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The effects of education on agricultural productivity under traditional and improved technology in northern Nigeria: an endogenous switching regression analysis

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Abstract This paper estimates a more efficient version of an endogenous switching regression model to examine the effects of farmer education—schooling and extension contact—on cowpea production under traditional and improved technology in northern Nigeria. The results revealed significant productivity-enhancing effects of schooling and extension contact only under improved technology. Factors that promote technology adoption will thus indirectly raise the marginal contributions of farmer education; these include schooling, participatory technology evaluation, improved seed supply, and market access. The results demonstrate that schooling not only enhances agricultural productivity following technology adoption but also promotes adoption itself.

Keywords Cowpea · Schooling · Extension · Technology adoption · Nigeria

1 Introduction

A lot of empirical work on education and agricultural productivity (e.g., Moock 1981; Jamison and Moock 1984; Appleton and Balihuta 1996) has been motivated by the interest to test the hypothesis that education (i.e., formal and non-formal) plays a key role in the development process through its effect on agricultural productivity (Welch 1970). However, most have failed to account

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for the fact that education plays a greater role in modernizing agriculture than in traditional agriculture, because the ability to deal with disequilibria induced by technological change in agriculture is largely a function of education and hence better educated farmers adjust more successfully than less educated farmers (Schultz 1975; Ali and Byerlee 1991). The assumption imposed by past studies is that all farmers use a homogenous technology and the effects of conventional and non-conventional inputs on agricultural productivity are independent of technology adoption status (Moock 1981; Jamison and Moock 1984; Appleton and Balihuta 1996). Empirical analyses have thus been carried out in ways that obscure the true marginal contribution of education to agricultural productivity. In Africa, for example, concrete and consistent empirical evidence of a positive and significant effect of education on agricultural productivity has been lacking (Hossain and Byerlee 1995).

Education is thought to be most important to agricultural production in a rapidly changing technological or economic environment (Schultz 1975). The basic idea is that an appropriate response to technological change in agriculture requires the collection and processing of new information, and educated farmers would be expected to respond more quickly than others. In developing countries, technological change over the past three decades has largely involved the generation and dissemination of new crop varieties and the use of chemical fertilizer. In such situations, education affects agricultural productivity by first increasing farmers' adoption of these technologies and subsequently by increasing the ability of the farmers to produce more output from given resources through efficient use of the introduced technologies. Hence, education is expected to accelerate agricultural productivity by enhancing the productive capabilities of all producers by exposing them to a more systematic and dynamic production system and by enhancing their ability to choose the optimal levels of inputs and outputs (Welch 1970).

Agriculture in developing countries has undergone considerable technological change following the generation and transfer of modern high-yielding, disease-resistant, and drought-tolerant crop varieties and increased use of chemical fertilizer. Imposing the assumption of homogenous technology and using a single aggregate production function would thus be inappropriate and misleading. It is perhaps due to such misspecification problems that Appleton and Balihuta (1996) note that several African studies have generally not revealed any significant effect of schooling on agricultural output, although they do not explicitly attribute this to the problem of consistency of the design of the studies and analytical methods with the underlying theory that education has greater roles in modern agriculture. They rather suggest several other possible reasons for the lack of significance of education in the African studies, including small sample sizes, errors in measurement of farm production, and wide variation in the actual effects of education on agricultural output in different areas and under different farming systems. This illustrates the need for further investigation of the effects of farmer education on farm productivity in Africa.

The purpose of this paper is, therefore, to assess the effects of farmer education—schooling and extension contact—on traditional and improved cowpea production in northern Nigeria. By controlling for possible confounding factors such as factor endowments, farmer and farm characteristics, and other exogenous influences, we examine the differential effects of education on productivity using an endogenous switching regression model. To our knowledge, no study has explicitly accounted for underlying technological differences among farmers in assessing the effects of education upon agricultural productivity. The switching regression model accounts for both endogeneity of technology adoption and possible sample selection, and allows scarce factor endowments to have differential productivities associated with the respective varietal technologies. The remainder of the paper is organized as follows. The next section provides an overview of the role of cowpea and the development and transfer of improved varieties in northern Nigeria. The third section presents the endogenous switching regression model, whereas data and empirical procedures are discussed in the fourth section. The last section draws conclusions.

2 Improved cowpea variety development and transfer in northern Nigeria

Cowpea is an important component of the cropping systems of the semi-arid and marginal areas of West and Central Africa. Nigeria is the largest producer and consumer of cowpea. In the dry savannas of Nigeria, cowpea plays a key role as a source of protein-rich food, cash, and fodder for livestock. It has a considerable potential to enhance food security and the productivity and sustainability of the crop-livestock systems. Farmers traditionally cultivate cowpea as a sole crop or intercropped in various combinations with millet, sorghum, maize, and cotton, both for grain and fodder. Under traditional technology, however, the grain yield potential and the availability of good quality fodder are limited by several factors: insects, pests and diseases, low and erratic rainfall, and the long dry season (Inaizumi et al. 1999).

The International Institute of Tropical Agriculture (IITA), in collaboration with the International Livestock Research Institute (ILRI), has developed a number of improved cowpea varieties with generally high grain and fodder yields and resistance to major insect pests and diseases. These include IT90K-277-2, IT89KD-288, and IT93K-452-1. These varieties have potential grain yields of over 1 t/ha and fodder yields of 4–10 t/ha (Singh et al. 1997). Efforts to disseminate these varieties to farmers started in 1993/1994 and initial adoption levels and rates and the resulting benefits to adopting farmers were reported to be quite encouraging (Inaizumi et al. 1999; Kormawa et al. 2002). In 1997, a project was launched to promote farmer production and distribution of improved seeds where breeder seeds are supplied by IITA to the lead farmers each year and the rest of the farmers secure their seeds from the lead farmers. This farmer-to-farmer seed diffusion approach has enabled the wider dissemination of improved cowpea varieties in northern Nigeria.

