Information Interventions and Willingness to Pay for PICS Bags: Evidence from Sierra Leone

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Selected Paper prepared for presentation at the 2024 Agricultural & Applied Economics Association Annual Meeting, New Orleans, LA; July 28-30, 2024

Information Interventions and Willingness to Pay for a Agricultural Technology: Evidence from Sierra Leone

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Abstract

This study investigates the different impact of informational interventions on smallholder farmers' willingness to pay (WTP) for Purdue Improved Crop Storage (PICS) bags in Sierra Leone. Despite the proven efficacy of PICS bags in reducing post-harvest losses and maintaining crop quality, their adoption rates remain extremely low in Sierra Leone. Through a randomized controlled trial (RCT) involving 436 households, this research investigates how health and profit-oriented information impacts farmers' valuation of PICS bags. Participants were randomly assigned to receive either health benefits information, profit benefits information, or standard usage instructions (control group). The WTP was assessed using the Becker-DeGroot-Marschak (BDM) auction method. Results indicate that while profit-related information significantly increases WTP, health information does not. Further, heterogeneity analysis shows that risk-averse farmers exhibit a higher WTP in response to both types of information, suggesting a greater valuation of PICS bags' benefits. Conversely, households with higher dietary diversity scores display a diminished response to profit-oriented information regarding their WTP.

Keywords: Randomized controlled trial, Technology Adoption, Experimental Auction

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1 Introduction

In many regions of Sub-Saharan Africa, post-harvest losses present a formidable challenge to achieving food security, especially in areas dominated by smallholder farming. Sierra Leone, like many of its neighbors, grapples with significant post-harvest losses, which account for an estimated 20–30% loss of farm produce (Conteh et al., 2015). Such losses not only diminish the economic returns for farmers but also exacerbate food scarcity, particularly in rural areas where the majority rely on agriculture for their livelihood and sustenance. To address the issue of post-harvest losses, the introduction of Purdue Improved Crop Storage (PICS) bags and other hermetic storage bags has been heralded as a promising solution. PICS bags offer an easily adoptable hermetic storage solution for farmers, effectively protecting harvested grains from pests without chemical treatments (Sudini et al., 2015). However, despite the clear advantages offered by PICS bags, their adoption rate among smallholder farmers in Sierra Leone remains extremely low (Moussa et al., 2014; Mwaijande, 2017). This gap between the potential benefits of PICS bags and their actual uptake by farmers underscores the need for a deeper understanding of the factors influencing their adoption. This study seeks to explore the determinants of farmers' willingness to pay (WTP) for PICS bags in Sierra Leone, with a particular emphasis on the influence of varied informational interventions. Through a randomized controlled trial, we aim to unravel the nuanced effects of health and profit-related information on farmers' valuation and potential adoption of this innovative storage solution.

Post-harvest losses among smallholders occur between the harvest and consumption stages, and can be attributed to myriad factors, including pests, diseases, poor handling,

inadequate storage, and inefficient supply chains (Stathers et al., 2020). Such losses not only diminish the income potential for farmers but also have broader implications for food security, nutrition, and environmental sustainability (Affognon et al., 2015). A comprehensive review by Stathers et al. (2020) highlighted a range of interventions that have been proposed and implemented over the years to address PHL. These interventions span from improved drying techniques, enhanced supply chain management, to innovative storage solutions. Hodges et al. (2011) further emphasized the differential nature of PHL in developed versus less developed countries, suggesting that the opportunities to improve resource use and reduce losses might vary based on regional contexts. Among the various interventions, storage technologies have garnered significant attention. Kumar and Kalita (2017) underscored the importance of reducing PHL during grain storage to bolster food security in developing nations. Their study emphasized the potential of modern storage techniques, such as the Purdue Improved Crop Storage (PICS) bags, in preserving grain quality and minimizing losses. Chegere et al. (2022) also provided empirical evidence from small-scale farms in Tanzania, demonstrating the positive effects of storage technology and training on reducing PHL and improving sales. The integration of financial instruments with technological solutions has emerged as a promising approach. Channa et al. (2022) conducted a randomized controlled trial in Tanzania to explore the combined effects of harvest loans and storage technology on addressing smallholder farmers' post-harvest challenges. Their study revealed that the provision of harvest loans, coupled with the introduction of advanced storage solutions like PICS bags, significantly reduced post-harvest losses and improved the overall livelihoods of smallholder farmers. Their emphasis on PICS bags as a pivotal storage solution aligns with the broader literature that has consistently highlighted the effectiveness

of these bags in diverse settings (Kumar and Kalita, 2017; Chegere et al., 2022).

Developed through a collaborative effort between Purdue University and African institutions in the late 1980s, the PICS bag was initially conceptualized as a response to the devastating PHL of the crops. The genius behind the PICS technology lies in its simplicity. These bags employ a hermetic, or airtight, storage mechanism that effectively shields stored grains from pests without resorting to chemical treatments. This dual advantage of preserving grain quality while eschewing potentially harmful chemicals underscores the transformative potential of PICS bags in the realm of post-harvest storage. The adoption of PICS bags has significantly influenced post-harvest grain storage practices and has been the subject of various research studies. Omotilewa et al. (2018) conducted a study in Uganda, revealing that PICS bags not only improve storage but also indirectly encourage the adoption of modern agricultural inputs, enhancing food security. Meanwhile, Prieto et al. (2017) highlighted the role of PICS bags in reducing the spread of aflatoxins in Senegal, emphasizing their health and economic benefits. These studies underscore the multifaceted impact of PICS bags, from safeguarding health to promoting modern farming practices. Channa et al. (2019) embarked on an empirical exploration into the determinants influencing smallholder farmers' willingness to pay for new agricultural technologies. Their findings underscored that the prior awareness of the new technology can shape people's WTP. The economic dimensions of PICS bag adoption have also been a focal point in contemporary research. Omotilewa et al. (2019) explored the efficacy of subsidies as a catalyst for the uptake of improved grain storage bags in Uganda, highlighting the tangible impact of targeted subsidy interventions in bolstering adoption rates. This sentiment is echoed by Nindi et al. (2023), who examined incentive mechanisms designed to exploit intraseasonal price arbitrage opportunities for

