Centre for Climate Change Economics and Policy

An ESRC Research Centre

Crop productivity and adaptation to climate change in Pakistan

Ashley Gorst, Ben Groom and Ali Dehlavi

April 2015

Centre for Climate Change Economics and Policy
Working Paper No. 214

Grantham Research Institute on Climate Change and the Environment
Working Paper No. 189

ESRC Economic & Social Research Council

Grantham Research Institute on Climate Change and the Environment

University of Leeds

The London School of Economics and Political Science

The Centre for Climate Change Economics and Policy (CCCEP) was established by the University of Leeds and the London School of Economics and Political Science in 2008 to advance public and private action on climate change through innovative, rigorous research. The Centre is funded by the UK Economic and Social Research Council. Its second phase started in 2013 and there are five integrated research themes:

1. Understanding green growth and climate-compatible development
2. Advancing climate finance and investment
3. Evaluating the performance of climate policies
4. Managing climate risks and uncertainties and strengthening climate services
5. Enabling rapid transitions in mitigation and adaptation

More information about the Centre for Climate Change Economics and Policy can be found at: http://www.cccep.ac.uk.

The Grantham Research Institute on Climate Change and the Environment was established by the London School of Economics and Political Science in 2008 to bring together international expertise on economics, finance, geography, the environment, international development and political economy to create a world-leading centre for policy-relevant research and training. The Institute is funded by the Grantham Foundation for the Protection of the Environment and the Global Green Growth Institute. It has nine research programmes:

1. Adaptation and development
2. Carbon trading and finance
3. Ecosystems, resources and the natural environment
4. Energy, technology and trade
5. Future generations and social justice
6. Growth and the economy
7. International environmental negotiations
8. Modelling and decision making
9. Private sector adaptation, risk and insurance

More information about the Grantham Research Institute on Climate Change and the Environment can be found at: http://www.lse.ac.uk/grantham.

Crop Productivity and Adaptation to Climate Change in Pakistan*

Ashley Gorst[1,2], Ben Groom[1], Ali Dehlavi[3]

[1]Department of Geography and Environment, London School of Economics and Political Science

[2]Grantham Research Institute on Climate Change and the Environment, Centre for Climate Change Economics and Policy (CCCEP)

[3]World Wildlife Fund Pakistan

1 April 2015

Abstract

How effective adaptation practices in response to climate change are is a crucial question confronting farmers across the world. Using detailed plot-level data from a specifically designed survey conducted in 2013, this paper investigates whether there are productive benefits for farmers who adapt to climate change in Pakistan. The impact of implementing on-farm adaptation strategies is estimated for three of the most important crops grown across Sindh and Punjab provinces: wheat, rice, and cotton. This study finds that there exists significant positive benefits from adaptation for most of the farmers in the sample. For those that actually adapted, productive benefits are positive for wheat and cotton, but not significantly different from zero for rice. For those that did not adapt, the gains from adapting to climate change for all crops are predicted to be large. These findings provide evidence that the use of strategies to adapt to climate change can have a positive impact on food security. The large estimated gains for non-adapters, however, point to the existence of barriers to the adoption of these strategies. Policies aimed at reducing these barriers would be likely to both increase short term production of households and enable them to better prepare for the potential impacts of climate change.

JEL classification: Q18, Q54
Keywords: climate change, adaptation, productivity, Pakistan, wheat, rice, cotton

*We would like to thank Mintewab Bezabih, Salvatore Di Falco, Adil Najam, Charlie Palmer and Basharat Saeed for comments at various stages of this work. Thanks also goes to Ghulam Rasul for access to meterological data. A debt is due to members of the team at WWF-Pakistan who worked tirelessly on data collection. Sadaf Khan and Farrukh Zaman were instrumental in this regard. This project was kindly supported financially by the International Development Research Centre. The ESRC and the Grantham Foundation for the Protection of the Environment also provide individual funding to one of the authors. We also acknowledge the support of the Grantham Research Institute and the Centre for Climate Change Economics and Policy at the LSE for access to resources and knowledge.

1 Introduction

The impacts of climate change for Pakistan's farmers are likely to be problematic for the food security of many rural households. Projections suggest that future temperatures in South Asia will increase by $2-3\,^{\circ}\mathrm{C}$ between by the years 2046-2065. Rainfall is also predicted to be more erratic, with estimates indicating that annual rainfall will increase over time. Pakistan is expected to be one of the most affected of the countries in South Asia by climate change (Stocker et al., 2013). The vulnerability of rural households in Pakistan has recently been highlighted by the experience of heavy flooding in 2010 and 2011. A key question for Pakistan's economy is whether farm-level adaptation is adequate to deal with the potential effects of climate change on future crop productivity.

With 45% of the labour force employed in the agricultural sector and 24% of national GDP deriving from agriculture (Government of Pakistan, 2010), the resilience of agricultural production is of high importance to the development of Pakistan's economy. At the same time, identifying effective means of adaptation for farmers is vital to lowering the costs of climate change (Fankhauser et al., 1999). Since much of the burden of adaptation in agriculture will be put onto the shoulders of farmers themselves, it is crucial from both an academic and policy perspective to understand the factors that drive climate change adaptation behaviour and the impact of these practices on farm production. In addition, it is also important to study if there are short-term gains in terms of food security from undertaking climate change adaptation. If there exist such benefits in the short-term, the impetus to encourage adaptation from a policy perspective should be a primary condsideration for policymakers interested in immediate economic development goals.

The impact of adaptation on farm productivity outcomes has been studied by Di Falco et al. (2011) in Ethiopia. This paper used an endogenous switching regression model to show that farmers who had reported adapting to climate change were more food secure: adapters produced more than in the counterfactual case where they hadn't adapted. Similarly, predictions for non-adapters estimated that these farmers would gain as a result of adaptation. This framework has also been applied to study more specific forms of technology adoption in agriculture. Abduli and Huffman (2014) use the endogenous switching model in Ghana to study the impact soil and water conservation has on increasing the return to rice farming. Their findings suggest that adoption of these technologies improves household production and net revenue significantly.

Prominent methods to estimate the impacts of climate change on agriculture have primarily focused around the Ricardian approach suggested by Mendelsohn et al. (1994) and more recently the panel approach of Deschenes and Greenstone (2007). One of the key downsides to applying these approaches, however, is their treatment of the role of adaptation. Both methods do not model adaptation directly. Explicitly modelling the role of adaptation in production is, thus, an important step in the literature. Moreover, it is emphasised by Di Falco (2014) that it is crucial to account for a range of ecological, social, and institutional factors that affect the farm-level adaptation decision.

This paper is the first to study the impact of climate change adaptation strategies in Pakistan.[1] We use a new cross-sectional data set collected in 2013

[1] Most of the literature on the microdeterminants and impact of adaptation strategies has

from a specifically designed survey of 1,422 farm households of Sindh and Punjab provinces. The study was constructed to understand how agricultural households in the major agricultural areas of Pakistan produce and look at how various household and institutional features affect production. The survey also collected detailed information on the range of adaptation strategies that farmers use to adjust to long-term environmental change. Farmers use a variety of different strategies to cope with the the vagaries of the climate in Pakistan. These include farm-level strategies such as crop switching, crop diversification, soil and water conservation. Additionally, households may engage in off-farm work in order to diversify farm income.

This paper contributes to the literature on adaptation and development by using the endogenous switching framework applied by Di Falco et al. (2011) to the context of Pakistani agriculture. The application of this method to the context of Pakistan differs substantially from the Ethiopian context. Firstly, the type of crops grown and the agro-climatic conditions differ substantially. Accordingly, analysis of the impact of adaptation is done by separately looking at the effectiveness of adaptation for a pooled set of crops and then separately for each different crop. Considering the impacts of adaptation for different crops is an important contribution since crops may be grown in different seasons and face different growing constraints. Similarly, climate change impacts may have differing effects on different crops. Agronomic constraints and farm management options are also likely to play an important part in determining how productive these crops are. We examine how robust adaptation is at increasing productivity across these different crops and seasons. Increases in average temperature may be beneficial for some crops or changes in precipitation may differ in importance across crops (Siddiqui et al., 2014; Sultana et al., 2009). In order the study the impact that adaptation has on rural livelihoods more fully, we separately study the impact that adaptation has on the productivity of wheat, rice, and cotton crops. These crops are the three most numerous grown by farmers in our sample and represent the most commercially important crops grown in Pakistan.

Secondly, studying agriculture in Pakistan requires consideration of a range of complex institutional factors that affect both the productivity of farmers and their incentives to apply techniques that may help them to adapt to climate change effectively. Accordingly, data was collected on land tenure arrangements and farmers' links to agricultural markets, factors highly important to understanding Pakistan's agricultural sector. We consider both the role that more conventional factors, such as extension services, may have and also the existence of a rich informal sector that includes the role of middlemen and land contracts.

We constrain our interest in this study to the importance of autonomous adaptation, which are adaptations to climate change undertaken by individuals. This type of adaptation is important given that many adaptation decisions are likely be done most efficiently if they are done so based on private interests (Mendelsohn, 2000). While planned adaptations carried out by governments or other institutions may also be important at ameliorating the costs of climate change Lobell and Burke (2010), we constrain our interest to autonomous adaptation.

Studying the effectiveness of autonomous adaptation, however, is compli-

been conducted in the context of African agriculture. A useful review of these studies can be found in Di Falco (2014).

cated due to the likely existence of factors that simultaneously contribute to a farmers decision to adapt and also how productive they are. For instance, it may be the case that farmers who are inherently more skilled, and who are more productive, have a better sense of a changing climate and be more likely to undertake adaptive measures. In this scenario, standard regression techniques used to estimate the impact of adaptation in productivity, such as ordinary least squares, will fail to take into account farmer skill and thus bias the impact of adaptation on productivity. The importance of incorporating selection into the adoption of agricultural practices has recently been highlighted by Suri (2011) who showed that heterogeneous returns and comparative advantage in technologies seems to explain adoption of new technologies in Tanzania. To account for the possibility of selection bias in adaptation, we employ an endogenous switching regression model. The endogenous switching model has a number of advantages in the context of our survey. First, and as previously discussed, it accounts for selection that can bias the parameter of interest in ordinary least squares. Secondly, it is based on the premise that unobservable factors to the econometrician may be influencing selection and outcome equations. Another program evaluation technique that could plausibly be used in the context of our data is Propensity Score Matching (PSM). The use of PSM relies on a number of assumptions that might prove restrictive in our setting, however. Primarily, the requirement of unconfoundedness implies all variables that affect both the treatment and outcome must be observed (Caliendo and Kopeinig, 2008). The stringency of this assumption means that the implementation of the PSM method is invalid if unobservable characteristics of farmers simultaneously affect selection into adaptation and production. Since the endogenous switching method allows for selection on unobservables, we use this method to analyse the impact of adaptation on productivity.

The remainder of the paper is structured as follows. Section 2 describes the survey and the variables used in the paper. Section 3 outlines the empirical specification of the study and then Section 4 presents the results. Finally, Section 5 briefly discusses implications of the results and concludes.