3 A switching regression model of technology adoption and productivity

Microeconomic analysis of the impact of technology adoption on agricultural productivity and incomes is hampered by the fact that the "before" and "after" activities of a farm are rarely observed. Instead, researchers are usually left to compare adopters with non-adopters (Fuglie and Bosch 1995). However, the problem of endogeneity (Hausman 1978) of technology adoption arises due to the fact that technology adoption is either voluntary or some technologies are targeted to a given group of farmers. For example, farmers who are more productive are more likely to be those who are also adopting the technologies. In this case, self-selection into technology intervention is the source of endogeneity, and failure to account for this will overstate the true impact of the technology. In the case of targeted technology intervention, it is likely that farmers who are less productive are those adopting the technologies, and failure to account for this will understate the true impact of the technology. Because innate abilities and other circumstances responsible for differing initial conditions of adopters and non-adopters are known only to the farmer and not to the researcher, these cannot be directly controlled to single out the pure effect of technology adoption on productivity, income, or other outcome variables. The solution is to explicitly account for such endogeneity using simultaneous equation models (Hausman 1983).

After accounting for endogeneity, the question remains whether technology adoption should be assumed to have an average impact on productivity over the entire sample of farmers, by way of an intercept shift in the production function, or it should be assumed to raise the productivity of conventional (e.g., land, labor, fertilizer) and non-conventional factors of production (e.g., schooling, extension), by way of slope shifts in the production function. The former assumes that the effects of conventional and non-conventional inputs on agricultural productivity are independent of adoption status. If it is assumed that conventional and non-conventional factors of production have differential effects on agricultural productivity, separate production functions for adopters and non-adopters have to be specified, while at the same time accounting for endogeneity. The econometric problem will thus involve both endogeneity (Hausman 1978) and sample selection (Heckman 1979). This motivates an endogenous switching regression model that accounts for both endogeneity and sample selection and allows complete interactions between adoption and conventional and non-conventional inputs in the production function: one production function for adopters and another for non-adopters (Lee 1978; Feder et al. 1990; Goetz 1992; Fuglie and Bosch 1995; Freeman et al. 1998).

In the endogenous switching regression approach, the adoption decision is modeled by standard limited (i.e., binary) dependent variable methods. Equations for other decision variables (e.g., productivity) are then estimated separately for each group (i.e., adopters and non-adopters), conditional on the adoption decision. More specifically, the two-stage switching regression model uses a probit model in the first stage to determine the relationship between adoption of improved technology and a number of household, farm, and technology characteristics. In the second stage, separate regression equations are used to model agricultural production conditional on a specified criterion function. Let the adoption of new technology be a dichotomous choice, where a farmer decides to adopt the new technology when there is a positive difference between the marginal net benefits of adopting the technology and not adopting the technology. Let this difference be denoted as I^* so that $I^* > 0$ corresponds to the net benefit of adopting the technology exceeding that of not adopting the technology, and it is under this condition that the farmer decides to adopt the technology. However, I^* is not observable; what is observed is I, which represents the observed behavior of the farmer regarding adoption of the technology. This relationship can be expressed as

$$\begin{aligned} I^* &= \mathrm{Z}'\alpha + \varepsilon_{\mathrm{c}}, \\ I &= 1 \quad \text{if } I^* > 0, \\ I &= 0 \quad \text{if } I^* \leq 0. \end{aligned} \tag{1}$$

Equation (1) represents a probit model of adoption of a new technology, where Z is a vector of household, farm, and technology characteristics; α is a vector of unknown parameters to be estimated; and ε_{c} is a random error term with mean zero and variance σ_{c}^2. The error term includes measurement error and factors not observed by the researcher but known to the farmer. Variables in Z include measures of farm size, land quality, human capital, risk preferences, and other socio-economic and resource characteristics of a farm (Feder et al. 1985). Probit maximum likelihood estimation is used to estimate the parameter vector α in Eq. (1).

Adoption of new technology usually affects other decisions, such as agricultural production. Let $Y = f(X)$ represent the relationship between a decision variable Y (e.g., crop production) and a vector of conventional and non-conventional inputs X. In the switching regression model, a separate production function is specified for adopters and non-adopters as

$$\begin{aligned} Y_{\mathrm{n}} &= X'\beta_{\mathrm{n}} + \varepsilon_{\mathrm{n}} \quad \text{if } I = 1, \\ Y_{\mathrm{o}} &= X'\beta_{\mathrm{o}} + \varepsilon_{\mathrm{o}} \quad \text{if } I = 0. \end{aligned} \tag{2}$$

Variable Y_{n} is agricultural production under the new technology and variable Y_{o} is agricultural production under the old technology. That is, only Y_{n} or Y_{o} is actually observed for any given household, depending on the value of the criterion function $I^* = \mathrm{Z}'\alpha + \varepsilon_{\mathrm{c}}$. This implies that ordinary least squares (OLS) estimates of β_{n} and β_{o} will suffer from sample selection bias: the error terms in Eq. (2), conditional on the sample selection criterion, have non-zero expected values (Lee 1978; Maddala 1983). Lee (1978) treats sample selection as a missing-variable problem. The error terms ε_{c}, ε_{n}, and ε_{o} are assumed to have a tri-variate normal distribution with zero mean and non-singular covariance matrix specified as

$$\mathrm{cov}(\varepsilon_\mathrm{n}, \varepsilon_\mathrm{o}, \varepsilon_\mathrm{c}) = \begin{pmatrix} \sigma_\mathrm{n}^2 & \sigma_\mathrm{no} & \sigma_\mathrm{nc} \\ \sigma_\mathrm{no} & \sigma_\mathrm{o}^2 & \sigma_\mathrm{oc} \\ \sigma_\mathrm{nc} & \sigma_\mathrm{oc} & \sigma_\mathrm{c}^2 \end{pmatrix}, \tag{3}$$

