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# Economic and behavioral determinants of rice farmers' preferences and willingness to pay for mechanized harvesting services in Nigeria

**RESEARCH ARTICLE**

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## Abstract

Postharvest losses represent a significant challenge to the rice value chain and food security in Nigeria, with the majority of these losses occurring during harvesting phase. Traditional manual harvesting methods contribute notably to these losses. However, there is limited understanding of rice farmers' preferences and willingness to pay for mechanized harvesting services. We investigate the drivers of farmers' preferences and willingness to pay for mechanized harvesting services using two types of mechanized harvesters. We conduct a field survey employing the contingent valuation method and a two-stage approach to elicit farmers' willingness to pay. Findings indicate a strong preference for mechanized harvesters over manual methods, with the large-sized mechanized harvester being the most favored. A double-hurdle model analysis reveals that while farmers are willing to pay for the mechanized harvesting services, their willingness is constrained by the affordability, as they demand highly discounted prices. Furthermore, both socio-economic characteristics and individual perceptions of post-harvest losses significantly influence preferences and willingness to pay. Survival analysis suggests that the demand for mechanized harvesting services is highly elastic. These finding underscore the potential for targeted policies promoting mechanized harvesters, which could reduce post-harvest losses and improve food security in Nigeria.

**Keywords:** contingent valuation, elasticity, mechanized harvesters, postharvest losses, willingness to pay.
**JEL codes:** C25, D12, Q13, Q16

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# 1. Introduction

Post-harvest losses (PHL) remain a major constraint to food security and poverty alleviation in Sub-Saharan Africa (SSA), particularly in the context of rapidly growing food demand. PHL refer to a measurable reduction in both the quantity and quality of food along the postharvest value chain, spanning from harvesting to consumption (Grolleaud, 2002; Kader, 2013; Kok and Snel, 2019). With SSA's population projected to double by 2050, ensuring food security requires urgent interventions to minimize inefficiencies in agricultural production and distribution. However, persistent PHL exacerbate existing food insecurity, impeding progress toward the Sustainable Development Goals (SDGs), in particular zero hunger (SDG2) and no poverty (SDG 1) (Affognon *et al*., 2015; Hodges *et al*., 2011; Kumar and Kalita, 2017).

The scale of PHL is alarming. Estimates indicate that 20–40% of total food production in Africa is lost post-harvest, amounting to an annual economic loss of USD 4 billion, which is equivalent to the total cost of cereal imports in SSA (Abass *et al.* 2014; Affognon *et al*., 2015; Kumar and Kalita, 2017). Losses in staple crops such as maize, wheat, and rice are particularly detrimental, with rice losses alone accounting for 53% of total caloric losses, enough to meet the energy needs of over 48 million people (Kumar and Kalita, 2017).

The rice sector is particularly strategic for food security and poverty alleviation in Nigeria, where rice is the third most consumed stable crop and the fourth largest provider of calories (Cadoni and Angelucci, 2013). Nigeria is the largest rice producer in Africa, yet its rice value chain suffers from severe inefficiencies, particularly during harvesting (Castelein *et al*., 2022; Ogundele, 2022).

The postharvest segment of the rice value chain (VC) includes multiple stages—harvesting, threshing, winnowing, transportation, drying, parboiling, processing, storage, and marketing (Castelein *et al*., 2022; Ogundele, 2022). Among these, harvesting is consistently identified as the stage with the highest proportion of losses (Castelein *et al.*, 2022; Ogundele, 2022; Oguntade *et al.*, 2014).[1] However, estimated rice PHL in Nigeria vary significantly, with studies reporting rates ranging from 8 to 25% (Ogundele, 2022; Oguntade *et al.*, 2014; Sani *et al.*, 2022) equivalent to USD 153.24 million in economic losses (Castelein *et al.*, 2022). Moreover, these losses have severe environmental consequences, as CO2-equivalent emission from PHL represent 0.4% of Nigeria's total greenhouse gas (GHG) emission (Castelein *et al.*, 2022; Kumar and Kalita, 2017).

Historically, African government have implemented large-scale agricultural mechanization programs to modernize farming, notably during the 1960s and 1970s. However, these initiatives largely failed due to governance issues, lack of sustainability, and weak institutional support (Daum and Birner, 2020). In Nigeria, for instance, mechanized harvesters (MH) were introduced in previous decades, but adoption rates among smallholder farmers remained low due to economic and infrastructural constraints (Van Pham, 2016). Today, most farmers still rely on manual harvesting, typically using sickles, leading to high losses and labor inefficiencies (Kamai *et al.*, 2020; Oguntade *et al.*, 2014).

The low adoption of mechanized harvesting technologies stems from several barriers. Limited awareness and training prevent farmers from understanding and utilizing modern harvesting methods (Abass *et al.*, 2014). The scarcity of mechanization service providers further restricts access to these technologies (Castelein *et al*., 2022). High costs and affordability constraints make the upfront investment prohibitive for smallholder farmers (Kumar and Kalita, 2017). Additionally, weak market linkages hinder demand aggregation, limiting cost-sharing opportunities that could facilitate adoption (Oguntade *et al.*, 2014).

[1] Harvesting is an important phase in the postharvest system since it marks the beginning of a series of logically related functions after production operations. Furthermore, it has a considerable impact on the final yield and quality of the final product (Affognon *et al*., 2015).

Recognizing these challenges, recent policy and development interventions have prioritized mechanization as a key strategy to reduce PHL and improve rice productivity and food security. In collaboration with development partners, the Japanese International Cooperation Agency (JICA) and the World Bank-funded FADAMA III project have introduced advanced mechanized harvesting technologies in the Nigeria's two rice development hubs.[2] Through JICA initiatives, the rice reaper harvester (Figure 1, left) has been deployed in each of the rice hubs, while FADAMA III introduced the mini harvester (Figure 1, right) has been introduced in the Kano rice hub. These two technologies have been field-tested by extension services with the objective of large-scale dissemination among farmers. However, before scaling up, it is critical to understand farmers' preferences and willingness-to-pay (WTP) for mechanized harvesting services to ensure sustainable adoption.

While extensive research exists on farmers' preferences for storage technologies (e.g., Bokusheva *et al.*, 2012; Channa *et al.*, 2019; Gbénou-Sissinto *et al.*, 2018), there is limited empirical evidence on farmers' preferences and WTP for mechanized harvesting technologies. Recent work by Castelein *et al*. (2022) highlighted the impact of mechanized harvesting on reducing PHL and GHG emissions in Nasarawa State (Nigeria), showing that adoption of a mechanical reaper reduced paddy losses from 9.6% to 0.9%, increased output by 299 kg/ha, and boosted profits by USD 140.36 (₦50 531)/ha.[3] However, this study did not examine farmers' preferences, WTP, or determinants of technology adoption, critical factors that influence policy recommendations.

