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Impacts of improved maize varieties in Nigeria: ex-post assessment of productivity and welfare outcomes

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Abstract
Investment in agricultural research and development is an important intervention for improving crop productivity and household welfare in most developing countries where agriculture is the main source of livelihoods. This paper uses nationally representative plot- and household-level data from the major maize producing regions of Nigeria to assess the impacts of adoption of improved maize varieties on maize yield and household welfare outcomes. The paper employed an endogenous switching regression approach to control for both observed and unobserved sources of heterogeneity between adopters and non-adopters. Adoption of improved maize varieties increased maize grain yield by 574 kg/ha and per-capita total expenditure by US$ 77 (US$ 0.21/day). We found that the incidence of poverty among adopters would have been higher by 6% without adoption of the improved varieties. These findings underscore that investments and policy measures to increase and sustain the adoption of improved maize cultivars are critical for improving the productivity of maize in Nigeria and reducing poverty.

Keywords Adoption · Improved maize varieties · Nigeria · Productivity · Poverty

1 Introduction

In Nigeria, as in many other developing countries, agriculture-based rural transformation is crucial for achieving food security because agriculture is the main source of livelihoods for poor rural households (Alene et al. 2007; Alene 2010; Suri 2011). However, agriculture has been relatively neglected in the past and the rates of rural poverty and food insecurity have been increasing steadily over time. For instance, Nigeria's rural poverty measured at the food poverty line had increased from 33.6% in 2004 to 48.3% in 2010 (NBSN 2010). Renewed investment in the agricultural sector in general and technological change in agriculture in particular will therefore be critical as productivity growth is not possible without yield-increasing technologies (Kostandini et al. 2013; Dorosh and Thurlow 2018). In this regard, the development, dissemination, and adoption of high yielding improved varieties could provide a major pathway for improving productivity and welfare outcomes of farm households (Magrini and Vigani 2016; Abate et al. 2015; Wossen et al. 2017a, b).[1]

This paper focuses on the adoption of improved maize varieties by farmers in Nigeria. The country provides an interesting case study because the importance of maize as an income-generating food staple has been increasing steadily during the last two decades. National average grain yields have increased from 1.13 t/ha in 1990 to about 1.85 t/ha in 2014 (FAOSTAT 2016) and Nigeria has become the largest maize producer in West Africa. Farm households that adopt improved maize varieties can benefit directly from higher yields and indirectly from lower prices (as net buyers of food). Additionally, adoption could shorten lean periods when food is in short supply and increase agricultural incomes and welfare outcomes. For example, Bezu et al. (2014) documented that a 1% increase in the area planted to modern maize varieties in Malawi improved income by 0.48% and consumption by 0.34%. Similarly, Abate et al. (2015) suggested that the development and dissemination of widely adapted and profitable improved maize varieties have contributed to a

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[1] In this paper productivity is defined as maize output per unit of land. Hence productivity and maize yield are used interchangeably. Adoption here refers to the use of improved maize varieties, not areas under improved maize varieties

more than doubling in maize productivity in less than two decades in Ethiopia.

With the aim of increasing aggregate maize production, the government of Nigeria in collaboration with the International Institute of Tropical Agriculture (IITA) has recently invested significantly in the development and dissemination of improved maize varieties. As a result, more than 120 improved and high yielding maize varieties with different characteristics (including maturity groups and stress tolerances) have been released (NACGRAB 2016). However, despite significant varietal turnover, the empirical evidence on rates of adoption and on productivity and welfare-related outcome indicators is scant. There is a large body of empirical literature linking adoption with ex-post productivity and welfare outcomes in Africa but the focus of most of the existing literature has been in East Africa (e.g. Karanja et al. 2003; Shiferaw et al. 2008, 2014; Kassie et al. 2011; Asfaw et al. 2012; Amare et al. 2012; Mason and Smale 2013; Zeng et al. 2015; Abate et al. 2015; Magrini and Vigani 2016). Results from these studies underscore that the adoption of improved maize varieties has a significant positive effect on maize productivity (yields) and welfare outcomes (consumption expenditure). Understanding the main determinants of adoption, as well as the expected returns from adoption, in the context of Nigeria, is therefore important for the designing of policies that address supply-side constraints in West Africa.

This paper provides a comprehensive ex-post assessment of the potential impacts of adoption of improved maize varieties at the plot and household level in Nigeria. In particular, it seeks to address the following relevant key policy questions: What are the socio-economic and policy variables that affect a farmer's decision to adopt improved maize varieties? What is the productivity impact of adoption of improved maize varieties? Does adoption reduce poverty and improve household welfare? In addition to its empirical relevance, this study contributes to the existing adoption literature by examining the productivity and welfare effects using a rigorous approach that accounts for both observed and unobserved sources of heterogeneity between adopters and non-adopters. The rest of the paper is organized as follows: Section 2 presents our data sources and the empirical strategy used for examining the effect of adoption on productivity and welfare outcomes. Section 3 reports the main findings. Section 4 discusses the major results.

2 Data and methods

2.1 Data sources

This study used household survey data collected from rural Nigeria. The survey was carried out from November 2014 to February 2015. In the survey, we employed a multistage stratified random sampling technique to obtain nationally representative data. For the multistage stratified random sampling, the 36 states in Nigeria were divided into homogenous sub-groups based on the total area of land devoted to maize production in each state. This gave five groups, out of which 18 states were randomly selected. The selected 18 states contributed about 62.2% of the total land area devoted to maize production in Nigeria. Selection of households for the survey was also random. First, the list of all Enumeration Areas (EAs) in each of the selected states was obtained from the National Population Commission (NPC). The EAs were then divided by the number of Local Government Areas (LGAs) in each of the selected states to obtain the number of EAs per LGA. With the help of agricultural development programs (ADPs), the list of all maize producing households was obtained for all selected EAs from village administration units. From the list of these households, five farming households were randomly selected per enumeration area. Overall, this sampling framework generated a total of 2305 farming households.

