THREE ESSAYS IN DEVELOPMENT ECONOMICS

By

Joshua Gill

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ABSTRACT

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The three essays in this dissertation study how the rural poor in Pakistan make choices and how better program design can alleviate the constraints they face. The first essay investigates the participation decision of smallholder paddy farmers in a Warehouse Receipts Financing (WRF) program which can mitigate their credit and storage constraints, allowing them to increase their incomes. We a discrete choice experiment approach to study the decision-making process and find risk aversion and transaction cost erode the benefits for smallholder farmers making it an unattractive prospect. We find that likelihood of participation can be increased through better contract design which lower cost of participation and reduce exposure to price uncertainty. These findings have important implications for the optimal design of warehouse receipt financing contracts, as well as their general feasibility for marketing to small farmers. It also highlights that programs aimed to uplift smallholder farmers should not only address constraints of circumstance (e.g. access) but also internal constraints (e.g. risk aversion).

The second essay aims to alleviate information constraints regrading fertilizer usage as its indiscriminate and faulty use can affect soil health. Evidence shows that soil quality in Pakistan has been deteriorating which can be partially explain by poor nutrient management. In this study we conducted soil tests and provided recommendations on use of organic and inorganic fertilizer.

This study uses an experimental design with two treatment arms and a control group which received no information and its soil was not tested. The base treatment provided farmers with information on their soil health and recommended fertilizer use condition on the crops they

cultivate. The second treatment arm complemented this information with a peer comparison which was used an encouragement mechanism to improve the efficacy of information provided.

The study highlights some important constraints to information dissemination and provides some evidence on the use of peer comparison as a potential tool to improve efficacy of information campaigns. We see a statistically significant increase in manure usage and a heterogenous impact on Urea use but no impact on the overall fertilizer use. We find that farmers they were already using close to the recommended amount (within 1 bag deviation) increased their urea application rate. These findings suggest two underlying mechanisms at play. First, it alludes to liquidity constraints as farmers increased manure use which is cheap and those who could already afford higher quantities of Urea were able to respond to the recommendation of increasing application rates. The fact that we do not see impact on DAP further gives credence to this assumption as DAP is close to 3 times the cost of Urea. Alternatively, it could be that farmers who were away from the suggested fertilizer amounts did not trust the recommendations.

The third essay studies the dynamics of warehouse receipts financing (WRF) demand by small scale risk averse farmers in Pakistan. A dynamic model is used to investigate how risk and time preferences, transaction costs, and uncertainty reduce demand for WRF, and even lead to non-participation in the program. The model is calibrated and solved for a representative small-scale farmer that grows paddy. Results show high transaction costs to be a major barrier to participation. Similarly, expectations about future prices also affect participation which drops to zero if the subjective probability of prices falling goes beyond 10 percent.

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Abstract

Smallholder farmers in developing countries face numerous constraints in both input and output markets, that reduce their profit-generating potential. Warehouse Receipt Financing (WRF) has been promoted as an innovative solution that provides access to more remunerative markets and formal financial institutions. However, participation by smallholder farmers has been low despite its potential for profit generation. This paper considers the case of a WRF intervention in Pakistan which saw a similar outcome and aims to identify reasons for low take-up and how better contract design can improve participation. This study finds that risk aversion as an important factor for lack of participation. It highlights that smallholder farmers are unwilling to take on the entire risk of price uncertainty due to intertemporal arbitrage. Results from a choice experiment show that when smallholder farmers were offered the same WRF product with price certainty that resulted in a no loss scenario predicted participation increased by 32 percent. This result highlights that participation of smallholder farmers can be significantly increased by designing WRF products and contracts that meet the needs of the farmers. These findings have important implications regarding the demand for WRF and its general feasibility of marketing to smallholder farmers.

1.1. Introduction

In most developing countries agricultural markets are marred with inefficiencies that lead to a suboptimal equilibrium. Smallholder farmers are affected the most under these conditions as they suffer both in the input and output markets. They are underserved by financial institutions and have limited access to downstream buyers, as a result they rely on intermediaries who expropriate rents. The outcome is a vicious cycle of low investment and low earnings which inhibits their upward economic mobility. Moreover, a poorly functioning agriculture sector also hinders in achieving the development goals of poverty reduction and inclusive economic growth as majority of the poor live in rural areas and derive their livelihood from agriculture.

The desire to break this cycle has motivated numerous interventions (e.g. subsidies, information, infrastructure) that have provided little benefit to smallholder farmers (Barrett et al., 2012; Fafchamps and Minten, 2012; Fischer and Qaim, 2014; Jayne et al., 2018; Ricker-Gilbert et al., 2013; Shiferaw et al., 2011). Warehouse receipts financing (WRF) has lately been promoted as an innovative solution that can improve incomes of smallholder farmers by alleviating liquidity and market access constraints (Aggarwal et al., 2018; Basu and Wong, 2015; Burke, 2014; Omotilewa et al., 2018). However, smallholder farmer participation in these programs has not been very encouraging (William and Kaserwa, 2015). There is limited work which explores the reasons for low participation despite it being a profitable prospect (Miranda et al., 2017).

The purpose of this paper is to understand the marketing choices of smallholder rice farmers in Pakistan under a WRF program.[1] This study explores whether potential external and internal constraints made non-participation a subjectively rational decision. Three main factors are examined in this study: transaction costs, risk aversion, and impatience. The objective of the paper

[1] This program was implemented in 2017 and farmers cultivating less than 10 acres were targeted. However, despite high interest shown during village meeting, take-up was less than 2 percent among the target population at rollout.

is to test how better product and contract design can address these constraints and in doing so, improve participation and earning possibilities of smallholder farmers. This paper uses a Discrete-Choice Experiment (DCE), which has been used extensively to study consumer preferences and has been widely applied in many fields of applied and development economics (Caputo et al., 2013; Clark et al., 2014; Gibson et al., 2016; Lusk and Briggeman, 2009; Ortega et al., 2011; Scarpa and Willis, 2010; Tanaka et al., 2014; Ward and Singh, 2015). We collect information on risk and time preferences through incentivized games using a multiple price list approach. (Andersen et al., 2008; Ward and Singh, 2015). In addition, respondents were randomly assigned to one of three different experimental groups offering different hypothetical levels of price guarantees: Group 1 was guaranteed a high price 3 months after storage; Group 2 was guaranteed a low price; Group 3 was not given any price guarantees.

This study makes several contributions to the literature on WRF. First, we use a DCE framework to evaluate whether a market for WRF exists among smallholder farmers, and their willingness to pay (WTP) for this service. There is very limited and mixed evidence on the benefits of WRF to smallholder farmers (Aggarwal et al., 2018; Burke, 2014; Miranda et al., 2017; William and Kaserwa, 2015), and prior studies do not explicitly measure WTP. Information on farmers' WTP can be very useful in developing appropriate products for smallholder farmers, and in ascertaining whether such products would be financially feasible for providers. In addition, internal constraints can act as independent sources of disadvantage and can affect smallholder farmers' technology adoption decisions (Duflo et al., 2008; Liu, 2013; Ward and Singh, 2015). This study contributes to this body of literature by examining the role of risk aversion, time discounting, and uncertainty on one's decision to participate in WRF.

To our knowledge, only one other study has explicitly accounted for preference-related factors when evaluating the feasibility of WRF programs (Miranda et al., 2017). The authors highlight the role of preferences in eroding the profitability of WRF and suggest that WRF is not feasible for smallholder farmers. We differ from this study by exploring ways to redesign WRF products to address these issues.

Our results highlight that participation in WRF can be significantly increased if exposure to price risk can be reduced, and that this factor is more important to farmers than either the cost of transport or borrowing. Farmers in the price guarantee groups select the WRF option more often (approximately 30 percent), which suggests that price uncertainty is a major deterrent to participation. While marginal WTP decreases as interest rates increase, and increases if transport is provided, farmers in the price guarantee group are willing to pay more for credit in comparison to those in the other two treatment groups. Farmers who receive a price guarantee also have a lower willingness to pay for transport compared to those in the other treatment groups. In addition, who are relatively less risk averse or do no discount future payments are more likely to select WRF.

The remainder of the paper proceeds as follows: Section 1.2 provides background information on the context of this study of Basmati rice farmers in Pakistan; Section 1.3 outlines the experimental design; Section 1.4 outlines the estimation strategy; Section 1.5 discusses the data; Section 1.6 summarizes the results; and Section 1.7 concludes.

1.2. Background

Rice value chain in Pakistan is underdeveloped and smallholder farmers suffer the most in this environment. There is significant intertemporal and spatial price variation as the output markets are inefficient and fail to move the product from surplus to shortage periods. Smallholder farmers suffer more as they lack access to storage and sell their output immediately at harvest when prices are depressed low. In addition, the playing field is also tilted against them in the input market as they are underserved by formal financial institutions due to their small size and high poverty incidence. This not only leads to liquidity constraints during the production cycle but also limits the ability of smallholder farmers to invest in better technology. Taken together, these input and output constraints severely inhibit the ability of smallholder farmers to take risks, make necessary investments, and improve their productivity.

WRF has lately been promoted as a viable mechanism to develop the value chain and make it more inclusive. WRF can improve income of smallholder farmers through three channels. First, it provides access to storage allowing smallholder farmers to transfer produce from periods of surplus to shortage. Second, it provides access to formal financial institutions by using stored grain as collateral. Finally, the warehouse acts as a clearing house where product is graded and agglomerated thereby improving the bargaining power of smallholder farmers, reducing the transaction and search costs of doing business.

In 2017 a WRF program was piloted in the district of Hafizabad, Pakistan. The project was implemented in 50 randomly selected villages with the objective of improving returns for smallholder farmers through storage, credit, and better market linkages. Approximately, 1500 farmers cultivating under 10 acres registered for the program and gave soft commitments regarding the quantity they would store in the upcoming harvest. However, once the harvest season concluded less than 2 percent of the registered farmers had stored paddy at the warehouse. This outcome was very puzzling as WRF was a profitable prospect and the increase in income was not trivial as shown in Table 1.1.

Table 1.1: Cost Benefit of WRF

Year	Harvest Price	Post-Harvest Price		Net benefit	Profit
2016	Rs 1300/40 kg	Rs 1900/40 kg	Rs 240/40 kg	Rs 360/40 kg	Rs 10,800/acre
2017	Rs 1550/40 kg	Rs 2200/40 kg	Rs 240/40 kg	Rs 410/40 kg	Rs 12,300/acre

Note: This table shows the average prices at harvest and 3 month post-harvest in the project areas. The cost includes drying charges, storage charges, rent for jute bags, labor, mark-up on loan, and weight-loss due to drying. The profit figure is calculated using an average yield of 1200 kg per acre. These figures were provided by the warehousing management company and reflect the prices at which paddy was bought and later sold by them. The cost of storage was also shared by them based on the actual expenses incurred during the season.

`This paper aims to understand the participation choice of smallholder farmers and test if alternate designs can improve take-up. The first question we address is whether there is demand for WRF among smallholder farmers. Risk aversion, time discounting, and transaction costs are explored as potential factors depressing demand. The choice of these factors is based on literature which shows smallholder farmers to be price sensitive, reluctant to engage in risk prospects and value immediate rewards more than future rewards. The second question this study addresses is can participation be increased through better contract designs. We specifically test how a reduction in uncertainty on returns can improve participation by farmers. Finally, the paper quantifies the willingness to pay under different contract designs.

1.3. Experimental Methods

This section illustrates the experimental procedures. Respondents were first exposed to incentivized games to elicit risk and time preferences and then to DCE questions. The first subsection explains the games that were played to measure risk and time preferences and the DCE that was implemented to elicit farmers preferences for WRF. The second subsection describes the hypothetical price regimes farmers were randomly assigned to before participating in the DCE.

1.3.1. Experiments

This study utilizes risk and time discounting to explain farmer participation choice in WRF. Risk and time preference have been extensively used to explain a range of choice behavior such as technology adoption, investment, migration, education attainment, and smoking (Ashraf et al., 2006; Chavas and Holt, 2006; Jensen, 2010; Lawless et al., 2013; McKenzie et al., 2013; Warnick et al., 2011).

Multiple price list approach was used to elicit risk preferences. Two price lists with 14 questions in each list was used and the respondent had to choose between two lottery options labelled Option A and Option B. Option A offered a sure small return and Option B offered a higher expected return but with higher risk. Graphical images were used to help the respondent understand the probabilities involved under both lotteries.

One price list with 10 questions was used to elicit the discount rate. Respondents were given a token at the start of the game and informed that they could exchange it for real money based on the questions in the price list. Each question had two options labelled Option A and Option B offering different amount of money at different times in the future. Option A was for sooner smaller payment and Option B was for larger later payment. Picture of a calendar with dates corresponding to Option A and Option B was used to help the respondents understand the choices better. These games were incentive compatible, and respondents were informed that at the end of the game one of their responses will be randomly chosen for actual payment. Experimental protocols for these games are shown in the Appendix.

In the DCE, respondents were asked to choose between three alternatives; two warehousing products and an opt-out option. The warehousing products were described by three attributes as reported in Table 1.2. These three attributes were chosen based on the conversations with farmers. The cost levels reflect subsidized cost, true cost, and true cost plus a value-added service fee. Credit up to 70 percent of the value of the stored product was offered to relax liquidity constraints due to storage. The interest rate levels are reflective of the rate charged by government sponsored agricultural loans, conventional banks, and microfinance banks. Transport is another critical attribute considered as smallholder farmers do not own a truck and renting can be very costly given their low volumes. Two levels of this attribute are selected based either paddy is picked from farmgate or the farmer must arrange for the transportation.

Table 1.2: Choice Experiment Attribute and Levels

Warehouse Receipts Financing		
Attributes	Description	Levels
Cost	The cost of storage for a 40 kg bag of paddy.	Rs 10 per month Rs 20 per month Rs 40 per month
Interest	The depositor has the option to take loan of up to 70% of the value of the product stored at harvest.	No Interest 15 % per annum 30 % per annum
Transport	Paddy would be picked from the farmer's field for storage.	Present Absent

An orthogonal optimal design was used for the DCE as a full factorial design would have resulted in 324 possible choice questions. The questions were generated using Ngene software which showed that a minimum of 18 choice sets were required to achieve 100 percent D-efficiency. These questions were further divided into two blocks so that each respondent answered a set of 9 questions. This was done to avoid mental fatigue and loss of interest by the respondent, which can lead to poor responses. Each choice set had three options; two options of a WRF service and an opt out option. See appendix A for an example question.

1.3.2. Treatment Assignments

Respondents were randomly assigned to a group with a hypothetical price regime to estimate its impact on participation choice. Table 1.3 shows the three experimental groups.

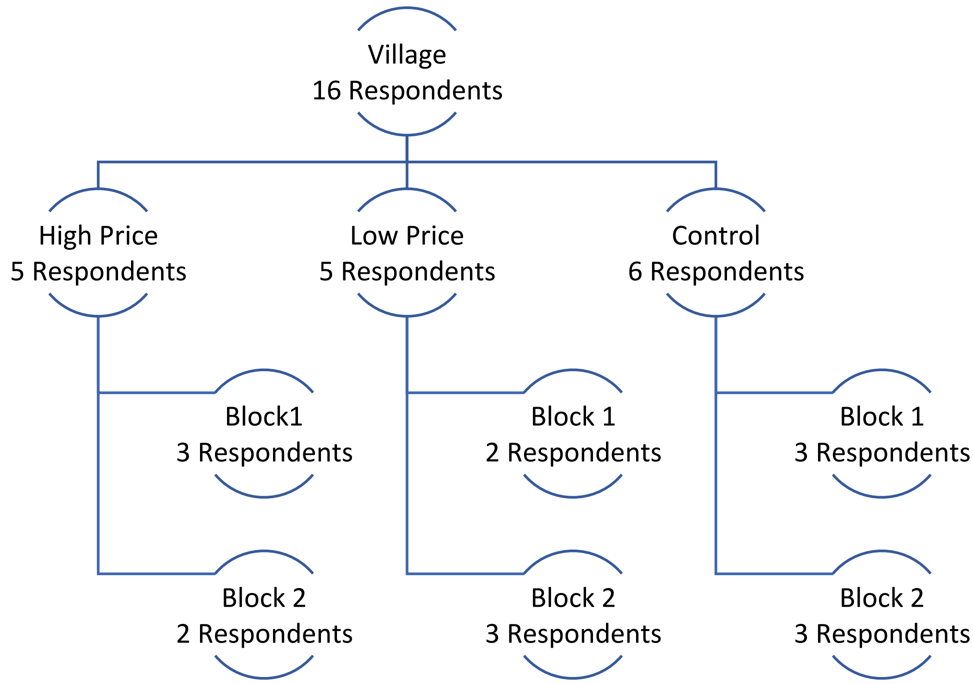
Table 1.3: Treatment Groups

Groups	Treatments	Description	Price Guarantee
Group 1	Control	No Price Guarantee	--
Group 2	High Price	High Price Guarantee	Rs 1800 /40 kg
Group 3	Low Price	Low Price Guarantee	Rs 1600/40 kg

Respondents in each group were read a script before the start of the DCE informing them regarding the hypothetical price scenario. Group 1 is the Control and respondents were informed that the expected price of paddy at harvest is Rs1300/bag and historically paddy prices tend to rise in the 3 months post-harvest. Hence, if they chose to store and sell later, they could earn a significantly higher profit. However, they were also informed that profits were not guaranteed as in any other business and prices can fluctuate unexpectedly. Group 2 is the High Price treatment and respondents were informed that the expected price of paddy at harvest is Rs1300/bag and historically paddy prices tend to rise in the 3 months post-harvest. Hence, if they chose to store and sell later, they could earn a significantly higher profit. However, they were given the guarantee that the warehouse would purchase at Rs1800/bag 3-month post-harvest irrespective of the market price. Group 3 is the Low Price treatment and respondents were informed that the expected price of paddy at harvest is Rs1300/bag and historically paddy prices tend to rise in the 3 months post-harvest. Hence, if they chose to store and sell later, they could earn a significantly higher profit. However, they were given the guarantee that the warehouse would purchase at Rs1600/bag 3-month post-harvest irrespective of the market price. The scripts are given in the appendix.

The sampling frame for this study consisted of 1500 farmers in 50 villages who had earlier shown interest in the WRF. A subsample of 800 individual was randomly drawn for this study. On average 16 farmers were picked from each of the 50 villages. Farmers were then randomly assigned to one of the three experimental groups and then to one of the two DCE blocks. Figure 1.1 outlines the sampling strategy.