2 Data

2.1 Survey Description

This paper uses data collected during April-June 2013 from a detailed household survey designed to specifically address the determinants and impact of climate change adaptation for agricultural households in Pakistan. In total, 1422 households were surveyed.

The survey region stretched across the provinces of Sindh and Punjab, the two most important areas for agriculture in the country. Importantly, survey sites were also spread out over differing agroclimatic growing areas. Figure 1 plots a map of Pakistan's agroclimatic zones and shows the zone in which each survey site falls. The sampling of our survey covers four areas: Barani (rainfed) agriculture in Punjab; cotton and wheat in Punjab; cotton and wheat in Sindh; and rice growing in Sindh. In Sindh, responses to the survey were gathered in villages across the districts of Sangar, Sukkur, and Larkana. In Punjab, the districts of Chakwal, Rawalpindi, Rahim Yar Khan, and Jhang were selected as sites. Detailed data were collected on a number of different aspects crucial to the analysis of the impact of climate adaptation practices.

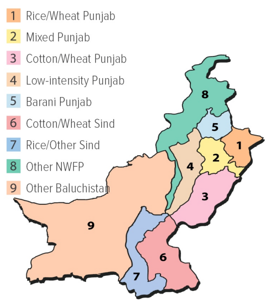
As a preliminary to the survey, a reconnaissance study was carried out in December 2012 to identify appropriate sites and to hold a series of focus group meetings. In total, 120 households took part in 18 focus groups that were held in 3 villages. Using information obtained from these meetings, a detailed household survey was designed. The total sample of farmers were then surveyed by a team of trained enumerators. Survey modules on household characteristics, production, inputs, institutional features and adaptation practices were collected as part of the survey.

2.2 On-Farm Adaptation to Climate Change in Pakistan

Of primary importance to the survey is determining whether farmers have previously adapted in response to climate change. Farmers in the the survey were asked, "How has your household adapted to cope with climatic changes?". Adaptation strategies were then grouped into categories. These were alterations in crop timing, crop switching, agricultural inputs, adoption of soil or water conservation, income diversification or public infrastructure. We now discuss these strategies as possible adaptations to climate change.

One adaptation could be to change to the time that crop planting takes place. For instance, to counter rising temperatures, farmers could shift planting to cooler times of the year (Sultana et al., 2009). Similarly, changes in long term precipitation patterns would mean that it would be optimal for farmers to plant seeds earlier or later, depending on when the seasonal rains arrive.

Another important adaptation strategy is changing the variety or type of crop grown. For instance, a farmer facing an increased likelihood of drought may switch to faster maturing varieties of the same crop or may could switch into a different crop that is more tolerant to lower water availability (Lobell and Burke, 2010). The efficacy of crop switching to adapt to climate change has been studied by Kurukulasuriya and Mendelsohn (2008) using a Ricardian framework. They find that the crop switching can significantly lower the costs



Agroclimatic Zones				
Map reference no (see left panel)	Name of zone	Sites Sampled	Numbers of household sampled	District population
5	Barani Punjab	Chakwal	219	1,951,728
		Rawalpindi	209	6,058,214
3	Cotton/wheat Punjab	Rahim Yar Khan	194	5,656,859
6	Cotton/wheat Sindh	Sanghar	181	2,616,821
		Sukkur	219	1,635,928
7	Rice/other Sindh	Larkana	200	3,470,537

Map source: adapted from International Food Policy Research Institute's Research Report No. 77 (IFPRI, 1989) based on an agro-climatic zone division proposed originally in Pakistan Agricultural Research Council's Collaborative Project Paper 86/7 (PARC/CIMMYT, 1986).

Figure 1: Map of Survey Sites and Agro-climatic Zones in Sindh and Punjab

of climate change across African farms.

Farmers may also change the input mix they apply to crops in response to past or expected climate change. A shift in temperature or precipitation patterns may make it optimal to alter the amount of productive inputs such as fertiliser, pesticides or water that are applied to crops.

The next group of adaptations are the adoption of soil and water conservation technologies. Increased temperatures and more erratic rainfall may have significant impacts on state of both soil and water in Pakistan. Higher temperatures are likely to increase the rate at which water is lost from the soil, meaning that farmers will have to exert more effort into maintaining soil moisture. In addition, increased heavy rainfall would increase the amount of soil erosion placing greater emphasis on the need to invest in techniques lessen these impacts. The availability of water is crucial to the resilience of Pakistan's agricultural sector. Qureshi et al. (2010) argue that the exploitation of groundwater resources has enabled farmers to increase production levels and also cushion themselves against some of the low rainfall. Qadir et al. (2014), however, highlight the unsustainability of water management in the Indus Basin by studying the impacts of soil salinity on crop yields and argue that agricultural productivity losses due to salt-induced land degradation are a growing concern across in Pakistan. Thus, accounting techniques that farmers use to conserve soil quality and keep crops suitably irrigated is a crucial aspect of adaptation to climate change in Pakistan.

For the present study, our interest is on the impact of autonomous, on-farm adaptation measures on productivity. We define an adapting household as one that has reacted to climate change by changing farming practices. To study this, we constrain our definition of adaptation to exclude income diversification. Finding new sources of income may well be an integral strategy that farmers use to cope with climate change. However, the benefits of income diversification to on-farm productivity are not immediately clear, so we do not include this in our measure of adaptation. Similarly, since our interest is in the impact of autonomous adaptation, we further exclude public infrastructure investments in our definition of adaptation. Such planned adaptations could include government investments in large-scale infrastructure such as damming. Planned adaptations, however, are not part of the farmers adaptation choice set. We therefore exclude adaptation strategies that are classified as such.

Table 1 shows how farm-level adaptation is spread across the different survey sites and regions. On-farm adaptation here is defined as a dummy variable, denoted *Adapt*, set equal to 1 if farmers have undertaken at least one of the on-farm practices in response to perceived changes in climate. This variable equals zero if a farm household has not undertaken any on-farm adaptations. In Table 1 we clearly see that there exist significant differences in adaptation across regions. Punjab has a much lower proportion of adapters when compared with Sindh, where over half of households engage in adaptation. It is also interesting to note the difference in the propensity to adapt in different districts in our sample. In Punjab, for instance, adapters vastly outnumber non-adapters in Rahim Yar Khan. However, in Rawalpindi the number of non-adapters is much higher than the number of adapters. In Sindh province the pattern of adapters versus non-adapters is remarkably similar across survey sites.

Table 1: Adaptation Across Survey Sites, N=1405

	Adapt Yes	Adapt No
Punjab		
Chakwal	48	171
Jhang	74	100
Rahim Yar Khan	134	57
Rawalpindi	27	180
Subtotal	283	508
Sindh		
Larkana	96	107
Sangar	98	107
Sukkur	118	106
Subtotal	312	302
Total	595	810

2.3 Variable Description

We now turn to the variables included in the empirical analysis. Table 2 displays the mean values of variables used in the analysis. These summary statistics are displayed for both the adapting group of farmers and the non-adapters. The final column in Table 2 shows the difference in means between the two groups of farmers.

We collected the data at the crop level to allow for a high level of detail in the responsiveness of crop yields to inputs. Since a number of crops are simultaneously grown by farmers in an agricultural season, it is crucial to determine accurate production functions at the crop level.[2] We see that adapters are on average more productive than non-adapters from the difference between average yields of adapters and non-adapters. It can be seen that adapters appear to be more intensive in their use of inputs than non-adapters: their use of key farm inputs such as pesticides, urea, DAPSOP and seeds tends to be higher. The use of technologies such as tubewells and canals, and also mechanisation, proxied by access to a tractor, is seen to be higher amongst adapters.

Household characteristics also appear to differ between adapters and non-adapters. For instance, average household size is larger for adapters. The composition of the household may also be important to the adaptation decision. Education is often cited as a key determinant of the adoption of new agricultural technologies (Jack, 2011). We include measures of household education such as whether the head is literate and the average education of the household.

[2]In the survey, we defined a contiguous area devoted to a crop as a 'parcel'. Parcels then make up 'plots' which may be a collection of parcel sub-divisions containing different crops. Plots can then be aggregated to get the total area under cultivation for each farmer in each season.

Table 2: Summary Statistics

	Adapters	Non-adapters	Difference
Productivity			
Yield	19.912	17.423	2.489***
Inputs			
Pesticides/acre	1.794	1.098	0.696***
Urea/acre	2.304	1.755	0.549***
DAPSOP/acre	0.927	0.765	0.162
Seed/acre	47.356	38.519	8.837***
Household Labour/acre	3.875	3.982	-0.107
Hired Labour/acre	1.624	1.033	0.591***
Water Apps./acre	3.235	2.889	0.346
Canal$^{\diamond}$	0.402	0.337	0.065***
Tubewell$^{\diamond}$	0.423	0.314	0.109***
Tractor$^{\diamond}$	0.336	0.307	0.029
Household			
Total Land (acres)	10.187	7.971	2.216***
Household Size	7.887	7.806	0.081
Literate$^{\diamond}$	0.201	0.253	-0.052***
% Females	0.470	0.436	0.034***
Credit$^{\diamond}$	0.351	0.354	-0.003
Off-farm Work$^{\diamond}$	1.004	1.349	-0.345***
Flood$^{\diamond}$	0.614	0.581	0.033
Drought$^{\diamond}$	0.137	0.125	0.012
Livestock	3.818	3.314	0.504***
Owns Land$^{\diamond}$	0.742	0.762	-0.02
Climate			
Ave. Kharif Rain	2.306	2.947	-0.641***
Ave. Rabi Temp.	17.359	16.218	1.141***
Ave. Kharif Temp.	34.608	33.401	1.207***
Ave. Rabi Rain	0.155	0.291	-0.136***
Weather			
Kharif Rain	3.588	6.031	-2.443***
Kharif Temp.	34.365	33.504	0.861***
Rabi Rain	0.146	0.264	-0.118***
Rabi Temp.	23.168	21.893	1.275***
Information			
Extension Services$^{\diamond}$	0.244	0.224	0.020
Peer$^{\diamond}$	0.660	0.649	0.011
Media$^{\diamond}$	0.133	0.149	-0.016
Middleman$^{\diamond}$	0.049	0.053	-0.004
Landlord$^{\diamond}$	0.074	0.078	-0.004
Observations	910	1040	

[a] $\diamond$ denotes a dummy variable
[b] *** when $p<0.01$

Mean values for a variable measuring the proportion of females in a household suggest that adapting households have a higher proportion of females than non-adapting ones. Numerous studies have cited the difficulty of obtaining credit as a crucial factor in determining the ability of farmers to adapt to climate change in other settings (Deressa et al., 2009; Maddison, 2007). Credit markets are an important feature of Pakistan's rural agricultural economy owing to the range of different types of lenders that offer credit (Aleem, 1990). Differential access to credit may be an important determinant of adaptation given that a number of adaptations require significant up-front investment that may have to be leveraged with credit. From Table 2 it appears that adapters use credit somewhat more than non-adapters.