smallholder farmers. Furthermore, the long-term adoption dynamics of storage technologies, such as PICS bags, have been scrutinized by Aker et al. (2023). Their research offers insights into the factors influencing sustained adoption, emphasizing the interplay between demand, supply, and the overarching economic landscape.

The adoption of any technology is often contingent upon the awareness and understanding of its benefits. In the agricultural sector, awareness plays a pivotal role in influencing farmers' decisions to adopt new technologies (Foster and Rosenzweig, 2010). However, even when farmers are aware of a technology, the depth of their understanding, particularly about its multifaceted benefits, can vary. While the intrinsic benefits of PICS bags are evident, many potential adopters might not be fully cognizant of all these advantages. This gap in understanding can be attributed to various factors, including limited exposure to information or the nature of information dissemination strategies employed. Drawing from advertising theories, it's well established that the framing and content of a message can significantly influence its persuasiveness (Heath et al., 2009).

Given this context, our research question emerges: How do different informational treatments, specifically emphasizing health versus profit benefits, influence farmers' willingness to pay for PICS bags? To empirically address this, we conducted a randomized controlled trial (RCT) to assess the differential effects of these informational treatments on farmers' valuation of PICS bags. we further explore to understand the overall heterogeneity of WTP and the heterogeneity in responses to our informational treatments. Specifically, risk preferences have been identified as a crucial determinant in technology adoption decisions (Liu (2013); Channa et al. (2021)). Furthermore, income levels and the Household Dietary Diversity Score (HDDS) can significantly influence technology adoption decisions(Parente and

Prescott (1994)). Given these insights, we incorporate risk attitude, income level and HDDS as pivotal factors in our heterogeneity analysis.

The key contributions of this research are as follows: Firstly, this study enriches the understanding within the agricultural technology adoption literature by exploring the impact of different types of informational treatments on farmers' WTP for PICS bags. Our analysis reveals that profit-oriented information significantly enhances WTP, whereas in our sample of smallholder farmers from Sierra Leone, health-related information does not. This finding helps fill the gap in knowledge about the effectiveness of various informational strategies in promoting agricultural technology adoption. Secondly, we extend the existing research by incorporating heterogeneity analysis. Our heterogeneity study demonstrates how risk preference level, income level and HDDS influence the effectiveness of informational treatments.The involvement of risk attitude, especially addressing a gap in understanding the role of behavioral attributes in farmers' decision-making processes in Africa. Lastly, by focusing on Sierra Leone, a context with distinct economic and developmental challenges compared to other African nations like Kenya or Tanzania with higher incomes, our research helps fill a geographical gap in the literature. As shown Table 1 (WorldBank (2024)), Sierra Leone is markedly one of the poorest countries in its region, with a significantly lower GDP and GDP per capita compared to other African nations on average. Agriculture plays a dominant role in its economy, contributing to over 60% of its GDP. This heavy reliance on agriculture, combined with the country's economic status, presents a unique set of challenges and opportunities for technology adoption. This contributes to a more comprehensive and inclusive understanding of technology adoption dynamics in varying economic contexts, particularly in lower-income countries.

Table 1: Sierra Leone Economic Performance Overview

	GDP (current US$, billion)	GDP per capita (current US$)	Agricultural land (% of land area)	Agriculture, forestry, and fishing, value added (% of GDP)
Sierra Leone	**4.09**	**475.8**	**54.7**	**60.4**
Sub-Saharan Africa	-	1701.2	44.1	17.3
Kenya	113.42	2099.3	48.7	21.2
Tanzania	75.93	1192.8	44.6	24.3
Nigeria	472.62	2162.6	75.4	23.7

The subsequent sections will delve into the methodology employed to empirically test these hypotheses, followed by a presentation and discussion of the findings.

2 Study Design

The research was conducted in Sierra Leone, specifically focusing on Moyamba District, a district in the Southern Province of the country. Figure 1 shows the location of Moyamba District, which is highlighted in light blue, with our survey sample points distinctly marked in dark blue. This district is predominantly rural, with its landscape marked by extensive farming activities that are central to the livelihoods of its residents. Households in Moyamba District cultivate rice, cassava, groundnuts, sweet potatoes, and oil palm (Yila et al., 2022). Our survey was conducted across various villages in Moyamba, selected for their proximity to one another, ensuring a coherent understanding of the local agricultural practices and community dynamics. A total of 436 households participated in the study. Figure 2 provides a detailed visualization of the sample distribution within Moyamba District. Our empirical approach comprises three distinct phases: the randomized controlled trial (RCT) design, the survey design, and the Becker-DeGroot-Marschak (BDM) auction to elicit willingness to pay (WTP).

