JAE Journal of Agricultural Economics

Journal of Agricultural Economics, Vol. 71, No. 1, 2020, 165–183
doi: 10.1111/1477-9552.12331

Adoption and Ex-post Impacts of Improved Cowpea Varieties on Productivity and Net Returns in Nigeria

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(Original submitted July 2018, revision received November 2018, accepted January 2019.)

Abstract

Cowpea covers the largest area of any grain legume in Africa and is especially important in West Africa where Nigeria and Niger alone account for over 75% of the total cowpea production in the world. Despite successes of international and national cowpea improvement research in the development and release of several improved varieties, there is limited empirical evidence of adoption and ex-post impacts of improved cowpea. Using a nationally representative survey data from a sample of 1,525 cowpea-growing households in northern Nigeria cultivating over 2,500 cowpea plots, we assess the adoption and impacts of improved cowpea varieties on cowpea yields, net returns and production costs. We apply a control function approach and propensity score matching models to estimate the causal effects of adoption of improved cowpea varieties. Our results show that 38% of the cowpea plots were planted with improved varieties, and cowpea yields, net returns and production costs increase significantly with the adoption of improved cowpea varieties. Adoption of improved cowpea varieties is associated on average with 26% yield gains, 61% increase in net returns and 14% increase in production costs. We also show that farmers who have a lower propensity to adopt improved cowpea varieties also face higher costs of production.

Keywords: *Cowpea*; *improved varieties*; *adoption*; *impacts*; *control function*; *propensity score matching*; *Nigeria*.

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JEL classifications: *I32, O33, Q16, Q18.*

1. Introduction

Cowpea covers the largest area of any grain legume in Africa and is especially important in West Africa, with Nigeria and Niger alone accounting for over 75% of the total cowpea production (Walker *et al*., 2014). It is an important food legume and an essential component of cropping systems in the savannas of sub-Saharan Africa where it is grown as a sole crop, relay, or inter cropped in various combinations with millet, sorghum and maize (Singh *et al*., 2002; Alene and Manyong, 2006; Kamara *et al*., 2010; Boukar *et al*., 2011). Cowpea is an important crop to small-scale farmers as a source of cash net returns, high quality protein food, and fodder for animals and also contributes to soil fertility improvement (Singh *et al*., 2002; Kristjanson *et al*., 2005; Mishili *et al*., 2009). It is often referred to as a poor man's meat because it is an important source of relatively cheap protein coupled with the fact that it does not require refrigeration making it possible for poor households to easily store the grain (Mishili *et al*., 2009). Nigeria is the largest cowpea producer in the world and, with about 25% of the population of Sub-Saharan Africa, is also the largest consumer and importer of cowpea in the region (Langyintuo *et al*., 2003; Alene and Manyong, 2007; Mishili *et al*., 2009).

Given its importance, increasing cowpea productivity is an essential policy objective in Nigeria. However, cowpea production in Nigeria is constrained by several factors which include biotic stresses (insect pests, striga and alectra infestations), abiotic stresses (drought, heat and low soil fertility) and poor access to seeds of improved varieties (Monyo and Gowda, 2014). The International Institute of Tropical Agriculture (IITA) and its partners such as the Institute for Agricultural Research (IAR) of Nigeria have developed and promoted improved cowpea varieties that are resistant to striga, alectra, insect pests, and are also drought tolerant (Singh *et al*., 2002; Boukar *et al*., 2018). Since 2007, two projects – Tropical Legumes II and III – have also supported the development and release of several varieties that have the beneficial traits mentioned above. Taken together, these efforts have resulted in the release of over 20 improved cowpea varieties in Nigeria since the early 1980s (NACGRAB, 2016). Through the Tropical Legumes projects, significant strides forward have also been made to improve the cowpea seed systems during the period 2010–2013 (Boukar *et al*., 2016). Despite all these positive developments with regards to cowpea improvement and dissemination, there is limited empirical evidence on the extent and impacts of adoption of improved cowpea varieties in Nigeria.

Several studies in Africa that have shown that adoption of improved agricultural technologies plays a vital role in increasing productivity and net returns (Abdulai and Huffman, 2014; Khonje *et al*., 2015; Manda *et al*., 2017; Wossen *et al*., 2018a) focused on other crops, rather than improved cowpea varieties (ICV). The few previous studies on adoption and impacts of improved cowpea varieties in Nigeria (e.g. Kristjanson *et al*., 2005; Alene and Manyong, 2006, 2007) were highly localised and covered few states that were not nationally representative. These studies mainly considered the determinants of adoption and did not rigorously assess the impacts of improved cowpea varieties on yields, net returns and production costs at plot level. In addition, most of these studies assumed that the returns to adoption are homogenous and ignored the possibility that there may be heterogeneity in the returns to improved agricultural technology adoption.

We contribute to the growing literature on adoption and impacts of agricultural technologies by estimating the determinants and impacts of the adoption of improved cowpea varieties on yields, net returns and production costs using rigorous econometric approaches and comprehensive plot and household level data. We contribute to the relevant literature on adoption and impacts of agricultural technologies as follows. First, to our knowledge, this is the first study in Nigeria to use unique recent nationally representative comprehensive household and plot level data to assess the adoption and impacts of improved cowpea varieties. Specifically, we apply the control function approach (CFA), which is an instrumental variable technique (Rivers and Vuong, 1988; Wooldridge, 2015), on a sample of 2,550 cowpea plots to estimate the impacts of adoption of improved cowpea varieties. Previously, CFA has mainly been used with panel data with continuous endogenous regressors (Mason and Smale, 2013; Bezu *et al.*, 2014; Mathenge *et al.*, 2014; Smale and Mason, 2014). The approach allows us to first study the nature of self-selection, similar to the Endogenous Switching Regression (ESR) model (Lee, 1978) where the coefficient on a binary endogenous explanatory variable is allowed to differ in both observed and unobserved ways across units (Wooldridge, 2015; Murtazashvili and Wooldridge, 2016). Second, we assess the marginal returns to adoption by estimating the marginal treatment effects (MTE) using the polynomial model. We use this MTE model because it is based on less restrictive assumptions compared with their parametric normal counterparts, which require the normality assumption to be satisfied. We explicitly examine whether the impact of improved cowpea varieties on yield, net returns and costs associated with cowpea production vary within a population in correlation with unobserved characteristics. To our knowledge, very few studies (e.g. Suri, 2011; Zeng *et al.*, 2015; Wossen *et al.*, 2018b) have assessed the marginal returns to agricultural technology adoption using rigorous econometric methods. We check the robustness of the CFA impact estimates by estimating the effects using a propensity score matching (PSM) approach. Finally unlike most studies that use farmers self-reported farm sizes, we use Global Positioning System (GPS) to accurately measure the area under cowpea production thereby reducing errors with either under- or over-estimating productivity, net returns and production costs.

The rest of the article is organised as follows. In the next section, we present the empirical framework for the estimation of the CFA and MTEs to assess the impacts of ICV on yields, net returns and production costs. Section 3 presents the sampling procedure and some descriptive statistics. The fourth section presents the empirical results, and section 5 draws conclusions and policy recommendations.