In the survey, we collected detailed information on socio-economic characteristics of the households, household expenditure on food and non-food items, information on adoption of improved maize varieties, outputs of maize and other notable crops, and income from various sources. The treatment variable, adoption of improved maize varieties, was constructed using the following survey question: "*Did you grow improved maize varieties during the last agricultural season*?" Based on this question, we constructed a dummy variable that took on a value of one if the farmer had used improved maize varieties in at least one of the plots, and zero otherwise. However, this measurement lumped together different improved varieties (including hybrids, open-pollinated varieties (OPVs), and drought-tolerant varieties). To further disaggregate the adoption variable based on specific groups of improved varieties, we administered follow-up questions where we asked farmers to report the names of the improved varieties they grew in the last agricultural season. Farmers gave us more than 650 different names and it was difficult to group them into improved and local varieties. We therefore used experts of the survey areas, including extension agents, plant breeders, agronomists, and seed dealers, to make an initial grouping of improved versus local varieties. We also assessed varieties based on the source of seeds. For example, for farmers who bought seeds from seed dealers, we were able to trace the seed and variety and identify whether the variety was improved or not, and the specific type of variety (hybrid versus OPV). From the data identified by experts and seed companies, we found that almost 22% of the adopter farmers grew drought tolerant maize varieties. The adoption rate of hybrids was less than 10%, and therefore, most of the improved maize varieties in Nigeria were found to be OPVs.

According to our survey, about 57% of farm households had used improved maize varieties in the survey season. The most common improved varieties identified in our survey included Oba Super9, Ba Hausa, EVDT 99, 3DT Com, Yar Masara and Sammaz37. There was also significant variation in the use of improved varieties across the different states of Nigeria. For example, in states such as Zamfara, Kastina and Kano adoption rates were as high as 60%. However, adoption of improved maize varieties in Cross-River and Benue states was comparatively low. In Zamfara, Katzina and Enugu, drought tolerant varieties, were dominant with an adoption rate of well over 50%. However, the adoption rate of such varieties was close to zero in states such as Benue, Kogi and Nasarawa.

Our main productivity outcome indicator was grain yield of maize while the main welfare outcome indicators included per-capita food expenditure and total per-capita expenditure. In addition, following the approach of Foster et al. (1984), we constructed a poverty headcount ratio as an additional welfare outcome indicator, where per-capita total expenditure was used to determine the poverty status of a household. The poverty headcount ratio (P_0) was calculated as:

$$P_0 = \frac{1}{N}\sum_{i=1}^{N} I\left(X_p < z\right) \tag{1}$$

Where X_p is per-capita total expenditure and N is the relevant population size. z is a scalar set at per capita total annual expenditure level of 91,250 (NBSN 2010).[2] $I(.)$ is an indicator function which takes on a value of 1 when $X_p < z$ and a value of zero when $X_p > z$.

Table 1 presents the descriptive statistics for the main outcome indicators based on adoption status. In addition, other variables that capture plot-specific and household-specific characteristics of maize producers are presented in Table 1. These are household characteristics such as age, household size, education, membership of different social groups, as well as wealth indicators such as land size and value of farms and non-farm assets. Plot-specific variables such as soil fertility status, the use of chemical fertilizer, pesticides, and herbicides were also included. These variables were collected at the plot level for both adopters and non-adopters. We assumed that control variables used in the regression analysis affected the adoption decisions of farmers as well as their productivity and ultimate welfare status. For example, education is considered as a proxy for farming skill. It is therefore expected to have a positive impact on technology adoption. Similarly, household size implicitly captures the labour force needed to adopt new technologies. Some previous studies have documented a positive effect of a larger supply of family labour as critical for adoption decisions (e.g., Kassie et al. 2011). Membership of associations such as cooperatives enhances adoption by reducing information, credit, labour, and insurance market imperfections (Wossen et al. 2015). We also used the risk-taking behaviour of farmers for new maize varieties as an additional control. In the survey, we collected data on each respondent's willingness to take risks on seeds of new maize varieties during the planting stage. Since agricultural production is inherently risky, due to the lag between production decisions and output realization, willingness to take risks on new maize varieties captures unobserved variation in the use of new varieties among maize producing farmers. The variable, risk aversion, was measured by a dummy variable which takes on a value of one if the respondent is willing to try any type of new variety, and zero otherwise.

Table 1 also presents the difference in means between adopters and non-adopters for the main control variables. A significant difference was found between adopters and non-adopters in terms of household size, land size, distance from seed sources, value of total household assets, farming experience, access to micro-credit, membership in associations, ownership and quality of housing. These differences between adopters and non-adopters suggest that a simple comparison in terms of the main outcomes of interest without accounting for the differences in observable characteristics may bias estimated impacts of adoption. In addition, results reported in Table 1 suggest that input allocation decisions of adopters and non-adopters were significantly different. In particular, application of chemical fertilizer (both NPK and urea) was significantly higher among adopters compared with non-adopters. However, labour use (measured in man days) was significantly higher among non-adopters compared to adopters. The use of pesticide and herbicide was also significantly different. Significant differences were also found for other important agronomic practices. For example, row planting of adopters and non-adopters was significantly different.

For our instrument, access to varietal information, a statistically significant difference was found between adopters and non-adopters. Access to varietal information was measured by a dummy variable which takes on a value of one if the household received information on improved maize varieties and zero otherwise. There was also significant variation in access to varietal information across the different states considered in this study. For example, in states such as Zamfara, Kastina and Kano, where adoption rates of improved maize varieties were quite high, access to varietal information did not seem to be a problem as more than 80% of the farmers reported having such access.

