively associated with food security. They constructed a food security index by using principal component analysis. Iqbal and Arif (2010) found that land and water resources were the base for food security. These resources were limited and prone to climate change. They further clarified that studies projected that crop yield losses due to climate change

would increase, growing season length would decrease, water requirements would increase while water availability would decrease in the future.

Above mentioned studies incorporated graphical analysis, logit model, propensity score matching technique, and Heckman treatment effect model. As farmers' decisions to adapt to innovative technologies are based on their observable characteristics (education, farm size, soil fertility, etc.) and unobservable characteristics (innate skills, risk preferences, motivation for adaptation, etc.), such decisions are non-random. Therefore, without accounting for these observable and unobservable characteristics, the results may be biased and inconsistent. The methodologies used in most of the studies mentioned above do not account for selection bias. Some recent studies (Di Falco et al. 2011; Abdulai and Huffman, 2014; Ma and Abdulai, 2016) used endogenous switching regression to account for observable and unobservable characteristics, but their analysis was based on a single crop. Most of the studies cited above used single crop such as wheat, rice, cotton, or maize to conclude their results on farm income and household welfare. However, the conclusion based on a single crop may under or overestimate the real impacts of adoption for several reasons. For instance, if multi-product farmer applies soil and water conservation techniques for the wheat crop, it might offer benefit to oilseed crops in the same season and increase the yield of cotton, rice, maize, etc. in the following season, which may not be captured if a researcher considers only wheat yield leaving out other crops. Furthermore, there might be a negative interaction between crops in a mixed setting, where one crop may increase the yield of other crops (Tessema et al., 2015). Additionally, Abdulai and Huffman (2014) analyzed the soil and water conservation impacts on rice yield and net returns without accounting for climate variables. Moreover, the inclusion of climate variables is quite crucial to account for plant growth and yield, and agriculture as a whole (Ray et al., 2015).

For sustainable agriculture production and farm household development, information on climate change impacts and potential adaptation strategies should be widely known to inform environmentalists and policy-makers as well as farm households. The present study examines an

in-depth analysis and consequently provides information on the potential effects of climate change on the welfare of farm households. The knowledge abstracted through this study would be important to agricultural producers for production planning under innovative adaptation technologies and their implementation at the micro-level. It would also serve as an important source for policymakers, environmentalists, and agriculture scientists for effective decision making and policy planning on different innovative technologies and their impact on agricultural production. It would also be helpful for government and research institutes for budget allocation, environment development programs, and development of new crop variety genotypes.

Fig. 1.1 illustrates a brief overview of climate change impacts on water resources, agriculture, food security, and household welfare.

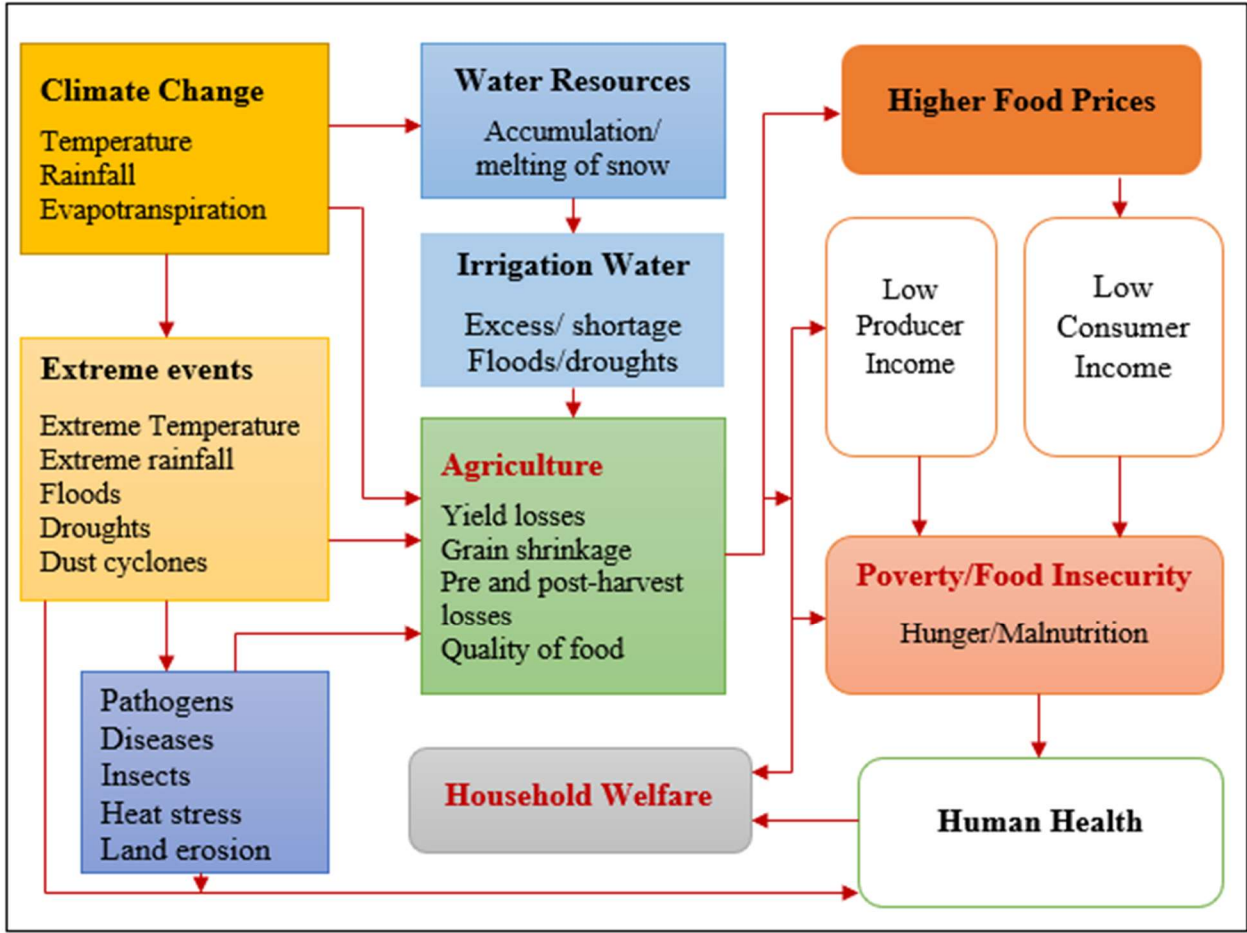


Fig. 1.1 Schematic diagram showing the impacts of climate change on water, agriculture, food security, and household welfare

For the future sustenance of an increasing population, we need adequate research, policy, and planning to feed an enormously growing population. As mentioned above, very few and limited studies have been carried out on climate change, and food security in Pakistan. Therefore, a comprehensive study on farm net returns and the climate situation in the country is widely needed (Abid et al., 2016a). Consequently, this study intends to make a healthy endeavor in analyzing the climate change effects on household welfare, investigate the influence of adaptation strategies on climate risk management, farm net returns, food security, and poverty. In addition to the country-specific contribution to literature, this study also extends the mixed cropping analysis by moving away from mono-cropping analysis to mixed-cropping that exploits the interlink benefits from multiple adaptation strategies. Also, limited studies have examined the adoption impacts of multiple adaptation strategies on farmers' productivity and exposure to risk, though from a mono-cropping perspective (Di Falco and Veronesi, 2013; Iqbal et al., 2015). We incorporate multiple adaptation strategies with multi-crops in our analysis.

The focus of this study is on the key factors influencing climate-smart adaptation strategies, as well as the impact of these adaptation strategies on farm household welfare, including food, nutrition security, and poverty in South Asian countries, using Pakistan as a case study. After addressing some conceptual issues, this study makes a healthy attempt in building the link between climate change (extreme weather events), agricultural productivity, climate risk management, food security and poverty, the role of climate-smart practices in mitigating the adverse impacts of climate change and extreme weather conditions as well as reducing production risks of rural households in Pakistan. A brief overview of climate and geography, climate change impacts, and agriculture in Pakistan with an overview of the study area is given below.

1.3. Climate and geography of Pakistan

On the world map, Pakistan is situated between the longitudes of 61° to 75° east and the latitudes of 24° and 37° north, spreading on a total area of 796096 square km. The country's climate is subtropical and semi-arid. The annual average rainfall ranges between 500-900 mm in the sub-

mountainous and northern plains, but it varies to 125 mm in extreme southern plains. Summer monsoon causes 70% rainfall in July to September, while 30% rainfall occurs during winter. Summers in Pakistan are sweltering (more than 40 °C), while in winter, the temperature is few degrees above the freezing point. In mountainous areas, the temperature is always lower than the other parts of the country (Khan, 2004). The climate of Pakistan is categorized by extreme temperature variants. High altitudes are cold while the temperature in the Baluchistan plateau is higher. In summers temperature reach great heights in some regions of the country. Northern mountains covered with snow with relatively lower temperatures. In summer, melting snow provides water for irrigation. A heavy rainy season supervene from June to September called Monsoon (Khan et al., 2009). Pakistan has been divided into ten agroecological zones based on climate, land use, physiography, and water availability (see Fig. 1.2). The brief introduction and climatic conditions are listed in Table 1.1, which illustrates the division of agroecological zones in Pakistan.

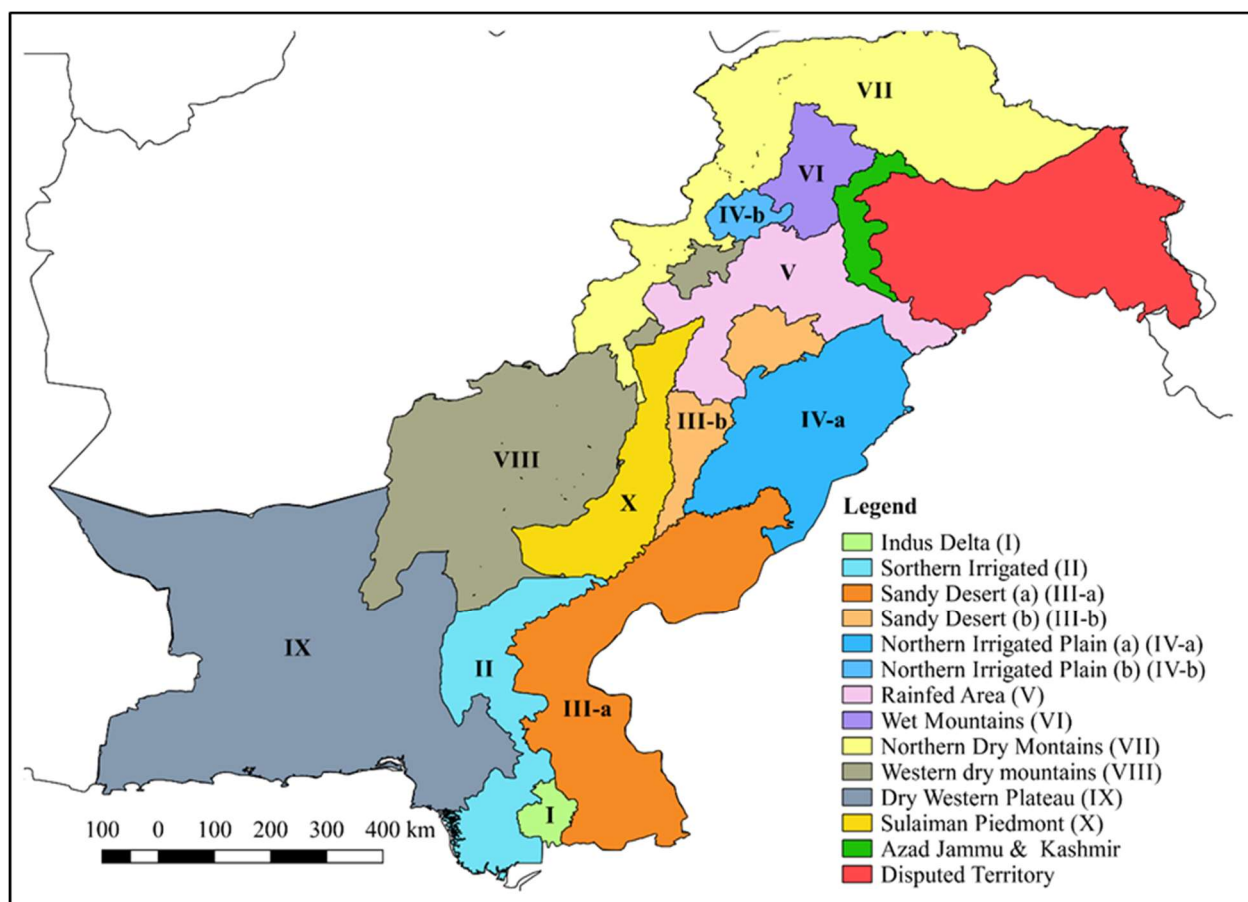


Fig. 1.2 Division of agro-ecological zones of Pakistan

Table 1.1 Climate, soil types and crops of agro-ecological zones in Pakistan

Zone ID	Zone name	Mean summer temp (°C)	Mean winter temp (°C)	Mean monthly summer rainfall (mm)	Mean monthly winter rainfall (mm)	Soil and land use	Crops
I	Indus Delta	30-40	19-20	75	<5	Clayey and silty soils, parts of clayey soils are under cultivation.	Rice, sugarcane, cotton millet, maize, barley, rape and mustard, gram, fodder, pulses, and vegetable
II	Southern Irrigated Plain	40-45	8-12	18-55	<1	Silty, sandy loam, calcareous loam and clayey	Cotton, wheat, sugar cane, rice, wheat, gram, berseem, and sorghum
III-a	Sandy Desert Zone-a	46-50	4-10	20-25	20-25	Sandy and loamy fine sand, land is used for grazing	Millet, wheat, rape and mustard, fodder, cotton, sugarcane, sorghum, rice, maize, and pulses
III-b	Sandy Desert Zone-b	40-48	3-10	25-30	25-30	Sandy and loamy fine sand, land is used for grazing	Cotton, sugarcane, rice, wheat, and gram. maize, sorghum and millet, pulses and vegetable
IV-a	Northern Irrigated Plain Zone-a	39.5-42	6.2	25-42	25-42	Sandy loam-clay loam, clay, calcareous, saline-sodic	Wheat, rice, sugarcane, oilseeds, millets, cotton, sugarcane, maize as well as citrus and mangoes
IV-b	Northern Irrigated Plain Zone-b	43-44	5	20-32	20-32	Silty clays and clay loams	Sugar cane, maize, tobacco, wheat, berseem, sugar beet, and orchards
V	Barani (Rainfed) Lands	38.5	4-7	7-17	30-50	Silt loams, calcareous loams	Rice, sorghum, millet, maize, pulses, groundnut, sugarcane, wheat, gram, rapeseed, mustard and barley
VI	Wet Mountains	35	0-4	20	10	Silt loam to silty clays, non-calcareous to slightly, calcareous, land is used for rain-fed agriculture.	Forest, wheat, apple, olives
VII	Northern Dry Mountains	36-40	-2.5-9	10-20	25-75	Deep, clayey, calcareous, non-calcareous, most land is used for grazing	Wheat and maize are grown rain-fed, rice is irrigated in local areas; fruits grown in flank streams
VIII	Western Dry Mountains	30-39	-3-7.7	30-95	63-95	Loamy, deep and strongly calcareous, mountains have shallow soil	Apples, peaches, plums, apricots, grapes, wheat and maize
IX	Dry Western Plateau	33-40.5	3-15	36-37	2.4	Silt loams, deep and strongly calcareous, land use is mainly grazing	Melons, sorghum, fruits, vegetables, and wheat is grown where spring or "Kareze" water is available
X	Sulaiman Piedmont	40-43	5.8-7.6	13	<1	Loams, calcareous, with narrow strips of salinity sodicity, torrent-watered cultivation is the main land use	Wheat, millets, gram, and rice.

Source: FAO, 2006; Khan, 2004.

There are four seasons in Pakistan: a cold and dry winter from December to February, spring season from March to May, summer or Monsoon season from June to September, and retreating monsoon period or autumn from October to November. Pakistan has two cropping seasons “Rabi (winter) season and Kharif (summer) season.” Rabi season crops are sown in October-December and harvested in March-April. Kharif season is slightly longer; it starts from February-March and continues up to December. Water from Northern areas flows into the Indus basin with its five tributaries named Chenab, Jhelum, Ravi, Sutlej, and Beas. Indus basin is the primary source of irrigation for agriculture in Pakistan (Khan, 2004).

1.4. Review of Pakistan’s agricultural sector and climate change impacts

The agriculture sector is the backbone of Pakistan’s economy. It contributes 19.8 percent to national GDP and employs 42.3 percent labor force of the country. Pakistan is ranked 5th in the world with 212.2 million inhabitants and plays a vital role in ensuring food security for this relatively huge growing population. In Asian countries, farm sizes are petite, approximately 89% of rural households in Pakistan are below 5 Hectare and cultivate 55% of the total agricultural area. Pakistan exports agro-based products to other countries and receive 80% of the country’s total export earnings. In this way, Pakistan’s agriculture has earned much enticing in recent years as a vast population is relying on agriculture for its livelihood. But the growth of the agriculture sector is dependent on favorable weather conditions. A strong relationship exists between agriculture and climate. Weather conditions like temperature, precipitation, and extreme events affect the economic performance of the country. Climate change has a significant impact on production, commodity prices, and economic growth. Climate change and food security are the incipient challenges that Pakistan faces currently. These challenges shifted the policy focus from a few years (Economic Survey of Pakistan, 2016).

In Pakistan, three major grain crops are grown. Wheat is the top leading food grain and accounts for 10.3 percent to value-added in agriculture and 2.2 percent to national GDP. Rice is the second major food grain crop; its share in value-added in agriculture is 3.1 percent and accounts for 0.7

percent in GDP. Maize is the third major enriched food grain adding 2.1 percent to value-added in agriculture and 0.4 percent to GDP. Gram, Jawar, Bajra, and Barley are the other grain crops grown in Pakistan. Timely rainfall at regular intervals and favorable weather conditions result in increased production of these crops. Due to floods and excessive rains, rice yield was not so impressive. Other grain crops declined their production due to unfavorable weather conditions (Economic Survey of Pakistan, 2014). Studies have shown that adaptation to climate change reduce the adverse impacts of unfavorable weather conditions and help to increase production and farm income. Some agriculture and socio-economic indicators of Pakistan are given in Table 1.2.

Table 1.2 Agriculture and socio-economic indicators of Pakistan

Index	Figure
GDP growth	5.5%
Agricultural growth	3.8% *
Agriculture value added (% of GDP)	23%
Arable land (% of total land)	40.3%
Agricultural land (% of total land)	47.8%
Agricultural irrigated land (% of total agricultural land)	50.5%
Population	212.2 million
Rural vs. urban population share	64% vs. 36%
Poverty headcount ratio at national poverty lines (% of population)	24.3% (2015)

Source: World bank indicator data 2016, * Economic Survey of Pakistan, 2018.

Climate change costs Pakistani Rupees 365 billion every year in the form of inadequate water supply, pollution, land degradation, and deforestation (Economic Survey of Pakistan, 2014). Besides, climate change has a direct negative impact on crop yields in Pakistan (Gill, 2016). Major crop yields are reduced with climate change adverse impacts (Janjua et al., 2010). Pakistan is below the wheat production potential; a 60% gap exists that should be narrowed down. The irrigated area of crops has been increased, but water availability has decreased. Water requirements have significant importance at different stages of growth; some stages are more vulnerable to water shortage and result in substantial wheat yield losses (PARC, 2013). Climate

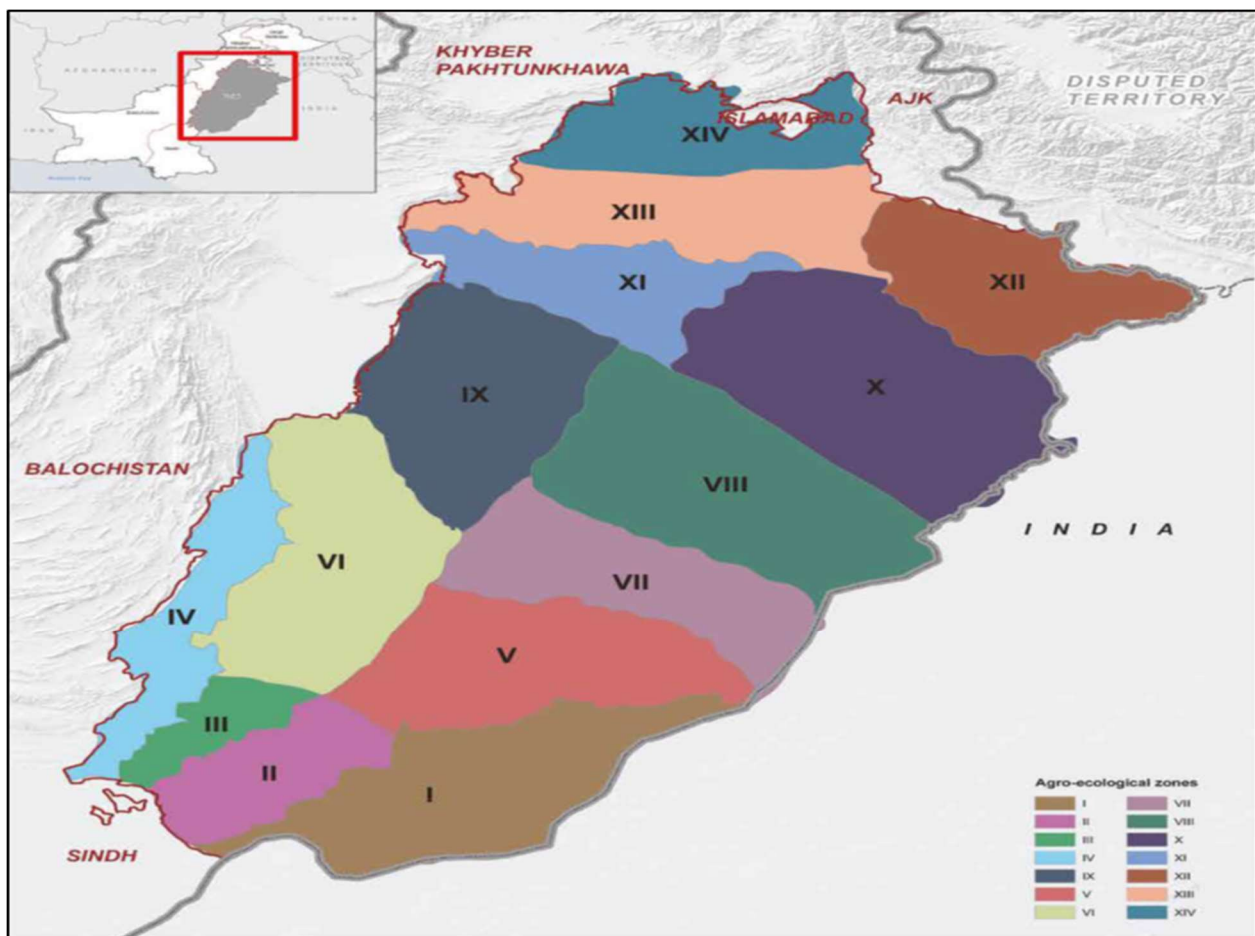
change affects the rice crop when it is in the flowering and milking stage (Ahmad et al., 2014). Maize yield has a negative relationship with temperature; higher temperature tends to low maize yield (Khaliq, 2008). Temperature also negatively affect arid zone crop production, but precipitation has a positive impact on crop yield. The combined effect of both is negative for the arid zone in Pakistan (Shakoor et al., 2011).

As mentioned above, the issue of food security has become inevitable to address because agricultural output has decreased with adverse impacts of climate change. The population of Pakistan is increasing enormously. This rapid growth of population renders economic stability and development of Pakistan. According to the National Nutritional Survey, about 60 percent population is food insecure, and 50 percent of women and children are underfed (Economic Survey of Pakistan, 2014). Punjab is the largest producer still has a 23.6 percent food insecure population (SDPI, 2009). Pakistan once an exporter of wheat is now in danger to fulfill the needs of domestic requirements for sustaining the growing population. The population of Pakistan will grow 227 million up to 2025. Out of 107 countries, Pakistan is miserably at the 76th number in the Global Food Security Index. Population growth, limited land for agriculture, increasing water stress, restricted agricultural technology, and varying consumption patterns are raising the threat of dearth and food shortage. Food security is a complex issue for Pakistan to resolve as it has many facets (Economic Survey of Pakistan, 2014).

1.5. Brief profile of Punjab province (study area)

Punjab province is located at 31.17° N and 72.70° E with an area of about 205,344 km². It is the most populous province of Pakistan spread over 26% of the land area. It borders with Balochistan, Islamabad Capital Territory, Khyber Pakhtunkhwa, Sindh, and Azad Jammu and Kashmir. From the Indian side, it borders with Indian Punjab, Rajasthan, and Indian Occupied Kashmir. Indus River is the longest river of Pakistan; it flows through Punjab with five tributaries Jhelum, Ravi, Sutlej, Chenab, and Beas. Punjab stems from Persian words “Punj” means five and “ab” means water, naming it the land of five rivers. Upper Indus plain is the most important part

that contributes to Pakistan’s agriculture sector. It is called the “Grain Basket of the Sub-continent” that shares the highest proportion of agriculture to the country’s gross domestic product (GDP). Climatically, Punjab province is located in arid to semi-arid region of the country, where the temperature ranges from $-2\text{ }^{\circ}\text{C}$ to $45\text{ }^{\circ}\text{C}$ usually but sometimes reach $50\text{ }^{\circ}\text{C}$ in summer and $-7\text{ }^{\circ}\text{C}$ in winter. The maximum average annual temperature ranges from $28\text{-}32\text{ }^{\circ}\text{C}$, while the minimum average annual temperature varies between $15\text{-}19\text{ }^{\circ}\text{C}$. There is an increasing trend in temperature over time that is estimated to be more than $0.5\text{ }^{\circ}\text{C}$. From the last five decades, rainfall shows an increasing trend with an average annual change of 228 mm . Punjab is blessed with four eminent seasons, spring, summer, autumn, and winter. There are fourteen agroecological zones in Punjab province with varying characteristics (FAO, 2019). Fig. 1.3 shows different agro-ecological zones of Punjab province, while Table 1.3 illustrates the essential characteristics and climatic conditions of these zones.



Source: FAO, 2019.

Fig. 1.3 Map of Punjab province divided into agro-ecological zones

Table 1.3 Climate and characteristics of agro-ecological zones of Punjab province

Zone ID	Zone name	Avg, rabi max temp (°C)	Avg, rabi min temp (°C)	Avg, kharif max temp (°C)	Avg, kharif min temp (°C)	Avg, annual rainfall (mm)	ET (mm)	Soil type
I	Cholistan desert	28.09	12.31	39.28	27.31	230	3.20	Mostly sandy
II	Arid irrigated	29.20	12.45	40.41	27.59	234	3.10	Loam, sandy loam (9%)
III	Cotton–sugarcane	28.67	12.40	39.93	27.49	243	2.93	Sandy loam, clay loam (10%), loam (35%)
IV	Rod-i-Kohi	27.73	12.61	39.42	27.28	255	3.10	Mostly sandy loam
V	Semi-desert irrigated	27.59	12.38	38.94	27.22	412	2.88	Loam, sandy loam (20%), clay loam (8%)
VI	Mix cropping	27.38	12.99	39.47	27.30	460	2.62	Sandy loam (55%), loam (45%), clay (5%), loam
VII	Cotton mix cropping	27.39	12.08	38.52	26.72	580	2.71	Loam, sandy loam (5%)
VIII	Maize wheat mix cropping	26.97	11.06	37.86	25.58	590	2.64	Loam, sandy loam (3%), clay loam (1%)
IX	Thal-Gram crop	27.51	11.35	39.21	26.24	612	2.25	Sandy loam (50%), sandy (35%), loam (10%), clay (5%)
X	Rice–wheat	26.34	11.80	36.96	25.74	760	2.74	Loam, clay loam (5%), sandy loam (3%)
XI	Thal zone 2	26.84	10.91	37.80	25.73	1 120	2.34	Sandy loam (45%), loam (45%), clay loam (5%)
XII	Rice zone	25.03	11.71	35.53	25.20	1 250	1.76	Loam (40%), sandy loam (20%), clay loam (10%)
XIII	Groundnut-medium rainfall	24.85	10.27	36.36	24.37	1 620	2.10	Loam (95%), sandy loam (5%)
XIV	High rainfall	23.35	9.45	34.50	22.96	1 780	1.95	Loam (95%), sandy loam (5%)

Source: FAO, 2019.

Being the most populous, Punjab is the leading province for the agricultural production in Pakistan. By covering 69% of the total cropped area, it contributes a significant share in the agricultural economy of the country. Notably, the province accounts for 97% of rice, 83% of cotton, 63% of sugarcane, and 51% of maize to the national crop production (FAO, 2019). Climate change poses a formidable challenge to the farmers in the province and reduced major crop yields. This year major crop growth rates are recorded negative, while the overall negative growth rate of 0.19% is observed in the agriculture sector of the country (Economic Survey of Pakistan, 2019). Therefore, climate risk management through adaptation may help to reduce the adverse impacts of climate change and extreme weather conditions. A rigorous analysis of these adaptation strategies may provide insights into which adaptation measures should be taken to cope with the adversities and which of them single or a combination may be useful in enhancing crop yields and farm income in the province.

1.6. Study objectives

The main objective of this research study is to assess the impact of climate-smart agriculture adoption on farm performance in Pakistan. Specifically, the aims of this study are:

- 1- To assess environmental risks to agriculture under extreme weather conditions and their management at the household level;
- 2- To determine the contributing factors to the household decision choices to adapt to different climate-smart agricultural practices and their impact on household welfare;
- 3- To estimate the impact of adoption of climate-smart agricultural practices on food and nutrition security and poverty reduction.

Future outlook of the study

This study analyses the climate change adoption impacts on agricultural production, climate risk management in agriculture, food and nutrition security, and poverty reduction. However, agriculture is mainly dependent on water resources available for irrigation in the country. In

Pakistan, most of the commercial farms have access to water. Notably, about 80% of the crop area is irrigated, and 90% of the farm output comes from irrigated land. Besides, monsoon rainfall plays a vital role in agricultural production in Pakistan. However, climate change is considerably affecting water resources and glacier cover. Approximately 75 percent of Himalayan glaciers will disappear from the surface of the earth by 2035 (Misra, 2014). These glaciers are the major and stable source of water for irrigation in Pakistan (Bashir and Rasul, 2010). It is further predicted that climate change has a considerable effect on water resources in the Indus Basin (Zhu et al., 2013). Pakistan is classified as a water-stressed country that is rafting toward water scarcity if adequate measures not taken (GOP, 2014; World Economic Forum, 2013). One leading cause of the reduction in agricultural output is water shortage for irrigation in Pakistan (Abid et al., 2016a). Further research on climate change impacts on water resources could be helpful in finding the possible solutions to conserve water resources of the country to improving agriculture and food production. As climate change tends to positively influence innovation processes through information sources and training, therefore, one domain could be the impact of information diffusion processes and cultural change on adoption of climate smart agriculture. Besides, assessment of the impact of adoption of climate smart agricultural technologies on farm input allocation and environmental efficiency could be another area of research.

Structure of the dissertation

This dissertation is a collection of research articles and organized as follows. The article in Chapter 2 explores the adoption of extreme weather conditions and farm performance in rural Pakistan. Extreme weather conditions pose a formidable challenge to the farmers and increase production risks to the community. To the extent that these risks vary across agro-ecological zones, and the decision to adopt extreme weather conditions is non-random. Therefore, we employ endogenous switching regression that accounts for observable and unobservable factors to ensure unbiased and consistent estimates. Specifically, we analyze the factors affecting adoption decisions of extreme weather conditions and the impact of adoption on farm net returns and the measures of risk

exposure such as variance, skewness, and kurtosis. Chapter 3 examines the adaptation implications of CSA practices in terms of climate risk management and farm household welfare. Specifically, chapter investigates the drivers of adoption of different CSA practices such as changing cropping calendar, diversifying seed variety, changing input mix and soil and water conservation, and the impact of adoption of these practices on farm net returns and downside risk exposure. In this chapter, we employ multinomial endogenous switching regression to account for selection bias and unobservable heterogeneity. Chapter 4 assesses the impacts of CSA practices on food and nutrition security and poverty reduction. Specifically, we examine heterogeneity in CSA effects on household welfare in Pakistan by employing marginal treatment effects approach. Chapter 5 presents the conclusion and policy implications of the study.

References

- Abdulai, A., & Huffman, W., (2014). The adoption and impact of soil and water conservation technology: An endogenous switching regression application. *Land Economics*, 90(1), 26-43.
- Abid, M., Schilling, J., Scheffran, J., & Zulfiqar, F., (2016a). Climate change vulnerability, adaptation and risk perceptions at farm level in Punjab, Pakistan. *Science of the Total Environment*, 547, 447-460.
- Abid, M., Schneider, U. A., & Scheffran, J. (2016b). Adaptation to Climate Change and Its Impacts on Food Productivity and Crop Income: Perspectives of Farmers in Rural Pakistan, *Journal of Rural Studies*, 47, Part A, 254-266.
- Ahmad, M., Mustafa, G., & Iqbal, M. (2015). Impact of Farm Households' Adaptations to Climate Change on Food Security: Evidence from Different Agro-ecologies of Pakistan.
- Ahmad, M., Nawaz M., Iqbal M., Javed, S. A. (2014). Analyzing the Impact of Climate Change on Rice Productivity in Pakistan. PIDE climate Change Working Paper Series. Paper No. 2: 2014.
- Ali, A., & Erenstein, O. (2017). Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Climate Risk Management*, 16, 183-194.
- Azeem, M. M., Muger, A. W., & Schilizzi, S. (2016). Living on the edge: Household vulnerability to food-insecurity in the Punjab, Pakistan. *Food Policy*, 64, 1-13.
- Bashir, F., & Rasul, G. (2010). Estimation of average snow cover over northern Pakistan. *Pakistan Journal of Meteorology*, 7(13), 63-69.
- Chmielewski, F. M., Muller, A., & Bruns, E. (2004). Climate changes and trends in phenology of fruit trees and field crops in Germany, 1961–2000. *Agricultural and Forest Meteorology*,

121(1), 69-78.

Clover, J. (2003). Food security in sub-Saharan Africa. *African Security Studies*, 12(1), 5-15.

Deressa, T., Hassan, R. M., & Ringler, C. (2008). Measuring Ethiopian farmers' vulnerability to climate change across regional states. *Intl Food Policy Res Inst.*

Di Falco, S., & Veronesi, M. (2013). How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia. *Land Economics*, 89(4), 743-766.

Di Falco, S., & Veronesi, M. (2014). Managing environmental risk in presence of climate change: the role of adaptation in the Nile Basin of Ethiopia. *Environmental and Resource Economics*, 57(4), 553-577.

Di Falco, S., M. Veronesi, and M. Yesuf. (2011). Does Adaptation to Climate Change Provide Food Security? A Micro-perspective from Ethiopia. *American Journal of Agricultural Economics* 93 (3): 829–46.

Economic Survey of Pakistan. (2018). Economic Advisor's Wing, Ministry of Finance, Islamabad, Pakistan.

Economic Survey of Pakistan. (2019). Economic Advisor's Wing, Ministry of Finance, Islamabad, Pakistan.

Economic Survey of Pakistan. (2014). Economic Advisor's Wing, Ministry of Finance, Islamabad, Pakistan.

Economic Survey of Pakistan. (2016). Economic Advisor's Wing, Ministry of Finance, Islamabad, Pakistan.

FAO. (2008). An Introduction to the Basic Concepts of Food Security Food and Agriculture Association of the United Nations (FAO, Rome).

FAO. (2013). Climate-Smart Agriculture Sourcebook. Food and Agriculture Organization, Rome.

- FAO. (2019). Climate-Smart Agriculture for Punjab, Pakistan. Food and Agricultural Organization (FAO), DOI: 10.13140/RG.2.2.25544.78083
- FAO. (2006). Country Pasture/Forage Resource Profiles. Food and Agriculture Association of the United Nations (FAO, Rome).
- FAO. (2010). "Climate-smart" agriculture: policies, practices and financing for food security, adaptation and mitigation. Rome.
- Foresight. (2011). The future of food and farming. Final Project Report. London, The Government Office for Science.
- Gill, H. A. (2016). Pakistan-adaptations measures to cope with the rising temperature, 1.5 degree regime. The Nature News, environment, climate change and science. Available at <http://thenaturenews.com/2016/08/pakistan-adaptations-measures-to-cope-with-the-rising-temperature-1-5-degree-regime/>
- GOP. (2014). Pakistan Vision 2025. Ministry of Planning and Development Government of Pakistan, Islamabad. Government of Pakistan, Islamabad.
- Hassan, R., & Nhemachena, C. (2008). Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. *African Journal of Agricultural and Resource Economics*, 2(1), 83-104
- IPCC (2007). Climate Change 2007: Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.
- IPCC. (2013). Fifth Assessment Report on Climate Change. Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.
- Iqbal, M. M., & Arif, M. (2010). Climate-change aspersions on food security of Pakistan. *A Journal of Science for Development*, 15.
- Iqbal, M., Ahmad, M., & Mustafa, G. (2015). Impact of Farm Households' Adaptation on

Agricultural Productivity: Evidence from Different Agro-ecologies of Pakistan.

- Issahaku, G., & Abdulai, A. (2020). Household welfare implications of sustainable land management practices among smallholder farmers in Ghana. *Land Use Policy*, 94, 104502.
- Janjua, P. Z., Samad, G. and Khan, N. U. (2010). Impact of Climate Change on Wheat Production: A Case Study of Pakistan. *The Pakistan Development Review* 49(4): 799–822.
- Javed, S. A., Ahmad, M., and Iqbal, M. (2014). Impact of Climate Change on Agriculture in Pakistan: A District Level Analysis. Pakistan Institute of Development Economics, Climate Change Working Papers No. 3.
- Khaliq, T. (2008). Modeling the impact of climate change on maize (zea mays l.) Productivity in the Punjab. A PhD thesis department of Agronomy, University of Agriculture Faisalabad, Pakistan.
- Khan, A. G. (2004). The characterization of the agro ecological context in which fangr (farm animal genetic resources) are found.
- Khan, A. G., Afzal, M., & Usmani, R. H. (2009). The characterization of the agro ecological context in which FAnGR (Farm Animal Genetic Resources) are found.
- Khan, F. A., & Salman, A. (2012). A simple human vulnerability index to climate change hazards for Pakistan. *International Journal of Disaster Risk Science*, 3(3), 163-176.
- Khan, S. (2019). Climate classification of Pakistan. *International Journal of Economic and Environmental Geology*, 10(2), 60-71.
- Kovats, R. S., & Hajat, S. (2008). Heat stress and public health: a critical review. *Annu. Rev. Public Health*, 29, 41-55.
- Ma, W., & Abdulai, A. (2016). Does cooperative membership improve household welfare? Evidence from apple farmers in China. *Food Policy*, 58, 94-102.

- McMichael, A. J., Woodruff, R. E., & Hales, S. (2006). Climate change and human health: present and future risks. *The Lancet*, 367(9513), 859-869.
- Misra, A. K. (2014). Climate change and challenges of water and food security. *International Journal of Sustainable Built Environment*, 3(1), 153-165.
- National Climate Change Policy. (2011). National Climate Change Policy, Ministry of Environment, Government of Pakistan.
- Nelson, G. C., Mensbrugghe, D., Ahammad, H., Blanc, E., Calvin, K., Hasegawa, T., ... & Lampe, M. (2014). Agriculture and climate change in global scenarios: why don't the models agree. *Agricultural Economics*, 45(1), 85-101.
- Nelson, G. C., Rosegrant, M. W., Palazzo, A., Gray, I., Ingersoll, C., Robertson, R., Tokgoz, S., Zhu, T., Sulser, T. B., Ringler, C., Msangi, S. and Liangzhi You, L. (2010). Food security, farming, and climate change to 2050: Scenarios, results, policy options (Vol. 172). Intl Food Policy Res Inst.
- PARC. (2013). Wheat in Pakistan. Wheat Plant Sciences Division Pakistan Agricultural Research Council Islamabad, Pakistan. A status paper.
- Parry, M. L., Rosenzweig, C., Iglesias, A., Livermore, M., & Fischer, G. (2004). Effects of climate change on global food production under SRES emissions and socio-economic scenarios. *Global Environmental Change*, 14(1), 53-67.
- Patz, J. A., & Kovats, R. S. (2002). Hotspots in climate change and human health. *British Medical Journal*, 325(7372), 1094.
- Patz, J. A., Campbell-Lendrum, D., Holloway, T., & Foley, J. A. (2005). Impact of regional climate change on human health. *Nature*, 438(7066), 310-317.
- Planning Commission of Pakistan. (2010). Final Report of the Task Force on Climate Change. Planning Commission of Pakistan, Government of Pakistan.

- Ray, D.K., Gerber, J.S., MacDonald, G.K., West, P.C. (2015). Climate variation explains a third of global crop yield variability. *Nat. Commun.* 6, 5989.
- Schwartz, P., & Randall, D. (2003). An abrupt climate change scenario and its implications for United States national security. California Institute of Technology Pasadena Ca Jet Propulsion Lab.
- SDPI. (2009). Food insecurity in Pakistan. Sustainable Development Policy Institute, Islamabad. Retrieved on 17 Oct 2016. Available at.
- Shakoor, U., Saboor, A., Ali, I., Mohsin, A. Q. (2011). Impact of Climate Change on Agriculture: Evidence from Arid Region. *Pak. J. Agri. Sci.* 48(4), 327-333
- Shannon, H. D., & Motha, R. P. (2015). Managing weather and climate risks to agriculture in North America, Central America and the Caribbean. *Weather and Climate Extremes*, 10, 50-56.
- Sharma, P., & Dobriyal, P. (2014). Climate Change and Agricultural Sector in Uttarakhand. *Journal of Studies in Dynamics and Change*, 1(1), 6-14.
- Soglo, Y.Y., Nonvide, G.M.A. (2019). Climate change perceptions and responsive strategies in Benin: the case of maize farmers. *Climatic Change* 155, 245–256.
- Tessema, Y., Asafu-Adjaye, J., Rodriguez, D., Mallawaarachchi, T., & Shiferaw, B. (2015). A bio-economic analysis of the benefits of conservation agriculture: The case of smallholder farmers in Adami Tulu district, Ethiopia. *Ecological Economics*, 120, 164-174.
- Tubiello, F., Schmidhuber, J., Howden, M., Neofotis, P. G., Park, S., Fernandes, E., & Thapa, D. (2008). Climate change response strategies for agriculture: challenges and opportunities for the 21st century. *Agriculture and rural development discussion paper*, 42.
- UNICEF. (2014). United Nations Children Fund. Pakistan Annual report 2013.

- Vogel, C., & Smith, J. (2002). The politics of scarcity: conceptualising the current food security crisis in southern Africa: commentary. *South African journal of science*, 98(7), 315-317.
- World Bank. (2008). World Development Report 2008. Agriculture for Development. World Bank Washington D.C.
- World Bank. (2010). Economics of adaptation to climate change - Synthesis report (English). Washington, DC: World Bank.
- World Bank. (2013). World Development Report, 2013. Development and Climate Change. World Bank Washington, D.C.
- World Bank. (2016). World indicator data. World Bank Washington D.C.
- World Economic Forum. (2013). The Global Risks report 2013, World Economic Forum, New York, USA.
- Zhu, T., Ringler, C., Iqbal, M. M., Sulser, T. B., and Goheer, M. A. (2013). Climate change impacts and adaptation options for water and food in Pakistan: scenario analysis using an integrated global water and food projections model. *Water International* 38(5), 651-669.

Chapter 2

Adaptation to Extreme Weather Conditions and Farm Performance in Rural Pakistan

Muhammad Faisal Shahzad and Awudu Abdulai

Department of Food Economics and Consumption Studies

Published in *Agricultural Systems* (Volume 180, 2020).

Abstract

Extreme weather conditions resulting from climate change pose a formidable challenge to many farmers worldwide. In this article, we analyze farmers' adaptation to extreme weather conditions using climate-smart farm practices (CSA practices), and the impact of adoption of these adaptation strategies on farm performance, using recent farm-level data from three agro-ecological zones of Pakistan. Most of the earlier studies on Pakistan used methods that did not account for unobserved characteristics such as innate skills and risk preferences, resulting in inconsistent estimates. We employ an endogenous switching regression model to account for potential endogeneity and selection bias arising from observable and unobservable factors. The empirical results show that adoption of CSA practices contributes to higher farm net returns. The findings further reveal that adoption of these practices significantly reduces volatility of farm net returns and farmers' exposure to downside risk. We also find that access to extension services and education of the household head positively influence the likelihood of adapting CSA practices in response to extreme weather conditions.

Keywords

Extreme weather conditions, climate-smart practices, impact assessment, farm performance, Pakistan.

2.1. Introduction

Adoption of climate-smart farm practices (CSA practices) that can mitigate extreme weather conditions in the face of climate change can improve farm performance and household welfare in developing countries, particularly through adopting new technologies against climate change. Many previous studies have highlighted the significant effects of climate change on profits, farm income, and farm productivity (e.g., Deschenes and Greenstone, 2007; Nhemachena et al., 2014; Huang et al., 2015). However, very few studies have investigated how adaptation to extreme weather conditions influence risk exposure of climate susceptible farmers and household welfare (e.g., Bouwer, 2019; Vasileiadou et al., 2014; IPCC, 2012). Some studies have shown that climate change adversely affects agriculture in Pakistan, while adaptation to climate change has had a shielding effect (Abid et al., 2016a; Ali and Erenstein, 2017). The adaptation strategies, generally referred to as climate-smart farm practices (CSA practices), commonly used by farmers in developing countries include changing input mix, change in cropping calendar, crop diversification, crop rotation, diversifying seed varieties, soil and water conservation, using improved seed variety, improving irrigation efficiency, and income diversification (Tubiello et al., 2008; Abdulai, 2018).

Extreme weather conditions such as extreme temperature, erratic rainfall, and climate-related shocks (floods, pest infestation, plant diseases, dust cyclones, drought, and weeds) have significantly affected agricultural systems of Pakistan (Economic Survey of Pakistan, 2016; Abid et al., 2016a). The average global temperature has risen by about 0.6-0.8 °C during the last decade and is likely to continue increasing at a rapid rate (World Bank, 2013). The rainfall in Pakistan has become extremely erratic and heavier for short periods (Khan, 2015), and in some months farmers face water shortages and sometimes drought. These variations in climate induce risks in farming activities, trigger ruin effects for geographic locations, instigate floods and water scarcity, which adversely affect agricultural activities (Shannon and Motha, 2015). Moreover, crop yields

appear to be declining with these extremes weather conditions (Bocchiola et al., 2019). These variations also have significant effects on water resources, food supply, farmers' welfare, and the global economy (FAO, 2011; IPCC, 2012). The predictions regarding climate change have revealed that local climate vulnerability remains persistent (Planning Commission of Pakistan, 2010).

Although socioeconomic characteristics and agronomic inputs play a role in enhancing crop yields, the importance of temperature and rainfall cannot be ignored, as these climatic factors cause one-third variability in crop yields (Ray et al., 2015). Climate extremes tend to have adverse impacts on crop yields, with the variance of crop yields ranging between 18-43 percent, depending on crop type (Vogel et al., 2019). Given these facts, there is a need for economic analysis of farm performance in the presence of extreme weather conditions that can undermine agricultural production, reduce farm net returns, and eventually affect rural household welfare in Pakistan.

Pakistan is the seventh most climate change-affected country worldwide (Kreft et al., 2017). Adverse climatic conditions cost the country about 365 billion Pakistani rupees (PKR) a year in terms of inadequate water supply, pollution, soil degradation, and deforestation (Economic Survey of Pakistan, 2014). Extreme weather-related risks also have an impact on soil degradation, waterlogging, soil moisture interaction, soil nutrients, and humidity (Anache et al., 2018; Nearing et al., 2004). Thus, managing agricultural farms through adaptation to extreme weather conditions is an inevitable choice for farmers facing risk exposure. In developing countries like Pakistan, small losses in agricultural production result in greater loss of income, because agriculture accounts for a greater share of gross domestic product (GDP). Deterioration in agricultural productivity is causing persistent poverty in farming communities and food insecurity as a whole (Ali and Erenstein, 2017), while climate risk management can play a significant role in reducing rural poverty (Hansen et al., 2019). However, the economic analysis of risk exposure caused by extreme weather events that affect the welfare of farmers in the country has been overlooked.

Available empirical evidence using farm-level data shows that the adoption of adaptation strategies in response to climate change contributes to higher farm productivity and income (Iqbal et al., 2015; Abid et al., 2016b; Arslan et al., 2015). For example, Abid et al., (2016b) found that adaptation to climate change has a significant and positive impact on wheat crop yield and net crop income, while a study by Iqbal et al. (2015) found that adaptation strategies positively impact on wheat crop net revenues. Another study by Ali and Erenstein (2017) concluded that farmers who adopted strategies in response to climate change are more food secure and face lower levels of poverty. Taking into account the importance of adaptation to extreme weather conditions in terms of productivity and farm net revenues that enhance the farm household welfare, evaluating the impact of adaptation to extreme weather conditions on farming outcomes such as farm net returns, and risk measures of farm net returns can offer valuable information on household agricultural performance, which can be used for agricultural policy design.

Many of the studies on adaptation to extreme weather conditions focused on highlighting farmers' experiences with changing climatic conditions, as well as adaptation strategies and the drivers and constraints to adoption (e.g., Vasileiadou et al., 2014; Boero et al., 2015; Lesk et al., 2016; Nagy et al., 2018). Although comparing differences in productivity and welfare measures between adopters and non-adopters may reveal some insights, these simple comparisons of mean differences do not account for confounding factors such as observed household and farm characteristics (e.g., farm size, education, and asset ownership) and unobserved characteristics such as risk perception and innate skills. Recent studies (Abid et al., 2016b; Ali and Erenstein, 2017) that use econometric methods such as propensity score matching approach also fail to account for unobserved factors. These unobservable attributes of farmers may affect the choice of adoption as well as farm net revenues. For example, if a farmer who has better innate skills adopts, then self-selection can affect the estimates of farm outcomes. To the extent that farmers' adoption decisions are based on both observed and unobserved characteristics, failure to account for these

factors result in inconsistent results (Ma and Abdulai, 2016a). We address these issues by employing the endogenous switching regression (hereinafter ESR) model that accounts for observed and unobserved heterogeneity by estimating selection and outcome equations simultaneously. Moreover, while most studies have focused on single crops, the present study takes into account the multi-cropping nature of farmers' production strategies, and as such, analyzes the drivers of adoption of adaptation strategies, as well as the impact of adoption on household welfare. Specifically, we examine the determinants of adoption of CSA practices and the impact of adoption on climate-induced risks and farm net returns.