where σ_c^2 is the variance of the error term ε_c in the criterion equation (i.e., technology adoption); σ_n^2 is the variance of ε_n; σ_o^2 is the variance of ε_o; σ_no is the covariance of ε_n and ε_o; σ_nc is the covariance of ε_n and ε_c; and σ_oc is the covariance of ε_o and ε_c. It can be assumed that $\sigma^2 = 1$, since α is estimable only up to a scalar factor. Given these assumptions, the expected values of the truncated error terms $(\varepsilon_\mathrm{n} \,|I = 1)$ and $(\varepsilon_\mathrm{o} \,|I = 0)$ are

$$E(\varepsilon_\mathrm{n} \,|I = 1) = E\left(\varepsilon_\mathrm{n} \,\middle|\varepsilon > -\mathrm{Z}'\alpha\right) = \sigma_\mathrm{nc}\frac{\phi\left(\mathrm{Z}'\alpha/\sigma\right)}{\Phi(\mathrm{Z}'\alpha/\sigma)} \equiv \sigma_\mathrm{nc}\lambda_\mathrm{n}, \tag{4}$$

$$E(\varepsilon_\mathrm{o} \,|I = 0) = E\left(\varepsilon_\mathrm{n} \,\middle|\varepsilon \leq -\mathrm{Z}'\alpha\right) = \sigma_\mathrm{oc}\frac{\phi\left(\mathrm{Z}'\alpha/\sigma\right)}{1 - \Phi(\mathrm{Z}'\alpha/\sigma)} \equiv \sigma_\mathrm{oc}\lambda_\mathrm{o}, \tag{5}$$

where ϕ and Φ are the probability density and cumulative distribution functions of the standard normal distribution, respectively. The ratio of ϕ and Φ evaluated at $\mathrm{Z}'\alpha$ is the inverse Mills ratio [λ_n and λ_o in Eqs. (4) and (5)]. The terms λ_n and λ_o can be treated as missing variables in Eq. (2).

Previous studies have used a two-stage method to estimate the endogenous switching model. These studies include the effect of unionism on wages (e.g., Lee 1978), the effect of credit on agricultural production (Feder et al. 1990; Freeman et al. 1998), and the effect of soil nitrogen testing on fertilizer demand, crop yields, and returns (Fuglie and Bosch 1995). In the first stage, a probit model of the criterion equation is estimated and the inverse Mills ratios λ_n and λ_o are derived according to definitions in Eqs. (4) and (5). In the second stage, these predicted variables are added to the appropriate equation in (2) to yield

$$\begin{aligned} Y_\mathrm{n} &= X'\beta_\mathrm{n} + \sigma_\mathrm{nc}\lambda_\mathrm{n} + u_\mathrm{n} \quad \text{if } I = 1 \quad \text{and} \\ Y_\mathrm{o} &= X'\beta_\mathrm{o} + \sigma_\mathrm{oc}\lambda_\mathrm{o} + u_\mathrm{o} \quad \text{if } I = 0, \end{aligned} \tag{6}$$

where u_n and u_o have zero conditional means. These residuals are, however, heteroscedastic (Maddala 1983). The coefficients of the variables λ_n and λ_o provide estimates of the covariance terms σ_nc and σ_oc, respectively. Since the variables λ_n and λ_o have been estimated, however, the residuals u_n and u_o cannot be used to calculate the standard errors of the two-stage estimates. Studies applying endogenous switching have followed Maddala's (1983, pp 223–228) procedure for estimating the correct variance–covariance matrix. However, this procedure requires potentially cumbersome adjustments to derive consistent standard errors, because the correct variance–covariance matrix of the estimates is very complicated (Lee 1978). Freeman et al. (1998) used weighted least squares to account for heteroscedastic errors; however, the use of weighted least squares is limited only to situations where the exact form of heteroscedasticity is known, which is rarely the case.

A more efficient version of the endogenous switching model can be estimated by full information maximum likelihood (FIML) method (Lokshin and Sajaia 2004; Greene 2000). The FIML method simultaneously estimates the probit criterion or selection equation and the regression equations to yield consistent standard errors. Given the assumption of trivariate normal distribution for the error terms, the logarithmic likelihood function for the system of Eqs. (1) and (2) can be given as (Lokshin and Sajaia 2004)

$$\begin{aligned}\ln L = \sum_{i=1}^{N} \Bigg\{ & I_i w_i \left[\ln F\left(\frac{\left(Z_i'\alpha + \rho_{\mathrm{nc}}(Y_{\mathrm{n}i} - X_{\mathrm{n}i}'\beta)/\sigma_{\mathrm{n}}\right)}{\sqrt{1-\rho_{\mathrm{nc}}^2}} \right) \right. \\ & \left. + \ln\left(f\big((Y_{\mathrm{n}i} - X_{\mathrm{n}i}'\beta)/\sigma_{\mathrm{n}}\big)/\sigma_{\mathrm{n}} \right) \right] \\ & + (1-I_i) w_i \left[\ln\left(1 - F\left(\frac{\left(Z_i'\alpha + \rho_{\mathrm{oc}}(Y_{\mathrm{o}i} - X_{\mathrm{o}i}'\beta)/\sigma_{\mathrm{o}}\right)}{\sqrt{1-\rho_{\mathrm{oc}}^2}} \right) \right) \right. \\ & \left. + \ln\left(f\big((Y_{\mathrm{o}i} - X_{\mathrm{o}i}'\beta)/\sigma_{\mathrm{o}}\big)/\sigma_{\mathrm{o}} \right) \right] \Bigg\}, \end{aligned} \tag{7}$$