A crucial aspect in the decision to conduct on farm adaptation may be the existence of off-farm substitutes for farm work. We include a dummy variable that indicates whether a household is engaged in off-farm labour. From a simple difference in mean between adapters and non-adapters, we see that a higher proportion of non-adapters are engaged in off-farm labour. In a similar vein to off-farm labour, the ownership of livestock may affect the decision to adapt. Livestock may act as an alternative income source. It does, however, appear that adapters own more livestock on average. Given the heavy losses endured during recent flooding in Sindh and Punjab, the experience of extreme events may condition whether farmers adapt to climate change. On the one hand, experience of extreme events may prime the farmer to the possibility of such events in future. On the other, extreme events may have prolonged effects impacts on the farmers ability to conduct adaptation. To measure the effects of such extreme events we include dummy variables indicating whether households have experienced flooding or drought in the past 15 years. The summary table suggests that experience of flooding and drought is marginally higher for households that have adapted to climate change.

The final variable included in household characteristics is a dummy indicating whether a household owns their land. This variable is included to test whether tenancy is an important institutional determinant of adaptation. Different forms of land rights may affect the decision to adapt. For instance, Jacoby and Mansuri (2008) link investments in land improving practices with the security of tenure. Additionally, the survey shows that a number of different tenancy regimes exist, from pure ownership to sharecropping. Similarly, Ali et al. (2012) show that investments in land and productivity in Punjab are lower for leased relative to owned land. According to this view, it may be expected that variation in tenure arrangements might affect the incentive for some farmers to invest in adaptation measures that require significant up front investment.

The survey data is also matched with climate and weather data from the Pakistan Meteorological Department. The data is based on monthly averages of temperature and precipitation spanning the years 1990-2012. We use monthly data climate and weather data to generate seasonal aggregates. The seasonal nature of weather is of particular importance to this study due to the analysis of different crops. In the analysis, variables are split separately into climate and weather. The climate variables represent long term averages of weather taken from 1990-2013. The weather variables correspond to meteorological readings in the year that farmers were surveyed about their agricultural activities. Climate variables are important in determining the agricultural yield potential of farmers. What crops farmers are able to grow and when crops are generally planted are determined by climate variables. We see that there exist significant differences in average climatic conditions between adapters and non-adapters. We see that adapters are more likely to experience high temperatures and less rainfall.

A set of dummy variables measuring where farmers get their information about farming practices from are also included. Since adaptation may involve prior knowledge about the how the climate is changing or what practices can be used to successfully adapt to climate change, inclusion of information variables are important for the analysis. Farmers may learn about technologies in a variety of ways and from different sources. Formal extension services may be one way in which farmers learn about new farming information. Earlier work by Hussain et al. (1994) concludes that the Training and Visit extension programme in Pubjab in the late 1980's was successful at encouraging the adoption of new agricultural technologies. Information may also be spread more informally through groups of neighbouring farmers or relatives. A number of studies have examined how peers affect farmer adoption of new technologies (Conley and Udry, 2010; Foster and Rosenzweig, 1995). Farmers-to-farmer connections may be important for both farmers expectations of future climate (Maddison, 2007). It is also important to consider the role that informal institutions play in spreading agricultural information the rural economy. One such example is the role of middlemen. By providing a link between the market and farmers, middlemen may play a part in the information set of farmers. They also play an important role as buyers of produce and sellers of inputs and often engage in the supply of credit and farm inputs (Lohano et al., 1998). Popular presentations of middlemen in Pakistan portray them as exploiting smaller farmers by charging below the market rate on produce.[3]. As is noted by Haq et al. (2013) in their study of 'arthis' in the Punjab, however, middlemen play a number of different roles and these roles vary across different crops. For instance, for the wheat crop middlemen are less prevalent due to lower input needs and lower credit needs from farmers after the returns from previous Kharif harvest. Similarly, wheat is a food crop for many farm households and farmers only sell what is in surplus to their annual consumption requirements. The relationship between the middleman and the farmer is also important. Thus, crops like cotton that are higher in input needs and not used as food crops are more profitable for middlemen. In this study we allow for the role of the middleman as a factor in farmers decisions about adaptation. Middlemen may play a key role in disseminating information to farmers and thus could affect how willing a farmer is engage in adaptation. Similarly, farmers who farm on rented land may get extensive information on practices from their landlord. The inclusion of a dummy variable if a household gets information from a landlord will thus measure if landlords affect the adaptation decision of households.

2.4 Crop Types

An important part of this study is the separate estimation of the success of adaptation on different crops. In contrast to Di Falco et al. (2011), who estimate a model using an aggregation of five major crop types, we study wheat, rice and

[3]Articles of the following tone commonly describe the role of middlemen in the rural economy: http://tribune.com.pk/story/798526/agriculture-dilemma-helped-by-weather-hurt-by-middlemen/

cotton crops separately. Aggregation over multiple crops may be advantageous for a number of reasons. Firstly, the 'overall' impact of adaptation on food security can be measured. Secondly, this approach implicitly allows for the possibility that farmers may switch crops as a means of adaptation. Aggregation of different crops into a single production function, however, may have significant disadvantages to studying food security of households.[4] Primarily, aggregation may confuse analysis when growing conditions differ significantly or inputs are used differently. This would be less of a problem for inputs such as labour, which can be more easily transferred across cropping activities, but may be less realistic for inputs such as water which may be used diversely on different crops. Similarly, the seasonal nature of production in Pakistan over the Rabi and Kharif seasons may also complicate the interpretation of an aggregated production function. To account for this, we estimate separate regressions for each crop and test whether the impacts of adaptation differ between crops.

The primary crop grown in our sample is wheat. According to FAO (2013), 80% of farmers in Pakistan grow wheat and the crop makes up around 37% of energy intake. Wheat production takes place over the Rabi (winter) season when temperatures and rainfall are lower. The lack of rainfall places importance on the need for good irrigation during this season. The production of wheat is thus of central importance to the agricultural sector. Yields of wheat, however, are low based the the agro-ecological potential of the growing environment. A lack of suitable irrigation infrastructure and access to productive inputs are argued to be behind persistent low yields (FAO, 2013). There is also a significant amount of variation in the varieties of wheat grown across Sindh and Punjab. Different varieties may be more suited to location-specific agronomic factors. Smale et al. (1998) use district-level data from Pakistan's Punjab to show that the diversity of wheat varieties grown is synonymous with higher yields and lower variance of yields in rainfed areas. The implications for wheat yields in the face of climate change are important to whether farmers adapt. If yields are expected to be negatively affected, the need for adaptation will be more pressing. Sultana et al. (2009) use agronomic crop models to predict the impacts of climate change on wheat yields across different climatic zones in Pakistan. They conclude that increases in temperature will decrease wheat yields in arid, semi-arid and sub-humid zones, although increases in temperature could increase yields in humid areas. The authors also explore the possibility of adaptation by shifting growing to cooler months and conclude that this might be an effective adaptation to mitigate the effects of increases in temperature. Siddiqui et al. (2014) estimate the yield response of district-level wheat to temperature and precipitation changes in Punjab. They conclude that projected climate change would have a non-negative impact on the production of wheat.

Rice is one of the most important Kharif crops grown in Sindh and Punjab. It is important as both a food crop and also a cash crop. Its growth requires access to a good water supply to irrigate the crop during the hot summer months. Since high summer temperatures are already experienced across rice growing areas, the effects of increased temperatures are projected to harm rice production as temperatures get more extreme(Siddiqui et al., 2014).

[4]To a certain degree, aggregation across different types of crop is hard to avoid. For instance, aggregation is done even within the same crop type. In our sample, 19 different wheat varieties are grown. It is plausible that factors such as input requirements may substantially differ even within crop types.

According to ITC (2011), Pakistan was the world's fourth largest cotton producer in 2009-10. However, despite the importance of cotton as a major cash cash crop in the economy, its growth is limited by the already high summer temperatures that occur during the summer growing season. Further heightened temperatures brought on by climate change would place greater stress on cotton growth. Siddiqui et al. (2014) find that cotton yields are likely to be adversely affected by climate change in the Punjab.

3 Methodology

3.1 Model

To model the impact of adaptation on farmer productivity an endogenous switching model is employed. The model has been applied to the study of climate adaptation and food security by (Di Falco et al., 2011)[5].

We assume that farmers are risk neutral in their decision-making and therefore maximise expected benefits in making their adaptation decision. Accordingly, farmers are split into two regimes depending on whether they have adapted or not. The production functions for the adapters and non-adapters take the following econometric form:

$$\text{Adapters:} \quad y_{1i} = X_{1i}\beta_1 + \epsilon_{1i} \tag{1}$$

$$\text{Non-Adapters:} \quad y_{2i} = X_{2i}\beta_2 + \epsilon_{2i} \tag{2}$$

The outcome variables y_i represents the crop yield. The vector X_i contains the full set of production inputs, as well as household characteristics and information sources. We also include a set of weather and climate variables that may affect the productivity of farmers.

Additionally we model the decision for a farmer to undertake adaptation. This is done by specifying the selection equation as

$$A_i^* = Z_i\pi + \omega_i \tag{3}$$

where the binary adaptation variable A_i^* takes the value of one if the farmer has adapted and zero if not. Z_i is a vector of farm inputs, characteristics, information sources and weather and climate variables, that may influence the net benefits of the adaptation decision. Also included is a set of variables to capture farmers perceptions of climate change. This includes a set of variables detailing how farmers perceive the climate to have changed.

Since it is assumed that farmers are risk-neutral profit maximisers, we expect the decision to undertake adaptation to be carried out if the expected benefits are positive. Thus, if $A_i^* = Z_i\pi + \omega_i > 0$ then we would expect $A_i = 1$. On the other hand, if $A_i^* = Z_i\pi + \omega_i \leq 0$ then $A_i = 0$.

The endogenous switching approach is preferable to an ordinary least squares approach to estimating the impact of adaptation when the presence of unobservable factors play a part in simultaneously affecting the adaptation decision and the productivity of farmers. If the econometrician is unable to explain all

[5] More explanation of extensions of the endogenous switching to climate adaptation are discussed extensively in a review by Di Falco (2014)

of the factors that affect the net benefit of adaptation to farmers, then resulting estimates obtained via OLS may be biased. It may be the case that farmers who are inherently more skilled in farm production are also more likely to adapt to climate change. Since a factor like farmer skill is hard to accurately control for, it will be left out of the list of explanatory variables. If skill is positively correlated with productivity and adaptation, then the impact estimate of adaptation will be biased upward by the presence of omitted unobservables. The impact of adaptation on productivity will therefore be overstated by ordinary least squares.

In the switching regression model, selection bias would manifest itself in the error terms ϵ and ω. Since farmer skill is unlikely to be captured by the explanatory variables, the error terms of the production and selection equation will be correlated such that $corr(\epsilon, \omega) \neq 0$.