Figure 1.1: Sampling strategy



1.4. Estimation Procedures

This section explains the estimation procedure for the preference data collected through the incentivized games and choice data collected in the DCE.

1.4.1. Risk Aversion

We estimate a Constant Relative Risk Aversion (CRRA) measure in this study and account for probability weighting (α) when estimating risk aversion (δ) (Kahneman and Tversky, 1979). Consider a game with two potential outcomes X and Y which can occur with the probabilities p and q, respectively. The value of the prospect can be given by

$$U(X, Y, p, q, \delta, \alpha) = V(Y) + w(p)[V(X) - V(Y)] for X > Y \tag{1.1}$$

where $V(X) = X^{\delta}$, $w(p) = exp(-(-\ln p)^{\alpha})$ and α and δ are jointly determined. Let us look at the following example for illustration. If a participant switches from the risk-free option (A) to the lottery (B) in question number 5 in both game 1 and game 2 then the following problem can be solved to derive α and δ.

$$200^{\delta} > 100^{\delta} + exp(-(-\ln 0.1)^{\alpha})\left(720^{\delta} - 100^{\delta}\right)$$

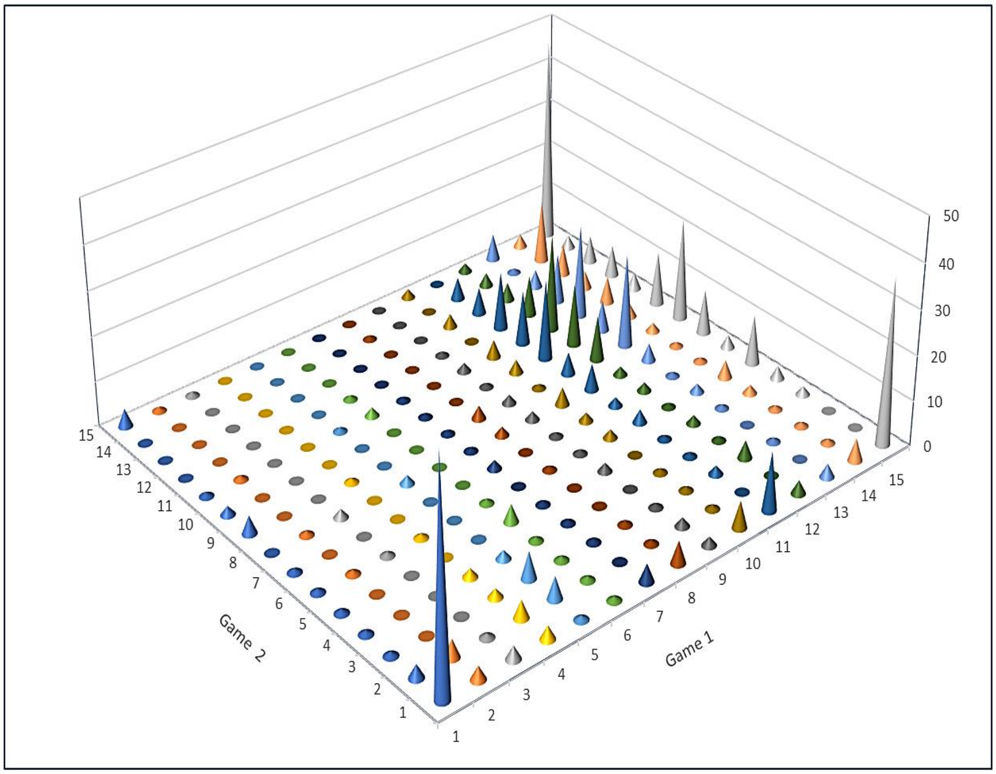
$$200^{\delta} < 100^{\delta} + exp(-(-\ln 0.1)^{\alpha})\left(820^{\delta} - 100^{\delta}\right)$$

$$800^{\delta} > 100^{\delta} + exp(-(-\ln 0.1)^{\alpha})\left(1240^{\delta} - 100^{\delta}\right)$$

$$200^{\delta} > 100^{\delta} + exp(-(-\ln 0.1)^{\alpha})\left(1300^{\delta} - 100^{\delta}\right)$$

Figure 1.2 illustrates the switching points in the two games. As expected, we see a larger proportion of switches happening later in the games suggesting the that the farmers are risk averse on average.

Figure 1.2: Switching Distribution



1.4.2. Time preferences

We estimate discount rates while controlling for concavity of utility and included a front-end delay of two weeks in the games. Literature highlights correcting for concavity of utility as ignoring it results in underestimating the discount factor and overestimating the impatience of the respondent (Cheung, 2016). Similarly, using a front-end delay is recommended to ensures that the transaction cost of receiving money is consistent across sooner and later payments (Andersen et al., 2008). Utility in each period can be expressed as

$$U(t) = D(t) \cdot V(X) \tag{1.2}$$

where utility $V(X) = X^{\delta}$, the discount function $D(t) = \frac{1}{(1+\rho)^t}$, and the interest rate is ρ .The respondent will select the sooner payment if the utility from it is higher compared to that in the future. δ is estimated from the risk game and ρ is estimated from the choices made by respondents in the time preference game.

1.4.3. Discrete Choice Models

DCE methodology is based on Lancaster theory of consumer demand and McFadden's random utility theory (Hensher et al., 2015). The former assumes utility is derived from the characteristics and properties of the good consumed rather than the good itself (Lancaster, 1966). The latter assumes individuals to be rational beings who compare alternatives and select the option that maximize their utility (McFadden, 1974). Formally, let U_{njt} represent the utility that an individual n derives from alternative j at time situation t. The decision maker evaluates all the alternatives and choses i if and only if $U_{nit} > U_{njt}\ \forall\ j \neq i$. However, the utility assigned by the decision maker is not known to the researcher and is partitioned into an observed and an unknown stochastic component ϵ_{njt}. The functional form of this utility can be written as:

$$U_{njt} = V_{njt} + \epsilon_{njt} \tag{1.3}$$

The most common assumption is that the observed part of the utility is linear in some observed factors and can be expressed as $V_{njt} = V(x_{njt}, z_n)$ where $\boldsymbol{x}_{njt}$ is a vector of product attributes, $\boldsymbol{z}_n$ is the vector of decision maker's characteristics, and ϵ_{njt} is assumed to be independent and identically distributed.

We used a mixed logit model with error components (MXL-EC) to analyze the choice data. Estimation of the model was carried out using a panel data structure which includes individual level risk aversion and discount rates as behavioral characteristics. MXL-EC was used as it is less restrictive and allows us to capture both systematic and random taste variations and accounts for correlations across utilities (Greene and Hensher, 2010). In addition, it also controls for the effects associated with the opt out option relative to the experimentally designed alternatives (Caputo et al., 2013; Scarpa et al., 2005, 2007). This utility structure can be expressed as follows:

$$U_{njt} = V_{njt} + 1_j(\eta_{nt}) + \epsilon_{njt} \tag{1.4}$$

where $1_j(\cdot)$ is an indicator function that takes the value of 1 for experimentally designed alternatives; and η_{nt} is normally distributed with zero mean respondent-specific idiosyncratic error component associated with the experimentally designed alternative but not with the opt-out option. The rest of the elements in equation (2) are same as in equation (1). The unconditional probability of individual *n* choosing alternative *j* under MXL-EC is given by:

$$P_{njt} = \int_{\beta_n} \int_{\eta_n} \prod_{t=1}^{T} \frac{exp\left(V_{njt} + 1_j(\eta_{nt})\right)}{\sum_j \ exp\left(V_{njt} + 1_j(\eta_{nt})\right)} \ f(\beta_n) f(\eta_{nt}) d\beta_n d(\eta_n) \tag{1.5}$$

where $f(\beta)$ and $f(\eta_n)$ are the probability densities over which the coefficients of β and $\eta_n$vary in the population.

Three MXL-EC models are estimated, one for each treatment group (Control, High Price, and Low Price). All models account for random taste variation by allowing the coefficients of attributes (cost, interest, and transport) to vary in the population following a one-sided triangular distribution2. Whereas, the OptOut is assumed to be normally distributed as the utility from the

[2] One-sided triangular distribution is used as symmetric distributions around zero, example normal can lead to implausible results, such as a positive coefficient for cost. Under the one-sided triangular distribution, the parameters in our specification are distributed as $\beta_i = \beta + \ \beta v_i, \ v_i \sim triangle[-1,1]$, where β_i is distributed between $(\beta, \ 2\beta)$ with mean β and variance $\beta^2/6$.

status quo option can both be positive or negative[3]. The risk variable measures the constant relative risk aversion (CRRA) and has a positive support. A value of 1 means the individual is risk neutral while values smaller than 1 imply risk aversion and higher values imply risk loving behavior. The time variable has a support between zero and 1, it measures the discount factor where zero implies future income has no value and 1 implies that future income is not discounted at all. These variables were interacted with the Opt-Out option as we assume that there might be heterogeneity in farmers' preferences with respect to selecting the WRF products. The utility function is expressed as follows for all treatment groups:

$$\begin{aligned} U_{njt} = OptOut + \beta_1 Cost_{njt} + \beta_2 Low\_Int_{njt} + \beta_3 Hi\_Int_{njt} + \beta_4 Transport_{njt} \\ +\gamma_1(OptOut * Risk) + \gamma_2(OptOut * Time) + 1_j(\eta_{nt}) + \varepsilon_{njt} \end{aligned} \tag{1.6}$$

where OptOut is an alternative-specific constant representing the opt-out alternative, $Cost_{njt}$ is a continuous variable indicating the monthly cost of storage for a bag of paddy; Low_Int and Hi_Int are effects coded variables indicating the per annum interest rate. Low_Int takes the value of 1 if the interest rate is 15 percent and Hi_Int takes the value 1 if the interest rate is 30 percent. If the interest rate is zero, then then variables are coded as -1. Transport is also effects coded and takes the value of 1 if the farmgate pick-up is provided and -1 otherwise.

Predicted probability of selecting an alternative in each choice set was computed using results from the MXL-EC model. Based on these probabilities a new variable "WRF participation" was created which takes the value 1 if one of the WRF alternatives was assigned the highest probability and zero otherwise. A probit model was then estimated with "WRF participation" as the dependent variable and treatment assignment as independent variables. The specification is given as

$$Y_{nt} = \delta_0 + \delta_1 Low\ Price\ Guarantee + \delta_2 High\ Price\ Guarantee \tag{1.7}$$

[3] The parameter is distributed as $OptOut_i = OptOut + \delta z_i + \sigma v_i,\ v_i \sim N[0,1]$, where $(OptOut + \delta z_i)$ is the conditional mean and σ is the standard deviation.

where Y_{nt} is a binary variable, δ_0 is the average participation rate in the control group and $\delta_1$and δ_2 are the treatment effects on participation relative to the control. In addition to estimating the impact on predicted choices a probit was also estimated on the actual choices made by the respondents in the DCE.

Willingness to pay across the three treatment groups was calculated in the WTP space. This outcome is important in establishing whether WRF has a market among smallholder farmers. WTP can be obtained by taking a ratio of the attribute and price coefficients. However, these estimators generally do not have finite moments as the ratios of the coefficients can have infinite variances under most distributions (Daly et al., 2012). One solution is to fix the coefficient estimate on price but that inherently assumes that everyone values money similarly. An alternate solution is to estimate the model in the willingness to pay space as it relaxes the assumption to have a fixed price coefficient (Scarpa et al., 2008). The coefficients can be directly interpreted as marginal WTP measures (Scarpa and Willis, 2010) and it is also a more feasible approach when making comparisons across treatments (Caputo et al., 2017).

An extended utility framework was used by pooling the data and including dummy variables for treatment assignment which were interacted with the attributes (Bazzani et al., 2017; De-Magistris et al., 2013; Lin et al., 2019). The data was pooled as high price guarantee vs control, low price guarantee vs control, and high price guarantee vs low price guarantee. For each of the experimental groups the utility in willingness to pay space can be specified as

$$U_{njt} = \theta_n \begin{bmatrix} -Cost_{njt} + \omega_{n1} Low_{Int_{njt}} + \omega_{n2} Hi_{Int_{njt}} + \omega_{n3} Transport_{njt} + OptOut + \\ \delta_1\left(Low\ Int_{njt} * T\right) + \delta_2\left(Hi\ Int_{njt} * T\right) + \delta_3\left(Transport_{njt} * T\right) + 1_j(\eta_{nt}) \end{bmatrix} + \varepsilon_{njt} \quad (1.8)$$

where θ_n is a random positive scalar representing the price parameter, ω_{ni} is the willingness to pay for each of the attributes which are defined above, $\delta_1, \delta_2, and\ \delta_3$ give the respective treatment effects of the experimentally designed attributes. The sign and significance of the δ_s determine how the willingness to pay for the different attributes varies under different treatments.

1.5. Data

Data for this study comes from two sources: a household level survey conducted in October 2017 and lab in the field experiments implemented in October 2018. Balance among respondents across socio demographics, farm characteristics, liquidity constraints, and price expectations is shown in Table 1.4. First three columns show the mean and standard deviation (brackets) of variables in the three experimental groups. The last three columns show the p-value for differences in means across the three groups. As shown in the table the variables are balanced across the treatment groups. Data for variables in panel A, B, and C comes from the household survey while data for panel D comes from the lab in the field experiments.

The average age of a respondent is 40 years with 7 years of schooling and a household of 5 persons. A farmer cultivates rice on around 7 acres of land and sell 150 maunds of paddy on average. Around 64 percent of the farmers report that they are liquidity constrained and around 55 percent of them reported that they were able to acquire a loan. Among those who had taken loans, a large proportion of them were from middleman. The prices reported suggest that on average farmers expect the price to increase over the 3-month period post-harvest.

Table 1.4: Balance Table

	Means			p-values		
Variables	**C**	**T1**	**T2**	**[T1=C]**	**[T2=C]**	**[T1=T2]**
A. Socio Demographic						
Age (years)	39.27 (0.87)	40.06 (0.95)	39.02 (0.86)	0.718	0.894	0.714
Education (years)	7.05 (0.31)	6.87 (0.36)	7.48 (0.34)	0.898	0.360	0.285
Household Size	4.76 (0.14)	4.70 (0.14)	4.79 (0.15)	0.180	0.868	0.389
Asset Index	0.062 (0.19)	-.026 (0.15)	0.131 (0.16)	0.352	0.976	0.376
B. Farm Characteristics						
Area (acres)	6.86 (0.33)	6.63 (0.34)	6.60 (0.33)	0.532	0.442	0.966
Commercial Farmer (0/1)	0.87 (0.03)	0.87 (0.03)	0.90 (0.03)	0.900	0.705	0.628
Quantity Sold (maunds)	146.39 (8.74)	141.25 (9.72)	159.31 (10.08)	0.875	0.204	0.245
Farm Gate Sales (0/1)	0.73 (0.02)	0.73 (0.03)	0.74 (0.03)	0.743	0.678	0.738
C. Credit Constraints						
Cash Constrained (0/1)	0.64 (0.05)	0.64 (0.04)	0.62 (0.05)	0.877	0.839	0.998
Borrowing (0/1)	0.57 (0.04)	0.53 (0.04)	0.55 (0.05)	0.446	0.993	0.328
Borrowing from Middleman (0/1)	0.47 (0.02)	0.45 (0.02)	0.47 (0.02)	0.576	0.999	0.763
Borrowing for Ag Inputs (0/1)	0.54 (0.03)	0.52 (0.03)	0.54 (0.03)	0.547	0.765	0.809

Table 1.4: (cont'd)

	Means			p-values		
	C	**T1**	**T2**	**[T1=C]**	**[T2=C]**	**[T1= T2]**
<u>D. Subjective Price Expectations (Rs/40kg)</u>						
Min Price at Harvest (Rs/40 kg)	1481.48 (25.82)	1479.19 (28.28)	1496.86 (26.03)	0.909	0.764	0.541
Max Price at Harvest (Rs/40 kg)	1701.14 (30.44)	1681.40 (38.15)	1721.02 (34.82)	0.720	0.756	0.393
Min Price 3-months Post Harvest (Rs/40 kg)	1953.96 (39.20)	1930.78 (38.52)	1933.57 (35.85)	0.671	0.679	0.945
Max Price 3-months Post Harvest (Rs/40 kg)	2221.14 (43.27)	2185.32 (43.90)	2183.18 (49.07)	0.558	0.543	0.968
N	214	203	224			

Note: The asset index score is was calculated using PCA and is composed of 23 items, which includes household items, savings in commodities, and modes of transport.

1.6. Results

The first subsection reports risk aversion and discount factor estimates. The second subsection reports results from the MXL-EC model, predicted probability of participation calculation, and WTP outcomes.

1.6.1. Risk and Time Preferences

Table 1.5 shows the estimated constant relative risk aversion (CRRA) and the discount factor. The average CRRA measure is 0.52 and average discount factor is 0.84. These results imply that majority of smallholder farmers in our target area are risk averse and compared to a risk neutral person would require higher returns to participate in WRF. Similarly, the discount factor highlights that value of income earned in the future is eroded due to discounting. Hence, the return from WRF would need to compensate for it as well to become an attractive prospect.

Table 1.5: Risk Aversion and Time Discounting Parameters

	Mean	**SD**	**Min**	**Max**	**Median**
CRRA	0.51	0.42	0.05	1.5	0.35
Discount Rate	0.84	0.13	0.46	0.99	0.88

The table also highlights that there is significant heterogeneity in the risk and time discounting traits as seen by the large range of the measures. This suggests that the utility derived from participating would also vary across farmers.

1.6.2. Program Participation

The results show that farmers are price sensitive as higher cost of storage and interest rate lowers utility and probability of participation. Tables 1.6 reports the MXL-EC estimates which show coefficient estimates for cost and interest rate to be negative and statistically significant at the 1 percent level across all treatment groups. This implies that higher cost and interest rates reduce utility derived from WRF and are associated with a lower probability of participation. The coefficient for transport is positive and statistically significant at the 1 percent level across all models. This suggests that farmgate pick up service increases the marginal utility of WRF and increases the probability of participation.

The result also shows dispersion around the mean of the sample population highlighting heterogeneity in preferences. The standard deviation (spread) estimates for all elements of the parameter vector are statistically significant at the 1 percent levels which implies that the respondents have different individual-specific parameter estimates which might be different from the mean parameter estimate. Therefore, the utility derived from WRF attributes could also differ across individuals.