2. Conceptual Framework and Empirical Procedure

Cowpea is well adapted to the northern drier Sudan savanna region in Nigeria, partly because it is a drought tolerant crop. Although predominantly produced in this region, cowpea has also tended to move south to the humid areas, where it is difficult to produce legumes because of increased pressure from pests and diseases, while carbohydrates have moved north (Langyintuo *et al.*, 2003). In terms of regional cowpea trade, Nigeria is a net importer of cowpea. While it imports cowpea from several countries including Cameroon, Chad and Benin, it is estimated that Nigeria's average annual imports from Niger accounts for about 73% of Niger's surplus production (Langyintuo *et al.*, 2003).

Production of cowpea is mainly done under rain-fed conditions by smallholder farmers and is usually intercropped in maize, sorghum and millet plots. These farmers grow cowpea both for consumption and for sale. However, the economic environment of rural households in developing countries is often characterised by imperfect or missing markets, resulting in non-separability of the household production and consumption decisions (Feder and Umali, 1993). Hence, the decision to grow either improved or local cowpea varieties can be viewed from the perspective of the well-known non-separable household model, in which family members organise their labour to maximise utility over consumption goods and leisure in an economic environment with market failures (de Janvry *et al.*, 1991; Pradhan and Quilkey, 1993). In this model, effective decision prices are endogenous and influenced by observed market prices and household characteristics, since consumption cannot be separated from production decisions. The decision to adopt ICV in this framework is influenced by household (e.g. education and household size) and market characteristics (transaction costs and price of inputs), as well as agro-ecological and plot characteristics (e.g. location and fertility of the plots). It is expected that the adoption of ICV will lead to an increase in productivity and cowpea net returns. In the initial years of adoption, production costs are also expected to increase, but gradually reducing with time.

The decision to adopt ICV, however, may be endogenous as farmers usually self-select into adoption based on both observable and unobservable characteristics. Without controlling for this, the effects of adoption on the outcome variables (yield, net returns and production costs) will be biased. To ensure that we account for selection bias and endogeneity, we use the instrumented CFA and the MTE models. Following Alene and Manyong (2006) and Shiferaw *et al.* (2014), we denote the utility derived from adopting ICVs on a plot as U_{1i} and the utility from growing local varieties as U_{0i}. A farmer will adopt ICV if $I_i^* = U_{1i} - U_{0i} > 0$. I_i^* is an unobserved latent variable that captures the benefit of adopting ICVs on a plot. What is observed is I, which represents the observed behaviour of the farmer regarding adoption of the technology:

$$I_i = \gamma Z_i + v_i, \tag{1}$$

where Z is a vector of observed household and farm characteristics determining adoption, γ is the vector of unknown parameters to be estimated, and v is the vector of random disturbances related with the adoption of ICV with mean zero. The subscript i denotes individual plot level observations. Denoting the adoption decision index by D, such that, 1 = if a farmer adopts ICV on a plot and 0 = otherwise, then the adoption decision can be expressed as:

$$D_i = \begin{cases} 1 & \text{if } I_i^* > 0 \\ 0 & \text{if } I_i^* \leq 0 \end{cases}.$$

The adoption (treatment) equation can then be expressed as:

$$D_i = E(D_i|Z_i) + v_i. \tag{2}$$

The empirical specification we outline below is based mainly on Wooldridge (2010) and Wooldridge (2015).

Let Y_{i0} denote the potential outcome for non-adopters and Y_{i1} for adopters, such that:

$$Y_{i0} = E(Y_{i0}|X_i) + \mu_{i0} = \alpha_{i0} + X\beta_{i0} + \mu_{i0}, \tag{3}$$

$$Y_{i1} = E(Y_{i1}|X_i) + \mu_{i1} = \alpha_{i1} + X\beta_{i1} + \mu_{i1}. \quad (4)$$

where X_i is a vector of exogenous explanatory variables, β represent the parameters to be estimated and u_{i0} is unobserved random component. The observed treatment and outcome can be expressed as:

$$Y_i = D_i Y_{i1} + (1 - D_i) Y_{i0}. \quad (5)$$

The unobserved components in the potential outcome should be independent of Z_i such that the correlation between D_i and the unobserved components must be equivalent to the correlation between u_{ij} and v_i. More formally this can be expressed as:

$$E(u_{ij}|X_i, Z_i) = E(u_{ij}|Z_i) = E(u_{ij}|X_i) = 0 \text{ for } j \in (0, 1). \quad (6)$$

Farmers usually take into consideration the potential benefits of new technologies when making adoption decisions (Abdulai and Huffman, 2014). However, in most cases, technology adoption is either voluntary or some technologies are targeted to a given group of farmers (Alene and Manyong, 2007). Farmers may decide to adopt a new technology due to their innate managerial and technical abilities in understanding and using new agricultural technologies. Thus, selection bias may result because farmers who would obtain lower than average returns for an improved technology, given prices and fixed factors, may choose not to adopt hence truncating the observed improved technology profit distribution (Pitt, 1983). Thus, the treatment variable D may be correlated with the error term in equations (3) and (4) such that:

$$E(u_{ij}|D) \neq 0 j \in (0, 1). \quad (7)$$

To break the correlation between the possibly endogenous treatment variable and unobservables affecting the outcome variable, we use the instrumental variable control function approach. An instrument is expected to fulfil the orthogonality condition, i.e. it must be strongly correlated with the treatment variable, but does not directly affect the outcome variables. Following Abdoulaye *et al.* (2018), Di Falco *et al.* (2011), Di Falco and Veronesi (2013) and Shiferaw *et al.* (2014), we use 'cowpea varietal information sources', i.e. information from extension agents, farmer groups and research organisations as identifying instruments. In the agricultural technology adoption theory, it is expected that farmers will only adopt an improved variety if they have information or know about the particular variety. When farmers become aware of a certain technology or variety, they decide whether or not to adopt it by evaluating the expected net benefits from the technology, taking into account the initial investment and related variable costs (Adegbola and Gardebroek, 2007; Zeng *et al.*, 2017). Government extension agents play a vital role in spreading information about new technologies including varieties. Similarly, research organisations through their varietal demonstration plots and field days also help in disseminating information about new varieties which can in turn help farmers to learn about new varieties. Other farmers who may not have access to information from extension agents or research organisations can obtain information about new agricultural technologies from their fellow farmers through farmer groups. Membership in farmer groups indicates the intensity of contact with other farmers (Adegbola and Gardebroek, 2007).

It is important to admit that finding a perfect instrument is almost impossible, hence even though the instruments are relevant, it may not necessarily imply that they are valid. It can be argued that, apart from learning about improved varieties, farmers might also obtain additional productivity or income enhancing information from these information sources. Second, it may also be argued that farmers who are more likely to adopt ICVs are also inclined to search for information relating to improved varieties. However, the use of these instruments can be justified because information on ICV should not directly affect yield, net returns and production costs other than through its effect on adoption. We test the relevance of these instruments in section 4.1 and the results show that these instruments are strongly correlated with the adoption (treatment) variable.

