AGRICULTURAL MECHANIZATION AND GENDER INFLUENCE: A CASE STUDY ON THE ADOPTION OF MACHINE HARVESTABLE CHICKPEAS IN KURNOOL, ANDHRA PRADESH, INDIA

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Master of Public Administration

by

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05 2023

ABSTRACT

The first machine-harvestable chickpea variety, NBeG47, was released in Andhra Pradesh, India in 2015 to reduce on-farm labor burden from manual harvesting and maintain sufficient protein supply. This paper uses logistic regression to study factors associated with households adopting machine-harvestable chickpeas, and OLS regression to study the association of adopting machine-harvestable chickpeas with reducing female on-farm working time, and household and female dietary quality in rural India. We found that factors including household composition and family labor availability are statistically significantly correlated with the probability of households adopting machine-harvestable chickpeas. We also discover that adopting machine-harvestable chickpeas does significantly associate with releasing female labor on farms, while no evidence shows its correlation with the change in household/female dietary diversity status. To further promote the adoption of machine-harvestable chickpeas in rural India, it is essential for policymakers and local communities to cooperate together to facilitate multi-field innovations to ensure the smooth chickpea variety transformation process.

Keywords: Machine-harvestable chickpeas, female labor, dietary quality, India

BIOGRAPHICAL SKETCH

Jialu Li was born on June 21st, 1998, in Changchun, Jilin, China. She completed her primary education in Changchun Mingde Primary School. She attended her junior and high school education at Changchun Foreign Languages School. She then joined Beijing Foreign Studies University in September 2016 and graduated with BA in Malay Language in June 2020.

After her graduation, she worked in Amazon Connect Technology Service (Beijing) Co., Ltd. for half year before starting her graduate program in Public Administration at Cornell University Jeb E. Brooks School of Public Policy in August 2021. During her graduate studies, she is also an Environmental Finance and Impact Investing (EFII) fellow. She interned with Cornell Atkinson Center for Sustainability, Tata-Cornell Institute for Agriculture and Nutrition (TCI) and Land O' Lakes Venture 37. She also participates in the Cornell REAL A cappella Group.

To my parents, Zhongmin Li & Hongjie Tang

ACKNOWLEDGMENTS

On August 2021, I arrived at Cornell University and began my graduate study. The two years have passed in the blink of an eye, and I have spent a rich and meaningful time at Cornell. I experienced the excitement of exploring a new field of study in sustainable agriculture development, and got to know many resourceful and supportive professors and lovely friends and fellows. Upon graduation and the completion of the thesis, I want to express my heartful gratitude to my professors, fellows and friends, relatives, and the department and university.

I would like to show my deepest gratitude to Professor Chris Barrett from the Dyson School of Applied Economics and Management, my thesis advisor. I might not have gone this far on my academic trajectory without his support. Joining Prof. Barrett's research group during my first graduate semester led me to the new world of agriculture and sparked my interest in academic research. I extremely appreciate Prof. Barrett's guidance on my research development and the wonderful research atmosphere he provided. He trained my research rigor and guided me through the research process, especially during the thesis construction. His in-time replies, thorough feedback, and encouragement made me feel confident and supported, and strengthened my courage to stride further on the path of academia.

I would also like to thank the support of Mathew Abraham from the Tata-Cornell Institute for Agriculture and Nutrition (TCI), Dr. R Padmaja from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), and Professor John

Sipple from the College of Agriculture and Life Sciences (CALS) for my graduate thesis. The fundamentals of my thesis, such as the theme and data, come from my summer internship with TCI and ICRISAT in 2022 under the guidance of Mathew and Padmaja. They have continued to provide me with additional information after the internship ended and I really appreciate it. Prof. Sipple's course, Quantitative Research Methods, provided me with insights into my thesis empirical methodology.

I am fortunate to have had the support of my parents, my boyfriend, Youshan Zhang, and friends from REAL during this challenging journey. Their love and encouragement have been of great motivation and inspiration. They cured me with their understanding and care when I was depressed and lifted me through the most difficult months. I was equally grateful for the happiness the 0713 Group brought me during those days with their songs and shows. As a computer science professional, Youshan also assisted me with data cleaning issues. For those, I am immensely grateful.

Finally, I would like to like to acknowledge the assistance and support of the professors and staff from the Cornell Brooks School of Public Policy throughout my graduate studies.

Thank you all for your contributions to my thesis and unwavering support throughout my graduate studies. I will always cherish our time together and thank all the moments that hone me to the finest.

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CHAPTER 1

INTRODUCTION

The agriculture sector in India contributes nearly 15% of the national GDP (Mehta et al., 2019), and rural populations mostly depend on agriculture activities for their livelihood. Female labor participation in agriculture, including field crops, fruit crops, plantation crops, livestock, forestry, fishery, etc., is prevalent in India. Out of 59% of overall rural employment, the agricultural sector contributes to nearly three-fourths of overall female employment (Jhajhria et al., 2020). Apart from participating in agriculture activities in the form of employment, female laborers are responsible for more unpaid family agriculture work. Female participation in agricultural operations such as weeding, harvesting, intercultural, and transplanting (Waris et al., 2016) is higher than males, mainly due to the harvest tasks that females dominate (Lamb, 2003). Therefore, mechanization in harvesting is expected to have a greater influence on female workers.

India accounts for nearly 70% of global chickpea production and consumption (Chaturvedi et al., 2014), but chickpeas are not India's main focus of agriculture mechanization. Most current chickpea cultivars are unsuitable for mechanical harvesting because of their plant heights and architecture (Dixit et al., 2019). The use of combined harvesters is not possible for chickpea production. This presents challenges to chickpea producers in India to satisfy the labor requirement for manual harvesting (Dhimate et al., 2018), particularly of female laborers primarily responsible for harvesting activities. India needs to intensify agricultural production, including chickpeas, a major pulse crop providing protein for the large vegetarian population, to satisfy the nutrition demand of the growing population (Ravula, 2020).

International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), collaborated with Regional Agricultural Research Station (RARS) in Nandyal, introduced the first machine-harvestable chickpea variety (NBeG47) in 2015 to various southern and central rural Indian villages to alleviate the physical burdens of manual chickpea harvesting (Jayalakshmi, 2016). Two rounds of quantitative surveys were conducted in 2019 and 2021 to evaluate the influence of the new chickpea variety on rural households, that is, how mechanically harvesting chickpea impacts women in chickpea farming systems in rural India. This paper will focus on three research questions:

1) What factors are associated with the adoption of machine-harvestable chickpeas?
2) Whether adopting machine-harvestable chickpeas is associated with reducing female on-farm working time?
3) Whether adopting machine-harvestable chickpeas is associated with household and female dietary status?

The contribution of this paper is three-fold. First, this paper is the first detailed case study since the introduction of the machine-harvestable chickpea variety in rural India, which offers implications to researchers and policymakers on ways to enhance the impact and effectiveness of the new variety on promoting labor-saving practices and improving dietary diversity in rural India. Second, this paper contributes to literature on the relationship between harvesting mechanization and improving household/female dietary diversity status. There is limited literature in this area focusing on the harvesting technology, which is the primary employment/working sector for rural female laborers. Finally, this study provides evidence for the offset among different agricultural operations due to technical improvement in one operation, and the tradeoff between improved nutrition status from increased agricultural production and more intense efforts dedicated to agricultural works.