Table 1.6: MXL-EC Model (Preference Space)

Variable	Pooled	Hi Price	Low Price	Control
Means				
Cost	-0.13***	-0.14***	-0.11***	-0.14***
	(0.01)	(0.01)	(0.01)	(0.01)
Low_Int	-0.32***	-0.30***	-0.28***	-0.47***
	(0.05)	(0.09)	(0.08)	(0.10)
Hi_Int	-1.85***	-1.58***	-1.85***	-2.11***
	(0.09)	(0.14)	(0.15)	(0.17)
Transport	1.02***	1.04***	0.91***	1.12***
	(0.05)	(0.09)	(0.08)	(0.10)
OptOut	4.78	10.65	-0.10	-1.30
	(4.17)	(7.94)	(5.85)	(4.86)
Standard Deviation				
Cost	-0.13***	0.14***	0.11***	0.14***
	(0.01)	(0.01)	(0.01)	(0.01)
Low_Int	-0.32***	0.30***	0.28***	0.47***
	(0.05)	(0.09)	(0.08)	(0.10)
Hi_Int	-1.85***	1.58***	1.85***	2.11***
	(0.09)	(0.14)	(0.15)	(0.17)
Transport	1.02***	1.04***	0.91***	1.12***
	(0.05)	(0.09)	(0.08)	(0.10)
Opt Out	4.02***	5.34***	5.90***	2.63***
	(0.40)	(0.66)	(0.61)	(0.57)
Error Component	4.02***	0.96	0.30	4.31***
	(0.40)	(0.99)	(0.45)	(0.48)
Heterogeneity in Mean				
OptOut x Risk	-4.68**	-6.41**	-3.56**	-2.24**
	(1.24)	(2.67)	(1.52)	(1.14)
OptOut x Time	-6.21	-14.00*	-1.40	-1.32
	(4.25)	(7.91)	(6.09)	(5.12)
AIC	**1.067**	**1.121**	**1.041**	**1.028**
Sample	**641**	**203**	**224**	**214**
Observations	**5769**	**1827**	**2016**	**1926**

Note: The table reports parameter estimates in the preference space. The model was estimated in Nlogit 6 utilizing 500 Halton Draws.

Risk aversion and discounting decrease utility from participation in WRF. However, the effect is statistically significant and consistent across the treatment groups only for risk aversion. The coefficient on the interaction terms of opt-out and risk is negative and statistically significant at the 5 percent level showing that as risk aversion decreases the disutility from not participating in the WRF program increases, ceteris paribus. Similarly, the coefficient on the interaction term between opt-out and discount rate is negative suggesting that as the discount factor increases (discounting declines) the disutility from not participating in the WRF program increases, ceteris paribus. However, this is only statistically significant for the high price guarantee group at the 10 percent level.

A product design which reduces exposure to risk, if financially feasible, could potentially increase smallholder participation. Table 1.7 reports results from a probit model which estimated the probability of participation across the three treatment groups. As expected, respondents in the price guarantees groups have a higher likelihood of selecting the WRF option and the increase is statistically significant at the 1 percent level as shown by the p-values. Model 2 reports the predicted probability of selecting the WRF option based on the MXL-EC results which controls for observable and unobservable preferences. The results are consistent with the actual choice but of higher magnitude. The probability of selecting the WRF is higher in the price guarantee groups and the difference between High Price and Low Price group is also statistically significant.

Table 1.7: Actual and Predicted Choices from MXL-EC model (Preference Space)

	(1)	**(2)**
Variable	**Actual Choices**	**Predicted Choices**
Control	0.51***	0.46***
	(.03)	(.01)
High Price Guarantee	0.67***	0.71***
	(.03)	(.01)
Low Price Guarantee	0.68***	0.78***
	(.02)	(.01)
Hypothesis Test p-value		
H_1: Control = High Price	0.001	0.000
H_2: Control = Low Price	0.000	0.000
H_3: High Price=Low Price	0.743	0.000

Note: Coefficients cannot be compared across different groups due to the scaling factor. Hence, we used the MXL-EC results to generate individual specific predicted probability of selecting an alternative in each choice set for the three groups. The probabilities are then pooled across the treatment groups and a Probit model is estimated with village fixed effects and standard errors were clustered at the village level. The probabilities were calculated using the margins command in stata. Column 1 reports the estimates on actual choices in the DCE for comparison.

WTP space estimates show that WTP is higher for credit in the price guarantee groups and lower for farmgate pickup. Table 1.8 reports the WTP estimates4 with the corresponding p-values related to the difference in marginal WTP for interest and transport attributes. Respondents in the High Price group show a higher WTP for credit compared to the control group. However, the difference is statistically significant only for the High Int level. WTP for transport on the other hand is lower in the high price guarantee group and the difference is statistically significant. Comparison between Low Price and Control groups shows that WTP for credit is higher with a price guarantee. However, in this case the difference is statistically significant only for the Low Int level. WTP for transport on the other hand is lower and the difference is statistically significant. Comparison between the High and Low Price guarantee groups shows WTP for credit is higher for credit and lower for transport in the high price guarantee. However, the differences are statistically significant only for Hi Int and transport.

Table 1.8: MXL-EC Model Estimates by Treatments (WTP Space)

Variable	**Coefficient**	**Standard Error**	**p-value**
$\underline{\boldsymbol{WTP^{High\_Price} = WTP^{Control}}}$			
Low_Int	1.84	1.25	0.140
High Int	3.27***	1.06	0.002
Transport	-2.53***	0.83	0.002
$\underline{\boldsymbol{WTP^{Low\_Price} = WTP^{Control}}}$			
Low Int	2.52**	1.27	0.048
High Int	1.01	1.15	0.380
Transport	-3.83***	0.68	0.000
$\underline{\boldsymbol{WTP^{High\ Price} = WTP^{Low\ Price}}}$			
Low Int	0.55	1.59	0.723
High Int	2.98**	1.41	0.035
Transport	-2.05*	1.22	0.094

Note: The model was estimated in Nlogit 6 utilizing 500 Halton Draws.

[4] The cost variable was divided by 10 and the estimates were multiplied by 10 to calculate WTP. The model was not estimated with risk and time interactions for two reasons: 1) We are interested in the overall WTP across the three treatment groups and 2) the models did not converge when these interactions were included.

These results show that if there is less uncertainty in returns farmers would be willing to pay a higher price for credit but would value farmgate pick-up less. These outcomes provide some evidence that contract designs which reduce exposure to price uncertainty can increase participation and allow the provider to charge slightly higher prices for WRF.

1.7. Conclusion

Smallholder farmers continue to face numerous constraints which discourage productivity enhancing investments. WRF has recently be promoted as a viable potential solution to address financial inclusion and market access constraints of farmers. The introduction of WRF for smallholder farmers in Hafizabad, Pakistan is a case in point. However, participation by smallholder farmers was very low despite it being a profitable prospect.

We find that external and internal constraints combined erode the profitability of WRF, making it a less attractive prospect. Results show that high transaction costs reduce the attractiveness of WRF as seen by the negative marginal utility on cost and interest rate parameter estimates. We also see that farmers value transport from the farm gate to the warehouse, a service which was not offered in the pilot. Risk aversion is another important factor that reduces the attractiveness of WRF as the program required farmers to take price risks. The experimental treatment design further validates this conclusion as we see an increase in predicted participation for WRF under the price guarantee groups. An important finding is that the increase in participation is also high under the low-price guarantee suggesting that smallholder farmers and they would be willing to participate as long they are assured that they will not incur a loss.

Since, this study uses stated preference data one can argue that the results suffer from hypothetical bias. This criticism is fair, but it does not diminish the findings of the study which highlights that the existing contract only focused on the constraints of circumstance and failed to address the internal constraints of smallholder farmers which made participation an unattractive prospect. These findings are particularly relevant for Pakistan as the agriculture value chains are very underdeveloped and WRF has the potential to improve and develop these value chain. Importantly, the federal government also recognizes this potential of WRF and the state bank of Pakistan and developed a regulatory framework to operationalize WRF. However, establishing a warehouse network is an expensive infrastructure endeavor and it is important to understand the markets appetite while designing WRF products, especially those that would target smallholder farmers. These results also highlight the need to incorporate the preferences of the target population while designing programs aimed to improve their welfare.

APPENDICES

APPENDIX A – DISCRETE CHOICE EXPERIMENT

Now I will present you with some choices regarding a warehousing service. In each of these questions I will present you with two versions of a warehousing product and a no-purchase option. The warehousing options vary across the questions in terms of cost of storage, pickup service from your farm, and future price after 3 months. For each of these questions, we would like to know if you are interested in either of the warehouse product. You can always choose the not interested option. If you are interested in the warehousing option, please also share what proportion of your harvest you would be interested in storing. For example, you will only store 50 out of your 150 bags of paddy.

There are a few things you should keep in mind when making these decisions:

- Assume there are no other options except for the ones we are showing you.
- All the choices are separate so do not try to remember your choices in the previous questions. In simple words treat each warehouse product option separately.
- Once you have made the choice you cannot go back and change it.

<u>Group 1 Script – High Price Guarantee</u>

Suppose your paddy is ready for harvest and the selling price of paddy is Rs1300 per maund if you take it to the mandi. Looking at past paddy prices there is a good chance that the price of paddy will rise in the future and you can earn more if you sell later. A company is offering farmers like you the option to store your paddy and earn better income by selling later. The company is guaranteeing to buy the paddy at a premium of Rs1800 after 4 months even if the prices are lower, so you have a guaranteed higher income.

Credit against the stored paddy is also available if required, for example if you store paddy worth Rs 100,000 you can get credit of upto Rs70,000 at a service charge. You can sell you paddy to anyone and anytime once you repay the credit. The sale option is also available at the warehouse.

Once the product arrives at the warehouse it will be cleaned, dried, graded, weighed, and bagged by the staff at the warehouse. After the bagging is complete your bags will be tagged using your id number and stacked in the warehouse. The warehouse staff will regularly check the paddy to ensure that the moisture level is controlled and will be responsible for the safety of the product. The warehouse charges are meant to cover these expenses. The service charge on loans is meant to cover the cost of employees and travel.

Group 2 Script – No loss Guarantee

Suppose your paddy is ready for harvest and the selling price of paddy is Rs1300 per maund if you take it to the mandi. Looking at past paddy prices there is a good chance that the price of paddy will rise in the future and you can earn more if you sell later. A company is offering farmers like you the option to store your paddy and earn better income by selling later. The company is guaranteeing to buy the paddy at a premium of Rs1800 after 4 months even if the prices are lower, so you have a guaranteed higher income.

Credit against the stored paddy is also available if required, for example if you store paddy worth Rs 100,000 you can get credit of upto Rs70,000 at a service charge. You can sell you paddy to anyone and anytime once you repay the credit. The sale option is also available at the warehouse. Once the product arrives at the warehouse it will be cleaned, dried, graded, weighed, and bagged by the staff at the warehouse. After the bagging is complete your bags will be tagged using your id number and stacked in the warehouse. The warehouse staff will regularly check the paddy to ensure that the moisture level is controlled and will be responsible for the safety of the product. The warehouse charges are meant to cover these expenses. The service charge on loans is meant to cover the cost of employees and travel.

Group 3 Script – No Price Guarantee

Suppose your paddy is ready for harvest and the selling price of paddy is Rs1300 per maund if you take it to the mandi. Looking at past paddy prices there is a good chance that the price of paddy will rise in the future and you can earn more if you sell later. However, the company gives no guarantee about future price.

Credit against the stored paddy is also available if required, for example if you store paddy worth Rs 100,000 you can get credit of upto Rs70,000 at a service charge. You can sell you paddy to anyone and anytime once you repay the credit. The sale option is also available at the warehouse. Once the product arrives at the warehouse it will be cleaned, dried, graded, weighed, and bagged by the staff at the warehouse. After the bagging is complete your bags will be tagged using your id number and stacked in the warehouse. The warehouse staff will regularly check the paddy to ensure that the moisture level is controlled and will be responsible for the safety of the product. The warehouse charges are meant to cover these expenses. The service charge on loans is meant to cover the cost of employees and travel.

Figure 1.3: Sample Question (DCE)

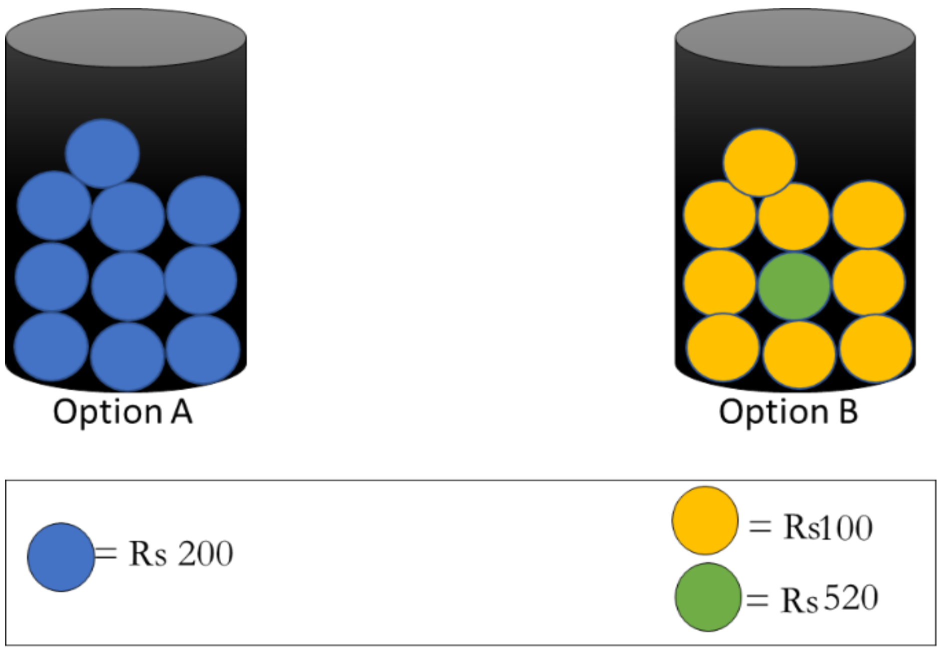
		
Option 1	Option 2	Option 3

APPENDIX B – RISK AVERSION

Instructions

This game gives you two options to choose from and the two options are labelled Option A and Option B like before. Please look at the handout which shows an example of the game.

Figure 1.4: Example Game



If you select Option A you draw a ball from the cylinder on the left and you will get Rs100 if you pick a blue ball which will be true every time as all balls are blue. If you select Option B then you draw a ball from the cylinder on the right. You will get Rs 2600 if you pick the green ball and Rs 500 if pick the yellow ball. The chance if picking a green ball is one out of ten. Here again, there are no correct or incorrect answers. We just want to know what you prefer and would choose. Now let's play a practice game so that you understand the game better.

Practice Game

As you see each question had two Options: A and B to earn some candies. These two options differ in the number of candies you can win depending on your choices. For example, in question number 1, under Option A, you always draw a blue ball and earn three candies for sure. For the same question, if you choose Option B, you can earn either five candies if you draw green ball or you earn only 1 candy if you draw the yellow. The number of candies you can earn in Option A under all the questions remains the same but in Option B, the number of candies you can win with the green ball increases, but if you get yellow colored ball it remains the same (1 candy), in all the questions.

Figure 1.5: Practice Game

	Option A	Option B
1	= 3 Candies	= 1 Candy = 5 Candies
2	= 3 Candies	= 1 Candy = 6 Candies
3	= 3 Candies	= 1 Candy = 7 Candies

Let's suppose that question 1 gets selected for actual payment. If you had chosen option A you will get 3 candies. Suppose you selected option B for question 1, ask the respondent to pull out one ball from the bag (which has 9 yellow and 1 green ball), if it is green pay five candies or if it is yellow, then give one candy. Do you understand the game? If yes, let's play the real game now.

Game Instructions

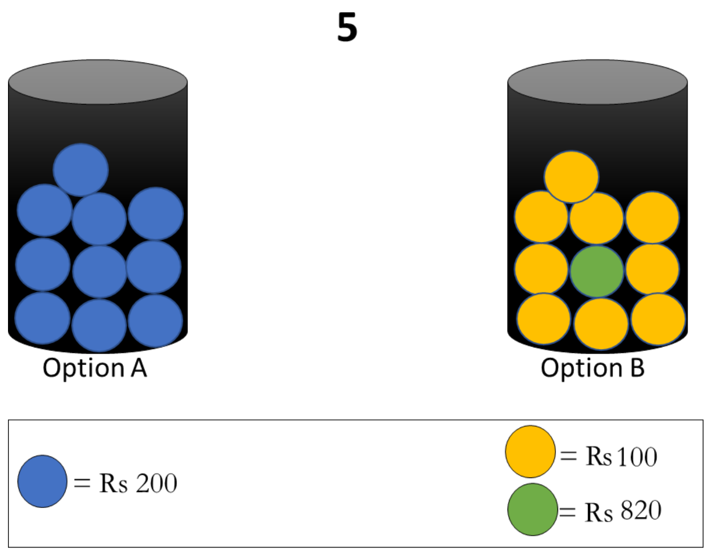
I will ask you to choose between option A and Option B for each of the pairs. The amount of money you can win in Option A is the same Rs 200. On the other hand, in Option B, you can win up to Rs 5600 if you draw a green ball (1 out of 10 chances) and you win Rs 500 if you draw the yellow ball (9 out 10 chances). So, look carefully at the questions as they come, and select your preferred option. You have the complete freedom to select Option B for any question or not select Option B at all. Table 1.9 shows the first price list that was used in the risk aversion game.

Table 1.9: Risk Aversion Choice List 1

	Option A		**Option B**	
No.	**Rupees you get**		**Rupees if you pick green ball**	**Rupees if you pick yellow ball**
1	200		520	100
2	200		560	100
3	200		640	100
4	200		720	100
5	200		820	100
6	200		940	100
7	200		1120	100
8	200		1260	100
9	200		1440	100
10	200		1700	100
11	200		2080	100
12	200		2660	100
13	200		3620	100
14	200		5600	100

The respondent was shown one choice task at a time in a graphical manner (shown below) and asked to make a choice. The respondent answered all 14 questions even if they switched earlier.

Figure 1.6: Sample Question (Risk Aversion)



The following set of questions are the same as before except for the fact that now that there are 7 green balls and 3 yellow balls. So the chance of winning the bigger reward are higher as compared to before.

The respondent was shown one choice task at a time in a graphical manner (as above) and asked to make a choice. The respondent answered all 14 questions even if they switched earlier.

