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Socio-Economic Stratification and its Implication for Adoption and Use Intensity of Improved Soybean Technology in Northern Nigeria

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Abstract: This study recognized, the differences in wealth and socio-economic status of households and investigated, the implication of wealth categories on improved soybean technology adoption and use intensity decisions of households. It combined qualitative data collected through key informants wealth ranking technique and quantitative data collected using structured questionnaire administered to 307 soybean-growing households randomly selected from five villages in Kaduna and Kano states of Northern Nigeria. Data were analyzed using descriptive and inferential statistics and regression techniques. Results revealed that 41.37, 46.58 and 12.05% of respondents were classified into the poor, middle class and rich categories, respectively. Descriptive analysis showed that significant differences existed in farm size, means of transport ownership and number of resident adult women between the rich and the middle class and middle class and poor households ($p<0.01$). Also, differences in yield were revealed between the rich and the poor ($p<0.01$) and middle class and poor households ($p<0.05$) in farming experience between rich and middle class and the middle class and poor households ($p<0.05$) in labour expenses between rich and middle class ($p<0.05$) and the rich and poor households ($p<0.01$). Regression analysis identified labour expenses as influencing adoption and use intensity decisions of all households and households of different wealth categories. Aside, it revealed that different set of variables influenced adoption behaviours for different wealth categories; level of commercialization and ownership of means of transport were specific determinants for the rich; number of residence adult women, extension services and yield were specific for the middle class while extension services and price were unique for the poor class of farmers. All factors, except level of commercialization for the rich had significant ($p<0.05$) positive influence on adoption and use intensity behaviours of households. Coefficients of elasticity show that total responsiveness of adoption and use intensity was highly elastic ($\varepsilon>1$) with respect to level of commercialization, labour expenses and ownership of means of transport for the rich, resident adult women and yield for the middle class and labour expenses, extension services and price for the poor farmer categories. When decomposed, results showed that marginal changes in all factors increased the probability of use intensity than they increased the probability of adoption for all wealth categories and all households. The study revealed the growing importance of use of paid labour for farming activities of all categories of households in the study area. The implication of the finding is that wealth classes of households is imperative and should be considered when introducing a crop-improvement technology in an area.

Key words: Socio-economic stratification, soybean, adoption, use intensity, households, Nigeria

INTRODUCTION

The need to improve the well-being of the rural poor farmers and enhance the national income has necessitated the development and dissemination of improved agricultural technologies by policy makers in Africa (Phiri *et al*., 2004). To elicit the desired impact, these innovations needed to be adopted. Hence, studies on farmers' adoption of improved innovations had sparked off the interests of agricultural economists and extensionists (Oladele, 2005). Adoption of an innovation refers to the decision to apply the innovation and to continue to use it (Oladele, 2005). The concept could further be explained in terms of incidence or pattern of adoption and intensity of use (Langyintuo and Mekuria, 2005). With respect to crop-improvement innovation, the incidence answers the question on whether a farmer has used the technology or not while the intensity explains the degree of use (Langyintuo and Mekuria, 2005). Giving the reasons why adoption studies were becoming increasingly important, Langyintuo and Mekuria (2005) asserted that they were used to: quantify the number of technology users over time to assess impacts or determine extension requirements; provide information for policy reform and provide a basis for measuring impact. Following the pioneer adoption research by Rogers

(1962), there has been a growing list of studies attempting to explain the adoption behaviours of rural farmers (Adesina and Zinnah, 1993). In sub-Saharn Africa including Nigeria studies that relate to adoption of crop improvement innovations are numerous (Polson and Spencer, 1991; Adesina and Zinnah, 1993; Adesina and Baidu-Forson, 1995; Adesina and Seidi, 1995; Rao and Rao, 1996; Alene *et al*., 2000; Phiri *et al*., 2004; Oladele, 2005; Nzomoi *et al*., 2007; Langyintuo and Mekuria, 2005; Langyintuo and Mungoma, 2008). The evidences are that there are three main paradigms for adoption analysis; the innovation-diffusion, economic-constraint or farm structure and the adopter-perception paradigms (for more on the paradigms refer to Adesina and Zinnah, 1993; Langyintuo and Mekuria, 2005). Albeit each of these paradigms is considered individually important, most recent adoption studies have attempted to incorporate the three into a single adoption model (Adesina and Zinnah, 1993).

Also, certain specific variables that influence adoption decisions have been identified. Strategically, these factors could be grouped under three broad categories; the socio-economic and demographic characteristics of the farmer, like his/her age, gender, years of experience as a farmer or sole decision-maker in own farm, level of education, etc., institutional factors and farm characteristics, like farm size, membership of association, leadership position in community, access to credit, exposure to information, access to input and output markets, etc. and broad technological attributes, like yield, taste and resistance to diseases and pests.