We fill this gap by proving a comprehensive analysis of rice farmers' preferences and WTP for two MH services. Specifically, we (1) assess farmers' preferences and WTP for two mechanized harvesting services using the mini-harvester and rice reaper, (2) identify socio-economic and behavioral factors influencing these preferences and WTP, and (3) estimate the own price elasticity of demand for the mechanized harvesting service, providing insights into price sensitivity. Following the existing literature on technology adoption in agriculture (e.g., Adesina and Baidu-Forson, 1995; Adesina and Zinnah, 1993; Channa *et al.*, 2019; Gbénou-Sissinto *et al.*, 2018; Horna *et al.*, 2007; Lazaridou *et al.*, 2019; Okello *et al.*, 2023), we hypothesize that farmers will exhibit a strong preference for mechanized harvesting service over traditional methods. Their WTP will be influenced by socio-economic factors and their perceptions of PHL.


**Figure 1.** (Left) Reaper-harvester (source: shellermachine.com); (right) mini harvester (source: farmpays.com).

[2] For more information on Rice Development Hub, see https://www.africarice.org/rice-sector-development-hubs.
[3] 1 USD=₦360. Naira (₦) is the local currency.

To achieve our research objectives, we conducted a field survey among a randomly selected, representative sample of rice farmers in Nigeria's two major rice hubs. A contingent valuation method combined with a two-stage approach was used to elicit farmers' preferences and WTP. Additionally, a double hurdle model was employed to analyze the determinants of farmers preferences and WTP, while the own price elasticity of demand was estimated using survival analysis.

Results indicate that most farmers prefer the harvesting services over manual methods services, with a strong preference for the reaper, the larger MH. However, their WTP is significantly discounted, and they are highly responsive to price variation. Socio-economic characteristics and perceptions of PHL play a key role in shaping their preferences and WTP.

To the best of our knowledge, no prior study has specifically investigated farmers' preferences for mechanized harvesting. The findings will provide critical information for rice stakeholder in the value chain in Nigeria. Policy decision-makers and development organizations can leverage these results to design more effective interventions that facilitate the adoption of mechanized harvesting. Finally, the study contributes to the limited body of research on farmers' preferences for postharvest technologies, especially harvesting innovations.

This research advances three key areas of literature. First, it deepens our understanding of farmers' preferences and WTP for post-harvest technologies services, addressing a gap in existing studies that have largely overlooked harvesting technologies. Second, it contributes to the growing field of behavioral agricultural economics by exploring how behavioral factors influence decision-making among agricultural value chain actors. Lastly, it enriches the literature on farming technology adoption by providing new insights into mechanized harvesting.

The rest of the paper is organized as follows. Section 2 provides a brief overview of recent development in rice mechanization in Nigeria. Section 3 describes the theoretical background and methods to estimate WTP, while Section 4 presents the methods and data collection process. Section 5 discusses the results, and Section 6 concludes with policy implications.

## 2. Recent developments in rice mechanization in Nigeria

The mechanization of rice harvesting in Nigeria has significant economic implications, especially in light of recent policy and investment trends.

After decades of stagnation, there has been renewed interest in agricultural mechanization as a strategy to improve food security and drive economic development. However, government investments have primarily targeted the production phase (pre-harvest) (Daum and Birner, 2020; Takeshima and Lawal, 2020) and, more recently, the processing sector, while critical post-harvest stage such as harvesting remain largely neglected. One key government initiative has been the provision of tractors at subsidized rates to farmers and/or private service providers, alongside the establishment of hiring schemes and assembly plants (Daum and Birner, 2020). Since 2018, the Nigerian Agricultural Mechanization Equipment Leasing Company has implemented an Agricultural Equipment Hiring Enterprises model, a Public-Private Partnership (PPP) aimed at improving access to mechanized equipment, including harvesters.[4] While this model has expanded mechanization opportunities, its effectiveness in increasing MH adoption is hindered by three major limitations. First, the program remains predominantly focused on tractors rather than comprehensive mechanization solutions. Second, it is primarily deployed in areas with high existing demand for mechanization, leaving other areas underserved. Finally, it imposes financial constraints by requiring farmers or cooperatives to make a 20% equity deposit and repay the cost of the equipment over several years, which limits affordability for small-scale farmers.

[4] See https://namel.ng/bridging-the-mechanization-gap-for-smallholder-farmers-the-aehe-revolution/

In parallel, significant investments have been made in rice processing capacity, making a notable shift in the value chain. In 2023, Nigeria inaugurated the largest rice processing unit in Africa and the third largest globally. This unit, which produces the Eko Rice brand, has a processing capacity of 32 tons/h and an annual output of 2.8 million bags of 50 kg, with the potential to generate 1500 direct jobs and 254 000 indirect jobs while reducing import dependency (Alade, 2023; Iwayemi, 2023). Additionally, private companies, such as OLAM International have invested in large-scale rice processing units to further strengthen local production capacity (Castelein *et al*., 2022).

Despite these advancements, mechanized harvesting remains largely absent from smallholder rice farmers, where manual harvesting continues to dominate (Kamai *et al*., 2020; Takeshima and Lawal, 2020). Given the critical role of harvesting in minimizing PHL and improving productivity, it is essential to investigate farmers' preferences and WTP for mechanized harvesting services as a part of ongoing mechanization efforts. Understanding these preferences will provide valuable insights for designing effective policies and interventions that promote the adoption of mechanized harvesting technologies.

## 3. Theoretical background and methods for assessing WTP

The theoretical foundation for assessing willingness to pay (WTP) is rooted in the theory of utility maximization, which postulates that people make economic decisions to maximize their utility given their constraints (Stigler, 1950). Extending this concept, random utility theroy (Thurstone, 1927) incorporates stochastic elements into decision-making, recognizing that the choices are driven by the alternative yielding the highest perceived utility at the moment it is made. Several random utility models (RUM) have been derived from this theory (McFadden, 1986; Train, 2009), providing the foundation for discrete choice modeling in WTP estimation. In a RUM, a decision-maker makes a choice among a set of $J$ alternatives. Each alternative $J$ provides a level of satisfaction (utility) to the decision-maker $i$ denoted as $U_{ij}, j=1,\dots J$. The individual selects the alternative that provides the largest utility. Therefore, the behavioral model suggests that an alternative is chosen only and only if $U_{ij}>U_{ik}\ \forall\ j\neq k$. This study is based on the random utility theory.