Table 1.10: Risk Aversion Choice List 2

	Option A		Option B	
No	**Rupees you get**		**Rupees if you pick green ball**	**Rupees if you pick yellow ball**
15	800		1120	100
16	800		1140	100
17	800		1200	100
18	800		1240	100
19	800		1300	100
20	800		1380	100
21	800		1460	100
22	800		1540	100
23	800		1640	100
24	800		1740	100
25	800		1900	100
26	800		2100	100
27	800		2380	100
28	800		2740	100

APPENDIX C – TIME PREFERENCES

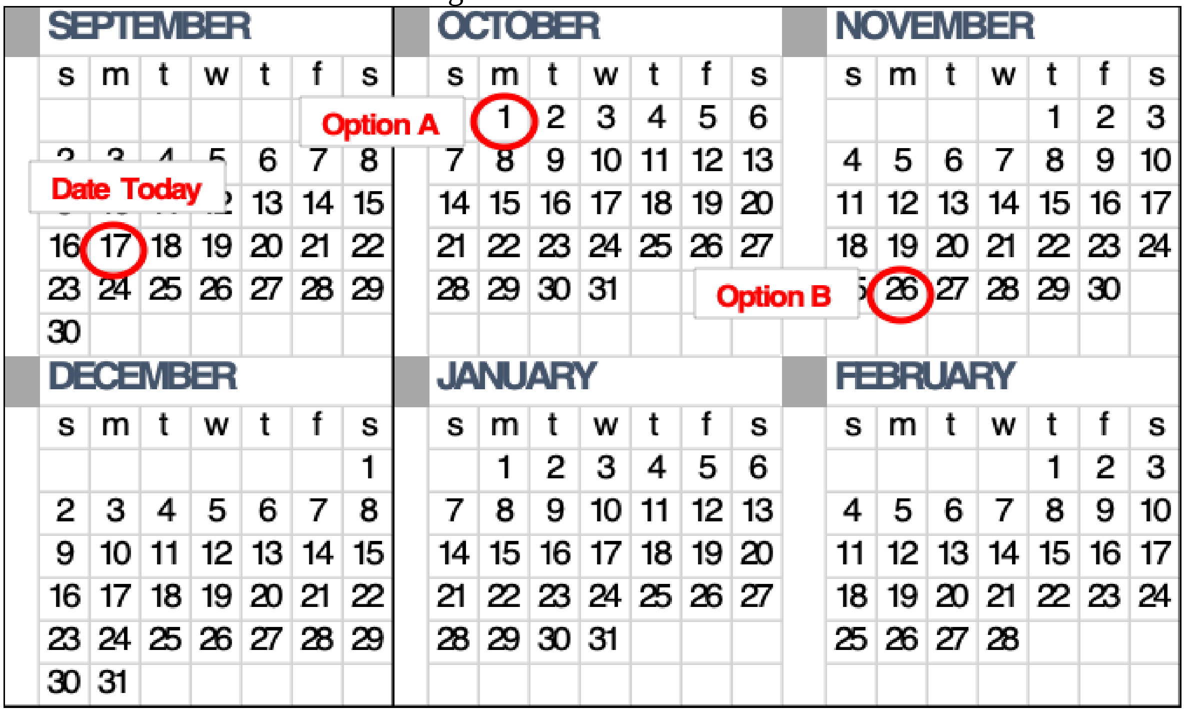
Instructions

I am giving you a token (hand over a token) and you can exchange this token with me for real money. I will give you two options labelled Option A and Option B offering different amount of money at different times in the future. How much money you receive will depend on which option you choose. Let me give you an example, [hand over the sheet 1 with the example] you will get Rs1000 in 2 weeks if you select Option A and Rs 1100 in 8 weeks if you select Option B [Show the calendar to the respondent to make the choice easier to understand]. So you get additional money for waiting. As you go down the questions, you can see that Option A does not change but how much you earn in Option B increases. As you can see Option A gives you money in two weeks and Option B gives you money 2 months later than Option A. We would like to know which option you prefer for each question. I would like to reiterate that there is no wrong or correct answer. We just want to know what options you prefer and hope that you would find the games interesting.

Table 1.11: Sheet 1

Task	Horizon in Months	Option A	Option B
1	2	1000	1100
2	2	1000	1200
3	2	1000	1300

Figure 1.7: Calendar Sheet



We will now randomly select a question, let’s suppose question 2 in this game is selected for actual payment. The reward will now be based on your choice – 1000 in two weeks if you selected Option A or 1200 in 8 weeks if you had selected Option B.

Now let’s play the actual game. The structure of this game is very similar to the practice game. Option A is for sooner smaller payment and Option B is for larger later payment. The questions differ in the waiting period and the amount in the later period. Let me remind you again that these questions are eligible to be selected for a real payment at the end of the survey. Do you have any questions? If no, then let start the game.

Table 1.12: Time Discounting Choices

Task	Horizon in Months	Earlier Payment	Delayed Payment	Annual Interest Rate
1	4	500	517	10
2	4	500	525	15
3	4	500	533	20
4	4	500	542	25
5	4	500	550	30
6	4	500	558	35
7	4	500	567	40
8	4	500	575	45
9	4	500	583	50
10	4	500	592	55

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Essay 2 :Does peer comparison encourage adoption of best practices among farmers in Pakistan?

Abstract

Poor nutrient management has contributed towards deteriorating soil quality in Pakistan. Despite years of experience, non-convergence to optimal practices suggests constraints to learning. Informing farmers about optimal organic and inorganic fertilizer use, given soil and crop type, can address this challenge. This study takes an experimental approach with treated farmers receiving this information either with or without a peer comparison, while the control farmers receive no information. Results show that majority of the soils are in poor health, manure use is very low, and 93 percent of farmers are underusing fertilizers. The intervention increased manure and urea use in the peer comparison group. However, urea increase was concentrated among farmers that were applying fertilizers closer to the recommended quantities at the baseline. These findings provide some evidence on the effectiveness of peer comparisons and highlights the presence of other constraints in addition to information.

2.1 Introduction

Sustainable agricultural systems are essential for addressing poverty and ensuring food security. The current agricultural systems have significantly degraded the natural resource base, especially soils, reducing its productive capacity and efficiency of land, making food security and poverty alleviation an increasingly difficult task to achieve. According to the Global Land Degradation Assessment (GLADA) land degradation is increasing and almost one-quarter of the total global land area has undergone it. Estimates show that in 2007 about 1.5 billion people in some way depended on degraded areas for their livelihoods while in excess of 42 percent of the world's very poor population lived on degraded areas (Nachtergaele et al., 2010). Pakistan has also been severely affected by land degradation due to unsustainable land management practices and increasing demands on natural resources (Zia et al., 2004). Around 68 million hectares of land across Pakistan has been affected and the issue has been worsening in the absence of effective policies (Khan et al., 2012). Several studies have highlighted that land resource degradation due to nutrient mining is a dominant factor for poor productivity in Pakistan (Ali and Byerlee, 2002; Khan et al., 2012; Malik et al., 2017; Pingali and Shah, 2001). Since, agriculture continues to be the prime source of livelihood for the country's poor and a major contributor to the economy, growth in this sector is important for achieving economic growth and broader developmental goals.

Improper use of fertilizers is one of the core factors for declining soil health as it leads to nutrient mining and yield stagnation (Concepcion, 2007). Each soil and crop type has a specific mineral requirement and under or overuse of fertilizers can cause damage to the productive capacity of soils (Ahmed and Gautam, 2013; Bumb and Baanante, 1996; Coulter, 2008). Existing practices in Pakistan have caused the soil organic matter concentration to fall to extremely low levels reducing its fertility and its ability to efficiently use fertilizers. This is also one of the factors behind decreasing returns to fertilizer application (Ali et al., 2017; Lal, 2014). Field experiments in Pakistan suggest that use of compost manure along with inorganic fertilizers can significantly improve soil health and yields (Ibrahim et al., 2008; Sangeetha et al., 2013; Sarwar et al., 2007).

Non convergence to ideal practices despite decades of experience using fertilizer technology suggests barriers to complete adoption. Two streams dominate this discourse, one argues is that there is heterogeneity in cost and/or returns and farmers might have possibly internalized the cost of this resource degradation. Alternatively, there might be informational and behavioral factors such as perceived risks, learning, and limited attention driving incomplete technology adoption (Janvry et al., 2016).

This study alleviates the information constraint by providing fertilizer recommendations based on soil tests which provide an objective means to ascertain fertilizer requirements based on crop and soil type. This in itself is not a novel idea but the impact of providing customized information on nutrient management has not been encouraging (Corral et al., 2016; Fishman et al., 2016). Therefore, this study complements information provision with peer comparison which has been shown to be a useful, low cost nudge to alter behavior in various contexts such as energy conservation, residential water use, and charitable giving among other things (Cooter et al., 2008; Goldstein et al., 2008; Martin and Randal, 2008; Schultz et al., 2007). The paper addresses two main questions regarding fertilizer application: (1) Does information on soil quality improve fertilizer use? and (2) Does including peer comparison to information improve fertilizer use? Moreover, since small farmers face numerous constraints and the intervention only alleviated the information constraint. The study focuses on heterogenous impacts.

Incomplete adoption of fertilizers is relatively understudied. Most of the existing work on fertilizer adoption has focused on heterogenous adoption of fertilizer across farmers due to availability, affordability, risk and information (Jack, 2013). While some authors have looked at differential marginal returns and barriers to learning as potential factors for incomplete adoption (Duflo et al., 2008; Janvry et al., 2016; Marenya and Barrett, 2009). Recently, a few papers have evaluated the role of information and knowledge on fertilizer application (Corral et al., 2016; Fishman et al., 2016). However, the results are mixed where Corral et al. (2016) find an increase in fertilizer rate but it is not statistically significant. While Fishman et al. (2016) found no impact of providing the information.

This study adds to this sparse literature by evaluating the impact of information on agricultural practices such as fertilizer. Results show that 87 percent of the farmers could recall receipt of the SHC and 75 percent of the reported that they trusted the information on it which is very encouraging as Fishman et al. (2016) attribute lack of trust as the reason for null effect.

Secondly, the study also contributes to the literature on social comparisons by testing this nudge in an agricultural setting. A random subset of farmers was also given peer comparisons in addition to information to induce behavioral change. Results show that manure use increased in the peer comparison group while there was no change in the information group. These results validate earlier finding that information provision might not be sufficient to change practices.

Another contribution this paper makes is that it measures the heterogenous impact of information provision which the earlier two studies did not. We find a statistically significant increase in urea use among farmers who were given the peer comparison and were applying urea within one bag of recommended quantity at baseline. These findings provide some evidence that peer comparisons can be a useful level to alter behavior.

The remainder of this paper is as follows. Section 2 outlines the conceptual framework, section 3 explains the experimental design, followed by intervention details in section 4, section 5 describes the data, section 6 gives the empirical strategy and results, and section 7 gives the conclusion.

2.2 Conceptual Framework

Social comparison theory postulates that individuals have a "unidirectional upward drive" to improve their performance and conform with their peers (Festinger, 1954). A generalized utility maximization framework with a social comparison function following (Levitt and List, 2007) to understand farmer response to information in the SHCs is given below

$$max_a \; U_i(a, d, s; x, \theta) = f(a; x, \theta) - \frac{\gamma_i a_i^2}{2} + P(a, d, s; \theta) \tag{2.1}$$

where each farmer chooses an action $a_i \geq 0$, incurs a cost $\frac{\gamma_i {a_i}^2}{2}$, γ_i captures heterogeneity that is inversely proportional to the wealth of the farmer, $f(a; x, \theta)$ is the benefit from the action given other inputs x and farmer characteristics θ, and the Peer Comparison function depends on action a, deviation from peers (d), and deviation from an objective standard (s). f(•) and P(•) are assumed to be quasi-concave in (a) while P(•) is decreasing in both (d) and (s).

The model shows that farmer behavior is influenced by the subjective cost-benefit, self-evaluation against an objective standard, and relative to peers. The SHCs provide information regarding (d) and (s) to the farmer following an experimental design (explained in the following section). One random subset of farmers only received (d) in the form of soil health which provides the farmer information of his own performance as a steward of his land against an objective measure. The other random subset of farmers receives this information and information about the soil health of a peer for comparison. The remaining farmers serve as the control group and receive no information.

The design of our experiment allows us to test the following hypotheses:

Hypothesis 1: SHC informs farmers on their optimal use of fertilizers, and farmers adjust their fertilizer use accordingly, provided they do not face other binding constraints

The first and most important assumption that this hypothesis rests on is that information is the only binding constraint. Second, once the information is provided farmers would be able to understand it. Third, once farmers understand the information, they will trust it and update their beliefs regarding optimal fertilizer quantities. Fourth, once the farmers update their beliefs they will act on these changed beliefs. This is strongly linked with the first assumption that information is the only binding constraint.

If the farmer faces other constraints such as liquidity, water availability, and fertilizer availability then it will lead to a null result as those constraints are not removed through this intervention. As we expect farmers in developing countries to face these constraints we will focus on the heterogeneous impact of this intervention.

Hypothesis 2: Peer Comparison increases the efficacy of information and results in higher compliance to the fertilizer recommendations.

The second hypothesis rests on the idea that augmenting information with social comparison will improve compliance to the recommendations. Peer comparison will induce a 'competitive behavior' as it will highlight that others are doing better. Peer comparisons will also raise the aspirations of the farmers. For example, without information on the soil health of peers, a farmer could easily assume that they are performing equally as well as everyone else. Social comparison will inform them that a better outcome is possible, encouraging them to adopt the recommendations provided on the card.

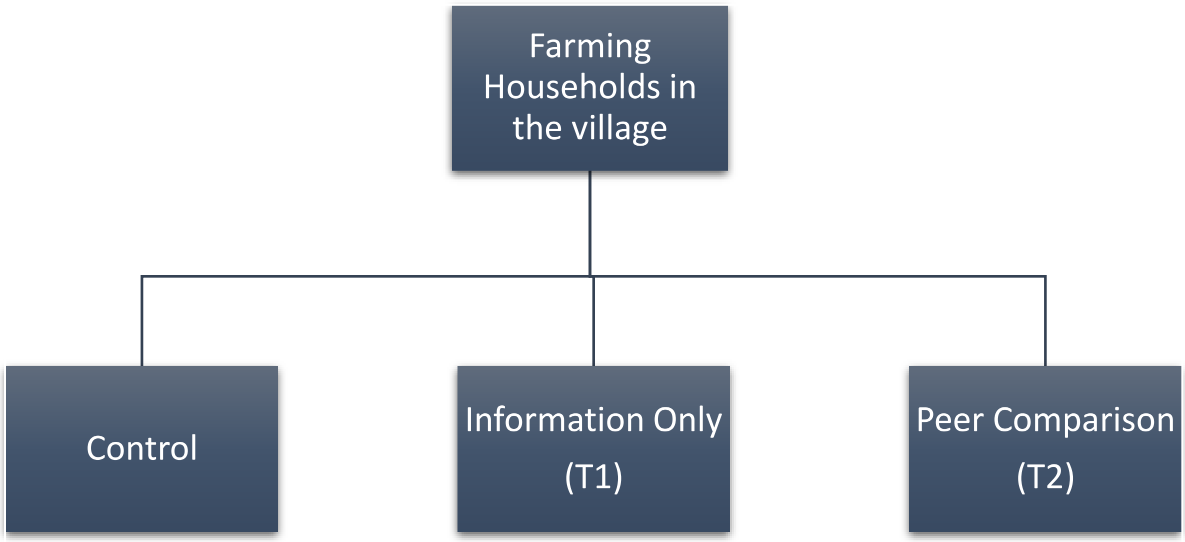
2.3 Experimental Design

The study had three experimental groups (two treatment and a control) shown in figure 2.1. Randomization was done at the individual level and farmers were randomly assigned to one of the groups in each of the 90 villages in the study area. Treatment 1 (Information Only) group received information on soil health score[5] and recommendations on manure and fertilizer use based on the soil and crop type. Treatment 1 provided farmers with an objective feedback on the fertility of their soil which was also reflective of their ability to manage their land. The aim was to improve learning and knowledge of the farmer and induce change in practices. Treatment 2 (Peer Comparison) group received the same information and a nudge in the form a peer comparison. Farmers in this group were also given information on the best soil health score among their peers. Treatment 2 was designed learning from earlier studies which had failed to bring change from information provision. The peer comparison was aimed to stimulate the competitive nature of farmers by comparing them against a better performing peer. Secondly, it also aimed to encourage them and raise their aspiration for a better equilibrium.

The intervention was implemented in 90 villages spread across four districts of south Punjab. A random sample of agricultural households6 in each village was selected for the intervention and randomly assigned to the treatment and control groups as shown in Fig 2.1.

[5] Soil health information was provided as a score out of ten for simplification. A higher number represented better soil health. This information was also presented graphically so that it was cognitively less demanding.
[6] Households engaged in the production of wheat or cotton were selected as these are the main crops. This exercise let to the identification of approximately 4200 households.

Figure 2.1: Study Design



2.4 Intervention Description

Learning in the agricultural setting is a complicated process for many reasons. First, farmers can choose from numerous inputs and there could potentially be several optimal bundles. Secondly, there is a significant unobservable component of the underlying production function which is not completely understood. Third, there are exogenous stochastic shocks to farm output in the form of weather. Fourth, the production process takes a long time and updating of beliefs can usually happen once a year. Finally, returns to inputs can be heterogenous conditional on the underlying resource base. This is particularly true in the case of fertilizer response and land quality. This intervention provided farmers with objective information on soil health and fertilizer requirements based on soil testing. In addition, mental accounting and reminders were also used. Details are provided in the sub-sections below.

2.4.1 Soil Health Cards

Soil samples were collected, tagged, and delivered to the district soil testing laboratories. Soil samples were not collected from all the farmers but limited to farmers assigned in the treatment groups only. This was done to avoid an effect on the control group through the soil collection activity as it could have led them to seek out information on soil testing and fertilizer recommendations leading to some changes in practices. Once the soil testing was complete the information was used to create a soil health score. Organic matter content and availability of macro nutrients (Nitrogen, Phosphorous, and Potassium) was used to assign a soil health score between 0 to 10 points, with 10 being the ideal score. This score was highlighted on the front of the card along with a labelling of the soil as very poor, poor, medium, and fertile. To make the interpretation of the score results easier this information was also presented graphically showing the ideal score and the score of the farmer's plot next to each other. The peer comparison group also included the best soil health score of a peer farmer to act as a behavioral nudge.[7] The back side of the card had detailed information on the quantity of fertilizer to be used for kharif crops.