Although, substantial research on the influence of some socio-economic variables on adoption have evolved (Voh, 1982; Rao and Rao, 1996) the influence of wealth status has been less discussed in adoption literature. Aside from, perhaps, Langyintuo and Mungoma (2008) who investigated the effect of household wealth on the adoption of Improved High Yielding Maize (IHYM) varieties in Zambia and found that factors influencing the adoption and use intensity of IHYM varieties could differ among the wealth categories, less of wealth related adoption studies have been cited. Among the reasons that could have accounted for this are the disagreement on the real definition of wealth (Bellon, 2001) the complexity and challenges associated with its measurement in developing countries (Worrall *et al*., 2003) and the likelihood of respondent's bias when supplying data of relating to income, expenditure and other wealth indicators (Adams *et al*., 1997; Filmer and Pritchett, 2001; Worrall *et al*., 2003; Hargreaves *et al*., 2007). This study recognizes the influence of wealth and households socio-economic status on their improved soybean technology adoption behaviours. To capture wealth status, efforts were made at classifying rural soybean growers into different wealth and socioeconomic categories and consequently, investigated the factors influencing adoption decisions for each category. In effect, the study has applies a quantitative analytical procedure to qualitative data generated from Participatory Wealth Ranking (PWR) process.

The combined use of quantitative and qualitative tools of data collection and analysis has been advocated by proponents of multidisciplinary approach to rural poverty analysis (Chambers, 1994a; Carvalho and White, 1996; World Bank, 2001; White, 2002; Barrett, 2005). Quantitative data are collected using structured questionnaire under the traditional survey system. On its part, qualitative research uses a wide array of interconnected techniques which include but not limited to use of case study, personal experience, introspective, life story, interview, observational, historical, interactional and visual texts (Denzin and Lincoln, 1994).

Chambers (1994b) argued succinctly that participation is the philosophy and mode of development of qualitative research. In it use is made of the Participatory Rural Appraisal (PRA) and Rapid Rural Appraisal (RRA) that integrate a growing family of approaches and methods intended to enable the local people express, enhance, share and analyze their own knowledge of life and conditions and to plan and to act (Chambers, 1994b).

Much has been written on the strengths of this emerging approach to scientific research. For example, Njeru (2005) observes that combining qualitative and quantitative approaches would optimize the quality and value of the rural household analysis. Recognizing their inter-relation also, Mayring (2001) upholds that the two paradigms stand to gain if they no longer ignore each other. This is because the quantitative paradigm gives greater proximity to the research subject while the qualitative paradigm by making the various stages of the research process more transparent and systematic helps to increase the generalisability of the results (Fielding and Schreier, 2001).

White (2002) observes that the oppositions between quantitative and qualitative approaches are false dichotomies because when combined both methods tend to yield more than the sum of the two approaches used independently. This thought is corroborated by the fact that qualitative data can add context to quantitative data collected in surveys while the PRA and RRA techniques can meaningfully contribute to understandings of poverty issues (Chambers, 1994a, b; World Bank, 2001). From an ontological position, it has also been argued that the competition between qualitative and quantitative research is resolved into complementarities since both approaches are essentially inter-related with quantitative research, contributing towards the precise identification of relevant processes and qualitative research providing the basis for their thick description (Fielding and Schreier, 2001). Although, Mwabu (2005) believes that all problems could not be analyzed by mixing qualitative and quantitative methods, he emphasizes the need for a good clarification of the intending challenges through simultaneous mixing of both methods.

MATERIALS AND METHODS

The study area: The study was conducted in five villages in Northern Nigeria. Three villages; Kaya, Gidan Hayaki and Ungwan Dan Mallam are in Kaduna state which lies between latitudes 9°042'-11°502'N and longitude 6°092'-10°412'E. The remaining two villages; Ungwan Dawa and Mariri are in Kano state which lies between latitudes 10°332'-12°372'N and longitude 7°342'-9°252'E. The ecology of Kaduna is the guinea savanna with annual rainfall range of 600-1200 mm and Length of Growing Period (LGP) of 150-200 days. The ecology of Kano is the sudan savanna. It has a rainfall range of 300-600 mm and 90-150 days LGP. The distribution of rainfall is uni-modal in both ecologies.

The farming systems in the zone are generally cereal-based with small-scale farmers producing the bulk of the total output. Farming and cattle rearing constitute the main occupations of the rural population. The area also produced grain-legume crops, mainly grown in upland fields but has great potential for irrigated agriculture.

Data collection: The study combined qualitative data generated through key informants rating and quantitative data collected through administration of structured household questionnaire. Wealth or well-being scoring and ranking which belong to the family of the PRA techniques is an indirect method of collecting information on households socio-economic status. Tiwari *et al.* (2005) contends that a household's socio-economic status would mean the ranking of the household in the milieu to which it belongs in respect of defined variables like physical assets, economic status, education, occupation, social position, social participation, caste, muscle power, political influence among others which could have the tendency to go together.