CHAPTER 2

LITERATURE REVIEW

There have been mixed attitudes towards agriculture mechanization form different times around the world. Pingali (2007) supported a positive relationship between agricultural mechanization and productivity and employment both on- and off-farm. Binswanger (1984), Dovring (1977) and Pingali et al. (1987) explored the trend and impacts of agriculture mechanization on different operations in developing countries. While indicating increasing adoption of agriculture mechanization, these studies also discussed possible externalities from the generalization of mechanization, such as unemployment and financial burden, especially in rural communities. The cost-effective of agriculture mechanization was also emphasized. Daum and Birner (2020) reviewed theories from different periods toward agriculture mechanization in African countries. Among nine propositions, there has been mixed evidence for statements such as "Mechanization increases unemployment" and "Mechanization benefits mostly men". This paper intends to dig into important factors that associate with the adoption of agriculture mechanization by smallholder farmers and the association of agricultural mechanization with reducing female laborer on-farm working time in rural India and increasing household/female dietary diversity status.

The fact that there will be a continuous reduction in farm power such as workers, draught animals, tractors power tillers, etc. (Mehta et al., 2014), especially female farming labor (Chand, 2019) in India makes the role of agriculture labor more critical to supporting food security. The Indian government has invested more in farm mechanization to relieve the negative prospects, while manual harvesting is still common in some parts of India. There are general manual harvesting problems, such as crop loss due to labor scarcity during harvest seasons and increasing costs from high labor wages. For women specifically, drudgery is a particular issue encountered during harvest seasons (Khandai et al., 2021). Agricultural mechanization is divided into three categories: manually operated tools, animal-operated implements, and equipment operated by mechanical and electrical power sources. Among all, tractors, power tillers, combine harvesters, rotavators, threshers, and rice transplanters are experiencing surging demand (Mehta et al., 2014).

The overall agricultural mechanization level on agricultural lands in India is about 45-50%, and the proportion is widely varied across agricultural operations. Mehta et al. (2019) studied factors that influence the adoption of farm mechanization. They found that different types of agricultural operations and government initiatives play great roles in promoting farm mechanization. Some studies focused on the diverse crop portfolio contributing to different farm mechanization levels (Mehta et al., 2019; Kulkarni et al., 2018, December; Khanal and Mishra, 2017; Paudel et al., 2019). Several studies also researched household socioeconomic factors that influence farm mechanization, such as age, education level, land size, and access to technologies and supports (irrigation, extension services, institutional credits, etc.). They found positive relationships between education level, land size, access to technologies and supports, and mechanization adoption, while a negative relationship between age and mechanization adoption (Barman et al., 2019; Aryal et al., 2021; Abbas et al. 2017).

Some papers also emphasized service provision for the mechanization adoption of smallholder farms (Aryal et al., 2021).

Farm mechanization positively impacts agriculture development in multiple ways, such as increasing agricultural outputs, increasing productivity of land and labor, and the potential of reducing production costs (Singh, 2005). Khandai et al. (2021) found that machine harvesting can reduce about two-thirds of the labor requirement compared to manual harvesting. The increased working efficiency with machines reduces drudgery for women workers and decreases crop loss due to on-time harvesting. Rajkhowa and Kubik (2021) found a positive relationship between farm mechanization and the probability of female labor participation on farms. In contrast, Ahmad and Murtaza (2021) found an inverse relationship between farm mechanization and labor participation rate, especially for females. Afridi et al. (2023) identified that female is more adversely impacted by farm mechanization than male when non-farm sector employment opportunities for female are not developed accompanying the replacement of female labor with machines. Afridi et al. (2020) also reached similar results that increased agricultural mechanization in India from 1999 to 2011 has led to a more than 22% fall in women's agricultural participation due to weeding mechanization. The resulting female labor displacement was in contrast with the better complementarity between men and machinery. Vemireddy and Choudhary (2021) systematically reviewed findings from papers studying different labor-saving technology innovations and their impact on female labor. The results vary largely based on different research contexts.

There has also been plenty of literature focusing on the relationship between farming and dietary diversity status in the developing world. Nandi and Nedumaran (2021) highlighted the potential of tank irrigation contributing to rural food and nutritional security in India through mediating pathways. The paper indicated that outcomes such as increased production, productivity and income that are achieved through farming mechanization play more determined role on household dietary diversity status. Fischer et al. (2019) also found subtle relationship between dietary improvement and farming mechanization for smallholders in Tanzania, and for females specifically, nutrition status was dependent on female access to resources and household consumption patterns. Kassie et al. (2020) emphasized the positive effect of agricultural technology adoption on women's dietary diversity score in Kenya, while also found that women empowerment would further enhance this effect, as similarly implied in Murugani and Thamaga-Chitja (2019), a study took place in South Africa. Although women empowerment would not result in significant effect on dietary diversity status unless farming technology and/or market access could be improved. Komatsu et al. (2019), however, indicated that although increased agricultural production could improve individual nutritional status by increasing agricultural income and food, time spent in agricultural work is negatively associated with Body Mass Index (BMI) for non-overweight individuals.

In the following parts of the paper, we will cover the data and measurement in Chapter 3, the empirical methodology and results in Chapter 4 and discussions in Chapter 5.

CHAPTER 3

DATA AND MEASUREMENT

3.1. Data source

The raw data for this paper comes from 2 rounds of quantitative surveys designed by ICRISAT that were conducted in 2019 and 2021 respectively. A field demonstration was conducted during 2013-2015 in Andhra Pradesh to test the suitability of the NBeG47 variety for machine harvesting. The demonstration showed that the machine-harvestable chickpea variety yielded similar or higher than other chickpea varieties and was amenable to machine harvesting. RARS then distributed the new chickpea seeds to households in the Kurnool and Prakasam districts of Andhra Pradesh.

The machine-harvestable chickpea adopted households (adopted households) from Kurnool were randomly selected across different mandals of Kurnool district as per the list provided by the RARS, Nandyal. The listing and selection of the households were done with the consultation of local progressive farmers and village elders. Adopted households consisted of households that voluntarily adopted the machine-harvestable chickpea variety when RARS held regional seed distribution fairs across demonstration districts. Some adopted households were also targeted households by RARS during the demonstration. Adopted households were accompanied by households that planted traditional chickpea varieties (traditional households). The number of adopted and traditional households in the first round were 50 and 205 respectively, in the second round were 55 and 199 respectively.

Before interviews, Field Enumerators were selected and trained for a week prior to official interviews on the questionnaire, tablets and other components required for conducting the survey. After household heads agreed on participating in the survey, enumerators would meet with respondents and collect data in the tablets running on CSPRo Software. In the first round, only household heads from selected households were interviewed. In the second round, household heads were still the primary respondents, while both household heads and their spouse were interviewed for the dietary diversity questionnaire and activity profile-time allocation questionnaire.

Data in the first round of survey are separated into household data, which provides evidence on household demographics and socio-economic status, and cultivation data, providing information of households' cropping characteristics, production and yield, and labor/machinery usage. Data in the second round, besides the two sets of data above, includes detailed reporting of household dietary status (food groups consumed within past 24 hrs and the past year), and activities and resources allocation (separated based on gender difference), providing additional insights into the impact analyses.

When analyzing the raw data, we found that during planting seasons, not all adopted households cultivated the new chickpea variety, therefore, the actual number of "adopted households" were limited. To adjust for this issue, we only regarded households and plots that actually cultivated machine-harvestable chickpeas as "adopted households" (cultivated households thereafter) and combined the two rounds of data, accounting for multiple plots that cultivated machine-harvestable chickpeas per household and allowing for repeated occurrence of households.