The delivery of the cards started in end of March before the planting of cotton which starts in the first week of April. Enumerators went through training before the delivery of the card and were also given a script to follow. The soil script was translated in the local language for the enumerators and covered the following points:

I. Explain the soil health status to the farmer and help them understand the score given to them.
II. Inform them that one of the major reasons for poor soil health is the poor nutrient management by the farmer.
III. Explain to the farmer that their soil health can be improved if they use the correct quantities and types of fertilizers and use manure to improve the organic content of their soils.

Farmers were also encouraged to call on the toll-free number given on the soil health card if they had any follow up questions.

[7] The best soil health card was chosen to avoid the boomerang effect as seen in other studies where sharing average scores resulted in better performing subjects gravitating towards the mean. The best performing peer was chosen from a cluster of villages based on their proximity. The cluster consisted of 6 villages on average.

2.4.2 Mental Accounting and Call Reminders

Once the enumerator went through the information on the soil health card, farmer was asked the amount of land that assigned to cultivation in the upcoming season for cotton. The enumerator then calculated the fertilizer requirement for the farmers based on the land reported and the results of the soil health card. The farmers were then asked to plan when they would go to get the fertilizer for the upcoming season. They were asked to plan the day, time of the day, and the location from where they would procure the fertilizers. This information was also recorded by the enumerator and reminder calls were made to the farmers around their planned date of purchase.

2.5 Data and Empirical Strategy

This paper utilizes three waves of data which were collected under the Punjab Economic Opportunities Program. Two rounds of survey were done preintervention and one post intervention. The first survey wave was conducted in August 2016 and a random sample of 12,700 households were surveyed in this round across the 90 villages. This dataset was used as the sampling frame to identify households engaged in farming. The second survey wave was conducted in February 2018 and is used as the baseline for the study. The intervention was rolled out in April 2018 (details in the next section) and the post treatment survey was conducted in April 2019.

This study focuses on cotton production as it is the main cash crop in this region, has significant forward market linkages, and is also a very input intensive. The following regression approach was used for balance checks on pre-treatment socio-demographic, soil characteristics, and production variables.

$$Y_{ij} = \beta_0 + \beta_1 T_{ij}^1 + \beta_2 T_{ij}^2 + \varepsilon_{ij} \tag{2.2}$$

The left-hand-side variable, Y_{ij}, refers to the value for household i in village j. T is a dummy variable indicating the household's treatment status, and standard errors were clustered at the village level. Table 2.1 shows the summary statistics and checks for balance across the treatment and control groups. The first three columns show the mean of the variables and the last three columns give the difference in means. Standard errors are reported in parenthesis and the asterisks show if the differences are statistically significant. Panel A shows household levels variables and Panel B shows plot characteristics for the largest plot cultivated by the household. Panel C reports yield and inputs, averaged across all plots managed by the household.

Panel A shows that households were balanced across the experimental groups for non-business assets, agricultural assets, land ownership and education. The asset indices were generated using principal component analysis (PCA) and then normalized. The non-business assets comprised of 34 items such as household furniture, electrical equipment, vehicles, and livestock while the agricultural asset index comprised of 12 items which included different kinds of agricultural machinery and equipment. There is imbalance for age of the household head and size of the households. Household heads are older in the Peer Comparison group (T2) with an average age of approximately 51 years as compared to 50 years in the other two groups. Similarly, the household size is larger in the Peer Comparison group (T2). The mean size is approximately 7.1 in T2 and 7 in the other groups. However, as can be seen in the table these differences even though statistically different are not very different in absolute terms.

Table 2.1: Balance Table

	Control	T1	T2	T1 vs C	T2 vs C	T1 vs T2
Panel A. Household Demographic						
Non-Business Asset Index	0.472	0.447	0.514	-0.057	0.010	-0.066
	(1.450)	(1.309)	(1.564)	(0.066)	(0.082)	(0.078)
Agricultural Asset Index	0.553	0.564	0.598	0.010	0.065	-0.060
	(1.843)	(1.687)	(1.935)	(0.095)	(0.106)	(0.112)
Land Owned (kanals)	24.398	24.581	22.645	0.656	-1.440	1.625
	(54.646)	(36.904)	(40.620)	(2.239)	(2.533)	(2.219)
Education (years)	3.542	3.760	3.507	0.083	-0.169	0.214
	(4.141)	(4.283)	(4.181)	(0.233)	(0.215)	(0.217)
Household Head Age (years)	49.730	49.464	50.989	-0.047	1.283*	-1.555*
	(13.463)	(13.375)	(13.320)	(0.807)	(0.725)	(0.786)
Household Size	6.833	6.945	7.084	0.077	0.255*	-0.164
	(2.785)	(2.886)	(2.773)	(0.159)	(0.151)	(0.166)
Panel B. Land Characteristics						
Suffer Waterlogging	0.183	0.184	0.199	0.001	0.017	-0.015
	(0.387)	(0.388)	(0.400)	(0.024)	(0.020)	(0.017)
Suffer Salinity	0.165	0.169	0.172	0.004	0.007	-0.003
	(0.371)	(0.375)	(0.378)	(0.023)	(0.022)	(0.023)
Suffer Soil Erosion	0.169	0.134	0.143	-0.035*	-0.026	-0.009
	(0.375)	(0.341)	(0.350)	(0.020)	(0.018)	(0.018)
Fertility Score (Likert Scale 1-5)	4.077	4.075	4.086	-0.002	0.009	-0.011
	(0.638)	(0.626)	(0.672)	(0.032)	(0.035)	(0.030)
Soil Type: Sandy	0.161	0.139	0.154	-0.022	-0.007	-0.015
	(0.368)	(0.346)	(0.361)	(0.018)	(0.017)	(0.015)
Soil Type: Sandy Clay	0.537	0.543	0.559	0.006	0.023	-0.016
	(0.499)	(0.499)	(0.497)	(0.027)	(0.027)	(0.027)
Soil Type: Clay	0.135	0.141	0.128	0.005	-0.007	0.013
	(0.342)	(0.348)	(0.334)	(0.017)	(0.018)	(0.018)
Soil Type: Clay Loam	0.059	0.050	0.062	-0.009	0.002	-0.011
	(0.236)	(0.219)	(0.241)	(0.013)	(0.012)	(0.017)
Soil Type: Loam	0.102	0.122	0.096	0.020	-0.006	0.027
	(0.303)	(0.328)	(0.294)	(0.017)	(0.015)	(0.019)
Access to Tubewell	0.891	0.911	0.896	0.020	0.005	0.015
	(0.311)	(0.285)	(0.305)	(0.019)	(0.023)	(0.016)
Access to Canal	0.740	0.750	0.736	0.010	-0.004	0.015
	(0.439)	(0.433)	(0.441)	(0.032)	(0.034)	(0.020)

Table 2.1: (cont'd)

	Control	T1	T2	T1 vs C	T2 vs C	T1 vs T2
Panel C. Production (Cotton)						
Yield (maund/kanal)	1.775	1.784	1.818	0.008	0.043	-0.035
	(1.268)	(1.130)	(1.241)	(0.079)	(0.084)	(0.064)
Manure (maund/kanal)	4.007	4.040	3.047	0.034	-0.960*	0.993
	(11.124)	(19.349)	(9.158)	(0.876)	(0.482)	(0.828)
DAP (kgs/acre)	40.902	41.804	42.794	0.902	1.892	-0.990
	(32.531)	(33.656)	(39.455)	(1.950)	(1.899)	(2.021)
Urea (kgs/acre)	71.734	70.072	72.311	-1.662	0.577	-2.239
	(58.049)	(55.801)	(61.854)	(3.570)	(3.173)	(3.382)
Use Potassium	0.008	0.010	0.011	0.002	0.003	-0.001
	(0.089)	(0.100)	(0.106)	(0.005)	(0.006)	(0.004)
N	1,012	597	617	1,609	1,629	1,214

Notes: This table shows the balance test for cotton farmers. Columns 1 - 3 provide the mean of each characteristic for the control group (C), information group (T1), and peer comparison group (T2), respectively. Columns 4 - 6 show the difference in mean across the groups. Standard errors are given in the parenthesis and the asterisks denote statistical significance. Panel A reports household variables which are continuous. Panel B reports soil characteristics of the largest plot managed by the household. All the variables are binary expect for fertility which is a Likert scale. Panel C checks for balance in production variables where yield is given in maunds per kanal. Urea and DAP is given in kg per acre. Manure is maunds per kanal. All variables are continuous except 'Use Potassium' which is a binary variable. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1

Panel B shows that plots across the experimental groups are similar across a broad range of properties such water logging, salinity, fertility, soil type, and access to irrigation. The only statistically significant difference is for soil erosion where farmers in the control group report a higher incidence. However, the difference again is not large in absolute magnitude Panel C shows balance on output and inputs. Cotton yield along with DAP, Urea and Potash application is balanced across the experimental groups. However, manure application is not balanced and statistically significant. Manure application is lower in the Peer Comparison group (T2) where manure application is a maund lower per kanal. This difference is also large in terms of absolute magnitude. Therefore, regressions are also estimated after controlling for these variables.

2.6 Estimation Methods

First, I estimate recall of SHC receipt and trust in the information as they are the prerequisite for having any impact on farmer practices. Then the main outcome of interest; manure application and heterogenous impact on fertilizer application is estimated. The empirical specifications are explained in the subsections below.

Since the assignment to treatment and control groups was random, we can measure the causal impact of the two treatment arms on outcomes of interest. The regressions are run at the household for cotton. First, a simple linear regression model without controlling for any village level fixed effects or pre-treatment covariates is estimated. Village fixed effects and controls are these subsequently included in the specifications. ANCOVA is used to improve the power of the study as it allows us to retain observations with missing values at the baseline. These observations were assigned a zero value and controlled for through an indicator variable in the regressions. The improvement in power is significant over the difference-in-differences (DID) estimator as a DID with equal power to the ANCOVA would require twice the sample size (McKenzie, 2012). The main specification used to measure the impact is given below.

$$Y_{ij} = \beta_0 + \beta_1 T_{ij}^1 + \beta_2 T_{ij}^2 + \varphi X'_{ij} + D_{ij} + \varepsilon_{ij} \quad (2.3)$$

where Y_{ij} is the outcome variable of individual i in village j at the endline, T_1 and T_2 are indicator variables for treatment assignment, X'_{ij} is a vector of controls, D is an indicator variable if the information for the household is missing in the baseline, ε_{ij} is the error term. β_1 and β_2 are the coefficients of interest and capture the intent-to-treat (ITT) effect of proving the information.

Farmers in developing countries face numerous constraints, alleviating only one constraint (information in our case) might not be sufficient to induce behavioral change (Karlan et al., 2014). Hence, heterogenous impact of the intervention are estimated. The sample is restricted to those who were underusing fertilizer compared to the recommended quantities, which is 90 percent of the sample. The deviation from the recommended quantity at baseline is used to generate an indicator variable which takes the value 1 if the deviation is less than a bag and zero otherwise.

Balance was also testing for this restricted sample and the results were same as for the original sample. The table is shown in the appendix. This indicator is a proxy for liquidity as those already using higher quantities of fertilizer should not be facing this constraint. The main specification used is given below

$$Y_{ij} = \beta_0 + \beta_1 T_{ij}^1 + \beta_2 T_{ij}^2 + \delta_1 T_{ij}^1 * \mathrm{Dev} + \delta_2 T_{ij}^2 * \mathrm{Dev} + \varphi X'_{ij} + D_{ij} + \varepsilon_{ij} \qquad (2.4)$$

where all the variables are the same except for the interaction term where Dev is the indicator for deviation from the recommendation at the baseline. I also estimate a Difference in Difference version of the above specification for robustness.

2.7 Results

This section presents the results of the study. The first subsection reports the take-up of the SHC followed by the impact of receiving information and peer comparison on our outcomes of interest – organic and inorganic fertilizer use.

2.7.1 Take-Up

Recall and trust variables provide important information on the receptiveness of the SHCs. We use these two variables as proxy for the take-up of the information as they are prerequisite to any change in beliefs or nutrient management practices of farmers in our treatment sample. Farmers were asked if they can recall receiving a SHC and did they trust the information provided[8].

Results show that close to 90 percent of the respondents could recall receiving a SHC and close to 70 percent stated that they trusted the information on the SHC. logit regressions with village fixed effects and cluster the standard errors at the village level were performed. Table 2.2

[8] Only farmers in the treatment groups were asked these question as we felt that asking this question from the control group would prime them and lead them to misreporting. Also, based on our knowledge there was no other intervention happening during this period which delivered SHC to farmers.

and 2.3 reports the average probabilities of being able to recall receipt of the card and trusting the information. the two treatment arms, across the different specifications.

Table 2.2: Predicted Probabilities of Recalling Receipt of SHC

VARIABLE	(1) Received SHC	(2) Received SHC	(3) Received SHC
Information[a]	.932***	.879***	.878***
	(.012)	(.011)	(.011)
Peer Comparison[b]	.918***	.858***	.860***
	(.014)	(.011)	(.010)
Observations	1888	1082	1082
p-value (a vs b)	0.267	0.353	0.393
Village Fixed Effects	No	Yes	Yes
Controls	No	No	Yes

Note: This table reports the average probabilities of recalling receipt of SHC based on a logistic regression (standard errors are reported in parenthesis). The results show that the average probability of recalling receipt of SHC would be around 90 percent if everyone in the data was given the information or the peer comparison treatment. This question was only asked from the treatment group who were delivered the card under the treatment. Including village fixed effects reduces sample as there was no variation in responses within the village. The sample for this analysis includes everyone who was given the card irrespective of the crop they grow. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1

Table 2.3: Predicted Probabilities of Trust in SHC

VARIABLE	(1) Trust SHC	(2) Trust SHC	(3) Trust SHC
Information[a]	.742***	.720***	.720***
	(.024)	(.009)	(.009)
Peer Comparison[b]	.762***	.742***	.742***
	(.021)	(.009)	(.008)
Observations	1888	1742	1742
p-value (a vs b)	0.249	0.236	0.236
Village Fixed Effects	No	Yes	Yes
Controls	No	No	Yes

Note: This table reports the average probabilities of trust in SHC based on a logistic regression (standard errors are reported in parenthesis). The results show that the average probability of trusting the information on the SHC would be around 72 percent if everyone in the data was given the information treatment or the peer comparison treatment. This question was only asked from the treatment group who were delivered the card under the treatment. Including village fixed effects reduces sample if there was no variation in responses across the village. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1

2.7.2 Manure Use

In this subsection, we test whether farmers change their practice of using manure. This was one of the primary advices given to farmers as the organic matter in soils was below the ideal threshold. The dependent variable is the quantity of manure applied in maunds per kanal for cotton. Tobit model was estimated with the lower bound at zero and no upper bound and the results are reported in Table 2.4.

Table 2.4: Tobit Estimates of Manure Applied (maunds/kanal)

VARIABLE	(1) Manure (maund/kanal)	(2) Manure (maund/kanal)	(3) Manure (maund/kanal)
Information[a]	4.65**	4.66**	4.79***
	(2.03)	(2.00)	(2.03)
Peer Comparison[b]	6.731***	5.57***	6.58***
	(2.45)	(2.34)	(2.38)
Manure baseline	0.23*	0.19	0.19
	(0.12)	(0.12)	(0.12)
Missing Dummy	-0.67	0.53	0.57
	(2.87)	(3.45)	(3.44)
Constant	-19.38***	-17.57***	-9.47
	(4.82)	(4.07)	(8.28)
Observations	2226	2226	2226
p-value (a vs b)	0.333	0.367	0.416
Village Fixed Effects	No	Yes	Yes
Controls	No	No	Yes

Notes: The dependent variable is maunds of manure used in a kanal of land. This table provides the ITT estimates of the treatments on manure use. Information and peer comparison are binary variables indicating treatment assignment. Manure baseline is the quantity of manure that was applied at baseline. Control variables include education, household size, non-business and agricultural asset indices, soil type, agriculture training, soil fertility, access to irrigation, waterlogging, salinity, erosion, and land ownership. All regressions are estimated using Tobit and the standard errors are clustered at the village level. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1

The results show that manure use increased in both treatment arms and the increase was statistically significant. The increase in manure application is higher in the peer comparison group as shown in the table, however, the difference is not statistically significant but substantially large in absolute terms. This outcome provides some support to the hypothesis that peer comparisons can act as a good encouragement device and improve the efficacy of information. Since an

ANCOVA specification was used, the baseline value of manure use was also included in the regression along with an indicator variable to control for missing values in the baseline. The results show that they are not strongly correlated to manure use at endline.

2.7.3 Fertilizer Use

Earlier interventions in India and Mexico which only alleviated the information constraints on fertilizer use have not been very successful (Corral et al., 2016; Fishman et al., 2016). Lack of trust and availability of fertilizers were cited as the factors responsible in India and Mexico respectively. These results validate the finding by Karlan et al. (2014) that smallholder farmers face many constraints which need to be removed simultaneously to induce behavioral change. Therefore, this paper focuses on the heterogenous impact as compared to the overall change in fertilizers as that might be attenuated.

First, I restrict my sample to farmers that were underusing fertilizer (90 percent of the sample). Then I generate a variable that captures deviation from the recommended quantity at baseline[9]. This variable takes the value 1 if the deviation is less than a bag and zero otherwise. Results are given in table 2.5 which show a statistically significant increase in Urea application for farmers in the peer comparison group that were underusing by less than 1 bag.

Urea use increased in peer comparison group by 10 kg per acre among farmers that were within 1 bag deviation compared to those who were further away. The coefficient is statistically significant at the 10 percent level and consistent across the three specifications. The impact in the information only group is negligible suggesting the peer comparison was a successful encouragement design for this sub-sample of farmers.

[9] Soils tests were only conducted for treatment groups and exact deviation from mean cannot be calculated for the control group. I impute values for these observations and use the median recommended quantities at village level.