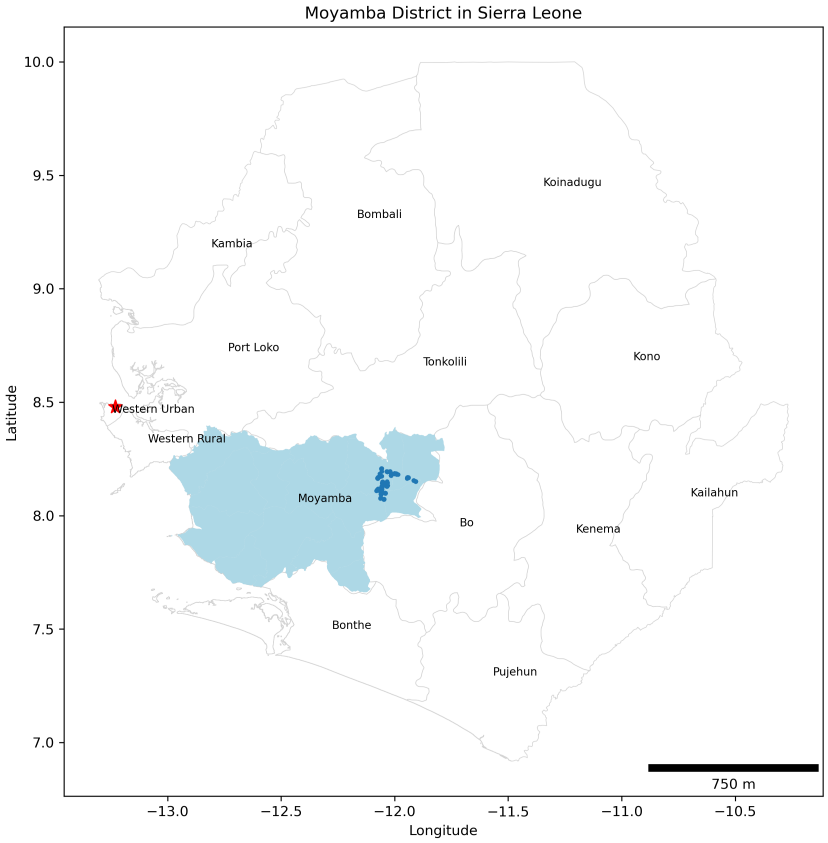

Figure 1: Map of Sierra Leone and Study Area

2.1 Randomized controlled trial design

The randomized controlled trial (RCT) was the foundational element of our research design, aimed at understanding the differential impacts of specific information on participants' perceptions of the PICS bags. At the inception of each interview, participants were systematically randomized into one of three intervention groups. This allocation was determined by the sequence in which they were approached by the enumerator. There are in total of three intervention groups:

1. **Health Information Group.** Participants in this group were informed about the

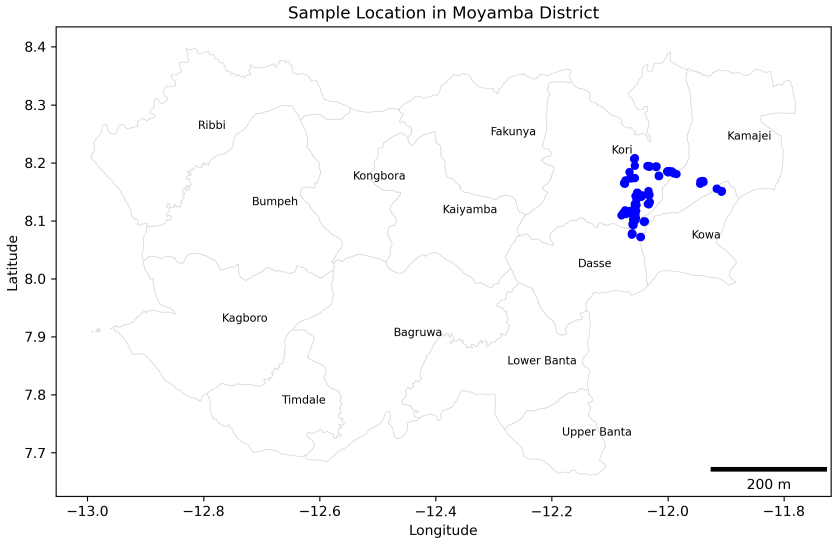

Figure 2: Map of Moyamba District and Sample Distribution

health benefits associated with the user instruction of PICS bags during the introductory phase. The discussion emphasized the bags' proficiency in protecting crops from pests and molds, which not only ensures safer grain storage but also significantly enhances food security. By using PICS bags, households can substantially reduce the risk of consuming contaminated grains, which are often linked to severe health issues such as diarrhea and certain types of cancer.

2. **Profit Information Group.** This group of participants was informed about the economic advantages of using PICS bags. The focus was on the potential for reduced post-

harvest losses and the opportunity to achieve higher profits from selling more grains at better prices.

3. **Control Group.** Participants in the control group were provided with standard user instructions for the PICS bags without any supplementary information on health or profit benefits.

Treatment group	Group 1: Health information	Group 2: Profit information	Group 3: Control group
Number of observations	170	133	111
% of the sample	41.06%	32.13%	26.81%

Table 2: Treatment Distribution

Following the random assignment, Table 2 presents the distribution of participants across the three intervention groups. As can be observed, the Health Information Group (Group 1) makes up 41.06% of the total sample. The Profit Information Group (Group 2) has 133 participants, accounting for 32.13% of the sample. The Control Group (Group 3) consisted of 111 participants, representing 26.81% of the total.