Since this paper focuses on factors that associate with the adoption of machine-harvestable chickpeas and the correlation between adopting machine-harvestable chickpeas on reducing female on farm drudgery and household/female dietary diversity status, only plots that cultivated chickpeas are selected as observations, and those observations reporting "blank" or "0" main chickpea product quantity were excluded from analysis.

3.2. Variables of interest

This section will present key variables for the three primary research questions, see Table A1 in Appendix A. Descriptive statistics for these variables can be found in Table 1 and Table B1 in Appendix B.

Table 1: Summary statistics for categorical variables

Variable	*Definition*	*Round 1*		*Round 2*	
		No. of Obs.	Percentage (%)	No. of Obs.	Percentage (%)
Round		398	55.35	321	44.65
Variety types	NBeG47	19	4.77	21	5.61
	Others	379	95.23	300	94.39
Mechanization status	Manual	380	95.48	128	39.88
	Machine	18	4.52	193	60.12
Farm size	Large farm	264	66.33	211	65.73
	Small farm	134	33.67	110	34.27
Member of orgs	Non-org	373	93.72	306	95.33
	Org	25	6.28	15	4.67
Receiving training	Not received	319	80.15	247	76.95
	Received	79	19.85	74	23.05

3.2.1. Analysis on factors associated with the adoption of the machine-harvestable chickpea variety

In the first research question, we analyze factors that are associated with the adoption of machine-harvestable chickpeas, so the outcome of interest in this question is supposed to be the adoption of machine-harvestable chickpeas. The definition of this variable originally combined two conditions that whether plots grew machine-harvestable chickpeas and were harvested using combined harvesters, as the intention of introducing the new machine-harvestable chickpea variety is to encourage households to use combined harvesters for chickpea harvesting.

However, we found that the number of plots that actually satisfied the two conditions are too limited, only 3 plots in Round 1 and 9 plots from Round 2. Therefore, we instead split this question into two, analyzing factors that are associated with the adoption of machine-harvestable chickpeas and the use of combined harvesters for chickpea harvesting. Both variables are dummy variables with 1 as adopted and 0 as non-adopted, and the low correlation (0.0038) between the two outcome variables also justify this separation.

3.2.2. Analysis on the correlation between adopting machine-harvestable chickpea variety and female labor and household/female dietary diversity status

This part of the analysis of the paper focuses on studying the correlation between adopting machine-harvestable chickpea variety and aspects of household female labor-saving and household/female dietary diversity status. We intend to study whether introducing machine-harvestable chickpeas will associate with reduced female labor drudgery in rural India and increasing household/female nutrition status.

As for the second research question on female labor-saving status, we select two outcome variables of interest, female on-farm working days per acre across operations, and female harvesting days per acre during the whole planting season. The detailed construction of these variables can be found in Appendix A.2. The first variable helps us identify the association between adopting machine-harvestable chickpeas and the time female laborers spent on all sort of farm works per acre, while the second variable provides us with more direct association between adopting machine-harvestable chickpeas and its impact on the time female laborers spent on harvesting work per acre.

For the third research question, we select two outcome variables of interest, the Household Dietary Diversity Score (*HDDS)*, and the Minimum Dietary Diversity for women (*MDD_W*), to study the correlation of adopting machine-harvestable chickpeas with household and female dietary diversity respectively. The detailed construction of these two variables can be found in Appendix A.3. As the dietary data was only collected in the second round of the survey, we will only use data from the second round for this research question. The explanatory variables would stay the same as the second research question, while control variables vary as some variables will be excluded according to literature reviews and results from previous questions.

CHAPTER 4

EMPIRICAL METHODS AND RESULTS

4.1 Methods and results for factors associated with the adoption of machine-harvestable chickpeas

To study factors that are associated with the adoption of machine-harvestable chickpeas and the harvesting mechanization, we use logistic regression (logit model). The dependent variables follow the Bernoulli distribution, suitable for both logit and probit model. We choose logit model for this question mainly due to two aspects. Logit model works better than probit model when there are extreme values in independent variables. As seen in Table B1, some variables, such as household annual incomes, plot yield per acre and material costs per acre, have extreme values that are much larger than the median value. On the other hand, the dependent variables do not follow the Gaussian distribution, or normal distribution, as there are significant regional differences in variables, therefore, logit model would better fit the situation.

Independent variables in the equation are divided into two categories: household demographic characteristics and farm-level characteristics. Labor variables are excluded due to endogeneity. The analysis unit of this paper is mostly at the plot level, except for household/female dietary diversity status, which means that there is potentially clustering effect because each household may have multiple plots included in the data and participate in both rounds of surveys. To adjust for the potential clustering effect, we cluster the standard errors at the household level which is the level that household variables are documented at and are repeated in two rounds of the quantitative surveys. The odds ratio equation is expressed as follows:

$$e^{\log\left(\frac{p}{q}\right)} = \frac{p}{q} = e^{\beta_0 + \beta Xi + \varepsilon i}$$

where p is defined as the probability of the event for dependent variables occurs, that is, using combined harvesters for chickpea harvesting and the cultivation of the machine-harvestable chickpea variety, q is defined as the probability of the event for dependent variables does not occur, β_0 is the constant, X_i is the vector contains demographic and farm-level independent variables that might have effects of interest on dependent variables, β are coefficients for independent variables, and ε_i is the error term. Robust standard errors for the coefficients are clustered at the household level.

Table 2: Regression results for the adoption of machine-harvestable chickpeas

Machine-harvestable chickpeas adoption	*Model 1 (Household)*	*Model 2 (Farm level)*	*Model 3 (Combined)*
Household size	1.356***		1.410**
	(0.160)	–	(0.244)
Male rate	0. 101**		0.059**
	(0.113)	–	(0.076)
Female rate	18.800***		14.000**
	(19.098)	–	(15.141)
Dependent rate	0.034		0.006
	(0.084)	–	(0.020)
Education level	1.350**		1.294
	(0.170)	–	(0.209)
Age	0.985		0.979
	(0.019)	–	(0.022)
Annual incomes	1.000***		1.000
	(5.29e-07)	–	(8.24e-07)
Member of Orgs	1.003		1.852
	(0.790)	–	(1.468)

(Continued table)

Machine-harvestable chickpeas adoption	*Model 1 (Household)*	*Model 2 (Farm level)*	*Model 3 (Combined)*
Receiving training	2.754** (1.209)	–	2.588* (1.376)
Smallholder	–	0.160** (0.123)	0.295 (0.223)
Harvesting mechanization	–	0.967 (0.322)	0.853 (0.398)
Household crop number	–	1.194 (0.142)	1.076 (0.138)
Plot yield/acre	–	1.002*** (0.001)	1.001*** (0.001)
Material costs/acre	–	1.000*** (0.000)	1.000*** (0.000)
Chickpea rate	–	1.017 (0.041)	1.024 (0.051)
Chickpea harvesting loss percentage	–	1.001 (0.004)	1.005 (0.010)
No. of Obs.	719	609	609
Pseudo R-squared	0.153	0.138	0.266

Note: The table reports odd ratios as results, i.e., the likelihood of adoption relative to non-adoption, and robust standard errors for coefficients in parentheses. *indicates significance at the 10% level, **indicates significance at the 5% level, *** indicates significance at the 1% level. "_" indicates non-existence. Robust standard errors clustered at the household level.