The study utilizes data from a recent survey of 540 farmers in the Punjab province of Pakistan. In this region, climate change varies across different ecological zones, whereby extreme weather events are changing the agricultural system in Pakistan. Farmers face extreme temperature shocks, rainfall extremes (floods and droughts), surface water shortage, crop diseases, pest attack, human and animal diseases, hailing, dust cyclones, and weeds. The aforementioned climate-related risks cause volatility in farm net returns, increase exposure to risk, and result in crop failure. Despite many constraints, farmers in Pakistan have been using adaptation strategies like changing input mix, changing cropping calendars, variety diversification, soil and water conservation, improved seed varieties, crop rotation, crop diversification, off-farm income, and migration to enable them cope with climate change and variability (Iqbal et al., 2015; Abid et al., 2016a). A rigorous analysis of the drivers of these adaptation strategies and the impact of adoption on productivity and farm net returns will aid policymakers in designing relevant adaptation strategies.

The rest of the paper is structured as follows. The next section describes the materials and methods used in the empirical analysis. The third section presents the results obtained from the empirical analysis. The fourth section highlights the discussion on the empirical results, while the fifth section contains summary, conclusion and policy implications.

2.2. Materials and methods

2.2.1. Modeling adaptation to extreme weather conditions

Consider a risk-averse farm household i utilizing conventional farm inputs $W_c = (W_1, W_2, \dots, W_k)$ and adoption strategies $W_a = (W_1, W_2, \dots, W_m)$ where $W = (W_c, W_a)$ to produce N multiple outputs $Q_n = (Q_1, Q_2, \dots, Q_N)$. If we denote the conventional input prices as $C_c = (C_1, C_2, \dots, C_k)$, adaptation costs as $C_a = (C_1, C_2, \dots, C_m)$ and output prices as $P_n = (P_1, P_2, \dots, P_N)$ and also assume that adaptation costs, input, and output prices are non-random and known to the farmers when production decisions are made. The farmer uses production technology described by concave, twice differentiable, and continuous production function $Q = f(W_c, W_a, e)$, where e is a vector of stochastic factors, whose distribution is exogenous to the farmer's activities. We treat this vector of stochastic factors as a random variable, which captures production risks under imperfect predictability of output quantities due to factors beyond farmer's control (e.g., extreme temperatures, extreme rainfall, and climate-related shocks such as floods, droughts, and pest infestation). For simplicity, e represents climate risks to the farm household. Given these conditions, we assume that farmer maximizes the expected utility of farm net returns $E[U(\pi_i)]$ from agricultural production under risk aversion by the following expression:

$$Max E[U(\pi_i)] = Max E \left\{ U \left[\left(\sum_{n=1}^N P_n Q_n(W_c, W_a, e) \right) - C_c W_c - C_a W_a \right] \right\} \quad (2.1)$$

where $U(\cdot)$ is the von Neumann-Morgenstern utility function, and $\frac{\partial U(\cdot)}{\partial \pi_i} > 0$ and $\frac{\partial^2 U(\cdot)}{\partial^2 \pi_i} < 0$, E is the expectation operator, π_i denotes the total farm net returns of the i th farmer from multiple crop production. Summation of the monetary values of different crops minus inputs and adaptation costs indicate that our analysis is based on farm net returns from multiple crop production. Let W_a^1 and W_a^0 denote the optimal adaptation strategies under adaptation and non-adaptation,

respectively. A risk-averse farm net returns maximizing farmer will adapt to extreme weather conditions if the expected utility of farm net returns with adoption $E[U(\pi_i^1)]$ is greater than the expected utility of farm net returns without adoption $E[U(\pi_i^0)]$, i.e., $E[U(\pi_i^1)] - E[U(\pi_i^0)] > 0$.

Assuming a strictly interior solution, the first-order condition from Eq. (2.1) for adaptation strategies under production uncertainty can be specified as:

$$W_a^1 = E[\partial U(\pi_i^1)/\partial \pi_i^1 | W] = E\left[(\partial U(\pi_i^1)/\partial \pi_i^1) \cdot \frac{P(\partial Q_n^1(\cdot)/\partial c_a^1)}{\partial c_a^1}\right] \quad (2.2a)$$

Eq. (2.2a) can be rearranged to obtain the following specification:

$$\frac{W_a^1}{P} = E\left[\frac{(\partial Q_n^1(W_c, W_a, e)/\partial c_a^1)}{\partial c_a^1}\right] + \frac{cov[\partial U(\pi_i^1)/\partial \pi_i^1; \partial Q_n^1(\cdot)/\partial c_a^1]}{E[\partial U(\pi_i^1)/\partial \pi_i^1]} \quad (2.2b)$$

The term with the covariance in Eq. (2.2b), which is associated with production uncertainty, is the risk premium associated with the farmer's decision problem. Then for a risk-neutral farmer, the covariance term on the right side becomes zero and the ratio $\frac{W_a^1}{P}$ equals the expected marginal product of modern strategies used for adaptation to extreme weather conditions. On the other hand, for a risk-averse farmer, this term becomes different from zero and captures deviations from the neutrality case (Groom et al., 2008; Mukasa, 2018). As risk preferences generally affect farmer's behavior and welfare and risk-averse farmers have an incentive to reduce risk exposure (Di Flaco and Veronsi, 2014). The Arrow-Pratt risk aversion coefficient, which is defined as $R_a^1 = -\left(\frac{\partial^2 U(\pi_i^1)/\partial^2 \pi_i^1}{\partial U(\pi_i^1)/\partial \pi_i^1}\right)$, is normally used to examine risk aversion. Thus, when $\partial U(\pi_i^1)/\partial \pi_i^1 > 0$, risk aversion implies a positive risk premium, with $\partial^2 U(\pi_i^1)/\partial^2 \pi_i^1 < 0$, and $R_a^1 > 0$. While the foregoing discussion includes mean and variance of production, it ignores aversion to downside risk. This can be incorporated by considering $\frac{\partial R_a^1}{\partial \pi_i^1} = -\left(\frac{\partial^3 U(\pi_i^1)/\partial^3 \pi_i^1}{\partial U(\pi_i^1)/\partial \pi_i^1}\right) + (R_a^1)^2$, where R_a^1 denote Arrow-Pratt measure of absolute risk aversion, decreasing absolute risk aversion implies

$\partial^3 U(\pi_i^1)/\partial^3 \pi_i^1 > 0$, which indicates aversion to unfavorable downside risk. Farmers exhibiting downside risk aversion will generally adopt strategies that reduce exposure to such risks.

2.2.2. Selection into adaptation to extreme weather conditions

To derive an adoption specification from the model in the previous section, let y_i^* be the difference between expected utility of farm net returns from adoption $E[U(\pi_i^1)]$ and non-adoption $E[U(\pi_i^0)]$, then farmer i will choose to adapt to extreme weather conditions, if $y_i^* > 0$. To the extent that y_i^* cannot be directly observed, since it is a latent variable, we express it as a function of observable elements in the following latent variable model:

$$y_i^* = Z_i \beta_i + \eta_i, \quad y_i = 1, \quad \text{if } y_i^* > 0 \quad (\text{selection equation}) \quad (2.3)$$

where y_i is a binary indicator variable representing household i , and is equal to 1, if a farmer is an adopter, and zero otherwise. Z_i is a vector of explanatory variables, which include extreme weather conditions (temperature anomaly, rain anomaly, and climate-related shocks), climate-related variables (average temperature, average rainfall), farmers' personal characteristics (age, education, family size), farm characteristics (farm size, soil types), regional variables such as agro-climatic zones (cotton zone, rice zone, mix cropping zone), assets (animals and farm machinery), institutional and financial variables (access to extension services and credit constraint), access to climate change information and perception of extreme weather conditions. β_i is a vector of parameters to be estimated, and η_i is the error term assumed to be normally distributed with zero mean and constant variance.

2.2.3. Impact assessment of adaptation to extreme weather conditions

In line with previous studies, we use the moment-based approach to compute indicators of risk exposure (Antle, 1983; Di Flaco and Veronsi, 2014). According to Antle (1983), maximization of the expected utility of farm net returns $E[U(\pi_i)]$ is equal to the maximization of the relevant moments of the risk exposure (e) distribution, conditional on input use. To proceed with the

estimation process, we estimate the residuals from farm net returns function to compute the simple moments (variance, skewness, and kurtosis) for each farmer as risk measures of farm net returns.¹ To the extent that farm net returns can be considered as income that is used to support current consumption expenditures of farm households, we use farm net returns and the risk measures (variance, skewness, and kurtosis) of this outcome variable as an indicator of farmers' welfare in the empirical analysis. The variance is the second moment of the farm net returns function and measures the dispersion of farm net returns from mean values. We use this variable to measure the volatility of farm net returns. The greater the dispersion from mean values, the higher the risk faced by farmers and vice versa. To the extent variance captures upside and downside risks, we extend our analysis to skewness, which is the third moment of farm net returns function and denotes the downside risk exposure – the risk of the actual farm net returns being below the expected farm net returns, or the uncertainty about the magnitude of that difference (McNeil et al., 2015). Since farmers are risk-averse and elude extreme weather conditions, we also include the fourth moment of farm net returns function in our analysis, i.e., kurtosis—the measure of extreme infrequent (extremely low and extremely high) deviations in farm net returns. These infrequent extreme deviations increase the chances of getting extremely low or extremely high farm net returns, and as such, increase farm households' exposure to risk.

In order to examine the impact of adoption of CSA practices or adaptation to extreme weather conditions on farm net returns and risk measures of this outcome variable, we assume that the vectors of these outcome variables are a linear function of explanatory variables. This linear relationship can be specified as follows:

$$V_i = X_i\alpha + y_i\psi + \varepsilon_i \tag{2.4}$$

¹ We use natural logarithm of farm net returns as a dependent variable in specifying the farm net returns function from which we obtain the residuals to compute the variance, skewness and kurtosis. In the interest of brevity, the procedure of moment based approach and estimation of farm net returns function is given in Appendix. (See Moments of farm net returns and Table 2.A1).

where V_i is the vector of outcome variables (farm net returns, volatility, downside risk exposure, and kurtosis), and X_i is the vector of explanatory variables such as age, education, family size, farm characteristics (e.g., farm size, location of the farm, farm machinery), soil types (clay loam, loam, and sandy loam) and institutional and financial variables (e.g., access to extension services and credit). As in Eq. (2.3), y_i is a dummy variable capturing the adoption of CSA practices, α and ψ are parameters to be estimated, while ε_i represents the error term.

2.2.4. Estimation and identification

Given that we use survey data and selection into adaptation is not random, we need to employ an approach that accounts for selection bias. We employ an endogenous switching regression (ESR) model to account for selection bias (Lokshin and Sajaia, 2004; Abdulai and Huffman, 2014). The model is based on two stages: in the first stage, the decision to adopt is considered as specified in the selection equation (Eq. 2.3); and in the second stage, two equations for adopters and non-adopters are specified as outcome equations as follows:

$$\text{Adopters: } V_i^1 = X_i \alpha_i^1 + \mu_i^1 \quad (2.5a)$$

$$\text{Non-adopters: } V_i^0 = X_i \alpha_i^0 + \mu_i^0 \quad (2.5b)$$

where V_i^1 and V_i^0 are the outcomes (such as volatility, downside risk exposure, kurtosis, and farm net returns) for adopters and non-adopters, respectively. X_i is a vector of explanatory variable assumed to influence the outcomes, α_i^1 and α_i^0 are the parameters to be estimated, and μ_i is the random error term associated with the outcome variables.

In the estimation, Z_i from the selection equation and X_i from the outcome equations are allowed to overlap. However, for proper model identification at least one variable in Z_i should not appear in X_i . In the present study, we used climate change information and perception about extreme

weather conditions variables as instruments to identify the model. These instrumental variables are expected to influence adoption only, but not the outcome variables².

The ESR model accounts for selection bias arising from unobservable factors as omitted variable problem. To account for selection bias, the inverse Mills ratio λ_i and covariance term $\sigma_i^1 = cov(\eta_i, \mu_i^1)$ and $\sigma_i^0 = cov(\eta_i, \mu_i^0)$ are incorporated in the above-given equations 2.5a and 5b, respectively.

$$V_i^1 = X_i\alpha_i^1 + \sigma_i^1\lambda_i + \xi_i^1 \quad \text{if } y_i = 1 \quad (2.6a)$$

$$V_i^0 = X_i\alpha_i^0 + \sigma_i^0\lambda_i + \xi_i^0 \quad \text{if } y_i = 0 \quad (2.6b)$$

where ξ_i^1 and ξ_i^0 are the error terms with conditional zero mean. We use the full information maximum likelihood (FIML) method introduced by Lokshin and Sajaia (2004) to estimate the selection and outcome equations simultaneously.

After running the ESR model, we obtain correlation coefficients ρ_μ^1 and ρ_μ^0 of the covariance between selection and outcome equations. If the value of ρ_μ^1 or ρ_μ^0 is significant, it means that selection bias is present in the data due to unobservable factors. Selection bias is positive if $\rho_\mu < 0$, and negative if $\rho_\mu > 0$. If the values of ρ_μ^1 and ρ_μ^0 have alternate signs, it means that the decision to adopt is based on comparative advantage. However, if the signs are the same, it implies “hierarchical sorting,” i.e., adopters obtain above-average outcomes, compared to the non-adopters, independent of the adaptation decision.

² To test the validity of the instrumental variables, we run a probit model of the selection equation and simple OLS regression for the outcome equations of non-adopters. In the selection equation, these variables are significant, but insignificant in the outcome equations. A further test of correlation confirms that all the instruments used in the analysis are uncorrelated with outcome variables. See Appendix for the results (Tables 2.A3, 2.A4 and 2.A5).

Average treatment effects on the treated

The estimates from the ESR model can be used to compute the Average Treatment Effects on the Treated (ATT).

From equations 2.6a and 2.6b, the ATT can be specified as:

$$\begin{aligned} \text{ATT} &= [X_i\alpha_i^1 + \sigma_i^1\lambda_i] - [X_i\alpha_i^0 + \sigma_i^0\lambda_i] \\ &= X_i(\alpha_i^1 - \alpha_i^0) + \lambda_i(\sigma_i^1 - \sigma_i^0) \end{aligned} \quad (2.7)$$

In the selection equation, the variables (extension contact and credit constraint) could be potentially endogenous because extension officers may provide information related to extreme weather conditions and encourage them to adopt particular CSA practices for better farm production, which makes extension services potentially endogenous. When farmers adapt to extreme weather conditions, they tend to increase their farm productivity (as well as income). With higher incomes, farmers may be less liquidity constrained and may have the ability to offer collateral to get credit, thus making credit constraints potentially endogenous. As both of these variables are dichotomous in nature, this study applies the control function approach suggested by Wooldridge (2015) to account for potential endogeneity arising from these variables. In order to apply this approach, we specified the endogenous variables (extension contact and credit constraint) as functions of all other variables used in the selection equation in addition to instrumental variables in the first-stage estimation, such as:

$$G_i = Z_i\beta_i + I_i\theta + \zeta_i \quad (2.8)$$

where G_i is the vector of potential endogenous variable, I_i is the vector of instrumental variables and ζ_i is the random error. To identify this simple model, we used distance to the extension office as an instrumental variable that affects access to extension services but has no direct influence on adaptation to extreme weather conditions. For the credit constraint, we used personal relations (family relative or friend working) in credit institution as an instrumental variable. It is also worth

noting here that the instrumental variable should not correlate with other instrumental variables used for the ESR model identification. We incorporated both the observed values of the potential endogenous variables and estimated residuals in the selection equation to account for endogeneity as follows³:

$$y_i^* = Z_i\beta_i + G_i\varphi + R_i\phi + v_i \quad (2.9)$$

where R_i is the vector of residuals calculated from Eq. (2.8) for the endogenous variables. These residuals serve as a control function in the second-stage estimation and endogenous variables are consistently estimated. This approach leads to a robust, regression based Hausman test for the exogeneity of the potentially endogenous variables (Wooldridge, 2015).

2.2.5. The empirical specification

The conceptual framework used in this study is based on farmers' decisions to adopt CSA practices that help them to cope with extreme weather conditions to reduce risks of crop failure and increase farm net returns. The primary data we collected show that farmers in Pakistan adopt CSA practices, such as changing cropping calendar, diversifying seed varieties, changing input mix to minimize the impact of extreme weather conditions at their farms. Taking into account the adoption and non-adoption decisions of farmers as a binary variable, farmers who practice one or more CSA practices are classified as adopters, while those who do not practice any of the adaptation strategies are referred to as non-adopters. As farmers self-select themselves into adoption of CSA practices, depending on the expected farm net benefits, and given that the adaptation process is non-random, it is obvious that the results may be biased without accounting for selection bias. Thus, we use the ESR model to account for selection bias. We follow the idea given in theoretical Model of Private Proactive Adaptation to Climate Change (MPPACC) and

³ In the interest of brevity, first stage estimation of residuals and correlation matrix of instrumental variables is given in the Appendix. (See Table 2.A2 and Table 2.A5)

other economic models for the selection of ESR model variables (see Grothmann and Patt, 2005; Mitter et al., 2019; Abdulai and Huffman, 2014; Ma and Abdulai, 2016b).

The estimated coefficients from the ESR model may be interpreted in terms of the relationship between the explanatory variables and the conditional probability of adoption. Specifically, the vector Z_i from Eq. (2.9) contains variables that accelerate or retard adoption decision on CSA practices. The main candidates of variables from vector Z_i are average temperature, average rainfall, extreme temperature, extreme rainfall, previous climate-related shocks, access to extension services, education and age of household head, liquidity constraints, and location fixed effects. Temperature and rainfall are quite crucial for plant growth and agriculture as a whole. The average temperature over the past decades is expected to influence the adoption decision positively and may have a negative impact on farm outcomes. As rainfall is erratic in the region, it may have differential impacts on adoption and farm outcomes. Average temperature and rainfall are the mean values that can undermine the extreme changes in temperature and rainfall. So, the inclusion of temperature and rainfall anomalies is quite crucial. Increasing fluctuations in temperature from its mean drive the farmers to adopt CSA practices, while positive fluctuations in rainfall may negatively affect the adoption decision. This is due to the fact that higher rainfalls may lower the temperature intensity. Previous climate-related shocks like floods, droughts and climate-related pest infestation and diseases may also have a positive influence on the adoption decision. Farmers who have experienced climate-related shocks like floods and droughts may be more inclined to implement preventive measures to reduce the adverse impacts of future floods and droughts. To mitigate the effects of pest infestation and diseases, farmers change the input mix including pesticides, or change in cropping calendars. The key variables that represent climate change and extreme weather conditions considered in this model are average temperature, average rainfall, extreme temperature, extreme rainfall, and previous climate-related shocks.

Agricultural extension is a major source of information on climate change and technological progress in developing countries like Pakistan. The diffusion of new technology and existing CSA practices may, therefore, be influenced by farmers' access to extension services. It is, therefore, hypothesized that farmers who have more frequent contacts with extension agents could make innovative decisions and are more likely to adopt CSA practices. Education is another prime candidate among variables that influence the adoption decision. Following the human capital theory, allocative skills are assumed to be acquired or learned, rather than inborn and tied to formal education. This helps farmers in adopting new technologies and innovations in agriculture. With higher education, farmers can better understand the mechanism and implementation of new agricultural technologies on their farms. Furthermore, farmers can make evaluative comparisons of the productive characteristics and cost of adopting innovations that enable them to distinguish more easily those advancements whose adoption provides an opportunity for farm net return gains from those that do not (Huffman, 2001). The age of farm household head is an important variable that represents the experience of farmers. Older heads of farm households may have more experience (Bekele and Drake, 2003), and they also have perceived past weather extremes from which they can make a profitable change in the adoption of CSA practices. However, if CSA practices requires significant investment costs, then farmers may be severely credit constrained (Abdulai and Huffman, 2005).

Uncertainty in agriculture and asymmetric information among lenders and borrowers can also create imperfections in the credit markets, including credit constraints that may affect adoption behavior. Farmers are classified as credit constrained if they asked for credit, but did not obtain it, or if they obtained credit, but it was not sufficient for purchases of farm inputs. Those who did not ask for credit or received sufficient credit are not credit constrained (Kleemann et al., 2014). The location of the farm is also an important variable influencing adoption decision. Agro-ecological zones are heterogeneous and have different climatic conditions.

Other attributes of farm households including family size, farm size, farm machinery, animals at the farm, soil type may also affect adoption rates. In agriculture, most of the labor comes from family labor, so the inclusion of family size is quite crucial in capturing labor availability. In addition, size or scale variable, as measured by the landholdings, has been frequently used and shown to be significant in adoption studies (for example, see Ma and Abdulai, 2016a; Rahm and Huffman, 1984; Ma and Abdulai, 2016b; Ali and Erenstein, 2017). Ownership of animals or herd size is another variable that may affect the adoption decision. Also, farmyard manure obtained from animals is typically used in soil conservation to improve the organic matter in the soil, and consequently increase the water holding capacity of the soil (Bettencourt et al., 2015). Soil type is also a key factor in analyzing the adoption of CSA practices. Less fertile soils may be more prone to extreme weather conditions, and as such, may require adaptation strategies.

The variables that directly affect the adoption decisions are climate change information and perception about extreme weather conditions. The adopters are well informed about climate change and weather extremes in Pakistan. Their preferred information sources are agricultural extension, print media, past weather records, and personal exchange with neighboring farmers. The adopters of extreme weather conditions reported a variety of perceived changes in regional climate change and attributed their perceptions to that change. They already experienced negative impacts and expect that these impacts would affect their agricultural activities in the future as well. We used the variables climate change information and perception about extreme weather conditions to identify our model by excluding these variables in the second stage estimation.

2.2.6. Study area

We selected Punjab province from Pakistan as it is the main agricultural region, with 56 percent share in the total cultivated area; the province also accounts for 74 percent of total cereal production in Pakistan (Abid et al., 2014). The study is carried out in the region because of its significance to agricultural output and contribution to the national GDP. Increasing the occurrence

of extreme weather conditions, including extreme temperatures, erratic rainfall, and climate-related shocks, are becoming major threats to the crops in the region (Economic Survey of Pakistan, 2018). Major crops in the province are prone to extreme weather conditions and declining yields (Gill, 2016). Wheat is the staple food crop, accounting for 56 percent of the calorie needs of the province, which is prone to climate-related extreme events (Siddiqui et al., 2012). In the future, temperature hikes, and changes in the precipitation, –which lead to water availability will be critical factors for wheat production (Janjua et al., 2010). Estimates show that around 60 percent of the yield gap in wheat is due to the adverse effects of climate change and input constraints. In particular, climate change has resulted delay in harvesting of previous season crops, and unavailability of timely inputs tend to reduce wheat output (PARC, 2013). Maize yield has a negative relationship with temperature, whereby higher temperatures tend to reduce yields (Khaliq, 2008), while cotton crops are prone to floods and heavy erratic rainfalls in the region (Iqbal et al., 2016).

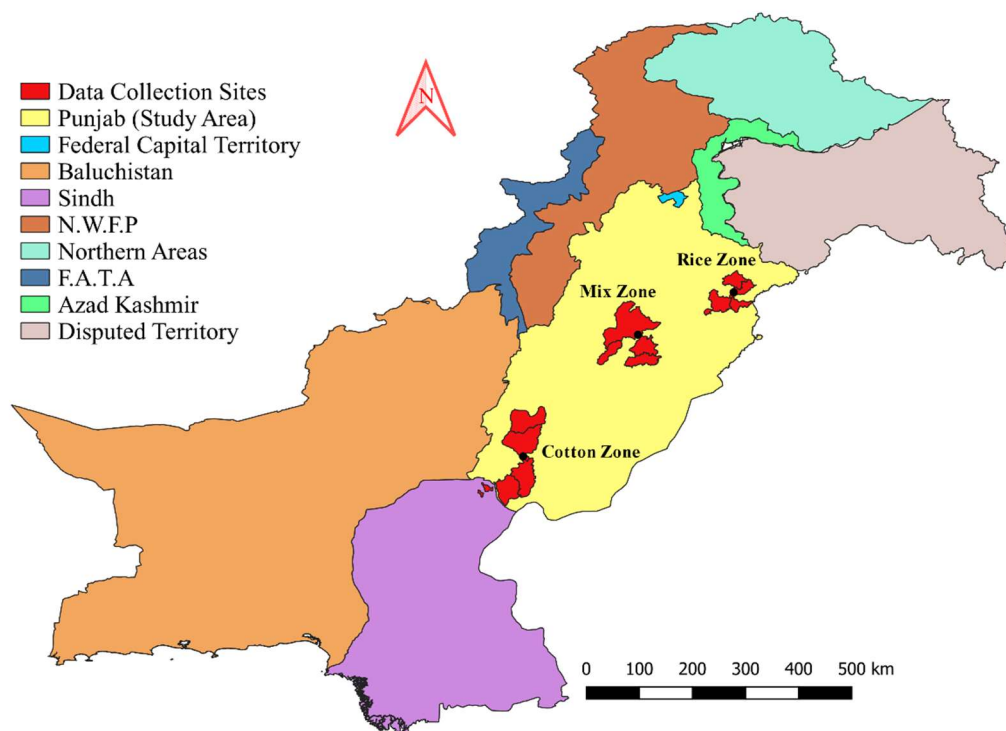


Fig. 2.1 Map of Pakistan showing study area and agro-ecological zones

The study area and data collection sites are shown in Fig. 2.1. There are three important cropping zones in Punjab, namely wheat rice-zone, central-mix zone, and wheat-cotton zone (PARC, 2015), for simplicity, these zones are described as rice zone, mix zone, and cotton zone respectively. The rice zone is known for rice production. In the central mix cropping zone, multiple crops are grown, while the cotton zone is eminent in cotton production (PARC, 2018). Farming characteristics and agronomic practices, including input use, may also vary depending on crop cultivation. The inclusion of these three important crop zones implies that our analysis is based on multiple crops grown under heterogeneous climatic conditions.

2.2.7. Data collection and data description

The cross-sectional data used in this study come from a survey conducted during January to March 2017 in Pakistan by the authors. The farm household sampling frame was developed to ensure representation for the study region. For the data collection, we considered the cropping pattern, agricultural activities, percent of cultivated land area, climate and weather variability within agro-ecological zones. The data were collected from six administrative units of the Punjab province. The selected zones have different climate conditions and cropping patterns. A multi-stage stratified random sampling procedure was used to collect data from farmers. During the first stage, three zones from the Punjab province were selected purposively on a climate and agroecological basis. In the second stage, two districts from each zone were randomly selected. In the third stage, two *Tehsils* were randomly chosen from each district, and then three villages were randomly selected from each *Tehsil*.⁴ In the fifth stage, fifteen farmers were randomly selected from each village. Overall, 540 farmers were interviewed for the data collection. A structured questionnaire was used to collect socio-economic and farm-level information from the respondents, through face

⁴Tehsil is an administrative sub division of a district in Pakistan. It is an area of land within a city that serves as its administrative center, with number of towns and villages.

to face interviews. The authors own this data and reserve the right to use it for empirical analysis.

The collected data include information on farm households, agricultural practices, production and costs, irrigation water use, access to extension, social networking, perceptions of climate change and climate risks, responses to climate change, access to credit, farm and household assets, other income sources, consumption, and expenditure. One section of the questionnaire was mainly designed to capture climate change perceptions and climate risks and understanding of adaptation responses against climate extremes. Questions were included in asking the farmers whether they have noticed long term changes in temperature and precipitation over the last twenty years. Overall, erratic rainfalls and an increase in temperatures are perceived in the study area.

Furthermore, the questions investigated how farmers have responded to long term changes in temperature and rainfall in order to mitigate weather extremes. Change in cropping calendar, diversifying seed varieties, changing input mix, and soil and water conservation are the main adaptation strategies followed by the farmers in the study region. Questions related to climate risks revealed that farmers face climate-induced water shortage, extreme temperatures and rainfall shocks, cyclones, hailing, weeds, pest infestation, plant, and animal diseases in the study area. There exist significant spatial variations between agro-ecological zones in Pakistan, including temperature and rainfall variability, topography, soil type, and soil fertility (FAO, 2004). The agricultural system is traditional, employing both family and hired labor as major inputs in the production process.

Secondary information related to temperature and rainfall was collected from the National Center for Environmental Prediction (NCEP)⁵. The collected information was from 1979 to 2014 on a daily basis, which was converted to monthly and yearly averages. We used the inverse distance

⁵Satellite data is available online from (1979-2014). Details of the data can be found at <https://globalweather.tamu.edu/>. To obtain regional data related to our study sights, we contacted the head office of the Pakistan Meteorological Department in Karachi, although they do not have data for some regions and the available data is only recorded up to a maximum of fourteen years.

method of spatial interpolation to calculate location-specific farm-level temperature and rainfall. For this purpose, we used the global positioning system (GPS) to record the farm location (elevation, longitude, and latitude) during the data collection. The recorded farm locations were employed in interpolation analysis to obtain information on farm-level temperature and rainfall. Subsequently, we calculated the temperature and rainfall anomalies.

2.3. Empirical Results

2.3.1. Descriptive statistics and mean differences between adopters and non-adopters.

Table 2.1 presents the definition and descriptive statistics of the variables used in the empirical analysis. The dependent variable used in the analysis is a dummy variable that takes the value one if the household adopted farm practices in response to extreme weather conditions, and zero otherwise. The outcome variables used in this analysis are the variance, skewness, kurtosis, and household farm net returns per acre. Here, the variance represents the volatility of farm net returns, while skewness and kurtosis represent downside risk exposure. These variables, which are the second, third, and fourth moments of the farm net returns function, respectively, are calculated by using a moment-based approach. Household farm net returns are calculated as the difference between the value of crop yields and their total variable input costs. The inputs used are seeds, hired labor, fertilizers, pesticides, irrigation, and plowing.

Table 2.1 shows that about 48 percent of households are classified as adopters of CSA practices, with the remaining 52 percent as non-adopters. The average daily temperature is about 27 degrees Celsius, while the average daily rainfall is recorded around 1 millimeter over the past 36 years. Mean rainfall anomaly is positive, indicating positive rainfall shocks in the study area, while mean temperature anomaly indicates adverse temperature shocks. The average farm size is 9.40 acres, which shows that the majority of farm households are small farmers. Households, on average, include 6-7 members. On average, 57 percent of farmers were visited by extension agents, and about 24 percent of farmers are classified as credit constrained. On average, farmers earn PKR

67,659 annually from farming activities. Negative mean skewness indicates that farmers face downside risk exposure in the study area.

Table 2.1 Definition and descriptive statistics of selected variables

Variable	Definition	Mean	SD
Adaptation	1 if farmer adapts to climate change, 0 otherwise	0.4852	0.5002
Avg_tem	Average annual temperature in (Degrees Celsius)	26.8782	1.0776
Avg_rain	Average daily rainfall (millimeters)	0.6600	0.5449
Tem_anomaly	Change in temperature relative to baseline ^a (number)	-0.0142	0.0135
Rain_anomaly	Change in rainfall relative to baseline (number)	1.4440	0.9306
HH_age	Household head age (years)	47.009	11.382
Family_size	Number of people residing in household (number)	6.0630	2.1954
Farm size	Total number of acres farm household cultivate (acres ^b)	9.4032	9.1382
Education	Number of schooling years household head completed (years)	6.4314	4.4954
Credit_const	1 if farmer is liquidity constraint, 0 otherwise	0.2352	0.4245
Ext_services	1 if farmer has contact with extension agent, 0 otherwise	0.5722	0.4952
CC_shock	1 if farmer faces climate shock in past three years, 0 otherwise	0.2537	0.4355
Animal	Number of animals at farm (number)	3.4833	1.9295
Machinery	1 if farmer has own farm machinery, 0 otherwise	0.1704	0.3763
Sandy loam	1 if soil at farm is sandy loam, 0 otherwise	0.1352	0.3422
Loam	1 if soil at farm is loam, 0 otherwise	0.7056	0.4562
Clay loam	1 if soil at farm is clay loam, 0 otherwise	0.1611	0.3689
Cotton_zone	1 if farmer resides in cotton zone, 0 otherwise	0.3315	0.4712
Rice_zone	1 if farmer resides in rice zone, 0 otherwise	0.3333	0.4718
Mix_zone	1 if farmer resides in mixed cropping zone, 0 otherwise	0.3352	0.4725
CC-info	1 if farmer has obtained climate change information, 0 otherwise	0.4907	0.5003
CC_perception	1 if farmer perceives extreme weather conditions, 0 otherwise	0.4592	0.4987
Variance	Second central movement of farm net returns function	0.1575	0.0338
Skewness	Third central movement of farm net returns function	-0.0005	0.0161
Kurtosis	Fourth central movement of farm net returns function	0.0014	0.0078
Farm net returns	Annual farm revenue minus variable costs per acre (PKR ^c)	67,659.27	21,564.47
No of observations			540

^aAnomaly= (current year mean -long term mean)/long term mean

^b 1 acre= 0.40 hectare

^c PKR (Pakistani Rupee) is Pakistani currency (1 \$ = 104.67 PKR during the year of data collection).

Table 2.2 Descriptive statistics and mean difference between adopters and non-adopters

Variable	Adapters		Non_adopters		Mean difference
Avg_tem	26.8340	(0.0673)	26.9199	(0.0639)	-0.0859 (0.0928)
Avg_rain	0.6859	(0.0349)	0.6357	(0.0315)	0.0501 (0.0469)
Tem_anomaly	-0.0139	(0.0008)	-0.0144	(0.0008)	0.0005 (0.0012)
Rain_anomaly	1.4374	(0.0576)	1.4501	(0.0558)	0.0127 (0.0802)
HH_age	48.4809	(0.7027)	45.6223	(0.6737)	2.8586*** (0.9728)
Family_size	6.3206	(0.1387)	5.8201	(0.1272)	0.5005*** (0.1883)
Farm Size	12.9714	(0.6651)	6.0405	(0.3278)	6.9309*** (0.6533)
Education	7.1985	(0.2642)	5.7086	(0.2748)	1.4898*** (0.3681)
Ext_services	0.8473	(0.0222)	0.3129	(0.0279)	0.5343*** (0.0361)
Credit_const	0.0954	(0.0182)	0.3669	(0.0290)	-0.2715*** (0.0347)
Animal	4.1946	(0.1343)	2.8130	(0.0817)	1.3817*** (0.1552)
Machinery	0.2405	(0.0265)	0.1043	(0.0184)	0.1361*** (0.0319)
Sandy loam	0.0840	(0.0172)	0.1835	(0.0232)	-0.0995***(0.0292)
Loam	0.7710	(0.0260)	0.6439	(0.0288)	0.1271***(0.0389)
Clay loam	0.1450	(0.0213)	0.1763	(0.0217)	0.0312 (0.0280)
Cotton_zone	0.3092	(0.0286)	0.3525	(0.0287)	-0.0434 (0.0406)
Rice_zone	0.3435	(0.0294)	0.3237	(0.0281)	0.0198 (0.0407)
Mix_zone	0.3473	(0.0295)	0.3237	(0.0281)	0.0236 (0.0407)
CC_shock	0.4618	(0.0309)	0.0576	(0.0139)	0.4042*** (0.0331)
CC-info	0.8625	(0.0213)	0.1403	(0.0209)	0.7223*** (0.0298)
CC_perception	0.8435	(0.0225)	0.0971	(0.0178)	0.7464*** (0.0285)
Variance	0.0151	(0.0019)	0.0156	(0.0026)	-0.0005 (0.0230)
Skewness	0.0007	(0.0008)	-0.0015	(0.0015)	0.0022* (0.0013)
Kurtosis	0.0012	(0.0003)	0.0021	(0.0009)	-0.0009 (0.0009)
Farm net returns	74,711.47	(1249.47)	61,012.96	(1240.93)	13,698.51***(2298.328)

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

Table 2.2 describes the mean differences between adopters and non-adopters of CSA practices. Generally, adopters appear to be more educated and also have larger farm sizes than non-adopters. Adopters have larger numbers of animals, and they have a higher probability of owning agricultural machinery, which represents wealth. Adopters also have stronger links with extension agents, as well as better access to climate change information and a higher probability of

perceiving climate change. Climate-related variables hardly differ between adopters and non-adopters.

In the lower part of Table 2.2, mean differences in variance, skewness, kurtosis, and farm net returns are presented. It can be observed that adopters earn significantly higher farm net returns than non-adopters. However, measures of risk (variance and kurtosis of farm net returns) hardly differ, while skewness significantly differs between adopters and non-adopters. It is significant to note that these are simply mean differences and, as such, do not account for the effect of other factors and characteristics of farmers. Therefore, we modeled adaptation to extreme weather conditions as a selection process, by employing an endogenous switching regression approach to account for selection bias and to capture the differential impacts from adoption and non-adoption. The estimates of the factors that influence farmers' decisions to adapt to extreme weather conditions and the impact of adaptation on the volatility of farm net returns, downside risk exposure, and farm net returns are presented in Tables 2.3-2.6. Selection and outcome equations are jointly estimated by using Full Information Maximum Likelihood (FIML) approach. Selection equations that represent the factors affecting the adaptation decisions are given in the second column of each table. Outcome equations, which represent the impact on the volatility of farm net returns, downside risk exposure, and farm net returns, are given in the third and fourth columns of Tables 2.3-2.6, respectively. The coefficients of two variables representing the residuals derived from the first-stage regression⁶ of the extension contact and credit constraint are also included and stated in the second columns of Tables 2.3-2.6. These residuals are not statistically significant, suggesting that the specifications are consistently estimated (Wooldridge, 2010). An interesting finding in Tables 2.3 and 2.5 are the signs and significance of the covariance terms (ρ_{μ}^1 and ρ_{μ}^0). The results indicate that the covariance terms for the non-adopters in Tables 2.3 and 2.5 are highly

⁶Given that residuals are not focus of our study and in the concern of brevity, the first-stage regression estimations are reported in the appendix (see Table 2.A2).

significant and positive, suggesting that self-selection occurs in adaptation (Lokshin and Sajaia, 2004). Moreover, the positive sign of ρ_{μ}^0 indicates a negative selection bias, suggesting that farmers who face less volatility and kurtosis in their farm net returns are more likely not to adapt to CSA practices. In Tables 2.4 and 2.6, the signs of ρ_{μ}^0 are negative and significant, suggesting a positive selection bias, indicating that farmers with lower-average downside risk exposure and above-average farm net returns are more likely not to adapt to extreme weather conditions.

2.3.2. Determinants of adaptation to extreme weather conditions

All the variables in the selection equations given in the second columns of Tables 2.3-2.6 are the same, whereby the interpretation of the selection equations is almost the same for all tables. Since the coefficients can be interpreted as normal probit coefficients, we will discuss the results given in all the tables together. The coefficient of temperature anomaly is positive (74.670) and statistically significant (at the 5% level), suggesting that farmers facing temperature extremes are more likely to adapt to extreme weather conditions. However, the coefficient of rainfall anomaly is negative (-0.506) and significant (at the 5% level), suggesting that high rainfall negatively affects the adaptation decision.

The coefficient of the variable representing household age is positive (0.017) and statistically significant (at the 10% level), indicating that older farmers are more likely to adopt CSA practices. The coefficient of the education variable is also positive (0.148) and statistically significant (at the 5% level), suggesting that more educated farmers are more likely to adapt to extreme weather conditions, a finding that is consistent with the idea that education helps farmers in their decisions to adapt to new technologies and innovations (Huffman, 2001; Issahaku and Abdulai, 2019).

The coefficient of livestock ownership (number of animals) is positive (0.269) and significant (at the 5% level), indicating that farmers with larger herd sizes are more likely to adopt. These findings are in line with the study conducted in Ethiopia by Deressa et al. (2011). The extension services variable is also positive (1.745) and statistically significant (at the 5% level) in all the

specifications, supporting the notion that farmers with contacts to extension agents are more likely to adopt CSA practices. The coefficient of the previous climate-related shocks is highly significant (at the 1% level) and positive (0.967), indicating that farmers who have faced climate-related shocks (such as floods, droughts, cyclones, and climate-related pest infestation and diseases) in the past are more likely to adopt. The location variable also has a positive and significant effect on adaptation, indicating that farmers living in the cotton cultivation zone are more likely to adapt to extreme weather conditions. The coefficient of the soil quality variable is positive and significant, suggesting that farmers cultivating on sandy loam soils are more likely to adopt CSA practices, compared with farmers who are cultivating on loamy soils. On the other hand, the estimates suggest that average temperature, average rainfall, family size, farm size, credit constraint, and agricultural machinery do not significantly affect adaptation to extreme weather conditions.

2.3.3. Volatility of farm net returns

The third and fourth columns in Table 2.3 present the estimates of the volatility of farm net returns. The coefficient of average rainfall is positive (0.023) and significant (at the 10% level) for non-adopters, indicating that average rainfall tends to increase the volatility of farm net returns for non-adopters. However, the negative sign, albeit statistically insignificant, coefficient of average rainfall (-0.002) for adopters shows that average rainfall reduces the volatility of farm net returns for adopters. The coefficient of the temperature anomaly variable is negative (-0.925) and statistically significant (at the 10% level), indicating that adaptation to extreme temperature variations has reduced the volatility of the farm net returns for adopters.

On the other hand, rainfall anomaly is negative (-0.007) and significant (at the 5% level), implying a reduction in the volatility of farm net returns for non-adopters. The coefficient of farm size variable is positive (0.001) and statistically significant (at the 5% level), suggesting that larger farm size tends to increase the volatility of farm net returns for non-adopters. The finding of an

inverse relationship between farm size and volatility of farm net returns is in line with the findings of Guttormsen and Roll (2014). Previous climate-related shocks (such as floods, droughts, cyclones, and climate-related pest infestation and diseases) have increased the volatility of farm net returns of non-adopters.

Table 2.3 Determinants of adaptation to extreme weather conditions and its impact on the volatility of farm net returns.

Variables	Selection		Variance (volatility)			
			Adopters		Non-adopter	
Constant	2.675	(8.962)	-0.239	(0.181)	-0.169	(1.193)
Avg_Tem	-0.345	(0.346)	0.008	(0.007)	0.006	(0.039)
Avg_Rain	0.022	(0.884)	-0.002	(0.015)	0.023*	(5.474)
Tem_anomaly	74.670**	(34.678)	-0.925*	(0.529)	0.566	(0.044)
Rain_anomaly	-0.506**	(0.214)	0.000	(0.004)	-0.007**	(0.176)
HH_age	0.017*	(0.010)	0.001**	(0.000)	0.000	(0.023)
Family Size	0.096	(0.074)	0.002*	(0.001)	0.001	(0.001)
Farm_Size	0.011	(0.020)	-0.000	(0.000)	0.001**	(0.014)
Education	0.148**	(0.059)	0.001	(0.001)	-0.000	(0.009)
Ext_services	1.745**	(0.838)	0.005	(0.007)	0.000	(0.073)
Credit_const	0.738	(2.096)	0.006	(0.008)	-0.001	(0.061)
Animal	0.269**	(0.127)	0.001	(0.002)	-0.005**	(0.012)
Machinery	-0.122	(0.350)	-0.011**	(0.005)	-0.002	(0.447)
Clay loam	-0.495	(0.400)	-0.008	(0.007)	-0.002	(0.035)
Sandy loam	1.148**	(0.461)	0.042***	(0.009)	0.027***	(0.108)
CC_Shock	0.967***	(0.311)	-0.003	(0.005)	0.018**	(0.043)
Cotton Zone	2.556***	(0.826)	-0.010	(0.012)	0.027**	(0.066)
Rice Zone	1.298	(1.081)	-0.024	(0.018)	0.013	(0.080)
CC_info	1.883***	(0.270)				
CC_perception	2.385***	(0.303)				
Res_ext	-0.089	(0.307)				
Res_credit	-0.276	(0.889)				
$\ln\sigma_\mu$			-3.435***	(0.044)	-3.566***	(1.217)
r_μ			0.218	(0.374)	0.366**	(0.159)
σ_μ			0.0322***	(0.001)	0.283***	(0.001)
ρ_μ			0.2142	(0.357)	0.3505***	(0.135)
LR test of indep. Eqs.	4.30**					
Wald χ^2	65.94***					
Log likelihood	1046.76					
Number of obs.	540		262		278	

Note: The dependent variable is variance, i.e., the second central moment of the production function. Standard errors are in parentheses. The reference region is mix cropping zone; the reference soil type is loam soil. Res_ext and Res_credit denote the residuals from first stage regression for extension contact and credit constraint, respectively.

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

2.3.4. Downside risk exposure and kurtosis

To the extent that variance analysis does not differentiate between farm net returns variability and exposure to downside risk (Di Falco and Veronesi, 2014; Mukasa, 2018), we also report the estimates on the impact of adaptation to extreme weather conditions on the skewness of farm net returns in Table 2.4. The estimates show that both average rainfall and temperature do not influence exposure to downside risk, but the rainfall and temperature anomalies (extremes) tend to significantly influence skewness. Temperature anomaly has a significant (at the 10% level) and positive effect (0.489) on the skewness of farm net returns for adopters and a significant (at the 5% level), but negative (-0.550) impact on the skewness of farm net returns for non-adopters, indicating that temperature anomaly reduces the risk of crop failure of adopters. In contrast, skewness of farm net returns decreases for non-adopters, which means non-adopters are more exposed to downside risk and crop failure due to temperature extremes. Rainfall anomaly is positively correlated (0.004) with the skewness of non-adopters and has a significant effect (at the 5% level). Excessive rainfall is beneficial to water-intensive crops and helps to reduce irrigation costs. It also reduces downside risk exposure of non-adopters of CSA practices, since no special practices are required with rainfall.

Farm size has a significant (at the 10% level) and negative (-0.001) impact on the skewness of non-adopters, suggesting that larger farms are more exposed to downside risks, compared to smaller farmers. To the extent that an increase in farm net returns' skewness implies a reduction in the probability of crop failure, and skewness captures the exposure to downside risks, larger farms are more exposed to downside risks because they are generally less productive than smaller farms. The number of animals that a farm household owns has a positive (0.002) and significant effect (at the 5% level) in terms of increasing the skewness of non-adopters and hence reducing crop failure.

Table 2.4 Determinants of adaptation to extreme weather conditions and its impact on downside risk exposure.

Variables	Selection	Skewness (downside risk)				
		Adopters		Non-adopter		
Constant	4.817	(8.858)	0.076	(0.091)	0.044	(0.063)
Avg_Tem	-0.412	(0.344)	-0.003	(0.003)	-0.002	(0.002)
Avg_Rain	-0.139	(0.875)	0.005	(0.008)	0.001	(0.006)
Tem_anomaly	68.719**	(33.823)	0.489*	(0.266)	-0.550**	(0.230)
Rain_anomaly	-0.416**	(0.194)	-0.001	(0.002)	0.004**	(0.002)
HH_age	0.015	(0.010)	0.000	(0.000)	0.000	(0.000)
Family Size	0.086	(0.073)	-0.001**	(0.001)	-0.001*	(0.001)
Farm Size	0.013	(0.020)	-0.000	(0.000)	-0.001***	(0.000)
Education	0.143**	(0.060)	-0.001**	(0.000)	0.000	(0.000)
Ext_services	1.616*	(0.845)	-0.002	(0.003)	0.001	(0.002)
Credit_const	0.585	(2.139)	0.001	(0.004)	-0.002	(0.002)
Animal	0.260**	(0.131)	0.001	(0.001)	0.002**	(0.001)
Machinery	-0.121	(0.353)	0.003	(0.003)	0.000	(0.003)
Clay loam	-0.443	(0.403)	0.000	(0.004)	0.001	(0.003)
Sandy loam	1.089**	(0.464)	0.009**	(0.004)	-0.005*	(0.003)
Cotton Zone	2.298***	(0.779)	0.010*	(0.006)	-0.017***	(0.005)
Rice Zone	1.144	(1.086)	0.012	(0.009)	-0.020**	(0.008)
CC_Shock	0.996***	(0.303)	0.002	(0.002)	-0.003	(0.004)
CC_info	1.912***	(0.265)				
CC_perception	2.346***	(0.302)				
Res_ext	-0.074	(0.315)				
Res_credit	-0.211	(0.902)				
$\ln\sigma_\mu$			-4.120***	(0.044)	-4.311***	(0.043)
r_μ			-0.030	(0.226)	-0.330**	(0.141)
σ_μ			0.162***	(0.001)	0.013***	(0.001)
ρ_μ			-0.030	(0.226)	-0.318***	(0.127)
LR test of indep. Eqs.	3.11*					
Wald χ^2	48.04***					
Log-likelihood	1432.02					
Number of obs.	540		262		278	

Note: The dependent variable is skewness, i.e., the third central moment of the production function. Standard errors are in parentheses. The reference region is mix cropping zone; the reference soil type is loam soil. Res_ext and Res_credit denote the residuals from first stage regression for extension contact and credit constraint, respectively.

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

Sandy loam soil has a positive (0.009) and significant effect (at the 5% level) in increasing the skewness of adopters and a negative (-0.005) and significant effect (at the 10% level) on non-adopters, suggesting that sandy loam soil reduces the risk of crop failure for adopters and increases the risk of crop failure for non-adopters, taking loamy soil as a base. Cotton zone and rice zone

farmers who are non-adopters are more exposed to downside risk, compared to their counterparts living in the mixed cropping zone. Non-adopters living in the mixed cropping zone have benefitted from multi-crop farming which reduces their exposure to downside risk.

Table 2.5 Determinants of adaptation to extreme weather conditions and its impact on Kurtosis.