2.2 Methods

We assumed that a profit maximizing maize producer adopts improved maize varieties based on expected benefits.[3] In

[2] This value is based on the World Bank's US$1.25 per day per capita.

[3] Note that improved maize varieties refer to OPVs, hybrids and drought tolerant varieties, while unimproved varieties are considered 'landraces'

Table 1 Descriptive statistics of the maize farmers in Nigeria by maize variety adoption status

	Full sample ($n = 1907$)	Adopters ($n = 1070$)	Non-adopters ($n = 837$)	Mean diff
Welfare outcome indicators				
Per capita total expenditure (in US$)[a]	395.4	410.6	382	28.6
Per capita food expenditure (in US$)	192.6	210.3	177	33.3***
Poverty headcount ratio (1 = poor, 0 = otherwise)	0.70	0.71	0.69	0.01
Productivity indicator				
Maize grain yield (kg/ha)	2128	2336	1946	390***
Other controls				
Access to varietal information (yes = 1, 0 = otherwise)	0.46	0.58	0.37	0.21***
Age (years)	48.5	48.15	48.8	−0.65
Household size	7.4	7.6	7.2	0.4*
Land size (ha)	4.5	4.9	4.2	0.7***
Education (years of formal schooling)	7.4	7.3	7.5	−0.2
Gender (1 = male, 0 = female)	0.91	0.88	0.879	0.001
Distance from the nearest seed source (km)	17.26	16.25	18.13	−1.88***
Farming experience (years)	29.2	28.3	29.9	1.6***
Ownership of farmland (yes = 1)	0.87	0.88	0.87	0.01
Total household asset ($)	3740	4040	3480	560***
Ownership of house (1 = yes, 0 = otherwise)	0.88	0.91	0.86	0.05***
House painted (yes = 1, 0 = otherwise)	0.24	0.25	0.23	0.02
Roofing sheets (Yes = 1, 0 = otherwise)	0.88	0.92	0.86	0.06***
Access to electricity (yes = 1, 0 = otherwise)	0.47	0.52	0.43	0.08***
Access to credit (yes = 1, 0 = otherwise)	0.15	0.12	0.18	−0.06***
Membership of organisation (yes = 1, 0 = otherwise)	0.66	0.60	0.70	−0.10***
Number of years' resident in the village (years)	42.3	41.9	42.7	−0.83
Drought shock (1 = yes, 0 = otherwise)	0.19	0.20	0.18	0.02
Risk aversion (1 = yes, 0 = otherwise)	0.73	0.67	0.79	−0.12***
Labour (man days)	79.5	72.3	85.8	−13.5***
NPK fertilizer (in kg/ha)	269	314	230	84***
Urea fertilizer (in kg/ha)	137	167	111	56***
Use of pesticide (yes = 1, 0 = otherwise)	6.9	8.8	5.2	3.6*
Use of herbicide (yes = 1, 0 = otherwise)	18.7	16.6	20.5	−3.9***
Good soil (yes = 1, 0 = otherwise)	0.77	0.83	0.72	0.11***
Medium soil (yes = 1, 0 = otherwise)	0.20	0.15	0.24	−0.09***
Poor soil (yes = 1, 0 = otherwise)	0.03	0.02	0.04	−0.02***
Use of soil and water conservation (SWC) (yes = 1, 0 = otherwise)	0.458	0.458	0.457	−0.001
Men managed plots (yes = 1, 0 = otherwise)	0.66	0.68	0.65	0.03**
Women managed plots (yes = 1, 0 = otherwise)	0.06	0.063	0.062	−0.001
Jointly managed plots (yes = 1, 0 = otherwise)	0.28	0.257	0.288	−0.031
Row planting (yes = 1, 0 = otherwise)	0.64	0.67	0.61	0.06***
Intercropping (yes = 1, 0 = otherwise)	0.35	0.34	0.36	0.02

[a] Note that the official exchange rate was (1 US$ = 280 Naira,) during the survey period

particular, a rational farmer adopts improved maize varieties if the gain from adoption is greater than from non-adoption. Assuming the net gain from adoption (compared with that of non-adoption) for a given farmer is Y^*, then $Y^* > 0$ implies that the benefit from adoption is greater than from non-adoption. Obviously, it is impossible to observe Y^*. However, the gain from adoption (Y^*) can be expressed as a function of an observable vector of covariates in a latent model presented below:

$$Y^* = \beta X_i + \mu_i, \quad \left\{ \begin{matrix} T_i = 1 \text{ if } Y^* > 0 \\ 0, \text{ otherwise} \end{matrix} \right\} \tag{2}$$

Where T_i is a binary indicator variable that equals 1 if a farmer is an adopter and zero otherwise. β is a vector of parameters to be estimated and X_i is a vector of socio-economic/demographic characteristics as well as farm-level and institutional variables. μ_i is a household-specific error term assumed to be normally distributed. In the above framework, isolating the causal effect of adoption on productivity and hence on household welfare is difficult due to endogeneity bias. As such, identification of causal effects of adoption on productivity requires controlling for both observable and unobservable sources of heterogeneity between adopters and non-adopters (Alene and Manyong 2007; Wooldridge 2010). For example, those farmers who adopt improved maize varieties might be different from non-adopters in terms of their inherent farming abilities. Failure to account for both observable and unobservable sources of heterogeneity will bias parameter estimates as such heterogeneity affects the probability of adoption as well as productivity and welfare outcomes. As a result, an endogenous switching regression approach (ESR) has been employed as it accounts for both observed and unobserved sources of bias (Lokshin and Sajaia 2004). Causal identification in ESR requires an instrument that affects productivity and welfare outcomes through the adoption of improved maize varieties. In much of the adoption literature, awareness of the technology by farmers/exposure to it has been used as an instrument (Alene and Manyong 2007). Following the literature (e.g., Alene and Manyong 2007; Shiferaw et al. 2014), we used access to information about maize varieties as an instrument. It is plausible to assume that access to varietal information cannot affect productivity and welfare without adoption and use of the variety. After a relevant instrument is identified, the ESR approach addresses the problem of endogeneity by estimating the selection (first stage) and the outcome equations (second stage) simultaneously, using the full information maximum likelihood (FIML) (Lokshin and Sajaia 2004).

