JAE Journal of Agricultural Economics

Journal of Agricultural Economics
doi: 10.1111/1477-9552.12296

Poverty Reduction Effects of Agricultural Technology Adoption: The Case of Improved Cassava Varieties in Nigeria

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(Original submitted August 2017, revision received April 2018, accepted June 2018.)

Abstract

We use DNA-fingerprinting to estimate the poverty reduction effect of adoption of improved cassava varieties in Nigeria. We estimate the counterfactual household income distribution of cassava producers by combining farm-level treatment effects with a market-level model. Our results suggest that adoption of improved cassava varieties has led to a 4.6 percentage point reduction in poverty, though this is sensitive to the measurement of adoption status. Therefore, accurate measurement of adoption is crucial for a more credible estimate of the poverty reduction effect of adoption. Our analysis also suggests that farmers who are more likely to be adopters are also likely to face higher structural costs. Addressing structural barriers that make improved technologies less profitable for the poor would therefore be important to increase the poverty reduction effect of improved cassava varieties.

Keywords: *Adoption*; *DNA*; *heterogeneity*; *Nigeria*; *poverty*; *productivity*.

JEL classifications: *O33, Q11, Q12, D13, C26*.

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1. Introduction

Technological change is critical for agricultural productivity growth and poverty reduction in developing countries especially in sub-Saharan Africa (SSA) (Gollin *et al*., 2002; Alene *et al*., 2009; Suri, 2011; Zeng *et al*., 2015). It is widely recognised that the development and dissemination of improved crop varieties and complementary agronomic practices are major drivers of smallholder agricultural productivity growth (Alene *et al*., 2009; Suri, 2011; Zeng *et al*., 2015; Kassie *et al*., 2017; Abdoulaye *et al*., 2018). However, empirical evidence on the relationship between agricultural research and poverty reduction suggests that improved agricultural technologies may not necessarily lead to poverty reduction as the poor are often constrained by structural barriers that make improved technologies inaccessible and less profitable for them (Suri, 2011; Zeng *et al*., 2015; Kassie *et al*., 2017). Therefore, understanding how and why farm households adopt improved varieties and their subsequent effects on productivity and poverty outcomes is important to the design of an effective pro-poor technology dissemination strategy.

This article estimates the poverty reduction effect of adoption of improved cassava varieties in Nigeria, the largest producer of cassava in the world. In Nigeria, there has been substantial investment in the development and dissemination of improved cassava varieties by national and international research and development organizations. As part of a major long-term crop improvement effort the International Institute of Tropical Agriculture (IITA) in collaboration with national partners such as National Roots Crop Research Institute (NRCRI) initiated cassava research in the early 1970s with a focus on developing varieties that are resistant to major diseases such as cassava mosaic virus disease (CMD) and cassava bacterial blight (CBB). Other breeding traits included high yield, good root quality, high dry matter, low cyanogens, and resistance to lodging. These efforts by IITA and its partners led to a successful deployment of CMD and CBB-resistant cassava varieties in Nigeria (Dixon *et al*., 2011; Alene *et al*., 2012). In addition, Nigeria's national extension programme under the National Accelerated Food Production Programme (NAFPP) and the Agricultural Development Projects (ADPs) invested significantly for disseminating these varieties to smallholders (Alene *et al*., 2012).

Despite these major efforts and the importance of cassava for rural livelihood, there is a lack of comprehensive and rigorous evidence on adoption rates and impacts of improved cassava varieties on productivity and poverty related outcomes. Much of the empirical evidence on adoption and impacts has focused on other crops such as maize (Alene *et al*., 2012; Zeng *et al*., 2015; Wossen *et al*., 2017). In addition, most studies have focused on productivity effects without assessing the effects on poverty. However, adoption of improved technologies may lead to productivity growth that may not necessarily be pro-poor. It is, therefore, important to assess the poverty reduction effect of adoption beyond establishing causality between adoption and productivity.

We use unique nationally representative adoption data to measure adoption rates and to estimate the poverty reduction effect of improved cassava varieties in Nigeria. We contribute to the existing literature in three main ways. First, we use DNA-fingerprinting to identify varieties grown by farmers as a more reliable measure of adoption (Rabbi *et al*., 2015). In the agricultural technology adoption literature, data from household surveys are used to identify the varieties grown by farmers. However, in the presence of imperfect seed markets, farmers may not correctly identify the variety they grow (whether it is improved or not) due to input market imperfections (e.g. seed adulteration by dealers) or lack of awareness and technical information on the characteristics of improved varieties (Wossen *et al.*, 2018).[2] Using DNA-based adoption data, we document the extent to which measurement error in self-reported adoption status may bias the poverty reduction effect of adoption. Second, we also use GPS to measure farm size. In many household surveys, farm sizes are measured by simply asking farmers to estimate the size of their farm plots. However, self-reported farm size estimates might be prone to measurement error (Carletto *et al.*, 2013). Consequently, such measurement errors in farm size may affect productivity estimates and hence the estimated poverty reduction effect of adoption. Third, following Zeng *et al.* (2015) and Kassie *et al.* (2017), we link farm-level treatment effects to a market level model to measure the aggregate poverty reduction effect of adoption. The rest of the paper is structured as follows. Section 2 outlines the context and data sources. Section 3 describes the empirical strategy. Section 4 discusses main results and section 5 concludes.