where *f* and *F* are the probability density and cumulative distribution functions of the standard normal distribution, respectively; w_i is an optional weight for observation i $(i = 1, 2, \ldots, N)$ and $\rho_{\mathrm{nc}} = \sigma_{\mathrm{nc}}/\sigma_{\mathrm{n}}\sigma_{\mathrm{c}}$ is the coefficient of correlation between ε_{n} and ε_{c} and $\rho_{\mathrm{oc}} = \sigma_{\mathrm{oc}}/\sigma_{\mathrm{o}}\sigma_{\mathrm{c}}$ is the coefficient of correlation between ε_{o} and ε_{c}. To make sure the estimated ρ_{nc} and ρ_{oc} are bounded between -1 and 1 and the estimated σ_{n} and σ_{c} are always positive, the maximum likelihood directly estimates $\ln\sigma_{\mathrm{n}}$, $\ln\sigma_{\mathrm{c}}$, and $a\tanh\rho_{j\mathrm{c}}$ where $a\tanh\rho_{j\mathrm{c}} = \frac{1}{2}\ln\left[(1+\rho_{j\mathrm{c}})/(1-\rho_{j\mathrm{c}})\right]$. The FIML estimates of the parameters of the endogenous switching regression model can be obtained using the *movestay* command in STATA (Lokshin and Sajaia 2004).

The signs of the correlation coefficients ρ_{nc} and ρ_{oc} have economic interpretations (Fuglie and Bosch 1995). If ρ_{nc} and ρ_{oc} have alternate signs, then individuals adopt new technology on the basis of their comparative advantage: those who adopt have above-average returns from adoption and those who choose not to adopt have above-average returns from non-adoption. On the other hand, if the coefficients have the same sign, it indicates hierarchical sorting: adopters have above-average returns whether they adopt or not, but they are better off adopting, whereas non-adopters have below-average returns in either case, but they are better off not adopting.

4 Data and empirical procedures

4.1 Study area and data

The study was conducted in Kano and Kaduna states in northern Nigeria during the 2003/2004 cropping season. Kano and Kaduna represent the Sudan and the northern Guinea savannas, respectively. These agro-ecological zones have mean annual rainfall ranging from 500 mm in the northern fringes to 1,600 mm along the southern boundary. Rainfall is uni-modal and allows 75–180 days growing period across the north–south gradient. There are distinct and striking differences in farming practices between the two zones. For example, the northern Guinea savanna or moist semi-arid zone is a maize belt in which sorghum becomes important only towards its drier northern margins while in the Sudan savanna or the semi-arid zone, sorghum and millet are the major cereals grown in combination. In the Sudan savanna, millet assumes higher importance as one moves towards its northern fringes. In effect, the area could also be defined in terms of a maize belt to the south and a sorghum–millet belt to the north (Manyong et al. 1996; Okike et al. 2001).

A sampling frame was developed to facilitate the selection of representative sample farmers. An initial exploratory field survey was carried out to identify major cowpea-producing areas in Kano and Kaduna states. This involved extensive discussions with officials of the Agricultural Development Programs (ADPs), Institute for Agricultural Research (IAR), IITA-Kano, extension staff, key informants, and village farmer groups. A total of 24 villages were randomly selected from the two states (16 villages from Kano and 8 villages from Kaduna). The list of households in each village was obtained from village heads in cooperation with ward heads. The research team with assistance from ADP staff and the enumerators, who were selected and trained before the sampling, developed fresh lists of farmers living in the selected villages upon securing the cooperation of the village and ward heads as well as the farmers in the villages. Regardless of their status as adopters or non-adopters, 20 farmers were randomly selected from each of the selected 24 sample villages. Therefore, the survey data were collected from a total of 480 sample farmers in the two states. Data on socio-economic characteristics, crop production and cropping systems, improved cowpea adoption and diffusion processes, and constraints to cowpea production were collected through household-level surveys using structured and pretested questionnaires and village level focus group meetings.

4.2 Empirical models

The probit model of adoption of improved cowpea varieties was specified and estimated as

$$\begin{aligned}\text{ADOPTION} = f\big(&\text{ECOZON, FARMSZ, LNDOWN, LNDQLTY, ADMALE}\\ &\text{CPEXP, EDUHD, EDUMR, NONFARM, SOCKAP, LVSTK}\\ &\text{CREDT, EXNSN, OFPE, MKTDIS, DEALER, YLDXIC}\\ &\text{FODXIC, MATXIC, PRICXIC, QLTXIC, GSZXIC}\big). \qquad (8)\end{aligned}$$

The dependent variable in the probit model (i.e., criterion equation) is the adoption status of the farmer (ADOPTION). This variable takes on a value of 1 if a farmer has adopted improved cowpea varieties and 0 otherwise. The explanatory variables comprised both continuous and binary variables. A site dummy variable (ECOZON) was included to account for differences in adoption across agro-ecological zones due to differential resource endowments and farming conditions. Farm characteristics (Feder et al. 1985) included size of cultivated land in ha (FARMSZ), ownership of the cowpea land (LNDOWN), quality of cowpea land (LNDQLTY), and ownership of livestock (LVSTK). Generally, farm characteristics are hypothesized to have a positive influence on adoption. Household characteristics and institutional variables (Feder et al. 1985) included experience in cowpea production (CPEXP), the number of adult male laborers in the household (ADMALE), schooling status of the household head, defined as 4 years of schooling or more (EDUHD), schooling status of the household members, defined as the proportion of other school-age household members who have completed primary school (EDUMR), participation in on-farm participatory evaluation of improved cowpea (OFPE), access to credit (CREDT), regular contacts with extension (EXTSN), non-farm employment opportunities (NONFARM), social capital defined as group memberships in the community (SOCKAP), existence of a seed dealer in the nearby town (DEALER), and distance to the nearest input and product market (MKTDIS).