Table 2.5: Heterogenous Treatment Effect on Urea

VARIABLE	(1) Urea *(kg/acre)*	(2) Urea *(kg/acre)*	(3) Urea *(kg/acre)*
Information ● Dev[a]	2.63	2.20	2.05
	(4.51)	(4.26)	(4.35)
Peer Comparison ● Dev[b]	10.03**	9.22*	9.11*
	(4.63)	(4.83)	(4.88)
Dev	-5.48	4.84	5.97
	(6.09)	(4.21)	(4.21)
Information	-2.89	-2.89	-2.91
	(3.08)	(2.62)	(2.56)
Peer Comparison	-1.35	-0.64	-0.47
	(2.84)	(2.64)	(2.63)
Missing Dummy	18.58***	2.16	1.45
	(6.98)	(5.41)	(5.43)
Urea baseline	0.18*	-0.01	-0.03
	(0.09)	(0.06)	(0.06)
Constant	79.02***	73.36***	74.38***
	(6.66)	(3.65)	(10.00)
Observations	2035	2035	2035
p-value (a vs b)	0.182	0.198	0.199
Village Fixed Effects	No	Yes	Yes
Controls	No	No	Yes

Notes: This table provides the coefficient estimates for heterogenous treatment effects based on the deviation from recommended amounts at the baseline. Dev is an indicator variable which takes the value of 1 if deviation was less than 1 bag and 0 otherwise. The Information ●Dev and Peer Comparison ●Dev are interaction terms which capture the impact for farmers in the treatment groups that were within a deviation of 1 bag. Urea baseline is the quantity used at baseline and missing dummy controls for values that were missing in the baseline. Control variables include education, household size, non-business and agricultural asset indices, soil type, attended agriculture training, soil fertility, access to canal and tube well, waterlogging, salinity, erosion, and land owned. Standard errors are clustered at the village level. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1

2.8 Conclusion

I find that approximately 90 percent of farmers could recall receiving the SHC and around 72 percent stated that they trusted the information provided on the cards. This suggests that the intervention was successful in proving improved information to majority of the farmers. Delivery of SHC led to an increase in manure application in the both treatment groups. The magnitude of impact was substantially larger in the peer comparison group but not statistically significant. Urea use also increased among across the two treatment groups, however, in this case the impact was only statistically significant in the peer comparison group among those farmers that were close to the recommended quantities at the baseline.

The results provide some evidence that peer comparisons can be used in an agricultural setting to promote more sustainable practices. The results show that the nudge works and leads to impacts of higher magnitude, however it is not strong enough to have an impact which is statistically different than the traditional mechanism of information dissemination. The heterogenous impact on fertilizer use also provides suggestive evidence that other binding constraints might be limiting use of fertilizers according to recommendations. Farmers who were already using high quantities of fertilizer might not be facing as stringent liquidity constraint as those very far from it and when they were given information on correct fertilizer recommendations that could improve their soil health, they changed their practices. The impact on manure application and the lack of impact on DAP further supports the financial constraints hypothesis as the cost of DAP is almost twice as that of Urea whereas manure is usually available at a very low cost. However, an alternative mechanism could be that those who were operating far from the recommended quantities discounted the recommendations. This points towards confirmation bias, because if the farmers felt they were using the correct or near correct quantities they would not accept recommendation that asks them to change application by more than a bag per acre. However, we cannot identify the mechanism at play for the heterogenous impact and more research is needed to disentangle the reasons for low adoption.

The findings of this study have important policy relevance as soils in Pakistan have been severely affected by land degradation and desertification due to farm practices and environmental factors. Degrading soils have made increasing agricultural productivity an increasingly difficult task to achieve. This has important food security implications for Pakistan which is has a burgeoning population and an economy that is heavily dependent on agriculture. This experiment provides some evidence on the role of information dissemination programs to encourage adoption of sustainable practices through soil health cards. It also highlights that the impact of such programs can be intensified through low cost peer comparisons. Finally, the study highlights that in the presence of other binding constraints (e.g. liquidity, apriori bias) programs that only alleviate the information constraint would not be enough.

APPENDIX

APPENDIX

Table 2.6: Balance Table (Restricted Sample for Heterogeneity)

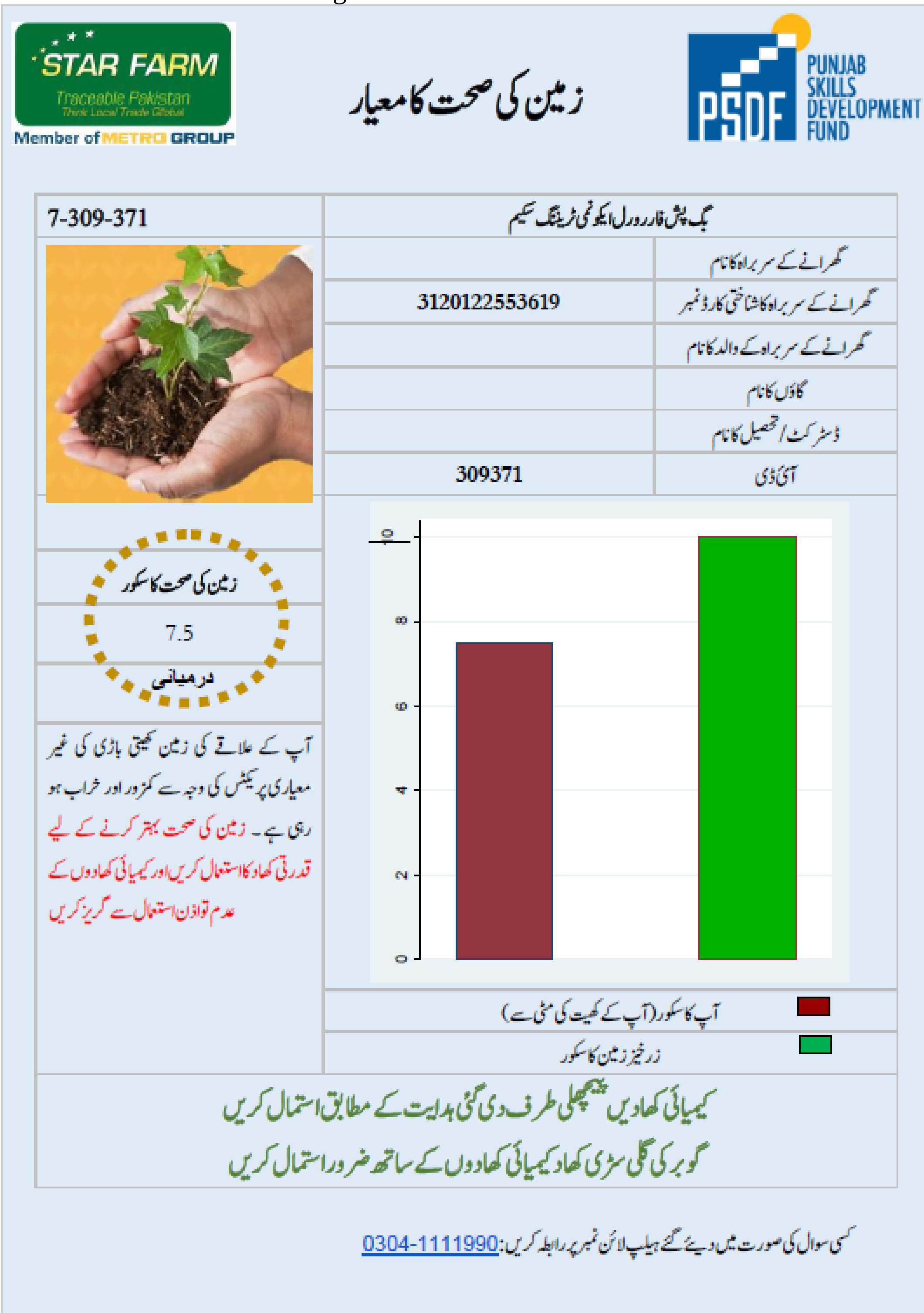
	(1) C	(2) T1	(3) T2	(4) [CvsT1]	(5) [CvsT2]	(6) [T1vsT2]
Panel A. Household Demographic					p-values	
Non-Business Asset Index	0.502 (0.096)	0.495 (0.101)	0.588 (0.109)	0.007	-0.085	-0.093
Agricultural Asset Index	0.592 (0.094)	0.616 (0.100)	0.644 (0.108)	-0.024	-0.052	-0.028
Land Owned (kanals)	25.259 (2.806)	26.096 (2.229)	23.461 (2.297)	-0.836	1.798	2.634
Household Head Education	3.593 (0.229)	3.943 (0.229)	3.672 (0.245)	0.349	-0.079	0.270
Household Head Age	49.871 (0.677)	49.588 (0.718)	50.932 (0.789)	0.283	-1.061	-1.344
Household Size	6.892 (0.106)	7.010 (0.142)	7.115 (0.154)	-0.117	-0.222	-0.105
Panel B. Land Characteristics						
Suffer Waterlogging	0.177 (0.031)	0.199 (0.038)	0.207 (0.034)	-0.023	-0.030	-0.008
Suffer Salinity	0.169 (0.027)	0.178 (0.032)	0.179 (0.030)	-0.009	-0.010	-0.001
Suffer Soil Erosion	0.154 (0.016)	0.134 (0.020)	0.124 (0.019)	0.020	0.030*	0.010
Fertility (Likert Scale 1-5)	4.078 (0.027)	4.069 (0.033)	4.089 (0.035)	0.009	-0.010	-0.020
Soil Type: Sandy	0.166 (0.022)	0.142 (0.023)	0.156 (0.027)	0.025	0.010	-0.015
Soil Type: Sandy Clay	0.527 (0.027)	0.540 (0.028)	0.559 (0.031)	-0.014	-0.033	-0.019
Soil Type: Clay	0.139 (0.017)	0.140 (0.018)	0.137 (0.019)	-0.001	0.002	0.002
Soil Type: Clay Loam	0.054 (0.009)	0.052 (0.012)	0.055 (0.012)	0.002	-0.001	-0.003
Soil Type: Loam	0.106 (0.013)	0.123 (0.022)	0.090 (0.017)	-0.016	0.016	0.032
Access to Tubewell	0.882 (0.028)	0.900 (0.028)	0.893 (0.028)	-0.018	-0.010	0.008
Access to Canal	0.769 (0.045)	0.774 (0.041)	0.753 (0.043)	-0.005	0.016	0.021
N	**883**	**522**	**531**			

Table 2.6: (cont'd)

	(1) **C**	**(2)** **T1**	**(3)** **T2**	**(4)** **[CvsT1]**	**(5)** **[CvsT2]**	**(6)** **[T1vsT2]**
Panel C. Production (Cotton)				Difference in Means		
Yield (maund/kanal)	1.763	1.818	1.846	-0.55	-0.083	-0.028
	(0.091)	(0.094)	(0.096)			
Manure (maund/kanal)	4.007	4.040	3.047	-0.034	0.960*	0.993
	(0.445)	(0.898)	(0.461)			
DAP (kgs/acre)	43.078	42.793	44.443	0.285	-1.364	-1.649
	(1.396)	(1.606)	(1.814)			
Urea (kgs/acre)	76.065	72.490	75.294	3.574	0.771	-2.803
	(3.319)	(3.228)	(3.433)			
Use Potassium	0.007	0.011	0.011	-0.005	-0.005	0.000
	(0.003)	(0.004)	(0.004)			
N	**883**	**522**	**531**			

Notes: This table provides a check on the randomization for the full data. Columns 1 - 3 provide the mean (and standard errors) of each baseline characteristic for the control group (C), information group (T1), and peer comparison group (T2), respectively. Columns 4 - 6 give difference in means. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1

Figure 2.2: Soil Health Card



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PSDF PUNJAB SKILLS DEVELOPMENT FUND

7-309-371	بگ پش فار رورل اکونمی ٹریننگ سکیم	
		گھرانے کے سربراہ کا نام
	3120122553619	گھرانے کے سربراہ کا شناختی کارڈ نمبر
		گھرانے کے سربراہ کے والد کا نام
		گاؤں کا نام
		ڈسٹرکٹ / تحصیل کا نام
	309371	آئی ڈی

زمین کی صحت کا سکور

7.5

درمیانی

آپ کے علاقے کی زمین کھیتی باڑی کی غیر معیاری پریکٹس کی وجہ سے کمزور اور خراب ہو رہی ہے۔ زمین کی صحت بہتر کرنے کے لیے قدرتی کھاد کا استعمال کریں اور کیمیائی کھادوں کے عدم توازن استعمال سے گریز کریں

0
2
4
6
8
10

آپ کا سکور (آپ کے کھیت کی مٹی سے)

زرخیز زمین کا سکور

کیمیائی کھادیں پچھلی طرف دی گئی ہدایت کے مطابق استعمال کریں

گوبر کی گلی سڑی کھاد کیمیائی کھادوں کے ساتھ ضرور استعمال کریں

کسی سوال کی صورت میں دیئے گئے ہیلپ لائن نمبر پر رابطہ کریں: 0304-1111990

Figure 2.2: (cont'd)

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زمین کی صحت کا معیار

ہدایات کھاد فی ایکڑ			7-309-371
یہ ہدایات آپ کی زمین کی صحت اور ضرورت کو دیکھتے ہوے مرتب کی گئی ہیں			
فصل	یوریا	ڈی اے پی	ایس او پی
کپاس (بی ٹی) ۱۲۰۰ کلو فی ایکڑ	3.25	0	1
کھاد کے اوقات کے متعلق ہدایات	بوائی کے وقت تمام ڈی اے پی اور ایس او پی استعمال کریں۔ اگر اپریل میں بو آئی کریں، تو تمام یوریا کا 1/4 حصہ بو آئی کے ایک مہینہ بعد اور باقی فصل اور موسم کو دیکھ کر استمال کریں۔ مئی میں کاشت فصل میں سفارش کردہ یوریا کا 1/3 حصہ ایک مہینہ بعد، 1/3 حصہ ڈوڈیاں بنتے وقت، اور 1/3 حصہ ٹنڈے بنتے وقت برابر مقدار میں ڈالیں		
	یوریا	ڈی اے پی	ایس او پی
چاول (باسمتی) ۱۹۰۰ کلو فی ایکڑ	2	1	.25
کھاد کے اوقات کے متعلق ہدایات	تمام ڈی اے پی، ایس او پی اور آدھی بوری یوریا پنیری کی منتقلی سے پہلے ڈالیں۔ بقیہ یوریا دو برابر حصوں میں پنیری کی منتقلی کے 25 دن اور 50 دن بعد ڈالیں۔		
	یوریا	ڈی اے پی	ایس او پی
چارہ (مکی) ۲۸۰۰ کلو فی ایکڑ	3.75	1.5	1.25
کھاد کے اوقات کے متعلق ہدایات	بوائی کے وقت تمام ڈی اے پی اور ایس او پی استعمال کریں۔ سفارش کردہ یوریا کا 1/3 حصہ پانچ سے چھ پتے نکلنے پر، 1/3 حصہ آٹھ سے دس پتے نکلنے پر، اور 1/3 حصہ پھول انے سے دو ہفتہ قبل ڈالیں		

آئندہ سیزن کیلیے کھاد کی کل مقدار

فصل	کاشت رکبہ	یوریا	پی اے ڈی	ایس او پی
کپاس				
چاول				
چارہ (مکی)				

کسی سوال کی صورت میں دیے گئے ہیلپ لائن نمبر پر رابطہ کریں: 0304-1111990

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Essay 3 :A Dynamic Model for Warehouse Receipts Financing Demand in a Developing Country

Abstract

This paper studies the dynamics of warehouse receipts financing (WRF) demand by small scale risk averse farmers in Pakistan. A dynamic model is used to investigate how risk and time preferences, transaction costs, and uncertainty reduce demand for WRF, and even lead to non-participation in the program. The model is calibrated and solved for a representative small-scale farmer that grows paddy. Results show high transaction costs to be a major barrier to participation. Similarly, expectations about future prices also affect participation which drops to zero if the subjective probability of prices falling goes beyond 10 percent.

3.1. Introduction

Warehouse receipts financing (WRF) has been promoted as a potential solution to some of the fundamental issues that affect agricultural markets in developing countries (Aggarwal, Francis, & Robinson, 2018; Basu & Wong, 2015; Burke, 2014). WRF essentially provides small farmers access to storage facilities where their product is weighed, graded, and agglomerated. The storage organization issues a receipt stating the value of the product stored. This warehouse receipt can be used as collateral to acquire loans from financial institutions such as banks. WRF gives farmers bargaining power as they can choose time of sales, provides access to downstream buyers due to quality control and higher volumes, and most importantly access to formal financial institutions for loans. The establishment of a mechanism under which warehouse receipts can be traded has the potential of modernizing the agricultural value chains, improving market practices on quality control, standardization of product, and promoting exports.

However, the demand for WRF programs has been weak and these services mostly end up being used by large farmers, traders, and processors (William & Kaserwa, 2015). Several authors have postulated that poor farming households face multiple constraints which need to be relaxed simultaneously (Duflo, Kremer, & Robinson, 2011; Karlan et al., 2014). Lack of WRF take up also suggests that access to a storage or financial institutions are not be the only binding constraints. Other aspects such as risk aversion, present bias, and uncertainty also play an important role in the decision making of farmers. Since, WRF has the potential to significantly improve the agricultural value chains in developing countries it is important to understand under what conditions small farmers would be willing to participate.

WRF requires farmers to take on the role of speculators who are expecting to make money off future prices increases. However, in the absence of financial products that can be used to hedge, farmers have to take on the entire risk of price volatility. We have ample evidence that small farmers are generally risk averse might not invest in options which have risky cash flows (Feder, Just, & Zilberman, 1985; Liu, 2013; Ward & Singh, 2015). Given the possibility of a downward price shock it is possible that WRF is not a profitable venture for small farmers under the expected profit margins. Apart from risk considerations, storage is also a choice between foregoing current income for future income. This is important for farmers as they earn bulk of their income in lump sum at harvest and engaging in WRF would mean less cash available in the current period to payoff outstanding debt, meet current consumption needs, invest in next crop cycle, and plan for anticipated and unanticipated expenses during the post-harvest period. These factors individually or collectively can make WRF non-participation a subjectively rational choice, making it important to understand the conditions under which participation is feasible for a small farmer.

Risk and time preferences introduce dynamic considerations into storage and marketing choices of small farmers. The main goal of this paper is to explicitly model the dynamics of WRF in the context of Pakistan. This paper adds to the existing literature on WRF programs, most of which have taken a reduced form approach to evaluate the benefits of WRF (Aggarwal et al., 2018; Basu & Wong, 2015; Burke, 2014). Miranda et al. (2017) develop a dynamic model to evaluate WRF for an average smallholder Ghanaian farmer while and find WRF not to be a viable product for small farmers. The motivation for this paper is to estimate demand for WRF in Pakistan which has two agricultural cycles instead of one due to irrigation, most farmers are commercial growers, and there is a lot interest by the government to establish a WRF system in the country.