Table 3: Regression results for the adoption of harvesting mechanization

Harvesting mechanization	*Model 1 (Household)*	*Model 2 (Farm level)*	*Model 3 (Combined)*
Household size	1.023 (0.096)	–	0.949 (0.096)
Male rate	2.334 (1.361)	–	3.168* (2.057)
Female rate	1.290 (0.897)	–	0.796 (0.662)

(Continued table)

Harvesting mechanization	*Model 1 (Household)*	*Model 2 (Farm level)*	*Model 3 (Combined)*
Dependent rate	2.151		1.457
	(2.419)	–	(1.898)
Education level	1.000		1.001
	(0.063)	–	(0.076)
Age	0.994		0.987
	(0.010)	–	(0.013)
Annual incomes	1.000		1.000
	5.00e-07)	–	(6.25e-07)
Member of Orgs	1.468		1.808
	(0.545)	–	(0.715)
Receiving training	1.000		0.936
	(0.312)		(0.334)
Smallholder		1.180	1.083
	–	(0.344)	(0.335)
Adopting machine-harvestable chickpeas		0.789	0.858
	–	(0.304)	(0.356)
Household crop number		1.070	1.079
	–	(0.125)	(0.128)
Plot yield/acre		1.001**	1.001**
	–	(0.000)	(0.000)
Material costs/acre		1.000	1.000
	–	(0.000)	(0.000)
Chickpea rate		1.071***	1.084***
	–	(0.024)	(0.024)
Chickpea harvesting loss percentage		1.000	1.003
	–	(0.005)	(0.006)
No. of Obs.	719	609	609
Pseudo R-squared	0.011	0.043	0.063

Note: The table reports odd ratios as results, i.e., the likelihood of adoption relative to non-adoption, and robust standard errors for coefficients in parentheses. *indicates significance at the 10% level, **indicates significance at the 5% level, *** indicates significance at the 1% level. "_" indicates non-existence. Robust standard errors clustered at the household level.

According to Table 2 that reports the regression results for the adoption of machine-harvestable chickpeas, the values of Pseudo R-squared indicate that model 3 is more suitable for explaining the proportion of probability variation in dependent variables. Among household variables, three variables, the household size and proportion of male and female members per household, have statistically significant association with the adoption of machine-harvestable chickpeas at 5% level. A person increase in household size is associated with a 41% increase in the probability of households adopting machine-harvestable chickpeas. A unit increase in the proportion of male members per household is associated with 94% decrease in the likelihood of households adopting machine-harvestable chickpeas. A unit increase in the proportion of female members per household is associated with 14 times more likely for households to adopt machine-harvestable chickpeas.

For farm-level variables, only plot yield per acre and household material costs per acre are statistically significant associated with household adoption of machine-harvestable chickpeas at 1% level. However, the magnitude of change in the association between these two variables and the odd ratios of household adoption of machine-harvestable chickpeas is small. Therefore, we can infer that the features of household members play significant roles in the adoption of machine-harvestable chickpeas. As indicated in Afridi et al. (2020) and Pattnaik and Lahiri-Dutt (2020), the proportion of family and hired female labor on farm is approximately equal in India, while family male labor on farm formed a larger share (65%) of total male labor usage and better complementarity for agricultural operation mechanization. It implies that household characteristics are associated with labor characteristics in ways that more proportion of male or female members per household is associated with more family male or female labor availability on farm work. From this aspect, the odd ratios for the household variables give us additional information that more family female labor availability is positively associated with the adoption of machine-harvestable chickpeas, while more family male labor is negatively associated with the adoption of machine-harvestable chickpeas. We will revisit this finding in Section 4.2, combining with the results of correlation between the adoption of machine-harvestable chickpeas and reducing female drudgery on farm.

Referring to Table 3 that reports the regression results for the adoption of harvesting mechanization, the low values of Pseudo R-squared for all three models imply that the variables included are not suitable for explaining the probability variation of household using machinery for harvesting chickpeas, although the variable chickpea main product rate is still statistically significantly associated with household adoption of harvesting mechanization at 5% level. A unit increase in chickpea main product rate is associated with an 8.4% increase in the probability of households adopting chickpea harvesting mechanization. This finding is somehow self-justifiable as the cost of machinery should be balanced off in some way so that households would have the incentive to replace labor with machines, and the increase in product rate would make up such compensation. Due to the small magnitude of change of the association between plot yield per acre and the odd ratios of household adoption of machine-harvestable chickpeas, although plot yield per acre is statistically significant in the model, it is dropped in the interpretation.

Combining the results from the two models, we can see that household composition has statistically significant association with the odd ratio of households adopting machine-harvestable chickpeas, which may give us additional insights on the link between labor characteristics and the adoption of machine-harvestable chickpeas. The chickpea main product rate is also statistically significant associated with the odd ration of households adopting machine-harvesting chickpeas.

In addition, factors mentioned in the survey question "comment on discontinuing cultivating machine-harvestable chickpeas", particularly market limitation presented in Table C2, more to be discussed in Chapter 5, should also be considered.

4.2 Methods and results for the correlation between the adoption of machine-harvestable chickpeas and reducing female labor working time on farm

We run OLS regressions to study the correlation between adopting machine-harvestable chickpeas and reduced female labor on-farm working time. To adjust for the potential clustering effect, we also cluster the standard errors at the household level. The model for the female labor on-farm working days is expressed as follows:

$$\Delta DAYS_i = \beta_0 + \beta_1 MECH_i + \beta_2 VARIETY_i + \delta W_i + \sigma_m + \varepsilon_i,$$

where the dependent variable $\Delta DAYS_i$ is the change in female labor working days per acre on plot i, β_0 is the constant, $MECH_i$ is the explanatory variable of whether plot i used combined harvesters for harvesting chickpeas, $VARIETY_i$ is the other explanatory variable of whether plot i grew machine-harvestable chickpeas, β_1 and β_2 are coefficients for the two explanatory variables, W_i is the control vector that includes control variables household size, household male and female member rate, education level of household head, household annual incomes, participating in agricultural organizations and receiving training, farm size and household crop number, δ represents the coefficients for control variables, σ_m is the regional fixed effect that controls for unobserved characteristics at the mandal level that potentially affect the adoption of machine-harvestable chickpeas, and ε_i is the error term.

Table 4: Regression results for female labor on-farm working days

	Outcome variables		
	Female labor working days/acre	Female harvesting days/acre	Female weeding days/acre
Harvesting mechanization	-2.667*** (0.491)	-3.293*** (0.160)	0.895** (0.380)
Machine-harvestable chickpeas adoption	2.136*** (0.863)	0.398 (0.482)	1.207*** (0.488)
Household size	0.020 (0.149)	-0.057 (0.059)	0.160 (0.104)
Male rate	-0.390 (0.968)	-0.200 (0.391)	-0.123 (0.778)
Female rate	-2.717** (1.319)	-0.448 (0.511)	-2.539*** (0.898)
Education level	0.136 (0.131)	0.052 (0.060)	0.093 (0.088)
Annual incomes	-2.16e-06*** (8.36e-07)	-2.60e-07 (4.28e-07)	-1.66e-06*** (5.92e-07)
Member of Orgs	0.612 (1.069)	-0.408 (0.483)	0.401 (0.668)
Receiving training	-1.512*** (0.494)	-0.227 (0.235)	-1.035*** (0.362)
Smallholder	1.367*** (0.473)	0.679*** (0.203)	0.182 (0.313)
Household crop number	-0.134 (0.094)	-0.067 (0.043)	-0.054 (0.072)
No. of Obs.	719	719	719
Adjusted R-squared	0.152	0.430	0.061

Note: The table reports variable coefficient estimates and robust standard errors in parentheses. *indicates significance at the 10% level, **indicates significance at the 5% level, *** indicates significance at the 1% level. Standard errors clustered at the household level.