The estimation of the CFA proceeds in two steps; in the first step, we use a probit model to fit equation (2) (including the instruments) and obtain the generalised residual, $\hat{v}_i$ as the difference between the treatment and the estimate $E(D_i|Z_i)$. Following Wooldridge (2015) we can include the residuals in the linear outcome equation in the second step such that:

$$E(Y_{ij}|X_i, v_i, D_i = j) = X_i'\beta_{1j} + \dot{\hat{v}}_i\beta_{2j} \text{ for } j \in (0, 1). \tag{8}$$

Finally, we estimate the average treatment effect on the treated (ATT) using the generalised method of moments (GMM). The ATT can generally be represented as:

$$\text{ATT} = E(Y_{1i} - Y_{0i}|X, D = 1) = (u_{1i} - u_{0i}) + E(v_{1i} - v_{0i}|X, D = 1). \tag{9}$$

We also estimated the propensity score matching (PSM) model to assess the robustness of the CFA model. For the sake of brevity, we do not explain the estimation procedure for the PSM, which is provided by Wooldridge (2010).

Lastly, we estimated the marginal treatment effects (MTEs) (Björklund and Moffitt, 1987; Heckman *et al.*, 2006) to assess the relationships between yield, net returns and production costs with a change in the propensity score. In other words, the MTEs allow us to capture heterogeneity in the treatment effect along the unobserved dimension in the propensity not to be treated or resistance to treatment (Scott and Walstrum, 2014; Andresen, 2018). Following Scott and Walstrum (2014), we can redefine equation (1) as:

$$I > 0 \Leftrightarrow \gamma Z > v \Leftrightarrow F_v(\gamma Z) > F_v(v) \Leftrightarrow P(Z) > u_D. \tag{10}$$

where F_v is the cumulative distribution function of v and $P(Z)$ is the propensity score which denotes the probability of treatment; and u_D is a uniformly distributed random variable between 0 and 1 representing the propensity not to be treated or resistance to treatment. Following Carneiro *et al.* (2017), we can rewrite equation (5) as:

$$Y_{i1} - Y_{i0} = \alpha_{i1} - \alpha_{i0}X(\beta_{i1} - \beta_{i0}) + \mu_{i1} - \mu_{i0}. \tag{11}$$

The return to adoption varies across individuals and plots with different X's and different μ_i, μ_{i0}. This distinction between marginal returns and average returns emphasises heterogeneity in returns (Carneiro *et al.*, 2017). Combining equations (10) and (11), the MTE can be defined following Andresen (2018), Carneiro *et al.* (2011), Heckman *et al.* (2006) and Scott and Walstrum (2014), as:

$$\begin{aligned} \text{MTE} &= E(Y_{i1} - Y_{i0}|X = x, u_D = u) \\ &= \underbrace{x(\beta_1 - \beta_0)}_{\text{Heterogeneity in observables}} + \underbrace{E(u_{1i} - u_{0i}|u_D = u)}_{\text{Heterogeneity in unobservables}} \end{aligned} \tag{12}$$

Equation (12) shows that the MTE can alternatively be interpreted as the average effect of treatment for persons on a margin of indifference between participation and non-participation in treatment (Brinch *et al.*, 2017). Heckman and

Vytlacil (2005) show that the ATT can be constructed as a weighted average of the MTE. We adopt the notation used by Carneiro *et al*. (2017) and define the ATT from MTEs models as:

$$\mathrm{ATT} = \int \mathrm{MTE}(x, v) F_{(v|x)(v|x)dv}. \tag{13}$$

3. Survey Design, Data Collection and Descriptive Statistics

3.1. Survey design and data collection

Our data come from a survey conducted in 2017 by IITA under a project called Tropical Legumes III. This was a nationally representative sample of 1,525 cowpea producers and 2,550 cowpea plots in Nigeria. A survey questionnaire was prepared and administered using computer assisted personal interviewing (CAPI) based software (Surveybe) by trained enumerators who collected data from households through personal interviews. The survey was conducted in 10 states – Borno, Bauchi, Gombe, Jigawa, Kaduna, Kano, Katsina, Kebbi, Sokoto and Zamfara – which represent about 75% of the total cowpea production in Nigeria. These states mainly fall within the Sudan Savanna, which is the major agro-ecological zone for cowpea production in Nigeria. Figure A1 (online Appendix) shows the distribution of the sampled households across the 10 states.

A multistage stratified sampling procedure was used to select the households. In the first stage a list of villages and Local Government Areas (LGAs) used for conducting national census in Nigeria was obtained from the National Population Commission (NPC). The 10 states were first grouped into two geopolitical zones; northeast and northwest. In the second stage, 25 and 13 LGAs were selected in each region using probability proportional to size (PPS) sampling. Only 13 LGAs were selected in the northeast region because only three states were considered (Borno, Bauchi and Gombe) due to security problems experienced in that region during the survey. In the third stage, five cowpea producing villages were then randomly selected from each of the selected LGAs. With the help of the extension agents from the Agricultural Development Programme (ADPs) in the selected villages, cowpea growing households were listed and a sampling frame was developed. In the final stage, eight households were randomly selected from each village resulting in 995 and 530 households selected in the northwest and northeast regions, respectively.

The survey collected information on several factors at both plot and household levels. Seed samples of the popular local and improved varieties were used to facilitate the interviews with farmers about whether and when they have adopted particular improved varieties. To avoid measurement errors common with self-reported plot sizes, we used GPS devices to measure the area under cowpea varieties. Data were also collected on production systems, technology choices and preferences, input use, farmers' patterns of resource use, socioeconomic characteristics of households and plot-specific characteristics.

3.2. Definition of variables and descriptive statistics

Adoption in this study was defined at plot level in terms of whether or not an improved variety was planted on the plot. Table A1 (online Appendix) shows the adoption of ICV by some of the popular varieties at plot level[2] for the all the cowpea plots. On average, about 88% of plots intercropped cowpea with other crops such as millet and sorghum. We asked farmers during the survey to estimate the percentage of the area covered by cowpea and other crops. We then used this percentage to adjust the area we measured using GPS to account for intercropping. Table A2 (online Appendix) also shows that, on average, about 96% of the farmers owned one cowpea plot and only 4% possessed more than one cowpea plot. Overall, 38% of the plots were planted with ICV with the most widely adopted variety being Sampea 11 (on 7% of the plots) (Table A1). Released in 2009, Sampea 11 variety is popular with farmers because it is resistant to nematodes, aphids, major insect pests and has good seed quality with a yield potential of 2 tons/ha. Interestingly, the adoption rates in Table A1 indicate that other popular varieties have not yet been released, implying that farmers obtained these varieties from demonstration plots, which are usually conducted across several agro-ecological zones before the variety is finally released. About 5% the households adopted Sampea 9, a dual purpose variety with both good grain and folder yields, suggesting that livestock ownership may also be important in increasing the adoption of ICV (Kristjanson *et al.*, 2005) especially in northern Nigeria where livestock ownership is a vital part of the farming system.