Variables	Selection		Kurtosis			
			Adopters		Non-adopter	
Constant	4.558	(8.848)	-0.073	(0.045)	-0.042	(0.029)
Avg_Tem	-0.407	(0.344)	0.002	(0.002)	0.002	(0.001)
Avg_Rain	-0.111	(0.872)	-0.000	(0.004)	0.005*	(0.003)
Tem_anomaly	70.517**	(33.888)	-0.288**	(0.132)	0.051	(0.107)
Rain_anomaly	-0.416**	(0.194)	-0.000	(0.001)	-0.001	(0.001)
HH_age	0.017*	(0.010)	0.000**	(0.000)	-0.000	(0.000)
Family Size	0.085	(0.074)	0.001*	(0.000)	0.000	(0.000)
Farm Size	0.010	(0.020)	-0.000	(0.000)	0.000*	(0.000)
Education	0.141**	(0.059)	0.000	(0.000)	-0.000	(0.000)
Ext_services	1.708**	(0.847)	0.002	(0.002)	0.001	(0.001)
Credit_const	0.583	(2.110)	-0.000	(0.002)	-0.000	(0.001)
Animal	0.260**	(0.127)	0.000	(0.000)	-0.001***	(0.000)
Machinery	-0.126	(0.352)	-0.003**	(0.001)	-0.000	(0.001)
Clay loam	-0.487	(0.404)	-0.000	(0.002)	-0.000	(0.001)
Sandy loam	1.173**	(0.461)	0.007***	(0.002)	0.004***	(0.001)
Cotton Zone	2.348***	(0.771)	-0.002	(0.003)	0.004	(0.002)
Rice Zone	1.213	(1.086)	-0.007	(0.004)	0.002	(0.004)
CC_Shock	0.987***	(0.302)	-0.001	(0.001)	0.001	(0.002)
CC_info	1.930***	(0.267)				
CC_perception	2.364***	(0.301)				
Res_ext	-0.103	(0.309)				
Res_credit	-0.204	(0.890)				
$\ln\sigma_\mu$			-4.822***	(0.044)	-5.071***	(0.043)
r_μ			-0.012	(0.179)	0.265**	(0.128)
σ_μ			0.008***	(0.000)	0.006***	(0.000)
ρ_μ			-0.012	(0.179)	0.259**	(0.119)
LR test of indep. Eqs.	2.30					
Wald χ^2	51.39					
Log likelihood	1826					
Number of obs.	540		262		278	

Note: Dependent variable is kurtosis i.e. fourth central moment of the production function. Standard errors are in parentheses. The reference region is mix cropping zone; the reference soil type is loam soil. Res_ext and Res_credit denote the residuals from first stage regression for extension contact and credit constraint respectively.

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

Since farmers are averse to extreme weather events, the analysis has been extended to the fourth moment of the farm net returns function (Antle, 2010; Mukasa, 2018) to derive the kurtosis function's coefficients reported in Table 2.5. Similar to the variance results, temperature anomaly is negative (-0.288) and significant (at the 5% level) for adopters, indicating that temperature anomaly reduces the kurtosis of adopters. The coefficient of temperature anomaly is positive (0.051), which means that temperature anomaly increases the kurtosis for non-adopters, although it is not significant. Ownership of agricultural machinery has a negative and significant effect on the kurtosis of adopters, whereby the ownership of agricultural machinery reduces the kurtosis of adopters.

2.3.5. Farm net returns

The estimates of the determinants of adaptation to extreme weather conditions and the impact of adaptation on farm net returns are presented in Table 2.6. The variable representing the temperature anomaly is positive for adopters (7.059) and negative (-7.033) for non-adopters and is significant (at the 5% level) in both cases, indicating that adopters have benefited from adaptation to extreme weather conditions and earn higher farm net returns by the adjustment to temperature extremes. Because crops generally require specific temperatures at different stages of crop growth, adjusting temperature extremes in line with crop development stages can help to increase farm net returns, as observed for adopters. The coefficient of the rainfall anomaly variable is positive (0.042) and statistically significant (at the 10% level) for non-adopters, suggesting that rainfall anomaly increases farm net returns of non-adopters. This is probably because farmers who could not adapt to water shortage tend to benefit from excessive rainfall, thereby stabilizing their incomes. These findings are in line with that of Emran and Shilpi (2018), who found a positive relationship between rainfall shocks and crop yields for Bangladesh.

Table 2.6 Determinants of adaptation to extreme weather conditions and its impact on household farm net returns

Variables	Farm net returns					
	Selection		Adopters		Non-adopter	
Constant	4.334	(8.863)	10.562***	(1.096)	11.290***	(0.859)
Avg_Tem	-0.390	(0.345)	0.004	(0.040)	-0.017	(0.031)
Avg_Rain	-0.172	(0.870)	0.037	(0.093)	0.084	(0.080)
Tem_anomaly	54.896*	(33.253)	7.059**	(3.192)	-7.033**	(3.159)
Rain_anomaly	-0.385**	(0.187)	-0.008	(0.022)	0.042*	(0.021)
HH_age	0.015	(0.010)	0.001	(0.001)	-0.001	(0.001)
Family Size	0.079	(0.072)	-0.002	(0.007)	-0.017*	(0.009)
Farm Size	0.015	(0.020)	-0.012***	(0.002)	-0.022***	(0.003)
Education	0.136**	(0.059)	0.040***	(0.005)	0.052***	(0.006)
Ext_services	1.593*	(0.836)	0.093**	(0.040)	0.060**	(0.028)
Credit_const	0.482	(2.131)	0.020	(0.046)	-0.086***	(0.027)
Animal	0.272**	(0.131)	0.047***	(0.010)	0.052***	(0.014)
Machinery	-0.073	(0.355)	0.004	(0.030)	0.040	(0.039)
Clay loam	-0.448	(0.399)	-0.001	(0.043)	0.116***	(0.037)
Sandy loam	1.259***	(0.463)	-0.132**	(0.052)	-0.300***	(0.037)
Cotton Zone	2.036***	(0.746)	0.115	(0.072)	-0.263***	(0.072)
Rice Zone	0.818	(1.082)	0.233**	(0.109)	-0.440***	(0.114)
CC_Shock	1.027***	(0.303)	0.037	(0.028)	-0.135***	(0.052)
CC_info	1.833***	(0.268)				
CC_perception	2.327***	(0.286)				
Res_ext	-0.080	(0.305)				
Res_credit	-0.141	(0.900)				
$\ln\sigma_\mu$			-1.633***	(0.044)	-1.694***	(0.043)
r_μ			0.205	(0.183)	-0.322*	(0.181)
σ_μ			0.1954***	(0.009)	0.1839***	(0.008)
ρ_μ			0.2018	(0.175)	-0.3117*	(0.016)
LR test of indep.	3.69*					
Wald χ^2	371.41***					
Log likelihood	53.42					
Number of obs.	540		262		278	

Note: The dependent variable is the natural logarithm of farm net returns. Standard errors are in parentheses. The reference region is mix cropping zone; the reference soil type is loam soil. Res_ext and Res_credit denote the residuals from first stage regression for extension contact and credit constraint, respectively.

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

The results in Table 2.6 also reveal that education is an important variable in explaining higher farm net returns among adopters and non-adopters of extreme weather conditions. The positive and significant coefficients of the education variable in all three equations suggest that good knowledge and firm understanding of adaptation to extreme weather conditions may increase the

benefits from CSA practices in terms of higher farm net returns. The negative and significant coefficients of farm size for adopters and non-adopters indicate that larger farms significantly obtained lower farm net returns compared with smaller farms. This inverse relationship between farm net returns and farm size is in line with previous studies such as Abdulai and Huffman (2014) and Sheng et al. (2019). The coefficients of the number of animals that a household owns are positive and statistically significant, indicating that the ownership of animals tends to be associated with higher farm net returns for both adopters and non-adopters. Sandy loam soil coefficients have negative signs and are significantly different from zero for both adopters and non-adopters, suggesting that sandy loam soil reduces farm net returns for both adopters and non-adopters.

The extension services variable coefficients are positive and significant (at the 5% level) in both the adopter (0.093) and non-adopters (0.060) equations, suggesting that extension services provided to farm households positively influence the farm net benefits for both adopters and non-adopters. The negative (-0.135) and highly significant (at the 1% level) sign of the coefficient of previous climate-related shocks indicates that previous climate-related shocks significantly and negatively affect farm net returns of non-adopters, probably because they failed to adapt strategies to cope with extreme weather conditions, resulting in lower yields and farm net returns.

The significance of location variables indicates that the location of the farm influences the farm outcomes. The coefficient of rice cropping zone is positive and significant for adopters, which means that rice-growing farmers gain higher net benefits from the adoption of CSA practices than their counterparts living in mixed cropping zone. On the other hand, the rice zone and cotton zone coefficients have negative and significant signs, suggesting that the farm net returns of non-adopters are lower compared with that of adopters living in mixed cropping zone. It is notable here that growing multiple crops is a risk management strategy, whereby farmers living in mixed cropping zone tend to benefit from multiple crop revenues.

2.3.6. Average treatment effects on the treated (ATT)

The estimates of the average treatment effects on the treated (ATT) – which show the impact of the adoption of CSA practices on the outcome variables are presented in Table 2.7. As mentioned earlier, adopters and non-adopters are systematically different from each other, whereby these ATT estimates account for selection bias arising from both observable and unobservable characteristics. The results show that ATT derived from farm net returns is positive (0.223) and highly significant (at the 1% level), indicating that adaptation to extreme weather conditions has significantly increased farm net returns. In particular, farm net returns have increased by about 2 percent as a result of the adoption of CSA practices. These findings are consistent with the notion that adaptation to climate change and weather extremes results in higher productivity and household income (Iqbal et al., 2015; Abid et al., 2016b).

Table 2.7 Impact of adaptation to extreme weather conditions on farm net returns, the volatility of farm net returns, and downside risk exposure.

Outcome Variables	Mean outcome		ATT	Change
	Adopters	Non-adopter		
Farm net returns ^a	11.179 (0.015)	10.956 (0.040)	0.223***	02.04%
Variance	0.016 (0.001)	0.024 (0.001)	-0.008***	33.33%
Skewness	0.001 (0.002)	-0.004 (0.023)	0.005***	125.00%
Kurtosis	0.0016 (0.000)	0.0017 (0.000)	-0.0001***	05.88%

Note: ATT is the average treatment effect on the treated.

^aAs farm net returns are in log forms, and the predictions are also given in log forms. Converting the means back to Pakistani rupee (PKR) would lead to imprecise results due to the arithmetic and geometric means inequality.

*** Significant at 1% level.

The results also reveal that adaptation to extreme weather conditions significantly reduces production risk and increases farm net returns. The negative (-0.008) and statistically significant (at the 1% level) difference in ATT derived from the variance of farm net returns using counterfactual analysis indicates that adaptation strategies have resulted in a reduction in the volatility of farm net returns by about 33 percent. The mean skewness changes from negative (-0.004) to positive (0.001) as a result of adaptation. Thus, the adoption of CSA practices against

weather extremes has contributed to a decline in downside risk exposure and crop failure by about 125 percent. This finding is consistent with the results reported by Di Falco and Veronesi (2014) for Ethiopia. Similar to the variance, the negative (-0.0001) and statistically significant (at the 1% level) value of ATT suggests that kurtosis has significantly declined by 5.88 percent, which implies that adaptation to extreme weather conditions on average reduces the probability of skimpy and high outcomes, and stabilizes farm net returns of adopters.

2.4. Discussion

Extreme weather conditions such as extreme temperatures and rainfall, climate-related shocks (floods, droughts, climate-induced crop diseases and pest attack, hailing, and dust cyclones) increase the risk of crop failure, while risk-averse farm households adopt measures such as CSA practices to mitigate the effects of these conditions. As part of their risk management strategies, farmers diversify their activities by using different seed varieties, which include drought-tolerant, genetically modified, and locally high yielding varieties, depending on the environment and location of the farm. Our analysis of adaptation to extreme weather conditions through the adoption of CSA practices provides technological options for managing climate risk in rural Pakistan. As indicated previously, adoption of CSA practices reduces the exposure to risk, increases farm net returns, which consequently increase the welfare of farmers in Pakistan.

However, complex interacting factors regarding new technology implementation contribute to some challenges. For example, conservation agriculture, which requires CSA practices, is knowledge intensive (Kassam et al., 2009). But extension services in developing countries have reduced farmers' access to training and expert guidance on these practices (Hellin, 2012). Our results (see Table 2.6) show that credit constraint is another critical obstacle to the adoption of CSA practices. When CSA practices are appropriately targeted to the farmers, they can stabilize farm net returns and reduce their risk exposure to extreme weather and climatic conditions; however, these practices may not be able to fully buffer the impacts of severe extreme weather

conditions such as floods and droughts. In this case, index-based insurance could be designed to trigger payouts for any level of these severe conditions (Lybbert and Carter, 2015). The provision of drought-tolerant seed varieties to the farmers could be another solution to mitigate the effect of drought.

Our empirical results on the effectiveness of CSA practices for managing extreme weather conditions and climate risks suggest several generalizations. Significant selection bias confirms that farmers self-select themselves into adaptation or non-adaptation. Adoption is significantly influenced by climate-related variables, socioeconomic, and farm-level characteristics. Our estimates reveal that the volatility of farm net returns is reduced by the adoption of CSA practices. We also found evidence that the adoption of CSA practices can be effective in stabilizing farm output and farm net returns, mitigating the impacts of extreme weather conditions on farm households, and resulting improvements in measures of farm household welfare in Pakistan.

The findings show that adoption of CSA practices help in reducing the volatility of farm net returns and downside risk exposure of farm households. In particular, farmers adapt to temperature variability by changing cropping calendars to provide crop-specific temperatures at certain stages of plant growth. It is evident that higher rainfall reduces the cost of irrigation and is also useful for plant growth of some water-intensive crops like rice and sugarcane. Consequently, positive rainfall anomaly significantly reduces the exposure to downside risk of non-adopters. Our results also show that adopters adjusted sowing dates of crops to avoid temperature hikes, which eventually reduce the kurtosis, which is a measure of infrequent deviations in farm net returns.

As mentioned earlier, farmers self-select into the adoption of CSA practices, so adaptation to extreme weather conditions is non-random, this decision may be endogenous and also led to the problem of selection bias (Heckman, 1979). The ESR model estimates selection and outcome equations simultaneously, employing the Full Information Maximum Likelihood (FIML) method for the estimation that can handle the unobservable factors influencing adaptation to extreme

weather conditions and non-adaptation (Cham et al., 2017). The limitation of the ESR model is that it accounts for selection bias by aggregating the unobservable heterogeneity that is the distribution of the unobservable characteristics, but this heterogeneity varies across individuals (Cornelissen et al., 2016).

2.5. Conclusion and policy implications

This paper examines the factors that influence farmers' decisions to adopt climate-smart farm practices (CSA practices) in response to adverse effects of extreme weather conditions, as well as the impact of adoption of CSA practices on farm net returns, volatility of farm net returns, and downside risk exposure among agricultural households in Pakistan. The paper utilizes farm-level cross-sectional data collected from three agro-ecological zones of Pakistan in 2017 from a randomly selected sample of 540 farmers. Simple comparisons of risk-related variables and farm net returns between adopters and non-adopters reveal some significant differences between the two groups. To the extent that these are merely descriptive statistics and may confound the impact of adaptation to extreme weather conditions, we used an endogenous switching regression model to examine the determinants of adaptation and the impact of adaptation on the outcome variables. The empirical results reveal that adaptation to extreme weather conditions reduces the volatility of farm net returns by 33 percent, downside risk exposure by 125 percent and kurtosis by 5.88 percent, it implies that adoption reduces exposure to risk and stabilizes farm net returns, which contribute to improving rural household welfare. Similarly, the results reveal that adaptation to extreme weather conditions results in an increase in farm net returns by 2 percent. This finding suggests that adoption of CSA practices can play a considerable role in increasing farm productivity and farm net returns to reduce rural poverty in Pakistan and help to improve farm households' welfare. Considering the factors that affect farm households' adaptation decisions to extreme weather conditions, the results indicate that temperature anomaly, education, ownership of animals, extension services and previous climate-related shocks (such as floods, droughts,

cyclones, and climate-related pest infestation and diseases) exert positive and significant effects on the adoption of CSA practices.

The findings also show that education has a positive and significant influence on adaptation to extreme weather conditions as well as farm net returns, indicating the importance of education and the provision of schools in the rural areas of Pakistan. Moreover, ownership of assets such as animals tends to have a positive effect on the probability of adapting CSA practices in response to extreme weather conditions. The positive and significant impact of extension services on the adoption of CSA practices and farm net returns indicate that enhancing access to extension services would contribute to improve the welfare of farmers. The government must put in place policy measures to promote extension services in remote areas. The negative and significant effect of liquidity constraints on farm net returns indicates that policymakers could help to improve farmers' access to formal and informal credit to promote the adoption of CSA practices. Effective targeting of these CSA practices also requires further research to identify the context under which innovations, particularly CSA practices, single practice, or a combination of them, can contribute to farm households' welfare.

Acknowledgments

The authors would like to thank, without implicating, the journal editor Dr. Emma Stephens and two anonymous reviewers for valuable comments and suggestions that have substantially improved the paper. A previous version of this paper was presented at the Agricultural and Applied Economics Association (AAEA) annual meeting 2019, in the session "Risk and Uncertainty: Climate Change and Development," held in Atlanta, GA, USA. We would like to thank session participants for useful comments and suggestions. The first author gratefully acknowledges the scholarship funding from the Higher Education Commission (HEC) of Pakistan, in collaboration with the German Academic Exchange Service (DAAD), Germany.

References

- Abdulai, A. (2018). Simon brand memorial Address: the challenges and adaptation to climate change by farmers in Sub-Saharan Africa. *Agrekon*, 57(1), 28-39.
- Abdulai, A., & Huffman, W. E., 2005. The diffusion of new agricultural technologies: The case of crossbred-cow technology in Tanzania. *American Journal of Agricultural Economics*, 87(3), 645-659.
- Abdulai, A., & Huffman, W., 2014. The adoption and impact of soil and water conservation technology: An endogenous switching regression application. *Land Economics*, 90(1), 26-43.
- Abid, M., Scheffran, J., Schneider, U. A., & Ashfaq, M., 2014. Farmers' perceptions of and adaptation strategies to climate change and their determinants; the case of Punjab province, Pakistan. *Earth System Dynamics Discussions*, 5(2), 1359-1406.
- Abid, M., Schilling, J., Scheffran, J., & Zulfiqar, F., 2016a. Climate change vulnerability, adaptation and risk perceptions at farm level in Punjab, Pakistan. *Science of the Total Environment*, 547, 447-460.
- Abid, M., Schneider, U. A., & Scheffran, J., 2016b: Adaptation to Climate Change and Its Impacts on Food Productivity and Crop Income: Perspectives of Farmers in Rural Pakistan, *Journal of Rural Studies*, 47, Part A, 254-266.
- Ali, A., & Erenstein, O., 2017. Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Climate Risk Management*, 16, 183-194.
- Anache, J. A., Flanagan, D. C., Srivastava, A., & Wendland, E. C., 2018. Land use and climate change impacts on runoff and soil erosion at the hillslope scale in the Brazilian Cerrado. *Science of The Total Environment*, 622, 140-151.

- Antle, J. M., 1983. Testing the stochastic structure of production: a flexible moment-based approach. *Journal of Business & Economic Statistics*, 1(3), 192-201.
- Antle, J. M., 2010. Asymmetry, partial moments, and production risk. *American Journal of Agricultural Economics*, 92(5), 1294-1309.
- Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., Cattaneo, A. and Kokwe, M., 2015. Climate-smart agriculture? Assessing the adaptation implications in Zambia. *Journal of Agricultural Economics*, 66(3), pp.753-780.
- Bekele, W., & Drake, L., 2003. Soil and water conservation decision behavior of subsistence farmers in the Eastern Highlands of Ethiopia: a case study of the Hunde-Lafto area. *Ecological Economics*, 46(3), 437-451.
- Bettencourt, E. M. V., Tilman, M., Narciso, V., Carvalho, M. L. D. S., & Henriques, P. D. D. S., 2015. The livestock roles in the welfare of rural communities of Timor-Leste. *Revista de Economia e Sociologia Rural*, 53, 63-80.
- Bocchiola, D., Brunetti, L., Soncini, A., Polinelli, F., & Gianinetto, M., 2019. Impact of climate change on agricultural productivity and food security in the Himalayas: A case study in Nepal. *Agricultural Systems*, 171, 113-125.
- Boero, R., Bianchini, L., & Pasqualini, D., 2015. Vulnerability and adaptation to severe weather events in the American southwest. *Weather and Climate Extremes*, 8, 12-25.
- Bouwer, L. M., 2019. Observed and projected impacts from extreme weather events: implications for loss and damage. In *Loss and damage from climate change* (pp. 63-82). Springer, Cham.
- Cham, H., Reshetnyak, E., Rosenfeld, B., & Breitbart, W., 2017. Full Information Maximum Likelihood Estimation for Latent Variable Interactions With Incomplete Indicators. *Multivariate behavioral research*, 52(1), 12-30.

- Cornelissen, T., Dustmann, C., Raute, A., & Schönberg, U., 2016. From LATE to MTE: Alternative methods for the evaluation of policy interventions. *Labour Economics*, 41, 47-60.
- Deressa, T. T., Hassan, R. M., & Ringler, C., 2011. Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *The Journal of Agricultural Science*, 149(1), 23-31.
- Deschenes, O., & Greenstone, M., 2007. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97(1), 354-385.
- Di Falco, S., & Veronesi, M., 2014. Managing environmental risk in presence of climate change: the role of adaptation in the Nile Basin of Ethiopia. *Environmental and Resource Economics*, 57(4), 553-577.
- Economic Survey of Pakistan, 2013-14. Economic Advisor's Wing, Ministry of Finance, Islamabad, Pakistan.
- Economic Survey of Pakistan, 2015-16. Economic Advisor's Wing, Ministry of Finance, Islamabad, Pakistan.
- Economic Survey of Pakistan, 2017-18. Economic Advisor's Wing, Ministry of Finance, Islamabad, Pakistan.
- Emran, S., & Shilpi, F., 2018. Agricultural Productivity, Hired Labor, Wages, and Poverty: Evidence from Bangladesh. *World Development*, 109, 470-482.
- FAO, 2004. Fertilizer Use by Crop in Pakistan. Land and Plant Nutrition Management Service. Land and Water Development Division. Food and Agriculture Organization of the United Nations, Rome.
- FAO, 2011. Global food losses and food waste – Extent, causes, and prevention. Food and

Agriculture Association of the United Nations (FAO, Rome).

- Gill, H. A., 2016. Pakistan-adaptations measures to cope with the rising temperature, 1.5-degree regime. *The Nature News, environment, climate change and science*, 16 Aug. Available at <http://thenaturenews.com/2016/08/pakistan-adaptations-measures-to-cope-with-the-rising-temperature-1-5-degree-regime/>
- Groom, B., Koundouri, P., Nauges, C., & Thomas, A., 2008. The story of the moment: risk averse cypriot farmers respond to drought management. *Applied Economics*, 40(3), 315-326.
- Grothmann, T., & Patt, A., 2005. Adaptive capacity and human cognition: the process of individual adaptation to climate change. *Global Environmental Change*, 15(3), 199-213.
- Guttormsen, A. G., & Roll, K. H., 2014. Production risk in a subsistence agriculture. *The Journal of Agricultural Education and Extension*, 20(1), 133-145.
- Hansen, J., Hellin, J., Rosenstock, T., Fisher, E., Cairns, J., Stirling, C., Lamanna, C., van Etten, J., Rose, A. and Campbell, B., 2019. Climate risk management and rural poverty reduction. *Agricultural Systems*, 172, 28-46.
- Heckman, J. J., 1979. Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, 153-161.
- Hellin, J., 2012. Agricultural extension, collective action and innovation systems: Lessons on network brokering from Peru and Mexico. *The Journal of Agricultural Education and Extension*, 18(2), 141-159.
- Huang, J., Wang, Y., & Wang, J., 2015. Farmers' adaptation to extreme weather conditions through farm management and its impacts on the mean and risk of rice yield in China. *American Journal of Agricultural Economics*, 97(2), 602-617.
- Huffman, W. E., 2001. Human capital: Education and agriculture. *Handbook of agricultural economics*, 1, 333-381.

- IPCC, 2012. Managing the risks of extreme events and disasters to advance climate change adaptation. In: A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (eds CB Field, V Barros, TF Stocker et al.), Cambridge University Press, Cambridge, NY, USA.
- Iqbal, M. A., Ping, Q., Abid, M., Kazmi, S. M. M., & Rizwan, M., 2016. Assessing risk perceptions and attitude among cotton farmers: A case of Punjab province, Pakistan. *International Journal of Disaster Risk Reduction*, 16, 68-74.
- Iqbal, M., Ahmad, M., & Mustafa, G., 2015. Impact of Farm Households' Adaptation on Agricultural Productivity: Evidence from Different Agro-ecologies of Pakistan.
- Issahaku, G., & Abdulai, A., 2019. Can Farm Households Improve Food and Nutrition Security through Adoption of Climate-smart Practices? Empirical Evidence from Northern Ghana. *Applied Economic Perspectives and Policy*, p. 1-22.
- Janjua, P. Z., Samad, G. and Khan, N. U., 2010. Impact of Climate Change on Wheat Production: A Case Study of Pakistan. *The Pakistan Development Review* 49(4): 799–822.
- Kassam, A., Friedrich, T., Shaxson, F., & Pretty, J., 2009. The spread of conservation agriculture: justification, sustainability and uptake. *International journal of agricultural sustainability*, 7(4), 292-320.
- Khaliq, T., 2008. Modeling the impact of climate change on maize (*Zea mays* l.) Productivity in the Punjab. A Ph.D. thesis department of Agronomy, University of Agriculture Faisalabad, Pakistan.
- Khan, M. A., 2015. Climate change risk and reduction approaches in Pakistan. In *Disaster Risk Reduction Approaches in Pakistan* (pp. 195-216). Springer, Tokyo.
- Kleemann, L., Abdulai, A., & Buss, M., 2014. Certification and access to export markets: Adoption and return on investment of organic-certified pineapple farming in Ghana.

World Development, 64, 79-92.

- Kreft, S., Eckstein, D., Melchior, I., 2017. Who suffers most from extreme weather events? Global Climate Risk Index 10.
- Lesk, C., Rowhani, P., & Ramankutty, N., 2016. Influence of extreme weather disasters on global crop production. *Nature*, 529(7584), 84.
- Lokshin, M., & Sajaia, Z., 2004. Maximum likelihood estimation of endogenous switching regression models. *The Stata Journal*, 4(3), 282-289.
- Lybbert, T. J., & Carter, M. R., 2015. Bundling drought tolerance and index insurance to reduce rural household vulnerability to drought. *In Sustainable Economic Development* (pp. 401-414). Academic Press, USA.
- Ma, W., & Abdulai, A., 2016a. Linking apple farmers to markets: Determinants and impacts of marketing contracts in China. *China Agricultural Economic Review*, 8(1), 2-21.
- Ma, W., & Abdulai, A., 2016b. Does cooperative membership improve household welfare? Evidence from apple farmers in China. *Food Policy*, 58, 94-102.
- McNeil, A. J., Frey, R., & Embrechts, P., 2015. Quantitative Risk Management: Concepts, Techniques and Tools-revised edition. *Princeton university press*.
- Mitter, H., Larcher, M., Schönhart, M., Stöttinger, M., & Schmid, E., 2019. Exploring Farmers' Climate Change Perceptions and Adaptation Intentions: Empirical Evidence from Austria. *Environmental Management*, 63(6), 804-821.
- Mukasa, A. N., 2018. Technology adoption and risk exposure among smallholder farmers: Panel data evidence from Tanzania and Uganda. *World Development*, 105, 299-309.
- Nagy, G., Azeiteiro, U., Heimfarth, J., Verocai, J., & Li, C., 2018. An assessment of the relationships between extreme weather events, vulnerability, and the impacts on human

- wellbeing in Latin America. *International journal of environmental research and public health*, 15(9), 1802.
- Nearing, M. A., Pruski, F. F., & O'neal, M. R., 2004. Expected climate change impacts on soil erosion rates: a review. *Journal of soil and water conservation*, 59(1), 43-50.
- Nhemachena, C., Hassan, R., & Chakwizira, J., 2014. Analysis of determinants of farm-level adaptation measures to climate change in Southern Africa. *Journal of Development and Agricultural Economics*, 6(5), 232-241.
- PARC, 2013. Wheat in Pakistan. Wheat Plant Sciences Division Pakistan Agricultural Research Council Islamabad, Pakistan. A status paper.
- PARC, 2015. Pakistan Agricultural Research Council. <http://www.parc.gov.pk/index.php/en/43-maps>.
- PARC, 2018. Pakistan Agricultural Research Council. Crop Sciences Research Institute. <http://www.parc.gov.pk/index.php/en/csi>.
- Planning Commission of Pakistan, 2010. Final Report of the Task Force on Climate Change. Planning Commission of Pakistan, Government of Pakistan.
- Rahm, M. R., & Huffman, W. E., 1984. The adoption of reduced tillage: the role of human capital and other variables. *American journal of agricultural economics*, 66(4), 405-413.
- Ray, D.K., Gerber, J.S., MacDonald, G.K., West, P.C., 2015. Climate variation explains a third of global crop yield variability. *Nat. Commun.* 6, 5989.
- Shannon, H. D., & Motha, R. P., 2015. Managing weather and climate risks to agriculture in North America, Central America, and the Caribbean. *Weather and Climate Extremes*, 10, 50-56.
- Sheng, Y., Ding, J., & Huang, J., 2019. The relationship between farm size and productivity in

- agriculture: evidence from maize production in Northern China. *American Journal of Agricultural Economics*, 101(3), 790-806.
- Siddiqui, R., Samad, G., Nasir, M., & Jalil, H. H., 2012. The Impact of Climate Change on Major Agricultural Crops: Evidence from Punjab, Pakistan. *The Pakistan Development Review*, 51(4), 261-276.
- Smit, B., & Skinner, M. W., 2002. Adaptation options in agriculture to climate change: a typology. *Mitigation and adaptation strategies for global change*, 7(1), 85-114.
- Tubiello, F., Schmidhuber, J., Howden, M., Neofotis, P. G., Park, S., Fernandes, E., & Thapa, D., 2008. Climate change response strategies for agriculture: challenges and opportunities for the 21st century. *Agriculture and rural development discussion paper*, 42.
- Vasileiadou, E., Hisschemöller, M., Petersen, A. C., Hazeleger, W., Betgen, C., de Hoog, I., & Min, E., 2014. Adaptation to extreme weather: identifying different societal perspectives in the Netherlands. *Regional Environmental Change*, 14(1), 91-101.
- Vogel, E., Donat, M. G., Alexander, L. V., Meinshausen, M., Ray, D. K., Karoly, D., ... & Frieler, K., 2019. The effects of climate extremes on global agricultural yields. *Environmental Research Letters*, 14(5), 054010.
- Wooldridge, J. M., 2010. *Econometric analysis of cross section and panel data*. MIT press.
- Wooldridge, J. M., 2015. Control function methods in applied econometrics. *Journal of Human Resources*, 50(2), 420-445.
- World Bank, 2013. *World Development Report 2013. Development and Climate Change*. World Bank Washington D.C.

Appendix A

A.1 Moment of the farm net returns

The mean equation of farm net returns is estimated as follows:

$$\pi_h = pq(Z_h, C_h; e) + \varepsilon_h \quad (2.a)$$

where $f(Z_h, C_h; e)$ is the mean farm net returns per acre of farmer h , Z_h is the vector of socio-economic variables, and C_h is the vector of inputs used that may shift the farm production, e is a vector of stochastic factors to be estimated, and ε_h is the error term distributed with zero mean $E(\mu_h) = 0$. If we assume that the independent variables in Eq. (2.1) are exogenous, then we can consistently estimate specification (2.1) by using OLS. The first moment of farm net returns is then estimated as follows:

$$\mu_1 \equiv E[\pi_h] = [pq(Z_h, C_h)]E[e] \quad (2.b)$$

Second moment can be written as:

$$\mu_2 \equiv E[\pi_h - E(\pi_h)]^2 = [pq(Z_h, C_h)]^2 E[e - E(e)]^2$$

The higher moments can be written as follows:

$$\mu_k \equiv E[\pi_h - E(\pi_h)]^k = [pq(Z_h, C_h)]^k E[e - E(e)]^k, \quad \text{where } k = 1, 2, 3, 4 \quad (2.c)$$

when $k = 1$ is mean, for $k = 2$ variance, for $k = 3$ skewness, and $k = 4$ kurtosis of the given net returns function. This is an approach to estimate the impact of past climate factors (temperature and rainfall variability), inputs (seeds, fertilizers, pesticides, irrigation, labor), assets (farm machinery and animals), soil characteristics (clay loam, loam, and sandy loam) and household characteristics (family size, household head age and education) on the distribution of net returns under uncertainty.

Table 2.A1 Log-linear farm net returns function estimation

Variables	Coefficients	Std errors
Constant	11.02943***	(0.46862)
Credit_const	-0.02956*	(0.01550)
Avg_Tem	-0.03198*	(0.01693)
Avg_Rain	-0.07297*	(0.04136)
tem_anomaly	-0.45108	(1.52895)
rain_anomaly	-0.00324	(0.01045)
HH_age	-0.00131**	(0.00051)
Familysize	-0.00687*	(0.00385)
Education	0.01132***	(0.00287)
farm_size	-0.00291**	(0.00115)
no_of_animal	0.01391**	(0.00553)
HH_fertilizers	0.00003***	(0.00000)
HH_pesticides	0.00005***	(0.00001)
HH_seed	0.00002***	(0.00000)
HH_labour	0.00002***	(0.00000)
HH_irrigation	0.00006***	(0.00001)
Sandy loam	-0.11277***	(0.02086)
Clay loam	0.00205	(0.01894)
Ext_services	0.02444*	(0.01470)
cc_shock	0.03912***	(0.01365)
Xcotton	0.05215	(0.03465)
Xrice	0.05581	(0.05337)
agri_machinery	0.03977**	(0.01575)

Note: The dependent variable is the natural logarithm of farm net returns. Standard errors are in parentheses. The reference region is mix cropping zone; the reference soil type is loam soil.

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

Table 2.A2 Residuals calculation of potential endogenous variables

Variables	Credit_constraint	Std. Errors	Ext_services	Std. Errors
Constant	-9.2528	(5.6327)	-10.6656	(6.5676)
Avg_Tem	0.3519*	(0.2020)	0.4387*	(0.2346)
Avg_Rain	0.8300*	(0.4529)	1.1182**	(0.4969)
Tem_anomaly	8.1094	(8.8071)	24.9232***	(9.4539)
Rain_anomaly	-0.1481	(0.1026)	-0.1624	(0.1088)
HH_age	0.0029	(0.0065)	0.0061	(0.0070)
Family Size	0.0572	(0.0483)	-0.1020**	(0.0475)
Education	-0.0656***	(0.0284)	0.0724**	(0.0299)
Farm Size	-0.0198	(0.0168)	0.0280**	(0.0135)
Animal	-0.2366***	(0.0640)	0.2827***	(0.0645)
Sandy loam	0.3927*	(0.2271)	-0.7749***	(0.2786)
Clay loam	-0.0773	(0.2561)	0.1080	(0.2482)
CC_Shock	-0.0041	(0.1787)	0.7765***	(0.1952)
Machinery	0.1716	(0.2203)	0.7303***	(0.2321)
Ext_services	-0.8840***	(0.1781)		
Credit_const			-0.9951***	(0.2122)
Dis_Ext_off			-0.2511***	(0.0281)
Relation_bank	-0.9217**	(0.4159)		

Note: Standard errors are in parentheses. The reference soil type is loam soil. Distance to the extension office and personal relationship in the credit institute are used to identify models of extension contact and credit constraint respectively.

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

Table 2.A3 Instrumental variables validation test (Probit model)

Variables	CC_adaptation	Std. Errors
Constant	3.9262	(7.9671)
Avg_Tem	-0.3694	(0.2905)
Avg_Rain	0.0205	(0.7922)
Tem_anomaly	69.9690**	(32.3940)
Rain_anomaly	-0.3995**	(0.1905)
HH_age	0.0165*	(0.0100)
Family Size	0.0840	(0.0721)
Education	0.1315***	(0.0502)
Farm Size	0.0099	(0.0183)
Animal	0.2513***	(0.0935)
Sandy loam	1.1743***	(0.4310)
Clay loam	-0.4914	(0.3967)
CC_Shock	1.0118***	(0.2811)
Machinery	-0.0959	(0.3377)
Ext_services	1.3812***	(0.3026)
Credit_const	0.0609	(0.3505)
Cotton Zone	2.2819***	(0.7238)
Rice Zone	1.1652	(1.0688)
CC_info	1.9187***	(0.2651)
CC_perception	2.3187***	(0.2916)
Wald χ^2 test for joint sig. of excluded instruments	92.73***	
LR χ^2 (19)	583.97***	
Pseudo R ²	0.7806	
Log likelihood	-82.0756	

Note: Standard errors are in parentheses. The reference region is mix cropping zone; the reference soil type is loam soil. CC_info and CC_perception are used as instruments for ESR model identification.

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

Table 2.A4 Instrumental variables validation test non-adopters (OLS)

Variables	Kurtosis		VAR		SK		Net_returns	
Constant	-0.0439	(0.0310)	-0.1833	(0.1393)	0.0385	(0.0661)	11.3391***	(0.8872)
Credit_const	-0.0003	(0.0010)	-0.0009	(0.0044)	-0.0018	(0.0021)	-0.0880***	(0.0287)
Avg_Tem	0.0016	(0.0011)	0.0069	(0.0050)	-0.0016	(0.0024)	-0.0195	(0.0319)
Avg_Rain	0.0044	(0.0029)	0.0220*	(0.0128)	0.0018	(0.0061)	0.0935	(0.0825)
Tem_anomaly	0.0361	(0.1132)	0.4836	(0.5080)	-0.4876**	(0.2413)	-6.2313*	(3.2488)
Rain_anomaly	-0.0008	(0.0008)	-0.0063*	(0.0034)	0.0036**	(0.0016)	0.0384*	(0.0221)
HH_age	-0.0000	(0.0000)	-0.0000	(0.0002)	0.0001	(0.0001)	-0.0007	(0.0011)
Family Size	0.0003	(0.0003)	0.0012	(0.0015)	-0.0012*	(0.0007)	-0.0147	(0.0095)
Education	-0.0002	(0.0002)	-0.0007	(0.0009)	0.0004	(0.0004)	0.0529***	(0.0059)
Farm Size	0.0002	(0.0001)	0.0009	(0.0005)	-0.0008***	(0.0002)	-0.0208***	(0.0034)
Animal	-0.0013***	(0.0005)	-0.0045**	(0.0022)	0.0023**	(0.0011)	0.0514***	(0.0143)
Sandy loam	0.0044***	(0.0013)	0.0263***	(0.0059)	-0.0044	(0.0028)	-0.2945***	(0.0382)
Clay loam	-0.0005	(0.0013)	-0.0023	(0.0061)	0.0013	(0.0029)	0.1261***	(0.0391)
Ext_services	0.0008	(0.0012)	-0.0009	(0.0052)	0.0028	(0.0025)	0.0733**	(0.0292)
CC_Shock	0.0005	(0.0018)	0.0143*	(0.0081)	-0.0019	(0.0038)	-0.1163**	(0.0523)
Cotton Zone	0.0033	(0.0026)	0.0247**	(0.0115)	-0.0157***	(0.0054)	-0.2423***	(0.0739)
Rice Zone	0.0019	(0.0041)	0.0133	(0.0184)	-0.0194**	(0.0088)	-0.4389***	(0.1177)
Machinery	-0.0002	(0.0014)	-0.0031	(0.0063)	0.0004	(0.0030)	0.0498	(0.0405)
CC_info	-0.0005	(0.0012)	-0.0020	(0.0054)	0.0021	(0.0026)	-0.0037	(0.0351)
CC_perception	-0.0013	(0.0014)	-0.0075	(0.0063)	0.0030	(0.0030)	0.0669	(0.0406)
Dis_Ext_off	0.0000	(0.0001)	0.0002	(0.0007)	0.0002	(0.0003)	-0.0027	(0.0042)
Relativ_bank	0.0005	(0.0018)	0.0065	(0.0082)	-0.0025	(0.0039)	-0.0733	(0.0527)
F-test	0.45	[0.6363]	0.36	[0.6979]	0.23	[0.7936]	0.16	[0.8509]

Note: The reference region is mix cropping zone; the reference soil type is loam soil. CC_info and CC_perception are used as instruments for ESR model identification. Distance to the extension office and relative in the credit institute are used to identify residuals from extension contact and credit constraint, respectively. Standard errors are in parentheses. The p-values are given in square brackets.

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

Table 2.A5 Instrumental variable correlation test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skewness (1)	1.0000							
Net returns (2)	0.2425	1.0000						
cc_info (3)	0.1054	0.2541	1.0000					
cc_percep (4)	0.0141	0.2025	0.5894	1.0000				
dis_ext (5)	0.0030	-0.1851	-0.1803	-0.1403	1.0000			
Res_ext (6)	0.0348	0.1589	0.2075	0.1509	-0.0970	1.0000		
Res_credit (7)	-0.0326	-0.1171	-0.0536	-0.1155	0.0260	0.1410	1.0000	
Relativ_bank (8)	-0.1069	0.2124	-0.0099	-0.0824	0.0608	0.0229	-0.0090	1.0000

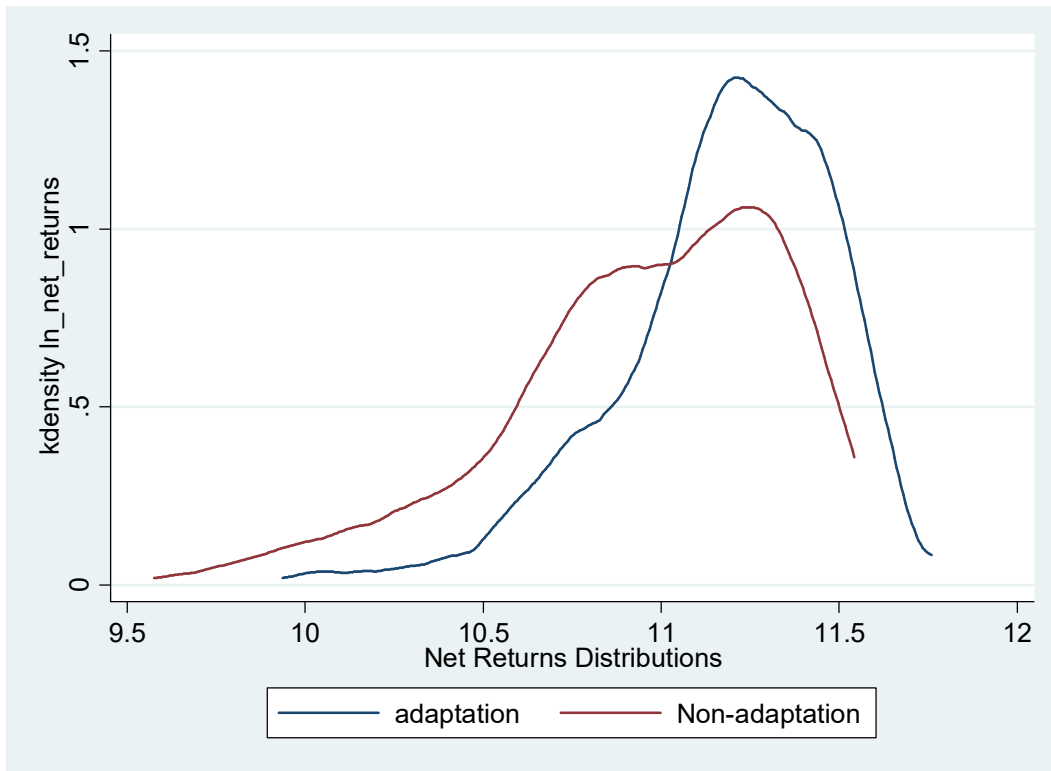


Fig. 2.A1 Kernel density plot for adopters and non-adopters (Net Returns)

Chapter 3

Climate Risk Management in Agricultural and Rural Household Welfare: Empirical Evidence from Pakistan

Muhammad Faisal Shahzad and Awudu Abdulai

Department of Food Economics and Consumption Studies

Submitted to Journal of International Development

Abstract

In this paper, we investigate the determinants of farmers' adaptation choices against climate change and analyze the impact of these choices on farm households' welfare. A recent farm-level data from three agro-ecological zones of Pakistan are used to estimate a multinomial endogenous switching regression for different climate-smart agriculture (CSA) practices, namely changing inputs mix, change in cropping calendar, diversifying seed variety and soil and water conservation, and the impact of each adopted practice on farm net returns and downside risk exposure. The results show that adoption of different CSA practices is determined by average rainfall, ownership of agricultural machinery, previous experience of climate-related shocks, education of household head, access to climate change information, and climate change perception. The findings also reveal that adoption of CSA practices positively and significantly improves the welfare of rural farm households and reduces their exposure to downside risk and crop failure. The results further revealed significant differences in the impacts of CSA practices adoption on farm net returns in different agroecological zones and quantiles of plot sizes. Thus, policy efforts to scale-up adoption of CSA practices should consider agroecological zone and farm size differences in addition to enhancing farmer education, extension, and access to climate change information.

Keywords: Climate change, adoption, impact assessment, selectivity correction, rural welfare, Pakistan.

JEL Codes: C21, C26, Q54, O33, D13.

3.1. Introduction

Climate change and extreme weather events are making the world weather uncertain and pose a devastating direct effect on agriculture, making this business riskier (Beddington, 2011; Shannon and Motha, 2015, Shahzad and Abdulai, 2020). Warm atmosphere, decrease in snowfall, rising sea level, unpredicted changes in precipitation and greenhouse gas emissions are causing extreme weather and climatic events (IPCC, 2013). The rise in temperature is the major driver of such changes (Wolkovich et al., 2012). Climate change and extreme weather events are the major threats to agriculture in the world, especially South Asian countries. Climate variability induces challenges to achieving food security, poverty reduction and rural development in these countries due to the vagaries of weather and other natural disasters such as extreme temperatures, extremely erratic rainfall, floods and droughts, dust cyclones, pest infestation and crop diseases coupled with low adoption rates of new technologies (IPCC, 2014). Variations in climate have a significant impact on water resources, agriculture production, food supply, farmers' welfare and finally the global economy (FAO, 2011; IPCC, 2012).

Climate-smart agriculture (CSA) has emerged as a framework for developing and implementing robust agricultural systems, which simultaneously improve food security, living conditions in rural areas, facilitate adaptation to climate change, and provide mitigation benefits (FAO, 2013). The global community has recommended the incorporation of climate-smart agriculture (CSA) practices into national development plans to mitigate the adverse impacts of climate change on agriculture (IPCC, 2007; World Bank, 2010). Climate-smart agriculture practice is a practice on the farm, which sustainably increases agricultural productivity, adapts and builds the resilience of agricultural and food systems to climate change, and reduces greenhouse gas emissions from agriculture (FAO, 2013). The CSA practices such as changing input mix and cropping calendar, crop diversification, diversifying seed variety, crop rotation, soil and water conservation, using improved seed variety, income diversification, crop and livestock integration and improving

irrigation efficiency are the strategies generally used to reduce climate change adverse effects (Tubiello et al., 2008; Soglo and Nonvide, 2019).

It is projected that by the middle of the 21st century, the largest number of food-insecure people will be found in South Asia due to the adverse effects of climate change (IPCC, 2014). Previous studies have shown that adoption of CSA practices plays a significant role in increasing farm productivity and household income, contributes to rural income growth, poverty reduction and food security (Abid et al., 2016b; Iqbal et al., 2015; Ali and Erenstein, 2017; Khanal et al., 2018). Moreover, adoption of CSA practices has been found to help smallholder farmers living in rural areas overcome production and income risks (Mukasa, 2018; Hansen et al., 2019). For these reasons, the significance of CSA practices in promoting farm households' adoption of CSA practices, improving their livelihood and welfare in South Asian countries has attracted considerable attention from researchers and policymakers.

Although, most of the previous studies on adoption of climate change in the agricultural sector are focused on developing countries in Africa. However, the literature on the adoption of climate change perspectives in Pakistan is rare and few studies (e.g., Abid et al., 2016b; Iqbal et al., 2015) have analyzed the impact of climate change adaptation from agricultural perspective. Abid et al. (2016b) found that adaptation to climate change improves farm productivity and crop income, while Iqbal et al. (2015) investigated farmers' choices of adaptation such as varietal change, delayed sowing and input intensification, using Heckman's Treatment Effects model, found a significant and positive impact of adaptation choices on wheat crop net revenues in Pakistan. Sabiha et al., (2017) concluded that high yielding varieties increase production efficiencies in Bangladesh, while Veetil et al., (2016) found that adoption of Bt-technology reduced environmental damage in India. Furthermore, divergent findings from these studies about adaptation impact on farm performance offer motivation for further empirical assessment with respect to topography and agroecology.

Despite the potential of CSA practices to enhance agricultural sustainability, adoption rates of CSA practices in Pakistan are reported to be very low. FAO (2019) reports that adoption rate of balance input use in irrigated area, use of heat and drought tolerant varieties in rainfed area, soil and water conservation practices for cotton farmers are less than 30%. The reasons for low adoption rates in Pakistan appear to be mixed. For instance, Salman et al., (2018) report that many farmers in Pakistan do not consider climate change as a potential threat to agriculture and therefore do not see the need to change their farming practices. Also, policy implementation regarding adaptation to climate change is weak and entails strong integration with other policies, institutions and financial funding in support of promoting CSA practices (FAO, 2019). Further, some studies attribute the low adoption rates to knowledge gap between researchers and policy-makers, which needs to be bridged for the development of a comprehensive plan of CSA practices for adoption (Ali et al., 2019).