Technology characteristics (Adesina and Zinnah 1993; Negatu and Parikh 1999) included farmers' own perceptions of the improved varieties of grain yield (YLDXIC), animal fodder yield (FODXIC), earliness of maturity (MATXIC), grain price (PRICXIC), cooking quality (QLTXIC), and grain size (GSZXIC). Farmers in the study area have been exposed to improved cowpea varieties through on-farm participatory evaluation since 1992 and through the farmer-to-farmer improved cowpea diffusion project, which has been underway since 1997. During the survey, the farmers were asked whether they participated in on-farm evaluation, or in the farmer-to-farmer diffusion, or both. It was revealed that the on-farm evaluation and the farmer-to-farmer diffusion provided the sample farmers with opportunities to evaluate the varieties. They were then asked to evaluate the varieties for grain and fodder yield, maturity, grain price, cooking quality, and grain size. Each of variables relating to technology characteristics was defined as a dummy variable that equals 1 if the farmer perceived the varieties as better than the local varieties and 0 otherwise.

Separate production functions for adopters (users of new technology, n) and non-adopters (users of old technology, o), of the following form, were specified and estimated jointly with the adoption equation

$$\begin{aligned}\ln(\text{YIELD})_j = {} & \beta_{0j} + \beta_{1j}(\text{ECOZON})_j + \beta_{2j}\ln(\text{LAND})_j + \beta_{3j}\ln(\text{LABR})_j \\ & + \beta_{4j}\ln(\text{FERT})_j + \beta_{5j}\ln(\text{MATR})_j + \beta_{6j}(\text{LNDQLTY})_j \\ & + \beta_{7j}\ln(\text{LVSTK})_j + \beta_{8j}\ln(\text{CPEXP})_j + \beta_{9j}(\text{EDUHD})_j \\ & + \beta_{10j}(\text{EDUMR})_j + \beta_{11j}(\text{EXTNSN})_j \\ & + \varepsilon_j, \quad j = \text{n}, \text{o}, \end{aligned} \tag{9}$$

where ln denotes the natural logarithm. The dependent variable in the production function is the natural logarithm of cowpea grain yield in kg (YIELD). Despite the importance of cowpea fodder, fodder yield data were not collected because, due to their strong preference for grains, farmers did two or three rounds of pickings (or harvests) until no fodder was left for harvest. Therefore, cowpea fodder production was not analyzed in this study. The description and summary statistics of the variables used in the analysis are given in Table 1.

The explanatory variables are a set of conventional and non-conventional factors of production. A site dummy variable (ECOZON) was also included to account for differences in cowpea yield across agro-ecological zones. The conventional inputs included land planted to cowpea (LAND), total labor input in man-days (LABR), inorganic fertilizer in kg (FERT), cost of materials such as seed and insecticide (MATR), quality of land (LNDQLTY), and livestock ownership (LVSTK). The non-conventional inputs included the number of years the household head has been growing cowpea (CPEXP), schooling status of the household head, defined as 4 years of schooling or more (EDUHD), the proportion of other school-age household members who have completed primary school (EDUMR), and regular contacts with extension (EXTSN), defined as weekly visits by an extension agent during the cropping season. Participation in extension activities is included to proxy, and hence to capture, the effect of non-formal education. Both conventional and non-conventional inputs are expected to have a yield-increasing effect. It is hypothesized that schooling and extension contact have differential effects on agricultural production under traditional and improved technology. That is, schooling and extension contact are likely to have a significant effect on agricultural production only under improved technology, compared to its effect under traditional technology.

The production functions did not include the technology characteristics. The maintained hypothesis is that these variables are not likely to influence cowpea production directly, except through technology adoption. Thus, the model is identified because there is at least one explanatory variable in the first stage probit regression that is not included in the second stage regression (Maddala 1983). The system of the adoption and production functions was estimated by full information maximum likelihood method (Lokshin and Sajaia 2004).

5 Empirical results

The maximum likelihood estimates of the probit model of adoption of improved cowpea varieties are presented in Table 2. Marginal effects indicate the effect

Table 1 Definitions and summary statistics of the variables used in the analysis

Variable	Definition	Mean	Std. Dev.
Dependent variables			
YIELD	Cowpea yield in kilograms (kg)	800	990
ADOPTION	Dummy for adoption of improved cowpea varieties (adopter = 1, 0 otherwise)	0.72	0.38
Independent variables			
ECOZON	Agro-ecological zone dummy (Sudan savanna = 1; northern Guinea savanna = 0)	0.67	0.31
FARMSZ	Farm size (total cultivated land in ha)	4.02	3.42
LAND	Land planted to cowpea in ha	0.95	1.06
LABR	Total labor used for cowpea production in man-days	50	42
FERT	Total chemical fertilizer used for cowpea production in kg	35	57
MATR	Cost of materials used for cowpea production in Naira	1,100	2,265
LNDOWN	Land ownership (=1 if inherited or purchased) and (=0 if borrowed, rented, or gifted)	0.36	0.48
LNDQLTY	Land quality (=1 if very fertile) and (=0 if less fertile or infertile)	0.64	0.48
CPEXP	Cowpea cultivation experience 12.78 (number of years the head has been growing cowpea)	11.35	
ADMALE	Number of adult males in the household	1.48	1.75
EDUHD	Education of the head (=1 if head acquired 4 years of education or more)	0.16	0.10
EDUMR	The proportion of other adult household members who have completed primary school	0.07	0.36
OFPE	Participation in on-farm improved cowpea evaluation (=1 if participated)	0.65	0.24
NONFARM	Number of non-farm activities of the head	1.14	0.85
SOCKAP	Social capital in terms of number of group memberships	1.25	1.08
EXTNSN	Regular (i.e., weekly) contacts with extension during cropping season (Yes = 1, No = 0)	0.27	0.12
LVSTK	Livestock ownership in Tropical Livestock Units	2.72	4.48
CREDT	Access to formal or informal credit (=1 if head has had access to credit for inputs)	0.40	0.49
MKTDIS	Market distance in kilometers	16.37	28.62
DEALER	Seed dealer in the nearby town (=1 if seed dealer available in nearby town)	0.34	0.47
YLDXIC	Yield characteristic of improved cowpea varieties (=1 if better than local varieties)	0.82	0.39
FODXIC	Fodder characteristic of improved cowpea varieties (=1 if better than local varieties)	0.15	0.35
MATXIC	Maturity characteristic of improved cowpea varieties (=1 if better than local varieties)	0.89	0.31
PRICXIC	Price characteristic of improved cowpea varieties (=1 if better than local varieties)	0.61	0.49
QLTXIC	Quality characteristic of improved cowpea varieties (=1 if better than local varieties)	0.64	0.48
GSZXIC	Grain size characteristic of improved cowpea (=1 if better than local varieties)	0.20	0.40