The tool provides a means of assessing relative wealth and well-being of individuals in a given community (Cramb and Purcell, 2001). The need for wealth and well-being ranking arises from the fact that knowledge of the character and determinants of poverty makes the formulation of poverty alleviation strategies easier. The argument has been that wealth ranking provides more accurate and realistic categorization of households by their wealth compared to the standard questionnaire method because the villagers take various aspects of the household into consideration while conducting the ranking.

Card sorting by key informants and social mapping by community focus groups are two ways of conducting wealth and well-being ranking. In this study, card-sorting approach to wealth ranking (Feulefack and Zeller, 2005) was used to garner data on households wealth categories from four key informants selected in each village. The data from the key informants were tabulated and scored for each farmer. Thereafter, the resultant indexes were used to classify respondents into the rich, middle class and poor farmers following suggestions by Cramb and Purcell (2001). Quantitative data were collected using structured household questionnaires administered by trained enumerators. The enumerators used for data collection were members of staff of the Agricultural Development Programs (ADPs) in the states, namely the Kaduna state Agricultural Development Programme (KADP) of Kaduna state and the Kano state Agriculture and Rural Development Agency (KNARDA) of Kano state.

The questionnaires were administered on 307 respondents drawn proportionate to size of listed farmers in the five villages.

Analytical procedure: The study used descriptive statistics, inferential statistics and regression analysis. The Tobit model was used to determine the factors affecting the average proportion of soybean farmland devoted to the improved variety which is a measure of adoption and use intensity by respondents in different wealth categories. Adoption of innovations is described as the decision to apply and continue to use the innovation (Oladele, 2005).

The incidence indicates whether a farmer has used a technology or not and the latter explains the degree of use of a technology. A number of working hypotheses have explained the formulation of the adoption model. It was hypothesized that a farmer's decision to adopt or not to adopt a new technology at any point in time is influenced by the combined or simultaneous effect of a number of factors relating to the farmer's objectives and constraints (CIMMYT, 1993). Following McDonald and Moffit (1980) and Maddala (1983), we specify a Tobit model that tests the factors affecting the incidence and intensity of soybean adoption as follows:

$$y_t = x_t\beta + u_t, \quad \text{if } x_t\beta + u_t > 0$$
$$= 0 \quad \text{if } x_t\beta + u_t \leq 0, \quad t = 1, 2, \ldots, n \qquad (1)$$

Where:

y_t = Proportion of soybean farm devoted to improved variety at a given stimulus level, x_t
x_t = Vector of explanatory variables
n = Number of observations in each wealth category
β_t = Unknown parameters to be estimated
u_t = Independently distributed error term assumed to be normal with zero mean and constant variance, σ^2

The quantity, $y = x_i\beta$ (coded ADO in this study) is the index reflecting, the combined effect of the independent variables (x_i) hindering or promoting adoption and use intensity of improved soybean. In this study, the index was specified as:

$$ADO = \beta_0 + \beta_1 x_1 + \ldots + \beta_{15} x_{15} + \xi_t \qquad (2)$$

Where:

β_0 = Constant and intercept of the equation
x_1 = AGE (age of the farmer in years)
x_2 = FMZ (farm size in hectares)
x_3 = DRA (dependency ratio, measured as the ratio of the dependants to the working population)
x_4 = RAW (number of resident adult women)
x_5 = COM (level of soybean commercialization, measured as quantity sold to total production)
x_6 = EDU (level of education measured as 0 = no formal education, 1 = primary education completed, 2 = secondary education completed, 3 = post secondary education attempted or completed)
x_7 = FEX (farming experience in years)
x_8 = LAB (expenses on hired labour, measured in Nigerian naira)
x_9 = TRA (ownership of means of transport, measured as 0 = if none was owned, 1 = if bicycle was owned, 2 = if motorbike was owned and 3 = if motor vehicle was owned)
x_{10} = INF (ownership of means of access to information (dummy: 1 = owned radio or television or both 0 = if otherwise)
x_{11} = MAS (membership of associations, dummy variable: 1 = member, 0 = otherwise)
x_{12} = EXT (access to extension services, dummy: 1 = if extension agents/staff visited in the last 6 months, 0 = if otherwise)
x_{13} = CRD (access to credit, dummy variable: 1 = if respondent received credit, 0 = if otherwise)
x_{14} = YLD (yield of soybean, measured in ton ha^{-1})
x_{15} = SPR (price of soybean, measured in Nigerian naira per kilogram)
ζ_i = Stochastic error term

AGE (x_1) is respondents age. The influence of the farmer's age (x_1) in explaining technology adoption decisions has been somewhat controversial and indeterminate going with evidence from the adoption literature (Langyintuo and Mekuria, 2005). The argument is that farmers' age can either generate or erode confidence in a new technology (Kotu *et al*., 2000). In other words with more experience, a farmer can become more or less risk-averse when judging new technology. Consequently, the age variable could have a positive or negative effect on an average farmer's decision to adopt improved soybean technology.