From the regression results in Table 4, we discover that both explanatory variables are statistically significant correlated with the change in female labor on-farm working days per acre per household at the 1% level. Using machines for chickpea harvesting is associated with 2.667 days decrease in female labor working days per acre on farm, while adopting machine-harvestable chickpeas is associated with 2.136 increase in female labor working days per acre on farm. The seemingly contradictory results correspond to the nature of observations (see Table 5) that around 70% of both traditional chickpea farmers and new variety adopters harvest chickpeas manually, and females are dominant in the harvesting work. Therefore, cultivating machine-harvestable chickpeas alone may not help achieve the labor-saving objective.

Table 5: Two-way frequency table for adopting machine-harvestable chickpeas and chickpea harvesting mechanization

Variety	*Names*	*Manually harvest*	*Harvesting mechanization*	*Total*
Other varieties	No. of Obs.	472	200	672
	Percentage (%)	70.24	29.76	100
Machine harvestable chickpeas	No. of Obs.	2	**11**	36
	Percentage (%)	69.44	30.56	100

For female harvesting days, only chickpea harvesting mechanization is statistically significantly associated with the change in female harvesting days per acre at the 1% level. Chickpea harvesting mechanization is associated with 3.293 days decrease in the time female labor spent on the harvesting operation per acre. The findings indicate that chickpea harvesting mechanization plays an important role in reducing female labor on-farm drudgery, especially for the harvesting operation, while cultivating the new chickpea variety is associated with increased time that female spent on farm operations. Therefore, we hypothesize that cultivating machine-harvestable chickpeas may associate with more female labor working days on farm operations other than harvesting, as it does not significantly associate with the change in days that female spent on harvesting.

To test this hypothesis, we include a third dependent variable, female weeding days per acre, to further explore the relationship between adopting machine-harvestable chickpeas and female labor on-farm working days, as according to the survey data, women spent most of their on-farm working time on harvesting and weeding. The regression results for female weeding days per acre show that both cultivating machine-harvestable chickpeas and chickpea harvesting mechanization is statistically significantly associated with the change in female weeding days per acre at or below 5% level. Chickpea harvesting mechanization is associated with 0.895 days increase in female weeding days, and cultivating machine-harvestable chickpeas is associated with 1.207 days increase in female weeding days.

These findings support our hypothesis that cultivating machine-harvestable chickpeas is associated with an increase in working time on operations other than harvesting, such as weeding, which corresponds to the finding in Komatsu et al. (2019) that it is possible that access to equipment reduced effort for one production activity, but increased work for other activities in the production process. It also shed light on the findings in Section 4.1 that more household female labor availability is associated with increased likelihood of cultivating machine-harvestable chickpeas, as weeding and harvesting is dominant by female labor, and the results show the significant relationship between adopting machine-harvestable chickpeas and increase female weeding days per acre.

4.3 Methods and results for the correlation between the adoption of machine-harvestable chickpeas and the household/female dietary diversity status

We apply OLS regressions to study the correlation between adopting machine-harvestable chickpeas and the household/female dietary diversity status, and cluster the standard errors at the household level. The model for the household/female dietary diversity status is expressed as follows:

$$\Delta Scores_i = \beta_0 + \beta_1 MECH_i + \beta_2 VARIETY_i + \delta W_i + \sigma_m + \varepsilon_i,$$

where the dependent variable $\Delta Scores_i$ represents the change in Household Dietary Diversity Score and Minimum Dietary Diversity for Women in plot i, β_0 is the constant, $MECH_i$ is the explanatory variable of whether plot i used combined harvesters for harvesting chickpeas, $VARIETY_i$ is the other explanatory variable of whether plot i grew machine-harvestable chickpeas, β_1 and β_2 are coefficients for the two explanatory variables, W_i is the control vector that includes control variables of household and farm-level characteristics, including household size, household male and female member rate, education level of household head, household annual incomes, farm size and household crop number, δ represents the coefficients for control variables, σ_m is the regional fixed effect that controls for unobserved characteristics at the mandal level that potentially affect the adoption of machine-harvestable chickpeas, and ε_i is the error term.

From the regression results in Table 6, we can see that neither adopting machine-harvestable chickepas nor chickpea harvesting mechanization is statistically significantly associated with the change in household/female dietary diversity status.

Table 6: Regression results for household/female dietary diversity status

	HDDS	*MDD_W*
Harvesting mechanization	0.047	0.098
	(0.104)	(0.112)
Machine-harvestable chickpeas adoption	0.137	0.125
	(0.127)	(0.153)
Household size	0.002	0.023
	(0.037)	(0.031)
Male rate	-0.321**	-0.218
	(0.163)	(0.203)
Female rate	-0.062	0.164
	(0.255)	(0.332)
Education level	0.034	0.023
	(0.027)	(0.025)
Annual incomes	-1.81e-08	-1.74e-07
	(2.38e-07)	(3.14e-07)
Smallholder	0.002	0.019
	(0.121)	(0.119)
Household crop number	0.057	0.054
	(0.057)	(0.039)
No. of Obs.	321	321
Adjusted R-squared	0.155	0.095

Note: The table reports variable coefficients as results and robust standard errors in parentheses. *indicates significance at the 10% level, **indicates significance at the 5% level, *** indicates significance at the 1% level. Standard errors clustered at the household level.

CHAPTER 5

DISCUSSIONS

From previous results in Chapter 4, we see that although adopting machine-harvestable chickpeas is not significantly associated with household/female dietary diversity change, chickpea harvesting mechanization is significantly associated with reduced female on-farm working days across all operations. Therefore, there is need to promote harvesting mechanization in rural India to induce labor-saving. We found that household and labor characteristics, such as male and female rates which link to on-farm family labor availability; market factors, such as chickpea market price and demand; and seed characteristics are all essential factors related to the adoption of machine-harvestable chickpeas. These findings reflect the concept of agricultural innovation bundling, which supports the combination of innovation for agriculture development from different fields, such as socioeconomic, technology, policy, legislation and institution, culture, etc. (Fleischer et al., 2011; Barrett et al., 2020)

Above all factors mentioned, one major constraint on household adoption of the machine-harvestable chickpea variety and harvesting mechanization in rural India is farmers' fear of unemployment caused by mechanization. The results from four focused group discussions (FGDs) in two villages, Balapnur and Kanala, demonstrated that both male and female laborers were worried about unemployment (nearly two-thirds of harvesting time reduction). This finding aligns with theories that support the mixed effects of agricultural mechanization (Afridi et al., 2023; Afridi et al., 2020). Studies also imply that women are more vulnerable than men facing agricultural mechanization due to the unbalanced complementarity of women for on-farm machinery work and off-farm opportunities (Chrisendo et al., 2020; Komatsu et al., 2019; Afridi et al., 2023). To incentivize household adoption of the machine-harvestable chickpea variety and harvesting mechanization, it is critical to establish supporting mechanisms for rural job alternatives, such as public work programmes and employment guarantee programmes at the village level (Das, U., 2015), to smooth the mechanization adaptation process. We should remember that villages experience different levels of mechanization and cropping systems, which make the requirement of job-supporting mechanisms different. For example, villages with a long history of agricultural mechanization experience greater unemployment effects. Villages with diversified cropping systems (cultivating chilies, green grams, black grams, etc.) will suffer less from employment loss because workers can earn wages from processing other crops.