Given the conceptual framework above, the outcome function conditional on adoption can be specified as an ESR model in the following manner:

$$Regime1: Y_{1i} = f(M, W, X, \beta_1) + \varepsilon_{1i} \text{ if } T_i = 1 \tag{3}$$

$$Regime2: Y_{2i} = f(\ W, X, \boldsymbol{\beta_2}) + \varepsilon_{2i} \quad \text{if } T_i = 0 \tag{4}$$

Where Y_{1i} represents outcome indicators for adopters (maize yield and welfare indicators) and Y_{2i} for non-adopters; ε_i is the error term of the outcome variable. The variable M represents the use of improved maize varieties while W captures farm inputs such as fertilizer at the plot level. The variable X measures other household, plot, and village level factors presented in Table 1. Finally, the variable T_i measures adoption status ($T_i = 1$, implies the farmer is an adopter). The error terms in the selection Eq. (2) and the outcome Eq. (3 and 4) are assumed to have a trivariate normal distribution with mean zero and covariance matrix (Ω) in the following manner:

$$\Omega = \begin{bmatrix} \sigma_\mu^2 & \sigma_{1\mu} & \sigma_{2\mu} \\ \sigma_{\mu 1} & \sigma_1^2 & . \\ \sigma_{\mu 2} & . & \sigma_2^2 \end{bmatrix}$$

Where $\sigma_\mu^2 = var\ (\mu_i)$, $\sigma_1^2 = var(\ \varepsilon_1\ )$, $\sigma_2^2 = var(\ \varepsilon_2)$, $\sigma_{1\mu} = cov\,(\mu_i, \varepsilon_1)$, $\sigma_{2\mu} = cov\,(\mu_i, \varepsilon_2)$. Furthermore, σ_μ^2 is *estimable* up to a scale factor and can be assumed to be equal to 1 (Maddalla 1983). Moreover, the correlation between the error term of the selection equation and the outcome equation is not zero (i.e., $corr(\mu_i, \varepsilon_1) \neq 0$ & $corr(\mu_i, \varepsilon_2) \neq 0$) which creates selection bias. ESR addresses this selection bias by estimating the inverse Mills ratios (λ_{1i} and λ_{2i}) and the covariance terms ($\sigma_{1\mu}$ and $\sigma_{2\mu}$) and including them as auxiliary regressors in Eq. (3 and 4). If $\sigma_{1\mu}$ and $\sigma_{2\mu}$ are significant, the absence of selection bias is rejected. The ESR model estimates can then be used to estimate ATT (Average treatment effect on treated households) as follows:

$$E\left(Y_{1i} | T_i = 1\right) = f(M, W, X, \beta_1) + \lambda_{1i}\sigma_{1\mu} \tag{5}$$

$$E\left(Y_{2i} | T_i = 0\right) = f(\ M, W, X, \boldsymbol{\beta_2}) + \lambda_{2i}\sigma_{2\mu} \tag{6}$$

$$E\left(Y_{2i} | T_i = 1\right) = f(M, W, X, \boldsymbol{\beta_2}) + \lambda_{1i}\sigma_{2\mu} \tag{7}$$

$$E\left(Y_{1i} | T_i = 0\right) = f(M, W, X, \boldsymbol{\beta_1}) + \lambda_{2i}\sigma_{1\mu} \tag{8}$$

The ATT is then defined as the difference between Eq. (5 and 7).

$$\text{ATT} = E\left(Y_{1i} | T_i = 1\right) - E\left(Y_{2i} | T_i = 1\right) \tag{9}$$

3 Results

3.1 Effect of adoption on maize yield

This section presents our main results. The first column in Table 2 (the selection equation) reports the determinants of adoption.[4] In the next two columns the determinants of maize

[4] Note that these results are associations or correlations, and not necessarily causal effects.

yield for adopters and non-adopters are shown. The selection equation suggests that sex of the household head, distance from seed markets, risk aversion, and the number of years the household head has resided in the village were negatively associated with the probability of adopting improved maize varieties. As expected, wealth indicators, such as house ownership and quality of the house were positively associated with the probability of adopting improved maize varieties. Furthermore, there was a positive association between adoption of agronomic practices such as row planting and pesticide use and the adoption of improved maize varieties. In the selection equation, the coefficient on access to varietal information was positive and statistically significant (at a 1% significance level). This result suggests that farm households with access to varietal information are more likely to adopt improved maize varieties, underscoring the relevance of the selected instrument.

Next, the determinants of maize yield for adopters and non-adopters were examined. Membership of social networks, intercropping, fertilizer (NPK) use and drought shock had positive and statistically significant effects on the maize yield of adopters. For instance, a 1% increase in the application of NPK increased maize yield by 0.03% for adopters. Similarly, membership of an association increased yield for adopters by 0.103% and intercropping by 0.2%. For non-adopters, plot management, the use of soil and water conservation, and application of pesticide or herbicide, the use of intercropping, and labour were significant determinants of maize yield. Increasing labour use by 1% increased maize yield by 0.098% among non-adopters. There was no significant effect of chemical fertilizer on yield among non-adopters.