of one unit change in an exogenous variable on the probability of adoption. These are obtained by multiplying the coefficient estimates $\hat{\alpha}$ by $\phi(Z'\hat{\alpha})$ at the mean values of the explanatory variables, Z (Maddala 1983). Goodness-of-fit

Table 2 Probit model estimates of adoption of improved cowpea varieties

Variable	Estimate	Marginal effects
Constant	−0.554 (−1.922)*	−0.935 (−1.835)*
ECOZON	0.510 (1.420)	0.102 (1.458)
FARMSZ	0.031 (0.775)	0.003 (0.745)
LNDOWN	0.042 (0.233)	0.011 (0.274)
LNDQLTY	0.155 (0.668)	0.022 (0.588)
CPEXP	0.025 (1.077)	0.003 (0.911)
EDUHD	0.102 (1.972)**	0.035 (1.812)*
EDUMR	0.022 (1.110)	0.002 (0.933)
ADMALE	0.033 (0.466)	0.002 (0.355)
NONFARM	−0.153 (−1.220)	−0.041 (−1.722)*
SOCKAP	−0.055 (−0.833)	−0.005 (−0.422)
OFPE	0.622 (1.978)**	0.125 (2.742)***
LVSTK	0.105 (0.066)	0.003 (0.845)
CREDT	0.212 (1.004)	0.018 (0.438)
EXTNSN	−0.066 (−1.426)	−0.008 (−1.244)
MKTDIS	−0.014 (−1.877)*	−0.012 (−1.187)
DEALER	0.744 (2.522)**	0.135 (2.589)***
YLDXIC	0.108 (1.755)*	0.088 (1.702)*
FODXIC	0.205 (1.305)	0.102 (1.355)
MATXIC	1.655 (4.567)***	0.388 (4.322)***
PRICXIC	0.066 (0.526)	0.023 (0.287)
QLTXIC	0.382 (1.658)*	0.022 (0.688)
GSZXIC	0.133 (0.388)	0.029 (0.785)
Likelihood ratio test	128*** ($\chi^2_{0.99, 22\,df} = 40.29$)	
Percentage of correct predictions		
Adopters	89%	
Non-adopters	65%	
Overall	76%	
Pseudo R^2	0.62	

Figures in parentheses are *t* ratios

*, ** and *** represent significance at 0.1, 0.05, and 0.01 levels, respectively

measures indicate that the estimated models fit the data reasonably well. Likelihood ratio tests showed that the parameter estimates were statistically significantly different from zero at less than 1% significance level. The model correctly predicted the choice of technology for 76% of the sample and the pseudo R-squared measure of 0.62 is also reasonably high.

The results show that the coefficients of most of the variables hypothesized to influence adoption of improved cowpea varieties have the expected signs. Education status of the household head (EDUHD), participation in on-farm participatory evaluation of improved cowpea varieties (OFPE), existence of a seed dealer in the nearby town (DEALER), and earliness of maturity (MATXIC), yield (YLDXIC), and cooking quality (QLTXIC) characteristics of improved cowpea varieties have a positive and significant influence on adoption. The significant influence of education of the household head indicates that household heads with 4 years of schooling or more are more likely to adopt improved cowpea varieties. The insignificance of education status of household members

(EDUMR) may be indicating that the household heads make most farming decisions including technology adoption. Participation in improved cowpea evaluation (e.g., on-farm participatory evaluation) raises farmers' awareness of the benefits of improved varieties and gives them the opportunity to evaluate the varieties based on their perceived advantages and disadvantages. On-farm improved variety evaluations are organized mainly by extension agents in the area as part of the strategy to promote adoption of the improved cowpea varieties. The positive and significant effect of participation in on-farm participatory evaluation confirms the role of participatory evaluation in raising awareness and promoting technology adoption. Participation in the farmer-to-farmer diffusion is highly correlated with the on-farm participatory evaluation variable because most farmers who participate in the on-farm evaluations are actually those leading the farmer-to-farmer diffusion. Moreover, on-farm participatory evaluations are more effective than the informal farmer-to-farmer diffusion mechanisms because they are organized by extension agents, researchers, and other stakeholders to demonstrate to farmers the benefits and methods of cultivation using the improved technology. Therefore, participation in farmer-to-farmer diffusion was not included as an explanatory variable. Although insignificant, extension contact (EXTNSN) has turned out to have unexpected negative influence on adoption. The unexpected negative sign could be due to its correlation with participatory evaluation (OFPE), which is mainly carried out by extension agents. That is, farmers who participate in on-farm evaluations more likely receive extension visits as well. The earliness of maturity of improved varieties (MATXIC) has a positive and significant influence on the adoption improved cowpea varieties. The marginal probabilities (Table 2) show that farmers who perceive the early-maturing property of the improved varieties have, relative to farmers who do not perceive this property, a 39% higher probability of adopting the varieties. About 89% of the sample farmers indicated that the improved varieties are better than the local varieties in terms of earliness of maturity. This characteristic of the technology seems to have promoted improved cowpea varieties more than any of the other characteristics. Because the improved varieties are early-maturing, they are ready for harvest at a critical period during the year when most farmers have already depleted their food stocks. These varieties thus play an important food security role in the study areas. The positive and significant influence of fodder yield on adoption confirms the fact that farmers place high premium on livestock and crop-livestock integration.