Additionally, the market limitation for the machine-harvestable chickpea variety is also emphasized in the FGDs. Both villages reported limited demand for new chickpea variety products, mainly due to the slightly larger pod size. The larger pod size causes more difficulties in by-product production, because producers cannot use previous production machines that do not fit the size of the new chickpea pods, leading to an increase in manual production requirements and associated costs. Lower demand resulted in lower product prices and profits, making the new chickpea variety less attractive to farmers than other varieties or crops. Some regional markets may have a greater capacity to absorb new chickpea products than others, leading to unbalanced market demand and flow of products. Therefore, policymakers should ensure enough market for the new chickpea products to avoid a large supply surplus.

As for factors in household characteristics, although participating in agricultural organizations and receiving training for machines are not statistically significantly associated with the adoption of machine-harvestable chickpeas, they still play important roles in promoting the adoption of machine-harvestable chickpea and chickpea harvesting mechanization. The percentage of household harvesting chickpea mechanically improved greatly in the second round because of the efforts of ICRISAT and affiliated organizations to increase the delivery of information and technical training to rural communities and the frequency of connection with households. Besides, farmers also gained information of fertilizers and chemicals, pest and disease management, new varieties, extreme weather prevention, and market trends from extension services provided. Future efforts are needed to strengthen the connection between households and community-based organizations. Bizikova et al. (2020) and Bachke, M. E. (2019) found positive association between farmers' organizations (FOs), such as associations, cooperatives, producer organizations, self-help and women's groups. Abraham et al. (2022) identified aggregation models, such as farmer producer organizations (FPOs), farmer groups, enterprises, etc., as important channels for smallholder farmers to jointly access financial credits, input and information sources, technology, extension services, and product markets.

Meanwhile, we should also keep in mind of the trade-off between agricultural labor work intensity and dietary status, and the offset of working time spent on different agricultural operations due to the technical improvement in one operation. Promoting the adoption of machine-harvestable chickpeas in rural India requires innovation bundling from multiple fields to develop a virtuous cycle of chickpea supply and demand. Facing the situation that some villages have given up chickpeas for other more profitable crops, policymakers and local communities should partner to provide farmers with a favorable environment to cultivate machine-harvestable chickpeas so that they can help release female labor from over-drudgery on farm works.

CHAPTER 6

CONCLUSION

This paper presents a case study on the first machine-harvestable chickpea variety adopted in rural India. We use the data from two rounds of quantitative surveys conducted by ICRISAT in 2019 and 2021 to test factors that are associated with the adoption of machine-harvestable chickpeas and chickpea harvesting mechanization, and the correlation between adopting machine-harvestable chickpeas and reduced female labor working days on farms and household/female dietary diversity status. We use the logistic regression and OLS regression models for each research question.

We found that household composition, family labor availability, and other factors, such as additional labor requirements for the new variety, as well as market and awareness constraints, will significantly associate with household adoption of machine-harvestable chickpeas and chickpea harvesting mechanization. While the machine-harvestable chickpea variety is still at the initial stage of adoption, and it is not associated with the change household/female dietary diversity status, we discover its association with reducing female labor working time on farms on the condition that households harvest chickpeas mechanically. However, the implication may be weak due to the limited adoption rate and the unclear female participation pattern in the chickpea farming systems. For future research, additional data and information are needed to understand how female workers would benefit from adopting machine-harvestable chickpeas; and how they would allocate time saved from harvesting mechanization to other on-farm and non-farm work such as housework and employment from National Rural Employment Guarantee Act (NREGA). Besides, it would be more beneficial to study the casual relationship between the adoption of machine-harvestable chickpeas and labor-saving as well as increasing household/female dietary diversity status.

The development of the machine-harvestable chickpea variety is possible to satisfy the need of compensating labor shortages in various states in India. We admit that agricultural mechanization has potential negative spillover effects on community development, such as temporarily reduced profits or unemployment. However, we could limit these effects by facilitating combined innovations in multiple fields, such as policy and legislation, culture and social economy, technology and service extensions, etc., before the wider promotion of machine-harvestable chickpeas in other regions. Identifying the social impact of adopting machine-harvestable chickpeas and solutions would ease the agricultural practice transformation process, and achieve optimal results in reducing female labor drudgery on farms, increasing household/female dietary diversity status and encouraging their participation in more non-farm economic and community activities.

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APPENDIX A

VARIABLE CONSTRUCTION

A.1. Variable summary

Here displays a variable list containing variables of interest in the paper:

Table A 1: Variable list

Variable Name	*Definition*
	Household demographics
Household Size	The number of household members
Male rate	The number of household males (aged 15-49)/HHSize
Female rate	The number of household females (aged 15-49)/HHSize
Dependent rate	The number of household children (aged -5)/HHSize
Education level	Education level of household heads
Age	The age of household heads
Annual incomes	Household annual incomes (rupees)
Member of Orgs	Whether household heads participated in agriculture organizations
Receiving trainings	Whether household heads received technical training
	Farm-level characteristics
Harvesting mechanization	Whether plots were harvested using combined harvesters
Machine-harvestable chickpeas adoption	Whether plots cultivated machine-harvestable chickpeas
Land owned	Acres of land owned per households (acre)
Smallholder	Whether the household is a smallholder (owning 5 acres or fewer land)
household crop number	The number of crops cultivated per household
Plot yield/acre	Plot yield per acre (kg)
Material costs/acre	Plot material costs per acre (rupees)
Chickpea rate	The price of main products per plot (rupees/kg)
Chickpea harvesting loss percentage	Percentage of production loss in quantity

(Continued table)

Variable Name	Definition
	Labor characteristics
Female working days/acre	Female working days per acre across operations (days)
Male working days/acre	Male working days per acre across operations (days)
Female harvesting days/acre	Female harvesting days per acre for completing the operation (days)
Female weeding days/acre	Female weeding days per acre for completing the operation (days)
Hired female harvesting rate	Hired female harvesting rate per acre (rupees/day)
Hired female weeding rate	Hired female weeding rate per acre (rupees/day)
	Dietary diversity status
HDDS	Household dietary diversity score (0-12)
MDD_W	Minimum dietary diversity for women (0-10)

A.2. The calculation of female on-farm working days per acre

The two outcome variables, household female on-farm working days per acre across operations and household female harvesting days per acre during the whole planting season, are constructed using that variable, *UNIT_LAB*, that reports the number of units females spent on agricultural operations/harvesting/weeding operation per household. Female labor weeding days per acre during the whole planting season per household is included as a test variable during the analysis, constructed in the same way. Female labor in this case includes family females, exchange females and hired females. Exchange female labor means that having family females work in each other's farms in lieu of wages. The reported units for these two variables include both "day" and "acre". We only include observations that reported "day" as the unit to keep the calculation uniformity. Almost all observations with “acre” as the unit are for hired female labor.