2.2 Survey design

Following the introduction and information treatment, enumerators administered a comprehensive survey to each respondent. The survey was designed to capture a range of demographic, socio-economic, and behavioral variables. Key questions included but not limited to household income and expenditure, assets, dietary diversity, self-reported risk preference, food security status, and Poverty Probability Index (PPI) score. Additionally, participants will be asked questions related to post-harvest loss and agricultural technology, such as whether they have previously experienced post-harvest loss, whether they have received

any training on the subject, and so on. The survey data serves multiple purposes. First, it provides context and descriptive statistics about the study population, enhancing our understanding of the sample's characteristics. Second, the data facilitates an exploration into the key drivers influencing variations in willingness to pay (WTP). By analyzing these factors, we can have a deeper understanding of the heterogeneity of WTP across different segments of the population.

2.3 Experiment to elicit willingness to pay for a PICS bag

We adopt The Becker-DeGroot-Marschak (BDM) auction (Becker et al., 1964) to elicit the willingness to pay for the PICS bags. The BDM auction is based on the premise that an individual's WTP for a good is equal to the expected utility that the good provides. In this auction, participants are asked to bid a price that they are willing to pay for a good. If their bid is higher than a randomly chosen price, they have to pay the randomly chosen price and receive the good; if their bid is lower than the randomly chosen price, they do not have to pay anything and do not receive the good. BDM auction ensures that the bid is a true WTP and avoids hypothetical bias by requiring participants to pay if they win the auction.

In order to elicit the participants' willingness to pay, the participants will then participate in a BDM auction on the PICS hermetic bag. Respondents will be asked to state the amount they are willing to pay for the bags. A random price will then be generated, ranging from 10 SLL to 55 SLL (the market price of a PICS bag), and if the participant's stated price is higher than the randomly generated price, they will be required to purchase the bag at the random price. Participants will select a card from 5 different cards with values of 10

SLL, 20 SLL, 30 SLL, 40 SLL, and 50 SLL, which will determine the random price. Before revealing the random price, participants can adjust their initial bid price, and if their bid price is lower than the random price, they will not be required to purchase the bag.

3 Empirical Analysis

3.1 Descriptive statistics

3.1.1 Sample characteristics and balance check

In Table 3, we present a comprehensive descriptive analysis across three distinct types of variables—Demographics, Wealth, and Food Security—to elucidate the baseline characteristics and variations among the three groups in our study. Row 5 - Row 7, representing the p-values from the t-tests, serves as a balance check, ensuring that the distribution of these variables is statistically indistinguishable across the groups, thereby affirming the efficacy of our randomization process.

Panel 1 firstly delineate the demographic composition of our study's participants, which presents an overview of selected demographic indicators, segmented across three groups, with each variable's mean and standard deviation. The age distribution across the triad of groups gravitates around 43 years, exhibiting minimal inter-group variance. The sex distribution underscores an equitable gender representation. There is around a 50% male composition across all groups. The education variable shows the respondent's highest attained educational level. It encompasses a spectrum from individuals with no formal schooling, differentiating between literacy capabilities, to those with post-secondary educational experiences. The

mean values intimate that a significant proportion of respondents have either culminated their primary education or achieved some level of secondary schooling. The risk propensity variable is a self-reported measure capturing the respondent's inclination towards risk-taking. The data suggests a median risk disposition among respondents, skewing slightly towards risk aversion.

Panel 2 in Table 3 displays the descriptive statistics of the wealth indicators of the respondents, segmented across the groups. The income variable is the cumulative household income accrued over 12-month period. The Household Asset Index is an aggregated metric, generated from the ownership status of various household commodities including items such as radios, televisions, mobile phones, computers, and vehicles, among others. The in-home assets considered are in total of 10 items. Similarly, for the farm asset index, we considered ownership of agricultural land, granaries, tractors, mechanical threshers, and other farm-related equipment (in total of 16 items), summing the presence of these items to create a comprehensive index that quantifies the farm assets owned. On average, households possess around 2 to 3 assets, both within the home and on the farm. The most popular reported assets within the home were mobile phone and radio, while for the on-farm assets, agricultural and non-agricultural lands, granary are the most commonly owned assets.

We display the variables related to food security in Panel 3. A predominant issue in the past 12-month across all groups is food loss *"Have you ever experienced any post-harvest loss in the past 12 months?*", with an overwhelming majority, exceeding 95% of respondents, reporting such experiences. This ubiquity suggests that food loss is not an isolated problem but a pervasive challenge across the sample. Complementing this finding, the average number of food loss occurred in the past pass year was between approximately 37 kg to 46 kg for the

groups.

Despite these challenges, the Household Dietary Diversity Score (HDDS) remains relatively high across all groups, approximating a score of 9. This suggests that households, irrespective of the adversities associated with food loss, endeavor to maintain a diverse dietary intake. However, the undercurrents of food insecurity are prominent. Over half of the respondents across the groups, with proportions ranging from 55% to 66%, express their concerns about potential food shortages. Furthermore, a non-trivial segment, between a quarter to a third of households, recounted instances of absolute food scarcity due to resource constraints in the past month. The data indicates that a modest majority, spanning from 48% to 58% across groups, report having undergone some form of training of preventing post harvest loss. In the question "*Are you willing to pay for a new storage bag to reduce post harvest loss?*", we observe an overwhelming willingness to pay for a storage technology, with proportions exceeding 95% across all groups, which underscores a collective recognition of the problem and draws our interest in tangible solutions.

The p-values, which are shown in the row 5 to row 7, are consistently over standard significance benchmarks. This provides evidence for that no statistically significant differences exist in these variables' distribution across the groups. This validates the effectiveness of the RCT's randomization, ensuring that the groups are comparable based on the outlined variables, thereby setting a solid groundwork for the subsequent RCT impact analysis.