We define climate-smart agriculture practice broadly to include adoption strategies such as changing cropping calendar, diversify seed varieties, changing input mix and soil and water conservation (FAO, 2013). The present study contributes to the growing literature on the adoption of CSA practices, by examining the factors influencing these practices, as well as estimating the impact of these CSA adoption choices on farm net returns and downside risk exposure. In addition to the country-specific contribution to literature, we also extend the cropping mixed analysis by moving away from mono-cropping analysis to mixed-cropping that exploits the interlink benefits from multiple climate-smart practices. Very few studies have examined the adoption impacts of multiple CSA practices on farmers' productivity and exposure to risk, though from mono-cropping perspective (Di Falco and Veronesi, 2013; Iqbal et al., 2015). However, the conclusion based on a single crop may under or overestimate the real impacts of adoption for several reasons. For instance, if a farmer in mixed crop setting changes the input mix for rice crop it may increase or decrease the production of other crops on the field. In the same way, for a coherent

understanding, if multi-product farmer applies soil and water conservation techniques for wheat crop, it might offer benefit to oilseed crops in the same season and increase yield of cotton, rice, maize in the following season, which may not be captured if a researcher considers only wheat yield leaving out other crops. Furthermore, there might be a negative interaction between crops in mixed setting, where increase in yield of one crop may lead to decrease the yield of other crops (Tessema et al., 2015).

Since smallholder farmers predominantly cultivate mixed-crops as part of risk minimization strategy, we depart from the previous studies that analysed farm level risk based on monocropping cropping context (e.g., Kassie et al., 2014; Di Falco and Veronesi, 2013) by considering the multi-cropping nature of farming in Pakistan in our analysis. Furthermore, we examine factors that influence farmer's choice of different CSA practices, since understanding linkages between these choices and farm outcomes can also provide significant information to policymakers on possible promotion and scaling up of different CSA practices. Analysis of CSA adoption choices may also provide insights into which adaptation choice is a more effective option for multi-product farmers. To the extent that CSA overlaps other development goals such as food security, poverty reduction, and rural development (Vale, 2016; Abdulai, 2018), results obtained from this study can inform climate change policy design, especially in developing country settings similar to Pakistan. To achieve our research objective, we combine spatial climate data with recent survey data from three important agro-ecological zones of the Punjab province of Pakistan to estimate the multinomial endogenous switching regression (MESR) and implement counterfactual analysis. For robustness check, we employ multivariate treatment effect regression to compare the results.

The rest of the paper is organized as follows. The next section presents the data and descriptive statistics. The third section presents methodology which discusses the conceptual framework as well as the empirical analytical approach. The fourth section addresses the results and discussions, while the final section presents the conclusion and policy implications of the study.

3.2. Data and descriptive statistics

The cross-sectional data used in this study come from a survey conducted between January and March 2017 in Pakistan by the authors. A farm household sampling frame was developed to ensure representation for the study region. For the data collection, we considered the cropping pattern, agricultural activities, percent of cultivated land area, climate, and weather variability within agro-ecological zones. The data were collected from six administrative units of the Punjab province. Three important zones (cotton zone, rice zone, and mix cropping zone) were selected purposively based on climatic and agro-ecological cropping patterns (see Fig. 3.1). The selected zones have different climatic conditions and cropping patterns. A multi-stage stratified random sampling procedure was applied to collect data from farmers. During the first stage, three zones from the Punjab province were selected purposively on a climate and agro-ecological basis. In the second stage, two districts from each zone were randomly selected. In the third stage, two tehsils were randomly chosen from each district, then three villages were randomly selected from each tehsil. In the fifth stage, fifteen farmers were randomly selected from each village. Overall, 540 farmers were interviewed for the data collection. In total, they were cultivating 748 agricultural plots. A structured questionnaire was used to collect socio-economic and farm-level information from the respondents, through face to face interviews.

The collected data were comprehensive, which include information on farm households, agricultural practices, production and costs, irrigation water use, access to extension, social networking, perceptions about climate change and climate risks, responses to climate change, credit access, farm and household assets, other income sources, consumption, and expenditure. One section of the questionnaire was particularly designed to capture climate change perceptions and climate risks and understanding of adaptation responses against climate change. Questions were included to ask the farmers whether they have noticed long term changes in temperature and precipitation over the last twenty years. Secondary information related to temperature and rainfall

was collected from the National Center for Environmental Prediction (NCEP) and World Weather Online. The collected information ranges from 1979 to 2016, the same year in which we obtained data from farmers. It was converted from monthly to yearly averages and calculate daily average rainfall and daily average temperature over the years at household level. As the Punjab province is mostly flat, we used the inverse distance method of spatial interpolation to calculate location-specific farm-level temperature and rainfall. For this purpose, we used the global positioning (GPS) system to record the farm location (elevation, longitude, and latitude) during the data collection. The recorded farm locations were employed in interpolation analysis to obtain information on farm-level temperature and rainfall. Subsequently, we calculated the temperature and rainfall anomalies, taking 2016 as a base year in which we collected primary data from farmers.

Evidence from the data shows that CSA practices were mainly related to farm net returns measures (see Table 3.1). The data also indicate that at least one CSA practice was adopted on 54% of cultivated plots, with no adoption taking place on the remaining 46 percent cultivated plots. In particular, diversification of seed variety was used as a strategy on 11% of plots, changing cropping calendar on 14%, changing input mix on 13% of plots, while soil and water conservation measures were adopted on 15% of cultivated plots. Thus, we identify four main adaptation strategies (1) seed variety diversification, (2) changing cropping calendar, (3) changing input mix, and (4) soil and water conservation.⁷ The average daily temperature and rainfall are recorded at 27°C and 1 millimeter over the last 38 years, respectively. Temperature and rainfall shocks are captured in rainfall anomalies. Temperature anomaly is positive in the area showing that on average, temperature anomalies are recorded 0.22°C, while on an average rainfall anomaly shows

⁷ As we have limited data (total number of adopted plots are 401), the adopters of multiple adaptation strategies range between 5-40 that is small in number. With this small number of observations MESR generates inconsistent estimates because with small number of observations the identification of the covariance matrix between all model residuals may become intractable. Therefore, we considered these main CSA practices in the analysis.

a reduction of rainfall by 0.37 millimeters. On average, 28 percent of farmers are credit constrained with an average plot holding of 5.9 acres. On average, 25 percent of farmers have agricultural machinery at their farms. In the past three years, about 39 percent of farmers were exposed to climate-related shocks such as floods, droughts, pest infestation, and diseases. Furthermore, we also captured the plot-variant characteristics such as soil fertility, erosion, and distance from farmers' houses to the plot. On average, 43 percent of plots are fertile, with an average distance of 2 km between farmer's house and the plot. On average, 21 percent of plots face moderate to severe erosion.

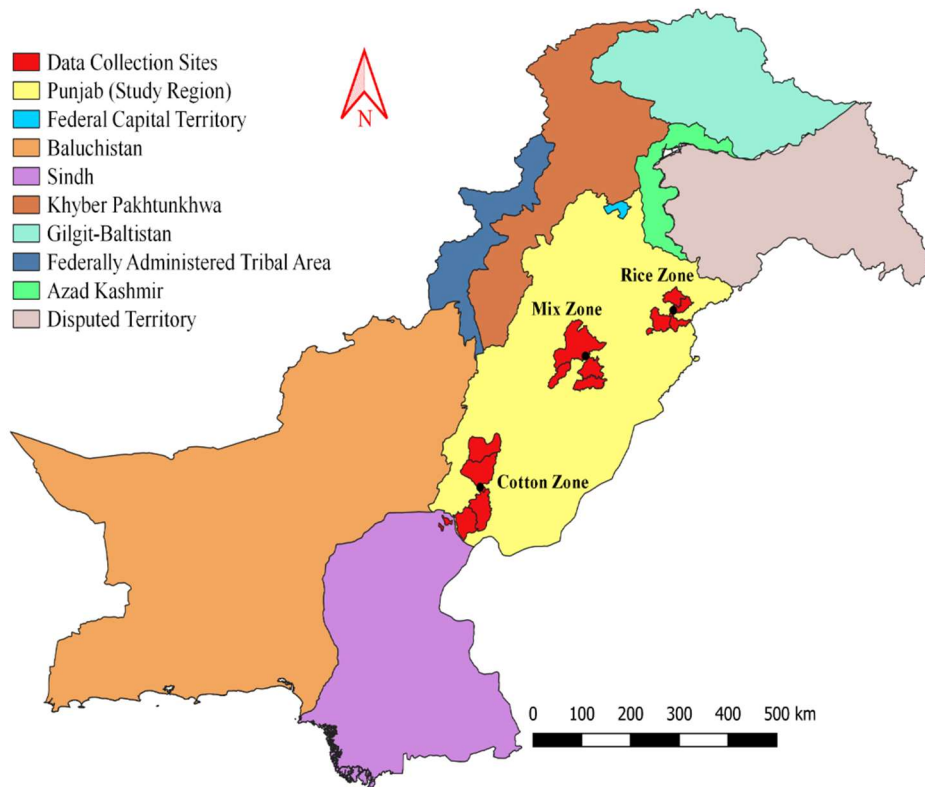


Fig. 3.1 Map of Pakistan showing study area and data collection sites

Table 3.1 Definition and descriptive statistics of selected variables

Variables	Definition	Mean	SD
No adaptation	1 if farmer chose not to adapt to climate change, 0 otherwise	0.464	0.499
Seed variety diver.	1 if farmer chose seed varieties diversification at the farm, 0 otherwise	0.112	0.316
Cropping calendar	1 if farmer chose to change sowing dates of crops, 0 otherwise	0.142	0.349
Input mix	1 if farmer chose to change input mix, 0 otherwise	0.131	0.338
SWC	1 if farmer chose to adopt soil and water conservation, 0 otherwise	0.151	0.358
Credit_const	1 if farmer is liquidity constraint, 0 otherwise	0.282	0.450
Avg Tem	Average annual daily temperature in (degrees Celsius)	27.334	1.110
Avg Rain	Average annual daily rain (millimeters)	0.639	0.553
Int TxR	Product of average daily temperature and average daily rainfall	16.882	13.821
Tem anomaly	Change in temperature relative to baseline ^a (number)	0.217	0.032
Rain anomaly	Change in rainfall relative to baseline (number)	-0.369	0.194
HH age	Household head age (years)	47.219	11.259
Family size	Number of persons residing in a household (number)	6.147	2.223
Education	Number of schooling years household head completed (years)	6.524	4.293
Plot size	Total number of acres a farm household cultivate at one place (acres ^b)	5.937	3.580
Herd size	Number of animals a farm household owns (number)	4.052	2.360
Machinery	1 if farmer has own farm machinery, 0 otherwise	0.247	0.432
cc_shock	1 if farmer exposed to climate-related shocks in the past three years, 0 otherwise	0.386	0.487
Ext services	1 if farmer has contact with govt. extension agent, 0 otherwise	0.290	0.454
Cotton zone	1 if farmer resides in cotton growing zone, 0 otherwise	0.310	0.463
Rice zone	1 if farmer resides in mix cropping zone, 0 otherwise	0.334	0.472
Mix zone	1 if farmer resides in rice growing zone, 0 otherwise	0.356	0.479
Fertile	Mean fertility=1 if soil is fertile, 0 otherwise	0.434	0.437
Erosion	Mean erosion=1 if agricultural plot has moderate to severe erosion, 0 otherwise	0.210	0.532
Plot distance	Mean distance to agricultural plot from farmer's house (km)	2.122	1.421
cc info	1 if a farmer receives current information related to climate change, 0 otherwise	0.373	0.484
cc perception	1 if farmer perceives changes in climate change, 0 otherwise	0.356	0.479
Farm net returns	Gross farm revenue minus variable costs (Thousand PKR ^c)	59.119	17.569
Skewness	Third central movement of the farm net returns function	-0.001	0.013
Total no. of obs.			748

^aAnomaly= (current year mean -long term mean)/long term mean

^b 1 acre= 0.405 hectare

^c PKR (Pakistani Rupee) is Pakistani currency (1 \$=104.67 PKR during the year of data collection).

We use the moment-based approach proposed by Antle (1983) to capture farmers' exposure to risks. Employing this flexible moment-based approach allows us to avoid specifying a functional form for the farmer's risk preferences, the probability function of farm net returns, and the distribution of risks. The approach accounts for exposure to risks by using the sample moments of farm net returns to capture the skewness, which is the third central moment. This method involves regressing farm net returns per acre on production inputs and other socio-economic variables, after which residuals are obtained. Then the third central moment of farm net returns (skewness) is calculated by raising the obtained residuals to the third power. The estimated skewness is used as an outcome variable to ascertain the impact of adoption on exposure to risks. The lower part of Table 3.1 shows that average skewness of farm net returns is negative, suggesting that crop failure and income risks prevail in the study area. Figure 3.2 displays unconditional farm net returns distributions by different CSA practices adopted in the study region. The figure clearly shows negative skewness of farm net returns for non-adopters with respect to adaptation.

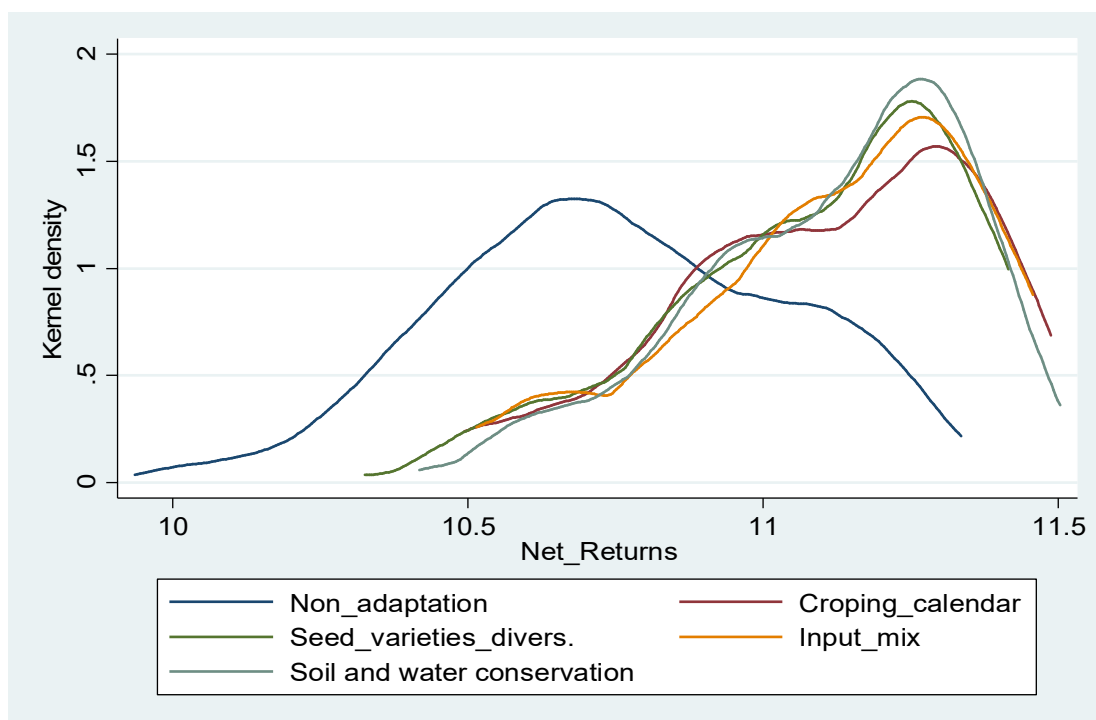


Fig. 3.2 Unconditional farm net returns distributions by CSA practices

Table 3.2 Summary statistics of the variables used for the CSA adopters and non-adopters

Variables	Non-adaptation (n = 347)		Seed variety diver. (n = 98)		Cropping Calendar (n = 106)		Input mix (n = 84)		SWC (n = 113)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Credit_const	0.343	0.475	0.225	0.419	0.189	0.393	0.298	0.460	0.221	0.417
Avg Tem	27.249	1.118	27.392	1.140	27.435	1.055	27.341	1.149	27.442	1.079
Avg Rain	0.670	0.572	0.630	0.553	0.587	0.509	0.653	0.565	0.590	0.527
int TxR	17.642	14.246	16.670	13.832	15.605	12.780	17.248	14.150	15.661	13.226
Tem anomaly	0.213	0.030	0.218	0.032	0.220	0.032	0.219	0.033	0.223	0.034
Rain anomaly	-0.353	0.188	-0.387	0.194	-0.386	0.195	-0.375	0.204	-0.384	0.206
HH age	47.228	11.468	47.122	11.268	46.226	10.727	48.655	11.177	47.142	11.234
Family size	5.968	2.139	6.112	2.252	6.330	2.114	6.571	2.495	6.239	2.316
Education	4.559	3.810	8.071	3.923	8.151	3.685	8.607	4.186	8.142	4.073
Plot size	5.899	3.793	5.715	3.296	6.259	3.447	6.015	3.145	5.885	3.609
Herd size	3.856	2.152	4.306	2.526	4.387	2.635	3.964	2.686	4.186	2.266
Machinery	0.058	0.233	0.480	0.502	0.321	0.469	0.441	0.499	0.416	0.495
cc_shock	0.199	0.400	0.653	0.478	0.557	0.499	0.393	0.491	0.566	0.498
Ext services	0.285	0.452	0.316	0.467	0.302	0.461	0.250	0.436	0.301	0.461
Xcotton	0.334	0.472	0.306	0.463	0.274	0.448	0.310	0.465	0.274	0.448
Xrice	0.257	0.437	0.398	0.492	0.387	0.489	0.393	0.491	0.425	0.497
Xmix	0.409	0.492	0.296	0.459	0.340	0.476	0.298	0.460	0.301	0.461
Fertile	0.337	0.405	0.489	0.447	0.510	0.444	0.556	0.452	0.525	0.451
Erosion	0.323	0.708	0.105	0.260	0.130	0.314	0.131	0.281	0.089	0.234
Plot_distance	2.452	1.603	1.594	1.127	1.892	1.097	1.967	1.171	1.895	1.256
cc info	0.020	0.141	0.633	0.485	0.689	0.465	0.726	0.449	0.673	0.471
cc perception	0.023	0.150	0.694	0.463	0.585	0.495	0.667	0.474	0.637	0.483
Farm net	48.571	13.782	68.543	16.015	67.118	15.021	68.569	15.591	68.810	14.610
Skewness	-0.005	0.016	0.001	0.004	0.002	0.009	0.002	0.004	0.003	0.006

Table 3.2 presents the summary statistics of the variables used in the analysis, classified into CSA practices by adopters and non-adopters. The table shows that adopters of CSA practices earned higher farm net returns and reduced their exposure to income risks (positive skewness) than non-adopters (negative skewness) in all adoption cases.

3.3. Methodology

3.3.1. Conceptual framework

The conceptual framework used in the analysis is based on the assumption that farmers normally made adoption decisions from a given set of CSA adoption choices in order to minimize the adverse effects of climate change. We assume a multi-product farmer producing under uncertain climate scenarios with different choices of adaptation strategies. As indicated previously, the specific CSA practices considered in this study are changes in cropping calendar, diversifying seed variety, changing input mix, and soil and water conservation. Previous studies have linked adoption of planting dates to farmers' adaptation behavior (Abid et al., 2016b; Iqbal et al., 2015; Di Falco and Veronesi, 2014). Diversification of seed varieties includes the use of drought-resistant and early maturing varieties that enable farmers to cope with erratic rainfall or very low rainfall (Kassie et al., 2017). Changing the input mix includes changing fertilizer types and quantities, changes in pesticide use, changing irrigation, changing the use of herbicides or weedicides, and micro-nutrients (Arslan, 2015). Soil and water conservation refers to soil erosion reduction and other measures to prevent soil and nutrient loss, and conserve soil moisture with practices such as practicing crop rotation to prevent nutrient loss in the soil, sowing cover crops to fix nitrogen in the soil, planting on ridges, making soil bunds at an appropriate distance to reduce soil erosion and water loss, planting shade trees to reduce evapotranspiration, and use of farmyard manure with minimum tillage which increases the soil's water holding capacity (Hudson, 1987; Gicheru et al., 2004).

We assume that farmers are risk-averse and consider farm net benefits from an adaptation strategy

on the i th plot in their decision-making process. The farm net benefits considered in the present study is farm net returns (π_i) from multiple crops, derived under inputs mix (I) and adaptation strategies (A) at a cost. The farmer is assumed to be using a production technology, which is continuous, concave, and at least twice differentiable. The farmer's production function can be represented as $Q = f(I, A, e)$, where e is a vector of the stochastic factors unknown to the farmer when production decisions are made. The vector e is treated as a random variable, whose distribution is exogenous to farmers' actions (Kim and Chavas, 2003; Mukasa, 2018). Hence, e captures the climate risks under imperfect predictability of farm net returns beyond farmer's control (such as extreme temperature, erratic rainfall, floods and droughts, production losses due to pest infestation and diseases). In the short run, farmers are price takers, so the assumption related to non-randomness of output and input prices is not critical (Groom et al., 2008). Therefore, we assume that output prices, input, and technology adoption costs are non-random and known to the farmer when production decisions are made.

With the above-given conditions, the farmer is assumed to maximize expected farm net returns as follows:

$$Max E[U(\pi_i)] = max E \left[U \left\{ \left(\sum_{n=1}^N p_n Q_n(I_n, A_j, e) \right) - \sum_{n=1}^N w_n I_n - \sum_{j=2}^M w_j A_j \right\} \right] \quad (3.1)$$

Where π_i is the farm net returns obtained from plot i , E is an expectation operator, Q_n and p_n are the output quantity and output price of n th crop, w_n is a vector of input prices used to grow crop n and I_n is the vector of inputs used, w_j is the vector of prices incurred in adopting j th CSA practice and A_j is the j th practice from a combination of CSA practices (e.g., changing inputs mix, change in cropping calendar, seed variety diversification, and soil and water conservation). We consider ($j = 1$) as a reference category i.e. non-adoption. We assume that the farmer compares

the farm net returns from adopting j th CSA practice A_{ij}^a for plot i and the farm net returns obtained from non-adoption A_{i1}^n . A risk-averse farmer will adopt j th CSA practice if the expected utility of farm net returns with adoption $E[U(A_{ij}^a)]$ is greater than the expected utility without adoption $E[U(A_{i1}^n)]$. This can be expressed as $E[U(A_{ij}^a)] - E[U(A_{i1}^n)] > 0$.

3.3.2. Empirical Strategy

Given that farmers self-select into adoption of climate-smart agriculture (CSA) practices, selection bias may arise due to observed and unobserved characteristics. Therefore, analyzing impact of adoption using ordinary least square (OLS) might lead to biased and inconsistent estimates. To assess the decision of farmers to adopt different CSA practices, the present study employs a multinomial endogenous switching regression (MESR) approach. The MESR model is a two-step estimation procedure that considers the selection bias correction among all alternate choices in question (Bourguignon et al., 2007; Di Falco and Veronesi, 2013). In the first step, factors affecting the adoption of CSA practices are considered. In the second step, consistent estimates of parameters of all explanatory variables of interest are evaluated to identify impacts of these variables on outcomes of interest (mean farm net returns and skewness of farm returns). Based on these consistent estimates, the outcome equations can be specified.

First stage: Selection Model of Climate-Smart Farm Practices

As mentioned above, the farmer adopts CSA practices, if the expected farm net benefits from adoption are positive. Given that the expected farm net benefits are unobservable, we can represent it with a latent variable A_{ij}^* which can be expressed as a function of observed (Z_i) and unobserved (ζ_{ij}) characteristics as follows:

$$A_{ij}^* = Z_i\gamma_j + \zeta_{ij} \quad (3.2)$$

where j represents different CSA practices, such that $j = 1, 2, 3, \dots, M$.

Let A_i be an index of a set of CSA practices choices that a farmer can decide to implement at plot

i to maximize farm net returns such that:

$$A_i = \begin{cases} 1 & \text{iff } A_{i1} > \max_{k \neq 1}(A_{ik}^*) \text{ or } \varepsilon_{i1} < 0 \\ \vdots & \vdots \\ M & \text{iff } A_{iM} > \max_{k \neq M}(A_{ik}^*) \text{ or } \varepsilon_{iM} < 0 \end{cases} \quad (3.3)$$

where $\varepsilon_{ij} = \max_{k \neq j}(A_{ik}^* - A_{ij}^*) < 0$. From equation (3.3), it is obvious that a farmer will implement j th CSA practice on i th plot if the selected practice provides greater expected farm net benefits than any other alternate option $k \neq j$.

It is important to state that equation (3.2) includes the deterministic component $Z_i\gamma_j$ and an idiosyncratic component ζ_{ij} . The latter captures the variables that a farm household takes into account when making adoption decisions, but these factors, which include farming skills, the motivation for adoption of CSA practices, cognitive and innate abilities are unknown to the researcher. We can interpret these factors as the unobserved individual propensity of adoption. The deterministic component (Z_i) includes the factors that affect the likelihood of selecting CSA practice j , such as farm household characteristics (e.g. age, education, family size), the ownership of assets such as herd size and farm machinery, location of the farm (rice zone, cotton zone, and mixed cropping zone), past climatic factors (e.g. average rainfall and temperature, extreme temperature and rainfall as anomalies), past experience of extreme weather events captured as past climatic shocks (such as floods, droughts, pest infestation, and diseases), institutional variables such as contact to extension services and liquidity constraints. To account for unobserved heterogeneity at the plot level, we also include in the vector \bar{Z}_i plot-specific characteristics (e.g., mean soil fertility, mean soil erosion, mean plot distance from farmer's house) (Kassie et al. 2014). We assume from equation (3.2) that ζ_{ij} are independently and identically Gumbel distributed (so-called independence of irrelevant alternatives (IIA) assumption), then we can specify the multinomial logit model as given below:

unobservable characteristics may simultaneously affect both error terms in equations (3.4) and (3.5a-3.5m), i.e. $corr(\zeta_{ij}, \mu_{ij}) \neq 0$. When this occurs, the estimates of β_j and θ_j from the ordinary least squares (OLS) may not be consistent. We employ a model proposed by Bourguignon et al., (2007) to correct this potential inconsistency (selection bias). This model takes into account the potential correlation between the error terms ζ_{ij} and μ_{ij} . To overcome potential inconsistency, we define the standard normal variables given below:

$$\zeta_{ij}^* = J(\zeta_{ij}) = \Phi^{-1}\{g(\zeta_{ij})\}, \quad \text{where } j = 1, 2, 3, \dots, M \quad (3.6)$$

For each j , we assume that the expected values of μ_{ij} and ζ_{ij}^* are linearly related. Under a classical assumption, it holds that μ_{ij} is normal and (μ_{ij}, ζ_{ij}^*) is bivariate normal for any adoption category j . If ρ_j represents the correlation between μ_{ij} and ζ_{ij}^* , then to derive the selection bias-corrected outcome equations, we can express the μ_{ij} in the following linear combination:

$$E(\mu_{ij} | \zeta_{i1} \dots \zeta_{iM}) = \sigma_j (\sum_{j=1}^M \rho_j \zeta_{ij}^*) \quad (3.7)$$

Taking into account the above expression and following Bourguignon et al., (2007), we derive the selection bias-corrected equations which can be used to estimate the consistent β_j in the farm net returns equations (3.5a)-(3.5m). The corrected equations can be specified as follows:

$$\begin{aligned} \text{Regime 1: } y_{i1} &= X_i \beta_1 + \bar{X}_i \theta_1 + \sigma_1 \left[\rho_1 m(P_{i1}) + \sum_{j=2}^M \rho_j m(P_{ij}) \frac{P_{ij}}{P_{ij-1}} \right] + \omega_{i1}, & \text{if } A_i = 1 & \quad (3.8a) \\ & \vdots & & \vdots \\ & \vdots & & \vdots \end{aligned}$$

$$\text{Regime M: } y_{iM} = X_i \beta_M + \bar{X}_i \theta_M + \sigma_M \left[\rho_1 m(P_{i1}) + \sum_{j=2}^M \rho_j m(P_{ij}) \frac{P_{ij}}{P_{ij-1}} \right] + \omega_{iM}, \quad \text{if } A_i = M \quad (3.8m)$$

Where $\lambda_{ij} = \sum_{j \neq 1}^M \rho_j \left[m(P_{i1}) + m(P_{ij}) \frac{P_{ij}}{(P_{ij-1})} \right]$ refers to inverse mills ratio computed from estimated probabilities of MNL model in Eq. (3.4), $m(P_{i1})$ and $m(P_{ij})$ are conditional expectations of ζ_{i1} and ζ_{ij} , which are used to correct selectivity bias, ρ_j is the coefficient of correlation between μ_{ij} and ζ_{ij} , σ_j is the standard deviation of disturbance terms from net returns equations and ω_i is the error term. From Eqs. (3.8a and 3.8m), it implies that the number of bias

correction terms in each equation are equal to the number of total adoption choices in question. Therefore, this method provides efficient estimates compared to available methods.⁸

In the estimation, Z_i from the selection equation and X_i from the outcome equations are overlapping. In this case, proper model identification is required. Thus, to ensure model identification, we need to have instruments that directly affect the selection decision at first stage but does not affect the outcome variables in the second stage. We use access to climate change information and perception as instrumental variables. Access to climate-specific information is expected to enhance farmers' understandings about climate change and directly influence their adoption decisions (Issahaku and Abdulai, 2019). On the otherhand, perceptions and expectations of future events may shape behavior, feelings and thoughts (Almlund et al., 2011) and are assumed to be good predictor of economic behavior. Indigenous knowledge of farmers also influences climate change perception behavior (Paudel et al., 2019). However, their validity may depend on the methods used to elicit such opinions and might raise the concerns of possible reverse causality (Delavende et al., 2011). In the present study, climate change perception is determined based on the farmers' experiences of past twenty years. Moreover, we perform Wald test for joint significance of the excluded instruments, which shows that these instrumental variables jointly and significantly influence adoption decisions of all four CSA practices (see lower part of Table 3.3). We also perform F-test for the excluded instruments that indicate instrumental variables do not significantly affect outcome variables of farmers that did not adopt (see Table 3.B2 and 3.B3 in Appendix B). Hence, the results from both regressions confirm that climate change information and perception are valid instruments (Issahaku and Abdulai, 2019; Di Falco et al., 2011). Adding

⁸ Previous literature on selection bias correction for the MNL model shows that Lee (1983) estimated only one correction term ($\zeta_{ij} - \zeta_{i1}$) for the selection bias correction for all choices, while Dubin and McFadden (1984) estimated (M-1) choices as to selection bias correction. Another method also provided by Dahl (2002) for selection bias correction, which is suitable when a large number of observations are available and the choices of adoption in the selection model are small. On the other hand, we have a small number of observations available in which the identification of the covariance matrix between all model residuals may become intractable. However, Bourguignon et al., (2007) show that their method is more robust than previous methods.

these instruments to equation (3.2), can be specified as follows:

$$A_{ij}^* = Z_i \gamma_j + \bar{Z}_i \partial_j + I_i \varphi_j + \tau_{ij} \quad (3.9)$$

where I_i indicates the set of instrumental variables used to identify the MNL model, φ_j is the parameters of the instrumental variables and τ_{ij} is the error term with zero mean and constant variance.

Another issue that deserves attention is the potential endogeneity of extension contact and credit constraint variables in the selection equation. This is because extension service officers may provide information related to particular CSA practices and farmers adopt these practices against climate change for better farm production. Credit constraint variable is potentially endogenous because non-adopters might be more prone to lower incomes, which worsen their credit worthiness, and hence their liquidity status. This study applies control function approach suggested by Murtazashvili and Wooldridge, (2016) to account for potential endogeneity arising from these variables. In the control function approach, the potentially endogenous variables (extension contact and liquidity constraint) are specified as a function of all other variables used in the selection equation in addition to instrumental variables. As both of these variables are dichotomous in nature, we estimate first-stage probit models of these variables to calculate generalized residuals and predicted values of these variables by using the distance from local agricultural advisory office and personal relationship in the credit institute as instruments, respectively. Distance from a local advisory office is a good predictor of extension contacts and expected to negatively affect the extension services, but it is not expected to affect the personal characteristics of farm households such as motivation of adoption and innate abilities that would affect farm net returns. Thus, distance from a local advisory office is expected to correlate with extension contacts, but it is exogenous to the omitted variables contained in the error term (Cawley, et al., 2018). Moreover, the location of farms in Pakistan is not a conscious choice where to locate but is largely due to inheritance, thus the distance to the local advisory office is

$$\begin{aligned}
E(y_{i1}|A_i = 2) &= X_i\beta_1 + \bar{X}_i\theta_1 + \sigma_1\lambda_{i2} & (3.11a) \\
\vdots & & \vdots \\
E(y_{i1}|A_i = M) &= X_i\beta_1 + \bar{X}_i\theta_1 + \sigma_1\lambda_{iM} & (3.11m)
\end{aligned}$$

The impact of adopting j th CSA practice is denoted as average treatment effects on the treated (ATT), which can be calculated by subtracting equations [3.10a from 3.11a] or [3.10m from 3.11m], as follows:

$$\begin{aligned}
ATT_2 &= X_i(\beta_2 - \beta_1) + \bar{X}_i(\theta_2 - \theta_1) + \hat{\lambda}_{i2}(\sigma_2 - \sigma_1) & (3.12a) \\
\vdots & & \vdots \\
ATT_M &= X_i(\beta_M - \beta_1) + \bar{X}_i(\theta_M - \theta_1) + \hat{\lambda}_{iM}(\sigma_M - \sigma_1) & (3.12m)
\end{aligned}$$

where the terms $\bar{X}_i(\cdot)$ and $\hat{\lambda}_{i2}(\cdot)$ account for unobserved heterogeneity and selection bias, respectively.

3.4. Results and discussion

3.4.1. Determinants of climate-smart farm practices

Table 3.3 presents the results obtained from the multinomial logit model (MNL) displaying the influence of the explanatory variables on the various CSA practices. The potential endogeneity arising from extension services and credit constraint variables is controlled by using a control function approach. The coefficients of the generalized residuals of extension contact (*Res_ext*) and credit constraint (*Res_Credit*) are insignificant in all the CSA practices choices, suggesting that the variables are consistently estimated (Murtazashvili and Wooldridge, 2016).⁹ The results show that climate variables positively and significantly affect adoption decisions. The coefficient of the variable representing average rainfall (*Avg_Rain*) is positive and significant for all the CSA practices, suggesting that average rainfall plays a positive role in the adoption of all the CSA

⁹ In the interest of brevity, the probit estimates of potential endogenous variables for residuals calculation are reported in Appendix B (See Tables 2.B5 and 2.B6).

practices. The coefficient of the variable climate-related shocks (*cc_shock*) is positive for all CSA practices, but it is significant for three adoption categories except changing input mix, suggesting that past experience of climate-related shocks positively and significantly drives the adoption decision of these CSA practices. The coefficient of variable rainfall anomaly is positive and significant for soil and water conservation (SWC), but it is insignificant for all other adoption practices, suggesting that long term deviations in rainfall tend to increase the probability of adopting soil and water conservation practices. The coefficient of the variable average temperature negatively and significantly influences adoption decision of changing cropping calendar and soil and water conservation. To account for the combined effect, we also introduced the interaction term between average rainfall and temperature (*int_TxR*), which is negative and significant for all the CSA practices, indicating that increasing temperature, combined with higher rainfall would negatively and significantly affects adoption decisions. This may be due to the fact that rainfall and temperature are inversely related, therefore, higher rainfalls usually lower the temperature intensity that may result in negative influence on adoption decisions. A finding that is consistent with the study conducted by Deressa et al. (2011), who argued that an inverse relationship exists between rainfall and temperature. The coefficient of the variable education of household head positively and significantly influences adoption of all CSA practices except seed variety diversification, suggesting that education plays a positive and significant role in the adoption of CSA practices. A finding that is consistent with Huffman (2020), who argued that education positively related to technology adoption decisions in a dynamic and technical environment. The coefficient of the variable agricultural machinery is positive and highly significant for all the CSA practices, indicating that ownership of agricultural machinery positively and significantly influences the adoption of all CSA practices. These findings are in line with that of Abdulai and Huffman (2014), who argued that ownership of machinery plays a role in the adoption of modern technology. The coefficient of the variable extension services is positive for all the CSA practices, but is only statistically significant in adoption of seed variety diversification, indicating that

extension services positively influence the implementation of seed variety diversification. The mean plot variant variables also significantly affect adoption decisions (Di Falco and Veronesi, 2013).

Table 3.3 Determinants of CSA practices choices, MNL model estimation

Variables	Seed variety diver. (<i>n</i> = 98)		Cropping Calendar (<i>n</i> = 106)		Input mix (<i>n</i> = 84)		SWC (<i>n</i> = 113)	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
Constant	34.043	(39.395)	64.403*	(38.316)	26.335	(43.841)	71.299*	(38.492)
Credit_const	-3.287	(5.013)	-0.494	(4.531)	-2.345	(5.314)	-2.326	(4.671)
Avg_Tem	-1.111	(1.345)	-2.211*	(1.319)	-1.085	(1.495)	-2.424*	(1.32)
Avg_Rain	65.521***	(24.757)	57.550**	(23.509)	63.330**	(26.455)	69.418***	(23.423)
int_TxR	-2.663**	(1.047)	-2.461**	(0.99)	-2.571**	(1.123)	-2.956***	(0.989)
Tem_anomaly	-13.287	(12.059)	-4.902	(11.129)	10.116	(13.395)	3.134	(11.353)
Rain_anomaly	-0.247	(1.757)	1.333	(1.686)	2.048	(1.888)	2.840*	(1.703)
HH_age	-0.027*	(0.016)	-0.030**	(0.015)	-0.008	(0.017)	-0.023	(0.015)
Family size	-0.253***	(0.094)	-0.204**	(0.089)	-0.178*	(0.093)	-0.229**	(0.089)
Education	0.085	(0.095)	0.206**	(0.092)	0.224**	(0.101)	0.153*	(0.091)
Plot size	0.047	(0.072)	0.071	(0.066)	0.134**	(0.067)	0.052	(0.067)
Herd size	0.090	(0.111)	0.032	(0.105)	-0.078	(0.116)	0.020	(0.108)
Machinery	2.240***	(0.487)	1.416***	(0.483)	2.647***	(0.513)	2.034***	(0.477)
Ext_services	7.552*	(3.988)	2.284	(3.977)	4.191	(4.373)	1.703	(3.998)
cc_shock	2.184***	(0.638)	1.655***	(0.605)	1.042	(0.642)	1.716***	(0.598)
Xcotton	-1.489	(1.139)	-0.231	(1.153)	-0.868	(1.249)	0.374	(1.142)
Xrice	-0.568	(0.970)	-0.063	(0.935)	-1.370	(1.048)	0.441	(0.946)
Fertility	-1.026*	(0.599)	-0.478	(0.574)	0.635	(0.609)	-0.248	(0.565)
Erosion	-2.314***	(0.780)	-1.404*	(0.715)	-1.555**	(0.781)	-2.608***	(0.748)
Plot_distance	-0.375***	(0.145)	-0.182	(0.134)	-0.057	(0.147)	-0.103	(0.132)
cc_info	3.623***	(0.524)	4.027***	(0.504)	4.250***	(0.54)	3.829***	(0.508)
cc_perception	3.958***	(0.512)	3.427***	(0.499)	3.900***	(0.531)	3.649***	(0.498)
Res_Credit	3.654	(3.596)	0.835	(3.184)	3.413	(3.802)	2.546	(3.308)
Res_ext	-4.247	(2.74)	-0.783	(2.706)	-3.548	(2.878)	-0.620	(2.713)
Wald χ^2 for joint sig. of excluded instruments	52.83***	[0.000]	51.77***	[0.000]	54.54***	[0.000]	58.26***	[0.000]
Wald χ^2 for joint sig. of plot-level heterogeneity (θ_j)	7.76*	[0.051]	6.72*	[0.081]	17.23***	[0.000]	13.86***	[0.003]
Wald χ^2 for MNL model	768.32***	[0.000]						
Pseudo R^2	0.359							
N	748							

Note: Standard errors are in parentheses. The reference region is a mix-cropping zone.

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

The coefficients of mean plot variant variables (soil erosion, soil fertility, and household distance from cultivated plots) are negative for all the CSA practices, indicating that they have a negative impact on adaptation. Except for the causal interpretation, the Wald χ^2 for the joint significance of the mean plot-level characteristics shows significant heterogeneity in all the CSA practices.¹⁰ Particularly, mean soil erosion and mean household distance from plots negatively and significantly affect the adoption decision. The erosion of agricultural plots occurs due to heavy floods, which is difficult for farmers to adapt to. The large mean distance from farmers' houses to agricultural plots negatively influences the adoption decisions. This is probably because farmers require motorized transportation of inputs and operational tasks over long distances. The estimates of climate change information are positive and significant for all the CSA practices, indicating that farmers who have access to climate change information are more likely to adopt CSA practices. Similarly, the coefficient of the variable climate change perception is positive and significant for all CSA practices, suggesting that climate change perception positively and significantly influences all the CSA practices.

3.4.2. Economic implications of climate-smart agricultural practices

In this section, we explain the economic impacts of adopting a particular CSA practice, on farmers' farm net returns. Table 3.4 presents the second stage results obtained from the MESR model. The five types of CSA adoption choices generate five selectivity terms denoted by Mills m1-m5. All the estimated variances are bootstrapped by 50 replications to deal with heteroskedasticity (Bourgoignon et al., 2007). The results indicate that the selectivity correction terms are significant in some of the CSA practices options [seed variety diversification, input mix, and soil and water conservation (SWC)], indicating the presence of sample selectivity effects in these specifications. Hence, accounting for selectivity is necessary to ensure unbiased and

¹⁰ See Wald χ^2 for joint significance of plot level heterogeneity (∂_j) in the lower part of Table 3.3.

consistent estimates of the coefficients in the farm net returns equations. For example, the estimates show a negative selectivity coefficient for adoption of seed variety diversification in the specification explaining the impact of adoption of soil and water conservation. This finding suggests lower farm net returns for farmers adopting seed variety diversification than randomly chosen farmers, as a result of farmers with better-unobserved attributes shifting from adoption of seed variety diversification to the adoption of SWC measures. In general, a negative (positive) selectivity coefficient for the adoption of a specific CSA practice indicates lower (higher) farm net returns for the farmer compared to a randomly selected farmer. Thus, farmers with unobserved characteristics linked to lowering farm net returns tend to shift to other CSA practices with higher farm net benefits. Quite interesting is the finding that there is no statistically significant sample selection bias for seed variety diversification in the specification explaining the impact of seed variety diversification on farm net returns. This finding suggests that even if after correcting selectivity bias, farmers with better (or worse) unobserved characteristics who adopted seed variety diversification would not have experienced higher (lower) farm net returns than randomly selected farmers.

Results in Table 3.4 show that seed variety diversification and SWC constants are significant, implying that if all other variables are set equal to zero, then adopters of these CSA practices would get positive farm net returns. The coefficient of the credit constraint variable is negative and significant for non-adopters, suggesting that farmers who are credit constrained had negative effect on farm net returns among non-adopters relative to adopters. It also signifies the role of access to credit in enhancing the adoption of CSA practices and farm productivity as found in previous studies (e.g., Di Falco et al., 2011; Abdulai and Huffman, 2014).

Table 3.4 Impact of CSA practices choices on farm net returns, second stage MESR estimation

Variables	Non-adaptation		Seed variety diver.		Cropping Calendar		Input mix		SWC	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
Constant	-22.040	(91.411)	926.028*	(502.231)	306.605	(261.090)	573.443	(365.026)	620.694**	(280.041)
Credit_const	-16.353***	(5.081)	-14.874	(22.116)	-20.818	(18.759)	-41.035	(26.981)	-23.331	(15.599)
Avg_Tem	3.202	(3.164)	-28.666*	(17.004)	-7.553	(8.877)	-14.268	(11.724)	-19.622**	(9.819)
Avg_Rain	8.381	(64.391)	256.495	(227.868)	198.172	(164.616)	64.965	(238.366)	164.098	(177.373)
int_TxR	-0.033	(2.668)	-13.128	(9.624)	-8.775	(6.753)	-3.844	(9.749)	-8.562	(7.372)
Tem_anomaly	-80.827***	(27.670)	-77.572	(130.667)	-14.378	(103.225)	-207.901*	(124.103)	-47.307	(103.685)
Rain_anomaly	2.211	(3.675)	11.333	(21.066)	14.202	(14.275)	-16.780	(16.654)	13.988	(21.934)
HH_age	-0.055	(0.036)	-0.162	(0.134)	0.036	(0.108)	-0.317**	(0.131)	-0.170	(0.114)
Family size	0.204	(0.182)	0.018	(0.808)	-0.166	(0.493)	-0.606	(0.688)	-0.480	(0.720)
Education	-0.158	(0.342)	-1.366	(0.850)	-1.157*	(0.654)	-1.828*	(1.016)	-1.630**	(0.789)
Plot size	0.447***	(0.167)	-0.235	(0.491)	-0.600	(0.515)	-0.121	(0.613)	0.212	(0.506)
Animal	-0.533**	(0.248)	-0.027	(0.870)	0.525	(0.640)	0.675	(0.713)	-0.408	(0.829)
Machinery	4.347	(2.745)	4.606	(3.833)	9.351***	(3.427)	-2.065	(3.583)	1.329	(2.874)
Ext_services	21.307***	(5.082)	23.046*	(12.721)	20.965*	(12.028)	42.297***	(15.330)	30.390**	(12.441)
cc_shock	-1.629	(2.059)	1.382	(7.858)	1.800	(6.316)	12.974	(8.820)	5.431	(5.651)
Xcotton	-7.261**	(2.836)	19.974	(15.470)	7.505	(9.768)	0.675	(11.893)	16.477	(10.930)
Xrice	4.637***	(1.720)	21.853*	(11.154)	12.916*	(7.397)	12.144	(11.078)	19.584**	(9.618)
Fertility	3.124***	(1.152)	13.590**	(6.444)	8.273	(5.443)	-2.544	(4.808)	4.131	(4.643)
Erosion	-0.202	(2.022)	-2.319	(7.152)	-6.353	(5.669)	2.307	(6.522)	-7.270	(7.407)
Plot_distance	-0.632**	(0.295)	0.933	(1.896)	0.316	(1.224)	-3.016**	(1.521)	-0.503	(1.213)
_m1	-3.661	(4.965)	1.982	(16.644)	-5.384	(10.388)	-11.388	(13.121)	-4.952	(10.154)
_m2	-0.267	(12.199)	-7.152	(8.376)	-9.512	(15.486)	4.841	(15.408)	-35.164*	(18.247)
_m3	10.304	(14.344)	-18.312	(26.957)	-8.613*	(5.210)	40.730*	(21.818)	-4.690	(22.033)
_m4	-1.982	(17.417)	-26.883	(26.507)	-10.414	(15.333)	-19.788***	(7.511)	-46.403***	(17.656)
_m5	-16.645	(19.307)	34.798	(28.763)	30.306	(23.434)	-12.345	(25.397)	14.439*	(7.394)

Note: Bootstrapped standard errors are in parentheses. The reference region is a mix-cropping zone.

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

The coefficient of ownership of agricultural machinery is positive and significant for changing cropping calendar, indicating that ownership of agricultural machinery positively influences the farm net returns of farmers who adopted changing cropping calendar. With ownership of agricultural machinery farmers can make in time and efficient decisions of sowing and harvesting of crops rather hiring machinery does not have self-control, thus effective implementation of changing cropping calendar might improve farm net returns. The coefficient of the variable representing the cotton zone is negative and significant for non-adopters, suggesting that farm net returns of non-adopters are negatively and significantly affected in comparison with their counterparts living in mixed cropping zone (the base category). The coefficient of the mean soil fertility is positive and significant for seed variety diversification and non-adaptation, which suggests soil fertility positively influences farm net returns of adopters of seed variety diversification as well as non-adopters. The coefficient of the variable mean plot distance from farmer's house is negative and significant for non-adopters and changing input mix farmers, indicating that the plot distance from household's residence negatively influences the farm net returns of non-adopters and input mix adopters. This is probably because changing input mix requires transportation, so the larger the distance of plot from farmer's home the greater the cost of transportation and operational tasks. We also use a counterfactual analysis to examine the impact of CSA adoption on farm net returns. We split the analysis into overall treatment effects, location wise treatment effects, and treatment effects based on quantiles of plot sizes.

Table 3.5 presents the results for overall treatment effects on the treated (ATT) for farm net returns and risk exposure.¹¹ It shows the expected farm net returns under the observed cases in which farmers adopted CSA practices and in counterfactual cases if they did not adopt CSA practices.

¹¹ For robustness check, we also run multivariate treatment effects regression to examine the impact of CSA practices on farm net returns and risk exposure (Tambo and Mockshell, 2018), and compare the results. The results presented in the Table 3.B9 in the Appendix B are generally consistent with that of MESR. In both of the regression analyses results are in the same direction showing increase in farm net returns and reduction in downside risk exposure of farm households adopting CSA practices.

The results reveal that farmers who adopted seed variety diversification on average earned 16,125 PKR higher farm net returns per acre than their counterparts that did not adopt, resulting in an increase in farm net returns by about 31% for adopters. In the same way, adopters of changing cropping calendar on an average earned 15,212 PKR farm net returns compared to non-adoption, indicating an increase of 29%. Farmers who adopted input mix on average earned 16,185 PKR higher farm net returns compared to non-adoption, indicating a positive change of 31%. These findings are in line with Teklewold et al., (2013), who found that adaptation strategies either in isolation or in combination, significantly improves farm net returns in Ethiopia.