The literature provides two categories of methods to elicit WTP. First, stated preference methods include hypothetical methods such as hypothetical discrete choice experiments and contingent valuation methods (CVM) (Carson and Louviere, 2011). In these approaches, respondents directly state their value for a good or service or their preferences among a set of alternatives (Boxall *et al*., 1996). However, the main weakness of stated preference approaches is the hypothetical bias. It is defined as "the potential error induced by not confronting the individual with an actual situation, i.e., an organized market with well-defined prices" (Schulze *et al.*, 1981). Second, revealed preference methods derive consumers' valuations for goods or services from their observed behavior in a real market situation (Mendelsohn, 2019). Because of the nature of the technology (MH) assessed and its availability at the time of the study, we used a CVM. CVM aims at identifying how subjects make economic tradeoffs to put a value on a good via survey questions (Carson, 2012; Carson and Louviere, 2011). These methods are more suitable for valuation research in agriculture and are popular in Sub-Saharan Africa (Durand-Morat *et al*., 2016; Horna *et al*., 2007).

The elicitation technique used in the CVM is paramount. The literature proposes several techniques to estimate WTP using CVM: an iterative bidding (IB) game, a payment card, a dichotomous choice (DC), a double-bounded dichotomous choice, a stochastic payment card, and randomized card sorting (Durand-Morat *et al*., 2016; Willis, 2002). We used the bidding game format as it provides many advantages and is preferable to other techniques. It combines the features of the DC and the double-bounded DC, and the technique is developed based on an English auction mechanism. In an IB game, a sequence of DC (Would you be willing to pay X dollars for this offer?) is asked to respondents, and it offers several rounds of bids. The bidding ends when the iterations have converged to a point estimate of WTP with the final question being open-ended (what is the maximum you will be willing to pay for this offer?) (Willis, 2002). IB games encourage respondents to consider their preferences carefully, provide relatively better results since it gives market context, and the researcher could obtain the maximum WTP value. In addition, it allows generating in detail the demand curve. This method is, nevertheless, subject to the anchoring bias, which occurs when the initial price influences an individual's final WTP (Willis, 2002).

## 4. Methods

### *4.1 Study area and data collection*

The study was conducted in the two rice development hubs in Nigeria as established by the National Cereal Research Institute (NCRI) in partnership with the Africa Rice Center (AfricaRice, 2011). Lafia rice hub includes Nasarawa and Benue states, while Kano rice hub includes Kano State. Throughout the rest of the paper, we will use Lafia to denote the Lafia rice hub and Kano to indicate the Kano rice hub. Random multistage sampling was used. Local governments, villages, and farmers were successively randomly selected. 296 farmers were sampled, including 192 and 104 farmers in Lafia and Kano, respectively. Before the data collection, from July to August 2017, a diagnostic survey was conducted in May 2017 to refine the research protocol and questionnaires.

### *4.2 Contingent valuation procedure*

We designed and implemented the IB game following a rigorous procedure. First, focus group discussions were conducted to assess farmers' perceptions on PHL, estimate the cost of the traditional method of harvesting, and investigate their perceptions about the cost of the service provided with a MH relative to the TH. The results indicate that farmers pay up to US D 55.55 (₦20 000) with an average of USD 47.22 (₦17 000) per hectare for harvesting service using TH, mainly sickles. Furthermore, farmers stated that the cost of a harvesting service using MH should be lower compared to the TH. Therefore, analogously to Houessionon *et al.* (2017), we applied a successive reduction rate of 12, 21, 29, 41 and 50% to the average cost of the harvesting service using TH. This process yielded the following WTP/ha points, respectively: USD 41.67 (₦15 000), USD 37.50 (₦13 500), USD 33.33 (₦12 000), USD 27.78 (₦10 000), and USD 23.61 (₦8500).

In combination with the IB, we applied a two-stage approach and an upgrade method to elicit farmers' WTP for mechanized harvesting services (Channa *et al*., 2019; Demont *et al*., 2012; Diagne *et al*., 2017). Moreover, we used the traditional method as the benchmark. The two selected MH were used as the upgraded methods. To create a real experience context of the MH, a video was shown for 30 seconds prior to the elicitation task. The video showed, for each technology, a real-life application of the MH on a rice farm. Based on our focus group, this duration was adequate for farmers to grasp how the technologies work and to gain realistic experience with the harvesters. This was done to reduce the hypothetical nature of the technology since most farmers may have never seen these two MH. Moreover, surveyors presented the main characteristics of the harvesters to farmers. The mini harvester is a small-size MH with a field capacity of 0.51 ha/day and a loss rate of 2.3% (Bora and Hansen, 2007). The reaper is a large-size MH with a capacity of 2–4 ha/day (IRRI, n.d.) and a loss rate of less than 0.5%. During the surveys, and for each MH, each farmer was asked if he/she prefers the MH to the traditional method. If he/she answered positively, then the IB game was presented to elicit his/her WTP/ha. If the answer was no, then the WTP is set to 0. The IB game started with the highest amount by asking the dichotomous question, "Would you be willing to pay at least USD 41.67/ha for a harvesting service using this equipment?". If the answer is yes, we then ask the farmers an open-ended question to get the maximum amount. This provides the advantage of capturing the actual WTP instead of considering this first bid as the highest WTP. If the answer was no, we moved to the lower value, and the iteration stopped when the farmer answered yes to one of the bids. If he/she also answered no for the last bid, then we asked an open-ended question.

*4.3 Empirical strategies*

*4.3.1. Farmers' preferences and WTP*

We used descriptive statistics to report farmers' preferences and WTP. We computed farmers' price premiums for the harvesting service using a MH relative to the traditional method. We also compared the price premium for the reaper harvester related to the mini harvester. Equations 1 and 2 present the formulas of the price premiums.

$$\mathrm{MPP}_{ij} = \frac{\mathrm{WTP}_{ij} - \mathrm{CT}}{\mathrm{CT}} \; (j = 1 \text{ or } 2) \tag{1}$$

$$\mathrm{RPP}_{i} = \frac{\mathrm{WTP}_{i2} - \mathrm{WTP}_{i1}}{\mathrm{CT}} \tag{2}$$

where $\mathrm{MPP}_{ij}$ denotes MH price premium of farmer $i$ and for technology $j$ (1=mini-harvester and 2=reaper), and CT the average cost of the TH method. $\mathrm{RPP}_i$ represents price premium for reaper harvester. Therefore, MPP and RPP are expressed in proportion of the average cost of the traditional harvesting method.