Table 1 presents the definition of the outcome and explanatory variables together with the mean differences in these variables by adoption status. We draw on existing literature on the theory of farm household decision-making under imperfect markets and past adoption and impact studies to identify these covariates (e.g. de Janvry *et al.*, 1991; Feder and Umali, 1993; Kristjanson *et al.*, 2005; Abdulai and Huffman, 2014). We consider three outcome variables: cowpea yield (total harvest per ha. in the 2016 season), net returns (gross value less input costs per ha) and total variable costs[3] of cowpea production (purchase of seed, insecticides, herbicides, and hired labour). The average yield of 643 kg/ha is quite low compared to the potential yield of 800 kg/ha for some of the improved varieties, although adopters had obtained slightly higher yields than non-adopters (Table 1). The average net returns per ha for the sample plots was about ₦193,068 (US$ 633),[4] with adopters achieving ₦17,818.49, significantly more than non-adopters. Non-adopters also had greater production costs compared with adopters by about ₦1,150 on average.

Our explanatory variables include household characteristics such as household size, age of the household head and the extent of education (whether the household head attended junior secondary school). The size of the household (labour endowment) was greater for adopters. Adopters were a bit older than non-adopters and they spent 0.02 more years in junior[5] secondary school than non-adopters. As proxies for human capital these variables are expected to encourage ICV adoption (Mason and Smale, 2013). Livestock ownership (equines), measured in Total Livestock Units (TLU) is also proxy for household wealth. Adopters had more horses and donkeys than non-adopters. Especially in the hot and dry northern part of Nigeria, these animals are

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[2]All the analyses in the subsequent sections were done at plot level.

[3]Note that in the subsequent sections, we use costs, production costs and total variable costs interchangeably.

[4]The official exchange rate at the time of the survey was 1 US$ = 305 ₦.

[5]In the Nigerian school system, junior secondary school consists of three years after completing primary school.

Table 1
Variable names, definitions, and descriptive statistics

Variables	Definition	Full sample mean	Non-adopters	Adopters	Difference
Outcome variables					
Cowpea yields	Cowpea output (kg/ha)	643.20	633.44	659.45	−26.01
Net returns	Total cowpea revenue minus input and hired labour costs per hectare (Naira)	83,992.00	81,544.74	88,038.52	−6,493.78**
Total cowpea variable costs	Total cowpea variable costs (Naira) associated with cowpea production	39,842.35	40,275.81	39,125.62	1,150.19
Household characteristics					
Household size	Total household size (number)	8.74	8.62	8.94	−0.32*
Age of the household head	Age of the household head (number)	44.32	44.28	44.38	−0.10
Attended junior secondary school	=1 if attended junior secondary school, 0 otherwise	0.32	0.03	0.05	−0.02**
Total land cultivated	Total area of land cultivated (ha)	1.27	1.35	1.13	0.21***
Livestock ownership	Equines measured in Tropical Livestock Units	0.03	0.02	0.04	−0.02**
Traders	Number of trusted cowpea traders	9.56	9.63	9.46	0.17
Number of years	Number of years the household has lived in the village	37.04	36.86	37.34	−0.48
Agricultural implement index	Agricultural implement index (number)	0.14	0.13	0.17	−0.04
Wealth index	Household asset index (number)	−0.04	0.13	−0.06	0.19**
Access to off farm income	=1 if farmer has access to off farm income, 0 otherwise	0.86	0.86	0.86	0.00
Government support	=1 if household relies on government support such as food aid in times of crop failure	0.48	0.48	0.48	0.00
Male labour units	Male labour units in person days	97.53	100.49	92.65	7.84**
Pesticide prices	Average village level pesticide prices (Naira)	1,671.23	1,661.28	1,687.69	−26.41
Herbicide prices	Average village level herbicide prices (Naira)	654.50	719.15	547.60	171.55***

Table 1
(*Continued*)

Variables	Definition	Full sample mean	Non-adopters	Adopters	Difference
Wage rate	Average village level wage rate per hour (Naira)	6.16	72.66	66.50	70.34**
Plot characteristics					
Female manager	=1 if female is a plot manager, 0 otherwise	0.05	0.05	0.04	0.01
Pest and disease stress	=1 if experienced pest and disease stress, 0 otherwise	0.48	0.49	0.46	0.02
Animal trampling stress	=1 if experienced animal trampling stress, 0 otherwise	0.02	0.02	0.02	0.00
Flat slope	=1 if plot has flat slope, 0 otherwise	0.74	0.72	0.78	−0.05**
Medium slope	=1 if plot has medium slope, 0 otherwise	0.22	0.24	0.19	0.05**
Medium fertility	=1 if plot has medium soil fertility, 0 otherwise	0.71	0.71	0.70	0.01
Good fertility	=1 if plot has good soil fertility, 0 otherwise	0.25	0.25	0.24	0.01
Field distance	Distance from homestead to field in minutes	27.53	29.22	24.72	4.50***
Information sources					
Government extension	=1 if obtained information about improved cowpea varieties from extension agents, 0 otherwise	0.06	0.05	0.07	−0.02**
Farmer group	=1 if obtained information about improved cowpea varieties from farmer group, 0 otherwise	0.09	0.08	0.10	−0.02**
Research organisations	=1 if obtained information about improved cowpea varieties from research organisation, 0 otherwise	0.01	0.01	0.01	−0.01*
Number of observations		2,550	1,589	961	

Notes: $*P < 0.10$, $**P < 0.05$, $***P < 0.001$. The difference is measured by the two-sample *t*-test with equal variances.

important in land cultivation as well as transportation of crop produce to the market, and are also expected to encourage adoption. Some of the ICVs are dual purpose varieties especially bred to produce both higher grain yield as well as high quantities of nutritious fodder for livestock (Kristjanson *et al.*, 2005), hence we expect farmers who have more livestock to adopt these varieties.

Social capital (the norms and networks that facilitate collective action, Woolcock, 1998) plays an important role in not only enhancing the adoption of improved agriculture technologies but also in mitigating against production and net returns risks. The number of cowpea traders trusted by the household and the number of years the household head has lived in the village are our proxies for trust and social capital. We proxy wealth using agricultural implement and wealth indices constructed using principal component analysis (PCA). Agricultural implements include ploughs, hoes and ox/donkey carts. Our wealth index includes all assets owned by the household (bicycles, motorbikes, cars, television sets, radios and cellphones) following Aguilar *et al.* (2015). We expect household's adoption of ICV to increase with the agricultural implements and wealth.

To capture variations in agro-ecological conditions, topography, and soil type and soil fertility (Di Falco and Chavas, 2009), we included plot-level characteristics such as crop stresses and self-reported slope of the plot (steep, moderately steep or flat) and soil fertility (poor, moderate and good). We include the gender of the plot manager, which has been suggested as a better proxy for gender than that of the household head. Crop stresses usually affect adoption decisions in a negative way and we expect the same effect on the outcomes variables (Kassie *et al.*, 2013; Teklewold *et al.*, 2013). The distance of the plot from the homestead reflects the costs associated with the movement of inputs to the farm as well as produce from the farm to the market; hence it is expected that adoption will reduce with the distance. Adopters of ICV had significantly more improved cowpea varietal information compared with non-adopters.