Table 3.5 Overall average treatment effects on the treated

Adaptation strategies	Obs.	Adopters	Non-adopters	ATT	St. Err.	Percent change
		Mean	Mean			
Farm net returns						
Seed variety diver.	98	68.543	52.419	16.125***	(0.700)	30.76
Cropping calendar	106	67.118	51.906	15.212***	(0.567)	29.31
Input mix	84	68.570	52.384	16.185***	(0.649)	30.90
SWC	113	68.810	52.451	16.359***	(0.647)	31.19
Skewness (downside risk exposure)						
Seed variety diver.	98	0.001	-0.001	0.002**	(0.001)	200
Cropping calendar	106	0.002	-0.003	0.005***	(0.001)	167
Input mix	84	0.002	-0.001	0.003**	(0.001)	300
SWC	113	0.003	-0.002	0.005***	(0.001)	250

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

It is obvious from Table 3.5 that downside risk exposure of adopted plots is significantly declined from the adoption of CSA practices. In particular, seed variety diversification reduced the downside risk exposure by 200%, cropping calendar by 167%, changing input mix by 300%, and

soil and water conservation by 250%. These findings signify the role of CSA practices in minimizing the risk exposure of farmers, through a reduction in the probability of crop failure.¹²

Table 3.6 Location-wise average treatment effects on the treated

Zones	Adaptation strategies	Adopters	Non-adopters	ATT	St. Err.	Percent change
		Mean	Mean			
Cotton zone	Seed variety diver.	59.154	42.169	16.985***	(1.399)	40.28
	Cropping calendar	57.314	40.990	16.324***	(1.252)	39.82
	Input mix	57.361	42.485	14.876***	(1.262)	35.01
	SWC	59.811	42.800	17.012***	(1.438)	39.75
Mix zone	Seed variety diver.	62.357	47.698	14.659***	(1.188)	30.73
	Cropping calendar	61.416	47.384	14.032***	(0.910)	29.61
	Input mix	64.353	47.045	17.307***	(1.204)	36.79
	SWC	61.678	45.062	16.616***	(1.339)	36.87
Rice zone	Seed variety diver.	80.447	63.955	16.493***	(1.064)	25.79
	Cropping calendar	79.058	63.596	15.463***	(0.844)	24.31
	Input mix	80.807	64.367	16.440***	(0.946)	25.54
	SWC	79.267	63.487	15.780***	(0.789)	24.86

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

To the extent that cropping zones are heterogeneous in climatic conditions, we further analyze the differential impacts by cropping zones. Table 3.6 shows the ATT results by location of zones. It is clear from the table that cotton zone farmers obtained higher farm net returns in all the CSA practices than the other two climatic zones, except input mix option, which is higher in mix cropping zone. Farmers who adopted input mix as a CSA practice in mix cropping zone earned higher farm net returns than the other two climatic zones. In particular, adoption of seed variety

¹² For the interest of brevity, second stage MESR model results for skewness (downside risk exposure) are given in the Appendix B (See Table 3.B1).

diversification has the highest (40%) positive and significant effect on farm net returns in the cotton zone. Changing input mix in the cotton zone exerts a positive and significant effect on farm net returns by 35%. In the mix cropping zone, soil and water conservation and changing input mix significantly increase farm net returns by 37%, seed variety diversification and changing cropping calendar improve farm net returns by 31% and 30%, respectively. In the rice zone, seed variety diversification, changing cropping calendar, changing input mix and soil and water conservation significantly increase farm net returns by about 26%, 24%, 26%, and 25%, respectively. These results generally indicate that CSA practices can play a significant role in raising farmers' incomes, irrespective of the agroecological location.

As impacts of CSA practices may vary by landholding due to management issues, and cost of implementation of CSA practices, we extended the analysis of ATT by plot-level quantiles. Table 3.7 displays the ATT by quantiles of plot size. Change in input mix and seed variety diversification in the first quantile has the highest positive and significant effect on farm net returns by about 34%. Changing cropping calendar positively and significantly increase the farm net returns by 31%, while soil and water conservation improves the farm net returns positively and significantly by 29%. Soil and water conservation adoption have a lower impact on the lower quantiles, but its impacts for the second and third quantiles are increasing and again lower in the fourth quantile. In the second quantile, changing cropping calendar enhances farm net returns positively and significantly by 31%. The other two CSA practices (seed variety diversification and change in input mix) have positive and significant effect on farm net returns by 28% and 27%, respectively. In the third quantile, SWC measures positively and significantly increased farm net returns by 33%, while changing input mix has a positive and significant effect (32%) on farm net returns, followed by seed variety diversification which is 30%, and changing cropping calendar positively and significantly influences the farm net returns by 26%. In the fourth quantile, adopters of seed variety diversification earn the highest (31%) positive and significant farm net returns, followed

by soil and water conservation which is also positive and significant (30%). Changing cropping calendar and input mix has a positive and significant impact on farm net returns by about 29%. These findings suggest that promotion and upscaling of CSA practices should take into consideration heterogeneities in farm size distribution as impacts of adoption differ based on quantiles of plot sizes.

Table 3.7 Quantile-wise average treatment effects on the treated

Quantiles	Adaptation strategies	Adopters	Non-adopters	ATT	St. Err.	Percent change
		Mean	Mean			
1st quantile	Seed variety diver.	72.298	54.045	18.253***	(1.203)	33.77
	Cropping calendar	77.264	58.871	18.394***	(1.216)	31.24
	Input mix	75.616	56.236	19.380***	(1.184)	34.46
	SWC	73.067	56.718	16.349***	(1.319)	28.83
2nd quantile	Seed variety diver.	71.303	55.830	15.474***	(1.680)	27.72
	Cropping calendar	70.115	53.626	16.489***	(0.873)	30.75
	Input mix	70.197	55.066	15.131***	(1.413)	27.48
	SWC	70.642	53.309	17.334***	(1.034)	32.52
3rd quantile	Seed variety diver.	69.114	53.257	15.857***	(1.396)	29.77
	Cropping calendar	65.178	51.645	13.533***	(1.140)	26.20
	Input mix	68.423	51.913	16.510***	(1.234)	31.80
	SWC	66.427	49.964	16.464***	(1.683)	32.95
4th quantile	Seed variety diver.	60.201	46.050	14.151***	(1.274)	30.73
	Cropping calendar	58.009	44.908	13.101***	(1.008)	29.17
	Input mix	60.503	46.719	13.784***	(1.129)	29.50
	SWC	63.401	48.614	14.787***	(1.381)	30.42

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

3.5. Conclusion and policy implications

This paper examined the drivers of adoption of different climate-smart agricultural (CSA) practices (changing cropping calendar, diversifying seed variety, changing input mix and soil and water conservation), and the impact of adoption of these practices on farm net returns and downside risk exposure. The study utilized recent cross-sectional plot-level data of multi-product farmers collected from three important cropping zones of Province Punjab, Pakistan between January and March 2017 from a randomly selected sample of 540 farm households cultivating 748 agricultural plots. We employed the multinomial endogenous switching regression (MESR) for the analysis as the model corrects for selection bias correction among all alternate choices in a multinomial setting. The results revealed that the choice of seed variety diversification as a climate-smart agricultural strategy was positively and significantly influenced by average rainfall, ownership of agricultural machinery, extension services, and previous experience to climate-related shocks. The choice of changing cropping calendar was positively and significantly associated with average rainfall, education of household head, ownership of agricultural machinery, and exposure to previous climate-related shocks. The choice of input mix was positively and significantly influenced by the average rainfall, education of the household head, plot size and having agricultural machinery at the farm. The choice of soil and water conservation was positively and significantly determined by average rainfall, rainfall anomaly, household head's education, ownership of agricultural machinery, and previous climate-related shocks.

Concerning the factors that influence the selection of CSA practices toward farm net returns, we observed that seed variety diversification was positively and significantly influenced by extension services, location of the farm and soil fertility while changing cropping calendar was positively affected by agricultural machinery, extension services and the location of the farm. Furthermore, input mix was positively affected by extension services and soil and water conservation was positively influenced by extension services and the location of farm. The results further

demonstrated that soil and water conservation as a CSA practice exerted the highest positive influence on farm net returns, followed by input mix, diversifying seed variety, and changing cropping calendar, respectively. The findings also revealed that all the CSA practices significantly reduced downside risk exposure and therefore reduced the probability of crop failure of farm households. The findings also showed differences in the impacts of adoption of CSA practices by cropping zones. While in the cotton zone, adoption of seed variety diversification resulted in the highest impact on farm net returns, it is the adoption of soil and water conservation measures that yielded the greatest impact on farm net returns in the mixed cropping zone. The implication of this finding is that the promotion of CSA practices should consider the agro-ecology or cropping zone to yield higher farm net returns. Also plot level quantiles results show that there exists heterogeneity in farm sizes distribution as impacts differ based on quantile of plot sizes.

Overall, the findings showed that CSA practices can help in reducing the adverse impacts of climate change and should therefore be promoted across the country. The policy implication is that promoting and scaling up the adoption of CSA practices could help farmers raise their incomes and reduce their exposure to crop failure and income falls. Therefore, CSA practices should be promoted across the farmers in the country, either in isolation or in a combination of these practices. Furthermore, policies that enhance access to extension services and access to credit and education, as well as timely information on climate change would facilitate the adoption of CSA practices and contribute to improving rural farm household welfare. Hence, policymakers could promote effective measures to enhance farmers' access to credit and extension services. In particular, enhancing farmers' knowledge and skills through better training would help in facilitating adoption of CSA practices and raising farm incomes. The significance of education in the adoption results indicates that the provision of schools in remote areas could enhance the education level of rural farm households for a better understanding of modern technology adoption. A high correlation between information related to climate change and the adoption of

CSA practices suggests that the provision of timely information on climate change to the farmers can also enhance the adoption rates. As agricultural machinery and input mix contribute to enhancing the adoption rate of CSA practices, policymakers could promote microfinance or subsidy schemes to help farmers to purchase agricultural machinery and inputs. In the study area, farmers also complained about the bad marketing channels when they sell their produce because no regulated agricultural markets exists in the country that imbalance supply and demand causing volatility in output prices such as low prices in the harvest season and high seed prices at the sowing time. The food storage facilities are also limited due to which farmers are forced to sell at low prices, however, a significant amount of agricultural produce is left to spoil and destroyed. Therefore, the government of Pakistan would facilitate farmers through support price, marketing and storage facilities in the country.

References

- Abdulai, A. (2018). Simon brand memorial Address: the challenges and adaptation to climate change by farmers in Sub-Saharan Africa. *Agrekon*, 57(1), 28-39.
- Abdulai, A., & Huffman, W. E. (2005). The diffusion of new agricultural technologies: The case of crossbred-cow technology in Tanzania. *American Journal of Agricultural Economics*, 87(3), 645-659.
- Abdulai, A., & Huffman, W., (2014). The adoption and impact of soil and water conservation technology: An endogenous switching regression application. *Land Economics*, 90(1), 26-43.
- Abid, M., Schilling, J., Scheffran, J., & Zulfiqar, F., (2016a). Climate change vulnerability, adaptation and risk perceptions at farm level in Punjab, Pakistan. *Science of the Total Environment*, 547, 447-460.
- Abid, M., Schneider, U. A., & Scheffran, J. (2016b). Adaptation to Climate Change and Its Impacts on Food Productivity and Crop Income: Perspectives of Farmers in Rural Pakistan, *Journal of Rural Studies*, 47, Part A, 254-266.
- Ali, A., & Erenstein, O. (2017). Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Climate Risk Management*, 16, 183-194.
- Ali, S. M., Khan, A. N., & Shakeel, H. (2019). Climate Adaptation Governance in Pakistan. In Oxford Research Encyclopedia of Natural Hazard Science.
- Almlund, M., Duckworth, A. L., Heckman, J., & Kautz, T. (2011). Personality psychology and economics. In *Handbook of the Economics of Education* (Vol. 4, pp. 1-181). Elsevier.
- Antle, J. M., 1983. Testing the stochastic structure of production: a flexible moment-based approach. *Journal of Business & Economic Statistics*, 1(3), 192-201.

- Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., Cattaneo, A. and Kokwe, M. (2015). Climate-smart agriculture? Assessing the adaptation implications in Zambia. *Journal of Agricultural Economics*, 66(3), pp.753-780.
- Beddington, J. R. (2011). The future of food and farming: Challenges and choices for global sustainability;[final project report of the UK government foresight global food and farming futures]. Government Office for Science.
- Bourguignon, F., Fournier, M., & Gurgand, M. (2007). Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons. *Journal of Economic Surveys*, 21(1), 174-205.
- Cawley, A., O'donoghue, C., Heanue, K., Hilliard, R., & Sheehan, M. (2018). The impact of extension services on farm-level income: An instrumental variable approach to combat endogeneity concerns. *Applied Economic Perspectives and Policy*, 40(4), 585-612.
- Dahl, G. B. (2002). Mobility and the return to education: Testing a Roy model with multiple markets. *Econometrica*, 70(6), 2367-2420.
- Delavande, A., Giné, X., & McKenzie, D. (2011). Measuring subjective expectations in developing countries: A critical review and new evidence. *Journal of Development Economics*, 94, 151–163.
- Deressa, T. T., Hassan, R. M., & Ringler, C. (2011). Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *The Journal of Agricultural Science*, 149(1), 23-31.
- Di Falco, S., M. Veronesi, and M. Yesuf. (2011). Does Adaptation to Climate Change Provide Food Security? A Micro-perspective from Ethiopia. *American Journal of Agricultural Economics* 93 (3): 829–46.
- Di Falco, S., & Chavas, J. P. (2009). On crop biodiversity, risk exposure, and food security in the

- highlands of Ethiopia. *American Journal of Agricultural Economics*, 91(3), 599-611.
- Di Falco, S., & Veronesi, M. (2013). How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia. *Land Economics*, 89(4), 743-766.
- Di Falco, S., & Veronesi, M. (2014). Managing environmental risk in presence of climate change: the role of adaptation in the Nile Basin of Ethiopia. *Environmental and Resource Economics*, 57(4), 553-577.
- Dubin, J. A., & McFadden, D. L. (1984). An econometric analysis of residential electric appliance holdings and consumption. *Econometrica: Journal of the Econometric Society*, 345-362.
- FAO (2004). Fertilizer Use by Crop in Pakistan. Land and Plant Nutrition Management Service. Land and Water Development Division. Food and Agriculture Organization of the United Nations, Rome.
- FAO (2011). Global food losses and food waste – Extent, causes and prevention. Food and Agriculture Association of the United Nations (FAO, Rome).
- FAO (2013). Climate-Smart Agriculture Sourcebook. Food and Agriculture Organization, Rome.
- FAO (2019). Climate-Smart Agriculture for Punjab, Pakistan. Food and Agricultural Organization (FAO), DOI: 10.13140/RG.2.2.25544.78083
- Gabel, M., and Scheve, K. (2007). Estimating the Effect of Elite Communications on Public Opinion Using Instrumental Variables. *American Journal of Political Science* 51: 1013–28.
- Gicheru, P., Gachene, C., Mbuvi, J., & Mare, E. (2004). Effects of soil management practices and tillage systems on surface soil water conservation and crust formation on a sandy loam in semi-arid Kenya. *Soil and Tillage Research*, 75(2), 173-184.
- Groom, B., Koundouri, P., Nauges, C., & Thomas, A. (2008). The story of the moment: risk-

- averse Cypriot farmers respond to drought management. *Applied Economics*, 40(3), 315-326.
- Hansen, J., Hellin, J., Rosenstock, T., Fisher, E., Cairns, J., Stirling, C., Lamanna, C., van Etten, J., Rose, A. and Campbell, B. (2019). Climate risk management and rural poverty reduction. *Agricultural Systems*, 172, 28-46.
- Heckman, J., Tobias, J. L., & Vytlačil, E. (2001). Four parameters of interest in the evaluation of social programs. *Southern Economic Journal*, 211-223.
- Hudson, N. (1987). Soil and water conservation in semi-arid areas (No. 57). Food & Agriculture Organization FAO, Rome Italy.
- Huffman, W. E. (2020). Human Capital and Adoption of Innovations: Policy Implications. *Applied Economic Perspectives and Policy*, 42(1), 92-99.
- IPCC (2007). Climate Change 2007: Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.
- IPCC (2012). Managing the risks of extreme events and disasters to advance climate change adaptation. In: A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (eds CB Field, V Barros, TF Stocker et al.), Cambridge University Press, Cambridge, NY, USA.
- IPCC (2013). Fifth Assessment Report on Climate Change. Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.
- IPCC (2014). Climate Change: Impacts, Adaptation, and Vulnerability, Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.
- Iqbal, M., Ahmad, M., & Mustafa, G. (2015). Impact of Farm Households' Adaptation on Agricultural Productivity: Evidence from Different Agro-ecologies of Pakistan.

- Issahaku, G., & Abdulai, A. (2019). Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana. *Australian Journal of Agricultural and Resource Economics*, 59, 1-25.
- Janjua, P. Z., Samad, G. and Khan, N. U. (2010). Impact of Climate Change on Wheat Production: A Case Study of Pakistan. *The Pakistan Development Review* 49(4): 799–822.
- Kassie, G. T., Abdulai, A., Greene, W. H., Shiferaw, B., Abate, T., Tarekegne, A., & Sutcliffe, C. (2017). Modeling preference and willingness to pay for drought tolerance (DT) in maize in rural Zimbabwe. *World Development*, 94, 465-477.
- Kassie, M., Jaleta, M., & Mattei, A. (2014). Evaluating the impact of improved maize varieties on food security in Rural Tanzania: Evidence from a continuous treatment approach. *Food Security*, 6(2), 217-230.
- Khanal, U., Wilson, C., Lee, B. L., & Hoang, V. N. (2018). Climate change adaptation strategies and food productivity in Nepal: a counterfactual analysis. *Climatic change*, 148(4), 575-590.
- Kim, K., & Chavas, J. P. (2003). Technological change and risk management: an application to the economics of corn production. *Agricultural economics*, 29(2), 125-142.
- Lee, L. F. (1983). Generalized econometric models with selectivity. *Econometrica: Journal of the Econometric Society*, 507-512.
- Mukasa, A. N. (2018). Technology adoption and risk exposure among smallholder farmers: Panel data evidence from Tanzania and Uganda. *World Development*, 105, 299-309.
- Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica*, 46:69-85.
- Murtazashvili, I., & Wooldridge, J. M. (2016). A control function approach to estimating switching regression models with endogenous explanatory variables and endogenous

- switching. *Journal of econometrics*, 190(2), 252-266.
- Paudel, B., Zhang, Y., Yan, J., Rai, R., Li, L., Wu, X., Chapagain, P. S., & Khanal, N. R. (2019). Farmers' understanding of climate change in Nepal Himalayas: important determinants and implications for developing adaptation strategies. *Climatic Change*, 1-18.
- Sabiha, N. E., Salim, R. & Rahman, S. (2017). Eco-efficiency of high-yielding variety rice cultivation after accounting for on-farm environmental damage as an undesirable output: an empirical analysis from Bangladesh, *Australian Journal of Agricultural and Resource Economics*, 61:247-264.
- Salman, A., Husnain, M. I., Jan, I., Ashfaq, M., Rashid, M., & Shakoor, U. (2018). Farmers' Adaptation to Climate Change in Pakistan: Perceptions, Options and Constraints. *Sarhad Journal of Agriculture*, 34(4), 963-972.
- Shahzad, M. F., & Abdulai, A. (2019). Production Risk Management in Agriculture and Farm Performance in Rural Pakistan: Role of Adaptation to Climate Change. *In 2019 Annual Meeting, July 21-23, Atlanta, Georgia* (No. 291283). Agricultural and Applied Economics Association.
- Shahzad, M. F., & Abdulai, A. (2020). Adaptation to extreme weather conditions and farm performance in rural Pakistan. *Agricultural Systems*, 180, 102772.
- Shannon, H. D., & Motha, R. P. (2015). Managing weather and climate risks to agriculture in North America, Central America and the Caribbean. *Weather and Climate Extremes*, 10, 50-56.
- Soglo, Y.Y., Nonvide, G.M.A. (2019). Climate change perceptions and responsive strategies in Benin: the case of maize farmers. *Climatic Change* 155, 245–256.
- Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of agricultural economics*, 64(3), 597-623.

- Tessema, Y., Asafu-Adjaye, J., Rodriguez, D., Mallawaarachchi, T., & Shiferaw, B. (2015). A bio-economic analysis of the benefits of conservation agriculture: The case of smallholder farmers in Adami Tulu district, Ethiopia. *Ecological Economics*, 120, 164-174.
- Tambo, J. A., & Mockshell, J. (2018). Differential impacts of conservation agriculture technology options on household income in Sub-Saharan Africa. *Ecological economics*, 151, 95-105.
- Tubiello, F., Schmidhuber, J., Howden, M., Neofotis, P. G., Park, S., Fernandes, E., & Thapa, D. (2008). Climate change response strategies for agriculture: challenges and opportunities for the 21st century. *Agriculture and rural development discussion paper*, 42.
- Vale, P. M. (2016). The changing climate of climate change economics. *Ecological Economics*, 121, 12–19.
- Veetil, P. C., Krishna, V. V. & Qaim, M. (2016). Ecosystem impacts of pesticide reductions through Bt cotton adoption, *Australian Journal of Agricultural and Resource Economics*, 61: 115–134.
- Wolkovich, E. M., Cook, B. I., Allen, J. M., Crimmins, T. M., Betancourt, J. L., Travers, S. E., Pau, S., Regetz J., Davies, T.J., Kraft, N.J.B., Ault, T.R., Bolmgren, K., Mazer, S.J., McCabe, G.J., McGill, B.J., Parmesan C., Salamin, N., Schwartz, M.D. and Cleland, E. E. (2012). Warming experiments underpredict plant phenological responses to climate change. *Nature*, 485(7399), 494-497.
- Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data* MIT Press. Cambridge, MA, 108.
- World Bank. (2010). *Economics of adaptation to climate change - Synthesis report (English)*. Washington, DC: World Bank.

Appendix B

Table 3.B1 Impact of CSA practices on risk exposure, second stage MESR estimation

Variables	Non-adaptation		Seed variety diver.		Cropping Calendar		Input mix		SWC	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
Constant	0.03628	(0.26823)	0.29792	(0.25590)	0.19908	(0.42937)	0.19706	(0.31410)	0.02621	(0.24854)
Credit_const	-0.00323	(0.00992)	0.00530	(0.01140)	-0.01619	(0.03432)	-0.00376	(0.02376)	-0.01794	(0.01351)
Avg_Tem	0.00043	(0.00908)	-0.01018	(0.00862)	-0.00594	(0.01453)	-0.00538	(0.01017)	0.00209	(0.00841)
Avg_Rain	0.06378	(0.19669)	0.09471	(0.15378)	0.32194	(0.34441)	-0.00527	(0.25039)	-0.01252	(0.19403)
int_TxR	-0.00253	(0.00830)	-0.00478	(0.00634)	-0.01321	(0.01406)	-0.00024	(0.01022)	0.00116	(0.00797)
Tem_anomaly	-0.14928	(0.09828)	0.01656	(0.05081)	0.13051	(0.15198)	-0.16041	(0.12002)	-0.15006	(0.13445)
Rain_anomaly	0.00168	(0.01073)	0.00247	(0.01164)	0.02728	(0.01827)	-0.02207	(0.01525)	-0.04345**	(0.01811)
HH_age	-0.00010	(0.00009)	-0.00004	(0.00008)	0.00005	(0.00013)	-0.00011	(0.00011)	-0.00018	(0.00011)
Family size	-0.00002	(0.00045)	0.00016	(0.00045)	0.00001	(0.00067)	0.00009	(0.00058)	-0.00020	(0.00057)
Education	-0.00210**	(0.00105)	-0.00049	(0.00054)	-0.00231*	(0.00128)	-0.00100	(0.00086)	-0.00161**	(0.00079)
Plot size	0.00115**	(0.00052)	-0.00037	(0.00025)	-0.00094	(0.00087)	0.00031	(0.00053)	0.00002	(0.00045)
Animal	-0.00110	(0.00092)	0.00000	(0.00046)	0.00010	(0.00095)	-0.00002	(0.00058)	0.00001	(0.00062)
Machinery	-0.00106	(0.00460)	0.00153	(0.00206)	0.00198	(0.00573)	-0.00868**	(0.00387)	-0.00678**	(0.00277)
Ext_services	0.02283*	(0.01340)	-0.00529	(0.00863)	-0.00166	(0.01410)	0.01553	(0.01243)	0.01423	(0.01311)
cc_shock	-0.00807	(0.00557)	0.00157	(0.00315)	0.00237	(0.01024)	0.00539	(0.00752)	0.00957**	(0.00446)
Xcotton	-0.00419	(0.00697)	0.00680	(0.00739)	0.01028	(0.01513)	-0.00646	(0.00997)	-0.01344	(0.00977)
Xrice	0.00255	(0.00630)	0.00606	(0.00637)	0.00538	(0.01143)	-0.00010	(0.00804)	-0.01207	(0.00759)
Fertility	0.00096	(0.00256)	0.00302	(0.00353)	0.01051*	(0.00628)	-0.00270	(0.00474)	-0.00272	(0.00373)
Erosion	-0.00024	(0.00421)	-0.00480	(0.00414)	-0.01328	(0.00927)	0.00939	(0.00650)	0.00485	(0.00571)
Plot_distance	-0.00251**	(0.00126)	0.00061	(0.00086)	0.00133	(0.00166)	-0.00076	(0.00110)	-0.00297***	(0.00098)
_m1	0.00659	(0.01015)	0.00220	(0.00923)	0.01090	(0.01447)	-0.00335	(0.01067)	0.01360	(0.00941)
_m2	0.00896	(0.02426)	-0.00075	(0.00460)	-0.00991	(0.02010)	-0.00155	(0.01673)	0.03175**	(0.01574)
_m3	0.02590	(0.04804)	-0.02589*	(0.01572)	-0.00600	(0.00889)	0.04198**	(0.01998)	0.05874***	(0.01993)
_m4	-0.00280	(0.03785)	-0.00984	(0.01522)	0.00072	(0.02034)	-0.00564	(0.00705)	-0.00568	(0.01738)
_m5	0.01021	(0.04610)	0.02607*	(0.01411)	0.04839	(0.04580)	-0.04882**	(0.02201)	-0.01214*	(0.00695)

Note: The dependent variable is the skewness i.e. third central moment of net returns function. Bootstrapped standard errors are in parentheses. The reference region is a mix-cropping zone.

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

Table 3.B2 Test on the validity of selection and potential endogenous variable instruments (Farm net returns)

Net_returns	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]
cc_info	-0.071	5.291	-0.01	0.989	-10.477	10.336
cc_perception	1.344	5.037	0.27	0.790	-8.563	11.252
dis_Ext_off	-0.053	0.220	-0.24	0.810	-0.485	0.379
Relativ_bank	-1.276	3.054	-0.42	0.676	-7.283	4.732
Constant	48.969***	2.097	23.36	0.000	44.845	53.092
Mean dependent var		48.442	SD dependent var			13.749
R-squared		0.001	Number of obs			351.000
F-test		0.073	Prob > F			0.990
Akaike crit. (AIC)		2844.693	Bayesian crit. (BIC)			2863.997

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.B3 Test on the validity of selection and potential endogenous variable instruments (Skewness)

Skewness	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]
cc_info	0.002	0.006	0.32	0.750	-0.010	0.014
cc_perception	-0.003	0.006	-0.45	0.652	-0.014	0.009
dis_Ext_off	0.000	0.000	0.00	0.997	-0.001	0.001
Relativ_bank	0.001	0.004	0.25	0.799	-0.006	0.008
Constant	-0.005*	0.002	-1.86	0.064	-0.010	0.000
Mean dependent var		-0.005	SD dependent var			0.016
R-squared		0.001	Number of obs			351.000
F-test		0.084	Prob > F			0.987
Akaike crit. (AIC)		-1884.099	Bayesian crit. (BIC)			-1864.795

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.B4 Parameters estimates of net returns function

Net returns	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]
Credit_const	-0.10351***	0.01421	-7.29	0.000	-0.131	-0.076
Avg_Tem	-0.07815*	0.04652	-1.68	0.093	-0.169	0.013
Avg_Rain	2.87233**	1.28931	2.23	0.026	0.341	5.404
int_TxR	-0.12055**	0.05383	-2.24	0.025	-0.226	-0.015
tem_anomaly	3.48012***	1.18309	2.94	0.003	1.157	5.803
rain_anomaly	-1.58543***	0.56263	-2.82	0.005	-2.690	-0.481
TXR	7.65604***	2.59287	2.95	0.003	2.566	12.747
HH_age	0.00008	0.00044	0.19	0.853	-0.001	0.001
familysize	-0.00128	0.00269	-0.47	0.635	-0.007	0.004
Education	0.02845***	0.00184	15.49	0.000	0.025	0.032
plot_size	-0.00277	0.00199	-1.39	0.165	-0.007	0.001
no_of_animal	0.00519*	0.00302	1.72	0.086	-0.001	0.011
Ext_services	0.12373***	0.01294	9.56	0.000	0.098	0.149
Clay_soil	-0.02816*	0.01491	-1.89	0.059	-0.057	0.001
Sandy_soil	-0.02446	0.01559	-1.57	0.117	-0.055	0.006
cc_shock	-0.06866***	0.01296	-5.30	0.000	-0.094	-0.043
Xcotton	-0.05897*	0.03385	-1.74	0.082	-0.125	0.007
Xrice	0.16790***	0.03871	4.34	0.000	0.092	0.244
Machinery	0.09475***	0.01319	7.18	0.000	0.069	0.121
Fertilizers	0.00000*	0.00000	-1.84	0.066	-0.000	0.000
pesticides	0.00000	0.00000	0.40	0.687	0.000	0.000
seed	0.00002***	0.00000	6.42	0.000	0.000	0.000
labour	0.00000	0.00000	0.25	0.800	0.000	0.000
irrigation	0.00001***	0.00000	3.01	0.003	0.000	0.000
manure	0.00000	0.00001	-0.46	0.642	-0.000	0.000
plowing	0.00000	0.00000	-0.79	0.431	-0.000	0.000
Constant	12.27207***	1.24618	9.85	0.000	9.825	14.719
Mean dependent var		10.94015	SD dependent var			0.31697
R-squared		0.84266	Number of obs			748.00000
F-test		148.51127	Prob > F			0.00000
Akaike crit. (AIC)		-926.40390	Bayesian crit. (BIC)			-801.73402

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.B5 Parameter estimates of potential endogenous variable credit constraint

Credit cons	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]
Avg_Tem	0.385	0.523	0.74	0.462	-0.640	1.409
Avg_Rain	21.289**	9.227	2.31	0.021	3.205	39.374
int_TxR	-0.779**	0.390	-2.00	0.046	-1.543	-0.015
tem_anomaly	-3.887	4.256	-0.91	0.361	-12.229	4.455
rain_anomaly	-0.457	0.562	-0.81	0.416	-1.558	0.644
HH_age	-0.003	0.006	-0.53	0.594	-0.015	0.009
familysize	-0.015	0.039	-0.38	0.705	-0.090	0.061
Education	-0.085***	0.025	-3.45	0.001	-0.133	-0.037
plot_size	0.028	0.023	1.22	0.221	-0.017	0.074
no_of_animal	-0.055	0.038	-1.46	0.144	-0.129	0.019
Ext_services	-1.034***	0.187	-5.53	0.000	-1.400	-0.668
Clay_soil	0.262	0.227	1.16	0.248	-0.182	0.707
Sandy_soil	0.080	0.205	0.39	0.697	-0.322	0.482
cc_shock	0.865***	0.143	6.03	0.000	0.584	1.146
Xcotton	-0.884**	0.448	-1.97	0.049	-1.763	-0.005
Xrice	-0.320	0.353	-0.91	0.366	-1.012	0.373
Relativ_bank	-0.714**	0.317	-2.25	0.024	-1.335	-0.093
Constant	-9.820	15.214	-0.65	0.519	-39.640	20.000
Mean dependent var		0.282	SD dependent var			0.450
Pseudo r-squared		0.440	Number of obs			748.000
Chi-square		391.808	Prob > chi2			0.000
Akaike crit. (AIC)		534.181	Bayesian crit. (BIC)			617.294

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.B6 Parameter estimates of of potential endogenous variable extension services

Ext_services	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]
CreditConstant	-1.046***	0.195	-5.36	0.000	-1.429	-0.664
Avg_Tem	0.104	0.444	0.23	0.815	-0.767	0.974
Avg_Rain	2.285	7.989	0.29	0.775	-13.373	17.944
int_TxR	-0.049	0.339	-0.14	0.886	-0.713	0.616
tem_anomaly	6.120	4.318	1.42	0.156	-2.343	14.583
rain_anomaly	-0.627	0.588	-1.06	0.287	-1.780	0.526
HH_age	0.005	0.005	0.99	0.324	-0.005	0.016
familysize	-0.021	0.032	-0.67	0.505	-0.084	0.041
Education	0.185***	0.021	8.82	0.000	0.144	0.226
plot_size	-0.057**	0.024	-2.40	0.016	-0.103	-0.010
no_of_animal	0.020	0.034	0.58	0.563	-0.047	0.086
Clay_soil	0.133	0.177	0.75	0.452	-0.213	0.479
Sandy_soil	-0.224	0.200	-1.12	0.264	-0.617	0.169
cc_shock	-0.155	0.162	-0.96	0.339	-0.472	0.162
Xcotton	-0.450	0.381	-1.18	0.238	-1.196	0.296
Xrice	-0.397	0.316	-1.25	0.209	-1.016	0.223
dis_Ext_off	-0.048**	0.021	-2.29	0.022	-0.090	-0.007
Constant	-5.544	13.229	-0.42	0.675	-31.472	20.384
Mean dependent var		0.386	SD dependent var			0.487
Pseudo r-squared		0.347	Number of obs			748.000
Chi-square		346.715	Prob > chi2			0.000
Akaike crit. (AIC)		687.257	Bayesian crit. (BIC)			770.370

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.B7 Suest-based Hausman tests of IIA assumption

Ho: Odds (Outcome- j vs Outcome- k) are independent of other alternatives.

CSA practices Choices	chi2	df	P>chi2
Non-adaptation	30.704	72	1.000
Seed variety diver.	39.385	72	0.999
Cropping calendar	38.224	72	1.000
Input mix	34.986	72	1.000
SWC	42.231	72	0.998

Note: A significant test is evidence against Ho.

Table 3.B8 Correlation matrix

	Skewness	Net_returns	dis_Ext_office	Rel_bank	cc_info	cc_perception
Skewness	1.0000					
Net_returns	0.3425	1.0000				
dis_Ext_office	0.0003	-0.0152	1.0000			
Rel_bank	0.0086	-0.0215	0.1019	1.0000		
cc_info	0.0171	0.0007	-0.0628	-0.0378	1.0000	
cc_perception	-0.0224	0.0101	0.0094	0.1910	-0.0218	1.0000

Table 3.B9 Robustness checks

Treatment effects of adoption on farm net returns and downside risk exposure: multivariate treatment effect regression

CSA practices	Obs.	Adopters	Non-adopters	ATT	St. Err.	%age change
		Mean	Mean			
Farm net returns						
Seed variety diver.	98	68.543	58.572	9.971***	1.593	17.02
Cropping calendar	106	69.019	58.572	10.447***	1.581	17.84
Input mix	84	69.559	58.572	10.987***	1.713	18.76
Soil and water conservation	113	69.940	58.572	11.368***	1.688	19.41
Skewness						
Seed variety diver.	98	0.002	-0.007	0.002***	(0.001)	128.57
Cropping calendar	106	0.005	-0.007	0.005***	(0.001)	171.43
Input mix	84	0.002	-0.007	0.003***	(0.001)	128.57
Soil and water conservation	113	0.004	-0.007	0.005***	(0.001)	157.14

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

Chapter 4

The Heterogeneous Effects of Adoption of Climate-Smart Agriculture on Household Welfare in Pakistan

Muhammad Faisal Shahzad and Awudu Abdulai

Department of Food Economics and Consumption Studies

Published in Applied Economics (Volume 52, 2020).

Abstract

In this study, we analyze the heterogeneity in the impacts of adoption of climate-smart agricultural (CSA) practices on welfare indicators such as food and nutrition security and poverty reduction in Pakistan. We employ the marginal treatment effects (MTE) approach to estimate the treatment effects heterogeneity and policy-relevant treatment effects (PRTE). The findings show substantial heterogeneity in benefits from adoption of CSA with respect to both observed and unobserved household characteristics. In particular, the estimates show that households with higher unobserved benefits are more likely to adopt CSA practices. The empirical results show that adoption of CSA practices significantly reduces household food insecurity and increases household dietary diversity but reduces the poverty headcount and severity of poverty of the households at the lower level of unobserved resistance to adoption. The PRTE indicate that sources of climate change information and climate-resilient trainings could help to reduce rural poverty and improve food and nutrition security in Pakistan.

Keywords: Climate-smart agriculture, food and nutrition security, poverty reduction, marginal treatment effects, Pakistan.

JEL Codes: Q18, I32, Q54, C36, O33, D13.

4.1. Introduction

Climate change and variability continue to undermine national and global efforts to achieve poverty reduction and food security, particularly among vulnerable populations in developing countries. Many studies on climate change impacts indicate that rural populations in developing countries are the most vulnerable because of their dependence on rainfed agriculture as a source of livelihood (e.g., Barbier and Hochard, 2018; Tol, 2018). Most of these countries, which are mainly agrarian, have adapted to changing climate to enable them feed their growing populations to sustain livelihoods. In particular, the achievement of some of the sustainable development goals (SDGs) that involve no poverty, zero hunger, climate action, sustainable cities, and communities, relies heavily on fostering climate-smart food systems to feed the growing global population, providing secure livelihoods and consuming natural resources (World Bank, 2015).

Many studies project that if no mitigation or adaptation strategies are adopted, global poverty could increase by 35 to 122 million under climate change scenarios, mainly from decreasing agricultural incomes and reductions in the growth of GDP (FAO, 2016). For example, Hertel et al. (2010) report that a decrease in crop yields would lead to increases in prices of major food staples by 10-60% in 2030. A study by Earls (2019) argues that the number of malnourished children could increase as a result of climate change. The diverse effects of climate change, such as increasing heat stress, decreasing cold stress, worsening drought, crops growing faster as a result of carbon dioxide fertilization, often make it difficult to quantify the impacts (Tol, 2018). Therefore, researchers try to focus on welfare indicators such as production efficiency, income, poverty reduction, and food security (Khanal et al. 2018; Barbier and Hochard, 2018; Badibanga and Ulimwengu, 2020).

The variation of climate change across the globe also implies that the impact of adaptation to climate change and, for that matter, effects of climate-smart agricultural (CSA) practices on welfare will vary across the globe. The FAO (2013) identified the CSA practices as the surest way to sustainable agricultural development for food security under climate change impacts.

According to FAO (2013), CSA employs sustainable land management practices together with drought-tolerant varieties with the aim of enhancing farmers' ability to adapt to a changing climate, as well as mitigation of greenhouse gas emissions, and sustainably increasing agricultural productivity and food security. Despite the advantages of CSA in helping farmers adapt to the adverse effects of climate change, there are profitable trade-offs such as slower productivity growth and lower emissions between the goals of CSA (World Bank, 2015). To minimize these trade-offs and to ensure positive outcomes for the three goals of food security, adaptation, and mitigation, CSA seeks to contribute to broader development goals (Tol, 2018; World Bank, 2015; Vale, 2016). In particular, previous literature shows that farm households have adopted different adaptation strategies such as CSA practices, including changing input mix, change in cropping calendar, crop diversification, crop rotation, diversifying seed varieties, soil and water conservation, using improved seed variety, improving irrigation efficiency, and income diversification (Abdulai, 2018; Di Falco and Veronesi, 2013; Issahaku and Abdulai, 2019). Some of the practices mentioned above have already been employed by farmers in combination or isolation to enhance farm production. Some studies refer to these practices as adaptation strategies (e.g., Iqbal et al. 2015; Di Falco and Veronesi, 2013); other studies call them climate-smart practices (e.g., Teklewold et al., 2019; Issahaku and Abdulai, 2020).

Many studies have analyzed the drivers and impacts of adoption of CSA over the past decade (e.g., Abdulai and Huffman, 2014; Di Falco et al., 2011; Bocchiola et al., 2019; Lipper et al., 2014; Michler et al., 2019; Mutenje et al., 2019). The impacts are normally categorized into direct and indirect economic impacts. The direct impacts refer to the benefits attributed to the application of specific CSA practices (such as adoption of conservation agricultural practices and drought-tolerant varieties, etc.) at farm and household levels, while the indirect impacts include the enhancement of carbon sinks and carbon dioxide (CO₂) sequestration processes. In this study, we focus on the direct impacts of CSA, which is on the welfare of farm households. The empirical evidence on the direct impacts of CSA suggests that these adaptation strategies could play a crucial

role in the achievement of SDG's in reducing hunger, improving food security, and conserving natural resources (Iqbal et al. 2015; Abid et al. 2016; Ali and Erenstein, 2017; Issahaku and Abdulai, 2019; Dakpo et al., 2019; Salim et al., 2020, etc.). A study by Issahaku and Abdulai (2019) on Ghana concluded that adoption of CSA practices increased food and nutrition security of smallholder farmers, while Abid et al. (2016) found that wheat productivity and crop income increased as a result of adoption of CSA practices by farmers in Pakistan.

The studies outlined above-employed methods like propensity score matching (PSM), Heckman's treatment effect model or the endogenous switching regression (ESR) approaches to analyze the impact of adoption of CSA practices on farm performance and household welfare (e.g., Ali and Erenstein, 2017; Iqbal et al., 2015; Issahaku and Abdulai, 2020; Shahzad and Abdulai, 2020). The shortcomings of the PSM approach has been widely documented in the literature (e.g., Di Falco et al. 2011; Abdulai and Huffman, 2014). Heckman's treatment effect model is estimated in two steps, whereby a notable shortcoming of two-step estimation is that it generates the heteroskedastic residuals that cannot be used to obtain consistent standard errors without adjustments (Lokshin and Sajaia, 2004). Although the ESR model accounts for both observable and unobservable factors, its critical limitation is that it accounts for selection bias by aggregating the unobservable heterogeneity, but this heterogeneity actually varies across individuals (Cornelissen et al., 2016).

To account for heterogeneity across households, the present study contributes to the literature by employing the marginal treatment effects (MTE) approach to examine the drivers and impact of adoption of CSA practices on household welfare outcomes such as food and nutrition security, poverty, and severity of poverty using recent data from 540 farmers from Pakistan. We use household dietary diversity score (HDDS) and household food insecurity access scale (HFIAS) to capture food and nutrition security (Swindale and Bilinsky, 2006; Coates et al., 2007), and then the poverty headcount and poverty gap to measure the poverty status of farm households. The MTE approach takes into account both observable and unobservable factors influencing adoption

of CSA practices based on propensity scores and draws the MTE curve against varying levels of unobservable resistance to CSA adoption. The approach further allows us to estimate the treatment effect heterogeneities, and also simulate the effects of policy changes on the welfare indicators.

The rest of the paper is structured as follows. The next section presents the conceptual framework and empirical specification. In section 4.3, we discuss the data and descriptive statistics. Section 4.4 presents the empirical results, while the final section concludes with policy implications.

4.2. Conceptual framework and estimation

In this section, we present a simple framework to illustrate how adoption decisions of farm households impact on welfare. We assume that in the decisions to adopt CSA practices, farmers consider the potential net benefits from adoption. Thus, if the potential benefits of adopting CSA practices are greater than the benefits of non-adoption, farmers tend to adopt. The adoption decision is expected to impact welfare outcomes such as food and nutrition security measures and poverty status of households.

Consider y_i to be the outcome variables such as household dietary diversity score (HDDS), household food insecurity access scale (HFIAS), poverty headcount index and poverty gap index, and A_i as the adoption status of the i th farmer, where A_i takes the value of one in case the farmer adopts CSA practices, and zero otherwise. The empirical relationship between outcome variables and adoption is specified as follows:

$$y_{ij} = \beta_j X_i + \theta L_i + u_{ij}, \quad j = 0, 1. \quad (4.1)$$

where X_i is a vector of household and farm level controls such as household characteristics (age education, dependency ratio), the ownership of assets (such as ownership of animals), past climatic factors (e.g., average daily temperature, average daily rainfall, temperature anomaly, rainfall anomaly, and their interactions), off-farm income, past experience of extreme weather events captured as past climate shocks, access to extension services, credit constraints, and soil

characteristics (soil types). L_i captures location fixed effects, β and θ are the parameters to be estimated, and u_i represents derivations from the mean, assumed to have zero mean and constant variance. For simplicity, we drop L_i from the further derivation of equations. The j subscript denotes adoption status where $j = 1$ represents adopter, and $j = 0$ represents non-adopter.

As indicated above, farmer i will adopt CSA practices, if the expected gains from adoption (y_{i1}) are higher than the gains from non-adoption (y_{i0}). Let A_i^* be the expected net gains from adoption, then $A_i = 1$, if $A_i^* = y_{1i} - y_{0i} \geq 0$, otherwise $A_i = 0$. A_i^* is the latent propensity to adopt. To the extent that adoption of CSA practices is non-random, as farmers self-select into adoption based on observable and unobservable characteristics, the decision to adopt is endogenous. The latent variable A_i^* cannot be directly measured but can be specified as a function of observable characteristics. We can thus model farmers adoption decisions as follows:

$$A_i^* = f_a(X_i, Z_i) - V_i \quad (4.2)$$

where A_i^* is the latent variable that captures the expected gains from adoption, Z_i represents excluded instruments used for identification of the model, and V_i measures the unobserved heterogeneity in the propensity to adopt. The negative sign in Eq. (4.2) shows that unobserved resistance restricts farmers from adopting CSA practices. Following Cornelissen et al. (2018), the transformation of the selection rule in Eq. (4.2) can be specified as:

$$f_a(X_i, Z_i) - V_i \geq 0 \Leftrightarrow f_a(X_i, Z_i) \geq V_i \Leftrightarrow g_v[f_a(X_i, Z_i)] \geq g_v(V_i),$$

where g_v denotes the cumulative distribution function of V_i (in our case, standard normal distribution). The term $g_v[f_a(X_i, Z_i)]$, also denoted by $g_v[f_a(X_i, Z_i)] \equiv P(X_i, Z_i)$ is the propensity score (the probability that farmer i with observed characteristics X_i , and excluded instruments Z_i will adopt CSA practices), and $g_v(V_i)$ denoted by $g_v(V_i) \equiv U_{Ai}$ represents the quantiles of the distribution of unobserved resistance to adoption (V_i). Given the potential outcome specification in Eq. (4.1), and the adoption decisions in Eq. (4.2), heterogenous expected gains conditional on observed and unobserved characteristics of farmers can be specified as follows:

$$Y_i = A_i y_{1i} + (1 - A_i) y_{0i} = y_{0i} + A_i (y_{1i} - y_{0i}) = X_i \beta_0 + A_i \underbrace{[X_i (\beta_1 - \beta_0) + U_{1i} - U_{0i}]}_{y_{1i} - y_{0i} \equiv \Delta_i} + U_{0i} \quad (4.3)$$

here $\Delta_i \equiv y_{1i} - y_{0i} = X_i (\beta_1 - \beta_0) + U_{1i} - U_{0i}$

To identify the parameters of the model in Eqs. (4.2) and (4.3), the standard instrumental variable (IV) assumptions should be satisfied. In particular, the conditional independence (exclusion restriction) assumption that (U_{0i}, U_{1i}, U_{Ai}) is statistically independent of Z_i , given X_i , needs to be satisfied.

In the analysis, we use the number of climate-information sources from which a farm household obtains information related to climate change and the number of climate-resilient trainings attended as excluded instruments. Climate change tends to positively influence innovation processes through information sources and training (Hakimi and Inglesi-Lotz, 2020; Véganzonès-Varoudakis, and Plane, 2019). These climate-information sources such as agricultural extension, print media, past weather records, television (TV), information and communication technology (ICT), and personal exchange with neighboring farmers positively influence innovation processes and are good predictors of adoption decisions of farmers (Di Falco et al., 2011; Lu, 2011). These sources enable farmers to obtain information about the prevailing weather trends and the expected weather changes. Similarly, climate-resilient trainings help farmers to understand the effects of climate change and the various adaptation measures available to farmers (Aryal et al., 2018). It is important to note that these climate-resilient preparations may be endogenous if trainers focus on a specific group of adopters of CSA practices, or adopters of particular practices interested in getting these trainings that may affect the outcomes. However, our survey shows that all farmers had equal chances of participating in these trainings, irrespective of specific adopter groups or practices. Further to check internal validity of these two instrumental variables, we conducted several statistical tests. The Wald test for the joint significance of these instruments at the first stage probit estimation shows that the instruments jointly and significantly influence adoption of

CSA practices, while simple OLS regression for outcome equations of these variables is insignificant for non-adopters. A further test of correlation confirmed that these instruments are uncorrelated with outcome variables, indicating the validity of the excluded instruments.¹³

Following Eq. (4.3), the marginal treatment effects can be defined as a function of the quantiles, or the treatment effect at a particular value of U_{Ai} (Cornelissen et al., 2016).

$$\text{MTE}(X_i = x, U_{Ai} = u_a) = E[\Delta_i | X_i = x, U_{Ai} = u_a] \quad (4.4a)$$

The treatment effect for an individual with observed characteristics $X_i = x$ who are at u_a -th quantile of the V_i distribution will have a propensity score $P(X_i, Z_i) = u_a$. This implies that such a farmer is indifferent to adoption. Now invoking the assumption that MTE is additively separable into observable and unobservable components, it can be expressed as:

$$\begin{aligned} \text{MTE}(x, u_a) &= E(\Delta_i | X_i = x, U_{Ai} = u_a) \\ &= \underbrace{x(\beta_1 - \beta_0)}_{\text{observed component}} + \underbrace{E(U_1 - U_0 | U_{Ai} = u_a)}_{\text{unobserved component}} \end{aligned} \quad (4.4b)$$

Given Eq. (4.3) and the propensity score, the outcome equation can be estimated as a function of the observed characteristics as defined above, and the propensity score as:

$$E(Y_i | X_i = x, P(X_i, Z_i) = p) = X_i\beta_0 + X_i(\beta_1 - \beta_0)p + K(p) \quad (4.5)$$

where Y_i measures the returns to adoption for households with different levels of observable characteristics, $X_i = x$, the propensity score p , and $K(p)$ is a nonlinear function of the propensity score.