*4.3.2 Drivers of farmers' preferences and WTP*

Since there is a possibility of 0 WTP, the dependent variable is limited. The Tobit model is the most appropriate for this type of variable, which is mostly used in "corner-solution" and censored data models. Although this approach is a good fit for models with a corner solution in the predicted variable, it assumes that the decision process is identical for those with 0 WTP and those with a greater WTP (Amemiya, 1984). This assumption is violated in our study since we used a two-step approach to elicit farmers' WTP. The literature suggests the double hurdle model of Cragg (1971) as more suitable for two-stage data, and it provides a better result (Channa *et al*., 2019; Diagne *et al*., 2017; Saz-Salazar and Rausell-Köster, 2008). This model provides the advantage of isolating the process of "participating" from the valuation process. The double hurdle model was therefore used. Let us assume $D_{ij}$, the variable representing the willingness to upgrade from the traditional harvesting method to the MH $j$ for farmer $i$. Let $\mathrm{WTP}_{ij}$ denote the maximum amount this farmer is willing to pay for this MH. The two decision processes are presented in Equations 3 and 4 (Diagne *et al*., 2017):

$$D_{ij} = X_i\beta + u_{ij} \tag{3}$$

$$\mathrm{WTP}_{ij} = X_i\gamma + \varepsilon_{ij} \tag{4}$$

where $X_i$ is a vector of independent variables describing farmers socioeconomic and behavioral characteristics. $\beta$ and $\gamma$ are vectors of coefficients, respectively for the participation decision and the valuation decision. $u_{ij}$ and $\varepsilon_{ij}$ are error terms.

The first hurdle is the farmer's decision of whether to use the MH. The probability that the respondent prefers the TH ($\mathrm{WTP}_{ij} = 0$) is expressed by:

$$\mathrm{Prob}(\mathrm{WTP}_{ij} = 0) = \Phi(-X_i\beta) \tag{5}$$

where $\Phi$ is the standard normal density function.

The second hurdle determines the effect of independent variables on $\mathrm{WTP}_{ij}$, given $\mathrm{WTP}_{ij} > 0$. The distribution of $\mathrm{WTP}_i$ conditional on being positive is truncated at zero with mean and variance $\sigma^2$. The second hurdle is formulated as:

$$f\left(\left(\text{WTP}_{ij}|\text{WTP}_{ij}>0\right)\right)=\frac{\left(\frac{1}{\sigma}\right)\Phi\left[(\text{WTP}_{ij}-X_i\gamma)/\sigma\right]}{\Phi(X_i\gamma)/\sigma} \tag{6}$$

In the first and the second hurdles, the dependent variable was regressed on the same set of explanatory variables. Evidence suggests that socio-economic variables influence farmers' choices (Gbénou-Sissinto *et al*., 2018; Horna *et al*., 2007; Lazaridou *et al*., 2019). Furthermore, Adesina and Baidu-Forson (1995), Adesina and Zinnah (1993), and Affognon *et al.* (2015) have emphasized the need to consider perceptions in farmers' adoption decisions. Farmers' perceptions were therefore included in the independent variables. We asked farmers to rank the most important post-harvest activities, i.e., agricultural operations where PHL is the highest. A dummy variable was created, and it takes the value one when the farmer states harvesting as the first most critical post-harvest operation and 0 otherwise. Similarly, we asked farmers about the principal causes of PHL and generated a dummy variable for each of them.

*4.3.3 Elasticity estimation*

The own price elasticity of demand for a harvesting service using each MH was estimated. We used farmers' WTP for harvesting service using each technology to estimate the market demand curve. We evaluated the market demand curve using survival analysis. Following StataCorp (2015) and Channa *et al.* (2019), the demand was estimated as the proportion of farmers willing to pay for the service at different price levels. The formula of this proportion, the product-limit estimate of the survivor function, is as follows (Channa *et al*., 2019; StataCorp, 2015).

$$S_j=\prod_{k=1}^{j}\frac{n_k-d_k}{n_k} \tag{7}$$

where $n_k$ denotes the number of farmers willing to pay for the service at price level $k$, $d_k$ represents number of farmers whose WTP are less than $k$. The standard error of the proportion $S_j$ is computed using the following formula.

$$st_j=S_j*\sqrt{\sum_{k=1}^{j}\frac{d_k}{n_k(n_k-d_k)}} \tag{8}$$

The own price elasticity of demand for harvesting service using MH represents the elasticity of the proportion of farmers and is computed as follow:

$$\varepsilon_s=\%\Delta S_j/\%\Delta \text{Price}_j \tag{9}$$

Since WTP for the harvesting services using a MH was based on 1 ha, we generate the elasticity with the assumption that each farmer pays for the harvesting service for only 1 ha.

## 5. Results and discussion

*5.1 Descriptive statistics*

Table 1 presents the respondents' characteristics and perceptions, with the difference between the two study hubs, Lafia and Kano, analyzed using a two-tailed paired *t*-test. The farmers surveyed are middle-aged adults, with an average age of 41.12 years, though there is a significant age difference between hubs. Rice production remains male-dominated, with 83.5 % of farmers being male in Lafia compared to 70.6% of farmers in Kano.

**Table 1.** Farmers' socioeconomic characteristics and perceptions

| Variable | Lafia | | Kano | | Pooled sample | | Student's *t* |
|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | |
| Age | 38.479 | 10.663 | 45.99 | 13.247 | 41.121 | 12.158 | 5.25*** |
| Male | 0.835 | 0.372 | 0.706 | 0.458 | 0.79 | 0.408 | –2.6*** |
| High junior school | 0.08 | 0.272 | 0.088 | 0.285 | 0.083 | 0.276 | 0.25 |
| Household size | 10.181 | 6.055 | 11.578 | 7.991 | 10.672 | 6.818 | 1.67* |
| Member of association | 0.564 | 0.497 | 0.598 | 0.493 | 0.576 | 0.495 | 0.56 |
| Married | 0.872 | 0.335 | 0.941 | 0.236 | 0.897 | 0.305 | 1.84* |
| Rice income (USD) | 2238.655 | 2110.079 | 1916.859 | 1299.991 | 2125.471 | 1869.571 | –1.40 |
| Contact with extension | 0.41 | 0.493 | 0.539 | 0.501 | 0.455 | 0.499 | 2.13** |
| Access to credit | 0.271 | 0.446 | 0.245 | 0.432 | 0.262 | 0.441 | –0.48 |
| Trained on improved PHT | 0.181 | 0.386 | 0.127 | 0.335 | 0.162 | 0.369 | –1.18 |
| Cultivated area | 2.39 | 1.76 | 1.46 | 1.04 | 2.07 | 1.61 | –4.83*** |
| Harvesting is first main PHA | 0.5 | 0.501 | 0.098 | 0.299 | 0.359 | 0.48 | –7.41*** |
| Ignorance is first main cause of PHL | 0.144 | 0.352 | 0.01 | 0.099 | 0.097 | 0.296 | –3.76*** |
| Inappropriate practices are main cause of PHL | 0.17 | 0.377 | 0.088 | 0.285 | 0.141 | 0.349 | 1.92** |
| Inappropriate technology is the first main cause of PHL | 0.16 | 0.367 | 0.108 | 0.312 | 0.141 | 0.349 | –1.21 |
| Unavailability of technology is the first main cause of PHL | 0.085 | 0.28 | 0.157 | 0.365 | 0.11 | 0.314 | 1.87* |
| Inaccessibility of Technology is the first main cause of PHL | 0.011 | 0.103 | 0.098 | 0.299 | 0.041 | 0.2 | 3.64*** |
| Number of observations | 188 | | 102 | | 290[a] | | |

***, ** and * denote significance of the difference in means at the 1, 5 and 10% level, respectively, between rice hubs. SD, standard deviation.