4. Empirical Results and Discussion

4.1. Determinants of adoption of improved cowpea varieties

Table 2 presents the first stage results of the control function endogenous treatment effect estimates of adoption of ICV for the cowpea yields, net returns and total variable costs. The results for the determinants of the outcome variables are presented in Table A3 in the online Appendix. Village cluster robust standard errors are reported in all specifications to account for heteroscedasticity and the sampling procedure. We checked the relevance of our instrumental variables by testing whether the instruments satisfied the orthogonality condition. The results show that all the instruments were statistically significant in explaining adoption at the 5% significant level, which suggests that the instruments are relevant.

Since the selection results are quite similar for the two equations, we focus on the results for yields and net returns (Table 2, column (2)). Most of the variables in the model have the hypothesised signs. Older farmers are less likely to adopt ICV, possibly reflecting older farmers' greater risk aversion. Education of the household head is strongly significant in supporting adoption (Smale *et al.*, 2018), in agreement with Alene and Manyong's (2006, 2007) results for adoption of ICV in northern Nigeria. The number of traders that a farmer knows and trusts increases the adoption of ICV (Kassie *et al.*, 2013).

Table 2
Control function endogenous treatment effects estimates (selection equation)

Variables	Yield/net returns	Total variable costs
Total household size	0.01 (0.01)	0.01 (0.01)
Age of the household head	−0.04* (0.02)	−0.04* (0.02)
Age of the household head squared	0.00* (0.00)	0.00* (0.00)
Attended junior secondary school	0.41** (0.18)	0.41** (0.17)
Total cultivated land	−0.04 (0.03)	−0.04 (0.03)
Ln Livestock ownership	0.42 (0.32)	0.46 (0.32)
Ln Traders	0.09* (0.06)	0.10* (0.06)
Agricultural implement index	0.03 (0.03)	0.03 (0.03)
Wealth index	−0.02 (0.03)	−0.02 (0.03)
Access to off farm income	0.08 (0.11)	0.08 (0.11)
Government support	0.01 (0.08)	0.01 (0.08)
Number of years	−0.00 (0.00)	−0.00 (0.00)
Ln Pesticide prices	0.41 (0.25)	0.41 (0.25)
Ln Wage rate	−0.44*** (0.13)	−0.45*** (0.13)
Ln Herbicide prices	−0.03** (0.02)	−0.03** (0.02)
Ln Male labour	−0.09* (0.05)	−0.08* (0.05)
Female plot manager	−0.06 (0.17)	−0.06 (0.17)
Pest and disease stress	−0.04 (0.06)	−0.03 (0.07)
Animal trampling stress	−0.17 (0.21)	−0.15 (0.21)
Flat slope	−0.01 (0.19)	−0.02 (0.19)
Medium slope	−0.09 (0.20)	−0.10 (0.20)
Medium soil fertility	−0.20 (0.14)	−0.19 (0.14)
Good soil fertility	−0.20 (0.15)	−0.18 (0.15)
Field distance from residence	−0.00* (0.00)	−0.00* (0.00)
Farmer group	0.30** (0.12)	
Research organisations	0.85** (0.34)	0.81** (0.34)
Government extension		0.32** (0.17)
Northwest region dummy	0.25** (0.12)	0.24** (0.12)
Constant	0.41 (2.03)	0.411 (2.03)
Observations	2,550	2,550

***Notes*:** Village cluster robust standard errors in parentheses. *$P < 0.10$, **$P < 0.05$, ***$P < 0.001$.

Adoption of ICV apparently reduces with the wage rate and herbicide prices (Table 2). Previous studies (e.g. Abdulai and Huffman, 2014) show that higher input prices reduce the net benefits of adoption, hence the higher the wage rate and herbicide prices the more costly it becomes for farmers to adopt improved ICV. Consistent with our theoretical expectations, the distance to the plot from the homestead is negatively associated with the adoption of ICV. Information on improved varieties, from farmer groups, research organisations, or extension agents is, as expected, significant for adoption. Finally, the region dummy reflects the agro ecological as well as security differences in the northern part of Nigeria. Relative to the northeast region, adoption of ICV is greater in the northwest region, which may reflect the security problems experienced in the northeast during the survey, which displaced farmers from their residential areas and affected cowpea production.

4.3. Average and marginal returns to the adoption of improved cowpea varieties

The estimates of the average treatment effect (ATT) on the treated from the CFA approach are shown in Table 3 accounting for both observed and unobserved heterogeneity. Adoption of ICV is associated on average with a significant 26% yield gain, comparable to the researcher and farmer managed on-farm trials reported in Kamara *et al*. (2010) for Nigeria. Net returns and production costs per hectare are greater on ICV plots on average by 61% and 14%, respectively. However, the net returns gain relative to the yield gain is higher and this is so because adopters faced relatively lower production costs than non-adopters (Table A4 in the online Appendix).

Since the estimation of marginal treatment effects (MTE) are conditional on a given realisation of the propensity score, we first checked whether there was considerable overlap between the adopters and non-adopters propensity scores. Estimating reliable MTEs requires this overlap because it implies that there are adopting and non-adopting households with similar characteristics. Figure A2 (online Appendix) shows that there is substantial overlap between adopters and non-adopters of ICV, and therefore we can proceed to estimate the effects. The identification of the MTE models depends heavily on the common support assumption for the propensity score, which requires that there exist positive values of the estimated propensity scores in the range of (0,1) for adopters and non-adopters (Scott and Walstrum, 2014).

Figure 1 shows the MTE estimates for yield, net returns and costs from the polynomial[6] model. The *x*-axis shows the unobserved resistance to treatment while the *y*-axis is the MTE. The yield and net returns MTEs have a negative slope (consistent with the results from Wossen *et al*., 2018b). This shows that the treatment effects are heterogeneous. This implies that the marginal return to ICV increases with the propensity to adopt ICV. Consistent with Suri (2011), this further suggest that based on their comparative advantage, farmers may self-select into adoption. Unlike the yield and net returns MTEs, the cost MTE is an increasing[7] function of the unobserved resistance to treatment i.e. farmers with a lower propensity to adopt face higher costs of production relative to those with a higher propensity to adopt. This suggests that there are structural differences between these two groups. Reducing these structural barriers that make adoption more expensive for famers with a lower propensity to adopt is imperative to fully harness the benefits from adoption (Wossen *et al*., 2018b).

Using equation (12), we also estimated ATTs for the polynomial[8] and parametric MTE model specification and the results are presented in Table A5 (online Appendix). The results show that adoption of ICVs increases yield, net returns and production costs, similar to the results presented in Table 3 for the CFA estimates. The results from these models therefore suggest that our CFA model was not misspecified.