Estimated coefficients of the correlation terms $\rho_{1\mu}$ and $\rho_{0\mu}$, that measure the correlation between the error terms of the selection equation and the outcome equation are reported in the bottom row of Table 2. The coefficient of $\rho_{0\mu}$ is negative and statistically significant while the coefficient of $\rho_{1\mu}$ is negative, albeit insignificant. This result underscores the presence of selection bias. As such, OLS estimates are biased and hence unobserved heterogeneity between adopters and non-adopters must be taken into account. In addition, the negative and significant effect of $\rho_{0\mu}$ suggests a positive selection bias. In particular, more productive farmers are more likely to adopt improved maize varieties. Finally, parameter estimates on state dummies suggested significant heterogeneity in maize yield across the different states of Nigeria. In particular, compared to farmers located in south-western parts of Nigeria, farmers located in the south-south and north-eastern part of the country are assessed as less productive, mostly due to low adoption rates.[5] Table 3 reports the counterfactual analysis on the effect of adoption on maize yield.[6] Even though the focus of this paper is on productivity and welfare outcome indicators, we estimated effects on net-returns to show the robustness of our results.[7] However, since data on costs of production are patchy, we based our main empirical analysis on productivity effects. Reported results in Table 3 show that adoption increased net-returns by about 14% and maize productivity (yield) by 574 kg/ha (that is 32.6% higher than the counterfactual). The maize yield of current adopters would have been lower by 32.6% if adopters had not adopted improved maize varieties.[8]

In addition, Table 3 presents heterogeneity effects based on farm size as it is the most relevant indicator in the context of Nigeria. Our results suggest that even within the different farm size groups, adoption of improved maize varieties tended to positively and significantly affect yield. The estimated effect size was, however, not significantly different for the different land quantiles suggesting that adoption improves the productivity of smallholders and farmers with greater areas of land in a similar fashion.

3.2 Effect of adoption on welfare outcomes

In the previous section, the productivity effects of adoption were reported. However, it is important to understand to what extent such gains in productivity from adoption are translated to welfare gains. In this section, the welfare effect of adoption is examined, with the results in Table 4. Adoption of improved maize varieties is associated with greater food expenditures and total expenditures. In addition, the incidence of poverty appears to have declined as a result of adoption. Per-capita total expenditure increased by 22% across Nigeria. Similarly, per-capita food expenditure increased by 46.5%.

[5] Adoption in these states is low as the farmers there have less access to improved seed. On average they are located about 25 km away from the nearest seed dealer. This is high compared to the average distance, which is about 18 km.

[6] The counterfactual analysis shows the level of outcome (e.g., the maize yield) had the farmer that uses improved maize varieties chosen not to adopt improved maize varieties. In Table 3, the average yield of farmers who adopted improved maize varieties was 2337 kg/ha. If these farmers were non-adopters, their average maize yield would have been 1763 kg/ha (this is the counterfactual outcome). The difference between the two values is interpreted as the effect of adoption on maize yield.

[7] First stage estimates for net-returns are available from the authors upon request. Net-returns are calculated as maize income (revenue) minus production cost incurred for producing maize per ha.

[8] We also estimated effects by measuring adoption based on maize area under improved maize varieties (the intensification rate). For each farmer, intensification rate is calculated by estimating area under improved maize varieties. Since maize area was self-reported, we opted to use binary adoption rate in our main analysis. Using two-stage least square, we found that maize intensification decision affects productivity positively, the effect size being about 33%, which was significant at the 1% significance level.

Table 2 Determinants of maize yield in Nigeria, from results of endogenous switching regressions

	Selection equation		Adopters		Non-adopters	
	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
Education	0.002	0.38	−0.001	−0.33	0.001	0.13
Age	0.011	0.79	0.015	1.3	−0.014	−1.45
Age^2	0.000	−0.8	0.000	−0.83	0.000	1.78
Sex	−0.314***	−2.84	0.142	1.54	0.088	1.12
Distance from seed source	−0.006*	−1.88	0.005	1.54	0.002	1.32
Land tenure	−0.198**	−2.12	−0.015	−0.19	−0.076	−1.22
Household size	−0.003	−0.41	0.002	0.22	0.006	1.25
Value of farm assets	0.007	0.76				
House ownership	0.329***	3.3				
House painted	0.035	0.52				
Roofing material of the house	0.219**	2.2				
Member of social networks	−0.014	−0.2	0.103*	1.91	−0.007	−0.14
Village residence	−0.005**	−2.1	0.000	−0.23	−0.003	−1.73
Risk aversion	−0.232***	−3.22	0.162***	2.85	−0.077	−1.35
Access to electricity	0.165***	2.68				
Access to credit	−0.154*	−1.84				
Drought shock	0.062	0.81	0.106*	1.78	−0.057	−1.03
Men managed plots	0.013	0.15	0.003	0.04	−0.103*	−1.77
Jointly managed plots	0.125	0.64	−0.068	−0.42	−0.297***	−2.6
Row planting	0.398***	4.83	−0.234***	−2.94	0.028	0.5
Intercropping	−0.063	−0.91	0.203***	3.79	0.175***	3.78
Use of pesticide	0.054*	1.82	0.023	0.98	−0.050**	−2.26
Use of herbicide	−0.031	−1.19	0.064	3.07	0.035**	1.98
Good soil	0.506**	2.44	−0.143	−0.66	0.143	1.3
Medium soil	0.297	1.4	0.012	0.06	0.106	0.94
Use of SWC	−0.057	−0.86	−0.060	−0.74	−0.108**	−2.33
labour (log)	−0.039	−0.95	0.026	0.82	0.098***	3.47
Application of NPK (log)	0.001	0.04	0.027*	1.88	0.007	0.63
Application of urea	−0.008	−0.53	0.003	0.2	0.005	0.49
Access to varietal information	1.449***	16.34				
North-west	0.475***	4.27				
South-south	−1.15***	−5.1	0.279	0.9	−0.290***	−2.93
North-central	−0.513***	−5.12	−0.066	−0.6	−0.148	−1.35
North-east	0.019	0.1	−0.067	−0.63	−0.268***	−3.77
South-east	0.203	1.43	0.040	0.27	−0.109	−1.02
$ln\sigma_1$			−0.24***	−3.31		
$\rho_{1\mu}$			−0.62**	−2.19		
$ln\sigma_0$					−0.33***	−16.45
$\rho_{0\mu}$					−0.06	−0.39
N	1907		1070		837	
Wald X^2	99.43***					
Log likelihood	−3854.7					