[a] 6 observations were deleted for systematic missing data.

Marriage is prevalent among respondents, with nearly 90% of farmers married, and a statistically significant variation between hubs. These demographic patterns are consistent with prior studies, such as Horna *et al.* (2007). Household size averages 10.67 members, though it varies significantly between hubs. Less than 50% of farmers (45.5%) have access to extension services, with a nobly higher proportion in Kano (53.9%). Similarly, 57.6% of respondents are members of an agricultural association. The average cultivated area across the sample is 2.07 ha, with farmers in Lafia cultivating significantly larger plots than those in Kano.

On average, farmers report an annual rice income of USD 2125.471, though income levels differ significantly between hubs. Farmers' perceptions of PHL vary between hubs. In Lafia, 50% of farmers identify harvesting as the most critical postharvest activity, compared to only 10% in Kano. Perceptions regarding the primary causes of PHL also differ. While 14.4% of farmers in Lafia cite ignorance as the leading cause of PHL, this proportion is only 1% in Kano, indicating substantial variation in awareness. Additionally, 14% of farmers attribute inappropriate postharvest practices and technology as the main drivers of losses. The unavailability of technology is identified as the principal cause of PHL by 11% of the farmers, with a significant discrepancy between hubs. These results reveal the heterogeneous perceptions of PHL across hubs, which may influence technology adoption.

### *5.2 Farmers' preferences and WTP for mechanized harvester services*

Table 2 presents the results of farmers' preferences and WTP, as well as price premium for mechanized harvesting services. All values are expressed per hectare. Farmers stated a strong preference for mechanized harvesting service over traditional methods. On average, 89% of farmers are willing to adopt the mini harvester, while 91% prefer the reaper harvester over the manual harvesting. The preference for the reaper harvester is particularly pronounced in Lafia, where a higher proportion of farmers express willingness to pay more for reaper services than for mini harvester services. The average WTP for a mini harvester service is USD 34/ha, although this value varies significantly between hubs. In Lafia, farmers are willing to pay an average of USD 32.15, whereas in Kano, the WTP is higher at USD 38.30/ha. For the reaper harvester, the average WTP is USD 37.03/ha, with no statistically significant difference between hubs.

Unlike the mini harvester, farmers in both hubs exhibit similar WTP for a reaper harvesting service, suggesting a more consistent demand for this service across different contexts. However, despite their stated preference for mechanized harvesting, farmers significantly discounted the service price for both harvesters. The mini harvester was discounted by 27.3% compared to the cost of traditional harvesting. This discount rate is significantly higher in Lafia (31.9%) than in Kano (18.9%), reflecting variations in cost sensitivity. Farmers also discounted the reaper service by 21.6%, which is 5.7 percentage points lower than the discount applied to the mini harvester. These findings suggest that while farmers are willing to pay more reaper services, they still expect price reductions to facilitate adoption. These findings are consistent with Paudel *et al.* (2019), who reported that farmers in Nepal were willing to pay 31% less than the actual cost of the mini-tiller.

**Table 2.** Rice farmers' willingness to upgrade, WTP/ha, price discount and price premium for service using mini harvester and the reaper.

| Variable | Lafia | | Kano | | Sample | | Student's $t$[b] | Proportion of zero WTP |
|---|---|---|---|---|---|---|---|---|
| | Mean[a] | SD | Mean | SD | Mean | SD | | |
| WTU to mini harvester | 0.872 | 0.335 | 0.922 | 0.27 | 0.89 | 0.314 | 1.277 | |
| WTU to reaper | 0.936 | 0.245 | 0.882 | 0.324 | 0.917 | 0.276 | –1.590 | |
| WTP to mini harvester (USD) | 32.155 | 17.568 | 38.303 | 19.447 | 34.317 | 18.453 | 2.74*** | 0.11 |
| WTP Reaper (USD) | 37.272*** | 19.183 | 36.574 | 17.279 | 37.027** | 18.508 | –0.306 | 0.083 |
| Price discount for mini harvester[c] | –0.319 | 0.372 | –0.189 | 0.412 | –0.273 | 0.391 | 2.74*** | |
| Price discount for Reaper | –0.211 | 0.406 | –0.225 | 0.366 | –0.216 | 0.392 | –0.306 | |
| Price premium for reaper | 0.108 | 0.411 | –0.037 | 0.455 | 0.057 | 0.432 | –2.762*** | |

***, ** and * denote significance of the difference in means at the 1, 5 and 10% level, respectively. SD, standard deviation; WTU, willingness to upgrade and is in proportion.

[a] A two-sided $t$-test was conducted to test whether WTP for reaper is equal to WTP for the mini harvester within each hub and for the whole sample.

[b] Student's $t$-test of difference in means across rice hubs.

[c] Price discount and price premium are in proportion.

A significant proportion of farmers (80%) prefer the reaper harvesting service, though there is a notable gap between the two hubs (Figure 2). In Lafia, 90% of farmers prefer the reaper, whereas in Kano, this proportion is approximately 70%. Despite the strong preference for the reaper, a non-negligible percentage of farmers, particularly in Kano, still prefer the mini harvester. This variation highlights the importance of region-specific pricing strategies and financial support mechanisms to encourage broader adoption of mechanized harvesting technologies.

*5.3 Determinants of farmers' willingness to upgrade and to pay for mechanized harvesting service*

The double hurdle model estimates presented in Table 3 provide insights into the determinants of farmers' willingness to use the MH service (first hurdle) and their WTP for these services (second hurdle). The analysis is conducted separately for the mini harvester and the reaper harvester, and the table also presents the average marginal effects for the two hurdles.