On the other hand, market distance (MKTDIS) is negatively and significantly related to adoption, indicating that farmers who are far from major input and product markets and, hence, have less access to improved seeds and other inputs, are less likely to adopt improved cowpea varieties. Farmers with poor access to markets find little or no incentive to adopt improved cowpea as a cash crop. Kristjanson et al. (2002) note that access to markets plays a key role in intensifying cowpea production in northern Nigeria. Alternative sources of improved seeds will thus have an important influence on adoption. The results show that seed dealer in a nearby town (DEALER) is positively and significantly related to adoption, implying that when there is a seed dealer in the nearby town, farmers are likely to adopt improved varieties. It should be noted that these are not just seed dealers; they are general input dealers supplying fertilizer, seeds, chemicals, farm tools, etc and who had been in the area long before the introduction of improved cowpea varieties. It necessarily follows that availability of seed dealers positively influenced adoption of improved cowpea varieties.

The FIML estimates of the endogenous switching regression model of cowpea production are presented in Table 3. The last rows give the estimates of the coefficients of correlation between the random errors in the system of equations. The estimated coefficient of correlation between the adoption equation and the adopters' production function, ρ_{nc}, is positive and significant. The adoption model results and the switching regression model results together suggest that both observed and unobserved factors influence the decision to adopt technology and the performance of the technology given the adoption decision. The significance of the coefficient of correlation between the adoption equation and the production function for adopters indicates that self-selection occurred in the adoption of improved cowpea varieties. That is, (1) improved cowpea varieties had a significant impact on cowpea production among adopters; and (2) adopters would have got greater benefits from improved cowpea varieties than non-adopters, had non-adopters chosen to adopt. However, the estimated coefficient of correlation between the adoption equation and the non-adopters' production function, ρ_{oc}, is not significantly different from zero, implying that

Table 3 Full information maximum likelihood estimates of the switching regression model

Variable	FIML estimate	
	Adopters	Non-adopters
Constant	5.255 (14.223)***	2.133 (2.171)**
ECOZON	0.266 (2.454)**	0.238 (1.866)*
LAND	0.418 (6.875)***	0.138 (2.120)**
LABOR	0.208 (2.799)***	0.673 (3.208)***
FERT	0.162 (3.755)***	0.084 (1.722)*
MATR	0.085 (4.525)***	0.004 (0.855)
LNDQLTY	0.142 (1.633)	0.199 (1.320)
CPEXP	0.011 (1.298)	0.025 (1.833)*
LVSTK	0.034 (1.128)	0.036 (0.698)
EDUHD	0.256 (2.627)***	0.350 (1.054)
EDUMR	0.087 (1.256)	0.012 (1.056)
EXTNSN	0.185 (1.980)**	0.022 (0.933)
σ_n	0.633 (18.022)***	
ρ_{nc}	0.615 (3.655)***	
σ_o		0.677 (10.235)***
ρ_{oc}		0.101 (0.241)
Returns to scale	0.873	0.899
Factor shares (traditional inputs)	0.626	0.811
Factor shares (modern inputs)	0.247	0.088

Figures in parentheses are *t* ratios

*,**, and *** represent significance at 0.1, 0.05, and 0.01 levels, respectively

adopters and non-adopters obtain the same mean cowpea production using the old technology, given their observed characteristics. The initial differences between adopters and non-adopters, albeit insignificant, brought about differential effects of technologies on the two groups, confirming the sensitivity of technology impacts to initial differences due to unobserved factors.

The results show that the coefficient of the agro-ecological zone dummy variable (ECOZON) is positively and significantly related to traditional and improved cowpea production, implying that, on average, the productivity of cowpea is higher in Kano (i.e., Sudan savanna) than in Kaduna (northern Guinea savanna). Cowpea is the second most important crop in Kano, next to sorghum, and IITA-improved cowpea varieties were introduced to Kano as early as 1994 and have since then been cultivated more widely, compared with Kaduna where improved varieties were introduced more recently. Farmers in Kano are thus expected to have better exploited the cowpea yield potential than farmers in Kaduna.

The coefficients of most of the conventional production factors (i.e., land, labour, fertilizer, and materials) have the expected positive signs and have significant but different effects on both traditional and improved cowpea production. The production function estimates give an indication of returns to scale and the relative importance of production factors. The results show that both adopters and non-adopters of improved cowpea operate under decreasing returns to scale. The sums of partial output elasticities (or function coefficients) for both adopters and non-adopters are less than unity, and a test of constant returns to scale was rejected. Although traditional inputs (i.e., land and labor) have a greater share in total output elasticity for both adopters and non-adopters, they are more important among users of traditional varieties (0.811) than among adopters (0.626). On the other hand, modern inputs (i.e., fertilizer and materials) are more important among adopters (0.247) than among users of traditional varieties (0.088). The results are consistent with the expectation and confirm the fact that while traditional farming relies heavily on land and labor, modern farming will tend to depend also on fertilizer and improved seeds.