FMZ (x_2) is the farm size. The amount of farm area cultivated by the farmer is an indicator of wealth and can perhaps serve as a proxy for social status and influence within a community (Kotu *et al*., 2000). It is expected to be positively associated with the decision to adopt improved wheat technology. However, a small area allocated to soybean could conceivably encourage farmers to intensify their production practices. In this case, larger farm size would be negatively related to the adoption decisions for all wealth categories.

DRA (x_3) is the dependency ratio. Dependants are technically defined as the sum total of all household members that are <15 years of age and those >65 years. Following Chianu and Tsujii (2004), dependency ratio is then expressed as ratio of the dependants children of 15 years and below and aging adults of >65 years to the working population, 16-65 years. It is expected that high dependency ratio would increase the obligatory role of the household head. Being preoccupied with thought on how to meet the immediate household needs, the household head would be less willing to devote resources on acquisition of new discoveries. Consequently, we hypothesize that dependency ratio and adoption behaviours of the household head are inversely related for all wealth categories. RAW (x_4) is the number of resident adult women. Women play vital roles in the provision and sustenance of food and nutrition security of households (Quisumbing *et al*., 1999).

In agriculture, adult women (mostly housewives) and children complement the activities of the men farmers and often take full charge in the absence of their husbands. It is hypothesized that for all wealth categories, the number of resident adult women would have a positive influence on the farmers decision to adopt or not to adopt a new technology. COM (x_5) is the level of commercialization of soybean. Soybean is usually grown as a cash crop in the study area. Thus, irrespective of the wealth category, the extent to which the market accepts the volume of production would determine the farmers willingness or otherwise to expand their capacity. It is hypothesized that the level of commercialization would have a positive influence on improved technology adoption and use intensity for all category of farmers.

EDU (x_6) is education attainment of respondent. Irrespective of the wealth class, education would have the propensity to increase the farmer's ability to obtain, process and use information relevant to the adoption of improved soybean innovation. We therefore, hypothesize a positive relationship between level of education and adoption decisions of soybean farmers of different wealth categories.

FEX (x_7) is the years of farming experience. Experience influences farmers' adoption behaviours. This is because relatively more experienced farmers, through interactions with neighbors and the outside world were generally better able to assess the relevance of new technologies (Langyintuo and Mekuria, 2005). For the same reason, older farmers would also be better equipped to acquire the needed skills to use the technologies compared with younger ones. We hypothesize that a positive relationship would exist between farming experience and improved soybean adoption decisions for all wealth categories of farmers.

LAB (x_8) is expenses on hired labor. Ease of access to hired labor is expected to have a positive influence on the farmers' adoption of improved soybean technologies. Usually, ability to hire labour is determined by farmers financial base hence, wealthier farmers would have more propensities to expend resources on hired labour. We hypothesize a positive relationship for all classes of farmers.

TRA (x_9) is the ownership of means of transport. Costs of conveying persons and materials have been on a continuous increase in most urban and rural communities in Nigeria due to dilapidating state of infrastructures, especially bad roads increasing costs of spare parts and maintenance and instability in the pump price of petrol. Thus, owners of their own means of transport have some advantages in terms of relative ease in facilitating movement of resources including planting materials, labour, fertilizer, etc., to their farms. It is expected that ownership of means of transport would have a positive influence on adoption and use intensity decisions of respondents irrespective of the wealth category and so, we hypothesize.

INF (x_{10}) is ownership of means of information. Ownership of means of information, like radio and television sets would break the barrier of lack of knowledge and provide access to information. It is hypothesized that ownership of means of information will have a positive influence on adoption and use intensity decisions for all wealth categories. MAS (x_{11}) is membership of association. Farmers associations including cooperatives, farmers meetings and clubs provide medium for accessing and sharing information on modern farming techniques. We hypothesized that membership of means of associations will have a positive influence on adoption and use decisions of different wealth categories of respondents.

EXT (x_{12}) is access to extension services. Agricultural extension services were the major sources of agricultural information in the study area. It is expected that irrespective of the wealth category, farmers contact with extension workers would increase the likelihood of their adoption and use intensity of the improved soybean technologies.

CRD (x_{13}) is household's access to credit. Farmers who have access to agricultural credit could minimize their financial constraints and consequently buy inputs more readily. Thus, it is expected that for all wealth categories, access to credit would increases the probability of adopting improved agricultural innovation for all category of farmers.

YLD (x_{14}) refers to the yield of soybean. It is expected that a high-yielding variety would be more attractive for farmers adoption and use, not withstanding the wealth category. It is hypothesized that yield of soybean will have a positive influence in respondents adoption decisions.