In the endogenous selection model, farmers are split into regimes depending on whether they have adapted or not.

$$y_{1i} = X_{1i}\beta_1 + \epsilon_{1i} \text{ if } A_i = 1 \tag{4}$$

$$y_{2i} = X_{2i}\beta_2 + \epsilon_{2i} \text{ if } A_i = 0 \tag{5}$$

As mentioned, selection may lead to correlation between the the errors in the production equations and the error in the selection into adaptation equation. The covariance matrix Σ contains the three error terms ϵ_{1i}, ϵ_{2i} and ω_i. These are assumed to be distributed with trivariate zero mean and that take the form:

$$\Sigma = \begin{vmatrix} \sigma_\omega^2 & \sigma_{\omega 1} & \sigma_{\omega 2} \\ \sigma_{\omega 1} & \sigma_1^2 & . \\ \sigma_{\omega 2} & . & \sigma_2^2 \end{vmatrix}$$

where σ_ω^2 represents the variance of the selection equation's error term. Similarly, the variances of the production equations are represented by σ_1^2 and σ_2^2. $\sigma_{1\omega}$ and $\sigma_{2\omega}$ are the covariances between production regimes 1 and 2 respectively. Since the outcomes of regimes 1 and 2 are not simultaneously observed for each farmer, the covariance between the two production equations are not specified and are represented as simply with a dot (.).

Because of the presence of selection bias, the expectations of the error terms for the two production regimes will be nonzero conditional on whether farmers have adapted or not. Thus, conditional on sample selection, the expected error terms can be expressed as follows:

$$\begin{aligned} E[\epsilon_{1i}|A_i = 1] &= \sigma_{\omega 1}\frac{\phi(Z_i\pi)}{\Phi(Z_i\pi)} \\ &= \sigma_{\omega 1}\lambda_{1i} \end{aligned} \tag{6}$$

and

$$\begin{aligned} E[\epsilon_{2i}|A_i = 0] &= -\sigma_{\omega 2}\frac{\phi(Z_i\pi)}{1 - \Phi(Z_i\pi)} \\ &= \sigma_{\omega 2}\lambda_{2i} \end{aligned} \tag{7}$$

where ϕ and Φ are standard normal probability distributions and standard normal cumulative distributions respectively. The terms λ_{1i} and λ_{2i} are interpreted as inverse Mills ratios (Heckman, 1979). These are then included in the production equations as explanatory variables to account for any selection bias.

The correlation between the error terms of the production and selection equations are shown as correlation coefficients,

$$\rho_1 = \sigma^2_{\omega 1}/\sigma_\omega \sigma_1 \tag{8}$$

and

$$\rho_2 = \sigma^2_{\omega 2}/\sigma_\omega \sigma_2 \tag{9}$$

The significance of the estimated correlation coefficients indicate the presence of selection bias. In the case where ρ_1 or ρ_1 are significantly different from zero, it can be concluded that there is evidence of sample selection in adaptation.

The estimation of the parameters of the model are estimated using full information maximum likelihood. This involves the simultaneous estimation of both the selection and production equations. This method of estimation is superior to two-step estimators which are inefficient in deriving standard errors (Lokshin and Sajaia, 2004).

3.2 Treatment Effects

Of primary interest to this study is the overall impact of adaptation on productivity. To estimate this impact, we adopt a treatment effects framework. Adaptation is defined as the treatment variable which can take discrete values 0 or 1, where $D = \{0, 1\}$. In order to calculate treatment effects of adaptation on the outcome variable Y_i, following Heckman et al. (2003), we first define the outcomes for adapters and non-adapters as:

$$E(Y_{i1}|D = 1) = X_{1i}\beta_1 + \sigma_{\omega 1}\lambda_{1i} \tag{10}$$

$$E(Y_{i2}|D = 0) = X_{2i}\beta_2 + \sigma_{\omega 2}\lambda_{2i} \tag{11}$$

The above equations represent the observed outcomes for the adapters and non-adapters. The switching regression framework can also be used to estimate counterfactual outcomes for adapters and non-adapters. For instance, the counterfactual for the adapters is the scenario where they don't adapt, and vice-versa for non-adapters.

$$E(Y_{i1}|D = 0) = X_{1i}\beta_1 + \sigma_{\omega 1}\lambda_{2i} \tag{12}$$

$$E(Y_{i2}|D = 1) = X_{2i}\beta_2 + \sigma_{\omega 2}\lambda_{1i} \tag{13}$$

The impact of adaptation can then be set in the generalised treatment effects framework, where the treatment effects of adaptation can be calculated for adapters and non-adapters. The average predicted effect of adaptation on those that adapted is calculated by the average treatment effect on the treated (ATT),

$$\begin{aligned} ATT &= E(Y_{i1}|D=1) - E(Y_{i2}|D=1) \\ &= X(\beta_1 - \beta_2) + (\sigma_{1\omega} - \sigma_{2\omega})\lambda_{1i} \end{aligned} \tag{14}$$

The predicted impact of adaptation on those that did not get treated can also be calculated by the average treatment effect on the untreated (ATU), defined as

$$\begin{aligned} ATU &= E(Y_{i1}|D=0) - E(Y_{i2}|D=0) \\ &= X(\beta_1 - \beta_2) + (\sigma_{1\omega} - \sigma_{2\omega})\lambda_{2i} \end{aligned} \tag{15}$$

3.3 Identification

In order for the estimation of the impact of adaptation on productivity to be valid in the switching regression, we need a suitable set of selection instruments that correlate well with the decision to adapt, but do not play a role in how productive farmers are. As selection instruments, we use the set of variables that describe farmers' perceptions of how the climate is changing.This set of variables includes perceptions of long term changes in average temperature and rainfall, and also other climatic trends that are important to Pakistan's farmers such as the onset of the rainy season and night time temperatures. We argue that these variables are likely to be good instruments since perceiving that the climate is changing should be a strong predictor of adaptation, but not how productive farmers are, conditional on the set of productive inputs and household characteristics.

In Table 3 we test the validity of the selection instruments. We see that the perception variables are significant drivers of the adaptation decision: their joint significance is high ($\chi^2 = 56.53$). Although we cannot directly test the exclusion decision that perceptions of climate change are not correlated with unobservables in the productivity equation, we use a method of falsification suggested in Di Falco et al. (2011). This involves testing whether perception variables are jointly significant in the productivity equation for non-adapters. The f-statistic of joint significance is 1.08 which is not significant at the 10% level. This suggests that perception variables are not significant drivers of productivity.

4 Results

4.1 Household Determinants of Adaptation

Table 4 displays the results from a probit regression run with the binary adaptation indicator as the dependent variable. Since adaptation is measured at the household level, the table shows which household characteristics affect the probability of adapting to climate change. A number of factors are significantly associated with the propensity for farmers to adapt to climate change at the household level. It seems that increased land size has a slight positive effect, suggesting larger households are more likely to adapt. A particularly strong result is that households with a higher proportion of females are much more likely to have adapted. Interestingly, it seems that households with members working off-farm are less likely to adapt, suggesting that there might be a trade off between on-farm and off-farm adaptation. Extreme weather events are also

Table 3: Test of the Validity of Selection Instruments

	Model 1 - Probit Adaptation 1/0	Model 2 - OLS Productivity of Households that did not Adapt
Perception		
Prec. Decrease	-0.210	0.148*
Prec. Increase	-0.144	0.190**
Prec. Onset	0.484***	0.278
Temp. Increase	0.406**	-0.010
Temp. Decrease	0.0818	-0.160
Temp. Night	-1.062***	-0.314
Temp. More Cold Spells	0.513	-0.236
Temp. Onset Hot	-0.783***	0.150
Constant	-0.352***	2.784
Wald Statistic	$\chi^2 = 56.53$***	F test=1.08
n	1759	921

[a] Standard errors are robust and clustered by region
[b] p<0.1, p<0.05, p<0.01
[c] In this table we omit the other covariates used in the regressions and only report the perception variables

linked to adaptation, with previous exposure to flooding meaning farmers are less likely to adapt. Since flooding is unlikely to be an extreme event that farmers can adapt to on-farm, we probably would not expect to see this positively affecting adaptation. Given that we in fact see a negative effect of flooding may be indicative of the prolonged effects of flooding on the ability of households to invest in adaptation measures. In contrast, previous exposure to drought suggests a higher probability of adaptation. It could be argued that drought is an extreme event that could be handled better on farm. Depending on the severity of drought, measures such as changing input use or even switching crop types or varieties could be viable strategies. Thus, drought may induce households into adapting to climate change. There is also evidence that the ownership of land is significantly associated with adaptation, in that households that own land relative to households that rent or sharecrop land are more likely to adapt. This is preliminary evidence of the effect of land tenure on profitable investments, according with previous work by Jacoby and Mansuri (2008) and Ali et al. (2012). It also appears that climatic factors may play a role, with a higher average amount of rain received in the Rabi season predicting lower probability of adaptation. Of high importance to policy is the impact that information services have on the probability of adapting. There, however, appears to be only one significant informational effect. This seems to happen through farmer-to-farmer interaction. Farmers that use other farmers to garner information on agricultural practices are more likely to have adapted in our sample.

4.2 Productivity Regressions

4.2.1 Ordinary Least Squares

To first discern the impact of adaptation on crop productivity, we run ordinary least squares regressions on a set of control variables including inputs, household characteristics, and weather and climate variables. To measure the impact of adaptation, we include a dummy variable in each equation equal to one if the households adapts and zero otherwise. The dependent variable is the crop yields

Table 4: Household Determinants of Adaptation

	Adapt (0/1)
Canel	-0.059
Tubewell	0.078
Tractor	-0.068
Total Land (acres)	0.009***
Household Size	-0.015
Literate	0.117
% Females	0.627***
Credit	-0.109
Off-farm Work	-0.066**
Flood	-0.213**
Drought	0.263**
Livestock	-0.009
Owns Land	0.167*
Ave. Kharif Temp.	-0.092
Ave. Kharif Prec.	-0.006
Ave. Rabi Temp.	0.066
Ave. Rabi Prec.	-0.843**
Extension Services	0.041
Peer	0.181**
Media	0.025
Middleman	-0.067
Landlord	0.213
Constant	-0.870
N	1405

[a] Standard errors are robust and clustered by region
[b] p<0.1, p<0.05, p<0.01

(maunds per acre)[6] and is our measure of productivity.

Table 5 displays the output from four OLS regressions. The first column is for the pooled sample of crops and the remaining columns present the results for each separate crop. Our parameter of interest is the coefficient on the variable *Adapt*. We see that for the pooled, wheat and cotton samples, the impact of adaptation, conditional on the set of control variables, appears to have positive effects on crop productivity. The impact of adaptation for rice farmers in our sample, however, does not appear to be statistically different from zero. The magnitude of the coefficients is such that adaptation is estimated to have a ??, ?? and ?? percentage point increase for the pooled, wheat, and cotton crop respectively.