Overall, the results from the control function and MTE models suggest that adoption of ICVs significantly increased yields and net returns. The net returns increase is higher than the yield increase and this is because adopters faced significantly lower

[6]We also estimated the parametric and semiparametric MTEs and the results are presented in Figures A3 and A4 in the online Appendix.

[7]Note that this is contrary to what we expected, hence this result must be interpreted with caution.

[8]We could not estimate the ATT using the semiparametric models because the full support is not generated in the semiparametric specification.

Table 3

Control function average treatment effects on adopters

Outcome variables	Adopters	Non-adopters	ATT[1]	Percent change
Cowpea yield (kg/ha)	6.24	4.94	1.31** (0.65)	26.43
Net returns (naira/ha)	10.28	6.37	3.91* (3.65)	61.40
Total variable costs (naira/ha)	9.99	8.73	1.26* (0.67)	14.43

Notes: [1]Estimates in natural logarithms; Village cluster robust standard errors in parentheses; $*P < 0.10$, $**P < 0.05$.

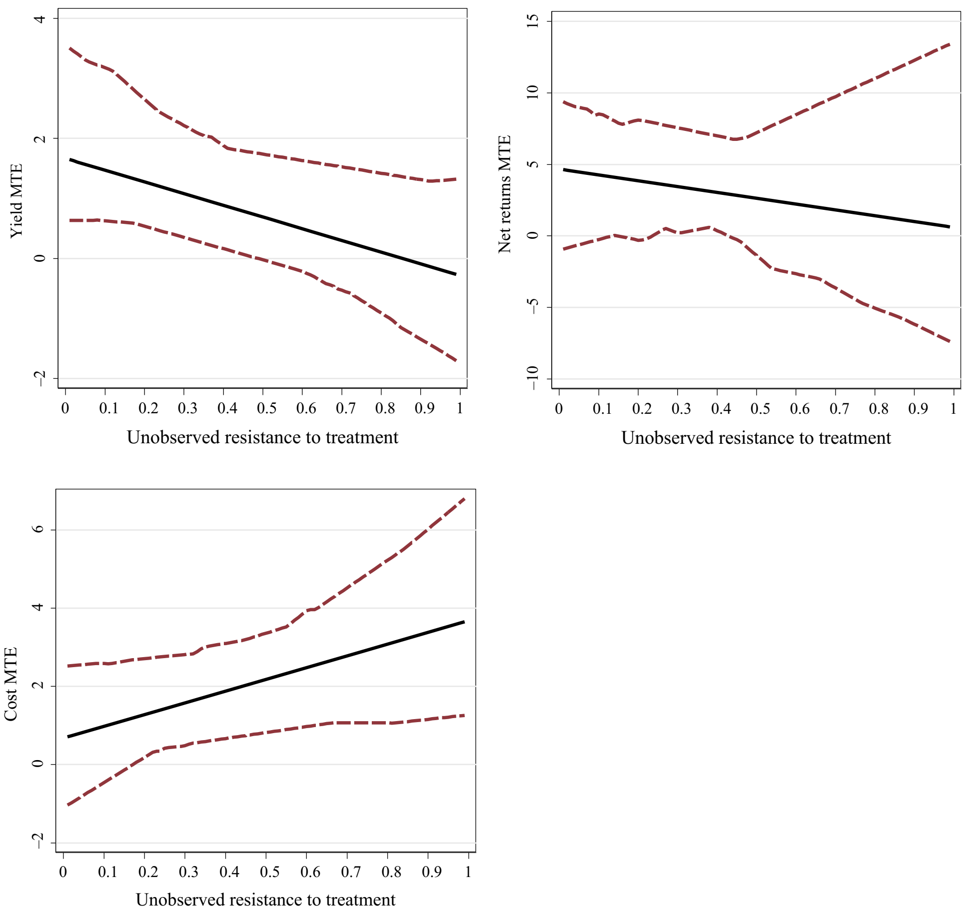

Figure 1. Polynomial yield, net returns and cost marginal treatment effect estimation. Solid lines show the estimated marginal treatment effects (MTE); dashed lines refer to 95% confidence intervals obtained through bootstrapping. [Colour figure can be viewed at wileyonlinelibrary.com]

production costs than non-adopters, a result confirmed by the cost MTE curves. The results in Table A4 (online Appendix) show that adopters had significantly lower pesticide and herbicide costs. This is because local varieties on average take longer to mature compared to improved short-duration varieties which may require less weeding. Consistent with Michler *et al*. (2018), farmers therefore may be adopting ICV not only because of their potential yield gains, but also for the potentially significant cowpea returns due to lower production costs. Finally, it is important to mention that the net returns were calculated using estimated costs based on farmers' responses which may also bias our results presented above. So despite our attempts to control for selection bias using the rigorous econometric methods, some bias may still be present especially that we are using cross-sectional data.

4.4. *Robustness checks*

We estimated the yield, net returns and cost ATTs using the PSM as a robustness check for the CFA estimates, though PSM only accounts for observed heterogeneity. The results in Table A6 (online Appendix) show that the adoption of ICV increases yields and net returns on average by 54 kg and ₦ 6,050, respectively. The cost of production however increases with the adoption of ICV. The cost of production increased by about ₦ 4,293 on average, which is lower than the increase in net returns. These results lend further evidence of the credibility of the CFA estimates in Table 3.

5. Conclusions and Policy Implications

We examine the adoption and impact of improved cowpea varieties on yield, net returns and production costs in northern Nigeria using plot and farm household survey data collected in 2017. Our data come from a representative sample of 1,525 cowpea producers using 2,550 cowpea plots. We use an instrumented control function to control for observed and unobserved heterogeneity, and a marginal treatment effects model to assess impact heterogeneity with propensity score matching to assess the robustness of the control function estimates.

Consistent with previous adoption studies, our results indicate that the main factors influencing adoption of improved varieties are age and education of the household head, distance of the cowpea plot from the homestead and varietal information sources. However, both higher hired labour and herbicide costs tend to reduce adoption rates according to our data.

The average treatment effects from all the estimation methods used in this study were largely consistent and indicate that improved cowpea adoption has a significant and positive impact on yields and net returns. Adoption of improved cowpea varieties is associated with an average 26% yield and 61% net returns gain, even though adoption also increases production costs by more than 14%.

Our marginal treatment effect (MTE) estimates show that the yield and net return gains are heterogeneous, with farmers adopting improved cowpea varieties based on their comparative advantage. The results for both yield and net returns consistently show positive selection on unobservable gains, implying that more productive and enterprising farmers are more likely to adopt improved cowpea varieties. The cost MTEs however showed that farmers with a lower propensity to adopt significantly faced higher production costs than those with a higher propensity to adopt improved cowpea varieties. In both cases, and in addition to the inconsistent net returns versus yield and cost treatment effects, our results suggest that, despite our attempts to control for selection bias in estimating the effects of improved variety adoption, some selection bias may still remain. In any case, our results suggest that removal of structural obstacles to adoption is important. This is important because in most cases farmers who have a lower propensity to adopt are also usually worse off in terms of access to information, credit and asset ownership (Manda *et al.*, 2017).