SPR (x_{15}) refers to price. It is expected that the price of soybean will have a positive influence in respondents adoption decisions through its influence on household income. Consequently, positive relationship is hypothesized for all farmers categories.

Elasticity decomposition framework: The elasticities are decomposed following a Tobit decomposition framework suggested by McDonald and Moffit (1980) and applied by Adesina and Zinnah (1993). The steps are described as follows; suppose the expected value of the dependent variable, ADO across all observations is represented by E (P). Also, suppose the expected value of the dependent variable conditional on the improved soybean variety growing household being above the threshold limit that is household is already an adopter and is currently concerned about use intensity is given as E (p) while the probability of the household being above the limit that is the probability of adoption is symbolized by F (z) where $z = XB/\sigma$. The relationship among E (P), E (p) and F (z) can be expresses as:

$$E(P) = F(z) * E(p) \tag{3}$$

For a given change in the relevant variable, the effect on improved soybean adoption behavior of the household can be split into two parts by differentiating Eq. 3 with respect to the specific variable change. Taking the partial derivative, we have:

$$\delta E(P)/\delta X_i = F(z)[\delta E(p)/\delta X_i] + E(p)[\delta F(z)/\delta X_i] \tag{4}$$

If multiplied through by X_i/E (P) the relationship in Eq. 4 can be converted into elasticity forms as follows:

$$[\delta E(P)/\delta X_i]X_i / E(P) = F(z)[\delta E(p)/\delta X_i]X_i / E(P) + E(p)[\delta F(z)/\delta X_i]X_i / E(P) \tag{5}$$

Rearranging Eq. 5 using Eq. 3, the result becomes:

$$[\delta E(P)/\delta X_i]X_i / E(P) = [\delta E(p)/\delta X_i]X_i / E(p) + [\delta F(z)/\delta X_i]X_i / F(z) \tag{6}$$

It follows from Eq. 6 that the total elasticity of a change in level for any specific variables consists of two effects; the change in the elasticity of the use intensities of the improved soybean varieties for households that are already adopters and the change in the elasticity of the probability of being an adopter.

RESULTS AND DISCUSSION

Wealth categories of respondents: The wealth categories of respondents are shown in Fig. 1. It shows that 41.37% of respondents were classified as poor, 46.58% as middle class and 12.05% as rich. Also, the composition of the wealth categories in the five villages is shown in Fig. 2. It shows that only very few of the respondents were ranked among the rich while in one of the villages none of the respondents was identified into the rich class.

Descriptive statistics of included variables: The descriptive statistics of the variables used in the empirical analysis is shown in Table 1 for the rich, middle class and poor farmers. The average age is 43.59 years for all farmers, 49.14 years for the rich, 44.48 years for the middle class and 40.98 years for the poor farmers. The differences in average ages are statistically significant between the rich and the poor (p<0.01) and between the middle class and the poor (p<0.05) but not between the rich and the middle class. At first sight, this tends to suggest that majority of the older farmers were rated as either rich or middle class, implying that perhaps, there could be a significant high correlation between age and wealth categories of respondents. Further investigation however, revealed that both variables were weakly correlated (r = 0.19). The aggregate average farm size is 1.24 ha. As expected, the rich owned larger farm sizes followed by the middle class households. The average farm size was calculated as 3.23 ha for the rich, 1.15 ha for the middle class and 0.61 ha for the poor households. The differences are statistically significant (p<0.01) between the various wealth categories.

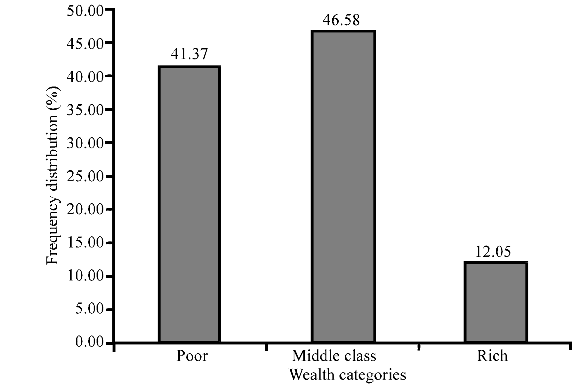

Fig. 1: Classification of all respondents by wealth categories

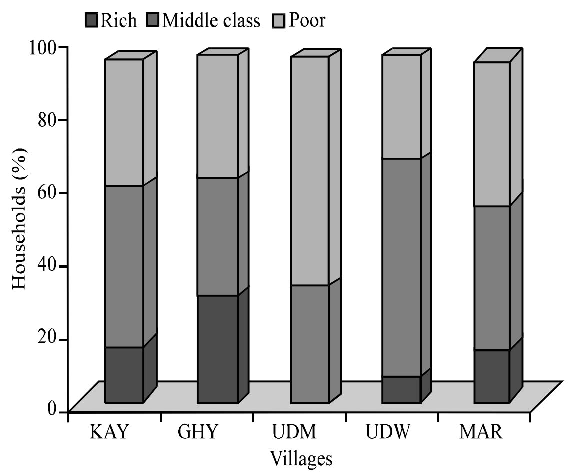

Fig. 2: Composition of wealth categories in villages KAY = Kaya; GHY = Gidan Hayaki; UDM = Ungwan Dan Mallam; UDW = Ungwan Dawa; MAR = Mariri