Examining the control variables included in the regression, we see that all of the statistically significant inputs have the expected positive sign. Fertiliser, labour, water and farm mechanisation (tractor) are important determinants of productivity for most of the different crops. Household characteristics also seem to have some important productive implications. There is evidence of households with more land being less productive in cotton production and larger households in terms of number of dependents being less productive in rice. Credit also seems to be associated with lower productivity as is seen by the negative coefficient on this variable for cotton. The negative sign on the variable indicating households

[6] 1 maund $\approx$ 40 kgs

have experienced drought is also negative, suggesting that drought might have long-term productive impacts for wheat farmers.

Looking at the weather and climate variables, it is clear that these variables appear to have no discernible impact on the the productivity of farmers. This is probably due to two factors. Firstly, the regional fixed effects could be soaking up the impact of these variables due to the lack of spatial variation in the weather and climate variables. Secondly, including both weather *and* climate variables may have a cancelling out effect on each other.

We also evidence that information variables are correlated with productivity outcomes. It appears that farmers who rely on peer and media information tend to be less productive. Interestingly, the relationship between middleman information and yield seems to vary across crops. For wheat it appears that middlemen are associated positively with yields. For rice, however, it appears they are strongly associated with lower yields.

4.2.2 Endogenous Switching Regressions

Tables 6 - 9 show the output from the endogenous switching regression models.

Table 6 shows the regression results for the pooled sample of wheat, rice and cotton crops. For non-adapters, the production inputs are generally statistically significant. Interestingly, irrigation variables are very important determinants of productivity for non-adapters in the sample, whereas irrigation is not shown to be significant for adapters. This is probably indicative of differences in farm-types, in that farms that do not select into adaptation have better access to irrigation. In terms of household characteristics, we notice that an increased percentage of females in a household is not associated with higher productivity for the adapters. This could be explained by the differences in gender roles in farm household production. This result accords with other studies that find female farm labour to have lower productivity than male labour. For adapters, it seems that the experience of recent drought has a negative relationship with productivity, which is suggestive of long-run effects of low water availability on farm production. The credit dummy variable is negative for non-adapters suggesting that low productivity farmers are more reliant on credit. For non-adapters experience of drought and floods has productive implications, with households having experienced flooding being more productive and those having experienced drought less so. Land tenure is also important, since for non-adapters owned plots are more productive on average.

The last column in Table 6 displays the estimates of the decision to undertake adaptation for the pooled sample. The dependent variable Adapt takes the value of 1 if farmers have adapted and 0 if not. We see that soil quality is positively related to adaptation. Larger households are also more likely to adapt. Interestingly, households with a higher proportion of females are positively associated with adaptation, suggesting that household composition may affect the decision to adapt. Experience of extreme weather events, in this case drought, is positively associated with adaptation suggesting previous experience of such an event may induce households into adapting. Although temperatures in the Kharif appear to be significant, we note that the weather and climate variables appear to cancel each other out in terms of magnitude, indicating a neutral effect of climate effects on adaptation for the pooled sample. None of the informational variables appear to be significant in the pooled sample, but as we will see, this arises because information has different effects on different crops, and so in aggregate these factors cancel. Finally, climate perception variables are important for the decision to adapt. Changing precipitation and less cold spells patterns suggest greater propensity to adapt. In contrast, farmers who thought that temperatures had decreased were less likely to adapt. Those who perceived the onset of the hot season to have changed were less likely to adapt. Overall, these perception results suggest that climate and climate perception have a complex relationship with agricultural activities in Pakistan.

The column labelled *Rho* is included in the regression output to test the assumption of unobservables affecting productivity and the decision to adapt. For the adapters, the coefficient is negative and significant which indicates positive selection bias, suggesting that those with higher unobserved productivity were more likely to adapt. The significance of this term supports our choice of method that accounts for unobservable factors.

For the wheat crop in Table 7, it is shown that yields are significantly affected by a number of agronomic and socioeconomic factors. Pesticides and water is shown to have positive effects on yield for adapters and non-adapters respectively. Household supply of labour is also important for productivity for both groups. Household characteristics may also affect how productive farmers are. For the adapters, it seems that previous household experience of extreme natural events, such as flood, are negatively associated with yield. More females in the household also reduces productivity for the adapters. Seasonal weather variables are shown to have strong impacts on yields. It is shown that high Kharif (summer) rainfall is of particular importance to the Rabi (winter) crop. We note here that the use of climatic data is not without its issues. Estimated coefficients can sometimes be very large. This seems to reflect difficulty in observing enough variation within study areas. As a test of robustness we omit all weather and climate variables to test for confounding effects on other variables. The coefficients change very little both in terms of magnitude and significance if these variables are excluded. Under the heading Information are included variables related to how farmers get information on farming practices. These variables are shown to be significantly associated with productivity of farmers. Those that rely solely on media for their information seem to be less productive, suggestive of lack of access to good information significantly reducing productivity for adapters and non-adapters. Interestingly, we notice that in the adapter's column, middlemen are associated with higher productivity outcomes. Although exactly how middlemen affect productivity cannot be ascertained from this model, this result suggests that there seems to be some matching between high productivity farmers and middlemen. This may be in accordance with the finding by Haq et al. (2013) that middlemen are not as prevalent in wheat production due to low margins and may choose to deal with farmers who are more productive.

The last column in Table 7 models the determinants of the adaption decision. A number of factors seem to be related to the adaptation decision. The use of more inputs seems to correlate with adaptation. For the household variables, a higher percentage of females in the household increase the likelihood of adapting. As was seen in the pooled regression, experience of drought seems to strongly increase the impetus to adapt. There is also some evidence to suggest that rainfall in the Kharif affects adaptation but the overall impact of rainfall is not clear owing to weather and climate variables going in opposite directions. The perception variables are not particularly strong predictors of adaptation in the wheat sample. Only farmers that perceive temperature to have decreased are evidenced as having a lower propensity to adapt. In accordance with the result from the pooled sample, the negative and significant *Rho* is indicative of positive selection bias into adaptation in the wheat sample: higher productivity wheat producers are more likely to adapt.

Yields for rice plots show a number of patterns that affect productivity in Table 8. There is evidence that fertiliser (Urea) is important for non-adapters as is the application of manure. Access to both household and hired labour is shown to be highly important for both adapters and non-adapters, suggesting that labour intensity is an important determinant of rice yields. Water-use also seems to be important, although the use of tubewell technology does not seem to be associated with increasing yield. The use of modern farm technology, such as tractors, is shown to be beneficial to rice production productivity for non-adapters. Both the variables household size and the proportion of females are correlated with lower yields. For adapters, we see that access to credit is significantly associated with higher productivity, speaking to credit's role in farmers being able to buy high quality and invest in farm improvement. An important result is that the ownership of land is associated with higher yields for both samples, indicating that rented or sharecropped farms are less productive than farms owned by the household. This accords with the finding by Ali et al. (2013) and Jacoby and Mansuri (2008) who find that rented land is farmed less productively. Disentangling the influence of climate on rice yields is difficult in this regression owing to the counteracting tendency of weather and climate variables. It does, however, seem that higher Rabi seems to have important positive effects on production, as would be expected for rice growing. For the information variables, there seems to be a complex relationship. Peer information seems to be good for productivity, while media and landlord information suggest lower productivity. The negative relationship between landlord information and productivity lends further support to the importance of tenancy as a negative factor to productivity. Interestingly, we also notice that the influence of middlemen seems to vary between adapters and non-adapters.

Turning to the determinants of adaptation for rice farmers, we see that households with more land are more likely to adapt. Crucially, it appears that credit constrained households are less likely to adapt. Since that adaptation may require costly up-front investment, credit may be very important in enabling farmers to have the resources to adapt. The impact of land ownership on adaptation is negative in the selection equation, suggesting that land owners are less likely to adapt for rice. For the weather and climate variables, it seems that high Rabi rainfall is associated with a higher probability of adapting. It also seems that information services for farmers may not be that effective at bringing about adaptation. The negative sign on the Extension Services variable suggests that this source of information is not effective at bringing about on-farm adaptation. Finally, we note the significance of *Rho* which suggests that, as with the wheat sample, farmers with higher unobserved productivity are more likely to adapt.

The increased use of nitrogen fertiliser, urea, is suggestive of higher yields for both adapters and non-adapters. Inputs such as manure, labour and water are also shown to be important for productivity, as is access to a tractor. For characteristics of the household, it is notable that the use of credit services is shown to be related to lower overall yields. Whilst credit is an important way for farmers to obtain inputs over the agricultural season, this result suggests that use of credit is primarily used by farmers with lower productivities. This contrasts with the results for rice which suggests credit is beneficial for yields. More work needs to be done to ascertain how credit is used differently across cotton and rice farmers. Work by Aleem (1990) highlights how complex credit markets are in Pakistan's rural economy. Other household factors such as flood, drought and off-farm work also appear to affect yields in different ways. Interestingly, the impact of land ownership seems on productivity seems to vary across adapters and non-adapters.

For the determinants of adaptation in the final column of Table 9, we see that larger households are more likely to adapt. Interestingly, we note that literacy does not seem to imply more adaptation; rather literate farmers are less likely to adapt. We continue to see the result that more females in the household are conducive to adaptation. Past extreme weather events also seem to matter, with flood experience positively related.

4.3 Impact Estimates

4.3.1 Impact Estimates

The results in Tables 10 - 13 show the impact of adaptation in terms of yield. Using the endogenous switching framework, counterfactual results are estimated to predict the impact of adaptation. For farmers that adapted, a counterfactual is constructed to model yields had these farmers not adapted. Conversely, for those farmers who did not adapt, predicted yields are estimated had they decided to adapt. The differences between yields under adaptation and non-adaptation are denoted as the ATT for adapters and by ATU for the non-adapters.

Table 10 shows these scenarios for the pooled sample. For adapters, it is predicted that adaptation is associated with increased yield a comparison of the observed adapting yield with the counterfactual on-adapting yield suggests an increase of 7%. This result compares in magnitude with the estimate from the OLS regression. As discussed earlier, the estimate from the switching regression is likely to be more robust given that there may be heterogeneity between adapters and non-adapters and selection bias. For non-adapting farmers the yield without adaptation is much higher than the predicted yield with adaptation suggesting large gains for non-adapters if they adapted.

For wheat growers in Table 11, we see a similar pattern to the pooled sample. Adapters are predicted to have gained by around 12% from adapting. The impact estimate for adapters is also of comparable size to the estimate from the OLS regression. Non-adapters are predicted to gain in terms of yield by close to 50%.

For farmers growing rice in Table 12, the impact for gain from adapting for adapters is 3%. However, this result is statistically insignificant suggesting that adaptation practices for rice growers have had negligible effect on productivity. This is echoed by the OLS prediction that shows up as insignificant. Non-adapters are predicted to have a lot to gain from undertaking adaptive measures, increasing their yields by as much as two-thirds current yield.

Estimated yields for cotton farmers show that adapters do not gain by about 9% by using adaptation practices. However, as with the estimated impacts on non-adapters for the other crops, non-adapters seem to have high gains in productivity from adapting, with around a 50% yield gain to be realised if they adapt.