Cowpeas play an important role in the livelihoods of many households not only in Nigeria but also in most parts of West and Central Africa. In view of considerable international and national cowpea improvement and extension investments, further research is needed to assess the economic rates of return on investment as well as the poverty impacts of adoption of improved cowpea varieties.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table A1. Plot level adoption of improved cowpea varieties.

Table A2. Number plots owned by households.

Table A3. Second stage control function endogenous treatment effects estimates.

Table A4. Cowpea production costs.

Table A5. Average treatment effects on adopters from the polynomial and parametric marginal effects models.

Table A6. Average treatment effects on adopters from propensity score matching.

Figure A1. Map of the study area.

Figure A2. Distribution of propensity scores by adoption status.

Figure A3. Parametric yield, net returns, and cost marginal treatment effect estimation.

Figure A4. Semiparametric yield, net returns and cost marginal treatment effect estimation.

References

Abdoulaye, T., Wossen, T. and Awotide, B. 'Impacts of improved maize varieties in Nigeria: ex-post assessment of productivity and welfare outcomes', *Food Security*, Vol. 10, (2018) pp. 369–379.

Abdulai, A. and Huffman, W. 'The adoption and impact of soil and water conservation technology: An endogenous switching regression application', *Land Economics*, Vol. 90, (2014) pp. 26–43.

Adegbola, P. and Gardebroek, C. 'The effect of information sources on technology adoption and modification decisions', *Agricultural Economics*, Vol. 37, (2007) pp. 55–65.

Aguilar, A., Carranza, E., Goldstein, M., Kilic, T. and Oseni, G. 'Decomposition of gender differentials in agricultural productivity in Ethiopia', *Agricultural Economics*, Vol. 46, (2015) pp. 311–334.

Alene, A. and Manyong, V. 'Endogenous technology adoption and household food security: The case of improved cowpea varieties in northern Nigeria', *Quarterly Journal of International Agriculture*, Vol. 45, (2006) pp. 211–230.

Alene, A. and Manyong, V. 'The effects of education on agricultural productivity under traditional and improved technology in northern Nigeria: An endogenous switching regression analysis', *Empirical Economics*, Vol. 32, (2007) pp. 141–159.

Andresen, M. E. 'Exploring marginal treatment effects: Flexible estimation using Stata', *Stata Journal*, Vol. 18, (2018) pp. 118–158.

Bezu, S., Kassie, G. T., Shiferaw, B. and Ricker-Gilbert, J. 'Impact of improved maize adoption on welfare of farm households in Malawi: A panel data analysis', *World Development*, Vol. 59, (2014) pp. 120–131.

Björklund, A. and Moffitt, R. 'The estimation of wage gains and welfare gains in self-selection models', *Review of Economic Statistics*, Vol. 69, (1987) pp. 42–49.

Boukar, O., Massawe, F., Muranaka, S., Franco, J., Maziya-Dixon, B., Singh, B. and Fatokun, C. 'Evaluation of cowpea germplasm lines for protein and mineral concentrations in grains', *Plant Genetic Resources*, Vol. 9, (2011) pp. 515–522.

Boukar, O., Boahen, S., Ranajit B., Kumar P.L., Fatokun, C., Abaidoo, R., Drabo, I., Mohammed, H., Touré, M., Adamou, M., Ishiyaku, M., Olufajo, O., Mligo, J., Makenge, M. and Amane, E. 'Enhancing cowpea productivity and production in droughtprone areas of sub-Saharan Africa'. in E. S. Monyo and R. K. Varshney (eds), *Seven Seasons of Learning and Engaging Smallholder Farmers in the Drought-Prone Areas of Sub-Saharan Africa and South Asia through Tropical Legumes South Asia through Tropical Legumes, 2007–2014* (ICRISAT, Patancheru, Telangana, 2016, pp. 236).

Boukar, O., Belko, N., Chamarthi, S., Togola, A., Batieno, J., Owusu, E., Haruna, M., Diallo, S., Umar, M. L., Olufajo, O. and Fatokun, C. 'Cowpea (*Vigna unguiculata*): Genetics, genomics and breeding', *Plant Breeding*, (2018) pp. 1–10.

Brinch, C. N., Mogstad, M. and Wiswall, M. 'Beyond LATE with a discrete instrument', *Journal of Political Economy*, Vol. 125, (2017) pp. 985–1039.

Carneiro, P., Heckman, J. J. and Vytlacil, E. J. 'Estimating marginal returns to education', *American Economic Review*, Vol. 101, (2011) pp. 2754–2781.

Carneiro, P., Lokshin, M. and Umapathi, N. 'Average and marginal returns to upper secondary schooling in Indonesia', *Journal of Applied Economics*, Vol. 32, (2017) pp. 16–36.

Di Falco, S. and Chavas, J. P. 'On crop biodiversity, risk exposure, and food security in the highlands of Ethiopia', *American Journal of Agricultural Economics*, Vol. 91, (2009) pp. 599–611.

Di Falco, S. and Veronesi, M. 'How can african agriculture adapt to climate change? A counterfactual analysis from Ethiopia', *Land Economics*, Vol. 89, (2013) pp. 743–766.

Di Falco, S., Veronesi, M. and Yesuf, M. 'Does adaptation to climate change provide food security? A micro-perspective from Ethiopia', *American Journal of Agricultural Economics*, Vol. 93, (2011) pp. 829–846.

Feder, G. and Umali, D. L. 'The adoption of agricultural innovations: A review', *Technological Forecasting Social Change*, Vol. 43, (1993) pp. 215–239.

Heckman, J. J. and Vytlacil, E. 'Structural equations, treatment effects, and econometric policy evaluation', *Econometrica*, Vol. 73, (2005) pp. 669–738.

Heckman, J. J., Urzua, S. and Vytlacil, E. 'Understanding instrumental variables in models with essential heterogeneity', *Review of Economics and Statistics*, Vol. 88, (2006) pp. 389–432.

de Janvry, A., Fafchamps, M. and Sadoulet, E. 'Peasant household behaviour with missing markets: Some paradoxes explained', *Economic Journal*, Vol. 101, (1991) pp. 1400–1417.

Kamara, A. Y., Ellis-Jones, J., Ekeleme, F., Omoigui, L., Amaza, P., Chikoye, D. and Dugje, I. Y. 'A participatory evaluation of improved cowpea cultivars in the Guinea and sudan savanna zones of north east Nigeria', *Archives of Agronomy and Soil Science*, Vol. 56, (2010) pp. 355–370.

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F. and Mekuria, M. 'Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania', *Technological Forecasting and Social Change*, Vol. 80, (2013) pp. 525–540.

Khonje, M., Manda, J., Alene, A. D. and Kassie, M. 'Analysis of adoption and impacts of improved maize varieties in eastern Zambia', *World Development*, Vol. 66, (2015) pp. 695–706.