Taking the derivative of Eq. (4.5) with respect to p delivers the MTE (Heckman and Vytlacil 2005; Carneiro et al., 2017; Cornelissen et al., 2016) as:

¹³ In OLS estimates of outcome variables for non-adopters, the F-test shows that the instruments are not jointly statistically significant (see Table 4.C1-4.C4 in Appendix C). For correlation test see Table 4.C5 in Appendix C.

$$\text{MTE}(X_i = x, U_{Ai} = p) = \frac{\partial E(Y_i | X_i = x, P(X_i, Z_i) = p)}{\partial p} = x(\beta_1 - \beta_0) + \frac{\partial K(p)}{\partial p} \quad (4.6)$$

We estimate the treatment effects by first estimating the selection Eq. (4.2) as a probit model to obtain estimates of $P(X_i, Z_i)$ as \hat{p} , and in the second stage, we estimate the outcome equations as:

$$Y_i = X_i\beta_0 + X_i(\beta_1 - \beta_0)\hat{p} + \sum_{k=1}^K \alpha_k \hat{p}^k + \xi_i \quad (4.7)$$

We derive the MTE curve from Eq. (4.7) by taking the derivative with respect to \hat{p} . We assume a second-order polynomial in \hat{p} (i.e., $k = 2$) in our baseline specification. To ascertain the sensitivity of the MTE curve to the functional form assumed, we also estimate MTE curves as robustness checks by using $k = 1$, $k = 3$, $k = 4$. As shown in Heckman and Vytlačil (2005), the MTE can be aggregated over U_{Ai} in different ways to obtain average treatment effects (ATE), average treatment effects on the treated (ATT), average treatment effects on the untreated (ATU), and local average treatment effects (LATE).¹⁴ Thus, different other parameters of interest can be estimated as the weighted averages of the MTE. To the extent that we are also interested in the impact of policy intervention on the returns to adoption, we use the policy-relevant treatment effects (PRTE) to simulate baseline and alternate policies as follows:

$$\text{PRTE}(X) = \frac{E[Y_i | X_i = x, \text{alternate policy}] - E[Y_i | X_i = x, \text{baseline policy}]}{E[A_i | X_i = x, \text{alternate policy}] - E[A_i | X_i = x, \text{baseline policy}]} \quad (4.8)$$

The PRTE measures the average returns to adoption for a farmer who is induced to change his adoption decision in response to specific policies. In the present study, the policy variables include climate information sources and climate-resilient trainings.

¹⁴ In the interest of brevity, the equations to calculate ATE, ATT, ATU, and LATE are given below:

$$\begin{aligned} \text{ATE} &= E[y_{1i} - y_{0i}] = E[\beta_1(X_i) - \beta_0(X_i)] & (a) \\ \text{ATT} &= E[y_{1i} - y_{0i} | A_i = 1] + E[U_1 - U_0 | A_i = 1] = E[\beta_1(X_i) - \beta_0(X_i) | A_i = 1] + E[U_1 - U_0 | A_i = 1] & (b) \\ \text{ATU} &= E[y_{1i} - y_{0i} | A_i = 0] + E[U_1 - U_0 | A_i = 0] = E[\beta_1(X_i) - \beta_0(X_i) | A_i = 0] + E[U_1 - U_0 | A_i = 0] & (c) \\ \text{LATE} &= E[y_{1i} - y_{0i} | A_{1i} > A_{0i}, X_i = x] = \beta_1(X_i) - \beta_0(X_i) + E[U_{1i} - U_{0i} | A_{1i} > A_{0i}, X_i = x] & (d) \end{aligned}$$

4.3. Study area, data collection and data description

4.3.1. Study area

The study is carried out in Punjab province of Pakistan. Punjab province is the central agricultural region in Pakistan, with about 56% share in the total cultivated area and 53% contribution to the national gross domestic product. The province also accounts for 74% of total cereal production in Pakistan (Economic Survey of Pakistan, 2014). Climate change has had direct negative impacts on crop yields in the province. Major crops are prone to environmental risks and declining yields. As indicated by Gill (2016), in the near future, climate change and water availability would be critical factors for wheat production in the region. In particular, the agriculture sector witnessed negative growth (-0.85%) in the country due to a decline in the growth of major crops (-6.55%) because of climate variability and extreme weather conditions, with Punjab province as the leading contributor (Economic Survey of Pakistan, 2019). Fig. 4.1 shows the study area and data collection sites. We selected three important cropping zones (cotton zone, rice zone, central mix zone) from the province.

4.3.2. Data collection and data description

The data used in this study come from a survey of 540 farm households from province Punjab in Pakistan, that are based on the 2015-16 cropping season. In the first step, three agroecological zones with varying cropping patterns, agricultural activities, and weather conditions were selected (see Fig. 4.1). In the second stage, we select two districts each from the three agroecological zones. In total, the six districts include Toba Tek Singh and Jhang in the mixed cropping zone, Gujranwala and Sheikhpura in the rice zone, Rahim Yaar Khan, and Rajan Pur in the cotton zone. In the third stage, we randomly selected two tehsils from each district. In the fourth stage, we selected three villages each from the twelve Tehsils. In the final stage, we selected fifteen farmers randomly from each village. A team of trained enumerators conducted face to face interviews with farmers using a structured questionnaire.

The collected data was comprehensive, including information on general households'

characteristics, landholding, agronomic practices, production and costs, types of crops cultivated, irrigation water use, access to extension, responses to climate change, access to credit, farm, and household assets, off-farm income sources, consumption, and expenditure. One section of the questionnaire was mainly designed to capture climate change perceptions, information, and climate risks in order to understand adaptation responses to climate change. Farmers were also asked if they had taken climate-resilient training in the past, as well as the number of sources they got information related to climate change. Most of the adopters were very well informed about climate change, but few farmers attended climate-resilient trainings, because there was no well-organized program from the government to support climate-resilient trainings. In line with previous adoption studies, we also captured plot-level characteristics such as soil types.

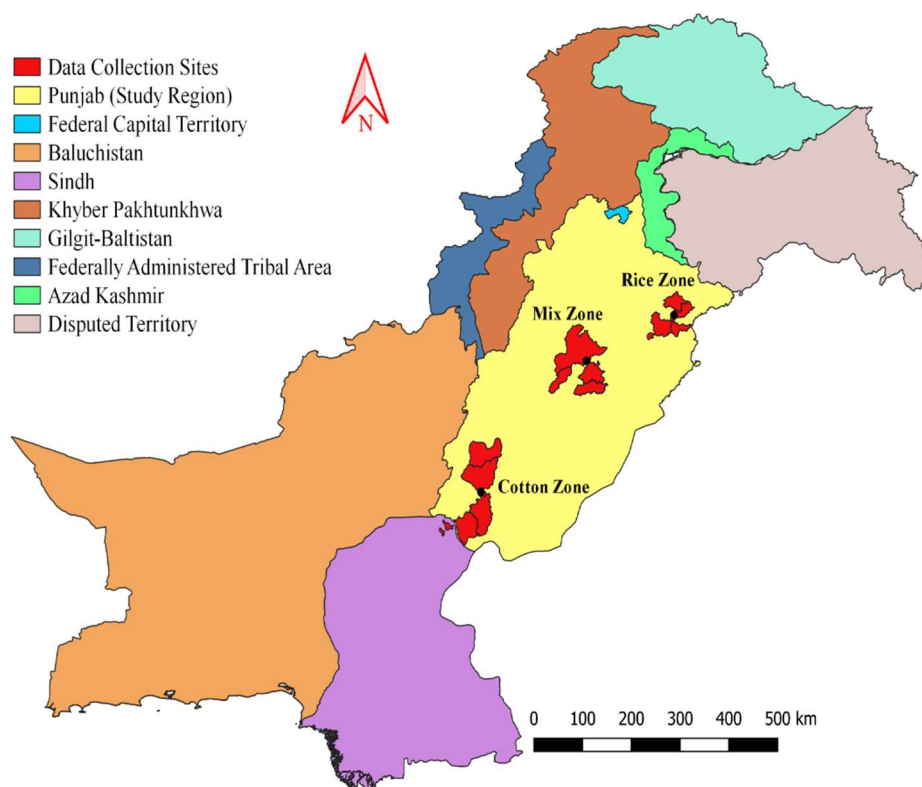


Fig. 4.1 Map of Pakistan showing study area and data collection sites

Information was also gathered on the adaptation strategies, specifically on climate-smart agricultural (CSA) practices. The main CSA practices include change in cropping calendar,

diversified seed varieties, changing input mix, and soil and water conservation measures. Evidence from our data shows that farmers adopt CSA practices, such as changing cropping calendar, soil and water conservation measures, diversifying seed variety, and changing input mix to cope with climate change and variability. Soil and water conservation measures employed include soil erosion control measures, such as soil bunds and crop rotation to conserve soil moisture and prevent nutrient loss in the soil, as well as cover crops to fix nitrogen in the soil. Diversification of seed varieties includes the use of drought-resistant and early maturing varieties that enable farmers to cope with erratic rainfall or very low rainfall. Changing input mix includes the changing fertilizer and application method, change in pesticide use, changing the use of herbicides or weedicides, and micro-nutrients.

Two sub-sections were specially developed to ask questions related to food and nutrition security. The food security access scale (HFIAS) and the household dietary diversity score (HDDS) are the two indicators used to measure food and nutrition security. The HSIAS is a scale that captures the psychological and behavioral dimensions of food insecurity in terms of access to food (Coates et al. 2007; Maxwell et al., 2014). The scale ranges between 0 and 27, with zero scores representing a household with no reported food insecurity. The maximum value of 27 represents the highest level of food insecurity, with high frequency of consuming less food and skipping meals due to insufficient access to food (Coates et al. 2007). For HDDS, following Swindale and Bilinsky (2006), we used seven days recall period, asking households on food consumed during the last seven days. The food items were divided into twelve food groups; cereals, tubers and roots, vegetables, fruits, meat and poultry, eggs, fish, pulses and nuts, legumes, milk and milk products, oils and fats, sugar and honey, and miscellaneous. Further, these groups were assigned numerical values (1 to 12) that were used to calculate the HDDS, which is a good predictor of dietary diversity at the household level. To measure poverty, we use the poverty headcount index and

poverty gap index (Foster et al., 1984).¹⁵

Secondary information related to temperature and rainfall was collected from the National Center for Environmental Prediction (NCEP) and World Weather Online. The collected information ranges from 1979 to 2016 up to the same year in which we obtained data from farmers. It was converted from monthly to yearly averages. As the Punjab province is mostly flat, we used the inverse distance method of spatial interpolation to calculate location-specific farm-level temperature and rainfall. For this purpose, we used the global positioning system (GPS) to record the farm location (elevation, longitude, and latitude) during the data collection. The recorded farm locations were employed to interpolate information on farm-level temperature and rainfall. Subsequently, we calculated the temperature and rainfall anomalies taking 2016 as a base year in which we collected primary data from farmers. We use binary variable for adopters and non-adopters; farmers who practice one or more CSA practices at the farm are considered adopters and assigned a value of one. In contrast, farmers who did not practice any of the CSA practices are categorized as non-adopters and assigned zero value.

Table 4.1 shows definitions and descriptive statistics of selected variables. On average, we find that 48% of farmers are adopters of CSA practices, with the remaining 52% classified as non-adopters in the sample. On average, farm households' food insecurity access scale is 7.36, with a dietary diversity score of 7.49. The estimated average headcount index shows that about 24% of farm households are below the poverty line, and do not have enough financial resources (dollar

¹⁵ We used the Foster–Greer–Thorbecke (FGT) (1984) indices to estimate poverty in our data sample by using the formula: $FGT_\gamma = \frac{1}{N} \sum_{i=1}^M \left[\frac{PL-h_i}{PL} \right]^\gamma$, where $\gamma = 0, 1$. When $\gamma = 0$ then $FGT_0 = \frac{M}{N}$ and for $\gamma = 1$, $FGT_1 = \frac{1}{N} \sum_{i=1}^M \left[\frac{PL-h_i}{PL} \right]$. where N is the total number of people in a household, PL represents the poverty line, h_i represents per capita income of the i th person in a household, and γ represents the poverty aversion parameter. When $\gamma = 0$, FGT_0 is simply the headcount index or the proportion of people that are poor. When $\gamma = 1$, FGT_1 is the poverty gap index, which reflects the severity or intensity of poverty defined by the mean distance to the poverty line. Thus, the poverty gap index, which captures the severity of poverty, is the average shortfall in income for the farm household, from the poverty line. Hence, FGT_1 represents the severity of poverty and reflects the extent of inequality among the poor households.

1.90 a day) for the minimum standard of living.¹⁶ The estimated poverty gap index is about 35%, indicating that the average shortfall in income from the poverty line for the sample is 35%.

Table 4.2 displays the mean differences in the characteristics of adopters and non-adopters. It is evident from the table that there are some statistically significant differences between adopters and non-adopters of CSA practices with respect to household and farm level characteristics. There appear to be differences in access to credit and farm sizes. On average, adopters cultivate 6 acres more land than non-adopters and are less credit constrained. The average 10 % of adopters are liquidity constraint, as much as 37% of non-adopters are credit constrained. There are also differences in terms of schooling year and access to extension services, adopters are more educated and have frequent contacts with extension agents compared with non-adopters. Adopters are also different than non-adopters in terms of climate knowledge acquisition. On average, adopters access at least one information source to acquire climate change information compared with non-adopters' 0.14 climate information sources. Adopters attend higher climate-resilient trainings than non-adopters. These simple comparisons also reveal that adopters are less food insecure, have higher dietary diversity, and experience lower levels of poverty as well as the severity of poverty. In particular, the average HFIAS of an adopter household is less than that of non-adopter household, indicating that the adoption of CSA practices plays a significant role in decreasing farm households' food insecurity. Similarly, the average HDDS is higher than that of non-adopters' HDDS, suggesting that adoption of CSA practices increases household dietary diversity. Adopters and non-adopters also appear to exhibit different poverty status. On average, 12% adopters of CSA practices are poor, while as much as 56% of non-adopters fall below the poverty line, indicating that adoption of CSA practices significantly reduces poverty of farm households. There is also a difference between adopters and non-adopters in terms of the poverty gap; the

¹⁶ We used international poverty line (dollar 1.90 a day) indicated by the World Bank to calculate poverty headcount and poverty gap indices of farm households.

average the shortfall of adopters from the poverty line is 5%, while the shortfall for non-adopters is 41%, which means that adoption reduces poverty severity.

Table 4.1 Descriptive Statistics and definition of selected variables

Variables	Definitions	Mean	Std. Dev.
CC_adoption	1 if farmer adapts to climate change, 0 otherwise	0.485	0.500
HFIAS_score	Household food insecurity access score (0-27 scale), where 0 represents that household is food secure, while 27 represents that household is food insecure	7.363	7.565
HDDS	Household dietary diversity score (0-12 scale), where 0 represents no diversity in food while 12 represents perfect food diversity in a household	7.491	2.722
Poverty_HC	1 if a household is living below the poverty line, 0 otherwise	0.235	0.419
Poverty_gap	Mean distance of poor household from the poverty line	0.346	0.476
Credit_const	1 if household is credit constrained, 0 otherwise	0.235	0.425
Avg_Tem	Average daily temperature in (Degrees Celsius)	27.328	1.129
Avg_Rain	Average daily rainfall (millimeters)	0.648	0.559
Int_TxR	Product of average temperature and average rainfall (number)	17.119	13.976
Tem_anomaly	Change in temperature relative to baseline ^a (number)	0.215	0.032
Rain_anomaly	Change in rainfall relative to baseline (number)	-0.372	0.192
Int_TxR	Product of temperature anomaly and rain anomaly (number)	-0.083	0.049
Off_farm	Farmer's income other than agricultural activities (000 dollars)	0.701	1.805
HH_age	Household head age (years)	47.009	11.382
Dep_ratio	Ratio off non-earning individuals to the earning individuals	4.420	1.723
Education	Number of schooling years household head completed (years)	6.431	4.495
Farm_size	Total number of acres farm household cultivate (acres ^b)	9.403	9.138
Herd size	Number of animals a farm household owns (number)	3.483	1.930
Ext_services	1 if farmer has contact with extension agent, 0 otherwise	0.572	0.495
CC_shock	1 if farmer faced climate shock in the past three years, 0 otherwise	0.254	0.436
Rice zone	1 if farmer resides in rice growing zone, 0 otherwise	0.333	0.472
Cotton zone	1 if farmer resides in cotton growing zone, 0 otherwise	0.331	0.471
Clay_soil	1 if the soil at farm is clay loam, 0 otherwise	0.161	0.368
Sandy_soil	1 if the soil at farm is sandy loam, 0 otherwise	0.135	0.342
info_sources	Number of sources from which a farmer obtains information related to sustainable agricultural practices (number)	0.526	0.607
CR_trainings	Number of training days a farmer attends on CSA practices (number)	0.331	0.699
No. of obs.		540	

^a Anomaly= (current year mean -long term mean)/long term mean

^b 1 acre= 0.40 hectare

Table 4.2 Descriptive statistics and mean difference between adopters and non-adopters

Variables	Adopters	Non adopters	Mean difference	Std. Errors
HFIAS_score	3.279	13.212	-9.934***	0.586
HDSD	8.736	6.316	2.420***	0.210
Poverty_HC	0.122	0.555	-0.434***	0.036
Poverty_gap	0.049	0.411	-0.362***	0.033
Credit_const	0.096	0.367	-0.272***	0.035
Avg_Tem	27.404	27.256	0.147	0.097
Avg_Rain	0.613	0.682	-0.070	0.048
Int_TxR	16.217	17.968	-1.752	1.202
Tem_anomaly	0.219	0.212	0.006**	0.003
Rain_anomaly	-0.379	-0.366	-0.012	0.017
Int_anom_TXR	-0.086	-0.080	-0.005	0.004
Off_farm	0.798	0.610	0.189	0.156
HH_age	48.481	45.623	2.858***	0.973
Dep_ratio	4.680	4.176	0.503***	0.147
Education	7.199	5.708	1.490***	0.382
Farm_size	12.972	6.040	6.931***	0.729
Herd size	4.194	2.813	1.382***	0.156
Ext_services	0.848	0.313	0.534***	0.036
CC_shock	0.462	0.058	0.405***	0.033
Xrice	0.344	0.324	0.020	0.041
Xcotton	0.309	0.352	-0.043	0.041
Clay_soil	0.145	0.176	-0.031	0.032
Sandy_soil	0.084	0.184	-0.100***	0.029
info_sources	0.931	0.144	0.787***	0.040
CR_trainings	0.626	0.054	0.572***	0.055
No of Obs.	262	278	--	--

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

These differences in averages of outcomes between adopters and non-adopters provide some useful information in terms of the positive impact of adoption. However, this comparison of average differences does not account for confounding factors such as observable and unobservable farm and household characteristics. We, therefore, use the marginal treatment effect (MTE) model to account for confounding factors, selection bias, and potential heterogeneity in impacts.

4.4. Results and discussion

In this section, we present the results from the empirical analysis. First, we discuss the estimates of the selection equation, which reveals the drivers of adoption of CSA practices. We then present the results of the second-stage estimation showing the impact of adoption on the outcome

variables. Finally, we outline the results of the PRTE. We report bootstrapped standard errors throughout the results, with clustering at the zonal level.

4.4.1. First stage (selection equation) results

Tables 4.3-4.6 displays the first-stage parameter estimates of the probit selection equation in the first columns. As indicated previously, we use climate-resilient trainings and the number of information sources as identifying instruments for our estimations. We test the joint significance of excluded instruments in the outcome equations by using a Wald test. The value of the Wald statistics (108.18) is highly significant (at the 1% level), indicating that the instrumental variables highly influence adoption decisions. To test the validity of the selection instruments, we also perform F-test, which shows that the instruments do not influence the outcome variables, signifying the validity of the excluded instruments from outcome equations.¹⁷ As we used the same variables to analyze all dependent variables, the results from the first-stage probit model are similar for all the specifications. Hence, we interpret the first columns' results of the Tables 4.3-4.6 together. Here, it is significant to explain the results shown in Fig. 4.2, exhibiting common support. Fig. 4.2 plots the frequency distribution of the propensity score by adoption status. The propensity scores are predicted from the baseline first stage probit regression in columns 1 of Tables 4.3-4.6. It is evident from Fig. 4.2 that the first-stage regression produces common support that ranges from 0.02 to 0.99. It shows the unconditional common support that is generated by variation in both the instruments and covariates in the second stage. This satisfies the assumption generally made in MTE applications that the shape of the MTE curve does not vary with control variables (Cornelissen et al., 2018).

From the first columns of Tables 4.3-4.6, it is clear that climate-resilient training, as well as using several climate information sources, are strong predictors of adoption of CSA practices, as

¹⁷ In the interest of brevity, the empirical results are reported in Appendix C (see Table 4.C1-4.C4).

expected. The coefficient of the variable representing climate change information sources is positive (1.879) and significant (at the 1% level), indicating that obtaining climate change information from different sources increases the likelihood of adoption. Similarly, a positive (0.836) and significant (at the 1% level) coefficient of climate-resilient training suggests that farmers who get climate-resilient training are more likely to adopt CSA practices. However, the coefficient of the variable representing credit constraints is negative and significant, suggesting that farmers who are credit-constrained are less likely to adopt CSA practices. This finding is similar to the results reported by Teklewold et al. (2019b), that credit-constrained farmers find it difficult to purchase farm inputs required for CSA practices, and therefore are less likely to adopt these practices.

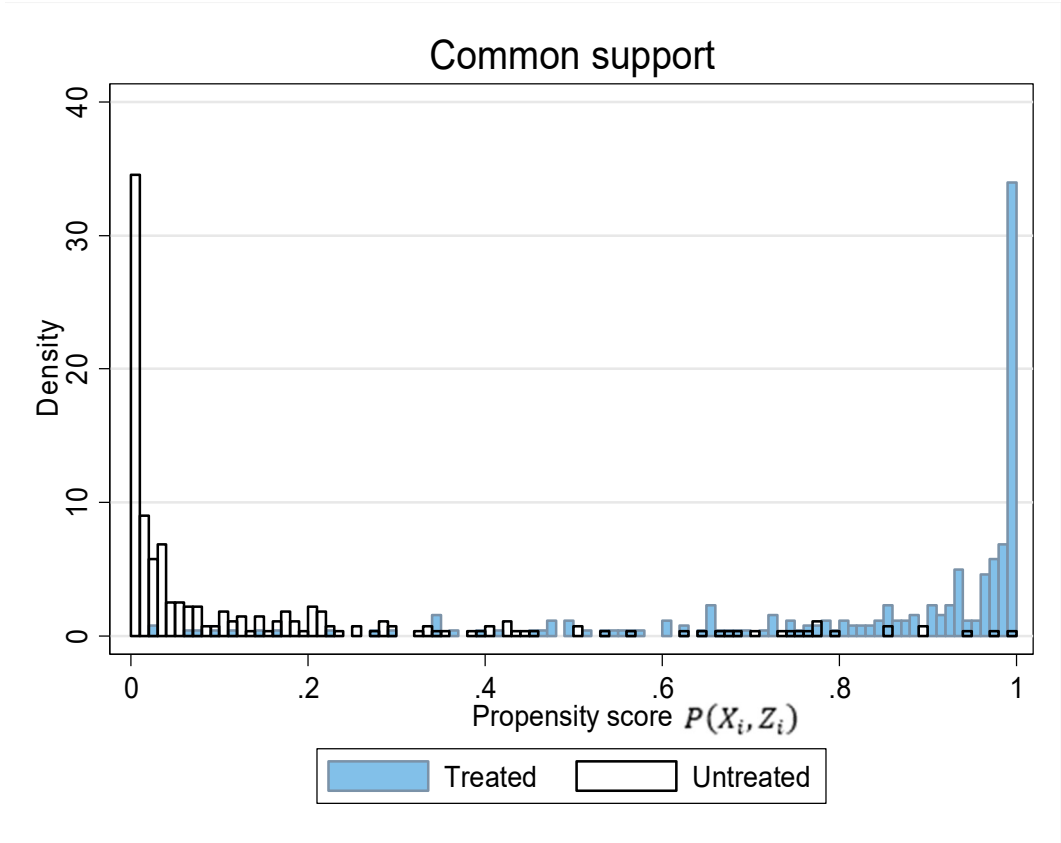


Fig. 4.2 Common support

(Frequency distribution of the propensity score by adoption status)

We use average daily temperature, average daily rainfall, temperature anomaly, rainfall anomaly, as well as interactions of these variables calculated at household level to capture the impact of these climate variables on adoption decisions. The coefficient of average daily rainfall is negative and significant, suggesting that average daily rainfall negatively and significantly affects adoption decisions. In Pakistan, average daily rainfall is generally low (0.65 mm, see Table 4.1), hence with increasing rainfall, farmers become less likely to invest in irrigation, which is an adaptation strategy. Although the coefficient of average daily temperature is positive, it is not statistically significant. Also, temperature and rainfall appear to be inversely related, higher rains associated with lower temperatures and vice versa (Deressa et al., 2011). To account for the cumulative effect of average daily temperature and rainfall, we use an interaction term as a product of these two variables. The coefficient of this interaction term is positive (2.380) and statistically significant (at the 5% level), indicating that if average daily rainfall remains constant, increasing average daily temperature has a positive impact on adoption of CSA practices. The coefficient of rainfall anomaly is positive and significant at the 5% level, suggesting that rainfall anomaly positively influences adoption. As rainfall anomaly shows negative shocks in the study area and depending on the water requirements of the crop, farmers adapt to these adverse shocks by implementing soil and water conservation schemes, which result in rainfall anomaly having a positive impact on adoption. On the other hand, temperature anomaly has a negative and statistically significant effect on adoption. To consider the cumulative impact of temperature and rainfall anomalies, we incorporated the product of these two variables as an interaction term into our analysis. The coefficient of these anomalies' interaction term is negative and statistically significant, showing that if rainfall anomaly remains constant, then temperature anomaly negatively influences adoption decisions.

The negative *albeit* statistically insignificant coefficient of off-farm income suggests that households participating in off-farm work are less likely to adopt CSA practices, a result that is in contrast to the study by Oseni and Winters (2009), who found that income from off-farm work

increases the likelihood of adoption due to the income effect. It is important to note that farmers who take part in off-farm work have to reduce the time allocated to on-farm practices, referred to as lost-labor effect. In our case, this lost-labor effect dominates the income effect, a finding that is consistent with Kousar and Abdulai (2016) for Pakistan, who found that inorganic fertilizer use declined with participation in off-farm work, supporting the notion of lost-labor effect on input use. The coefficient of the variable representing education is positive and statistically significant, highlighting the positive influence of human capital on adoption, a finding that is in line with the previous studies (e.g., Huffman, 2020). The coefficient of the variable representing extension services is positive and significant, indicating that the farmers who have frequent contacts with extension agents are more likely to adopt CSA practices. Previous studies also confirmed the positive and significant effect of extension contacts on adoption (e.g., Wossen et al., 2017; Di Falco et al., 2011). The coefficient of the variable climate-related shocks is positive (1.434) and significant at the 1% level, indicating that farmers who have already experienced climate-related shocks in the past are more likely to adopt CSA practices.

4.4.2. Second stage estimation

In this subsection, we report results from the second-stage estimation based on Eq. (4.7), in columns 2 and 3 of Tables 4.3-4.6, for the effect of the climate change variables and other controls as well as the treatment effects of these variables on the outcome variables. The results point to an equalizing effect of adoption on the outcome variables with different observed characteristics. The untreated state (β_0) is given in column 2, while the treated or adoption state ($\beta_1 - \beta_0$, which refer to gains from CSA adoption) is given in column 3 of each table. In next sub-sections, we will explain MTE curves shown in figures 4.3-4.6, that display MTE curves at the mean values of our observed characteristics (X_i), and relate the unobserved components of outcomes ($U_1 - U_0$), and the unobserved components of adoption choice (U_{Ai}). We also specify different functional forms of the MTE curve to check the sensitivity of the curve to such functional forms as robustness checks.

Household food insecurity access scale (HFIAS)

Table 4.3 displays estimates from the untreated state in column 2 and the treatment effects in column 3 to show the effect of adoption on the impacts of these variables on household food insecurity access scale (HFIAS). The positive and significant coefficient of the credit constraints variable at the untreated state, suggest that credit-constrained households are more likely to be food insecure by about 11 points on the household food insecurity access scale. However, when credit-constrained farmers adopt CSA practices, they are likely to reduce food insecurity by 8 points (see credit constraint in column 3 of Table 4.3, which refers to $\beta_1 - \beta_0$ in Eq. 4.7). Similarly, the coefficient of the variable dependency ratio is positive and significant at the untreated (non-adaptation) state, suggesting that households with high dependency ratios are more food insecure, but adoption of CSA practices tend to improve their food security by 1.38 points. The negative and significant coefficient of farm size at the untreated state indicates that larger farm size tends to reduce household food insecurity. However, the positive and statistically significant coefficient in the adoption state indicates that households with smaller farm sizes tend to almost catch up with households having larger farm sizes by reducing food insecurity by about 0.463 points when they adopt. The negative and significant coefficient of extension services variable indicates that extension contacts reduce food insecurity at the non-adoption state; however, gains after adoption are not significant, although positive, which suggests that farmers without extension contact may benefit more from adoption.

Table 4.3 Selection equation and outcome equations results for HFIAS

Variables	Selection		Outcome (β_0)		Outcome ($\beta_1 - \beta_0$)	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
Constant	-40.749	29.296	-22.633	74.747	-9.823	78.335
Credit_const	-1.240**	0.610	11.604***	2.223	8.084**	3.593
Avg_Tem	1.555	1.073	0.604	2.718	0.549	2.692
Avg_Rain	-56.227**	26.893	50.152	74.518	-40.915	83.819
Int_TxR	2.380**	1.131	-1.952	3.112	1.622	3.450
Tem_anomaly	-43.901*	25.302	69.353	75.083	-38.371	93.062
Rain_anomaly	24.575**	11.503	-25.733	34.286	8.023	38.239
Anom_TxR	-120.394**	54.508	141.131	157.540	-51.222	173.606
Off_farm_inc	-0.152	0.188	0.188	0.889	1.915*	1.018
HH_age	0.010	0.008	0.003	0.036	-0.009	0.050
Dep_ratio	0.022	0.079	1.587***	0.420	-1.384***	0.517
Education	0.140*	0.072	-0.099	0.364	-0.367	0.426
Farm_size	0.016	0.017	-0.549***	0.119	0.463***	0.134
Herd size	0.001	0.087	0.782	0.509	-0.295	0.623
Ext_services	0.966**	0.462	-3.577**	1.685	0.077	3.797
CC_shock	1.434***	0.269	-1.336	2.212	0.934	2.414
Clay_soil	-0.912**	0.360	-2.311*	1.308	1.240	1.686
Sandy_soil	0.456	0.373	0.396	1.182	-2.257	1.624
Xrice	-0.203	0.812	-0.826	1.393		
Xcotton	-2.020**	0.896	0.538	1.711		
Info_sources	1.879***	0.193				
CR Trainings	0.836***	0.174				
χ^2 for test of excluded instruments				108.18		
p -value for test of excluded instruments				0.000		
p -value for test of observed heterogeneity				0.000		
Observations				540		

Note: Bootstrapped standard errors are reported with 500 replications.

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

Household dietary diversity score (HDDS)

Table 4.4 presents the second-stage estimations for household dietary diversity scores (HDDS) at the non-adoption state in column 2 and gains from adoption in column 3. The coefficient of the credit constraints variable is negative and statistically significant at the non-adoption state, indicating that credit-constrained households have lower levels of food security. The coefficient of the off-farm income is negative and significant at the treatment state, indicating that participating in off-farm work negatively affects gains from adoption. As mentioned earlier, the lost labor effect dominates the income effect of participation in off-farm work. Thus, labor is invested in off-farm work at the expense of farm activities. However, the additional income from off-farm work is not used to improve household nutrition security. Also, farmers with higher off-farm income are less likely to adopt and these are those with higher dietary diversity in the non-adoption state. This implies households with lower off-farm income are more likely to adopt and tend to have higher dietary diversity when they adopt CSA practices.

The variable representing household head age is positive and statistically different from zero, suggesting that at the non-adoption state, older farmers tend to increase their HDDS, as older farmers are more experienced in farming and past climatic trends, which makes them operate their farms efficiently. However, the household head age does not significantly affect gains from adoption. The results also show that at the adoption state, gains from education is positive and significant, indicating that more educated household heads get higher benefits from adoption, and as such higher dietary diversity. The coefficient of the variable representing climate-related shocks, which is negative and significant at the non-adoption state, suggests that the farmers who experienced climate-related shocks in the past and did not adopt CSA practices had less diversified diets. On the other hand, the treatment effect at the adoption state is positive and significant, indicating that farmers who adopted the shocks by adopting CSA practices obtain higher benefits from adoption through better-diversified food. The p -value for the observed heterogeneity

reported in the lower part of the table is significantly different from zero, indicating that heterogeneity in treatment effects is in part due to observable characteristics across individuals.

Table 4.4 Selection equation and outcome equations results for HDDS

Variables	Selection		Outcome (β_0)		Outcome ($\beta_1 - \beta_0$)	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
Constant	-40.749	29.296	13.640	31.826	17.078	31.321
Credit_const	-1.240**	0.610	-2.313**	0.894	0.873	1.438
Avg_Tem	1.555	1.073	-0.278	1.157	-0.286	1.099
Avg_Rain	-56.227**	26.893	-16.386	23.126	0.911	26.745
Int_TxR	2.380**	1.131	0.623	0.983	-0.069	1.118
Tem_anomaly	-43.901*	25.302	2.788	24.525	-30.585	36.547
Rain_anomaly	24.575**	11.503	-2.486	11.380	17.733	15.604
Anom_TxR	-120.394**	54.508	8.433	50.626	-68.608	69.208
Off_farm	-0.152	0.188	0.192	0.216	-0.763**	0.313
HH_age	0.010	0.008	0.023*	0.013	-0.025	0.021
Dep_ratio	0.022	0.079	-0.687***	0.139	0.200	0.197
Education	0.140*	0.072	0.024	0.086	0.187*	0.112
Farm_size	0.016	0.017	0.166***	0.050	-0.069	0.061
Herd_size	0.001	0.087	0.032	0.171	-0.028	0.169
Ext_services	0.966**	0.462	0.628	0.586	0.097	1.191
CC_shock	1.434***	0.269	-1.476**	0.697	1.580**	0.736
Clay_soil	-0.912**	0.360	0.717*	0.374	-0.779	0.649
Sandy_soil	0.456	0.373	-0.077	0.442	0.042	0.773
Xrice	-0.203	0.812	0.359	0.637		
Xcotton	-2.020**	0.896	0.240	0.639		
Info_sources	1.879***	0.193				
CR Trainings	0.836***	0.174				
χ^2 for test of excluded instruments				108.18		
p -value for test of excluded instruments				0.000		
p -value for test of observed heterogeneity				0.000		
p -value for test of unobserved heterogeneity				0.092		
Observations				540		

Note: Note: Bootstrapped Standard errors are reported

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

The positive coefficient of the variable representing dependency ratio in the selection model and the negative treatment effects at the adoption state in column (3), suggests that farmers with higher dependency ratio tend to have lower poverty headcount when they adopt CSA practices. So, by the nature of the outcome variable, this indicates positive selection on observed gains, where farmers with higher dependency ratio are those who are more likely to adopt and also have higher reduction in poverty headcount after adoption. The negative and highly significant coefficient of

the farm size variable at the non-adoption state indicates that larger farm size reduces the poverty of farm households at the untreated state. However, at the adoption state, gains from smaller farm sizes are positive and highly significant, implying that the reduction in poverty for smaller farmers following adoption is greater than the reduction for farmers with larger farm sizes. This is a typical case of small farmers catching up with large farmers in terms of reducing poverty due to adoption. Thus, farmers with large farm sizes are more likely to adopt but gain less than farmers with small farms, when they adopt.

Poverty headcount and poverty gap index

In Table 4.5, we report estimates for the poverty headcount index. The estimates show that the coefficient of credit constraints variable at the non-adoption state is positive and statistically significant, indicating that credit-constrained households tend to have higher poverty levels. However, the gains from adoption on credit constraints are positive and statistically significant, suggesting that credit-constrained households that adopt CSA practices tend to benefit significantly from adoption in the form of reduced poverty. The dependency ratio variable has a positive and highly significant effect on the poverty headcount index at the non-adoption state, while at the adoption state, treatment effect is negative and significant, with the negative sign indicating reduction in poverty from adoption.

Table 4.6 presents the estimates of the poverty gap at the selection, non-adoption, and treatment states. The estimates reveal that the coefficient of temperature anomaly is positive at the non-adoption state, although not significant. But gains from adoption are positive and statistically significant, indicating that farmers with the high-temperature anomaly, who are less likely to adopt, tend to benefit more in reducing the effect of temperature anomaly on poverty when they adopt, than farmers who are more likely to adopt. Thus, adopters respond to temperature shocks by adjusting sowing dates to provide the optimal temperature at a certain stage of plant growth, thereby getting higher benefits from adoption. At the non-adoption state, the coefficient of the variable representing the age of the household head is positive and significantly different from

zero, suggesting that the intensity of poverty is much higher in households with older heads, compared to their counterparts with younger household heads, while at adoption state treatment effect is negative and significant, suggesting that the older household heads reduce poverty severity due to adoption.

Table 4.5 Selection equation and outcome equations results for poverty headcount

Variables	Selection		Outcome (β_0)		Outcome ($\beta_1 - \beta_0$)	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
Constant	-40.749	29.296	-4.570	4.985	-0.575	5.561
Credit_const	-1.240**	0.610	0.441**	0.182	0.520**	0.256
Avg_Tem	1.555	1.073	0.152	0.175	0.046	0.182
Avg_Rain	-56.227**	26.893	2.320	3.728	-2.279	4.047
Int_TxR	2.380**	1.131	-0.078	0.157	0.092	0.167
Tem_anomaly	-43.901*	25.302	2.843	4.754	-4.940	6.842
Rain_anomaly	24.575**	11.503	-1.344	2.258	2.234	2.970
Anom_TxR	-120.394**	54.508	6.787	10.053	-10.907	13.236
Off_farm	-0.152	0.188	0.001	0.051	-0.046	0.060
HH_age	0.010	0.008	-0.001	0.002	0.001	0.003
Dep_ratio	0.022	0.079	0.153***	0.032	-0.162***	0.037
Education	0.140*	0.072	-0.014	0.021	0.034	0.024
Farm_size	0.016	0.017	-0.031	0.009	0.031***	0.010
Herd_size	0.001	0.087	0.017	0.044	-0.008	0.048
Ext_services	0.966**	0.462	-0.037	0.131	-0.031	0.220
CC_shock	1.434***	0.269	-0.085	0.115	0.089	0.133
Clay_soil	-0.912**	0.360	-0.207**	0.089	0.266***	0.095
Sandy_soil	0.456	0.373	-0.009	0.084	0.080	0.135
Xrice	-0.203	0.812	-0.212**	0.105		
Xcotton	-2.020**	0.896	-0.199*	0.119		
Info_sources	1.879***	0.193				
CR_Trainings	0.836***	0.174				
χ^2 for test of excluded instruments					108.18	
<i>p</i> -value for test of excluded instruments					0.000	
<i>p</i> -value for test of observed heterogeneity					0.000	
<i>p</i> -value for test of unobserved heterogeneity					0.086	
Observations					540	

Note: Note: Bootstrapped Standard errors are reported

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

Table 4.6 Selection equation and outcome equations results for poverty gap (severity)

Variables	Selection		Outcome (β_0)		Outcome ($\beta_1 - \beta_0$)	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
Constant	-40.749	29.296	2.637	4.818	-3.755	5.965
Credit_const	-1.240**	0.610	0.720***	0.172	0.134	0.336
Avg_Tem	1.555	1.073	-0.077	0.177	0.043	0.211
Avg_Rain	-56.227**	26.893	5.605	4.631	7.200	4.865
Int_TxR	2.380**	1.131	-0.234	0.190	-0.271	0.200
Tem_anomaly	-43.901*	25.302	2.149	6.598	10.647*	6.423
Rain_anomaly	24.575**	11.503	-1.902	2.858	-4.532*	2.691
Anom_TxR	-120.394**	54.508	9.918	13.019	19.685*	11.876
Off_farm	-0.152	0.188	-0.036	0.059	0.041	0.069
HH_age	0.010	0.008	0.004*	0.002	-0.006**	0.003
Dep_ratio	0.022	0.079	-0.033	0.034	0.034	0.037
Education	0.140*	0.072	-0.022	0.027	0.006	0.029
Farm_size	0.016	0.017	-0.009	0.008	0.008	0.009
Herd size	0.001	0.087	-0.017	0.036	0.023	0.041
Ext_services	0.966**	0.462	0.021	0.110	-0.099	0.180
CC_shock	1.434***	0.269	0.145	0.151	-0.152	0.167
Clay_soil	-0.912**	0.360	-0.247***	0.094	0.373***	0.122
Sandy_soil	0.456	0.373	0.014	0.103	0.041	0.143
Xrice	-0.203	0.812	-0.197**	0.087		
Xcotton	-2.020**	0.896	0.138	0.108		
Info_sources	1.879***	0.193				
CR Trainings	0.836***	0.174				
χ^2 for test of excluded instruments				108.18		
p -value for test of excluded instruments				0.000		
p -value for test of observed heterogeneity				0.000		
p -value for test of unobserved heterogeneity				0.058		
Observations				540		

Note: Note: Bootstrapped Standard errors are reported

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

4.4.3. Marginal treatment effects (MTE) results

In this section, we report the MTE curves results shown in Figs. 4.3-4.6. The 95% confidence intervals shown around the MTE curves are based on bootstrapped standard errors with five hundred replications. In Fig. 4.3, it is evident that unobserved characteristics are inversely related to selection on gains from HFIAS, because higher values of U_{Ai} imply less likelihood of adoption. As indicated earlier, higher values of U_{Ai} imply lower probability of adoption, and as such can be interpreted as resistance to adoption. In Fig. 4.3, the MTE curve increases with the unobserved resistance to adoption, representing a pattern of reverse selection on gains found for observed characteristics of farm households. Hence, based on these unobserved characteristics, farmers who

are most likely to adopt CSA practices benefit the most in terms of reduced food insecurity, a pattern of heterogeneity (slope of MTE curve) that is shown to be statistically significant at the 10% level in the lower part of Table 4.7 (see the p -value for the test of unobserved heterogeneity). Furthermore, Fig. 4.4 shows the MTE curve for HDDS. The curve is downward sloping, suggesting that the gains from adoption decrease with increasing resistance to adoption. This indicates a pattern of positive selection on gains. Thus, farmers who are more likely to adopt CSA practices obtain higher benefits from adoption in terms of diversified food.

Fig. 4.5 displays the MTE curve for the poverty headcount index. It is evident from the curve that farmers with lower unobserved resistance to adoption get the higher benefits from adoption of CSA practices and experience less poverty. The figure shows that the observed resistance to adoption increases with decreasing gains from adoption, indicating positive selection on gains. Thus, lower levels of unobserved resistance to adoption is associated with lower poverty levels, but poverty tends to increase as the unobserved resistance to adoption increases to the right. Fig 4.6 shows the MTE curve for the poverty gap index. The upward-sloping MTE curve also implies that households with lower levels of unobserved resistance to adoption, have lower severity of poverty whereas households with the highest unobserved resistance to adoption tend to benefit less from adoption by having the highest severity of poverty. We observe a pattern of positive selection on unobserved gains from adoption of CSA practices across all the four outcomes. This observation is due to the fact that households that are more likely to adopt CSA practices tend to benefit more from adoption, because households who are less likely to adopt have higher gains than the average farmer in the non-adoption state, which is in line with the notion of adoption based on comparative advantage (Suri, 2011). The p -values for the test of essential heterogeneity reported in the lower part of Table 4.7 indicate that selection based on unobserved gains are statistically significant (a null hypothesis of zero slope of the MTE curve is rejected at the 10% level) for all outcome variables.

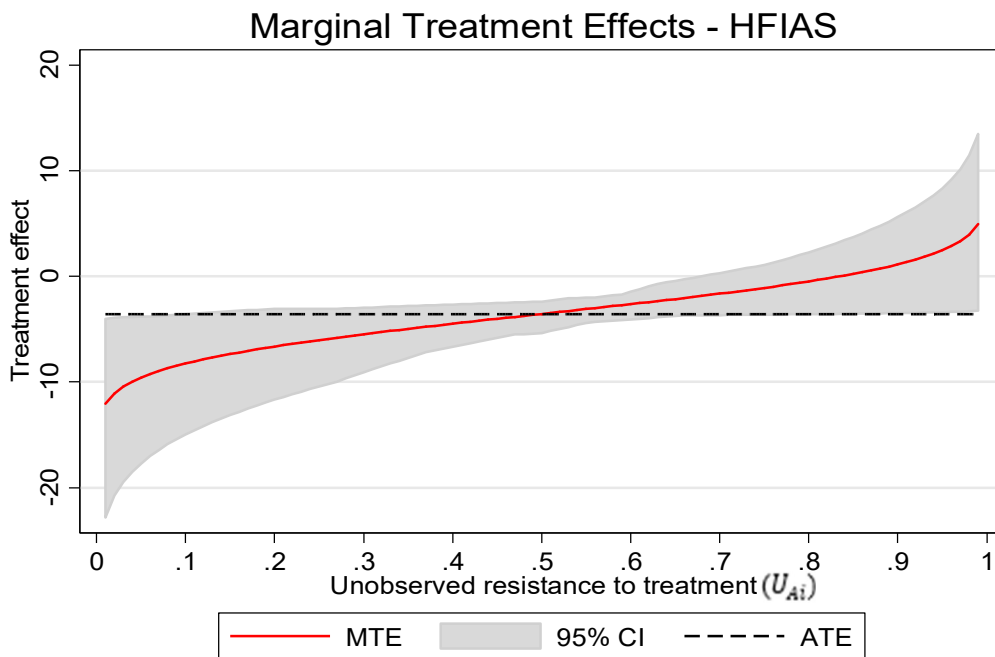


Fig. 4.3 MTE curve for household food insecurity access scale (HFIAS)

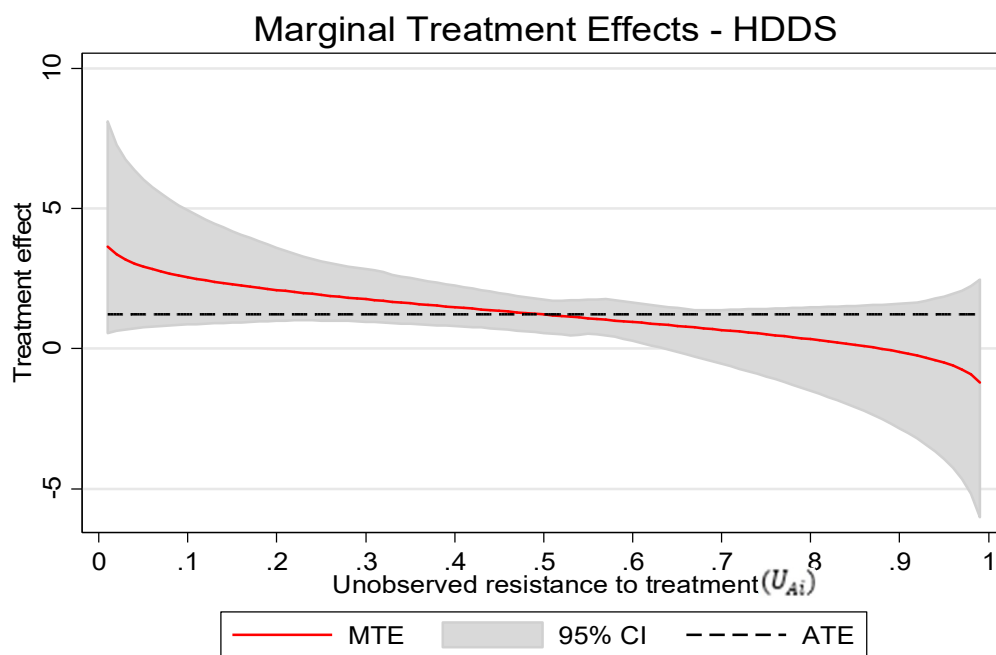


Fig. 4.4 MTE curve for household dietary diversity scores (HDDS)

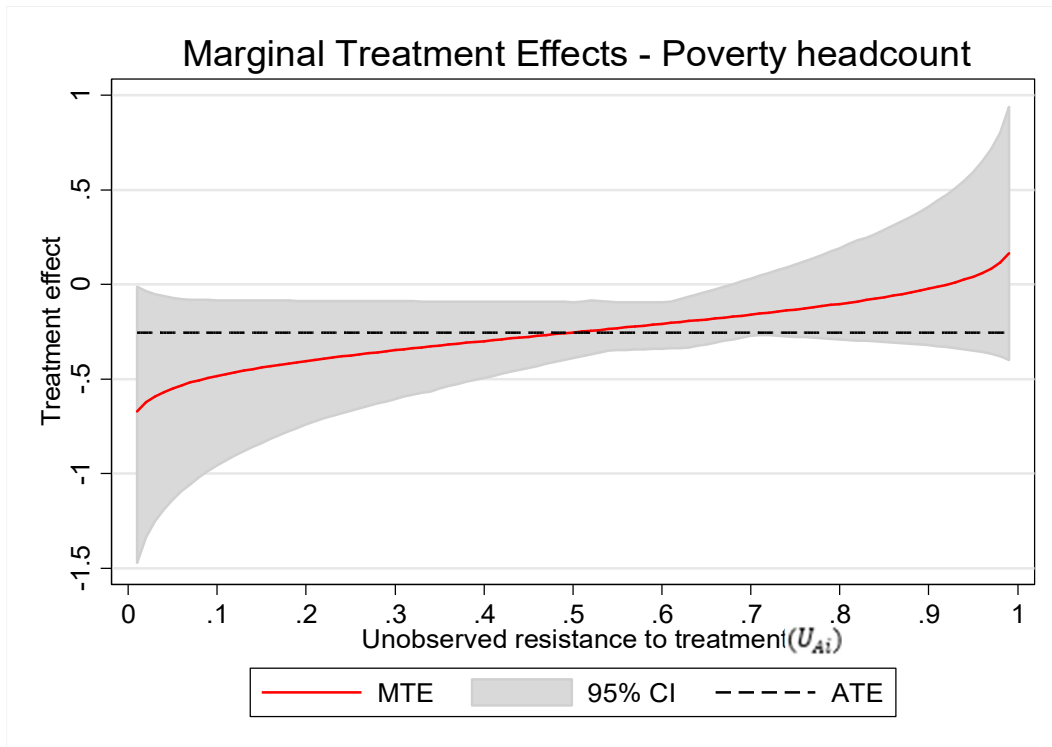


Fig. 4.5 MTE curve for poverty headcount index

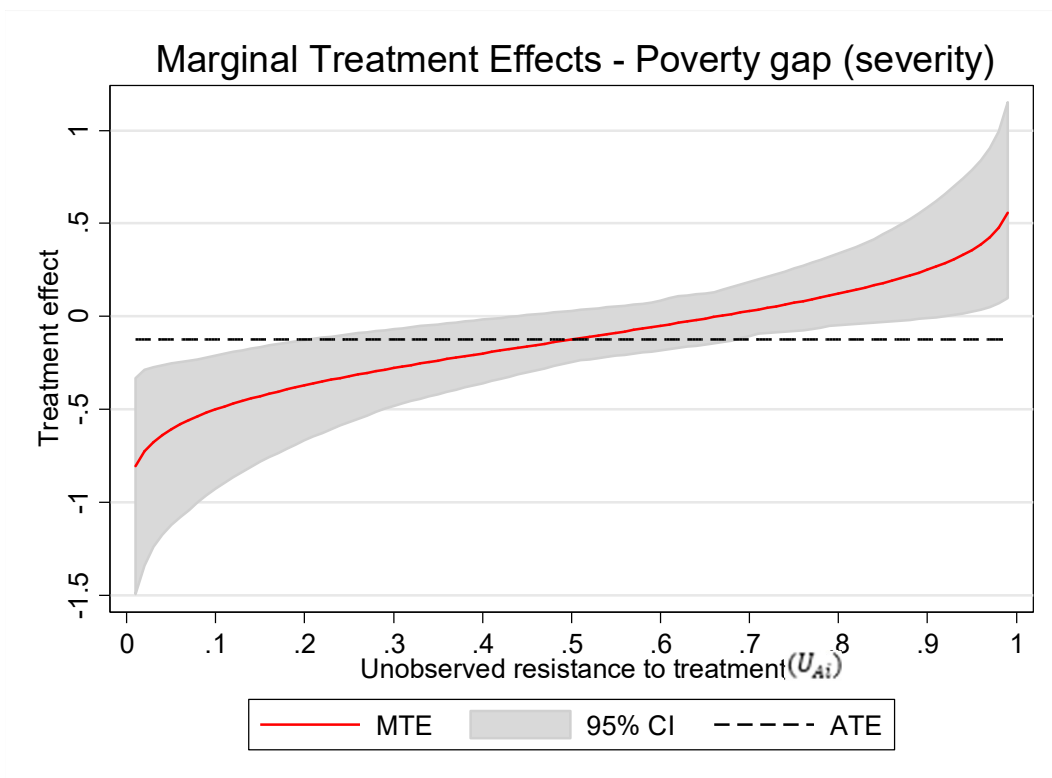


Fig. 4.6 MTE curve for poverty severity

4.4.4. Robustness checks

In this section, we show that the pattern of reverse selection on benefits documented in the estimates is robust to different alternative specifications. We estimate different specifications (linear, cubic, and quartic) of the propensity score in Eq. (4.7) as robustness checks that further confirm the results generally do not vary and are robust to the functional form (see Figs. 4.7-4.10). Fig. 4.7 shows that different functional forms (linear, cubic, and quartic of the propensity score) of the MTE curves for HFIAS and confirms a pattern that is observed in the baseline MTE curve. The nature of the curves generally does not vary from the baseline and are robust to functional form. Further, estimates using different functional forms of the MTE curves for HDDS confirm that our results are robust and do not vary by using linear and higher-order specifications (see Fig. 4.8). Further, Fig. 4.9 displays MTE curve trends for the poverty headcount index from different specifications of propensity score and confirm that the results are robust, and do not vary with different specifications. Similarly, estimates using different functional forms of the MTE curves for the poverty gap index confirm that our results are robust and do not vary by using linear and higher-order specifications (see Fig. 4.10).