3.1.2 Outcome of interest

The distribution of the bid price from the respondents is displayed in figure 3. Analyzing the data from 424 (after dropping 12 missing values) respondents, we found that the average bid

Table 3: Descriptive statistics and balance check

	Group 1	**Group 2**	**Group 3**	**t-test** group1-2	**t-test** group 1-3	**t-test** group 2-3
Panel 1: Demographics						
Age	43.74 (12.16)	43.30 (12.17)	43.43 (11.62)	0.62	0.83	0.80
Age of head of household	47.68 (11.13)	48.00 (11.57)	48.45 (11.34)	0.53	0.41	0.84
Household size	6.50 (2.19)	6.34 (1.80)	6.94 (2.48)	0.29	0.22	0.03*
Sex (Male = 1)	0.51 (0.50)	0.45 (0.50)	0.47 (0.50)	0.45	0.56	0.90
Sex of head of household (Male = 1)	0.71 (0.45)	0.69 (0.46)	0.66 (0.48)	0.97	0.43	0.44
Education(category 0-7)	2.97 (2.29)	2.86 (2.31)	2.83 (2.13)	0.82	0.72	0.90
Self-reported risk attitude	3.20 (1.67)	3.04 (1.64)	3.07 (1.67)	0.52	0.53	0.98
Panel 2: Wealth						
Income	25753.63 (59708.22)	19215.93 (44060.49)	18764.95 (283963.9)	0.28	0.24	0.87
Household asset	2.27 (1.13)	2.21 (1.00)	2.28 (1.20)	0.69	0.97	0.61
Farm asset	3.58 (0.88)	3.57 (0.80)	3.60 (0.77)	0.56	0.77	0.74
Number of rooms	4.21 (1.20)	4.35 (1.21)	4.25 (1.15)	0.71	0.35	0.16
Panel 3: Food Security						
Food loss (Yes = 1)	0.97 (0.17)	0.98 (0.12)	0.98 (0.14)	0.44	0.59	0.85
Number of food loss	37.61 (21.25)	42.02 (31.99)	45.50 (33.66)	0.18	0.01**	0.26
HDDS	9.19 (2.35)	9.09 (2.34)	8.77 (2.32)	0.74	0.17	0.32
Worried food	0.66 (0.47)	0.64 (0.48)	0.55 (0.50)	0.90	0.07	0.11
No food	0.31 (0.47)	0.31 (0.46)	0.25 (0.43)	0.97	0.39	0.40
Trained or not (Yes = 1)	0.55 (0.50)	0.58 (0.50)	0.48 (0.50)	0.77	0.10	0.07
WTP for a storage technology (Yes = 1)	0.96 (0.19)	0.96 (0.19)	0.95 (0.21)	0.06	0.92	0.14

price for PICS bag was approximately 21.27 Leones, which is less than half of the market price of PICS bag. Given this relatively low willingness-to-pay (WTP), it becomes imperative to explore the factors that can potentially drive higher purchase rates, especially considering the substantial benefits the PICS bags can offer to the users in terms of food security and reduction in post-harvest losses. By providing different information interventions, we aim to understand how enhanced knowledge and awareness about the benefits and profitability of PICS bags can influence individuals' valuation and their WTP, thereby potentially leading to increased adoption of agricultural innovations.

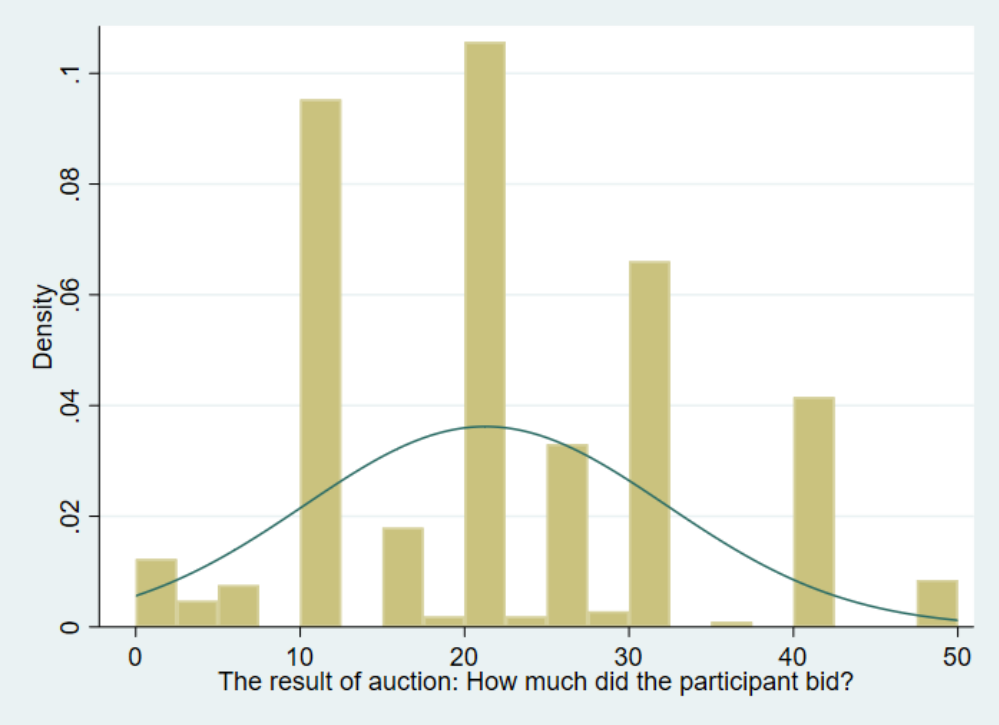

Figure 3: Bid Price Distribution

3.2 Econometrics framework

3.2.1 Impact evaluation of information intervention

To estimate the causal effect of the information interventions on the willingness to pay (WTP) for the PICS bags, we employ a linear regression model. Let Y_i denote the bid price for individual i. We use dummy variables to represent the treatment groups: D_{1i} for "Group 1: Health and food security" and D_{2i} for "Group 2: Profits". The error term is represented by ϵ_i.