5 Conclusion

Ascertaining whether there exist productive gains to farmers from adapting to climate change is of high importance. Many studies have emphasised the costs of climate change on agriculture and have often not adequately analysed the role of adaptation. Given the estimated negative impact of climate change on Pakistan's agricultural economy, understanding the possibilites for adaptation is a highly pertinent topic. Studying adaptation is also of high importance if we consider that short-term productivity is crucial to immediate development goals. Strategies farmers use to adapt to climate change may have considerable benefits if deployed right now.

Using data from a specifically designed survey of agricultural households in Sindh and Punjab we estimate that there do exist positive productive gains from implementing adaptation strategies. For wheat and cotton farmers, estimated yields are 12% and 9% higher for the farmers that adapted in our sample. Yield gains from adaptation in rice, however, are seen to be not significantly different from zero. The predicted gains for the farmers that did not undertake adaptation are large in comparison. According to the model, if this set of farmers adapted, their average yields would be larger than those of the adapters for all crops. Overall, the results suggest that adaptation to climate change is likely to be beneficial to farmers in the short-term. The size of these estimated gains for non-adapters necessitates more work to understand why these gains exist. It is possible that these results hide differences in regional characteristics that are not captured in the econometric specification or are the result of institutional factors that constrain the ability of farmers to undertake profitable strategies.

An important part of this paper was to discover what factors were associated with the probability of farmers adapting to climate change. At the household level, it was seen that higher composition of females in households significantly increases the probability of adaptation. Experience of extreme events also affects adaptation: drought increases the probability of farmers adapting while flooding reduces the probability. Household members undertaking work off-farm were also seen to be less likely to adapt, suggesting there may be some trade-offs between on and off-farm adaptation. There was also some evidence that institutional features play a role: households owning land relative to those who rent are more likely to adapt. The pattern of the adoption of adaptation strategies is more complex when disaggregated by crop. These results highlight the importance of considering the various crop-specific opportunites and constraints to adaptation in Pakistan.

A number of policy implications arise from this study. Firstly, we have observed that, on the whole, adaptation strategies deployed by farmers have a positive short-term influence on productivity. Thus, it is important from a policy point of view to encourage farmers to make decisions that will help them adapt to climate change. It was found in this paper, however, that current information sources available to farmers appear not to be effective at distributing information relevant to encouraging adaption behaviour in farmers. Policy should recognise that targeting resources into accurately informing farmers about climate change and appropriate adaptations is likely to be beneficial for food security. Secondly, it has been seen that adaptation decisions are associated with a number of factors that affect how able farmers are to adapt to cliamte change. Specifically, there is evidence that institutional features such as credit, land tenure, and the presence of middlemen affect both the adaptation decision and productivity of farmers. Understanding the exact role that these institutions play is important given that adaptation requires farmers to make long-term decisions. Further work needs to be done to establish how these complex institutions affect the costs and benefits of adapting to climate change.

References

A. Abduli and W. Huffman. The adoption and impact of soil and water conservation technology: An endogenous switching regression application. *Land Economics*, 90(1):26–43, 2014.

I. Aleem. Imperfect information, screening, and the cost of informal lending: A study of a rural credit market in pakistan. *World Bank Economic Review*, 4 (3):329–349, 1990.

A. Ali, A. Abdulai, and R. Goetz. Impacts of tenancy arrangements on investment and efficiency: Evidence from pakistan. *Agricultural Economics*, 43: 85–97, 2012.

M. Caliendo and S. Kopeinig. Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22:31–72, 2008.

T.G. Conley and C. Udry. Learning about a new technology: Pineapple in ghana. *American Economic Review*, 100:35–69, 2010.

T.T. Deressa, R.M. Hassan, C. Ringler, T. Alemu, and M. Yesuf. Determinants of farmers choice of adaptation methods to climate change in the nile basin of ethiopia. *Global Environmental Change*, 19(2):248–255, 2009.

O. Deschenes and M. Greenstone. The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97(1):354–385, 2007.

S. Di Falco. Adaptation to climate change in sub-saharan agriculture: Assessing the evidence and rethinking the drivers. *European Review of Agricultural Economics*, 41(3):405–430, 2014.

S. Di Falco, M Veronesi, and M Yesuf. Does adaptation to climate change provides food security? a micro perspective from ethiopia. *American Journal of Agricultural Economics*, 93(3):829–846, 2011.

S. Fankhauser, J. Smith, and R. Tol. Weathering climate change: Some simple rules to guide adaptation decisions. *Ecological Economics*, 30(1):67–78, 1999.

FAO. Pakistan: Review of the wheat sector and grain storage issues. Technical report, Food and Agriculture Organization of the United Nations (FAO), 2013.

A.D Foster and M.R. Rosenzweig. Learning by doing and learning from others: Human capital and technical change in agriculture. *The Journal of Political Economy*, 103:1176–1209, 1995.

Government of Pakistan. Agricultural census 2010. *Government of Pakistan Statistics Division Agricultural Census Organisation*, 2010.

A. Haq, A. Aslam, Chaudhry A.A., A. Naseer, K. Muhammad, K. Mushtaq, and M.S. Farooqi. Who is the 'arthi': Understanding the commission agent's role in the agriculture supply chain. *International Growth Centre (IGC) Working Paper*, 2013.

J. Heckman. Sample selection as a specification error. *Econometrica*, 47(1): 153–161, 1979.

J. Heckman, J.L. Tobias, and E. Vytlacil. Simple estimators for treatment parameters in a latent-variable framework. *The Review of Economics and Statistics*, 85(3):748–755, 2003.

S.S. Hussain, D. Byerlee, and P.W. Heisey. Impacts of the training and visit extension system on farmers' knowledge and adoption of technology: Evidence from pakistan. *Agricultural Economics*, 10:39–47, 1994.

International Trade Centre ITC. Cotton and climate change: Impacts and options to mitigate and adapt. *Geneva: ITC, 2011. xii, 32 p. (Technical paper)*, 2011.

K. Jack. Constraints on the adoption of agricultural technologies in developing countries. *White paper, Agricultural Technology Adoption Initiative, J-PAL (MIT) and CEGA (UC Berkeley)*, 2011.

H. G. Jacoby and G Mansuri. Land tenancy and non-contractible investment in rural pakistan. *Review of Economic Studies*, 78:763–788, 2008.

P. Kurukulasuriya and R. Mendelsohn. Crop switching as a strategy for adapting to climate change. *African Journal of Agricultural and Resource Economics*, 2:105–126, 2008.

D. Lobell and M. Burke. *Climate Change and Food Security*, chapter 8, pages 133–153. Springer Science + Business Media, 2010.

H. Lohano, L. Smith, and M. Stockbridge. Comparing the seed cotton and wheat marketing chains in sindh. *The Pakistan Development Review*, 37: 53–75, 1998.

M. Lokshin and Z. Sajaia. Maximum likelihood estimation of endogenous switching regression models. *The Stata Journal*, 4(3):282–289, 2004.

D. Maddison. The perception of and adaptation to climate change in africa. *World Bank Policy Research Working Paper 4308*, 2007.

R. Mendelsohn. Efficient adaptation to climate change. *Climatic Change*, 45: 583–600, 2000.

R. Mendelsohn, W. Nordhaus, and D. Shaw. The impact of global warming on agriculture: A ricardian analysis. *American Economic Review*, 84(4):753–771, 1994.

M. Qadir, E. Quillerou, V. Nangia, G. Murtaza, M. Singh, R.J. Thomas, P. Drechsel, and A.D. Noble. Economics of salt-induced land degradation and restoration. *Natural Resources Forum*, 38:282–295, 2014.

A.S. Qureshi, P.G McCornick, A. Sarwar, and B.R. Sharma. Challenges and prospects of sustainable groundwater management in the indus basin, pakistan. *Water Resources Management*, 24:1551–1569, 2010.

R. Siddiqui, G. Samad, M. Nasir, and Jalil H.H. The impact of climate change on major agricultural crops: Evidence from punjab, pakistan. *PIDE Working Paper*, 2014.

M. Smale, J. Hartell, P. Heisey, and B. Senauer. The contribution of genetic resoruces and diversity to wheat production in the punjab of pakistan. *American Journal of Agricultural Economics*, 80:482–93, 1998.

T. F. Stocker, Q. Dahe, and G. Plattner. Climate change 2013: The physical science basis. *Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Summary for Policymakers (IPCC, 2013)*, 2013.

H. Sultana, N. Ali, I. Mohsin, and A.M. Khan. Vulnerability and adaptability of wheat production in different climatic zones of pakistan under climate change scenarios. *Climatic Change*, 94:123–142, 2009.