The investigation of the effects of schooling and extension contact on traditional and improved cowpea production is of interest in this study. The results clearly show that non-conventional inputs (i.e., schooling and extension contact) have differential effects on cowpea production under traditional and improved technology. Initial analyses with only the two schooling variables—number of years of schooling of the household head and average number of years of schooling of household members—did not reveal any significant effect of schooling on traditional and improved cowpea production. That is, an additional year of schooling of the head as well as other members has no significant effect on productivity. Consistent with the empirical literature on farmer education and productivity [see, e.g., Lockheed et al. (1980) and Philips (1994) for reviews] a new schooling dummy variable (EDUHD) was defined as 4 years of schooling or more to account for any possible threshold effects. As expected, 4 years of schooling has turned out to have a significant positive effect on productivity under improved technology. The results show that 4 years of schooling of the household head raised improved cowpea production by an average 25.6%. However, schooling had no significant effect on traditional cowpea production. This shows that education has little or no significant marginal contribution to agricultural production under traditional technology. This could be due to the fact that farmers in traditional environments are already efficient and hence additional educational efforts will generate little or no marginal benefits in terms of increased food production (Schultz 1964). It could also be that the knowledge and skills gained from formal and non-formal educational programs are necessary only for modern agriculture and not for traditional agriculture. The results suggest that failure to account for differences in technology available to the farmers, even in the same production environment, is likely to confound the true effect of education on agricultural productivity.

For example, Lockheed et al. (1980) reviewed 18 studies on the effect of education on agricultural productivity in Africa, Asia, and Latin America, which make no distinction between traditional and improved farming conditions, and the average increase in agricultural productivity as a result of 4 years of formal education was only 7.4%. In 6 of the 37 data sets, education was found to have even a negative effect, whereas it had a positive but lower effect on agricultural productivity in the remaining 31 data sets. Given the interest to single out the effect of education on productivity in modern agriculture, Lockheed et al. (1980) regressed across studies the measured effects of education on productivity against the degree of modernization of the environment and other variables and found that the effect of education was, on average, 10% higher in modernizing environments than in traditional environments. Phillips (1994) also reviewed an additional 12 studies using 22 data sets (with more recent data and greater representation of Latin America), and used a similar procedure to confirm the general trends noted above. The average increase in output owing to an additional 4 years of schooling in the studies considered was 10.5%, with the relevant figures for traditional versus modern farming systems at 7.6 and 11.4%, respectively. However, by treating a given data set as coming from either a traditional or modern environment, the two studies assumed homogenous farming conditions in a given area and hence precluded the possible co-existence of traditional and improved farming conditions.

Regular contact with extension has a positive and significant effect on improved cowpea production. Although extension services are targeted to both varietal and non-varietal technologies so that farmers cultivating traditional varieties could still benefit from technical advice on management practices such as soil and water conservation, they have practically been biased in favor of varietal technologies, implying that farmers cultivating traditional crop varieties have not gained much from extension services. The results (Table 3) demonstrate that extension does not have a significant effect on traditional cowpea production. Under improved cowpea technology, however, regular contact with extension raises cowpea production by an average 18.5%. This is in agreement with recent evidence from Zimbabwe that access to agricultural extension services, defined as receiving one or two visits per agricultural year, raises farm production by about 15% (Owens et al. 2001). Birkhaeuser et al. (1991)

reviewed 15 studies on the impact of extension on farm productivity, with the highest estimate indicating that contact with extension services raises output by 27%. Bindlish and Evenson (1997) also find that access to extension services has a positive and statistically significant impact on farm production in Kenya.

6 Conclusions and implications

Several studies have been carried out to test the hypothesis that education plays a key role in the development process through its effect on agricultural productivity. However, most have failed to account for the fact that education plays a greater role in modernizing agriculture than in traditional agriculture. More importantly, past studies estimated a single production function for a potentially heterogeneous sample of farmers. This approach has largely understated the marginal contribution of education to agricultural productivity and, in Africa, concrete and consistent empirical evidence of a positive and significant effect of education on agricultural productivity has been lacking.

A more efficient version of an endogenous switching regression model, which accounts for both endogenous technology adoption and sample selection, was used to examine the effects of formal education and extension contact on traditional and improved cowpea production in northern Nigeria. The results clearly show that schooling and extension contact have differential effects on traditional and improved cowpea production, confirming the higher productivity-enhancing effects of schooling and extension contact under improved technology than under traditional technology.

The study demonstrates that the marginal contribution of farmer education to cowpea production is different among adopters and non-adopters of improved cowpea varieties. Farmer education has significant positive effects on improved, as opposed to traditional, cowpea production. Four years of education raises cowpea production under improved technology by 25.6%, but it has no significant effect on traditional cowpea production. It is concluded that farmer education has a higher payoff for farmers cultivating improved varieties and applying a package of new inputs than for farmers using largely traditional technology. When the production technology is traditional, it can be formalized and passed on from generation to generation by example, and formal education may have little or no contribution. Under improved technology, however, coping with the disequilibria induced by technological change in agriculture requires new knowledge and skills, and better-educated farmers are likely to adjust more successfully than less educated farmers.

The marginal contribution of extension contact to cowpea production is also different among adopters and non-adopters of improved cowpea varieties. The effect of regular contact with extension on cowpea production under improved technology has turned out to be 18.5%, but it has no significant effect on cowpea production under traditional technology. This confirms the greater role of extension services in raising the yields of improved varieties through the provision of adequate and timely advice on improved technological packages.

The results may suggest that extension services have a practical bias toward varietal technologies and against innovative management practices such as soil and water conservation that could also benefit traditional food crop production.

Both schooling and extension contact have thus much greater roles in raising agricultural productivity than available evidence would suggest. Schooling and extension contact are essential complementary inputs to research and development efforts aimed at technological change in agriculture. That is, investments in formal education and extension services would have higher returns, and are hence more justified, in farming communities that are undergoing significant technological change. Therefore, factors that promote technology adoption will indirectly raise the marginal contributions of schooling and extension contact. Schooling, participatory technology evaluation, improved seed supply, and greater market access promote the adoption of improved cowpea in northern Nigeria. Therefore, farmer education not only enhances agricultural productivity following adoption, but also promotes technology adoption itself. The results suggest that the generation and dissemination of improved technologies should be coupled with farmer education to have a maximum impact on agricultural productivity.

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