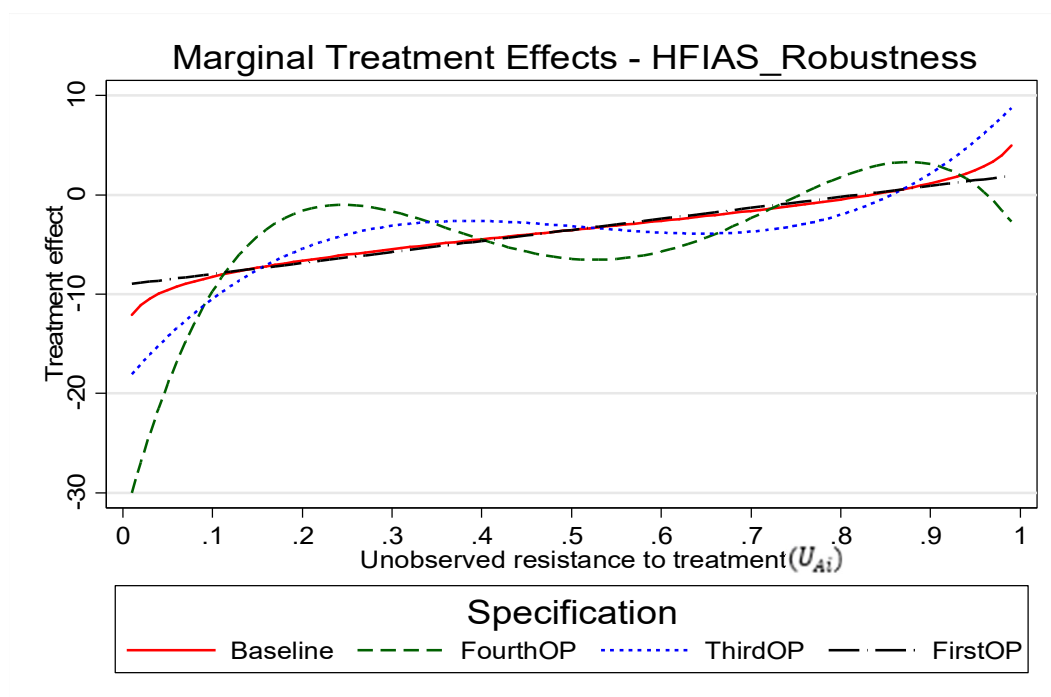


Fig. 4.7 MTE curves for HFIAS: functional form robustness checks

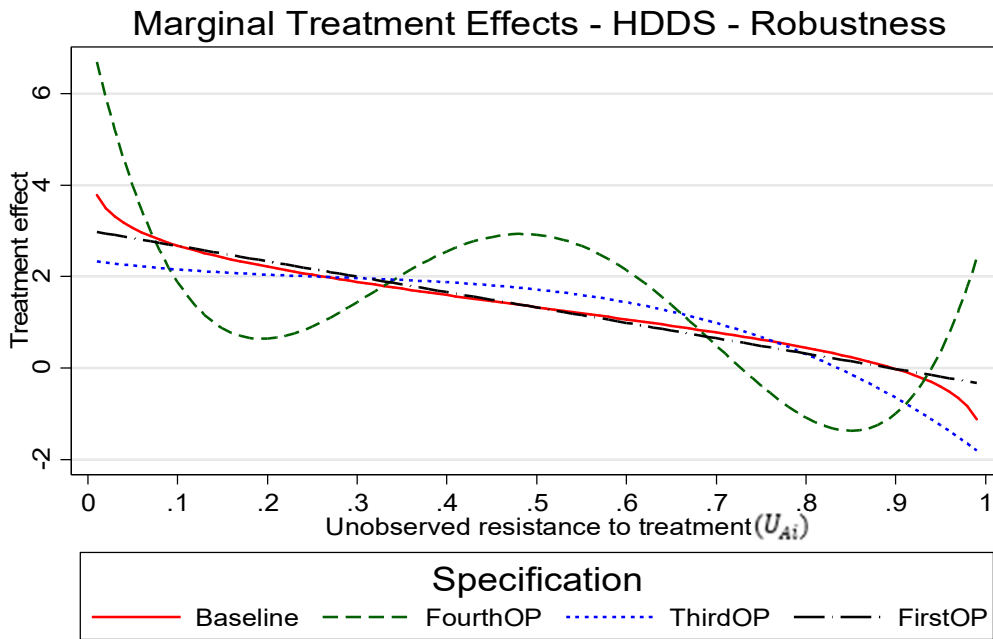


Fig. 4.8 MTE curves for HDDS: functional form robustness checks

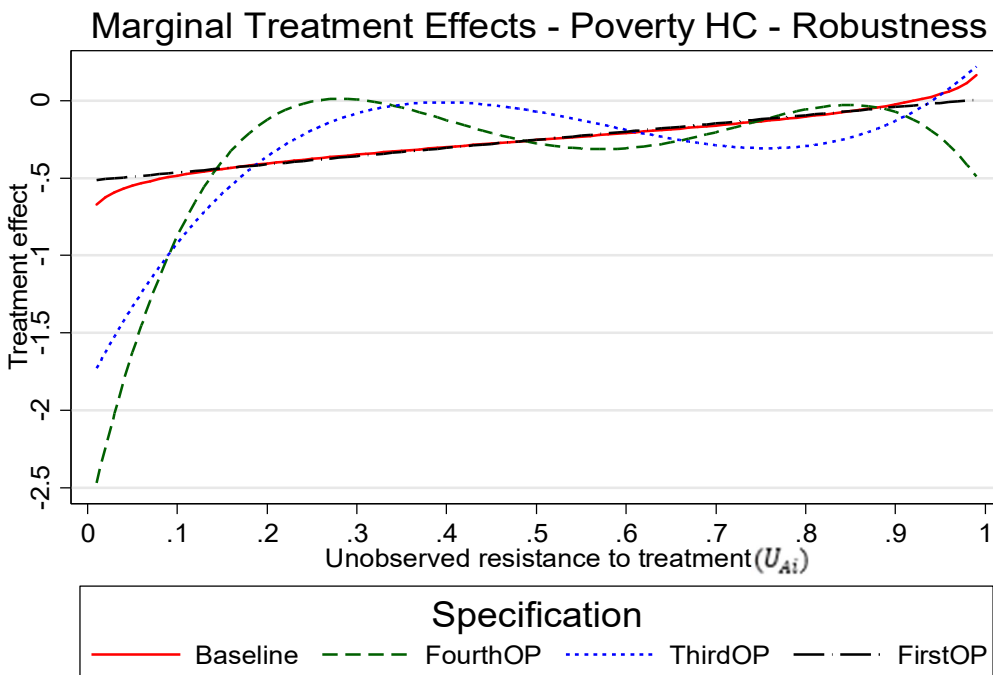


Fig. 4.9 MTE curves for poverty headcount: functional form robustness checks

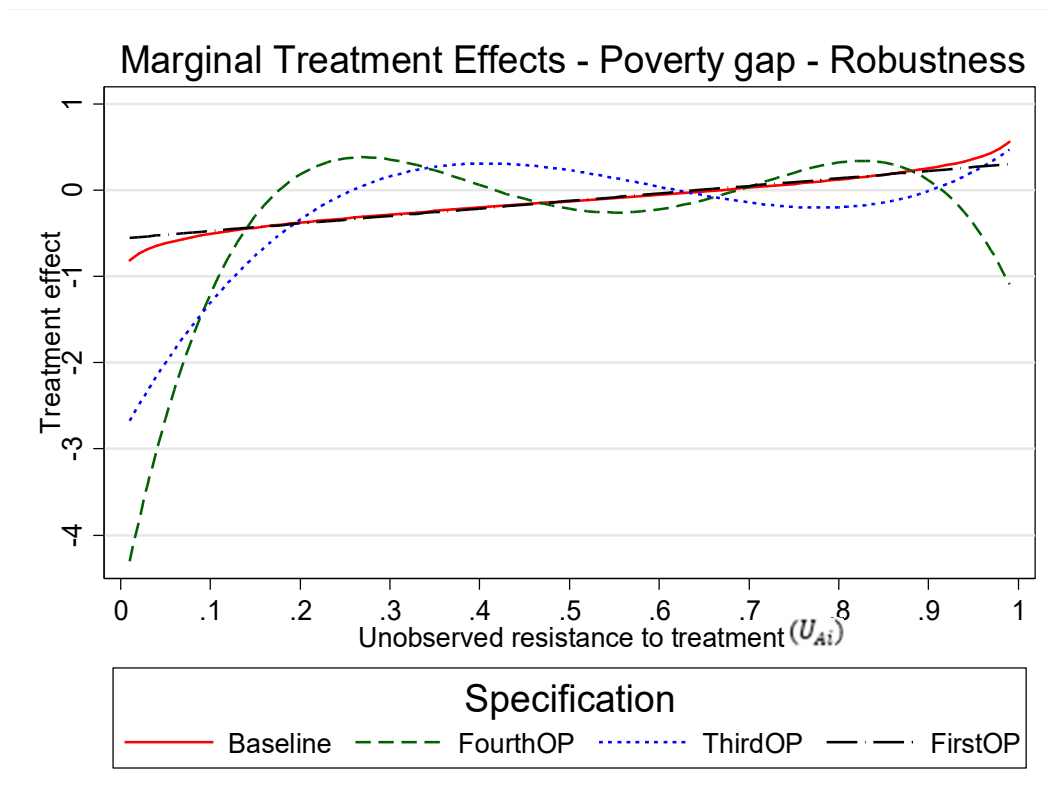


Fig. 4.10 MTE curves for poverty gap: functional form robustness checks

4.4.5. Summary of causal effects of adoption on food security and poverty

Table 4.7 illustrates the impact of adoption of CSA practices on food and nutrition security and poverty reduction based on our baseline specification. We report the estimates of treatment effects of adoption of CSA practices on the outcome variables. The results reveal that all outcome variables exhibit the same selection pattern, with the most beneficial effects of adoption accruing to farmers who are most likely to adopt (i.e., the treatment effects on the treated (ATT) being higher than the other parameters in all cases). Specifying positive selection on unobserved gains are thus statistically significant. Regarding the signs and magnitude of the treatment effects, the estimates of average treatment effects (ATE) show that the treatment effects are quite sizable and statistically significant. The ATE results imply that the adoption of CSA practices significantly (at the 1% level) reduces food insecurity by 37% and increases household dietary diversity by 17% for an average household. Similarly, adoption of CSA practices reduces the poverty headcount by 25% and the poverty intensity by about 13%.

Table 4.7 Impact of climate-smart farm practices on food and nutrition security and poverty

	HFIAS [†]			HDDS [†]			Poverty headcount			Poverty severity		
	Coef.	Std. Err.	%age change	Coef.	Std. Err.	%age change	Coef.	Std. Err.	%age change	Coef.	Std. Err.	%age change
ATE	-2.729***	0.898	37.1	1.330***	0.409	17.8	-0.254***	0.064	25.4	-0.126**	0.061	12.6
ATT	-3.250*	1.777	44.1	1.668***	0.625	22.3	-0.273**	0.110	27.3	-0.227*	0.118	22.7
ATU	-2.242**	0.940	30.5	1.014*	0.584	13.5	-0.237***	0.087	23.7	-0.032	0.085	03.2
LATE	-3.442***	0.642	46.7	0.741**	0.347	09.9	-0.290***	0.048	29.0	-0.066*	0.039	06.6
<i>p</i> -value of test for essential heterogeneity	(0.076)			(0.092)			(0.086)			(0.058)		

Note: The table reports the average treatment effects (ATE), the average treatment effects on the treated (ATT), the average treatment effects on untreated (ATU), local average treatment effects on the treated (LATE), and the *p*-value for a test of essential heterogeneity for the four outcomes. The *p*-values of test for essential heterogeneity are given in parentheses. Std. Err. represent bootstrapped standard errors with 500 replications.

†As HFIAS and HDDS variables are measured in scales the percentage change is calculated based on their mean values from the sample.

*** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

The ATT estimates indicate that for an average adopting household, adoption significantly reduces food insecurity by 44% and improves dietary diversity by 22%. The ATT estimate for poverty shows that for an average adopting household, adoption results in about 27% decrease in poverty, and about 23% reduction in the intensity of poverty. The treatment effects on untreated (ATU) are lower than that of ATE and ATT, confirming the positive selection on unobserved gains. In particular, the ATU results show that for an average non-adopting household, adoption of CSA practices would significantly reduce food insecurity by 30% and improve dietary diversity by about 14%. Similarly, for an average non-adopting household, adoption would significantly reduce poverty headcount by about 24%, but there is no statistically significant effect on poverty severity. In the lower part of Table 4.7 local average treatment effects (LATE) are reported, which shows that households who adopted because of more access to climate change information sources and climate-resilient trainings, significantly reduce household food insecurity by about 47% and improve dietary diversity by about 10%, while reducing poverty headcount by 29% and intensity of poverty by about 7%.

4.4.6. Simulating policy strategies

The results show that the identifying instruments play highly significant roles in the adoption of CSA practices. The higher returns to adoption imply that policies that attract high resistance farmers into adoption may have considerable benefits. In this section, we quantify these benefits for two policy interventions, using the identifying instruments, by doubling our policy variables (instruments). In particular, we compute policy-relevant treatment effects (PRTE, see Carnero et al., 2011; Cornelissen et al., 2018) as a weighted average of the MTE curve with the weights reflecting the number of farm households shifted into adoption by the policy change. In table 4.8, we report PRTE that describe the effect of policy variables on outcome variables under the alternate policy.

Table 4.8 Impact of different policies on propensity scores and outcome variables

Outcome Variables	Propensity scores		Info_sources			Propensity scores		CR_trainings		
	Baseline policy	Alternate policy	PRTE	St. Er.	%age change	Baseline policy	Alternate policy	PRTE	St. Er.	%age change
HFIAS [†]	0.48	0.69	-4.588***	1.056	62.3	0.48	0.55	-3.969***	0.969	53.0
HDDS [†]	0.48	0.69	1.582***	0.417	21.5	0.48	0.55	1.465***	0.386	19.6
Poverty HC	0.48	0.69	-0.371***	0.090	37.1	0.48	0.55	-0.324***	0.070	32.4
Poverty severity	0.48	0.69	-0.232***	0.069	23.2	0.48	0.55	-0.187***	0.069	18.7

Note: The table reports the policy relevant treatment effects (PRTE) of policy simulation strategies of doubling information sources and climate resilient trainings for household food insecurity access scale (HFIAS), household dietary diversity scores (HDDS), poverty headcount index and poverty severity. Std. Err. represent bootstrapped standard errors with 500 replications.

[†]As HFIAS and HDDS variables are measured in scales the percentage change is calculated based on their mean values from the sample.

*** Significant at 1% level.

We simulate a policy that increases the average adoption rate of 0.48 to a level of 0.69 by simply doubling climate information sources. This implies that if our goal is to increase the current adoption rate of 48% to a level of 69%, then we could double the access of farmers to climate-related information sources. The estimates indicate that doubling these information sources will reduce food insecurity by 62%, poverty level by 37%, poverty intensity by 23%, and increase dietary diversity significantly by about 22% (all values are significant at the 1% level). On the other hand, we can double climate-resilient trainings to shift the average adoption rate from 48% to a level of 55%. Specifically, doubling climate-resilient trainings would reduce household food insecurity by 53%, poverty level by 32%, poverty intensity by 19%, and enhance household dietary diversity by about 20% (all values are significant at the 1% level). Overall, enhancing access to climate change information sources as well as climate-resilient trainings are attractive policy options that may have substantial impact on increasing adoption rates to improve food and nutrition security and reduce poverty in Pakistan.

4.5. Conclusion and policy implications

Climate variability has made the world agricultural systems more uncertain, causing severe yield reductions and reproductive failure in many crops. At the same time, increasing population and poverty with increasing food demand put pressure on mitigating the impacts of climate change, as well as adapting to the adverse impacts of the changes that influence farmers' decisions to adopt climate-smart agricultural (CSA) practices. In this paper, we assess the heterogeneity in the effects of adoption of CSA practices on food and nutrition security and poverty levels of farm households in rural Pakistan. Simple comparisons of the measures of outcome variables reveal significant differences. However, these average differences are not significant to explain the impact of adoption on the outcome variables, since they do not account for other confounding factors. We, therefore, employ the marginal treatment effects (MTE) approach to provide evidence on heterogeneity in gains from adoption in both observed and unobserved factors that influence adoption of CSA practices.

Our empirical results show substantial heterogeneity in the benefits from adoption of CSA practices. In particular, we observe a pattern of positive selection on unobserved gains from adoption of CSA practices across all the outcome variables. This observation is due to the fact that households that are more likely to adopt CSA practices tend to benefit more from adoption. The average treatment effects on the treated (ATT) show that adopting CSA practices significantly reduces poverty level and poverty severity and improves food and nutrition security of farm households. We also used a policy simulation exercise to show that adoption rates of CSA practices could be increased significantly through improvement in climate-resilient trainings and access to climate change information sources.

Overall, our results show that enhancing the adoption of CSA practices can help in improving food and nutrition security, as well as reducing poverty among farm households in Pakistan. On the policy front, the findings reveal that the challenges facing farmers in rural Pakistan regarding the adoption of CSA practices can be reduced through government interventions that include improved access to credit, extension services, and weather information, and education. As argued by Abdulai and Huffman (2014), policy measures that help farmers overcome financial and information barriers that are crucial in enhancing the adoption of CSA practices. The significant impact of climate change information sources on climate change and climate-resilient trainings on the adoption of CSA practices suggests that measures that improve access to better information on climate change could be used to encourage and support farmers in adopting CSA practices. To the extent that large-scale farmers are more likely to adopt CSA practices, but that reduction in poverty and improvement in food security for smaller farmers following adoption is much greater than the reduction for farmers with larger farm sizes, this has significant implications for the design of pro-poor CSA adoption strategies. Thus, targeting small-scale farmers with appropriate measures to scale up their adoption of CSA practices can help in improving their food security and reducing their poverty levels. Promising policies in this direction include increasing their access to information to reduce uncertainty about CSA practices, as well as improving their access

to formal credit for them to overcome liquidity constraints. In addition, efforts to improve their human capital in the form of schooling and providing them with better infrastructure would go a long way to help facilitate the adoption of CSA practices.

Acknowledgments

Authors would like to thank the journal editor David Peel and anonymous reviewer for their comments that substantially improved the paper. First author would like to thank the Higher Education Commission (HEC) of Pakistan for scholarship funding in collaboration with German Academic Exchange Service (DAAD), Germany.

References

- Abdulai, A. (2018). Simon brand memorial Address: the challenges and adaptation to climate change by farmers in Sub-Saharan Africa. *Agrekon*, 57(1), 28-39.
- Abdulai, A., & Huffman, W. (2014). The adoption and impact of soil and water conservation technology: An endogenous switching regression application. *Land Economics*, 90(1), 26-43.
- Abid, M., Schneider, U. A., & Scheffran, J. (2016). Adaptation to Climate Change and Its Impacts on Food Productivity and Crop Income: Perspectives of Farmers in Rural Pakistan, *Journal of Rural Studies*, 47, Part A, 254-266.
- Ali, A., & Erenstein, O. (2017). Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Climate Risk Management*, 16, 183-194.
- Aryal, J. P., Rahut, D. B., Maharjan, S., & Erenstein, O. (2018). Factors affecting the adoption of multiple climate-smart agricultural practices in the Indo-Gangetic Plains of India. In *Natural Resources Forum*, 42(3), 141-158.
- Badibanga, T., & Ulimwengu, J. (2020). Optimal investment for agricultural growth and poverty reduction in the democratic republic of congo a two-sector economic growth model. *Applied Economics*, 52(2), 135-155.
- Barbier, E. B., & Hochard, J. P. (2018). The impacts of climate change on the poor in disadvantaged regions. *Review of Environmental Economics and Policy*, 12(1), 26-47.
- Bocchiola, D., Brunetti, L., Soncini, A., Polinelli, F., & Gianinetto, M. (2019). Impact of climate change on agricultural productivity and food security in the Himalayas: a case study in Nepal. *Agricultural systems*, 171, 113-125.
- Carneiro, P., Heckman, J. J., & Vytlačil, E. J. (2011). Estimating marginal returns to education.

American Economic Review, 101(6), 2754-81.

Carneiro, P., Lokshin, M., & Umapathi, N. (2017). Average and marginal returns to upper secondary schooling in Indonesia. *Journal of Applied Econometrics*, 32(1), 16-36.

Coates, J., Rogers, B. L., Webb, P., Maxwell, D., Houser, R., & McDonald, C. (2007). Diet diversity study (Final report to the World Food Programme). Medford, MA: Friedman School of Nutrition Science and Policy, Tufts University.

Cornelissen, T., Dustmann, C., Raute, A., & Schönberg, U. (2016). From LATE to MTE: Alternative methods for the evaluation of policy interventions. *Labour Economics*, 41, 47-60.

Cornelissen, T., Dustmann, C., Raute, A., & Schönberg, U. (2018). Who benefits from universal child care? Estimating marginal returns to early child care attendance. *Journal of Political Economy*, 126(6), 2356-2409.

Dakpo, K. H., Desjeux, Y., Jeanneaux, P., & Latruffe, L. (2019). Productivity, technical efficiency and technological change in French agriculture during 2002-2015: a Färe-Primont index decomposition using group frontiers and meta-frontier. *Applied Economics*, 51(11), 1166-1182.

Deressa, T. T., Hassan, R. M., & Ringler, C. (2011). Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *The Journal of Agricultural Science*, 149(1), 23-31.

Di Falco, S., & Veronesi, M. (2013). How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia. *Land Economics*, 89(4), 743-766.

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3), 829-846.

- Earls, M. (2019). Climate shocks could reverse gains in child malnutrition. *Scientific American E&E news* retrieved on March 16, 2020 from <https://www.scientificamerican.com/article/climate-shocks-could-reverse-gains-in-child-malnutrition/>
- Economic Survey of Pakistan. (2014). Economic Advisor's Wing, Ministry of Finance, Islamabad, Pakistan.
- Economic Survey of Pakistan. (2019). Economic Advisor's Wing, Ministry of Finance, Islamabad, Pakistan.
- FAO. (2013). *Climate-Smart Agriculture Sourcebook*. Food and Agriculture Organization, Rome.
- FAO. (2016). *The State of Food and Agriculture: Climate change, agriculture and food security*. Food and Agricultural Organization (FAO), Rome.
- Foster, J., Greer, J., & Thorbecke, E. (1984). A class of decomposable poverty measures. *Econometrica: Journal of the econometric society*, 761-766.
- Gill, H. A. (2016). Pakistan-adaptations measures to cope with the rising temperature, 1.5-degree regime. *The Nature News, environment, climate change and science*.
- Hakimi, A., & Inglesi-Lotz, R. (2020). Examining the differences in the impact of climate change on innovation between developed and developing countries: evidence from a panel system GMM analysis. *Applied Economics*, 52(22), 2353-2365.
- Heckman, J. J., & Vytlačil, E. (2005). Structural equations, treatment effects, and econometric policy evaluation 1. *Econometrica*, 73(3), 669-738.
- Hertel, T. W., Burke, M. B., & Lobell, D. B. (2010). The poverty implications of climate-induced crop yield changes by 2030. *Global Environmental Change*, 20(4), 577-585.
- Huffman, W. E. (2020). Human Capital and Adoption of Innovations: Policy Implications. *Applied Economic Perspectives and Policy*, 42(1), 92-99.

- Iqbal, M., Ahmad, M., & Mustafa, G. (2015). Impact of Farm Households' Adaptation on Agricultural Productivity: Evidence from Different Agro-ecologies of Pakistan.
- Issahaku, G., & Abdulai, A. (2019). Can Farm Households Improve Food and Nutrition Security through Adoption of Climate-smart Practices? Empirical Evidence from Northern Ghana. *Applied Economic Perspectives and Policy*, p. 1-22.
- Issahaku, G. and Abdulai, A. (2020). Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana. *Australian Journal of Agricultural and Resource Economics*, 64(2), 396-420.
- Khanal, U., Wilson, C., Lee, B. L., & Hoang, V. N. (2018). Climate change adaptation strategies and food productivity in Nepal: a counterfactual analysis. *Climatic change*, 148(4), 575-590.
- Kousar, R., & Abdulai, A. (2016). Off-farm work, land tenancy contracts and investment in soil conservation measures in rural Pakistan. *Australian Journal of Agricultural and Resource Economics*, 60(2), 307-325.
- Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., ... & Hottle, R. (2014). Climate-smart agriculture for food security. *Nature climate change*, 4(12), 1068-1072.
- Lokshin, M., & Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. *The Stata Journal*, 4(3), 282-289.
- Lu, X. (2011). Provision of climate information for adaptation to climate change. *Climate Research*, 47(1-2), 83-94.
- Maxwell, D., B. Vaitla, and J. Coates. (2014). How Do Indicators of Household Food Insecurity Measure up? An Empirical Comparison from Ethiopia. *Food Policy*, 47: 107–16.
- Michler, J. D., Baylis, K., Arends-Kuenning, M., & Mazvimavi, K. (2019). Conservation

- agriculture and climate resilience. *Journal of environmental economics and management*, 93, 148-169.
- Mutenje, M. J., Farnworth, C. R., Stirling, C., Thierfelder, C., Mupangwa, W., & Nyagumbo, I. (2019). A cost-benefit analysis of climate-smart agriculture options in Southern Africa: Balancing gender and technology. *Ecological Economics*, 163, 126-137.
- Oseni, G., and Winters, P. (2009). Rural nonfarm activities and agricultural crop production in Nigeria. *Agricultural Economics*, 40, 189–201.
- Salim, R., Hassan, K., & Rahman, S. (2020). Impact of R&D expenditures, rainfall and temperature variations in agricultural productivity: empirical evidence from Bangladesh. *Applied Economics*, 52(27), 2977-2990.
- Shahzad, M. F., & Abdulai, A. (2020). Adaptation to extreme weather conditions and farm performance in rural Pakistan. *Agricultural Systems*, 180, 102772.
- Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, 79(1), 159-209.
- Swindale, A., and Bilisnky, P. (2006). Household Dietary Diversity Score (HDDS) for Measurement of Household Food Access. Indicator Guide Version 2, Food and Nutrition Technical Assistance (FANTA), USAID.
- Teklewold, H., Mekonnen, A., & Kohlin, G. (2019). Climate change adaptation: a study of multiple climate-smart practices in the Nile Basin of Ethiopia. *Climate and Development*, 11(2), 180-192.
- Tol, R. S. (2018). The economic impacts of climate change. *Review of Environmental Economics and Policy*, 12(1), 4-25.
- Vale, P.M. (2016). The Changing Climate of Climate Change Economics. *Ecological Economics*, 121: 12–9.

Véganzonès-Varoudakis, M. A., & Plane, P. (2019). Innovation, exports, productivity and investment climate; a study based on Indian manufacturing firm-level data. *Applied Economics*, 51(41), 4455-4476.

World Bank. (2015). Future of Food. Shaping a Climate-Smart Global Food System. World Bank Washington, D.C.

Wossen, T., Abdoulaye, T., Alene, A., Haile, M. G., Feleke, S., Olanrewaju, A., & Manyong, V. (2017). Impacts of extension access and cooperative membership on technology adoption and household welfare. *Journal of rural studies*, 54, 223-233.

Appendix C

Table 4.C1 Test on the validity of the selection instruments HFIAS

HFIAS	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Info_sources	1.328	1.339	0.99	0.322	-1.308	3.964	
CR_trainings	1.517	1.575	0.96	0.336	-1.584	4.618	
Constant	12.939	0.509	25.41	0.000	11.937	13.942	***
Mean dependent var		13.212	SD dependent var		7.865		
R-squared		0.009	Number of obs		278.000		
F-test		1.229	Prob > F		0.294		
Akaike crit. (AIC)		1938.191	Bayesian crit. (BIC)		1949.073		

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4.C2 Test on the validity of the selection instruments HDDS

HDDS	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Info_sources	0.132	0.436	0.30	0.763	-0.727	0.990	
CR_trainings	-0.063	0.513	-0.12	0.902	-1.073	0.947	
Constant	6.301	0.166	38.00	0.000	5.975	6.627	***
Mean dependent var		6.317	SD dependent var		2.551		
R-squared		0.000	Number of obs		278.000		
F-test		0.047	Prob > F		0.954		
Akaike crit. (AIC)		1314.447	Bayesian crit. (BIC)		1325.330		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.C3 Test on the validity of the selection instruments poverty headcount index

Poverty HC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Info_sources	0.021	0.084	0.25	0.806	-0.145	0.186	
CR_trainings	0.075	0.099	0.76	0.451	-0.120	0.269	
Constant	0.587	0.032	18.36	0.000	0.524	0.649	***
Mean dependent var		0.594	SD dependent var		0.492		
R-squared		0.003	Number of obs		278.000		
F-test		0.375	Prob > F		0.687		
Akaike crit. (AIC)		398.881	Bayesian crit. (BIC)		409.764		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.C4 Test on the validity of the selection instruments poverty gap index

Poverty_gap	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Info_sources	-0.053	0.087	-0.61	0.541	-0.225	0.118	
CR_trainings	0.121	0.103	1.18	0.239	-0.081	0.323	
Constant	0.460	0.033	13.88	0.000	0.395	0.525	***
Mean dependent var		0.459	SD dependent var		0.511		
R-squared		0.005	Number of obs		278.000		
F-test		0.760	Prob > F		0.469		
Akaike crit. (AIC)		419.136	Bayesian crit. (BIC)		430.019		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.C5 Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Info_sources	1.000					
(2) CR_trainings	0.222	1.000				
(3) HFIAS	0.074	0.073	1.000			
(4) HDDS	0.017	-0.003	-0.693	1.000		
(5) Poverty_HC	0.026	0.050	0.747	-0.550	1.000	
(6) Poverty_gap	-0.022	0.064	0.516	-0.412	0.450	1.000

Chapter 5

Conclusion and policy implications

Extreme weather conditions and climate change directly affect agricultural systems in the world; particularly, developing countries are more vulnerable. As a result, traditional farming is under risk, and crop yields are declining. This demands to put in place new agricultural methods and tools. The need of innovative strategies for sustainable agricultural production is getting attention from researchers and policymakers. Also, the international community emphasizes the adoption of climate-smart agriculture (CSA) to achieve sustainable development goals by incorporating economic, social, and environmental aspects to overcome extreme weather events, climate change, and the challenges of food insecurity as well as poverty. As the growing world population requires an increasing level of food production, at the same time, environmental preservation is a priority. To take up the food production challenge, the benefit from climate-smart farm practices (CSA practices) constitutes exciting potentials. For example, optimal input use reduces greenhouse gas emissions preventing environmental degradation, increases farm production to meet dietary requirements, as well as increases higher farm incomes and household welfare. Farmers adapt to temperature variability by changing cropping calendars to provide crop-specific temperatures at certain stages of plant growth and adjusted sowing dates of crops to avoid temperature hikes, which eventually reduced the environmental risks and enhanced farm net returns. Multi-product farmers apply soil and water conservation techniques for wheat crop might offer benefit to oilseed crops in the same season and increase the yield of cotton, rice, maize in the following season. Some of the farmers use crop rotation as a soil conservation strategy to retain soil nutrients. As part of risk management strategies, farmers diversify their activities by using different seed varieties, which include drought-tolerant, genetically modified, and locally high yielding varieties, depending on the environment and location of the farm.

Climate-smart agriculture is getting attention as a sustainable agricultural system in South Asia, particularly in Pakistan. Local government in the country promoted a lot of activities and programs

to support climate-smart agriculture, while international agencies and other civil society organizations also took part to encourage participation in CSA. To our best knowledge, this study is one of the first studies that has empirically analyzed the impact of climate-smart practices from an agricultural perspective and investigated farm performance and risk exposure, examined food and nutrition security, explored poverty status, and rural farm households' welfare. At first, the study made a healthy endeavor in contributing to the existing literature by employing recent innovations in impact assessment literature and empirically analyzed the factors influencing farmers' decision to adopt CSA practices in response to extreme weather conditions and the impact of adoption on farm performance in rural Pakistan. In this study, we used moments of farm net returns function as risk exposure and welfare measures.

Secondly, the study examined factors influencing specific adaptable CSA practices choices disaggregated by specific adaptation strategies such as changing cropping calendar, diversifying seed variety, changing input mix, and soil and water conservation, as well as the impact of adopting these CSA practices on farm net returns and downside risk exposure. Hence, this study might help in CSA practices' policy mainstreaming and identify the contribution of the individual, as well as a combination of them. It is also useful for the betterment of the rural community in Pakistan as well as in the developing countries with similar settings like Pakistan. Finally, the study is one of the first studies that investigated factors influencing adoption of climate-smart practices and the impact on food and nutrition security and poverty reduction considering food insecurity access scale (HFIAS), household dietary diversity scores (HDDS), and poverty status of farm households. The study performed an in-depth analysis and provided information on the potential effects of CSA practices on food and nutrition security as well as on poverty. Besides, it provided information as a part of farmers' efforts to enhance adaptation and mitigation at the farm level to enhance rural household welfare. Also, varying consumption patterns influence different production systems and drive diverse dietary needs; implementing CSA practices at farm influenced important crop yields as well as income to fulfill desired dietary requirements and

reduce the poverty level. Under sub-headings, a summary of empirical methods employed to conduct empirical analysis, summary of empirical results, and policy implications based on the study are outlined.

5.1. Summary of empirical methods

The study used different empirical approaches to analyze results in different chapters, such as endogenous switching regression (ESR), multinomial endogenous switching regressions (MESR), probit model, marginal treatment effects (MTE) model, propensity score matching (PSM) approach and multivariate treatment effects regression. As farmers self-select themselves into adaptation to climate change based on observed and unobserved characteristics, the selection into adoption is non-random. In this case, observable and unobservable factors may also influence farm outcomes such as farm net returns, downside risk exposure, food and nutrition security, and poverty status of farm households. This may lead to potential selection bias arising from both observable and unobservable heterogeneity among farmers that should be addressed appropriately in estimating empirical results to obtain unbiased and consistent estimates in adoption impact analysis. Above mentioned methods (ESR, MESR, MTE) take into account the selection bias considering observable and unobservable factors, while PSM accounts for only observable factors.

In chapter 2, we employed an endogenous switching regression (ESR) model to examine the factors influencing farmers' decisions to adopt CSA practices and the impact of adoption decision in response to extreme weather conditions on farm performance as farmers self-select into the adoption of CSA practices. Hence, adaptation to extreme weather conditions is non-random. This decision may be endogenous and also lead to the problem of selection bias. Therefore, this potential inconsistency was accounted for by using the ESR model in the empirical estimations. The ESR model estimates the selection and outcome equation simultaneously by employing full information maximum likelihood (FIML) method. This method handles the unobservable factors influencing adaptation to extreme weather conditions and non-adaptation. The ESR model accounts for selection bias arising from unobservable factors as omitted variable problem. To

account for selection bias, the inverse Mills ratio and covariance term were incorporated into the outcome equations. After running ESR, we obtain correlation coefficients, i.e., the covariance between selection and outcome equations. A significant value of correlation coefficients means that selection bias is present in the data due to unobservable factors. Further, the ESR model was used to compute the average treatment effect on the treated (ATT). In this chapter, the probit model was used to calculate the residuals of potentially endogenous variables and further employed to check the validity of excluded instruments from the outcome equations.

Chapter 3 assessed the determinants of farmers' adaptation choices and the impact of these choices on farm household welfare. A two-stage selection correction approach, multinomial endogenous switching regression (MESR), was employed to estimate the impact of adaptation choices on the welfare of multi-product farm households. Mainly, this procedure explored the factors influencing adaptable CSA practices such as changing inputs mix, change in cropping calendar, diversifying seed variety, and soil and water conservation taking non-adaptation as a base category. As farmers self-select into adoption of CSA practices, selection bias may arise due to observed and unobserved characteristics. Therefore, the ordinary least square (OLS) might lead to biased and inconsistent estimates. To assess the decision of farmers to adopt different CSA practices, the study employed a multinomial endogenous switching regression (MESR) approach. The MESR model is a two-step estimation procedure that considers the selection bias correction among all alternate choices in question. In the first step, factors affecting the choices of CSA practices were considered, and selectivity correction terms were computed. Further, these selectivity correction terms were included in second stage estimation to ensure consistency in model parameters to identify impacts of adoption on farm net returns and downside risk exposure. To assess the impact of adoption on farm net returns and downside risk exposure, we computed overall, location-wise, and plot-level quantile wise causal effects. Moreover, a probit model was employed to calculate the generalized residuals and predicted values of potentially endogenous variables. We also tested the validity of instrumental variables by employing a probit model, Wald test, and F-test.

In chapter 4, we analyzed the heterogeneous effects of adoption of climate-smart agriculture on household welfare in Pakistan. As farmers self-selected into adoption of CSA practices depending on observable and unobservable characteristics that may raise the issue of selection bias. Therefore, we controlled for both observable and unobservable factors affecting adaptation decisions by assigning random adoption status. We employed instrumental variable (IV) approach to account for observable and unobservable heterogeneity among adopters and non-adopters to estimate household-level treatment effects of adaptation to climate change on food and nutrition security measures such as household food insecurity access scale (HFIAS) and household dietary diversity scores (HDDS), as well as poverty status. For poverty measures, we used the poverty headcount index and poverty gap index. We used marginal treatment effects (MTE) approach for data analysis that considers observable and unobservable factors influencing treatment (in our case adoption decision) based on propensity scores. The analysis framework of this recently growing approach is a generalized Roy model based on potential outcomes. We estimated different treatment effects of interest such as average treatment effects (ATE), average treatment effects on the treated (ATT), average treatment effects on untreated (ATU), and local average treatment effects (LATE). This approach is also flexible in finding policy-relevant treatment effects (PRTE). By using this approach, we also checked the robustness of our empirical results by employing different MTE specifications.

5.2. Summary of results

In chapter 2, we analyzed the factors that affect farm households' adaptation decisions to extreme weather conditions. The results indicated that temperature anomaly positively affected farmers' decision to adapt to extreme weather conditions, while rainfall anomaly negatively influenced the adaptation decisions. The household head age and education positively influenced adoption of CSA practices. Farmers who had livestock (number of animals) at farm were more likely to adopt. The extension services supported the notion that farmers with contacts to extension agents were more likely to adopt CSA practices. Exposure to climate-related shocks (such as floods, droughts,

cyclones, and climate-related pest infestation and diseases) in the past helped farmers to adopt to extreme weather conditions. The location zones and soil quality also had a significant effect on adoption of extreme weather conditions. The results further showed that adoption of extreme weather conditions exerted a positive and statistically significant impact on reducing net returns volatility, downside risk exposure, and kurtosis. The results further revealed that adoption contributed to higher farm net returns compared with non-adopters. It implied that adoption reduced exposure to risk and stabilized farm net returns, which contributed to improving rural household welfare.

In chapter 3, the estimated empirical results from the multinomial logit model on factors influencing adoption decision of available CSA practices choices revealed that the choice of seed variety diversification was positively and significantly influenced by average rainfall, ownership of agricultural machinery, extension services, and previous experience to climate-related shocks. The choice of changing cropping calendar was positively and significantly associated with average rainfall, household head education, ownership of agricultural machinery, and exposure to previous climate-related shocks. The choice of input mix was positively and significantly influenced by the average rainfall, education of the household head, plot size, and having agricultural machinery at the farm. The choice of soil and water conservation was positively and significantly determined by average rainfall, rain anomaly, household head's education, ownership of agricultural machinery, and previous climate-related shocks. Results also confirmed the significant selection bias correction terms in the adaptation choices indicating that without accounting for selection bias, results might be inconsistent. The results further revealed that soil and water conservation exerted the most considerable positive influence on farm net returns of adapted plots followed by input mix, diversifying seed variety, and changing cropping calendar, respectively. The findings also showed that all of the CSA practices significantly reduced downside risk exposure and crop failure of farm households. Segregated results by cropping zones indicated that all CSA practices positively and significantly enhanced farm net returns of adopters residing in these locations.

Further, analysis based on plot-level quantiles confirmed that changing input mix in the first quantile, soil and water conservation in the second and third quantile and diversifying seed variety in the fourth quantile exerted the highest positive impact on farm net returns compared with other practices.

Results from chapter 4, on controlling for household and farm level characteristics, climate variability, and location fixed effects confirmed that observable and unobservable heterogeneity significantly varied across individuals. Moreover, interaction of average temperature and rainfall, rainfall anomaly, household head education, extension contacts, climate change information sources, and climate-resilient trainings positively and significantly influenced adoption decisions, while credit constraints, average daily rainfall, temperature anomaly, and interaction between temperature and rainfall anomaly, clay soil, and location of the farm other than mix cropping zone negatively influence adoption decisions. At the non-adoption state, credit constraint positively influences household food insecurity, poverty headcount, and poverty gap as well as negatively affects household dietary diversity, while having more dependents in a household increases food insecurity and poverty as well as decreases dietary diversity. The results reveal that the adoption of CSA practices reduces household food insecurity and increases household dietary diversity at a lower level of unobserved resistance to adoption. Furthermore, adoption of CSA practices significantly reduces poverty headcount and poverty gaps of farm households at a lower level of unobserved resistance. There are differential impacts of observable characteristics of farm households that influence the gains from adoption. Impact assessment in terms of weighted average treatment effects such as ATE, ATT, ATU reveals that food and nutrition security is improved by adoption, and poverty declines. As the unobserved resistance to adoption increased, the gains from adoption were lowered. The findings from local average treatment effects (LATE) reveal that access to the number of climate sources and climate resilient trainings had a significant effect on reducing food and nutrition insecurity and poverty.

5.3. Policy implications

The findings from this study can be used to draw several important policy implications, which suggest CSA practices such as changing inputs mix, change in cropping calendar, diversifying seed variety and soil and water conservation can be welfare-enhancing in terms of increased farm net returns, food, and nutrition security and hence reducing poverty, exposure to risk and crop failure. The important role of these CSA practices in improving farm performance calls increased support from the government, farmer organizations, social peers, development agencies, and private companies to promote these practices in the study area. Therefore, for sustainable agriculture, these CSA practices should be promoted among the farmers in the country, either in isolation or in a combination of these practices.

The positive influence of extension contacts on adoption decisions indicates that enhancing access to extension services would contribute to improving the welfare of farmers. Therefore, policies that enhance access to extension services would facilitate the adoption of CSA practices. The negative and significant effect of liquidity constraints on farm net returns indicates that policymakers could help to improve farmers' access to formal and informal credit to promote the adoption of CSA practices. Hence, policymakers could promote practical measures to enhance farmers' access to credit and extension services. The significance of education in the adoption results indicates that the provision of schools in remote areas could enhance the education level of rural farm households for a better understanding of modern technology adoption. As agricultural machinery and input mix contribute to enhancing the adoption rate of CSA practices, policymakers could promote microfinance or subsidy schemes to help farmers to purchase agricultural machinery and inputs.

A high correlation between information related to climate change and the adoption of CSA practices suggests that the provision of timely information on climate change to the farmers could enhance the adoption rates. Climate-resilient training could be another policy-relevant treatment in increasing the adoption rates. Farmers also complained about lousy marketing channels when

they sell their produce in markets, for example, low prices in the harvest season and limited food storage facilities. The government could facilitate farmers through support price and marketing facilities in the country. Finally, policy initiative to improve farmers' access to education, extension services, access to credit, expanding irrigation facilities, improvement of marketing channel in the country, provision of climate change information, training on climate resilience could ease rural farm households' constraints, promote pro-poor agricultural growth and enhance the rural household welfare in Pakistan. Moreover, scaling up CSA to achieve the production as well as food demand challenges requires sound policies, strong institutions and secure financing at the local levels.