T. Suri. Selection and comparative advantage in technology adoption. *Econometrica*, 79:159–209, 2011.

Table 5: The Impact of Adaptation: OLS Regressions

	Pooled (1) Yield (maunds/acre) Coef./se	Wheat (2) Yield (maunds/acre) Coef./se	Rice (3) Yield (maunds/acre) Coef./se	Cotton (4) Yield (maunds/acre) Coef./se
Adapt	2.163***	1.565**	2.674	2.134*
	(0.568)	(0.625)	(1.647)	(1.088)
Inputs				
Pesticides/acre	0.164	1.033***	0.824*	-0.214
	(0.131)	(0.283)	(0.457)	(0.165)
Urea/acre	0.344**	-0.028	2.362***	1.202***
	(0.138)	(0.131)	(0.782)	(0.344)
DAPSOP/acre	0.044	0.027	1.613	1.357
	(0.080)	(0.068)	(1.161)	(0.860)
Manure/acre	0.661*	0.862**	1.849	-0.443
	(0.365)	(0.410)	(1.712)	(0.630)
Seed/acre	0.018*	0.006	-0.002	0.027
	(0.010)	(0.012)	(0.053)	(0.041)
Soil Qual.	0.260	-0.103	0.808	0.440
	(0.386)	(0.414)	(1.102)	(0.788)
Household Labour/acre	0.671***	0.659***	0.708***	0.555***
	(0.072)	(0.082)	(0.188)	(0.169)
Hired Labour/acre	0.206***	0.124	0.440**	-0.045
	(0.067)	(0.138)	(0.178)	(0.077)
Water Apps./acre	0.067***	0.379***	0.011	0.401***
	(0.023)	(0.134)	(0.038)	(0.147)
Canal	3.647***	0.519	6.945***	0.178
	(1.017)	(1.268)	(2.454)	(1.901)
Tubewell	1.449	1.164	1.571	-1.366
	(0.938)	(1.144)	(2.557)	(1.654)
Tractor	2.166***	1.151	5.141**	0.865
	(0.669)	(0.730)	(2.097)	(1.215)
Household				
Total Land (acres)	-0.060**	0.016	-0.097	-0.123**
	(0.030)	(0.037)	(0.075)	(0.060)
Household Size	-0.265***	-0.120	-0.439*	-0.086
	(0.096)	(0.105)	(0.254)	(0.234)
Literate	0.504	0.599	0.375	0.479
	(0.758)	(0.815)	(2.343)	(1.551)
% Females	-2.309	-0.174	-10.445*	-2.570
	(1.833)	(1.968)	(5.643)	(3.533)
Credit	-1.118*	-1.035	1.570	-3.860***
	(0.617)	(0.683)	(1.755)	(1.158)
Off-farm Work	-0.203	-0.232	-0.604	-0.237
	(0.206)	(0.223)	(0.663)	(0.376)
Flood	0.861	1.059	0.89	-2.314
	(0.879)	(0.937)	(2.914)	(1.618)
Drought	-1.412*	-2.313***	-3.771	2.102
	(0.842)	(0.886)	(2.916)	(1.709)
Livestock	-0.033	-0.022	0.044	-0.169
	(0.068)	(0.076)	(0.202)	(0.119)
Owns Land	1.586**	0.939	2.653	0.398
	(0.700)	(0.776)	(2.028)	(1.358)
Weather				
Kharif Rain	0.714	1.483	8.118	6.775
	(2.143)	(2.200)	(13.827)	(6.085)
Kharif Temp.	0.091	2.150	0.368	6.194
	(6.878)	(6.884)	(37.890)	(24.877)
Rabi Rain	4.745	21.527	-100.55	-110.513
	(35.770)	(35.129)	(194.138)	(155.148)
Rabi Temp.	-7.528	-5.003	-60.88	-47.889
	(12.217)	(11.675)	(72.235)	(58.594)
Climate				
Ave. Kharif Rain	-3.288	-4.944	-20.283	7.010
	(8.034)	(8.065)	(58.761)	(37.891)
Ave. Kharif Temp.	-6.149	-4.818	-6.275	6.412
	(7.772)	(7.917)	(39.558)	(27.000)
Ave. Rabi Rain	-34.414	-32.408	39.380	62.283
	(29.403)	(30.458)	(182.037)	(113.361)
Ave. Rabi Temp.	11.113	7.658	75.827	34.682
	(11.853)	(11.162)	(75.028)	(52.568)
Information				
Peer	-0.850	-1.194*	0.181	-2.183*
	(0.626)	(0.684)	(1.853)	(1.236)
Media	-3.633***	-3.876***	-3.478	-1.014
	(0.804)	(0.880)	(2.189)	(1.796)
Middleman	-0.167	2.629*	-6.391*	0.001
	(1.276)	(1.462)	(3.790)	(2.286)
Landlord	-0.554	0.779	-5.213	-0.171
	(1.051)	(1.161)	(3.243)	(1.918)
Constant	230.429**	84.878	434.568	91.547
	(94.167)	(91.971)	(403.997)	(285.773)
Region Dummies	Yes	Yes	Yes	Yes
N	1539	907	337	293
R-squared	0.267	0.273	0.403	0.455

[a] Standard errors are robust and clustered by region
[b] p<0.1, p<0.05, p<0.01

Table 6: Endogenous Switching Regression: Pooled Crops

	Yield Non-Adapters	Yield Adapters	Adapt(0/1)
	Coef./se	Coef./se	Coef./se
Inputs			
Pesticides/acre	0.263**	-0.02	0.077**
	(0.115)	(0.273)	(0.036)
Urea/acre	0.205	0.283	0.001
	(0.308)	(0.248)	(0.023)
DAPSOP/acre	0.090*	0.121	-0.001
	(0.051)	(0.095)	(0.012)
Manure/acre	0.973	0.369	0.077
	(0.761)	(0.905)	(0.064)
Seed/acre	0.015	0.009	0.004***
	(0.036)	(0.01)	(0.001)
Soil Qual.	0.127	-0.099	0.125*
	(0.844)	(0.602)	(0.065)
Household Labour/acre	0.826***	0.649*	-0.011
	(0.225)	(0.374)	(0.013)
Hired Labour/acre	0.460***	0.138	0.031
	(0.107)	(0.115)	(0.027)
Water Apps./acre	0.032	0.058	-0.001
	(0.027)	(0.046)	(0.004)
Canal	3.759***	3.207	0.002
	(1.308)	(2.141)	(0.301)
Tubewell	2.165*	0.624	-0.084
	(1.128)	(1.621)	(0.231)
Tractor	1.614	2.601	-0.025
	(1.309)	(2.31)	(0.236)
Household			
Total Land (acres)	-0.026	-0.090**	0.014*
	(0.097)	(0.041)	(0.008)
Household Size	-0.354***	-0.05	-0.01
	(0.124)	(0.122)	(0.011)
Literate	-0.227	1.121	-0.138
	(0.856)	(1.473)	(0.176)
% Females	3.14	-8.770*	0.675***
	(1.913)	(4.961)	(0.240)
Credit	-1.858**	-0.36	-0.083
	(0.874)	(0.501)	(0.127)
Off-farm Work	0.336	-0.659*	-0.053
	(0.358)	(0.394)	(0.047)
Flood	2.079*	0.902	-0.061
	(1.124)	(1.243)	(0.118)
Drought	-1.287	-3.513***	0.379**
	(1.121)	(1.045)	(0.158)
Livestock	-0.042	-0.096	0.000
	(0.078)	(0.062)	(0.016)
Owns Land	2.374*	-0.092	-0.066
	(1.368)	(1.813)	(0.209)
Weather			
Kharif Rain	0.218	5.04	0.288
	(1.874)	(3.981)	(0.213)
Kharif Temp.	1.021	-0.355	-3.089***
	(6.923)	(18.438)	(0.753)
Rabi Rain	16.389	-24.395	7.401
	(29.346)	(49.587)	(5.993)
Rabi Temp.	-4.88	-27.065*	2.211
	(11.759)	(16.296)	(2.396)
Climate			
Ave. Kharif Rain	-1.545	-17.185	-1.179
	(6.82)	(12.209)	(1.011)
Ave. Kharif Temp.	-11.685*	2.411	3.498***
	(6.786)	(18.329)	(0.417)
Ave. Rabi Temp.	8.976	31.590**	-2.683
	(11.857)	(15.726)	(2.406)
Ave. Rabi Rain	-65.858***	55.78	-0.868
	(19.697)	(72.294)	(4.332)
Information			
Extension Services	0.012	-0.111	-0.018
	(0.876)	(0.868)	(0.127)
Peer	-1.135	-0.157	0.191
	(1.233)	(1.263)	(0.203)
Media	-4.829***	-2.321***	0.246
	(1.645)	(0.853)	(0.275)
Middleman	2.333	-3.445	-0.075
	(1.625)	(3.674)	(0.332)
Landlord	-1.409	0.34	-0.008
	(2.598)	(4.211)	(0.525)
Climate Change Perceptions			
Prec. Decrease			-0.147
			(0.141)
Prec. Increase			0.028
			(0.155)
Prec. Onset			0.420***
			(0.132)
Temp. Decrease			-0.339*
			(0.175)
Temp. Cold Spell			0.812*
			(0.458)
Temp. Onset Hot			-0.773***
			(0.179)
Constant	344.350***	26.56	-20.388
	(132.419)	(272.476)	(18.839)
Sigma	2.257***	2.474***	
	(0.097)	(0.128)	
Rho	0.066	-0.462***	
	(0.209)	(0.16)	
Region dummies	Yes	Yes	Yes
N			1539

[a] Standard errors are robust and clustered by region
[b] p<0.1, p<0.05, p<0.01

Table 7: Endogenous Switching Regression: Wheat

	Yield Non-Adapters	Yield Adapters	Adapt(0/1)
	Coef./se	Coef./se	Coef./se
Inputs			
Pesticides/acre	0.853	0.839***	0.103*
	(0.692)	(0.210)	(0.059)
Urea/acre	-0.097	-0.054	-0.015
	(0.174)	(0.209)	(0.015)
DAPSOP/acre	0.094	0.029	-0.005
	(0.074)	(0.054)	(0.013)
Manure/acre	1.352	0.597	0.118*
	(0.972)	(0.826)	(0.067)
Seed/acre	0.017	-0.032	0.009***
	(0.061)	(0.026)	(0.002)
Soil Qual.	-0.414	-0.302	0.074
	(0.673)	(0.820)	(0.085)
Household Labour/acre	0.708***	0.737*	-0.027***
	(0.212)	(0.399)	(0.005)
Hired Labour/acre	0.193	0.059	0.032*
	(0.126)	(0.127)	(0.018)
Water Apps./acre	0.653	0.265	-0.003
	(0.445)	(0.453)	(0.035)
Canal	0.829	-0.835	-0.08
	(1.352)	(1.046)	(0.357)
Tubewell	2.946***	-0.238	-0.126
	(0.967)	(1.156)	(0.278)
Tractor	1.177	1.79	-0.123
	(1.411)	(2.056)	(0.248)
Household			
Total Land (acres)	0.059	-0.023	0.012
	(0.137)	(0.038)	(0.011)
Household Size	-0.175	0.085	-0.004
	(0.167)	(0.171)	(0.011)
Literate	0.137	0.976	-0.106
	(1.442)	(1.435)	(0.168)
% Females	3.529	-6.910*	0.562*
	(3.849)	(3.671)	(0.313)
Credit	-1.28	0.491	-0.177
	(1.151)	(0.959)	(0.150)
Off-farm Work	0.144	-0.568	-0.062
	(0.564)	(0.405)	(0.042)
Flood	1.787	0.018	-0.086
	(1.478)	(1.587)	(0.187)
Drought	-3.295	-5.026***	0.494***
	(2.604)	(1.057)	(0.137)
Livestock	-0.081	-0.071	-0.007
	(0.123)	(0.109)	(0.016)
Owns Land	2.082	-0.517	-0.098
	(1.338)	(1.519)	(0.139)
Weather			
Kharif Rain	-3.113	13.043***	0.141
	(3.317)	(3.957)	(0.354)
Kharif Temp.	1.87	-4.549	-2.474***
	(16.4)	(20.06)	(0.681)
Rabi Rain	-15.628	159.412***	2.937
	(27)	(55.293)	(7.38)
Rabi Temp.	-15.608	24.467	0.809
	(11.903)	(19.458)	(2.559)
Climate			
Ave. Kharif Rain	9.894	-47.812***	-0.524
	(10.493)	(12.832)	(1.492)
Ave. Kharif Temp.	-7.270	-0.207	3.351***
	(19.272)	(20.477)	(0.474)
Ave. Rabi Temp.	17.051	-17.621	-1.385
	(11.448)	(18.723)	(2.507)
Ave. Rabi Rain	-33.5	-85.812	3.336
	(30.411)	(72.133)	(6.376)
Information			
Extension Services	0.380	-2.180**	0.072
	(1.153)	(0.928)	(0.146)
Peer	-1.824	-0.196	0.246
	(2.285)	(1.069)	(0.264)
Media	-3.472***	-5.176***	0.267
	(1.146)	(1.023)	(0.232)
Middleman	2.667	3.274*	-0.23
	(3.152)	(1.713)	(0.291)
Landlord	0.604	0.628	0.022
	(3.74)	(2.965)	(0.522)
Climate Change Perceptions			
Prec. Decrease			-0.062
			(0.220)
Prec. Increase			0.059
			(0.297)
Prec. Onset			0.358
			(0.337)
Temp. Decrease			-0.377*
			(0.195)
Temp. Cold Spell			0.905
			(0.658)
Temp. Onset Hot			-0.39
			(0.395)
Constant	264.431	14.502	-27.594
	(178.512)	(310.946)	(20.51)
Sigma	2.111***	2.222***	
	(0.058)	(0.056)	
Rho	-0.013	-0.496**	
	(1.197)	(0.229)	
Region dummies	Yes	Yes	Yes
N			907