The regression equation is given by:

$$Y_i = \beta_0 + \beta_1 D_{1i} + \beta_2 D_{2i} + \epsilon_i \tag{1}$$

Where:

- β_0 captures the mean bid price for the reference group (Group 3: Basic information).
- β_1 represents the difference in mean bid price between Group 1 and the reference group.
- β_2 represents the difference in mean bid price between Group 2 and the reference group.

The coefficients β_1 and β_2 can be interpreted as the treatment effects of Group 1 and Group 2, respectively, relative to the control group (Group 3).

3.2.2 Heterogeneity of Willingness to Pay

In this section, we delve into the heterogeneity of willingness to pay (WTP) for PICS bags across different demographics and socio-economic segments within Moyamba District. Our

goal is to uncover how various factors contribute to the diverse WTP responses and how the effects of the information treatment vary across people with different characteristics.

Determinants and Overall Heterogeneity

We initially address the determinants of willingness to pay (WTP) for PICS bags, examining the overall heterogeneity in WTP responses. We use regression analysis to provide insights into direct relationship of WTP and various factors such as demographics and socio-economic status. The regression equation is:

$$WTP_i = \beta_0 + \beta_1 X_i + \beta_2 info_i + \epsilon_i \tag{2}$$

Where WTP_i is the willingness to pay of individual i, which is captured by the bid price in the auction. X_i represents the vector of predictor variables as shown in Table 4. We also include the treatment groups ($info_i$) as a control variable.

Treatment Impact Heterogeneity: Interaction Terms Analysis

We then shift our focus to the heterogeneity in treatment impacts. The subsequent section will involve specific interaction effects, exploring how individual characteristics influence responsiveness to health and profit-oriented information interventions. We apply the following regression model:

$$\begin{aligned} WTP_i = \beta_0 + \beta_1 \text{Health}_i + \beta_2 \text{Profit}_i + \beta_3 (\text{Health}_i \times \text{Characteristics}_i) \\ + \beta_4 (\text{Profit}_i \times \text{Characteristics}_i) + \epsilon_i \end{aligned} \tag{3}$$

Table 4: Operationalization of Predictor Variables

Predictor	**Measurement**	**Description**
Age of household head	Numeric	-
Sex of household head	Binary	= 1 if male, = 0 if female.
Age of respondent	Numeric	-
Sex of respondent	Binary	= 1 if male, = 0 if female.
Number of household member	Numeric	-
Education level of respondent	Categorical (0 to 7)	Numerical scale for educational attainment, ranging from '0' (no schooling, can't read/write) to '7' (Adult Education), including various levels of education and literacy.
Income level	Numeric	Represents households' annual income.
Farm asset index	Numeric	Aggregate index representing ownership of various farming assets, including land, machinery, and agricultural tools.
Household asset index	Numeric	Summative index of household items ownership, such as electronics, vehicles, and appliances.
Risk preference level	Categorical (1 to 5)	Self-assessment of risk preference, ranging from '1' for "not at all willing to take risks" to '5' for "very willing to take risks", with intermediate levels of risk willingness.
Experienced food loss	Binary	= 1, if experienced food loss in the past 12 month; = 0 otherwise.
Household dietary diversity score	Numeric	Cumulative score based on the consumption of various food groups, including grains, vegetables, fruits, meats, dairy, and others. Higher scores indicate greater dietary diversity.
No food to eat	Binary	= 1 if experienced no food to eat in the past 30 days, = 0 otherwise.
Trained or not	Binary	= 1 if ever been trained on storage techniques, = 0 otherwise.

Where:

- WTP_i represents the willingness to pay of individual i.
- Health_i and Profit_i are binary indicators for the health and profit informational treatments, respectively.
- Characteristics_i is the measure capturing different characteristics i. The characteristics we consider here include risk preference level, income level and HDDS of the households.
- The terms ($\text{Health}_i \times \text{Characteristics}_i$) and ($\text{Profit}_i \times \text{Characteristics}_i$) are interaction terms that capture the differential effects of the informational treatments across varying

levels of risk attitude, income and HDDS.

- ϵ_i is the error term.

The coefficients β_3 and β_4 are of primary interest as they capture the interaction effects between the informational treatments and individual characteristics. Specifically, β_3 measures the differential effect of the Health informational treatment on WTP across varying characteristics. Similarly, β_4 captures the analogous interaction effect for the Profit informational treatment. A significant positive (negative) coefficient would indicate that the impact of profit-related information on WTP is amplified (diminished) for individuals with certain characteristics. In the subsequent analysis, we will estimate this model using the collected data. Robust standard errors will be employed to account for potential heteroskedasticity.

4 Results

4.1 Effects of information intervention on WTP

Table 5 presents the primary findings from our evaluation of the information treatments. Column (1) offers the results without accounting for potential enumerator-specific effects. Despite all enumerators undergoing uniform training, individual nuances in their interview techniques and information delivery could exist. Such nuances might introduce variability in the way participants receive and process the information, potentially influencing their willingness to pay. To account for potential heterogeneity arising from these enumerator-specific effects, we cluster standard errors at the enumerator level. The results of this specification are reported in Column (2) of Table 5.