The results further show that, without adoption, the poverty headcount ratio would have been higher by 6%. This suggests that the 22% increase in per-capita total expenditure is translated into a 6% reduction in poverty headcount ratio.[9] Taken together, the results clearly emphasize that adoption of improved maize varieties is associated with improved productivity and consumption-based welfare outcomes of adopters. Therefore, further dissemination efforts of improved varieties to non-adopters will be essential to maximize benefits since significant numbers of farmers are still non-adopters (currently, only 57% of the farmers use improved varieties).

3.3 Robustness checks

Table 5 reports average treatment effects on the treated (ATT) using propensity score matching (PSM) and an inverse probability weighted regression-adjustment procedure (IPWRA) as a robustness check.[10] The idea behind PSM is to match each adopter with a similar non-adopter and then measure the average difference in maize yield and welfare outcome indicators between the adopters and non-adopters. Here we are interested in the question "*How would the outcome of adopters (in terms of maize yield and welfare outcomes) have changed had adopters chosen not to adopt improved maize*

[9] Incidence of poverty and poverty headcount ratio are used interchangeably

[10] Note that both PSM and IPWRA controls only for observed heterogeneity between adopters and non-adopters.

Table 3 Effect of adoption of improved maize varieties on maize yield in Nigeria - a counterfactual analysis

Outcome variables	Type of farmers	Farm household type and treatment effect	Treatment type		Treatment effects	Change
			With adoption	Without adoption		
Net-return (in US$)	All farmers	Adopters (ATT)	40.2	35.3	4.9***	13.8%
Average maize yield	All farmers	Adopters (ATT)	2337	1763	574***	32.6%
Average maize yield	All farmers	Adopters (ATT)	2337	1763	574***	32.6%
Average maize yield	25th quantile [a]	Adopters (ATT)	2104	1605	499***	31%
Average maize yield	Median	Adopters (ATT)	2587	1890	697***	36.9%
Average maize yield	75th quantile	Adopters (ATT)	2360	1840	520***	28.3%

[a] Note that, the quantiles are based on farm size

varieties?" Both PSM and IPWRA results are consistent with our main findings reported using an endogenous switching regression approach. However, the effect size, particularly on maize yield was smaller. This result suggests that failure to account for unobserved heterogeneity leads to biased estimates (hence the use of ESR is appropriate).

4 Discussion and conclusion

Using nationally representative plot and household data from the major maize producing regions of Nigeria, this study examined the productivity and welfare implications of adoption of improved maize varieties. Our empirical analysis suggests that the use of improved maize varieties increased maize grain yield by an average 574 kg/ha (32%). Current adopters would have produced 574 kg/ha less had they not adopted improved maize varieties, and instead relied on old unimproved varieties and landraces. The gain in maize yield due to adoption of improved maize cultivars should have increased per-capita total expenditure by US$ 77/year (22%) in 2015. In terms of poverty reduction, we found that the incidence of poverty among adopters would have been higher by 6% without adoption of improved maize varieties. Given these results, i.e., high returns in terms of productivity and welfare gains, we question why more farmers are not growing improved maize varieties, despite striking productivity differences between improved and traditional varieties in Nigeria. Currently, only 57% of maize growing farmers use improved varieties and often on only part of their maize area. The rest (43%) still grow landraces. In particular, in Cross-River state, the adoption rate was extremely low (about 7%). Our results on the main determinants of adoption (cf. Table 2) underscored that there are still major supply-side constraints that hinder adoption. These constraints include distance from seed source, land tenure system, soil fertility status, access to varietal information, as well as risk aversion. Therefore, maximizing benefits from adoption requires alleviating the above constraints by improving access to variety information and markets for improved seeds.

Since breeding is largely an incremental process in which subsequent generations of an OPV and new hybrids tend to be superior in desirable traits such as yield, pest and disease resistance and nutritional value (Abate et al. 2015; Shiferaw et al. 2014), farmers need to periodically replace old varieties with new and superior varieties that have higher genetic potential. This is particularly important as our survey shows that apart from drought tolerant varieties, the improved varieties used by farmers (hybrids and OPVs) are quite old; the average age of improved cultivars used by adopting farmers being about 13 years. In addition, seed replacement rates seem to be low. According to our survey, about 79% of the farmers used their own saved seed. Only 21% bought seed and the seed replacement rate among adopters of OPVs was very low, at about 6%. This might be due to the distance farmers have to travel to purchase improved maize varieties. Our survey suggests that, on average, farmers are located about 18 km away from the nearest seed source.