This paper employs dynamic programming to solve a two-period model for an agricultural year. Even though the model is for two period its findings are clear into how risk, time, and uncertainty undermine the benefits of WRF. The model is simulated for a representative farmer who grows rice as a cash crop on 5 acres of land and has an average harvest of 150 maunds. The model is calibrated to reflect a small farmer's risk and time preferences, subjective future expectations, and credit constraints. Results derived show that farmers will not store using modern approach of storing in silos due to high cost. However, under the traditional system which is 25 percent cheaper farmers would will store 24 percent of the harvested paddy. Sensitivity analysis further supports this claim as participation falls to zero if interest rate on loans offered against stored grain goes beyond 15 percent. This also highlights that liquidity is an important constraint for farmers who need the cash advance through WRF to participate. Results also show that farmers will not participate if the subjective probability of prices falling is more than 10 percent. Similarly, risk aversion also depresses the demand for storage as expected and the quantity stored increases as the farmer becomes less risk averse. These results highlight that reducing exposure to risk would also improve demand for WRF. Hence, a product design which reduces the transaction cost of participation and reduces future price uncertainty can significantly improve participation. Transaction costs can be decreased by registering farmers and forming small community groups so that costs can be reduced by economies of scale. Similarly, providing information about past prices and future expected prices can help the farmers develop price expectation which are closer to the true distribution. Alternatively, developing financial products through which the warehouse management companies can hedge their risk to price shocks can reduce uncertainty in future prices making WRF an investment with less volatile cash flows for warehousing companies, banks, and the farmers.

The rest of the paper is organized as follows. Section 2 outlines the dynamic model for a standard WRF product and decision rules are then presented under these scenarios. Derivations are initially shown for a scenario without liquidity constraint and perfect risk pooling, these constraints are then included in the model and their effect on demand is investigated. Section 3 lays out the specific functional form and explains the data collected to calibrate its parameters for a representative rice grower in central Punjab. Section 4 discusses the results from the analysis and shows how delayed payments and a reduction in price uncertainty through price floor can increase demand. Section 5 gives concluding comments.

3.2. Dynamic Storage Model

Consider a small farmer who has the option of participating in a WRF program, which allows intertemporal arbitrage and access to more remunerative markets through quality control and agglomeration of grain. However, intertemporal arbitrage inherently carries the risk of loss if future prices do not rise sufficiently. Also, it requires a compromise between current income over future income. Finally, beliefs about future also effect the choice about either selling now or storing and selling in the future after considering several factors.

I use a stylized model to represent the decision making of the farmer under risk aversion, time preferences and uncertainty. Risk and time preference play an important role in the decision making of individuals especially when it involves makes choices which have a time dimension and uncertainty such as technology adoption, investment, migration, education, and health (Ashraf, Karlan, & Yin, 2006; Engle Warnick, Escobal, & Laszlo, 2011; Jensen, 2010; Lawless, Drichoutis, & Nayga, 2013; McKenzie, Gibson, & Stillman, 2013). In any given year there are two time periods – the paddy harvest period and the wheat production period. In each period utility is a function of income and the objective of the farmer is to maximize the present value of utility derived over these two periods. Period one starts with the stock of freshly harvested paddy and there are no carryovers from the previous period. The farmer decides how much of this paddy to store and how to sell at the prevailing price. The income generated from sales is then allocated between saving and investment in the wheat crop which yields a return at the end of the second period. The farmer has a subjective probability regarding price of paddy at the end of period two (when he liquidates the stock) and believes that the prices will increase with a probability π_G to earn him a profit from storage.

The small holder farmer's formal two period dynamic optimization problem can be expressed as follows. I closely follow the approach used by Karlan et al. (2014):

$$\max_{y,z,a} U(\pi_0) + \beta \sum_{s \in S} \mu_s U(\pi_1^s) \tag{3.1}$$

Before grain is stored it needs to be transported, dried, cleaned, and graded. Once stored the farmer receives a warehouse receipt which can be used to acquire a loan which is equal to a fraction of the value of the grain stored. The loan is repaid at the end of period two when the farmer liquidates the stored grain. Another aspect that the farmer needs to consider is the return from other investment opportunities such as growing wheat. The resource allocation decision is made subject to

$$\begin{aligned} \pi_0 &= p_0(q - y + \gamma y) - a - z \\ \pi_1^s &= f(z) + Ra + \mathrm{y}(p_1^s - \tau - R\gamma p_0) \\ q &\geq y \\ y &\geq 0 \\ z &\geq 0 \end{aligned} \tag{3.2}$$

where $U(\cdot)$ is an increasing and concave utility function, π_0 is income in period 0, there are two states good and bad $s \in \{G, B\}$, π_1^s is income in period 1 for each state, μ_s is probability of each state, β is the discount factor, q is the amount of storable commodity in period 1, y is quantity stored, z is investment in wheat crop whose price is normalized to one, a is the net saving in financial market, γ is the advance rate set by the warehousing firm which allows the farmers to receive credit against the value of the stored grain, R is the return on the credit market or the cost of borrowing from the credit market or the WRF, τ is the per unit cost of storage, and μ_B is the probability of being in bad state.

Since, the main interest is storage choice under risk and credit constraint. The model is solved using the Lagrange method under four different market scenarios in which access to credit and risk pooling is varied.

Table 3.1: Lagrange Results

Scenarios	Storage	Wheat
Perfect Credit Market and Risk Pooling	$\frac{\bar{p}_1 - \tau}{p_0} = R$	$f'(z) = R$
Incomplete Credit Market and Perfect Risk Pooling	$\frac{\bar{p}_1 - \tau - R\gamma p_0}{p_0(1-\gamma)} = f'(z)$	$f'(z) > R$
Perfect Credit Market and Incomplete Risk Pooling	$p_1^G = \frac{Rp_0(1-\gamma)}{\tau + R\gamma p_0}\left[\frac{\mu_B U'(\pi_1^B)}{\mu_G U'(\pi_1^G)} + 1\right]$	$f'(z) = R$
Incomplete Credit Market and Risk Pooling	$p_1^G = \frac{f'(z)p_0(1-\gamma)}{\tau + R\gamma p_0}\left[\frac{\mu_B U'(\pi_1^B)}{\mu_G U'(\pi_1^G)} + 1\right]$	$f'(z) > R$

3.3. Model Parameterization

In order to provide a sense of the magnitude of the value of the insurance under various market conditions the model is fully parameterized so that we can solve it numerically. The utility function is assumed to take the form

$$U(\pi) = \begin{matrix} \pi^\sigma & if\ \pi \geq 0 \\ -(-\pi^\sigma) & if\ \pi < 0 \end{matrix}$$

where $\sigma > 0$ dictates the curvature of the function and can be thought of as a measure of risk.

The model parameters are calibrated to represent an average smallholder farmer. The average farmer sell approximately 150 maunds immediately at harvest as the quality of the paddy starts to deteriorate if it is not dried within a few days. We assume that a farmer would store paddy for 90 days as the prices stabilize at a higher equilibrium by that time. However, small farmers are also known to have high discount rates which can erode the profitability of investments. I collected data on time preferences of farmers using price lists which involve choosing between a smaller amounts sooner versus a larger amount later. The interest rate is gradually increased to elicit the subjective discount rate of the agent. However, if the utility is concave, then this approach leads to overestimation of the discount rates. This can be corrected by estimating discount rates conditional on the curvature of the utility function which is also a measure of risk aversion.

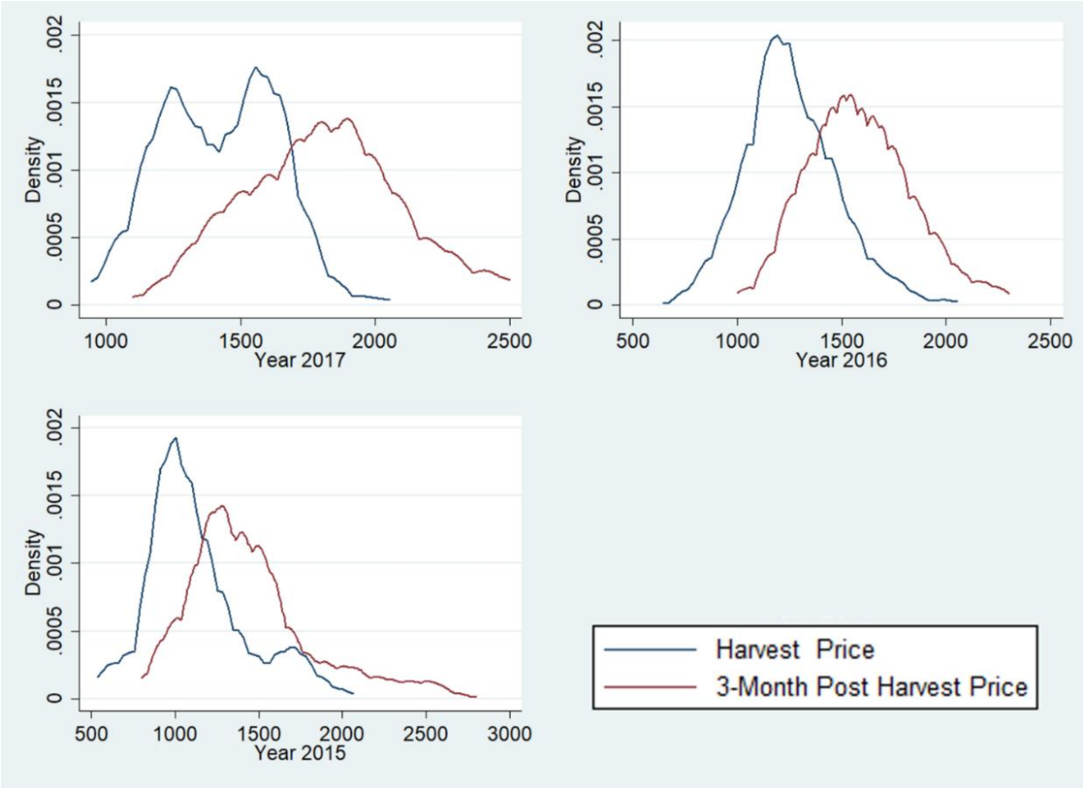
The risk task was based on the design of Holt and Laury (2002) where the agent was given a choice list of two lotteries. The agent chooses one lottery over the other and the expected value of the two lotteries is adjusted to elicit the subjective risk preferences of the agent. These games are carefully designed so that the pair of switching rounds can be used to identify the lower and upper bounds for the range of parameters for which the respondents' choices are consistent. The midpoint of this range is then used this as an approximation of the individuals' parameter values. Table 1 provides summary statics of both the risk aversion and time preference parameters and shows that there is significant heterogeneity in the preferences of respondents. The actual games are detailed in the appendix.

Table 3.2: Time and Risk Parameters

	Count	**Mean**	**SD**
Discount Rate	622	.21	.19
Risk Aversion	622	.55	.42

The decision to participate in WRF is not only shaped by preferences but expectations about future outcomes as well. Subjective price expectation is an important aspect in the decision-making process as the support of the expected price of paddy could make WRF an unprofitable prospect making non-participation a subjectively rational choice. Figure 3.1 below shows the historical prices at harvest and 3-month post-harvest as reported by farmers in the study area.

Figure 3.1: Historical Paddy Prices (PKR/maund)



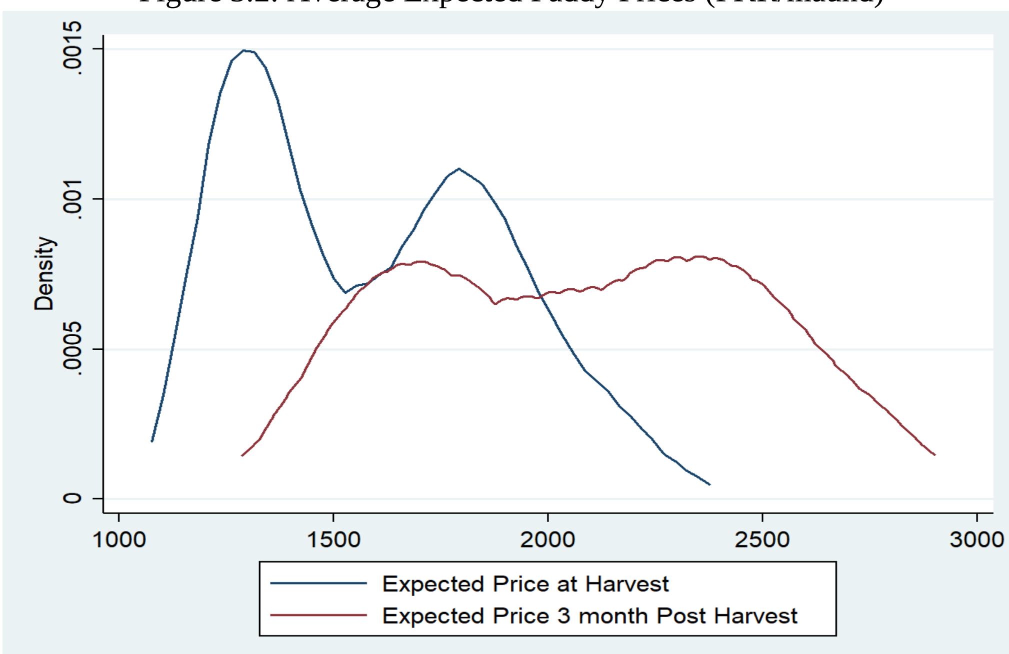
Since these prices are reported by the farmers, we can consider them as subjective prices based on which the farmers would form expectations about future prices. The figure also shows that on average post-harvest prices have been higher in the past three years. However, we also see that there is an overlap in the harvest and the post-harvest price distributions suggesting that there is a positive probability that the farmers could receive a lower price in the post-harvest compared to the price at harvest. Therefore, farmers' expectations about future prices at harvest and post-harvest were collected before the rollout of the warehouse receipts financing program. Farmers were asked to report the maximum and minimum price for the upcoming 2018 harvest and 3-months post-harvest. Table 3.3 shows the summary statistics of prices reported by farmers.

Table 3.3: Expected Prices (PKR/maund)

	N	Mean	SD	Min	Max
Min Harvest 2018	661	1482	272	1100	2100
Max Harvest 2018	661	1702	352	1200	2500
Min Post Harvest 2018	661	1938	378	1200	2800
Max Post Harvest 2018	661	2207	453	1350	3000

On average the farmers expected prices to be between rupees 1500 to 1700 at harvest and between rupees 1900 to 2200 post-harvest. I use the minimum and maximum expected prices to calculate averages and the distribution is shown in figure 3.2 which shows an overlap in the price distributions. This suggests that farmers do assign a positive probability to prices falling in the future.

Figure 3.2: Average Expected Paddy Prices (PKR/maund)



Another important consideration for participating in the WRF would be the transaction cost. A small holder will only use WRF if the premium earned from the stored grain adjusted for cost of warehousing is positive. Data on warehouse charges was obtained from a local warehouse management company which offered these services to small farmers in the study area. Table 3.4 reports the cost of warehousing which is substantial even when non-pecuniary costs such as arranging for labor and vehicles for transportation are not incorporated. Grading and weighting charges are assumed to be zero. Loading and dispatch is the labor cost for taking the paddy off the trucks and then loading them back at sale time. Preclearing is the cost of labor used to feed the paddy to the dryers. The moisture content needs to be reduced before its stored, mechanical drying is done by passing the paddy through dryers which dry it and clear it of impurities such as dust and empty kernels. Under mechanical drying paddy is stored in silos where moisture level is automatically maintained. In the case of traditional storage paddy is dried in the sun and overturned several times. Paddy is stored in jute bags and manually monitored to ensure moisture levels are within acceptable levels. The cost of drying and storage are higher for mechanical drying due to high energy costs and using off grid sources of electricity due to load shedding. Jute bags are available on rent from the warehouse or can be bought by the farmer themselves, a jute bag normally costs around PKR 250 and often short in supply at harvest time. The transport cost reported in the table is the mean, but cost can double depending on the distance from warehouse and availability at the time of harvest.

Table 3.4: Warehousing Cost (40kg bag)

Cost per bag	**Mechanical**	**Traditional**
Unloading and Dispatch	10	10
Preclearing	15	0
Drying cost	50	24
Storage 90 days	120	60
Jute bag rental 90 days	0	36
Transportation cost to warehouse	15	15
Total Warehousing Cost	**210**	**145**

If the farmer stores the paddy, it leads to 6 percent loss of weight under mechanical storage and a 2.5 percent weight loss under the traditional sun drying method on average. The weight loss is higher in the mechanical drying as it is more efficient in drying and removing impurities such as empty kernels, dust, and other debris. The total cost of mechanical drying is approximately

PKR60 per maund higher than the traditional drying, and the premium for mechanically dried paddy can vary between 0 to PKR 200 per maund.

The farmer is issued a warehouse receipts which records the amount of paddy stored and its value at the time of storage based on its quality. This warehouse receipt can be used to acquire a loan which needs to be repaid at the time of liquidating the stored grain. The advance rate is fixed at 70 percent of the value of the crop at the time of storage at an annualized interest rate of 28 percent. Base-case model parameters are set to the values given in Table 3.5.

Table 3.5: Base Case Parameter Values

Symbol	**Value**	**Description**
p_0	1550	Price/maund at harvest
p_1^G	2100	Price/maund 3-month post-harvest in the good state
p_1^B	1300	Price/maund 3-month post-harvest in the bad state
π_B	0.10	Subjective probability of being in the bad state.
β	0.79	Subjective annual discount rate
q	150	Harvest quantity in maunds
ra	0.55	Risk Aversion
τ^a	145	Per maund storage cost for 90 days
δ^a	0.025	Weight loss due to drying and cleaning
R	1.14	Annualized interest rate
γ	0.70	Advance rate for loan against warehouse receipts
α^b	1.25	Return on investment in wheat

[a]Warehousing cost and weight loss are given for traditional drying and cleaning.
[b]Return on wheat is based off the calculations provided by the agriculture department.

3.4. Results

The model is calibrated for a smallholder farmer and solved under the four market conditions derived earlier. Under complete credit market the farmer can borrow and solve from the market under the prevailing interest rate. Future price of paddy is assumed to be known and equal to the average of the good and bad state. However, to ensure that results are reflective of actual market outcome and unrealistic amounts are not borrowed, investment in wheat capped at PRK 200,000 which is the cost of production for 5 acres of land10. Results show that under these conditions the farmer would store the entire 150 maunds, borrow PRK 164,000 from the market, and invest PKR 200,000 in wheat production. The model is then solved with incomplete credit market, and to make this binding the farmer cannot borrow but can save at the prevalent rate. Other conditions are same where expected future price is known with certainty and the maximum amount that can be invested in wheat is capped. Results show that the farmer will store the entire 150 maunds again, invest PKR 55,000 in wheat and not save anything. Next the credit market is assumed to be functional but there is uncertainty in future paddy prices. Results show that the farmer will store the entire harvest, borrow lower quantities from the market and invest PKR 200,000 in wheat. Finally, the model is solved under the final market scenario where there is no credit market or risk pooling. The results show that the farmer will store 36 maunds of the produce, invest PKR 108,000 in wheat, and not save any money. A summary of these outcomes is given in table 3.6.