Rice income and contact with extension services increase farmers' likelihood of preferring each of the MH over their traditional methods. Farmers who attended high-junior schools, had access to credit, or received training on improved harvesters were more likely to choose the mini harvester. Additionally, farmers who identified inappropriate practices as the first main cause of PHL were more inclined to prefer the mini harvester. On the other hand, no common factors significantly reduce the likelihood of choosing either MH. However, the results indicate that married farmers, association members, and those with larger farm sizes are less likely to adopt the mini harvester. Additionally, the likelihood of choosing the reaper harvester declines with increasing age, while farmers who perceive a lack of available mechanized harvesting services exhibit a similar reluctance. These findings align with prior studies highlighting the positive effects of access to credit and extension services in technology adoption (e.g., Adegbola and Cornelis, 2007; Gbénou-Sissinto *et al*., 2018; Horna *et al*., 2007; Saz-Salazar and Rausell-Köster, 2008; Uaiene, 2011). Similarly, the effects of education and rice income are consistent with Horna *et al.* (2007) and Gbénou-Sissinto *et al.* (2018). The positive effect of household size corroborates findings from Horna *et al.* (2007), who observed a similar trend in Nigeria and Benin regarding improved rice varieties.

The second hurdle estimates show the partial effect of each independent variable on farmers' WTP. Rice income has a positive and statistically significant impact on WTP for both technologies, although its economic

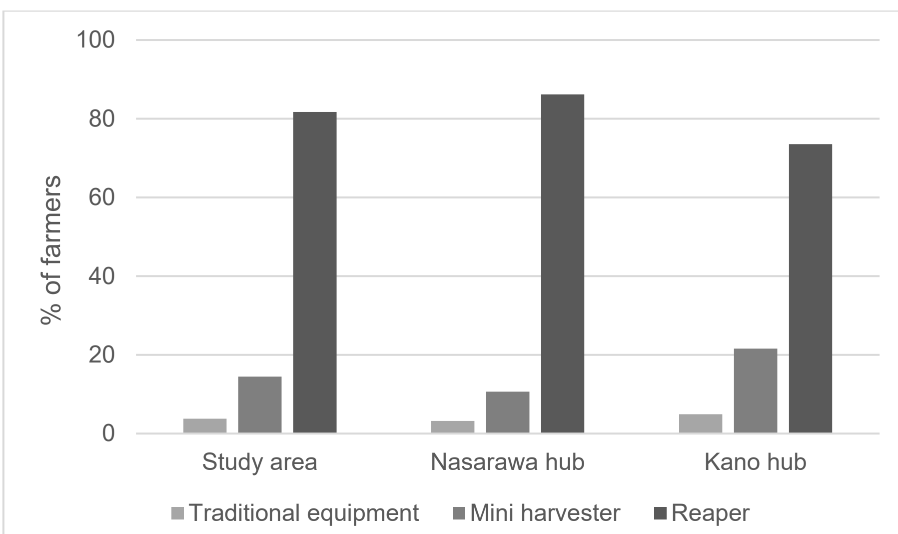


**Figure 2.** Farmers' preferences for harvesters per hub and in the study area.

**Table 3.** Determinants of farmers' willingness to upgrade and WTP for service using mechanized harvesters.

| Variable | Mini harvester | | | | Reaper | | | |
|---|---|---|---|---|---|---|---|---|
| | WTU | | WTP | | WTU | | WTP | |
| | First hurdle | AME | Second hurdle | AME | First hurdle | AME | Second hurdle | AME |
| Lafia rice hub | –0.288 | –0.0484 | –3.114 | –3.004 | 0.242 | 0.0313 | 0.109 | 0.106 |
| | (0.345) | (0.0581) | (2.540) | (2.425) | (0.324) | (0.0418) | (2.320) | (2.243) |
| Age | –0.0195 | –0.00329 | –0.00782 | –0.00754 | –0.0187* | –0.00243* | 0.00185 | 0.00179 |
| | (0.0120) | (0.00202) | (0.0769) | (0.0742) | (0.0110) | (0.00144) | (0.0879) | (0.0850) |
| Male | –0.414 | –0.0696 | 0.839 | 0.809 | 0.352 | 0.0456 | 1.203 | 1.163 |
| | (0.333) | (0.0562) | (2.444) | (2.355) | (0.292) | (0.0379) | (2.857) | (2.761) |
| High junior school | 4.478*** | – | 4.549 | 4.389 | –0.124 | –0.0160 | 1.127 | 1.089 |
| | (0.316) | | (4.975) | (4.736) | (0.408) | (0.0528) | (3.487) | (3.366) |
| Married | –0.872* | –0.147* | 1.259 | 1.214 | –0.372 | –0.0482 | 0.275 | 0.266 |
| | (0.471) | (0.0824) | (2.805) | (2.705) | (0.481) | (0.0624) | (3.619) | (3.500) |
| Rice income | 0.000231*** | 3.88e–05*** | 0.00171*** | 0.00165*** | 0.000345*** | 4.46e–05*** | 0.00137** | 0.00132** |
| | (8.08e–05) | (1.41e–05) | (0.000504) | (0.000486) | (9.70e–05) | (1.36e–05) | (0.000536) | (0.000520) |
| Contact with extension service | 0.831*** | 0.140*** | 1.543 | 1.489 | 0.552** | 0.0715** | 4.039** | 3.905** |
| | (0.288) | (0.0472) | (1.724) | (1.673) | (0.224) | (0.0311) | (1.986) | (1.892) |
| Access to credit | 0.995** | 0.167** | –2.323 | –2.241 | 0.432 | 0.0560 | 1.685 | 1.629 |
| | (0.420) | (0.0700) | (1.777) | (1.702) | (0.326) | (0.0424) | (2.586) | (2.483) |
| Household size | 0.0724*** | 0.0122*** | 0.0281 | 0.0271 | –0.0101 | –0.00131 | –0.316* | –0.305* |
| | (0.0272) | (0.00453) | (0.255) | (0.246) | (0.0166) | (0.00213) | (0.170) | (0.163) |
| Member of association | –0.728*** | –0.122*** | 0.221 | 0.213 | 0.0645 | 0.00836 | 1.001 | 0.968 |
| | (0.271) | (0.0439) | (1.863) | (1.800) | (0.251) | (0.0325) | (1.908) | (1.840) |
| Training on improved harvester | 4.885*** | – | –2.979* | –2.875* | –0.100 | –0.0130 | –7.433*** | –7.186*** |
| | (0.380) | | (1.736) | (1.666) | (0.352) | (0.0458) | (2.170) | (2.017) |
| Harvesting is the first PHA | 0.230 | 0.0387 | 5.884*** | 5.677*** | 0.0526 | 0.00682 | 5.643*** | 5.455*** |
| | (0.331) | (0.0555) | (1.821) | (1.762) | (0.295) | (0.0381) | (2.001) | (1.904) |