Table 4 Effect of adoption of improved maize varieties on household welfare indicators in Nigeria, in a counterfactual analysis

Outcome variables	Farm household type and treatment effect	Decision stage		Treatment effects	Change
		To adopt	Not to adopt		
Per capita total expenditure (US$)	Adopters (ATT)	425.5	348.2	77.3***	22%
Per capita food expenditure (US$)	Adopters (ATT)	215.3	146.9	68.4***	46.5%
Poverty headcount ratio	Adopters (ATT)	0.70	0.76	−0.06***	−7.9%

Table 5 Robustness checks using matching techniques

	PSM	IPWRA
Maize yield	179*	206.5***
	(93.2)	(81)
Log of per-capita total expenditure	0.198***	0.154***
	(0.06)	(0.044)
Log of per-capita food expenditure	0.215***	0.176***
	(0.064)	(0.047)
Poverty headcount ratio	−0.079***	−0.069***
	(0.0265)	(0.021)
Other controls	Yes	Yes
Observations	1907	1907

Robust standard errors are reported in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Several policy implications emerge from our findings. First, reducing seed market imperfections could foster adoption because our findings suggest that farmers living far from input dealers are less likely to adopt improved varieties. In addition, our results also suggest that access to varietal information is a key for adoption. The current seed distribution system for hybrid maize varieties in Nigeria is rather limited and most of the improved varieties adopted by farmers are OPVs (Abate et al. 2017). Understanding options for designing a well-functioning seed system would therefore be extremely important to maximize the benefits from adoption. In remote places with limited presence of agro-dealers, ensuring the local availability of affordable quality improved seeds through targeted public investment is crucial. Secondly, our analysis also suggests that risk aversion plays a significant role in the adoption decision by farmers. This result is consistent with the findings of Dercon and Christiaensen (2011) and Abdoulaye and Sanders (2005) for inputs including fertilizers in other parts of Africa. Given the lack of insurance markets in rural Nigeria, farmers may be reluctant to adopt improved varieties. Nevertheless, this doesn't mean that traditional varieties are risk free. It mainly reflects that farmers are likely to have enough experience to form better expectations about the distribution of yield from traditional varieties than from the new varieties (Rosenzweig 2010).[11] In this regard, the development and dissemination of risk-reducing technologies such as drought-tolerant maize varieties or insurance schemes will be crucial for enhancing adoption, especially in areas prone to drought (Dercon and Christiaensen 2011; Wossen et al. 2017b). Thirdly, our heterogeneity analysis suggests that adoption improves the productivity of small-scale and larger-scale farmers in a similar fashion. This is a good outcome as it helps to reduce rural poverty while at the same time improving agricultural production. In general, our results suggest that the further dissemination and adoption of improved maize varieties will continue to have an important role for agricultural transformation in Nigeria. The results of this study underscore the importance of adopting improved maize varieties to improve productivity and welfare. Finally, since the poverty reducing roles of growth in the agricultural sector are stronger than those for growth in non-agricultural sectors (e.g., Dorosh and Thurlow 2018), improving agricultural productivity through the dissemination of improved varieties will play an especially significant role in Nigeria.

The research reported in this paper has several limitations. Firstly, this paper doesn't consider quality issues. Bold et al. (2017) found that the use of sub-standard quality seeds is quite prevalent in Uganda. Their results suggest that hybrid maize seed sold in the local market contained less than 50% authentic seeds. This is also likely to be the case in Nigeria. Considering the authenticity of the improved seeds used by farmers would, therefore, be important for the understanding of farmers' adoption decision and productivity gains from adoption. Secondly, despite our best efforts to measure adoption rates at the plot level, there are likely to be measurement errors. Using a DNA-fingerprinting approach, Wossen et al. (2018) and Ilukor et al. (2017) documented that farmers misreport their adoption status. For example, with cassava, taking DNA-fingerprinted cassava adoption data as a benchmark, Wossen et al. (2018) documented that 20% of the households identified improved varieties as local varieties and 13% of them identified local varieties as improved varieties. Similarly, Ilukor et al. (2017) documented that 40% of farmers identified improved maize varieties as local varieties in Uganda. These results suggest that adoption data from household surveys can be prone to substantial measurement error. An important improvement for the future is therefore to systematically understand measurement issues in self-reported adoption data from household surveys and examine the extent that such misclassifications may affect reported productivity and welfare outcomes. Additionally, our results are based on cross-sectional data, and the use of panel data would be an important extension. Using panel data would allow the examination of not only the dynamics of adoption over time but also to credibly estimate

[11] This argument is based on the literature on "learning by doing". Farmers learn through self-experimentation. The more they experiment, the better would be their knowledge about expected yield. Since new varieties require advanced and new knowledge, expectations about yield would be more precise with local varieties, where farmers have conducted sufficient self-experimentation.

productivity and welfare outcomes through standard fixed-effect models. Finally, our survey lacks details on the characteristics of varieties grown by farmers as well as trait preference of farmers by gender and location. Future research along these lines would, therefore, be important to design best-fit policies that could have a significant role in enhancing the adoption of improved maize cultivars in Nigeria.

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Compliance with ethical standards

Conflict of interest The authors declared that they have no conflict of interest.

References

Abate, T., Shiferaw, B., Menkir, A., Wegary, D., Kebede, Y., Tesfaye, K., & Keno, T. (2015). Factors that transformed maize productivity in Ethiopia. *Food Security, 7*(5), 965–981.

Abate, T., Fisher, M., Abdoulaye, T., Kassie, G. T., Lunduka, R., Marenya, P., & Asnake, W. (2017). Characteristics of maize cultivars in Africa: how modern are they and how many do smallholder farmers grow? *Agriculture and Food Security, 6*, 30.

Abdoulaye, T., & Sanders, J. H. (2005). Stages and determinants of fertilizer use in semiarid African agriculture: the Niger experience. *Agricultural Economics, 32*, 167−179.