It follows that farm size is a very important socio-economic factor for assessing wealth categories in the study area. Other equally relevant socioeconomic factors are number of adult women resident in household, ownership of means of transport and farming experience. Whereas, differences in averages of the number of resident adult women and ownership of means of

Table 1: Descriptive statistics of variables used for empirical analysis

Variables		All farmers (n = 307)	Rich (n = 37) (A)	Middle class (n = 143) (B)	Poor (n = 127) (C)	Mean difference A and B	A and C	B and C
		Mean±SD						
ADO	Y	0.485±0.452	0.653±0.421	0.476±0.452	0.447±0.452	0.177^{**}	0.206^{**}	0.029
AGE	X_1	43.593±13.489	49.135±13.088	44.476±13.405	40.984±13.179	4.660	8.151^{***}	3.491^{**}
FMZ	X_2	1.235±1.588	3.227±3.301	1.145±0.613	0.755±1.046	2.082^{***}	2.472^{***}	0.390^{***}
DRA	X_3	0.537±0.209	0.605±0.168	0.567±0.234	0.484±0.183	0.038	0.120^{***}	0.082^{***}
RAW	X_4	1.780±0.829	2.490±0.768	1.830±0.769	1.520±0.785	-0.654^{***}	0.967^{***}	0.312^{***}
COM	X_5	0.804±0.167	0.848±0.094	0.776±0.176	0.822±0.169	0.072^{**}	0.026	-0.046^{**}
EDU	X_6	1.640±1.090	1.620±1.187	1.660±1.097	1.620±1.061	0.040	0.000	0.040
FEX	X_7	8.638±5.405	11.297±4.783	8.944±6.182	7.520±4.231	2.353^{**}	3.778^{***}	1.424^{**}
LAB	X_8	5.160±3.705	6.721±4.017	5.146±3.698	4.721±3.522	1.574^{**}	2.000^{***}	0.426
TRA	X_9	2.090±0.608	2.780±0.854	2.080±0.476	1.900±0.503	0.707^{***}	0.887^{***}	0.180^{***}
INF	X_{10}	0.870±0.334	0.950±0.229	0.870±0.341	0.860±0.350	0.079	0.088	0.009
MAS	X_{11}	0.550±0.499	0.590±0.498	0.580±0.495	0.500±0.502	0.014	0.099	0.084
EXT	X_{12}	0.450±0.499	0.620±0.492	0.430±0.496	0.430±0.497	0.195^{**}	0.189^{**}	-0.006
CRD	X_{13}	0.100±0.306	0.080±0.277	0.100±0.307	0.110±0.314	0.024	-0.029	-0.005
YLD	X_{14}	1.107±0.258	1.195±0.233	1.128±0.261	1.059±0.252	0.067	0.136^{***}	0.069^{**}
SPR	X_{15}	44.233±5.869	42.902±6.395	44.483±6.337	44.340±5.109	-1.581	-1.438	0.144

**Significant at 1%; **significant at 5%; *significant at 10%

Table 2: Determinants of adoption and use intensity for the rich, middle class and poor farmers