Dependent variable: Bid price	(1)	(2)
Treatment 1:	1.76	1.76
Health information	(1.31)	(1.18)
Treatment 2:	3.45**	3.45*
Profit information	(1.40)	(0.48)
cons	19.48***	19.48***
	(1.03)	(0.51)

Table 5: RCT main results

The coefficient for the Health Information treatment in Column (1) suggests a positive but statistically insignificant increase in the bid price by 1.76 Leones (the local currency) when participants are provided with health-related information about the PICS bags. The Profit Information treatment, on the other hand, indicates a statistically significant positive effect on the bid price, with participants willing to pay an additional 3.45 Leones, significant at the 1% level. In Column (2), with clustered standard errors, the Health Information treatment retains its positive direction but remains statistically insignificant. The Profit Information treatment's effect remains positive and statistically significant at 5% level, underscoring the robustness of this result. Our research contributes to the exploration of factors influencing the willingness to pay (WTP) for Purdue Improved Crop Storage (PICS) bags, complementing studies by Mwaijande (2017); Channa et al. (2019, 2021, 2022); Omotilewa et al. (2019) that identified key determinants including household income, education level, the presence of subsidies, and financial support. Diverging from the traditional focus on households' intrinsic characteristics or attempts to alter their circumstances through subsidies, our study examines the impact of information intervention as an external catalyst for decision-making and adds a new angle on the dynamics of adoption behavior.

In summary, our findings emphasize the strong influence of profit-related information on

participants' willingness to pay for PICS bags. Health-related information, while directionally positive, does not have a statistically significant impact on bid prices in our sample. The consistency of these results, even after adjusting for enumerator-specific effects, highlights the pivotal role of economic incentives in shaping adoption decisions among smallholder farmers.

4.2 Heterogeneity analysis

4.2.1 Overall heterogeneity of WTP

Our analysis, detailed in Table 6, explores the overall heterogeneity of WTP for hermetic bags through various regression specifications. The table presents findings from both an OLS model with pooled treatment variables and with specific treatment types as the controls. Among various factors considered, two variables stand out due to their statistical significance and potential implications: the Household Dietary Diversity Score (HDDS) and the risk preference level of individuals.

The negative coefficient associated with HDDS suggests that as the diversity of a household's diet increases, their WTP for hermetic bags decreases. This finding could indicate that households with more varied diets may allocate their resources differently, perhaps due to a broader range of food security strategies beyond hermetic storage. Alternatively, it might reflect varying priorities in households with different dietary patterns, with those having less diverse diets possibly perceiving a greater need for improved storage solutions like hermetic bags. The risk preference level of respondents also shows significant influence on WTP, with a negative association. This result implies that individuals who are more risk-averse are less

likely to invest in hermetic bags. This finding aligns with general economic theory, where risk-averse individuals are often more cautious about adopting new technologies, especially when the benefits are uncertain or perceived as risky. The implication for stakeholders is clear: to increase adoption rates, it is crucial to address these risk concerns, possibly by providing more information, demonstrations, or guarantees about the effectiveness of hermetic bags.

Table 6: Determinants of willingness to pay

Predictor	**(1)** **OLS (with pooled treatment)**	**(2)** **OLS (with specific treatment)**
Age of respondent	0.0886	0.0912
	(0.0578)	(0.0578)
Age of household head	0.0246	0.0206
	(0.0594)	(0.0595)
Sex of respondent	0.0991	0.1778
	(1.3226)	(1.3226)
Sex of household head	0.4384	0.3733
	(1.4503)	(1.4498)
Number of household member	0.1778	0.1950
	(0.2526)	(0.2527)
Education level of respondent	0.3383	0.3397
	(0.2557)	(0.2554)
Income level	4.45e-06	-0.0761
	(3.39e-06)	(0.3174)
Farm asset index	0.0354	0.0457
	(0.6764)	(0.6758)
Household asset index	0.9613	0.9687
	(0.5246)	(0.5242)
Risk preference level	-1.0374*	-1.0119*
	(0.4632)	(0.4632)
Experienced food loss	2.2941	2.0967
	(3.6267)	(3.6264)
Household dietary diversity score	-0.7412**	-0.7365**
	(0.2773)	(0.2770)
No food to eat	-1.8793	-1.8565
	(1.1432)	(1.1422)
Trained or not	1.1726	1.1232
	(1.2349)	(1.2343)
Pooled treatment	2.8066*	-
	(1.1843)	
Received health information	-	2.1289
		(1.2878)
Received profitability information	-	3.7442**
		(1.3764)
R-squared	0.1113	0.1151

4.2.2 Treatment impact heterogeneity

While the overall heterogeneity and the primary effects of informational treatments on WTP have been established, it is also important to examine how these effects vary across different sub-groups. Specifically, we are interested in understanding how individual characteristics, such as risk attitude, income levels, and household dietary diversity scores (HDDS), modulate the impact of our treatments.

Table 7 presents the results of our regression analysis, where we explore these interaction effects with two specific treatments. Each column represents a different model, focusing on the interaction between the informational treatments and one of the aforementioned individual characteristics.