Household Roster and Education

PID	1 Name	2 Sex	3 How old is [NAME]?		4 Relationship to head	5 What is the present marital status of (NAME)?	6. Is [NAME] able to read in any language with understanding?	9. Has [NAME] ever attended school?	10 What is the education of [NAME]?		11 Occupation Ask from older than age 15	12 Annual Income (RS.)		
	NAME	CODE	YEARS	MONTHS		CODE	CODE		CODE		Primary	Secondary	Primary	Secondary
	List household members (head, spouse, children, parents then others)	1 Male 2 Female	<div style="border: 1px solid black; padding: 2px; display: inline-block;">YEARS IF 6 YEARS OR OLDER</div> <div style="border: 1px solid black; padding: 2px; display: inline-block;">YEARS AND MONTHS IF LESS THAN 6 YEARS</div>		01 Head 02 Wife/husband 03 Child/adopted child 04 Grandchild 05 Niece/nephew 06 Father/mother 07 Sister/brother 08 Others_____	1 Currently married 2 Divorced 3 Separated 4 Widow or widower 5 Never married 6 Nikah without rukhsati	0 No 1 Yes, easily 2 Yes, with difficulty	0 No >> NEXT PERSON 1 Yes	0 Katchi/Pakki 1 Class 1 2 Class 2 3 Class 3 4 Class 4 5 Class 5 6 Class 6 7 Class 7 8 Class 8 9 Class 9 10 Class 10 11 Class 11 12 Class 12	13 BA/B.Sc (Hons) 14 MA/, MSc, M.Phil, PhD 15 MBBS Doctor 16 Engineer 17 Lawyer 18 Diploma 19 Adult Literacy program 20 Other Literacy program 21 Deeni Madrassa (Continued) 22 Deeni Madrassa (Incomplete) 23 Never enrolled 24 Dropped out without completing Class 1 Other (specify) _____				
01														
02														
03														
04														
05														
06														
07														
08														
09														
10														
11														
12														
13														
14														
15														

Roster Part 2: Household Health

P/ID	1-	2-	3-	4-	5-	6-	7-	8-	9-	10-	11-	12-	13-	14-
	Did [NAME] suffer from sickness in last 12 months? 1 Yes 0 No >> Q7	No of times person suffered from diseases?	Which person got easily suffered? Rank persons	Which diseases faced by [NAME]? list three major diseases	What are the causes of disease? 1 Climate change 0 Others >> Q7	How many times climate related disease attacked?	Have you health unit, hospital or dispensary in your village? 1 Yes >> Q9 0 No	How far is health unit, hospital or dispensary from your house? KM	Is it providing health facilities properly? 1 Very good 2 Good 3 Satisfactory 4 No	Have you access to safe and clean drinking water? 1 Yes 0 No	Have you toilet in your house? 1 Yes 0 No	Is sewage water properly drained? 1 Yes 0 No	Type of house 1 Pakka 2 Mix 3 Kaccha	Type of roads? 1 Concret 2 Bricks 3 Kacchi
	CODE	NO	RANK	CODE BOX-D	CODE	NO	CODE	KM	CODE	CODE	CODE	CODE	CODE	CODE
01														
02														
03														
04														
05														
06														
07														
08														
09														
10														
11														
12														
13														
14														
15														

CODE BOX-D			
1	Fever	10	Cholera
2	General weakness/ weight loss	11	Diarrhea
3	Headach	12	Skin problems
4	Joint pain	13	Eye problems
5	Toothach	14	Flue/Cold
6	Heart problem	15	Asthma
7	Hepatitis	16	Heat stress
8	Restlessness	17	Throught/Lungs problem
9	TB	18	Others

Section 1: Agriculture

Part 1: Plot Characteristics for Household-Managed Plots

PLOT #	1.	2.	3.	4.	5.	6.	7.	8.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
	Please list all owned plots, then rented in and then all shared cropped and then ask questions 2 to 17 for each plot	Plot area 1 Marla 2 Kanal 3 Bigha / Jareb 4 Acre 5 Square	Tenancy status 1 Own 2 Rent in 3 Rent out 4 Share in 5 Share out 6 Mortgaged & being self cultivated 7 Mortgaged but not being self cultivated Other (specify)	How much would this plot sell for per acre if it is sold today?	How much rent did you pay for your rented-in plot?	How much rent did you receive for your rented out plot?	What was the landlord's share of output?	What was the landlord's share of inputs?	Plot type 1 Home at agri land 2 Cultivable/arable land 3 Pasture 4 Bush/forest 5 Waste/non-arable land 6 Land in riverbed 7 Land in market place 8 Cultivable pond 9 Derelict pond 10 Natural seasonal reservoir 11 Homestead 12 Fellow in both seasons If answer to this question is code 1, 7, 8, 9 or 10, then don't ask Q11 to Q16 for such type of plot	Is this plot within or outside the (revenue) village? 1 In 2 Out	Distance of plot from your homestead if next to home write "0"	Soil type 1 Sandy 2 Sandy loam 3 Loam 4 Clay loam 5 Clay Other	Soil fertility 1 Very fertile 2 Moderate 3 Poor 4 Very poor 5 Not productive at all	Erosion 1 No erosion 2 Mild erosion 3 Severe erosion	Slope of plot? 1 Flat 2 Slight Slope 3 Moderate slope 4 Steep slope 5 Terraced	Did the plot experience waterlogging? 0 No 1 Yes	Did the plot experience salinity? 0 No 1 Yes	Did you have a tubewell / pump located on this plot? 0 No 1 Yes
	PLOT NAME	AREA	UNIT	CODE	RS/ACRE	RS./YEAR	RS./YEAR	PERCENT	CODE	CODE	KILOMETERS	CODE	CODE	CODE	CODE	CODE	CODE	CODE
1																		
2																		
3																		
4																		
5																		
6																		
7																		
8																		

Marlas	1-4	5-9	10-14	15-20
Kanals	0.25	0.5	0.75	1.0
1 Square = 25 acres 1 Acre = 2 Bighas / Jarebs = 8 Kanals 1 Bigha / Jareb = 4 Kanals 1 Kanal = 20 Marlas				

Code Box 1	
1	Earthen water conservation works
2	Masonry water conservation works with or without gates
3	Underground dam as a water conservation works
4	Timber crib water conservation works
5	Farm ponds
6	Waterways or diversion ditches/channels
7	Soil bunds
8	Stone bunds
9	Grass strips
10	Tree rows
11	Hedge rows
12	Contour leveling/terracing
	Other, specify

Section 1: Agriculture

Part 2: Land Management for Household-Managed Plots

Note: List all those PLOTS here and in all the Parts of Section 1 for which answer to Q3 is code 1, 2, 4 or 6 and answer to Q8 is code 2 or 11 in S1P1

SEASON	PLOT #	1	2	3	4		5	6	7	8	9			10	11	12		13	
		Did you leave crop residue on this plot? 0...No >> Q3 1...Yes If the plot had no crop in entire season, then write -99 and go to Q7	If yes, how much?	Did you use crop rotation? 0...No >> Q5 1...Yes	If rotating crops, which crops did you rotate on this plot? Rabi 2014-15 Rabi 2015-16		Did you practice zero or minimum tillage? 0...No 1...Yes	Did you periodically leave this plot fallow? 0...No 1...Yes	Did you use precision land leveling/laser land leveling? 0...No 1...Yes	Did the plot has soil and water conservation structures? 0...No >> Q10 1...Yes	If yes, which structures? Code Box 1			Did you use cover crops? 0...No 1...Yes	Did you use labour on this plot? 0...No 1...Yes	No of labourer used Permanent Temporary		Total cost (Rs.) Inkind+Cash If permanent labourers did work on all plots write total amount in 1st row Permanent Temporary	
		Code	Percent	Code	Crop code1	Crop code 2	Code	Code	Code	Code	1	2	3	Code	Code	Permanent	Temporary	Permanent	Temporary
Rabi 2015-16	1																		
	1																		
	1																		
	1																		
	1																		
	1																		
					Kharif 2015	Kharif 2016													
Kharif 2016	2																		
	2																		
	2																		
	2																		
	2																		
	2																		

Code Box 1 (Crops Grown)					
Rabi Crops (01-30)		Kharif Crops (31-60)		Orchard Code (61-90)	
1	Wheat	31	Rice	61	Mango
2	Gram/Chana Daal	32	Maize	62	Banana
3	Masoor Daal	33	Jawar (Sorghum)	63	Guava
4	Other Pulses(Rabi)	34	Bajra (Millet)	64	Apple/Plum/Peach/ Apricot
5	Rapeseed/Mustard	35	Cotton	65	Kino/Malta/Grapefruit
6	Sunflower	36	Sugarcane	66	Citrus
7	Other Oilseeds	37	Sugar-beets	67	Grapes
8	Potato	38	Moong Daal	68	Pomegranate
9	Onion	39	Mash Daal	69	Dates
10	Tomato	40	Other Kharif pulses	70	Mulberry
11	Peas	41	Groundnuts/Peanuts	71	Persimmon
12	Other Rabi vegetables	42	Sesamum	72	Nuts
13	Spices	43	Soybean	73	Tree for Wood
14	Tobacco	44	Castorseed	74	Firewood
15	Barseem/Lucern	45	Gwaraseed	75	Roses/cut flower
16	Oats	46	Other oil seed (Kharif)	76	Bamboo
17	Other Rabi fodder	47	Chillies	77	Strawberry
		50	Melons		Other fruits (specify)
		51	Water melons		

Code Box 2 (Codes for By-products)	
0 = No By-product >> Next crop/plot	6 = Rice husk
1 = Wheat straw	7 = Maize comb
2 = Sugarcane toppings	8 = Maize straw
3 = Sugarcane dry leaves	9 = Millet straw
4 = Cotton sticks	Other (specify)
5 = Rice straw	

CODE BOX 1: Buyer of Crop				CODE BOX 2: Place of Sale	
1	Landlord	7	Commission agent in market	1	Farm gate
2	Input dealer	8	Commission agent in village	2	Market
3	Middleman	9	Household/friend	3	Local market
4	Processor (factory)	10	Village shopkeeper	4	District market
5	Retailer in main market	11	Government	5	Home, warehouse, or storage place
6	Wholesaler		Other (specify)	-77	Don't know/remember
					Other (specify)

Section 1: Agriculture

Part 4: Crop Sales in the Past Year (Rabi 2015-16 and Kharif 2016)

Note: Report quantity in the unit used for question 6 of S1P3

Instruction for Q8: For the Orchard or crop for which there is contract farming in S1P3, write total value of sale in Q8 after writing crop code

SEASON	CROP CODE	1	2	3	4	5	6	7	8	9	10	11
		Quantity kept by own household (home consumption plus storage)	Quantity kept as feed for livestock	Quantity paid to laborers	Quantity given to the landlord Write -99 if no sharecropping	Quantity kept as seed for next season	Quantity given away as gifts or in exchange for other goods	Total amount sold If not sold out, write -99 >> Q12	What was the price per unit for sold [CROP]?	Who bought most of the crop?	Where was the crop sold?	Distance to location where output was sold If distance is less than 1 Km, write 0
		QUANTITY	QUANTITY	QUANTITY	QUANTITY	QUANTITY	QUANTITY	QUANTITY	RS./UNIT	CODE BOX 1	CODE BOX 2	KM
Rabi 2015-16	1											
	1											
	1											
	1											
	1											
	1											
	1											
	1											
	1											
Kharif 2016	2											
	2											
	2											
	2											
	2											
	2											
	2											
	2											

Section 1: Agriculture

Part 5: Manure, Compost & Chemical Fertilizers

ENUMERATORS: Plot and Crop #s should be copied from Part 3 of Section 1

SEASON	PLOT #	CROP #	2.		4.		6.		7.		8.		
			2a.	2b.	4a.	4b.	6a.	6b.	7a.	7b.	8a.	8b.	
			1.										
			Did you use any manure on this ..[PLOT-CROP]..?	How much manure did you use on this ..[PLOT-CROP]..?		How much compost did you use on this ..[PLOT-CROP]..?		Did you use any chemical fertilizer on this ..[PLOT-CROP].. during ..[SEASON]..?		What types of fertilizers did you use on this ..[PLOT-CROP].. during ..[SEASON]..?		Total number of 50kg bags of ..[FERTILIZER TYPE]..	
			0 No ▶ Q3 1 Yes	If sharecropped plot, make sure that tenant reports TOTAL amount used, not just his own share 1 Donkey load (=1 maund) 2 Cart load (=20 maund) 3 Trolley load (=80 maund)		If sharecropped plot, make sure that tenant reports TOTAL amount used, not just his own share 1 Donkey load (=1 maund) 2 Cart load (=20 maund) 3 Trolley load (=80 maund)		0 No ▶ NEXT PLOT-CROP / NEXT SEASON 1 Yes		1 DAP 2 Urea 3 2323 4 Other Nitro-Phos blend 5 Potash 6 Gypsum Report every type of fertilizer used for crop		NOTE: If sharecropped plot, make sure that tenant reports TOTAL amount used not just his own share	
			CODE	NO. OF LOADS	LOAD UNIT CODE	CODE	NO. OF LOADS	LOAD UNIT CODE	CODE	CODE	NUMBER OF BAGS	RS./BAG	
Rabi 2015-16	1												
	1												
	1												
	1												
	1												
	1												
Kharif 2016	2												
	2												
	2												
	2												
	2												
	2												

Section 1: Agriculture

Part 6: Farm machinery

ENUMERATORS: Plot and Crop #s should be copied from Part 3 of Section 1

Write -99 in column 'a' & 'b' for that machinery type which was not used and leave column 'c' & 'd' empty

SEASON	PLOT #	CROP #	1 TRACTOR				2 BULLOCK TRACTION				3 LASER LAND LEVELLER (LLL)				4 THRESHER/COMBINE HARVESTER			
			1a.	1b.	ASK FOR SHARECROPPED PLOTS ONLY		2a.	2b.	ASK FOR SHARECROPPED PLOTS ONLY		3a.	3b.	ASK FOR SHARECROPPED PLOTS ONLY		4a.	4b.	ASK FOR SHARECROPPED PLOTS ONLY	
			Hours of own tractor	Hours of rented tractor	1c. Did you pay for any part of your share of tractor rental costs through an advance by your landlord against the harvest (or through use of the landlord's own tractor)?	1d. Number of tractor rental hours, <u>from your share</u> , advanced by the landlord against the harvest?	hours of own bullock traction	Hours of rented bullock traction	2c. Did you pay for any part of your share of bullock rental costs through an advance by your landlord against the harvest (or through use of the landlord's own bullocks)?	2d. Number of bullock rental hours, <u>from your share</u> , advanced by the landlord against the harvest?	Hours of own LLL	Hours of rented LLL	3c. Did you pay for any part of your share of LLL rental costs through an advance by your landlord against the harvest (or through use of the landlord's own tubewell)?	3d. Number of LLL rental hours, <u>from your share</u> , advanced by the landlord against the harvest?	Hours of own thresher / combine harvester	Hours of rented thresher / combine harvester	4c. Did you pay for any part of your share of machine rental costs through an advance by your landlord against the harvest (or through use of the landlord's own machine)?	4d. Number of machine rental hours, <u>from your share</u> , advanced by the landlord against the harvest?
HOURS	HOURS	CODE	HOURS	HOURS	HOURS	CODE	HOURS	HOURS	HOURS	HOURS	CODE	HOURS	HOURS	HOURS	CODE	HOURS		
Rabi 2015-16	1																	
	1																	
	1																	
	1																	
	1																	
	1																	
	1																	
	1																	
Kharif 2016	2																	
	2																	
	2																	
	2																	
	2																	
	2																	
	2																	
	2																	

5 RENTAL PRICES PER ACRE			
5a.	5b.	5c.	5d.
TRACTOR	BULLOCK TRACTION	LASER LAND LEVELLER	THRESHER/ COMBINE HARVESTER
RS./ACRE	RS./ACRE	RS./ACRE	RS./ACRE

Wheat							Cotton							Rice					
Code	Variety Name	Code	Variety Name	Code	Variety Name	Code	Variety Name	Code	Variety Name	Code	Variety Name	Code	Variety Name	Code	Variety Name	Code	Variety Name	Code	Variety Name
1	Abdul Sattar	26	FAISALABAD-08	51	PASBAN 90	76	Uqab-2000	101	493/97	126	CIM-443	151	FH-685	176	MNH-552	201	Basmati Kernal	226	Pusa
2	AARI 2011	27	Faisalabad-2002	52	PAVON	77	Watan-93	102	840/97	127	CIM-446	152	FH-87	177	MNH-554	202	Basmati Super	227	Ranbir
3	ARZ	28	FAISALABAD-83	53	PB. 85	78	WL 711	103	AEC/73/3/89	128	CIM-448	153	FH-900	178	MNH-886	203	Basmati-198	228	RH-10
4	AS.2002	29	Fareed-06	54	POTHOWAR	79	YECORA	104	Ali Akbar-703	129	CIM-465	154	FH-901	179	MVH-518	204	Basmati-2000	229	Safidon
5	AUQAB 2000	30	FSD. 85	55	Punjab 2001	80	83	105	Ali Akbar-802	130	CIM-467	155	FH-941	180	NEELAM-121	205	Basmati-217	230	Shahanshah
6	BARANI-70	31	Gandam-711	56	PUNJAB 76	81	3094	106	Ali Akbar-905	131	CIM-473	156	FH-942	181	NIAB-78	206	Basmati-370	231	Shaheen basmati
7	BARANI-83	32	INQILAB 91	57	PUNJAB 81		Other (specify)	107	A-one	132	CIM-482	157	FS-631	182	NIAB-111	207	Basmati-385	232	Suganda
8	Bhakhar-02	33	IQBAL2000	58	PUNJAB 96			108	B32/97	133	CIM-483	158	FVH-137	183	NIBGE-115	208	Basmati-386	233	Taraori
9	BHAWALPUR-79	34	Kainat	59	PUNJNAD 88			109	B-496	134	CIM-496	159	FVH-28	184	NS-141	209	Bihar		Other (specify)
10	BLUE SILVER	35	KOHINOOR 83	60	RAWAL 87			110	B-622	135	CIM-499	160	FVH-49	185	RH-500	210	Dehradun		
11	C217	36	KOHISTAN 97	61	Resham			111	B-803	136	CIM-506	161	FVH-53	186	S-12	211	Fakhre Malakand		
12	C228	37	Kohsar-95	62	ROHTAS 90			112	B-820	137	CIM-573	162	FVH-55	187	S-14	212	GNY 50		
13	C250	38	LASANI.08	63	SA 42			113	B-821	138	CIM-598	163	FVH-57	188	Sitara-008	213	GNY 53		
14	C271	39	LU 26S	64	SA 75			114	B-842	139	CIM-768	164	GM-2085	189	SITARA-009	214	Haryana		
15	C273	40	LYALLPUR-73	65	SANDAL 73			115	B-850	140	Desi Ravi	165	IR-1524	190	SLH-317	215	Irri-6		
16	C518	41	Mairaj-06	66	SATLUJ 86			116	B-896	141	DNH-49	166	IR-3701	191	SLS-1	216	Irri-9		
17	C591	42	MEXIPAK	67	SEHER 06			117	BH-100	142	FDH-170	167	IR-NIBGE-3	192	TARZAN-1	217	JP-5		
18	Chakwal - 50	43	MH 97	68	SH.2002			118	BH-118	143	FH-113	168	IR-NIBGE 901	193	TCD-3H	218	Kasturi		
19	CHAKWAL-86	44	Millat 2011	69	SHAFaq 06			119	BH-160	144	FH-114	169	Karishma	194	TSR23-75	219	KS-282		
20	Chakwal-97	45	Ms-2011	70	SHAHKAR 95			120	BH-167	145	FH-628	170	MG-6	195	VH-259	220	KS-282		
21	CHENAB-2000	46	Nawab	71	SHALIMAR 88			121	BH-95	146	FH-629	171	MIAD-852	196	VS-135	221	KSK-133		
22	CHENAB-70	47	Nayab	72	Shehzor			122	CIM-109	147	FH-634	172	MNH-93		Other (specify)	222	Mahi		
23	CHENAB-79	48	PAK 81	73	Soraj			123	CIM-1100	148	FH-649	173	MNH-465			223	PB2 (Sugandh-2)		
24	DIRK	49	PARI 73	74	TD-1			124	CIM-240	149	FH-657	174	MNH-516			224	PB3		
25	Durum-97	50	PARWAZ 94	75	Ufaq-02			125	CIM-435	150	FH-682	175	MNH-536			225	Pukhraj		

Section 1: Agriculture

Part 7: Other purchased inputs for household managed plots

ENUMERATORS: Plot and Crop #s should be copied from Part 3 of Section 1

SEASON	PLOT #	CROP #	SEEDS								PESTICIDES/HERBICIDES/FUNGICIDES		ABIANA/AGRICULTURAL TAX			ELECTRICITY/STORAGE COSTS	
			1. Own Seed			2. Purchased Seed					3A.	3B.	4A.	4B.	4C.	5A.	5B.
			1A. Variety	1B. Quantity	2A. Variety	2B. Quantity	2C. Cost	2D. Source of purchased seed	2E. How long is distance from your house to this supplier ?	2F. In your opinion, what are the two most important traits in seed of this crop?	Type	Total Cost	Total cost of abiana	Did you pay any agricultural tax?	Total cost of agricultural tax	Total electricity cost	Total storage cost
CODE	Kgs	CODE	Kgs	Rs./Kg	CODE	KM	CODE1 CODE2	CODE	Rs.	Rs.	0 No 1 Yes	Rs.	Rs.	Rs.	Rs.		
Rabi 2015-16	1																
	1																
	1																
	1																
	1																
Kharif 2016	2																
	2																
	2																
	2																
	2																

Section 2: Agricultural Water Use

Part 1: General

ENUMERATORS: Plot and Crop #s should be copied from Part 3 of Section 1

Note: Ask all of SECTION 2 at the plot level (rather than plot-crop level) and write -44 in CROP #, UNLESS the plot uses drip irrigation in which case we can ask at the plot-crop level

Did the household irrigate any plots in last year ((Rabi 2015-16 and Kharif 2016)?

0 No >> Section 3 1 Yes

SEASON	PLOT #	CROP #	1.	2.	3.	4.	5.	6.	If groundwater is a source of water			If the canal is a source of water			14.	
			Primary source of water	Secondary source of water	Tertiary source of water	Type of irrigation method (applies to both SW and GW)	Usual irrigation depth	Maximum irrigation depth	What was the well type?	Water extraction method	Depth of well	What year was the well drilled?	Where is the plot located?	Distance of plot from mogha?	Water extraction method	Name of the minor/distributary that feeds this watercourse
			CODE	CODE	CODE	CODE	INCHES	INCHES	CODE	CODE	FEET	YEAR	CODE	KM	CODE	NAME
Rabi 2015-16																
Kharif 2016																

Section 2: Agricultural Water Use

Part 2: Water Quantity and Quality (Groundwater)

ENUMERATORS: Plot and crop #s should be copied from Part 1 of Section 2 for those plots/crops irrigated with groundwater

Note: Ask all of SECTION 2 at the plot level (rather than plot-crop level) and write -44 in CROP #, UNLESS the plot uses drip irrigation in which case we can ask at the plot-crop level

Did the household use groundwater in last year ((Rabi 2015-16 and Kharif 2016)?

0 No >> Part 3 of Section 2 1 Yes

SEASON	PLOT #	CROP #	Groundwater																		
			1. Water application from groundwater						2. Cost		3. Quality	4. Drainage			5. Buying GW			6. Selling GW			
			1a. Area irrigated	1b. Total number of irrigations	1c. Number of equal irrigations	1d. Average depth of equal irrigations	1e. Number of un-equal irrigation except Rauni If there are no unequal irrigations, write 0 >> Q2a	1f. Average depth of un-equal irrigations	1g. Average length of one irrigation turn?	1i. How long did it take you to irrigate one acre of your plot?	2a. Price per hour for tubewell irrigation	2b. Other irrigation costs per crop, plot & season	What was the quality of groundwater used for irrigation? 1 Good 2 Somewhat brackish 3 Brackish	4a. Did you use your tubewell for draining land? 0 No ▶ 5a 1 Yes	4b. How many hours did you pump for draining over the entire season?	4c. Irrigation Equipment: What was the rental fee for pump renting for the season?	5a. Did you <u>obtain</u> groundwater from anyone on your watercourse?	5b. How many hours did you <u>rent in GW per season?</u>	5c. How much money did you <u>pay for renting in GW per season?</u>	6a. Did you <u>sell</u> groundwater to anyone on your water course? 0 No ▶ Next Crop/Plot 1 Yes	6b. How many hours did you <u>rent out GW per season?</u>
Acres	No.	No	No.	Inches	Minutes	Minutes	RS.	RS.	CODE	CODE	HOURS	RS.	CODE	Hours	Rs.	CODE	Hours	Rs.			
Rabi 2015-16																					
Kharif 2016																					

Section 2: Agricultural Water Use

Part 3: Water Quantity and Quality (Canal Water)

ENUMERATORS: Plot and crop #s should be copied from Part 1 of Section 2 for those plots/crops irrigated with canal water

Note: Ask all of SECTION 2 at the plot level (rather than plot-crop level) and write -44 in CROP #, UNLESS the plot uses drip irrigation in which case we can ask at the plot-crop level

Did the household use canal water in last year (Rabi 2015-16 and Kharif 2016)?

0 No >> Section 3 1 Yes

SEASON #	PLOT #	CROP #	Canal Water																					
			1. Water application from surface water					2. Length of irrigations		3. Timing	5a. Cost	5b. other surface cost	5c. Cost	5d. Cost	5e. Cost	6a. Share of irrigation	6b. Share of irrigation	7a. Exchanging Turns	7b. Exchanging Turns	7c. Exchanging Turns	8a. Purchasing turns	8b. Buying turns	8c. Selling turns	8d. Selling turns
			1a. Area irrigated	1b. Total number of irrigations	1c. Number of equal irrigations	1d. Number of unequal irrigation except Rauni If there are no unequal irrigations, write 0 >> Q2a	1e. Average depth of irrigations	2a. Average length of one irrigation turn?	2b. How long did it take you to irrigate one acre of your plot?	(Warabandi) Was the timing of your canal water turn as per your needs? 0 No 1 Yes	What was the <i>abiana</i> paid? (if not available by plot, put total payment in row 1 for each season and mark with "")	Did you use a pump to extract water from the canal? 0 NO ► Q6a 1 Yes	Irrigation Equipment rental fee for pump renting for the season	Electricity cost per season	Diesel/fuel cost per season and crop	Did you use your full share of water allocation? 0 No turns 1 All turns ► Q7a 2 Most turns 3 Few turns	If you did not receive your full share, why not?	Did you exchange any turns with someone else on the canal? 0 No ► Q8a 1 Yes	How many irrigation turns did you exchange?	Did you exchange turns toward the tail or head or with a nearby neighbor? 1 = tail 2 = head 3 = head and tail 4 = neighbor	How many turns did you purchase from someone else along the canal?	Payment method for any turns bought 1=Cash 2=In kind	How many turns did you sell to someone else along the canal?	Payment method for any turns sold 1=Cash 2=In kind
Acres	No.	No.	No.	Inches	Minutes	Minutes	CODE	Rs.	CODE	RS.	RS.	RS.	CODE	CODE1	CODE	# of turns	CODE	# of turns	CODE	# of turns	CODE			
Rabi 2015-16																								
Kharif 2016																								

CODE BOX 1	CODE BOX 2
1. Information on inputs for crop production 2. Information on climate change 3. Information on inputs for livestock production 4. Information on new methods of crop production 5. Information on new methods for livestock production 6. Information on new crops or crop varieties 7. Information on new livestock or livestock breeds 8. Information on improving water, soil, forests 9. Information on obtaining & using fertilizer 10. Information on obtaining & using agrochemicals 11. Information on obtaining & using improved seeds 12. Information on obtaining credit/loans 13. Information on marketing crops or livestock Other (specify)	1. Found the advice they provided in the past to be unsuitable or unhelpful 2. Am not interested in changing production practices 3. Do not wish to borrow money 4. Do not wish to purchase inputs 5. No extension agents available in this muaza or district 6. Not enough extension agents available for all farmers in this muaza or district 7. Did not know about services offered by extension agents 8. Extension agents only help farmers with more land than my household has 9. Extension agents only help male farmers 10. Extension agents only help farmers who are friends or relatives of local officials or politicians 11. Extension agents only help farmers who are friends or relatives of large landowners 12. Extension agents only help educated farmers Other (specify)

CODE BOX 3
1. Agricultural research institutions 2. NGOs 3. Community-based organizations 4. Bank 5. Local farmers organization 6. Cooperatives Others specify

CODE BOX 4
1. Friends 2. Religious groups 3. Civil society groups 4. Local progressive farmers Others specify

Section 3: Part-1 Access to Extension

1	2	3	4	5	6	7	8	9	10	11	12	13
Did you receive any information on crop or livestock production within the past year from a source other than extension agent? 0...No >> Q3 1...Yes	If you received other crop or livestock information, how did you receive it? 1...Radio 2...Television 3...Mobile phone 4...Printed materials Other (specify)	Had you or any member of your household met with an extension agent within the past year? 0...No >> Q12 1...Yes	If you met with an extension agent, did the agent visit you, or did you visit the agent? 1...Agent visited you 2...You visited agent 3...Both 1 & 2	What type of extension activities did you participate in mostly during these meetings? (List 3 most important activities) 1...One-on-one advice 2..."Training and visit" activity 3...Farmer field school 4...Demonstration event 5...Farmer organization meeting Other, specify	Distance to extension office	If the extension agent visited you or you visited extension agent, how frequently in the last one year were you visited? 1...Every week 2...Every 2 weeks 3...Every month 4...Every 2 months 5...Every 3 months 6...Every 4 months 7...Every 6 months 8...Every year	During your most recent meeting with an extension agent, to whom did the extension agent give information/ advice? 1...Male head of household 2...Female head of household 3...Female spouse of household head 4...Other male household member 5...Other female household member	During the extension agent's most recent visit, from which organization did the extension agent come from? 1...Government agriculture extension department 2...Agricultural research institutions 3...NGOs 4...Community-based organizations 5...Business 6...Religious groups 7...Civil society groups 8...Local progressive farmers 9...Bank Other (specify)	If you were visited by an extension agent during the last year, what information/ advice was provided to you? (List 3 most important services provided)	Did the information provided by the extension agent meet your needs? (Answer for each service provided) 0...No 1...Yes, very 2...Yes, somewhat	What services would you like to receive that you are not currently receiving?	If you did not meet with an extension agent during the last year, why? (Multiple answers possible) Write -99 if answer to Question 3 is YES
CODE	CODE		CODE	CODE	KM	CODE	CODE	CODE	CODE BOX 1	CODE	CODE BOX 1	CODE BOX 2
				Activity 1:					Service 1:	Service 1:	Service 1:	Reason 1:
				Activity 2:					Service 2:	Service 2:	Service 2:	Reason 2:
				Activity 3:					Service 3:	Service 3:	Service 3:	Reason 3:

Section 3: Part-2 Social Networks

1-	2-	3-	4-	5-	6-	7-	8-	9-	10-	11-	12-	13-
Are you member of a social organization? 0...No >> Q5 1...Yes	Which organization member are you?	How active this organization in your local area? 1 Very active 2 Moderate active 3 Somewhat active 4 Not active Other, specify	How helpful this organization for you? 1 Very 2 Moderate 3 somewhat 4 Not	If you suffered agriculture related or financial problem from whom you get help? 1 Financially 2 Information only 3 Both 1 & 2 4 New technology adoption Other, specify	How can they help you? 1 Financially 2 Information only 3 Both 1 & 2 4 New technology adoption Other, specify	Where they live? 1 Same village 2 Other village in same distt. 3 Village in other distt. 4 Other province	Please name the five farmers in your network whom you share and get the information related to agricultural and new technology	Are your family relatives share information related to agricultural and new technology? 0...No >> Next Section 1...Yes	Where your relative family members live? 1 Same village 2 Other village in same distt. 3 Village in other distt. 4 Other province	Do you exchange information related to agricultural and new technology with them? 0 No >> Next Section 1 Yes	How can they help you? 1 Financially 2 Information only 3 Both 1 & 2 4 New technology adoption Other specify	Please name the five farmers in your network whom you share and get the information related to agricultural and new technology
CODE	CODE BOX 3	CODE	CODE	CODE BOX 4	CODE	CODE	Names	CODE	CODE	CODE	CODE	Names

BOX 1			
1	Fever	10	Cholera
2	General weakness/ weight loss	11	Diarrhea
3	Headach	12	Skin problems
4	Joint pain	13	Eye problems
5	Toothach	14	Flue/Cold
6	Heart problem	15	Asthma
7	Hepatitis	16	Heat stress
8	Restlessness	17	Throught/Lungs problem
9	TB		Others

Section 4: Climate Change

Part 1: Perceptions of Climate Change and Climate Risk

1	2	3			4	5	6	7	8	9			10	11		
Which option best describes your attitude towards climate change? 0 Not at all interested 1 Not very interested 2 Indifferent 3 Somewhat interested 4 Very interested	Are you concerned about climate change? 0 Not at all concerned >> Q4 1 Not very concerned >> Q4 2 Indifferent >> Q4 3 Somewhat concerned 4 Very concerned	If yes to Q2, why are you concerned? (List 3 most important reasons) 1 Reduced agricultural productivity 2 Water scarcity 3 Decrease in livestock fodder 4 More soil erosion 5 Health risks 6 Affect income sources 7 Increase poverty levels 8 Food insecurity 9 More natural disasters Others (specify)			Have you noticed any long-term changes in the average temperature over the last 20 years? (If too difficult: Have you noticed a change in the number of hot days over the last 20 years?) 0 No >> Q6 1 Yes -77 Don't know >> Q6	If you noticed a change in temperature, then what is change? 1 Increased 2 Decreased -77 Don't know	Have you noticed any long-term changes in the average rainfall over the last 20 years? (If too difficult: Have you noticed a change in the number of rainfall days over the last 20 years?) 0 No >> Q8 1 Yes -77 Don't know >> Q8	If you noticed a change in rainfall, then what is change? 1 Increased 2 Decreased -77 Don't know	Have you noticed any long-term changes in rainfall variability over the last 20 years? (If too difficult: Have you noticed a change in pattern of rainfall over the last 20 years?) 0 No >> Q10 1 Yes -77 Don't know >> Q10	If you noticed a change in rainfall variability, what changes have you noticed? (List 3 most important changes) 1 Rains have become more erratic 2 Rains come earlier 3 Rains come later 4 Rains are heavier 5 Longer periods of drought Other (specify)			Have you noticed any long-term changes in the frequency of extreme weather events over the last 20 years? (If too difficult: Have you noticed a change in number of climate shocks over the past 20 years?) 0 No >> S5P2 1 Yes -77 Don't know >> S5P2	If you noticed a change in the occurrence of extreme weather events, what changes have you noticed? (List 3 most important changes) 1 More frequent floods 2 More frequent drought 3 More frequent heatwaves 4 More frequent storms 5 Less frequent floods 6 Less frequent drought 7 Less frequent heatwaves 8 Less frequent storms Other (specify)		
CODE	CODE	CODE	CODE	CODE	CODE	CODE	CODE	CODE	CODE	CODE	CODE	CODE	CODE	CODE	CODE	

12	13	14			15	16			17	18	19	20	21	22		
Do you know climate change can cause human and child health issues? 1 Yes 0 No >> S4P2	If you noticed human health issues with changing climate, is these? 1 Increased 2 Decreased -77 Don't know>>Q15	What are the three major issues? Issue 1 Issue 2 Issue 3			Have you or your family affected by any climate related health issues? 1 Yes 0 No >> Q18	Which major issues you and your family faced? Write three most severe issues/diseases Issue 1 Issue 2 Issue 3			How severe was the impact of climate change on health? 1 Less severe 2 Medium 3 Very severe	Is changing climate also affecting child health? 1 Yes 0 No	Has changing climate affected child health from your family? 1 Yes 0 No	How severe affect was? 1 Less severe 2 Medium 3 Very severe	How you manage health issues, adult as well as child? 1 Doctor 2 Own treatment 3 Hakeem 4 Nothing	What are the affects/issues? write three most severe issues to child health Issue 1 Issue 2 Issue 3		
CODE	CODE	Box 1	Box 1	Box 1	CODE	Box 1	Box 1	Box 1	CODE	CODE	CODE	CODE	CODE	Box 1	Box 1	Box 1

CODE BOX 1: GROUP ADAPTATIONS	CODE BOX 2: IMPLEMENTING GROUP	CODE BOX 3: DESIRED ADAPTATIONS		CODE BOX 4: CONSTRAINTS TO ADAPTATION
1 Plant indigenous crops	1 Household / family	1 Change crop variety	9 Mix crop and livestock production	0 No need >> S6P1 1 No money
2 Increase planting of trees	2 Farmer organizations	2 Change crop type	10 Set up food storage facilities	2 No access to credit
3 Construct earth dams	3 Community-based organizations	3 Change planting dates	11 Build a water harvesting scheme	3 No access to land
4 Sink boreholes	4 NGOs	4 Increase amount of land under production	12 Build a diversion ditch	4 Not enough water
5 Construct SWC measures	5 Local government	5 Decrease amount of land under production	13 Plant trees	5 No access to inputs
6 Plant fodder/forages within the farm, e.g. within homestead and on SWC structures	6 Provincial government	6 Change field location	14 Use more water for irrigation	6 Shortage of labor
7 Protect springs	7 Federal government	7 Implement soil and water conservation	15 Seek off farm employment	7 No access to markets
8 Start-up tree nurseries	Other (specify)	8 Change fertilizer applications	16 Migrate to another piece of land	8 Lack of information about climate change or adaptation options
Other (specify)			Other (specify)	Other (specify)

Section 4: Climate Change

Part 2: Responses to Climate Change

If the respondent perceives climate change in S5P1, please answer the following questions

1. Have you made any changes in response to climate change in your household or in your community?

0 No >> Q2 1 Yes >> Q3

2. If you have not adapted to climate change, why not? (SEE CODE BOX 4)

>> Q7

3. What adjustments related to crop production have you made in response to long-term shifts in temperature and rainfall and increased variability?																
3a. Change crop variety 0 No 1 Yes	3b. Change crop type 0 No 1 Yes	3c. Change planting dates 0 No 1 Yes	3d. Increase amount of land under production 0 No 1 Yes	3e. Decrease amount of land under production 0 No 1 Yes	3f. Change field location 0 No 1 Yes	3g. Implement soil and water conservation 0 No 1 Yes	3h. Change fertilizer applications 0 No 1 Yes	3i. Increase fertilizer applications 0 No 1 Yes	3j. Decrease fertilizer applications 0 No 1 Yes	3k. Build a water harvesting scheme 0 No 1 Yes	3l. Build a diversion ditch 0 No 1 Yes	3m. Plant trees 0 No 1 Yes	3n. Use more water for irrigation 0 No 1 Yes	Other (specify)	Other (specify)	Other (specify)

4. What adjustments to your livelihood or risk mitigation strategies have you made in response to long-term shifts in temperature, rainfall and increased variability?											
4a. Mix crop and livestock production 0 No 1 Yes	4b. Change from livestock to crop production 0 No 1 Yes	4c. Change from crop to livestock production 0 No 1 Yes	4d. Seek off farm employment 0 No 1 Yes	4e. Receive training in other livelihood activities 0 No 1 Yes	4f. Migrate to another piece of land 0 No 1 Yes	4g. Members of the household migrate to an urban area 0 No 1 Yes	4h. Set up communal seed banks 0 No 1 Yes	4i. Set up food storage facilities 0 No 1 Yes	Other (specify)	Other (specify)	Other (specify)

5. Are there any adaptation measures that you have undertaken with other farmers or members of the community in a group? 0 No >> Q7 1 Yes >> Q6a									
5a. Group adaptation 1 CODE 1	5b. What group or organization implemented group adaptation 1? CODE 2	5c. Group adaptation 2 CODE 1	5d. What group or organization implemented group adaptation 2? CODE 2	5e. Group adaptation 3 CODE 1	5f. What group or organization implemented group adaptation 3? CODE 2	5g. Group adaptation 4 CODE 1	5h. What group or organization implemented group adaptation 4? CODE 2	5i. Group adaptation 5 CODE 1	5j. What group or organization implemented group adaptation 5? CODE 2

6. What are your most desired adaptation strategies and constraints to implementing these strategies? (list up to three adaptations and two constraints for each adaptation)								
6a. Desired adaptation 1 CODE 3	6b. What are the two main reasons for not adopting desired adaptation 1? CODE 4 CODE 4		6c. Desired adaptation 2 CODE 3	6d. What are the two main reasons for not adopting desired adaptation 2? CODE 4 CODE 4		6e. Desired adaptation 3 CODE 3	6f. What are the two main reasons for not adopting desired adaptation 3? CODE 4 CODE 4	

Section 5: Credit

Part 1: Credit rationing

Q.A: Did your household obtain or try to obtain a loan last year (Rabi 2015-16 and Kharif 2016)?

0 No >> QB 1 Yes >> Q1

Q.B: Why did your household not try to obtain a loan last year (Rabi 2015-16 and Kharif 2016)?

0 No need for loan

>> QB of S5P2

- 1 Inadequate collateral
- 2 Had outstanding loan
- 3 Past history of default
- 4 Bad credit history
- 5 Interest rates too high
- 6 Lenders not located nearby
- 7 Procedures too cumbersome
- 8 Need to pay bribes

ACCESS TO CREDIT FOR ALL HOUSEHOLDS

LENDER TYPE		Last 12 months									
		1.- Was your household successful in obtaining the loan from this [LENDER TYPE]?	2.- How much loan have you obtained from this [LENDER TYPE]?	3.- What was the main purpose of this loan?	4.- Was any interest charged on this cash loan?	5.- Annual Interest rate (%) or Annual Profit / Munaafa (%)	6.- Additional fees and other costs of getting this loan	7.- How much of what you owe on this loan has been repaid already?	8.- Total amount that still needs to be repaid, including all interest and fees.	9.- Did household try to obtain more credit from this [LENDER TYPE]?	10.- How much more loan you want to get?
Sr. No.	DESCRIPTION	CODE	RS.	CODE	CODE	%	RS.	RS.	RS.	CODE	RS
1	Commercial Banks										
2	Zarri Taraqiyati Bank										
3	NGO/ Micro-Finance Institution (Specify _____)										
4	Mill (such as sugar mill, cotton ginning factory etc.)										
5	Aarthi/Beopari/Trader										
6	Shopkeeper										
7	Money lender										
8	Relatives and Friends										
9	Landlord										
	Other, specify _____										

CODES FOR QUESTION 3: MAIN PURPOSE OF THE LOAN

1 Agricultural Production	5 Purchase of tubewell	9 Purchase/Improvement of family dwelling	13 For wedding
2 Purchase of agricultural land	6 Purchase of other farm equipment	10 To pay off old loans	Other, specify
3 Purchase of tractor	7 Medical expenses	11 For startup of a non-farm enterprise(s)	
4 Purchase of thresher	8 Other Consumption	12 For new investment in a non-farm enterprise(s)	

Section 5: Credit

Part 2: Goods and inputs purchased on credit in last year (Rabi 2015-16 and Kharif 2016)

This part includes all inputs and/or household consumption goods purchased on credit in last year (Rabi 2015-16 and Kharif 2016)

A. Did you purchase any input and/or home consumption good on credit in last year (Rabi 2015-16 and Kharif 2016)?

0 No >> S6P1

1 yes

		1	2	3	4	5	6	7	8	9	10	11
	Items	Did you purchase [ITEM] on credit in last year (Kharif 2011 and Rabi 2011-12)?	From whom did you purchase [ITEM]?	What was the value of [ITEM] purchased on credit?	Did the lender charge you any markup/ commission on the input price or prices (i.e. credit price higher than cash price)?	What was the % markup (average if lender gave several inputs)?	When did you pay for the items?	In what form did you pay?	Value of quantity sold	Did you receive prevailing market prices for [CROP]	What was prevailing market price of [CROP]	How much cash amount did you pay
		0 No >> Next item	1 Landlord 2 Input Dealer 3 Shopkeeper 4 factory Other (specify)		0 =No>> 6 1=Yes		1 After few days 2 after receiving salary 3 After one month 4 After harvest 5 Not paid till now >> Next item	1 Cash >> Q11 2 Gave harvest output >> Next item 3 Provided labor >> Next item 4 Other in-kind 5 Both 1 & 2 6 Both 1 & 4	If Answer to Q7 is only code 4, then answer this question and go to Next Item	0 No 1 Yes >> 11		If Answer to Q7 is only code 2, then don't ask this question
Sr. No.		CODE	CODE	Rs.	CODE	%	CODE	CODE	Rs.	CODE	Rs. / UNIT	Rs.
1	Fertilizer											
2	Seed											
3	Pesticide											
4	Diesel											
5	Other inputs											
6	Household consumption goods											

Section 6: Assets

Part 1: Farm Assets

Sr. No.	FARM ASSETS	1 How many ..[FARM ASSETS].. does your household own? NOTE: On jointly owned asset, report your share only. If not owned, write 0 >> Next asset	2 Year purchased of the oldest unit still in operation	3 How much did you spend on repairing [FARM ASSET] over past 1 year?	4 Total value if sold today? (If jointly owned, report value of share only)	5 Engine power or Pump capacity 1 HP 2 KwH 3 Litre per second	
	DESCRIPTION	NUMBER	Year	Rs.	Rs.	Capacity	Unit
01	Large tractor (>=12 HP)						
02	Small tractor (<12 HP)						
03	Diesel Tubewell						
04	Electric Tubewell						
05	Hand pump (treadle or rower pump)						
06	Sprinkler/drip irrigation						
07	Mechanical water pump						
08	Machine pulled plow or harrow						
09	Animal pulled plow or harrow						
10	Combine Harvester						
11	Thresher						
12	Rice Planter						
13	Manual Corn Sheller						
14	Mechanical Corn Sheller						
15	Chakki						
16	Fodder Chopper						
17	Motorized insecticide pump						
18	Hand insecticide pump						
19	Tractor Trolley						
20	Animal-driven Cart						
21	Generator/ Diesel Engine						
	Other (specify _____)						

Section 6: Assets

Part 2: Household assets

Asset code	1. Description of asset	2.	3.	4.
		Does your household own the item? No...0 >> Next asset Yes..1	Quantity	Total Current value if asset sold today how much will you receive?
		Code	(No.)	(Rs.)
1	Cooking range/stove			
2	Armoire/Cabinet			
3	Table / chair			
4	Electric fan			
5	Electric iron			
6	Radio			
7	Audio cassette/CD/DVD player			
8	Wall clock /watch			
9	Television (B/W)			
10	Television (Color)			
11	Camera/ Video Camera			
12	Computer			
13	Jewelry (gold/silver) <u>in tolas</u>			
14	Sewing machine			
15	Bicycle			
16	Rickshaw			
17	Van (tricycle van)			
18	Tonga			
19	Push cart			
20	Scooter			
21	Motorcycle			
22	Car			
23	Mobile phone set			
24	Land phone set			
25	Saw			
26	Hammer			
27	Masons equipment			
28	Potters Chaka			
29	Blacksmiths Hapor			
30	Spade			
31	Axe			
32	Shovel			
33	Guns			
34	Refrigerator			
35	Water Geyser			
36	Freezer			
37	Microwave oven			
38	Heater			
39	Washing machine			
40	Air conditioner / cooler			
41	Livestock animal			
	Other (specify: _____)			
	Other (specify: _____)			

Section 6: Assets

Part 3: Savings

Ask for all household members who are 15 years or older.

1. Does any household member (male or female) currently have any savings? 0 No, 1 Yes

2. Has any member of the household (male or female) had any savings in the past 1 year (May 2015-April 2016)? 0 No, 1 Yes

If no to both Q1 and Q2, then go to Section 4.

Ask how many accounts each individual (male or female) currently has and list them all. Each "account" should have a separate row.

If the individual has more than one "account", put in separate rows.

LINE NUMBER	3.	4.	5.	6.	7.
	Saver	Where do you save?	How do you use / plan to use the savings?	Total amount currently saved in this place	Total amount of saving currently in hand
	PID 1	CODE BOX 1	CODE BOX 2	Rs.	Rs.
1					
2					
3					
4					
5					
6					
7					
8					
9					
10					

Code Box 1: Where	Code Box 2: Use / Intended Use
At home1	To buy household goods1
NGO2	To buy productive assets2
Bank3	To start / help business3
Shop4	To buy land / house4
Post office / government institution5	For education / training5
Employer's provident fund6	For marriage / dowry6
Insurance company7	To build / repair house7
Relative / friend / neighbor8	To get loan8
Committee/bisi9	To lend to others9
Other (specify)10	To prepare for difficult times/danger ...10
	To send someone abroad for a job11
	For the future of children12
	Medical emergency13
	Other emergency/natural disaster.....14
	Other, specify15

Section 7: Other Income

Please tell me the amount (cash and cash equivalency of in-kinds) received during the last year (Rabi 2015-16 and Kharif 2016) from each of the sources

	1	2	3	4	5
	Source	Did your household receive any amount (cash and cash equivalency of in-kinds) during the last year (Rabi 2015-16 and Kharif 2016) from [source]?	What was the frequency of receipts?	For how many months, did your household receive any amount during the last year (Rabi 2015-16 and Kharif 2016) from [source]?	Total Amount
		0 No >> Next source 1 Yes	1 Monthly 2 Yearly >>Q5		
Sr. No.		CODE	CODE	NUMBER	Rs
1	Building rent				
2	Land rent				
3	Gifts/ assistance from family or friend				
4	Rent from equipment/tools/vehicle				
5	Rent from animals leased out				
6	Pension				
7	Remittances from a household member who migrated				
8	Net income from land shared out				
9	Net income from animals shared out				
10	Net Income from animal products (e.g. milk, butter etc)				
11	Net Income from animal soled out				
	Other (specify): _____				

Note: gifts do not include remittances

Section 8: Consumption and Expenditures

Part 1: Frequent Expenditures

Q1	Q2	Q3	Q4	
Item ID	Item name	In the last 30 days did your household spend money on [item]?	Amount spent on [item] in the last 30 days ?	Average monthly expenditure for the last 12 months
		0 No >> Q4 1 Yes		
		CODE	Rupees	Rupees
1	Fuel (firewood, charcoal, kerosene, gas)			
2	Expenses on travel (using own or available transport, within or outside village)			
3	Communication (cell phone, calling cards, phone, postage, internet, faxes)			
4	Education (fee, uniform, books, stationary)			
5	Expenses on utilities and maintenance (electricity, water, maintenance of house, furniture, vehicle)			
6	Wages to permanent agricultural labour			
7	Wages to permanent non-agricultural labour			
8	House Rent (imputed rent if own house)			
9	Labour costs of livestock			
	Other, (e.g., Pan, Cigarette, tobacco etc.)			

Part 2: Less Frequent Expenditures

Q1	Q2	Q3
Item ID	Item name	In the last 12 months, did your household spend money on [item]?
		0 No >> next item 1 Yes
		CODE
		Rupees
1	Clothes and shoes	What was your household's total expenditure on [item] over the last 12 months?
2	Social events (wedding, funeral, birthdays, etc)	
3	Housing improvement (latrine, new roof, new room, kitchen, etc)	
4	Human Health expenses (medication, consultation, hospitalization)	
5	Cultural/religious activities (e.g. Mela, Milad, quran khwani, etc.)	
6	Religious activities like slaughtering on Eid etc.	
7	Cost on land shared out	
8	Cost on animals shared out	
	Others_____	

Section 8: Consumption and Expenditures
Part 3a: Food Consumption

Item ID	Food item name	1-	2-	3-	4-	5-	6-	7-
		In the last 7 days did your household spend money on [item]?	How many times [item] used as food in the last 7 days ?	How much (average) quantity used in one time?	Price per unit of [item]?	Have you faced the constraint/shortage or any barrier for the purchase of [item]?	How many times in last 30 days ?	How many times in last 12 months ?
		0 No >> Next item 1 Yes CODE	NO	KG	RUPEES/KG	0 No >> Next item 1 Yes CODE	NO	NO
1	Wheat flour							
2	Rice							
3	Vegetables							
4	Pulses (Beans, Peas, Lentils)							
5	Meat							
6	Fruits							
7	Vegetable salad							
8	Dessert/Sweet dish							
9	Spices							
10	Cooking oil/Ghee							
11	Milk products							
12	Fish							
	Miscellaneous (Sugar, salt, tea... etc.)							

Section 8: Consumption and Expenditures

Part 3b: Household Food Insecurity Access Scale (HFIAS)

These questions are based on the past four weeks

Q ID	Questions	How many times in the past four weeks?
1	Did you worry that your household would not have enough food?	
2	Were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources?	
3	Did you or any household member have to eat a limited variety of foods due to a lack of resources?	
4	Did you or any household member have to eat some foods that you really did not want to eat because of a lack of resources to obtain other types of food?	
5	Did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food?	
6	Did you or any household member have to eat fewer meals in a day because there was not enough food?	
7	Was there ever no food to eat of any kind in your household because of lack of resources to get food?	
8	Did you or any household member go to sleep at night hungry because there was not enough food?	
9	Did you or any household member go a whole day and night without eating anything because there was not enough food?	