Table 3.6: Simulation Results

Scenarios	Paddy Stored (maunds)	Borrowing (PKR)	Investment in Wheat (PKR)
Perfect Credit Market and Risk Pooling	150	164,000	200,000
Incomplete Credit Market and Perfect Risk Pooling	150	0	55,000
Perfect Credit Market and Incomplete Risk Pooling	150	158,000	200,000
Incomplete Credit Market and Risk Pooling	36	0	108,000

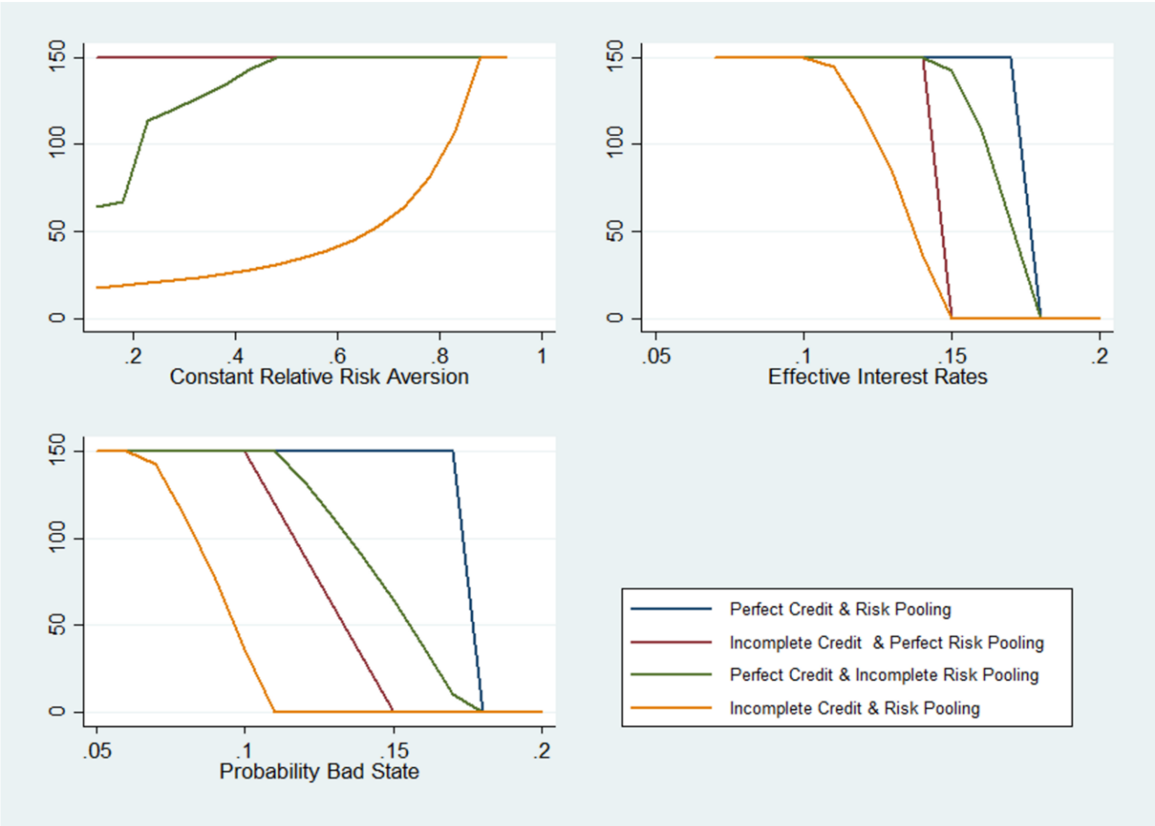
I then conduct a sensitivity analysis on how the demand for storage will change under different interest rates, probability of a bad state, and risk aversion. All of these parameters are changed individually to identify parameter values at which they become binding. Interest rates are varied from 7 percent to 20 percent with steps of 1 percent, probability of being in the bad state is varied from 5 percent to 20 percent, with steps of 1 percent. The subjective risk aversion parameters is

[10] I use the production costs for 2018-19 under average conditions in Punjab developed by the local agriculture department

varied one standard deviation above and below the mean. Figure 3.3 reports these sensitivity analysis results under the traditional storage method.

The results show that risk aversion does not impact storage when risk pooling is possible. When risk pooling is not possible risk aversion decreases quantity stored and as relative risk aversion decreases the farmer higher proportion of paddy. Similarly, at low interest rates the farmer would store the entire stock of paddy but as the interest rate increases the quantity of paddy stored decrease and goes to zero. The subjective probability of bad state also reduces participation, and farmers under incomplete credit markets are most sensitive this variable.

Figure 3.3: Storage Sensitivity Analysis



3.5. Conclusion

This paper develops a dynamic model of demand for a standard WRF product in the context of Pakistan in the presence of liquidity constraints, risk aversion, and price uncertainty. This paper adds to the existing literature by analyzing the feasibility of WRF in a context where there are two complete agricultural cycles. Most of the WRF evaluations and technical reports have been in contexts where there is primary growing season followed by a dry season in which limited agricultural activities can be carried out. I solve a two-period model for an agricultural year, and even though the model is for two period its findings are clear into how preferences and uncertainty affect the benefits of WRF. The model is calibrated to reflect a small farmer's preference and solved under four different market condition. Results show that farmers will store if either the credit market or insurance market is functioning. However, in a scenario where access to credit is constrained and risk cannot be pooled demand for storage would fall. I also find that farmers are sensitive to transaction cost of storage and would not store under the mechanized method as it is more costly, similarly the demand for storage also falls as interest rates increase. Risk also plays an important role in the decision to participate. Risk averse farmers have low demand when there is no risk pooling. Similarly, as the subjective probabilities of the prices falling in the future increases non-participation becomes the dominant strategy.

These results suggest that transaction costs of warehousing are significant and erode the profitability of WRF. The farmer is better off selling the paddy at harvest especially under mechanical storage as the weight loss due to drying and the cost of storage are very high and the premium over traditional methods is not certain. Participation in the WRF can be increased by offering lower interest rates on credit and reducing the exposure to risk. One mechanism could be that collateral management company's hedge the price risk in paddy against other commodities or buying futures. However, absence of these market in developing countries make the success of WRF difficult as it requires the small farmer to bear the entire risk.

A limitation of this model is that it assumes disutility from losses to be proportional to the utility from gains. Prospect theory highlights that this might not be the case as people derive higher disutility from losses. This might be particularly true in the case of small farmers who might be highly loss averse as one negative shock could push them into poverty. Hence, the results from this numerical solution must be viewed an upper bound to the storage demand. Future work can include loss aversion as an additional parameter to test the feasibility of this program.

Government and international organizations promoting warehouse receipts financing need to take the transaction and risk factor into account while planning this program. The direct impact of improving profitability of small farmers through intertemporal arbitrage would be limited unless access to this program is improved through measure which protect small farmers against large negative shocks. If we look past the distributional impact of WRF, it has many other benefits such as it could promote the development of agricultural value chains by making it more efficient and imposing quality controls and standards. It would also reduce the price volatility of the commodities, therefore reducing uncertainty and increasing investment.

APPENDIX

APPENIDX

Preferences over income in the first period and in the various states of the second period with probability of state and a discount factor are

$$U(\pi_0) + \beta \sum_{s \in S} \mu_s U(\pi_1^s) \tag{3.3}$$

where $U(\cdot)$ is an increasing and concave utility function, π_0 is income in period 0, there are two states good and bad $s \in \{G, B\}$, π_1^s is income in period 1 for each state, μ_s is probability of each state, and β is the discount factor. The farmer maximizes (1) under the following constraints

$$\pi_0 = p_0(q - y + \gamma y) - a - z$$

$$\pi_1^s = f(z) + Ra + \mathrm{y}(p_1^s - \tau - R\gamma p_0)$$

q is the amount of storable commodity in period 0, y is quantity stored, z is investment in wheat crop whose price is normalized to one, a is the net saving in financial market (negative if borrowing and positive if saving), γ is the advance rate set by the warehousing firm against the value of the stored grain11, $f(z)$ is the concave wheat production function, R is the return on the credit market or the cost of borrowing from the WRF, δ is the weight loss due to storage, and τ is the per unit cost of storage. Additional side conditions are imposed so that the farmer cannot store negative amounts or store more than quantity produced and investment in wheat is nonnegative.

$$q \geq y$$

$$y \geq 0, z \geq 0$$

Since the main interest is in storage choice under risk and credit constraint, storage rules under these environments are derived. The problem is initially solved under perfect credit and risk

[11] For simplicity I assume that the farmer would always take the maximum amount of cash advance through WRF.

pooling to arrive at a well-known intertemporal arbitrage optimal decision rule. Credit constraint and imperfect risk pooling are then introduced into the model, first individually and then together.

Case 1: Perfect credit market and risk pooling.

Under this market condition the farmer does not face liquidity constraints and consumes an average of the good and bad states due to perfect risk pooling $\{\bar{\pi}_1 = f(z) + Ra + \mathrm{y}(\bar{p}_1 - \tau - R\gamma p_0)\}$. This extreme case of perfect insurance later helps us to focus on the implications of a binding credit constraint when risk plays no role in the decision to allocate resources. The setup of the problem under Lagrange method is given below.

$$\max_{y,z,a} L = U(\pi_0) + \beta U(\bar{\pi}_1) + \lambda_1(q - y) + \lambda_2(p_0(q - y + \gamma y) - a - z) + \rho_1 y + \rho_2 z$$

The first order conditions are

$$\frac{\partial L}{\partial a} = -U'(\pi_0) + \beta R U'(\bar{\pi}_1) - \lambda_2 = 0$$

$$\frac{\partial L}{\partial z} = -U'(\pi_0) + \beta f'(z) U'(\bar{\pi}_1) - \lambda_2 + \rho_2 = 0$$

$$\frac{\partial L}{\partial y} = p_0(\gamma - 1)U'(\pi_0) + \beta(\bar{p}_1 - \tau - R\gamma p_0)U'(\bar{\pi}_1) - \lambda_1 + \lambda_2 p_0(\gamma - 1) + \rho_1 = 0$$

$$\lambda_1(q - y) = 0, \quad \lambda_2(p_0(q - y + \gamma y) - a - z) = 0, \quad \rho_1 y = 0, \quad \rho_2 z = 0$$

Using the above results, we can derive the decision rules for the farmer.

Assuming $\lambda_1 = 0,\ \lambda_2 = 0,\ \rho_1 = 0, and\ \rho_2 = 0.$

$$f'(z) = \frac{\bar{p}_1 - \tau}{p_0} = R$$

With perfect credit markets and risk-pooling, investment in wheat is independent of resources (q) and preferences. The investment is only determined by the cost of interest and the return from investment which depends on the production function and prices. Similarly, the choice of storage depends on expected price, current price, and the cost of storage. Neither reduction in risk or access to credit would influences the choices under this scenario.

Case 2: Imperfect credit market and perfect risk pooling.

In this case credit market is non functions and binding which essentially adds an additional constraint $a \geq 0$. Risk pooling is still available, so the farmer continues to earn the expected income. The setup of the problem under Lagrange method is given below.

$$\max_{y,z,a} L = U(\pi_0) + \beta U(\bar{\pi}_1) + \lambda_1(q - y) + \lambda_2(p_0(q - y + \gamma y) - a - z) + \rho_1 y + \rho_2 z + \rho_3 a$$

The first order conditions are

$$\frac{\partial L}{\partial a} = -U'(\pi_0) + \beta R U'(\bar{\pi}_1) - \lambda_2 + \rho_3 = 0$$

$$\frac{\partial L}{\partial z} = -U'(\pi_0) + \beta f'(z) U'(\bar{\pi}_1) - \lambda_2 + \rho_2 = 0$$

$$\frac{\partial L}{\partial y} = p_0(\gamma - 1)U'(\pi_0) + \beta(\bar{p}_1 - \tau - R\gamma p_0)U'(\bar{\pi}_1) - \lambda_1 + \lambda_2 p_0(\gamma - 1) + \rho_1 = 0$$

$$\lambda_1(q - y) = 0, \quad \lambda_2(p_0(q - y + \gamma y) - a - z) = 0, \quad \rho_1 y = 0, \quad \rho_2 z = 0$$

Using the above results, we can derive the decision rules for the farmer.

Assuming $\lambda_1 = 0,\ \lambda_2 = 0,\ \rho_1 = 0, \rho_2 = 0, and\ \ \rho_3 > 0.$

$$f'(z) > R$$

Due to the liquidity constraint, investment in wheat is constrained and lower than under functioning credit market. The choice of storage now depends on the relative return from wheat.

$$\frac{\bar{p}_1 - \tau - R\gamma p_0}{p_0(1 - \gamma)} = f'(z)$$

The choice of storage depends on the expected future prices, return in the credit market, advance rate in WRF, current prices, and return from investment in wheat. Preferences still do not enter the decision making for either of the investment options.

Case 3: Imperfect risk pooling but a perfect capital market.

In this scenario there is no risk pooling, but the capital market is complete, and the farmer can engage in income smoothing across the two time periods. The setup of the problem under Lagrange method is given below.

$$\max_{y,z,a} L = U(\pi_0) + \beta\{\mu_B U(\pi_1^B) + \mu_G U(\pi_1^G)\} + \lambda_1(q - y) + \lambda_2(p_0(q - y + \gamma y) - a - z)$$
$$+ \rho_1 y + \rho_2 z$$

The first order conditions are

$$\frac{\partial L}{\partial a} = -U'(\pi_0) + \beta R\{\mu_B U'(\pi_1^B) + \mu_G U'(\pi_1^G)\} - \lambda_2 = 0$$

$$\frac{\partial L}{\partial z} = -U'(\pi_0) + \beta f'(z)\{\mu_B U'(\pi_1^B) + \mu_G U'(\pi_1^G)\} - \lambda_2 + \rho_2 = 0$$

$$\frac{\partial L}{\partial y} = p_0(\gamma - 1)U'(\pi_0) - \beta(\tau + R\gamma p_0)\{\mu_B U'(\pi_1^B)p_1^B + \mu_G U'(\pi_1^G)p_1^G\} - \lambda_1 + \lambda_2 p_0(\gamma - 1)$$
$$+ \rho_1 = 0$$

$$\lambda_1(q - y) = 0, \quad \lambda_2(p_0(q - y + \gamma y) - a - z) = 0, \quad \rho_1 y = 0, \quad \rho_2 z = 0$$

Using the above results, we can derive the decision rules for the farmer.

Assuming $\lambda_1 = 0,\ \lambda_2 = 0,\ \rho_1 = 0, and\ \rho_2 = 0$.

$$f'(z) = R$$

The choice of investment in z is independent of resources (q) or preferences and only depends on the cost of credit and the return from wheat which depends on its production function and prices.

The decision rule for storage is given by

$$\frac{Rp_0(1-\gamma)}{\tau + R\gamma p_0} = \frac{\mu_B U'(\pi_1^B)p_1^B + \mu_G U'(\pi_1^G)p_1^G}{\mu_B U'(\pi_1^B) + \mu_G U'(\pi_1^G)}$$

Assuming $p_1^B = 0$ for simplicity

$$p_1^G = \frac{Rp_0(1-\gamma)}{\tau + R\gamma p_0}\left[\frac{\mu_B U'(\pi_1^B)}{\mu_G U'(\pi_1^G)} + 1\right]$$

Storage choice is influenced by return in the credit market, advance rate, current prices, cost of storage, future price in different states and their probabilities, and the preferences of farmers.

Case 4: Imperfect Credit and Risk Pooling

In this scenario there is no access to a credit market or risk pooling. The setup of the problem under Lagrange method is given below.

$$\max_{y,z,a} L = U(\pi_0) + \beta\{\mu_B U(\pi_1^B) + \mu_G U(\pi_1^G)\} + \lambda_1(q-y) + \lambda_2(p_0(q-y+\gamma y) - a - z)$$

$$+ \rho_1 y + \rho_2 z + \rho_3 a$$

The first order conditions are

$$\frac{\partial L}{\partial a} = -U'(\pi_0) + \beta R\{\mu_B U'(\pi_1^B) + \mu_G U'(\pi_1^G)\} - \lambda_2 + \rho_3 = 0$$

$$\frac{\partial L}{\partial z} = -U'(\pi_0) + \beta f'(z)\{\mu_B U'(\pi_1^B) + \mu_G U'(\pi_1^G)\} - \lambda_2 + \rho_2 = 0$$

$$\frac{\partial L}{\partial y} = p_0(\gamma - 1)U'(\pi_0) - \beta(\tau + R\gamma p_0)\{\mu_B U'(\pi_1^B)p_1^B + \mu_G U'(\pi_1^G)p_1^G\} - \lambda_1 + \lambda_2 p_0(\gamma - 1)$$

$$+ \rho_1 = 0$$

$$\lambda_1(q-y) = 0, \quad \lambda_2(p_0(q-y+\gamma y) - a - z) = 0, \quad \rho_1 y = 0, \quad \rho_2 z = 0$$

Using the above results, we can derive the decision rules for the farmer.

Assuming $\lambda_1 = 0,\ \lambda_2 = 0,\ \rho_1 = 0, \rho_2 = 0, and\ \rho_3 > 0$.

$$f'(z) > R$$

Due to the liquidity constraint, investment in wheat is constrained and lower than under functioning credit market. The choice of storage now depends on the relative return from wheat. The decision rule is given by

$$\frac{f'(z)p_0(1-\gamma)}{\tau + R\gamma p_0} = \frac{\mu_B U'(\pi_1^B)p_1^B + \mu_G U'(\pi_1^G)p_1^G}{\mu_B U'(\pi_1^B) + \mu_G U'(\pi_1^G)}$$

Assuming $p_1^B = 0$ for simplicity

$$p_1^G = \frac{f'(z)p_0(1-\gamma)}{\tau + R\gamma p_0}\left[\frac{\mu_B U'(\pi_1^B)}{\mu_G U'(\pi_1^G)} + 1\right]$$

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