Dependent Variable: WTP for PICS bag	(1) Risk Attitude	(2) Income	(3) HDDS
Treatment 1: Health	7.19 (1.95)	2.14 (1.26)	4.12* (0.57)
Treatment 2: Profit	8.12*** (0.25)	7.60 (2.38)	9.52** (0.53)
Interaction term: Health * RiskAttitude	-1.68* (0.35)	-	-
Interaction term: Profit * RiskAttitude	-1.51** (0.16)	-	-
Interaction term: Health * Income	-	-0.00 (8.48e-06)	-
Interaction term: Profit * Income	-	-0.00** (1.79e-06)	-
Interaction term: Health * HDDS	-	-	-0.80* (0.16)
Interaction term: Profit * HDDS	-	-	-0.67* (0.10)

Table 7: Heterogeneity of WTP based on different characteristics

Heterogeneity based on risk attitude

Driven by Liu (2013)'s investigation into the intersection of risk attitudes and technology

adoption, our research similarly focuses on the significance of risk preferences. Liu (2013) found a strong correlation between farmers' risk attitudes and their decisions to adopt new technologies. Echoing this finding, our study reveals the substantial impact of risk preferences on the responsiveness of farmers to informational interventions. Column (1) of Table 7 shows the heterogeneity in WTP based on participants' self-reported risk attitudes. The coefficients of interest are those associated with the interaction terms between the informational treatments and the RiskAttitude variable. Turning to the interaction effects, the coefficient for the interaction between the Health informational treatment and RiskAttitude is -1.68, significant at the 5% level. This negative interaction suggests that as participants become more willing to take risks (i.e., as their RiskAttitude score increases), the incremental effect of health-related information on their WTP diminishes. In essence, those with a higher propensity for risk seem to value the health benefits of PICS bags less than more risk-averse people. Similarly, the interaction between the Profit informational treatment and RiskAttitude yields a coefficient of -1.51, significant at the 1% level. This indicates that the more risk-averse farmers are, the less they increase their WTP in response to profit-oriented information. Specifically, as farmers become more risk-averse, the additional WTP attributable to profit-related information increases. This could be because risk-seeking farmers might already be more inclined to adopt new technologies or practices without needing as much persuasion from the profit perspective. On the other hand, risk-averse farmers might require more convincing about the potential profitability of the PICS bags to be willing to pay a higher price for them.

In summary, our findings suggest that the effectiveness of both health and profit-oriented information in influencing farmers' WTP for PICS bags varies based on their risk preferences.

Specifically, risk-averse farmers seem to value both types of information more, as reflected in their higher WTP when exposed to these treatments.

Heterogeneity based on income level

In our analysis, we use the total annual income reported by the participants. This indicator allows us to discern how willingness to pay for PICS bags varies across different income level, potentially reflecting differences in purchasing power, risk tolerance, and perceived value of the bags.

Column (2) of Table 7 reveals that the interaction between income levels and the Profitability information treatment yields a statistically significant outcome. However, the magnitude of the coefficient is minimal, suggesting that its economic significance is limited. This observation may indicate that perceptions of the health and profit advantages associated with PICS bags do not vary significantly among various income levels.

Heterogeneity based on HDDS The Household Dietary Diversity Score (HDDS) is a reflection of the economic ability of a household to access a variety of foods, and it can also be an indirect indicator of the nutritional adequacy of a household's diet. In our study, we explore how this measure of household well-being and nutritional access interacts with the informational treatments to influence WTP for PICS bags.

From the results in Column (3) of Table 7, the interaction between the Health informational treatment and HDDS yields a coefficient of -0.80, significant at the 5% level. This negative interaction suggests that as the dietary diversity of a household improves (indicating better economic and nutritional status), the incremental effect of health-related information on WTP decreases. This could be interpreted as households with better dietary diversity, possibly having better access to nutritious foods, place a reduced premium on the health

benefits of PICS bags. They might already have strategies in place to ensure food safety and might not see as much added value from the health benefits of the bags. Conversely, the interaction between the Profit informational treatment and HDDS has a coefficient of -0.67, also significant at the 5% level. This indicates a similar trend: households with higher dietary diversity scores, and potentially better economic standing, are less influenced by profit-oriented information in terms of their WTP.

5 Discussion and conclusion

We study the impact of distinct informational treatments on farmers' willingness to pay (WTP) for PICS bags, with a particular emphasis on health and profit benefits. Among the informational treatments, it was the profit-oriented information that significantly influenced farmers' WTP for PICS bags. This finding underscores the salient role that potential profitability plays in shaping farmers' valuation of agricultural technologies. On the contrary, health-related information, despite its inherent importance, did not manifest a significant effect on WTP in our sample. Furthermore, our study of the heterogeneity of responses illuminated that individual characteristics, notably risk attitude and HDDS, played pivotal roles in modulating the impact of our treatments. Income level did not exhibit any heterogeneity in its interaction with the treatments.

For agricultural extension services, NGOs, and other stakeholders aiming to promote the adoption of such technologies, emphasizing the economic benefits could be a strategic move. This aligns with the observed preferences of farmers and suggests that tailored messaging, focusing on profitability, can enhance the likelihood of successful technology adoption. Be-

yond the realm of information dissemination, there is a compelling case for comprehensive training programs. Such initiatives should not only introduce farmers to the technology but also equip them with the requisite skills to maximize profitability. This could encompass modules on optimal storage practices, understanding market dynamics, and even rudimentary financial management, ensuring farmers are well-positioned to harness the full economic potential of their produce. When evaluating the success of agricultural interventions, stakeholders might consider prioritizing economic metrics. Incorporating measures such as net income increases, return on investment, or cost-benefit ratios can provide a more resonant and clearer picture of an intervention's impact, given the motivations of farmers.

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