	Rich			Middle class			Poor			All farmers		
Variables	Coefficient	SE	t value	Coefficient	SE	t value	Coefficient	SE	t-value	Coefficient	SE	t value
Constant	1.295	0.819	1.582	-1.429^{**}	0.565	-2.532	-1.546^{***}	0.591	-2.616	-1.292^{***}	0.342	-3.775
AGE	-0.008	0.006	-1.479	-0.002	0.004	-.479	-0.002	0.004	-0.398	-0.523E-03	0.248 E-02	-0.212
FMZ	-0.003	0.024	-0.146	0.004	0.043	.086	-0.047	0.076	-0.615	0.584E-02	0.018	0.325
DRA	-0.264	0.404	-0.653	0.377	0.248	1.518	0.096	0.210	0.456	0.122	0.148	0.829
RAW	0.004	0.079	0.049	0.128^{**}	0.063	2.045	0.049	0.064	0.774	0.056	0.0399	1.413
COM	-1.847^{***}	0.611	-3.025	0.165	0.261	.632	0.241	0.277	0.871	0.246	0.181	1.365
EDU	0.017	0.050	0.337	-0.61E-04	0.47E-03	-.130	-0.018	0.042	-0.426	-0.53E-05	0.455E-03	-0.012
FEX	-0.008	0.012	-0.669	-0.005	0.009	-.570	0.021^{*}	0.012	1.784	-0.322E-03	0.603E-02	-.053
LAB	0.052^{***}	0.018	2.919	0.041^{***}	0.014	2.900	0.069^{***}	0.014	4.899	0.053^{***}	0.912E-02	5.847
TRA	0.242^{***}	0.073	3.328	-0.099	0.101	-.975	-0.79E-03*	0.47E-03	-1.676	-0.725E-03	0.463E-03	-1.565
INF	0.051	0.239	0.215	0.169	0.135	1.257	-0.222^{*}	0.127	-1.754	-0.015	0.0867	-0.173
MAS	0.169	0.119	1.418	0.122	0.088	1.376	0.085	0.089	0.943	0.143^{**}	0.578	2.474
EXT	0.123	0.141	0.878	0.427^{***}	0.099	4.293	0.532^{***}	0.100	5.322	0.444^{**}	0.063	7.002
CRD	0.349	0.292	1.193	0.179	0.131	1.371	0.022	0.138	0.156	0.112	0.091	1.235
YLD	0.477^{*}	0.250	1.911	0.559^{***}	0.177	3.151	0.139	0.178	0.782	0.398^{***}	0.112	3.545
SPR	-0.008	0.008	-1.008	0.006	0.007	.825	0.021^{**}	0.009	2.268	0.69E-02	0.489E-02	1.425
Sigma	0.247^{***}	0.034	7.380	0.447^{***}	0.034	13.228	0.431^{***}	0.037	11.663	0.446^{***}	0.023	19.012
L/Likelihood	-	-4.954	-	-	-87.712	-	-	-74.776	-	-	-194.041	-
OLS R^2	-	0.741	-	-	0.431	-	-	0.538	-	-	0.457	-
Cond. Mean	-	0.596	-	-	0.398	-	-	0.356	-	-	0.410	-
Scale factor	-	0.992	-	-	0.778	-	-	0.751	-	-	0.788	-
Sample size (n)	-	37.000	-	-	143.000	-	-	127.000	-	-	307.000	-

***Significant at 1%; **significant at 5%; *significant at 10%

transport were statistically significant at $p<0.01$ levels between the different wealth categories, farming experience was significant across categories at $p<0.05$ levels. The average yield of soybean for all households is 1.11 ton ha^{-1}. The rich had an average of 1.19 ton ha^{-1} as against 1.13 and 1.06 ton ha^{-1} for the middle class and poor households, respectively. The differences in yield were only statistically significant between the rich and poor ($p<0.05$) and the middle class and poor households ($p<0.05$). The differences could have resulted from similar differences in ages and farming experiences which could be associated better farm management practices. Differences were equally observed in average labour expenses at $p<0.05$ and $p<0.01$ levels between the rich and the middle class and rich and poor households, respectively. Similarly, there were differences in the rich households' access to extension services in comparison to the middle class and poor households ($p<0.05$).

Determinants of adoption and use intensity among wealth categories: The results of the Tobit regression analysis are shown in Table 2 for the different wealth categories. The variables level of commercialization ($p<0.01$), labour expenses ($p<0.01$) and ownership of means of transport ($p<0.01$) were significant in explaining the adoption behaviours of the rich category of households. Labour expenses and ownership of means of transport produced the expected positive signs, implying that decisions on adoption and use intensity increase with increases in the variables for the rich households. The level of commercialization produced a surprising negative sign, implying that adoption and use decisions shrink as the rate of commercialization increases. This is rather strange for a cash crop like soybean but can be possible if the rich households desire to grow soybean for household processing and food security needs. For the middle class households, number of residential adult women ($p<0.05$), expenses on hired labour ($p<0.01$), extension services access ($p<0.01$) and yield of soybean ($p<0.01$) were all significant and have positive influence on adoption decisions. The variables produced a priori positive signs, meaning that adoption and use intensity levels increase with increases in the variables. For the poor households, labour expenses ($p<0.01$), extension services visit ($p<0.01$) and price of soybean ($p<0.05$) were all positive and significant in explaining adoption decisions. Their positive signs show that adoption increases with increase in the variables. The results from the aggregated data reveal that labour expenses ($p<0.01$), membership of associations ($p<0.05$), extension services ($p<0.05$) and yield ($p<0.01$) have positive and significant influence on households adoption behaviours.

The results reveal that apart from expenses on labour which explained adoption for all households and all wealth categories of households, adoption decisions of households of different categories were influenced by different factors. This corroborated the findings by Langyintuo and Mungoma (2008) in their research on maize in Ethiopia. They recommended wealth group-specific interventions to increase the adoption and use intensity of such varieties and their subsequent impacts on food security and general livelihoods of the households. The significant and positive signs associated with labour expenses in all variants of regression have revealed the growing importance of the use of paid labour for farming activities of all categories of households in the study area.