**Table 3.** Continued.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Farm size | –0.168* | –0.0283* | –2.774*** | –2.676*** | –0.127 | –0.0165 | –2.042*** | –1.975*** |
| | (0.0880) | (0.0150) | (0.677) | (0.640) | (0.0896) | (0.0117) | (0.632) | (0.596) |
| Ignorance of PHL | –0.335 | –0.0564 | 3.025* | 2.918* | –0.269 | –0.0348 | 4.251* | 4.110** |
| | (0.300) | (0.0501) | (1.821) | (1.754) | (0.252) | (0.0332) | (2.170) | (2.063) |
| Inappropriate practices | 0.529* | 0.0890* | –3.261* | –3.146* | 0.272 | 0.0352 | –4.144* | –4.007* |
| | (0.314) | (0.0537) | (1.724) | (1.650) | (0.284) | (0.0371) | (2.307) | (2.194) |
| Inappropriate technology | 0.0838 | 0.0141 | –6.436*** | –6.210*** | –0.176 | –0.0228 | –6.334*** | –6.124*** |
| | (0.289) | (0.0483) | (1.798) | (1.730) | (0.267) | (0.0349) | (2.038) | (1.993) |
| Unavailability of technology | –0.417 | –0.0701 | –1.922 | –1.855 | –0.503* | –0.0652* | –2.107 | –2.037 |
| | (0.295) | (0.0499) | (2.169) | (2.105) | (0.276) | (0.0355) | (2.087) | (2.012) |
| Inaccessibility of technology | –0.0406 | –0.00683 | 3.828 | 3.694 | 0.315 | 0.0408 | 6.143** | 5.939** |
| | (0.340) | (0.0570) | (2.382) | (2.302) | (0.369) | (0.0478) | (2.902) | (2.800) |
| Constant | 2.522*** | | 39.16*** | | 1.757*** | | 39.86*** | |
| | (0.645) | | (3.481) | | (0.608) | | (3.789) | |
| Sigma | 13.69*** | | | | 14.19*** | | | |
| | (1.705) | | | | (1.543) | | | |
| Observations | 290 | | 290 | | 290 | | 290 | |
| Wald $\chi^2_{(18)}$ | 929.96*** | | | | 36.48*** | | | |
| log pseudolikelihood | –1104.0274 | | | | –1146.7868 | | | |

*** $p$<0.01, ** $p$<0.05, * $p$<0.1 Robust standard errors in parentheses. AME, average marginal effect. High junior school and training on improved harvesting method's dummy was dropped as they perfectly predict propensity of upgrading.

significance remains limited. This result is consistent with findings of Saz-Salazar and Rausell-Köster (2008), who found income to be a key determinant for Spanish consumers' valuation of urban green areas. Similarly, Horna *et al.* (2007) concluded that higher income levels positively affect farmers' preferences for improved production technologies in Nigeria. Given that technology adoption requires financial investment, this relationship is not surprising. Farmers who perceive harvesting as the most important postharvest activity or ignorance of PHL as the main cause of PHL pay more for the mini harvester and the reaper services. On average, those who consider harvesting as the most critical postharvest activity are willing to pay USD 5.68 more for the mini harvester services and USD 5.46 more for the reaper services. Likewise, those who attribute PHL to ignorance are willing to pay an additional USD 2.92 for the mini harvester and USD 4.11 for the reaper compared to farmers with different perspectives. Farmers in contact with extension services who think that inaccessibility of technology is the first cause of PHL were willing to pay a premium of USD 3.90 for the reaper and USD 5.94 for the mini harvester. These effects are in line with findings of Uaiene (2011), Saz-Salazar and Rausell-Köster (2008), and Horna *et al.* (2007).

However, some factors are negatively correlated with farmers' WTP. The farm size has a decreasing and highly significant effect on WTP, as each additional hectare in rice farm size reduces WTP by USD 2.68 for the mini harvester services and USD 1.98 for the reaper services. This result is similar to those of Gbénou-Sissinto *et al.* (2018) for improved storage technology in Benin, suggesting that larger-scale farmers expect price reductions for mechanized services. Moreover, farmers who perceived appropriate postharvest practices and the use of inappropriate technologies also discount the maximum amount they are willing to pay for the services. Specifically, for the reaper services, two additional variables contribute to lower farmers' WTP. First, household size negatively affects WTP, with each additional member reducing WTP by USD 0.31 on average. Although this effect is barely statistically significant, it has modest economic importance. Second, farmers trained on improved harvesters are willing to pay USD 7.19 less for harvesting services using the reaper. This result suggests that training programs may help farmers realize the cost-effectiveness of mechanized harvesting, leading them to adjust their perceived value of the service.

*5.4 Demand elasticity*

The demand curves for mechanized harvesting services using the mini harvester and reaper harvester, respectively, are presented in Figure 3. To estimate demand elasticity, we applied the arc elasticity method, which is particularly suited for cases where price differences are substantial. This approach also ensures consistency in elasticity estimates, preventing distortions as demand shifts between different price points along the curve. The proportion of farmers (SE in parentheses) demanding harvesting service at a price of USD 40/ha is 47.59% (8.3%) for mini harvester and 51.38% (8.57%) for the reaper. When the price increases to USD 60/ha, these proportions decline sharply to 3.1% (9.44%) and 4.85% (8.6%), respectively. The estimated price elasticity of demand for the mini harvester service is –4.39%, meaning that a 1% increase in the service price leads to a 4.39% decrease in demand when the price ranges from USD 40 to USD 60. Similarly, the elasticity of demand for the reaper harvester is –4.14%, indicating that a 1% increase in the price results in a 4.14% decline in demand over the same price range. These values suggest that demand for mechanized harvesting services is highly elastic, meaning that farmers are highly responsive to changes in services costs. These elasticities are similar to the findings of Channa *et al.* (2019), who reported a price elasticity of –4.3 for the Purdue Improved Crop Storage (PICS) bag in Kenya. However, based on the demand curves, the demand is highly elastic up to the price of USD 60. Afterward, it appears to be less responsive to price change. These findings underscore the importance of pricing policies in promoting mechanized harvesting adoption. Given the high price sensitivity, subsidies, price reductions, or alternative financing mechanisms could significantly increase the uptake of mechanized harvesting technologies. Policymakers and service providers should consider tiered pricing strategies, rental models, or cost-sharing initiatives to enhance affordability and encourage broader adoption among smallholder farmers.