Alene, A. D. (2010). Productivity growth and the effects of R&D in African agriculture. *Agricultural Economics, 41*, 223–238.

Alene, A. D., & Manyong, V. M. (2007). The effects of education on agricultural productivity under traditional and improved technology in northern Nigeria: an endogenous switching regression analysis. *Empirical Economics, 32*(1), 141–159.

Alene, A. D., Manyong, V. M., Tollens, E., & Abele, S. (2007). Targeting agricultural research based on potential impacts on poverty reduction: strategic program priorities by agro-ecological zone in Nigeria. *Food Policy, 32*(3), 394–412.

Amare, M., Asfaw, S., & Shiferaw, B. (2012). Welfare impacts of maize-pigeonpea intensification in Tanzania. *Agricultural Economics, 43*(1), 1–17.

Asfaw, S., Kassie, M., Simtowe, F., & Leslie, L. (2012). Poverty reduction effects of agricultural technology adoption: a micro-evidence from rural Tanzania. *Journal of Development Studies, 48*(9), 1288–1305.

Bezu, S., Kassie, G., Shiferaw, B., & Gilber, J. R. (2014). Impact of improved maize adoption on welfare of farm households in Malawi: a panel data analysis. *World Development, 59*, 120–131.

Bold, T., Kaizzi, K. C., Svensson, J., & Yanagizawa-Drott, D. (2017). Lemon technologies and adoption: measurement, theory and evidence from agricultural markets in Uganda. *Quarterly Journal of Economics, 132*(3), 1055–1100.

Dercon, S., & Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: evidence from Ethiopia. *Journal of Development Economics, 96*(2), 159–173.

Dorosh, P., & Thurlow, J. (2018). Beyond agriculture versus non-agriculture: decomposing sectoral growth–poverty linkages in five African countries. *World Development.* https://doi.org/10.1016/j.worlddev.2016.08.014.

FAOSTAT. (2016). Statistical database. Retrieved on 19 August 2016 from: http://faostat3.fao.org/browse/Q/*/E.

Foster, J., Greer, J., & Thorbecke, E. (1984). A class of decomposable poverty measures. *Econometrica, 52*(3), 761–765.

Ilukor, J. Kilic, T., Stevenson, J., Gourlay, S., Kosmowski, F., Kilian, A., Serumaga, J., & Asea, G. (2017). Blowing in the wind: the quest for accurate crop variety identification in field research, with an application to maize in Uganda. Paper presented at the CGIAR SPIA Conference on the Impact of Agricultural research: Rigorous Evidence for Policy, Nairobi, July 2017.

Karanja, D. D., Renkow, M., & Crawford, E. W. (2003). Welfare effects of maize technologies in marginal and high potential regions of Kenya. *Agricultural Economics, 29*, 331–341.

Kassie, M., Shiferaw, B., & Muricho, G. (2011). Agricultural technology, crop income, and poverty alleviation in Uganda. *World Development, 39*(10), 1784–1795.

Kostandini, G., La Rovere, R., & Abdoulaye, T. (2013). Potential impacts of increasing average yields and reducing maize yield variability in Africa. *Food Policy, 43*, 213–226.

Lokshin, M., & Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. *Stata Journal, 4*, 282–289.

Maddalla, G. S. (1983). *Limited dependent and qualitative variables in econometrics*. Cambridge: Cambridge University Press.

Magrini, E., & Vigani, M. (2016). Technology adoption and the multiple dimensions of food security: the case of maize in Tanzania. *Food Security, 8*(4), 707–726.

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

NACGRAB (National Centre for Genetic Resources and Biotechnology). (2016). Varieties released catalogue. Retrieved on 15 August 2016 from http://www.nacgrab.gov.ng/images/Varieties_Released_Catalogue.pdf.

NBSN (National Bureau of Statistics Nigeria). (2010). Nigeria poverty profile 2010. Retrieved on 15 August 2016 from: http://www.nigerianstat.gov.ng/pdfuploads/Nigeria%20Poverty%20Profile%202010.pdf.

Rosenzweig, M. R. (2010). Microeconomic approaches to development: schooling, learning, and growth. *Journal of Economic Perspectives, 24*(3), 81–96.

Shiferaw, B., Kebede, T. A., & You, Z. (2008). Technology adoption under seed access constraints and the economic impacts of improved pigeonpea varieties in Tanzania. *Agricultural Economics, 39*, 1–15.

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

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica, 79*(1), 159–209.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. USA: The MIT Press.

Wossen, T., Berger, T., & Di Falco, S. (2015). Social capital, risk preference and adoption of improved farm land management practices in Ethiopia. *Agricultural Economics, 46*(1), 81–97.

Wossen, T., Abdoulaye, T., Alene, A., Feleke, S., Gilbert, J. R., Manyong, V., & Awotide, B. A. (2017a). Productivity and welfare effects of Nigeria's e-voucher-based input subsidy program. *World Development, 97*, 251–265.

Wossen, T., Abdoulaye, T., Alene, A., Feleke, S., Menkir, A., & Manyong, V. (2017b). Measuring the impacts of adaptation strategies to drought stress: the case of drought tolerant maize varieties. *Journal of Environmental Management, 203*, 106–113.

Wossen, T., Abdoulaye, T., Alene, A., Nguimkeu, P., Feleke, S., Haile, M., Rabbi, I., & Manyong, V. (2018). Measuring the productivity impacts of technology adoption in the presence of misclassification. *Forthcoming, American Journal of Agricultural Economics.*

Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M., & Yirga, C. (2015). *Ex post* impacts of improved maize varieties on poverty in rural Ethiopia. *Agricultural Economics, 46*(4), 515–526.

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