[a] Standard errors are robust and clustered by region
[b] p<0.1, p<0.05, p<0.01

Table 8: Endogenous Switching Regression: Rice

	Yield Non-Adapters	Yield Adapters	Adapt(0/1)
	Coef./se	Coef./se	Coef./se
Inputs			
Pesticides/acre	-1.283***	1.051	0.036
	(0.168)	(1.119)	(0.054)
Urea/acre	5.891***	0.437	0.005
	(1.746)	(1.758)	(0.147)
DAPSOP/acre	0.053	3.857	0.117
	(0.947)	(2.389)	(0.123)
Manure/acre	2.910***	1.575	0.121
	(1.013)	(1.368)	(0.133)
Seed/acre	-0.027	-0.001	0.012***
	(0.05)	(0.062)	(0.005)
Soil Qual.	0.728	1.143	0.157***
	(0.702)	(1.668)	(0.055)
Household Labour/acre	0.595*	1.191***	-0.005
	(0.357)	(0.300)	(0.013)
Hired Labour/acre	1.771***	0.351***	0.060*
	(0.274)	(0.027)	(0.033)
Water Apps./acre	-0.020	-0.097*	-0.004
	(0.033)	(0.057)	(0.002)
Canal	6.045	8.787**	0.288
	(4.189)	(3.803)	(0.383)
Tubewell	-2.252	3.443	0.094
	(2.014)	(3.995)	(0.269)
Tractor	2.104*	3.988	0.371
	(1.141)	(5.046)	(0.328)
Household			
Total Land (acres)	0.017	-0.109***	0.016***
	(0.027)	(0.041)	(0.004)
Household Size	-0.601***	-0.112	-0.014
	(0.185)	(0.497)	(0.021)
Literate	-0.591	2.834	-0.205
	(3.550)	(5.198)	(0.216)
% Females	-2.474	-15.420***	0.518
	(7.159)	(5.293)	(0.344)
Credit	-2.513	5.243**	-0.233*
	(2.347)	(2.044)	(0.122)
Off-farm Work	0.930**	-1.326	-0.074
	(0.413)	(1.386)	(0.089)
Flood	4.360*	2.998	-0.096
	(2.451)	(4.534)	(0.207)
Drought	2.907	-3.865	0.276
	(3.621)	(2.462)	(0.301)
Livestock	0.039	0.029	0.045***
	(0.081)	(0.209)	(0.009)
Owns Land	3.061***	4.830*	-0.448**
	(0.956)	(2.549)	(0.212)
Weather			
Kharif Rain	26.753***	0.940	1.309
	(10.101)	(13.972)	(1.665)
Kharif Temp.	22.102	54.928*	-5.285
	(33.302)	(29.523)	(3.872)
Rabi Rain	528.507*	-277.506**	77.619***
	(303.243)	(132.085)	(21.507)
Rabi Temp.	104.761	-162.980***	30.721***
	(96.481)	(32.012)	(5.493)
Climate			
Ave. Kharif Rain	-161.715**	-57.361	-9.105
	(65.806)	(47.586)	(7.838)
Ave. Kharif Temp.	-42.821	-43.617	3.412
	(37.208)	(26.944)	(4.177)
Ave. Rabi Temp.	-68.054	198.660***	-30.341***
	(85.22)	(31.034)	(4.620)
Ave. Rabi Rain	-100.436	681.843***	-18.713
	(101.549)	(134.349)	(23.082)
Information			
Extension Services	-1.570	5.276*	-0.485*
	(2.053)	(2.776)	(0.287)
Peer	2.179**	0.638	0.08
	(1.015)	(3.971)	(0.328)
Media	-6.777***	2.652	-0.062
	(2.544)	(3.805)	(0.407)
Middleman	3.688*	-17.780*	0.033
	(2.151)	(9.086)	(0.339)
Landlord	-10.230**	1.829	-0.385
	(4.157)	(8.858)	(0.528)
Climate Change Perceptions			
Prec. Decrease			-0.38
			(0.247)
Prec. Increase			-0.155
			(0.103)
Prec. Onset			-0.062
			(0.189)
Temp. Increase			0.472
			(0.295)
Temp. Night			-1.017
			(0.744)
Temp. Cold Spell			-3.048**
			(1.275)
Temp. Onset Hot			-1.872***
			(0.363)
Constant	-402.839	-93.308	-107.474*
	(432.437)	(405.493)	(57.940)
Sigma	2.349***	2.662***	
	(0.220)	(0.097)	
Rho	0.395	-0.546***	
	(0.379)	(0.203)	
Region dummies	Yes	Yes	Yes
N			337

[a] Standard errors are robust and clustered by region
[b] p<0.1, p<0.05, p<0.01

Table 9: Endogenous Switching Regression: Cotton

	Yield Non-Adapters	Yield Adapters	Adapt(0/1)
	Coef./se	Coef./se	Coef./se
Inputs			
Pesticides/acre	-0.473	-0.165	0.017
	(0.355)	(0.157)	(0.036)
Urea/acre	1.082***	0.929***	0.114***
	(0.261)	(0.331)	(0.026)
DAPSOP/acre	0.693**	2.166	0.200
	(0.299)	(1.627)	(0.129)
Manure/acre	3.496*	-0.688	0.036
	(1.008)	(0.510)	(0.236)
Seed/acre	-0.004	0.093	0.004
	(0.029)	(0.123)	(0.006)
Soil Qual.	1.686	-0.401	0.327**
	(1.187)	(0.585)	(0.145)
Household Labour/acre	1.242**	0.341**	0.028
	(0.503)	(0.160)	(0.035)
Hired Labour/acre	0.319***	-0.010	0.019**
	(0.061)	(0.041)	(0.009)
Water Apps./acre	0.668***	0.178	0.037
	(0.201)	(0.250)	(0.029)
Canal	-0.322	-1.820	0.000
	(2.024)	(1.943)	(0.355)
Tubewell	-1.435	-1.639	0.113
	(1.328)	(2.403)	(0.291)
Tractor	2.458***	-0.703	-0.111
	(0.656)	(1.851)	(0.352)
Household			
Total Land (acres)	-0.010	-0.095***	0.024*
	(0.148)	(0.029)	(0.014)
Household Size	-0.198	0.003	-0.014
	(0.234)	(0.448)	(0.070)
Literate	-0.624	1.217	-0.366***
	(2.231)	(1.791)	(0.122)
% Females	1.465	-9.032	1.011*
	(4.038)	(5.753)	(0.534)
Credit	-4.584***	-4.241***	0.202
	(0.738)	(1.579)	(0.154)
Off-farm Work	0.226	-0.422**	0.01
	(0.712)	(0.182)	(0.057)
Flood	-1.402*	-1.213	0.393***
	(0.845)	(1.299)	(0.096)
Drought	4.343**	3.165	0.348
	(1.896)	(3.051)	(0.236)
Livestock	-0.020	-0.322***	-0.014
	(0.059)	(0.068)	(0.024)
Owns Land	1.824***	-1.581***	0.217
	(0.683)	(0.551)	(0.145)
Weather			
Kharif Rain	1.639	6.017	0.404
	(3.117)	(5.572)	(0.930)
Kharif Temp.	1.990	59.307	-7.295***
	(17.772)	(53.135)	(1.494)
Rabi Rain	-321.895***	-71.409	52.392***
	(105.001)	(128.459)	(14.725)
Rabi Temp.	-104.306***	-16.523	15.977***
	(38.295)	(41.495)	(5.331)
Climate			
Ave. Kharif Rain	43.151***	-20.406	-6.491
	(11.509)	(38.090)	(5.435)
Ave. Kharif Temp.	-1.842	-47.489	4.824**
	(20.093)	(45.824)	(2.096)
Ave. Rabi Temp.	88.586**	7.162	-12.774**
	(34.981)	(35.933)	(5.225)
Ave. Rabi Rain	-143.38	-139.821***	-11.93
	(140.284)	(37.169)	(28.910)
Information			
Extension Services	-0.732	0.016	0.337
	(1.122)	(2.051)	(0.213)
Peer	-4.333***	-2.208	0.323
	(0.869)	(1.789)	(0.198)
Media	-0.518	-0.695	0.388
	(2.033)	(1.951)	(0.308)
Middleman	0.031	-3.975	0.38
	(1.994)	(3.232)	(0.642)
Landlord	-2.833**	0.962	-0.294
	(1.215)	(2.315)	(0.807)
Climate Change Perceptions			
Prec. Decrease			0.022
			(0.397)
Prec. Increase			0.358
			(0.515)
Prec. Onset			0.679
			(0.422)
Temp. Decrease			-0.142
			(0.262)
Temp. Cold Spell			6.647***
			(1.190)
Temp. Onset Hot			0.239
		(0.601)	
Constant	833.833***	-21.047	-66.285
	(311.746)	(215.415)	(55.659)
Sigma	1.785***	2.048***	
	(0.181)	(0.140)	
Rho	0.367	-0.332	
	(0.372)	(0.285)	
Region dummies	Yes	Yes	Yes
N			293

[a] Standard errors are robust and clustered by region

[b] p<0.1, p<0.05, p<0.01

Table 10: Impact of Adaptation on Yields: Pooled

	Mean Outcome Adapt	Mean Outcome Not Adapt	Difference	% Change
Adapters	19.71	18.47	ATT = 1.24***	7
	(0.25)	(0.26)	(0.16)	
Non-adapters	27.69	17.02	ATU = 10.67***	63
	(0.30)	(0.24)	(0.02)	

Table 11: Impact of Adaptation on Yields: Wheat

	Mean Outcome Adapt	Mean Outcome Not Adapt	Difference	% Change
Adapters	19.55	17.38	ATT = 2.17***	12
	(0.30)	(0.31)	(0.20)	
Non-adapters	25.39	17.01	ATU = 8.38***	49
	(0.33)	(0.25)	(0.23)	

Table 12: Impact of Adaptation on Yields: Rice

	Mean Outcome Adapt	Mean Outcome Not Adapt	Difference	% Change
Adapters	22.85	22.16	ATT = 0.69	3
	(0.93)	(1.44)	(1.28)	
Non-adapters	33.37	19.92	ATU = 13.45***	67
	(1.25)	(0.98)	(0.96)	

Table 13: Impact of Adaptation on Yields: Cotton

	Mean Outcome Adapt	Mean Outcome Not Adapt	Difference	% Change
Adapters	16.79	15.21	ATT = 1.58**	9
	(0.58)	(1.00)	(0.79)	
Non-adapters	19.92	13.09	ATU = 6.83***	52
	(0.77)	(0.65)	(0.71)	