Kristjanson, P., Okike, I., Tarawali, S., Singh, B. B. and Manyong, V. M. 'Farmers' perceptions of benefits and factors affecting the adoption of improved dual-purpose cowpea in the dry savannas of Nigeria', *Agricultural Economics*, Vol. 32, (2005) pp. 195–210.

Langyintuo, A. S., Lowenberg-DeBoer, J., Faye, M., Lambert, D., Ibro, G., Moussa, B., Kergna, A., Kushwaha, S., Musa, S. and Ntoukam, G. 'Cowpea supply and demand in West and Central Africa', *Field Crop Research*, Vol. 82, (2003) pp. 215–231.

Lee, L. F. 'Unionism and wage rates: a simultaneous equations model with qualitative and limited dependent variables', *International Economic Review*, Vol. 19, (1978) pp. 415–433.

Manda, J., Khonje, M. G., Alene, A. D. and Gondwe, T. 'Welfare impacts of improved groundnut varieties in eastern Zambia: A heterogeneous treatment effects approach', *Agrekon*, Vol. 56, (2017) pp. 313–329.

Mason, N. M. and Smale, M. 'Impacts of subsidized hybrid seed on indicators of economic well-being among smallholder maize growers in Zambia', *Agricultural Economics*, Vol. 44, (2013) pp. 659–670.

Mathenge, M. K., Smale, M. and Olwande, J. 'The impacts of hybrid maize seed on the welfare of farming households in Kenya', *Food Policy*, Vol. 44, (2014) pp. 262–271.

Michler, J., Tjernstrom, E., Verkaart, S. and Mausch, K. 'Money matters: The role of yields and profits in agricultural technology adoption', *American Journal of Agricultural Economics*, (2018) pp. 1–22.

Mishili, F. J., Fulton, J., Shehu, M., Kushwaha, S., Marfo, K., Jamal, M., Kergna, A. and Lowenberg-DeBoer, J. 'Consumer preferences for quality characteristics along the cowpea value chain in Nigeria, Ghana, and Mali', *Agribusiness*, Vol. 25, (2009) pp. 16–35.

Monyo, E. S. and Gowda, C. L. L. *Grain Legumes Strategies and Seed Roadmaps for Select Countries in Sub-Saharan Africa and South Asia*. Patancheru, Telangana: International Crops Research Institute for the Semi-Arid Tropics, 2014.

Murtazashvili, I. and Wooldridge, J. M. 'A control function approach to estimating switching regression models with endogenous explanatory variables and endogenous switching', *Journal of Econometrics*, Vol. 190, (2016) pp. 252–266.

NACGRAB (National Centre for Genetic Resources and Biotechnology). *Varieties release catalogue*, 2016. Available online at: http://www.nacgrab.gov.ng/images/Varieties_Released_Catalogue.pdf (last accessed: 30 May 2018).

Pitt, M. M. 'Farm-level fertilizer demand in Java: a meta-production function approach', *American Journal of Agricultural Economics*, Vol. 65, (1983) pp. 502–508.

Pradhan, J. and Quilkey, J. 'Modelling the adoption of HYV technology in developing economies theory and empirics', *Review of Marketing and Agricultural Economics*, Vol. 61, (1993) pp. 239–261.

Rivers, D. and Vuong, Q. H. 'Limited information estimators and exogeneity tests for simultaneous probit models', *Journal of Econometrics*, Vol. 39, (1988) pp. 347–366.

Scott, B. and Walstrum, T. 'Estimating marginal treatment effects using parametric and semiparametric methods', *Stata Journal*, Vol. 14, (2014) pp. 191–217.

Shiferaw, B., Kassie, M., Jaleta, M. and Yirga, C. 'Adoption of improved wheat varieties and impacts on household food security in Ethiopia', *Food Policy*, Vol. 44, (2014) pp. 272–284.

Singh, B.B., Ehlers, J.D., Sharma, B. and Filho, F.R.F. *Recent progress in cowpea breeding. Challenges and opportunities for enhancing sustainable cowpea production. Proceedings of the World Cowpea Conference III held at the International Institute of Tropical Agriculture (IITA)*, Ibadan, Nigeria, 4–8 September 2000 (Ibadan, Nigeria: IITA, 2002), pp. 22–40.

Smale, M. and Mason, N. 'Hybrid seed and the economic well-being of smallholder maize farmers in Zambia', *Journal of Development Studies*, Vol. 50, (2014) pp. 680–695.

Smale, M., Assima, A., Kergna, A., Thériault, V. and Weltzien, E. 'Farm family effects of adopting improved and hybrid sorghum seed in the Sudan Savanna of West Africa', *Food Policy*, Vol. 74, (2018) pp. 162–171.

Suri, T. 'Selection and comparative advantage in technology adoption', *Econometrica*, Vol. 79, (2011) pp. 159–209.

Teklewold, H., Kassie, M. and Shiferaw, B. 'Adoption of multiple sustainable agricultural practices in rural Ethiopia', *Journal Agricultural Economics*, Vol. 64, (2013) pp. 597–623.

Walker, T., Alene, A., Ndjeunga, J., Labarta, R., Yigezu, Y., Diagne, A., Andrade, R., Muthoni Andriatsitohaina, R., De Groote, H., Mausch, K., Yirga, C., Simtowe, F., Katungi, E., Jogo, W., Jaleta, M. and Pandey, S. *Measuring the Effectiveness of Crop Improvement Research in Sub-Saharan Africa from the Perspectives of Varietal Output, Adoption, and Change: 20 Crops, 30 Countries, and 1150 Cultivars in Farmers' Fields* (Rome, Italy, Standing Panel on Impact Assessment (SPIA), CGIAR Independent Science and Partnership Council (ISPC), 2014).

Woolcock, M. 'Social capital and economic development: Toward a theoretical synthesis and policy framework', *Theory and Society*, Vol. 27, (1998) pp. 151–208.

Wooldridge, J. M. *Econometric Analysis of Cross Section and Panel Data*, 2nd ed. (Cambridge, MA: MIT press, 2010).

Wooldridge, J. M. 'Control function methods in applied econometrics', *Journal of Human Resources*, Vol. 50, (2015) pp. 420–445.

Wossen, T., Abdoulaye, T., Alene, A., Nguimkeu, P., Feleke, S., Rabbi, I. Y., Haile, M. G. and Manyong, V. 'Estimating the productivity impacts of technology adoption in the presence of misclassification', *American Journal Agricultural Economics*, Vol. 101, (2018a) pp. 1–16.

Wossen, T., Alene, A., Abdoulaye, T., Feleke, S., Rabbi, I. Y. and Manyong, V. 'Poverty reduction effects of agricultural technology adoption: The case of improved cassava varieties in Nigeria', *Journal of Agricultural Economics*, (2018b) pp. 1–16.

Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M. and Yirga, C. 'Ex post impacts of improved maize varieties on poverty in rural Ethiopia', *Agricultural Economics*, Vol. 46, (2015) pp. 515–526.

Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M. and Yirga, C. 'Agricultural technology adoption and child nutrition enhancement: Improved maize varieties in rural Ethiopia', *Agricultural Economics*, Vol. 48, (2017) pp. 573–586.