We summed up the working days of the three female labor types per household and divided the total number of labor days by the total plot areas per household. The total plot areas per household include both plots owned and leased by the household and are reported by the variable *PLOT_AREA*. All variables used for calculation can be found in the cultivation questionnaires for both rounds.

Figure A 1: Histograms for the distribution of female labor working days per acre

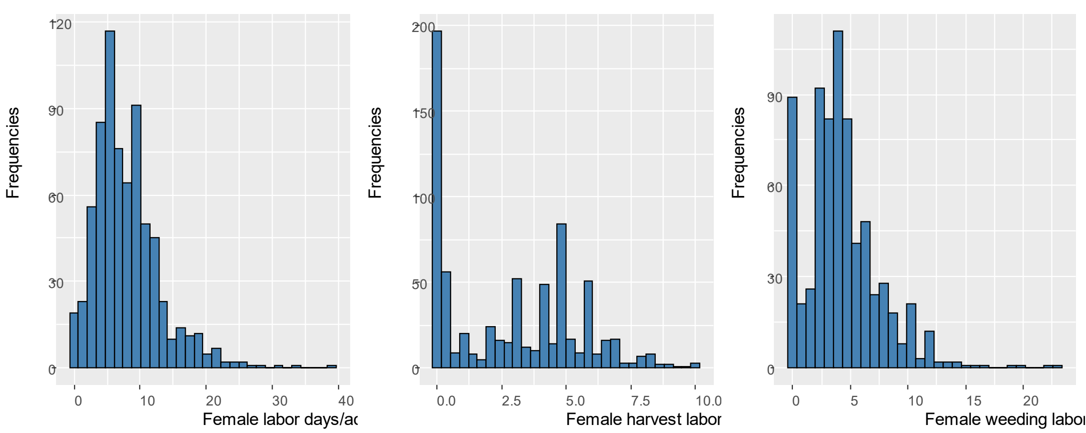

Figure A 2: Histograms for female labor working days per acre by mechanization

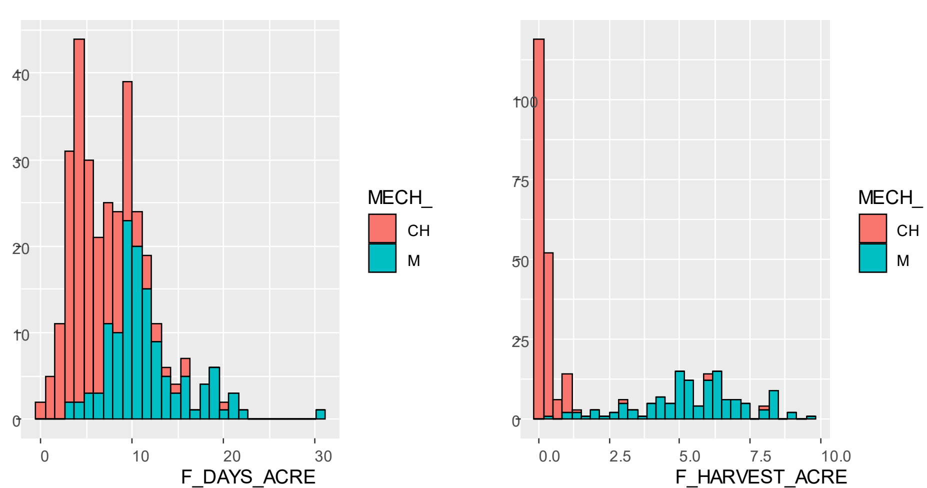

Figure A1 presents the distribution of female labor working days per acre for all farming operations and for harvesting/weeding operation only across all observations. Observations with zeros mean that households did not use female labor for respective operations. For harvesting labor days, we can see that almost 200 households did not use female labor for harvesting operations and the number of days that most household female labor spent are fewer than that of the weeding operation, which is also dominated by female labors. This phenomenon is corresponded to the adoption of harvesting mechanization, reflective in Figure A3, where households that adopted harvesting mechanization had female labor spend few days on farm work, especially for harvesting.

A.3. The calculation of dietary diversity scores

The two dietary diversity scores selected as indicators in this paper, Household Dietary Diversity Score (*HDDS*) and Minimum Dietary Diversity for Women (*MDD_W*), were calculated in reference to methods from International Dietary Data Expansion Project at Tufts University (INDDEX),[1] and the corresponding food groups from the questionnaire were identified in reference to *Guidelines for measuring household and individual dietary diversity* (Kennedy, G., Ballard, T., & Dop, M. C., 2011) and *Minimum Dietary Diversity for Women: A Guide to Measurement* (FAO, F., 2016). The INDDEX project enables the design and implementation of more effective food, nutrition, and agricultural policies and programs that improve the health, well-

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[1] https://inddex.nutrition.tufts.edu/

being, and livelihoods of people worldwide (International Dietary Data Expansion Project | INDDEX Project, n.d.).

In the second round of quantitative surveys, there was a questionnaire for dietary diversity, including information about different types of food consumed in a day (24 hrs) prior to the day of interview from one adult male and one adult female in the household. The 23 food groups contained in the questionnaire are listed in Table A2.

Table A 2: Food groups in the dietary diversity questionnaire

ID	*Food groups*
1	Foods made FROM grains
2	White roots and tubers and plantains
3	Pulses (beans, peas and lentils)
4	Chickpea
5	Nuts and seeds
6	Milk and milk products
7	Organ meat
8	Meat and poultry
9	Fish and seafood
10	Eggs
11	Dark green leafy vegetables
12	Vitamin A-rich vegetables, roots and tubers
13	Vitamin A-rich fruits
14	Other vegetables
15	Other fruits
16	Insects and other small protein foods
17	Red palm oil
18	Other oils and fats
19	Savoury and fried snacks
20	Sweets
21	Sugar-sweetened beverages
22	Condiments and seasonings
23	Any other beverages and food

A.3.1 Household Dietary Diversity Score (HDDS)

The Household Dietary Diversity Score provides information on household's ability to access food as well as its socioeconomic status based on the previous 24 hours (Household Dietary Diversity Score (HDDS) | INDDEX Project, n.d.). The 12 broad food groups used to calculate the *HDDS* indicator are list in Table A3, with the corresponding food group(s) from the questionnaire.

Each food group was assigned a score of 1 (if consumed) or 0 (if not consumed). All food groups from the questionnaire were used in the calculation of HDDS and were equally weighted. The household score ranges from 0 to 12 and is equal to the total number of food groups consumed by the household (Household Dietary Diversity Score (HDDS) | INDDEX Project, n.d.):

$HDDS = SUM\ (A + B + C + D + E + F + G + H + I + J + K + L)$

A.3.2. Minimum dietary diversity for women (MDD_W)

The Minimum Dietary Diversity for Women (*MDD-W*) is a population-level indicator of diet diversity validated for women aged 15-49 years old with the intake of 10 reported food groups (Minimum Dietary Diversity for Women (MDD-W) | INDDEX Project, n.d.). It was developed following the Women's Dietary Diversity Score (WDDS), which was calculated based on the reported intake of 9 broad food groups. According to the *MDD-W*, women who have consumed at least 5 of the 10 possible food groups over a 24-hour recall period are classified as having minimally adequate diet diversity. The use of this indicator to calculate the individual dietary diversity for women is also recommended by The Food and Agriculture Organization (FAO) and the United States Agency of International Development (USAID). The 10 broad food groups used to calculate *MDD-W* are listed in Table A4, with the corresponding food group(s) from the questionnaire.