Policy implications: Economic conclusions can be drawn based on the Empirical model by determining the degrees of responsiveness of probability of adoption and use intensity resulting from changes in the significant variables. These were computed as coefficients of elasticity based on Eq. 6, earlier derived. The results are shown in Table 3. They reveal that marginal changes in each of the variables would increase the probability of use intensity than it would increase the probability of adoption for all wealth categories and all households. For the rich class of households, elasticity estimates reveal highly elastic responses to changes in the significant variables; level of commercialization (COM), labour expenses (LAB) and ownership of transport means (TRA). Similar, highly elastic responses were also revealed for Resident Adult Women (RAW) and yield (YLD) for the middle class and for price (SPR), extension services (EXT) and labour expenses (LAB) for the poor class. Specifically for the rich class, a 10% improvement in the level of commercialization would result to about 24% an astounding decrease in probability of adoption and 26% increase in probability of use intensity giving a total elasticity of 50%. A similar, a 10% increase to amount expended to procure labour services would bring about a total of 11% increase in elasticity, comprising of 5% increase in probability of adoption and 6% increase in elasticity of use. Also, a 10% improvement in ownership of means of transport would result to a 10% increase in elasticity of probability of adoption and 11% increase in the elasticity of use intensity giving a total 21% increase in elasticity.

Table 3: Coefficients of elasticity

Categories	Variables	β-coefficient	Elasticity: Adoption	Use intensity	Total
Rich	COM	1.847^{***}	2.40	2.63	5.03
	LAB	0.052^{***}	0.54	0.59	1.13
	TRA	0.242^{***}	1.03	1.13	2.16
Middle class	RAW	0.128^{**}	0.49	0.59	1.08
	LAB	0.041^{***}	0.44	0.53	0.97
	EXT	0.427^{***}	0.39	0.46	0.85
	YLD	0.559^{***}	1.32	1.58	2.90
Poor	LAB	0.069^{***}	0.73	0.92	1.65
	EXT	0.532^{***}	0.51	0.64	1.15
	SPR	0.021^{**}	2.08	2.62	4.70
All farmers	LAB	0.053^{***}	0.57	0.67	1.24
	MAS	0.143^{**}	0.16	0.19	0.35
	EXT	0.444^{**}	0.41	0.49	0.90
	YLD	0.398^{***}	0.91	1.07	1.98

Calculated using field survey data ***significant at 1%; **significant at 5%; *significant at 10%

In the case of the middle class households, a 10% increment to the number of resident adult women, labour expenses, time of extension services visit and yield would result to 11, 10, 9 and 29% increases in total elasticity. This is split into the elasticities of adoption probability and use intensity components as follows; 5 and 6% for resident adult women, 5 and 5% for labour expenses, 4 and 5% for extension services and 13 and 16% for yield. For the poor class of farmers, a 10% increment in labour expenses, visitation of extension services and price of soybean will result to an increase in elasticity of probability of adoption and probability of use intensity by 7, 9, 5, 6, 21 and 26%, respectively. These amount to a total elasticity of 16, 11 and 47% as the case may be. Table 4 also shows the elasticity calculations for all farmers using the aggregate data. It shows that elasticity estimates reveal elastic responses to changes in labour expenses (LAB) and yield (YLD) and inelastic responses to changes in extension services visitation (EXT) and Membership of Associations (MAS).

It reveals further that marginal changes in all variables will increase the probability of use intensity than it will increase the probability of adoption for all households.

CONCLUSION

The study, revealed that labour expenses influences the improved soybean technology adoption decisions of all households including those of households of different wealth categories. Aside, it showed further that there were other different set of variables whose influences on adoption behaviours could vary from one wealth group to another. For instance, ownership of transport means and level of commercialization were unique to the rich class, residence of adult women and yield were peculiar to the middle class while price was exclusive in the case of the poor class of farmers. However, the influence of extension services was common to both the middle class and poor farmers.

The distinctiveness of labour expenses on adoption decisions of all households of varied wealth groups reveals, the increasing trend in the use of hired labour for farming activities in the area. This is not unconnected with the fact that reliance on free household labour is becoming increasingly less attractive for farmers as fewer hands are available for submission into such use. Perhaps, most households were becoming somewhat wiser and would prefer sending their children to school or to learn trade elsewhere. Most grown up male children were into motorcycle transport business while others would prefer to sale their services somewhere else make some money for self sustenance.

Notwithstanding, the study revealed that there were some factors whose influence on household adoption and use intensity decisions differ with from one wealth category to another. The implication of the finding is that wealth classes of households is imperative and should be considered when introducing a new technology in an area.

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