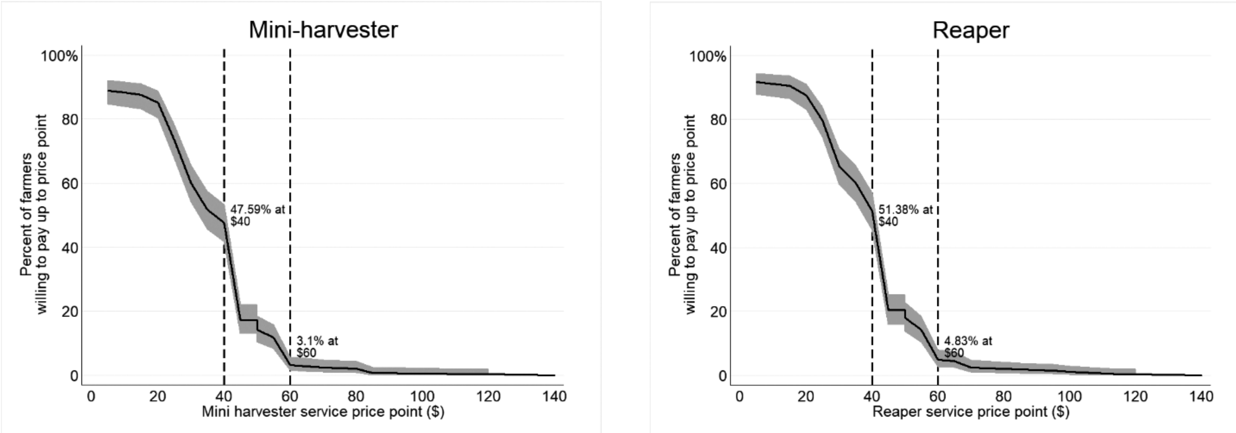


**Figure 3.** (Left) Proportion of farmers demanding harvesting service. (Right) Proportion of farmers demanding harvesting service using mini harvester at different price levels using reaper at different price levels. The estimates represent the proportion of respondents willing to pay at or above a given price. The gray shaded region represents 95% confidence interval.

The study has three main limitations. First, we used a hypothetical experiment to elicit WTP. Even though hypothetical bias is ubiquitous in stated preferences approaches (Durand-Morat *et al*., 2016; Fang *et al*., 2021), hypothetical studies yield similar results compared to non-hypothetical preferences methods, particularly when the experiment design is appropriate, pertinent, and suitable for respondents (Fuster *et al.* 2021), as it is the case in this study. Most studies in the agricultural economics literature show that hypothetical bias tends to inflate WTP (Penn and Hu, 2018, 2019). This means that farmers' WTPs reported in this paper are likely higher than their actual WTPs, amplifying their discount rate relative to the cost of harvesting service using TH. Second, the study is limited in geographical scope, as it focuses on only three states, restricting the generalization of the findings to the national level. Finally, we collected our data in 2017, and it is possible that farmers' behavior regarding MH may have changed over the last years. However, in line with the slow change in mechanization adoption over the past decades (Daum and Birner, 2020; Takeshima and Lawal, 2020), we expect negligible change in farmers' responses. Since this study only focused on the services themselves, future research could investigate farmers' valuation for mechanized harvesters' attributes.

## 6. Conclusion and policy implications

Post-harvest losses in Nigeria's rice value chain significantly undermine food security. We investigate the factors that influence rice farmers' preferences and willingness to pay for mechanized harvesting services, focusing on two mechanical harvesters, the reaper and the mini harvester in Nigeria. We also estimate the own-price elasticity of demand for these services to assess farmers' price responsiveness.

Results show that most farmers prefer mechanized harvesting services over manual harvesting services, with the reaper being the most favored option. However, despite their preference, farmers highly discounted their WTP, indicating affordability constraints. Both socio-economic characteristics and perceptions related to PHL significantly influence their choices and WTP. Furthermore, the demand for mechanized harvesting services exhibits high price elasticity, meaning that even modest price fluctuations can significantly impact adoption rates.

Our findings have important policy implications for enhancing food security in Nigeria. First, we provide evidence that rice income, contact with extension services, and access to credit are all positively associated with farmers' preferences for harvesting services using mechanized harvesters. Increasing income from rice production could indirectly stimulate mechanization adoption, as more financially secure farmers are better positioned to invest in productivity-enhancing technologies. To facilitate this, targeted agricultural programs aimed at increasing rice farmers' earnings should be prioritized. Furthermore, specific financing schemes, in collaboration with private agribusinesses, development organizations, and government agencies, could be designed to help farmers overcome financial barriers. Credit mechanisms tailored for small-scale farmers, including low-interest loans and leasing options, could improve affordability and encourage adoption. Access to credit and financial assistance would empower farmers to invest in mechanized harvesting, thereby increasing rice production and food availability, which are crucial to national food security. Additionally, we show that farmers' perceptions about the primary causes of PHL have a considerable impact on their WTP for the mechanized services. Extension programs could address this by offering community-based and field-based training to improve farmers' understanding of mechanized harvesting advantages. For instance, Castelein *et al.* (2022) found that adopting the reaper could offset its cost through yield gain, leading to profits of USD 140.36 (₦50 531)/ha. However, many farmers may not be aware of these potential gains, highlighting the need for targeted training programs. Capacity-building initiatives for lead farmers and opinion leaders in rice-production areas could further reinforce mechanization knowledge dissemination and promote widespread adoption.

Second, we report that farmers' WTP for mechanized harvesting service is lower than the estimated market price, and that demand is highly price sensitive. This suggests government institutions, development organizations, and other non-profit entities should explore subsidy programs to bridge the affordability gap.

Current estimates suggest that renting a reaper costs around USD 48.61 (₦17 500), excluding fuel and labor costs (Castelein *et al*., 2022). Given that this price exceeds many farmers' WTPs, a pricing mismatch between suppliers and demand-side affordability is evident. Without intervention, private service providers may struggle to reach widespread adoption. Subsidies could play a significant role in reducing costs and enabling private service providers to set a price aligned with smallholder farmers' WTP. In Nigeria, tractors subsidies have been implemented for several years (Daum and Birner, 2020), and a similar subsidy model for MH could be introduced. Moreover, given the high price elasticity of demand, price adjustments should be made cautiously and only when the adoption rate has reached a sustainable level. Financial support for service providers should also be considered to encourage long-term investment in mechanization services, ensuring an adequate supply of mechanized harvesting options.

Overall, by addressing key barriers to mechanized harvesting adoption, strategic policy interventions could significantly reduce PHL in Nigeria's rice sector. Given that up to 25% of total losses occur during harvesting, improving mechanization rates would directly contribute to increase domestic rice production, reduce reliance on imports and enhance national food security.

Our study is the first to investigate the demand for mechanized harvesting services among small-scale farmers in the rice value chain in Nigeria. Future research could extend this analysis in several ways. First, exploring farmers' preferences and WTP for postharvest technologies, including MH, in a non-hypothetical market setting would enhance the accuracy of demand estimation. Second, analyzing the supply-side dynamics — such as the willingness of youth to engage in mechanized harvesting as an agribusiness — could provide insights into how services provision could be expended. A deeper understanding of private sector engagement and business models for mechanization services would be valuable for designing effective mechanization policies.

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