Table A 3: Food groups used for HDDS calculation and corresponding food groups in the dietary diversity questionnaire

ID	*Food groups for calculation*	*Food groups in the questionnaire*
A	Cereals	Foods made FROM grains
B	Roots and tubers	White roots and tubers and plantains
C	Vegetables	Dark green leafy vegetables Vitamin A-rich vegetables, roots and tubers Other vegetables
D	Fruits	Vitamin A-rich fruits Other fruits
E	Meat	Organ meat Meat and poultry Insects and other small protein foods
F	Eggs	Eggs
G	Fish and other seafood	Fish and seafood
H	Legumes, nuts and seeds	Pulses (beans, peas and lentils) Chickpea Nuts and seeds
I	Milk and milk products	Milk and milk products
J	Oils and fats	Red palm oil Other oils and fats
K	Sweets	Sweets
L	Spices, condiments and beverages	Savoury and fried snacks Condiments and seasonings Any other beverages and food Sugar-sweetened beverages

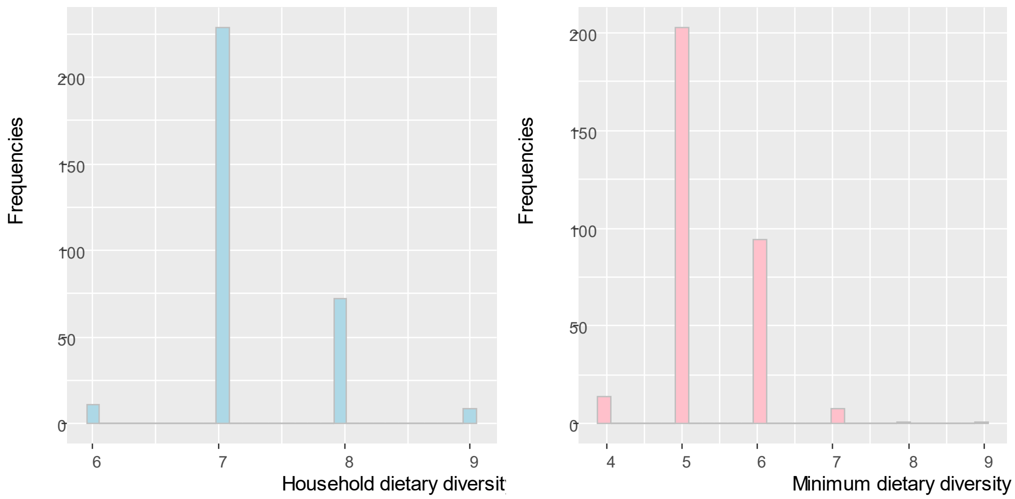
Each food group was assigned a score of 1 (if consumed) or 0 (if not consumed). Only 17 food groups from the questionnaire were used for the calculation of *MDD_W*, other food groups were considered optional and not counted towards the calculation (FAO, F., 2016). The total number of food groups consumed was summed into a score and all food groups were assigned equal weights (Minimum Dietary Diversity for Women (MDD-W) | INDDEX Project, n.d.).

Figure A3 presents the distribution of Household Dietary Diversity Score and Minimum Dietary Diversity for Women across all households in the second round. We can see that most households have a HDDS at 7 and MDD_W at 5.

Table A 4: Food groups used for MDD_W calculation and corresponding food groups in the dietary diversity questionnaire

ID	*Food groups for calculation*	*Food groups in the questionnaire*
A	Grains, white roots and tubers, and plantains	Foods made FROM grains White roots and tubers and plantains
B	Pulses (beans, peas and lentils)	Pulses (beans, peas and lentils) Chickpea
C	Nuts and seeds	Nuts and seeds
D	Dairy	Milk and milk products
E	Meat, poultry and fish	Fish and seafood Meat and poultry Insects and other small protein foods Organ meat
F	Eggs	Eggs
G	Dark green leafy vegetables	Dark green leafy vegetables
H	Other vitamin A-rich fruits and vegetables	Vitamin A-rich vegetables, roots and tubers Vitamin A-rich fruits Red palm oil
I	Other vegetables	Other vegetables
K	Other fruits	Other fruits

Figure A 3: Histograms for the distribution of HDDS and MDD_W



APPENDIX B

DESCRIPTIVE STATISTICS

Table B 1: Descriptive statistics for continuous variables

Variable	Mean	Std. Dev.	Min	Median	Max
Household Size	4	1	1	4	9
Male rate	0.251	0.175	0	0.25	0.8
Female rate	0.286	0.225	0	0.25	1
Dependent rate	0.028	0.087	0	0	0.5
Age	55	12	25	55	100
Annual incomes	248276.5	224387.0	4300.0	167500.0	1865500.0
Household crop number	2.84	1.78	1.00	2.00	11.00
Area planted	16.67	21.20	1.00	10.00	136.00
Land owned	12.42	13.12	0	9	90
Chickpea area	5.52	6.46	0.40	4.00	90.00
Plot yield/acre	556.29	261.35	21.43	585.00	3000.00
Chickpea rate	44.70	7.65	0.00	45.00	65.00
Material costs/acre	5356.48	2158.36	1060.00	5200.00	16383.33
Female working days/acre	8.08	5.01	0.00	7.00	39.00
Male working days/acre	4.40	4.52	0.00	3.20	36.00
Female harvesting days/acre	2.89	2.58	0.00	3.00	10.00
Female weeding days/acre	4.32	3.26	0.00	4.00	23.00
Hired female harvesting rate	256.27	183.47	2.00	200.00	2700.00
Hired female weeding rate	196.92	36.68	97.50	200.00	375.00
HDDS	7.25	0.56	6.00	7.00	9.00
MDD_W	5.32	0.64	4.00	5.00	9.00
LOSS_PRCT	42.49	24.29	0.00	40.00	100.00

APPENDIX C

ADDITIONAL FACTORS INFLUENCING THE NEW CHICKPEA VARIETY CULTIVATION

According to the survey documentation, there were 50 households documented as machine-harvestable chickpea adopters in the first round, and 55 households in the second round. However, at the time of the first-round survey, only 9 households still cultivated machine-harvestable chickpeas, with 17 households expressed willingness to continue cultivating. During the second round of the survey, only 16 households still cultivated machine-harvestable chickpeas, with 21 households expressed willingness to continue cultivating. The percentage of households willing to continue growing machine-harvestable chickpeas is less than 50%. Therefore, we dig into factors that may influence households' decision cultivating machine-harvestable chickpeas based on the qualitative survey results with adopted households from both rounds. Table C1 and C2 demonstrate some reasons that affect households' willingness to grow.

Table C 1: Reasons for households continuing growing machine-harvestable chickpeas

Reasons for continuing growing the NBeG47 variety	*Number of responses*
Increasing yield and income	19
Easy for machine harvesting (less drudgery and time consumed)	15
Drought resistant	3
Suitable for land	5
Self-motivation for new varieties	1
Institutional support	1

Table C 2: Reasons for households giving up on growing machine-harvestable chickpeas

Reasons for not continuing the NBeG47 variety cultivation	*Number of responses*
No market (Market rate is lower)	18
Less yield	15
No positive effect compared to other varieties (prefer other varieties)	7
Crop change (other crops more profitable than chickpea)	3
Not suitable for lands	5
Problem of harvesting	3
Lack institutional support (no seeds or subsidy)	3
Not resisted for water scarcity	2