2. Context and Data Sources

This study is based on the Cassava Monitoring Survey in Nigeria (CMS) which was conducted in 2015/16. The CMS project was designed by IITA to assess the adoption of improved cassava cultivars in Nigeria. To do so, data were collected from 16 states that together account for more than 80% of the total cassava production in Nigeria. These states were grouped into four geopolitical zones. In these regions, cassava is the main economic enterprise from which rural households derive most of their income. To collect a nationally representative dataset, we first obtained the list of Enumeration Areas (EAs) from the National Population Commission (NPC). From each region, 100 local government areas (LGAs) were selected using probability proportional to size (PPS) sampling approach. From each EA, five cassava growing households were randomly selected for interview. This gave a total of 625 households per region and a total of 2,500 farming households. From each surveyed household, data on socio-economic characteristics as well as other outcomes of interest such as production, expenditure on food and non-food items were collected. In addition, from each identified variety at each plot, samples of cassava leaves were collected for DNA-fingerprinting analysis. Leaf sample collections were done for each unique variety at plot level. A standard tracking system was implemented to reduce human error of sample mismatch and mix-ups during the collection of genotypes in the farmers' field. In particular, a tracking system with multiple layers was implemented using barcode labels, self-adhesive stickers, booklet and tablet computers for capturing samples and sample-associated information. Duplicate barcodes were also prepared and pasted both on sample collection tubes and booklets for each sample collected. For each collected sample, DNA was extracted and genotyped for varietal identification. Varietal identification was done by comparing varieties in the reference library (variety collections by IITA) with the genotyped data from farmers' fields.

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[2]Wossen *et al.* (2018) documented that misclassification of adoption status can lead to upward/downward bias as well as to sign reversal effects. A detailed theoretical exposition on how measurement error may bias productivity estimates is presented in Wossen *et al.* (2018).

3. Empirical Strategy

Identifying farm-level productivity impacts of adoption of improved cassava varieties is non-trivial due to selection bias. Identifying impacts require controlling for both observable and unobservable characteristics through random assignment of adoption status. We employ an instrumental variable (IV) regression approach that takes account of both observed and unobserved heterogeneities between adopters and non-adopters. Beyond farm-level productivity effects, technical change often affects market level outcomes such as poverty. Estimating such market level outcomes, however, requires a hybrid approach that combines some estimation of farm level productivity impacts with market level outcomes such as price changes (Zeng *et al.*, 2015). We combine farm level treatment effects with a market-level model to estimate the aggregate poverty reduction effect of adoption of improved cassava varieties in Nigeria.

To estimate farm-level treatment effects, we utilise the following empirical specification. Let Y_i be cassava yield of plot i and T_i be the self-reported adoption status. T_i takes a value of one if the farmer reports the use of an improved variety, and zero otherwise. The empirical relationship between productivity and adoption is then specified as follows:

$$Y_i = \alpha_0 + \theta T_i + \vartheta X_i + \varphi W_j + U_i \tag{1}$$

X includes a vector of household and plot level controls, W_j, captures village-level fixed effects to control for village-level general conditions (such as weather, market and prices) and θ measures the productivity effect of technology adoption (based on self-reported adoption status). In the above specification, the treatment (the decision to adopt improved cassava varieties) is endogenous as farmers self-select into adoption based on both observable and unobservable characteristics. The adoption decision of farmers can be modeled in the following way:

$$T_i^* = \gamma_t(X, {}^\sim Z) - V_i \tag{2}$$

T_i* measures the latent propensity to adopt improved cassava varieties. In the above specification, $T_i = 1$ if $T_i^* > 0$. Z is a vector of instruments and X is a vector of exogenous covariates affecting adoption decision. V_i is an idiosyncratic error term that measures the unobserved heterogeneity in the propensity to adopt improved cassava varieties. The equation implies that farmers self-select into adoption based on unobserved intrinsic characteristics, such as poor/better farming skills and management abilities, which are likely to be related to productivity levels. As such, causal identification of adoption impacts requires an instrument that satisfies the orthogonality condition (a variable that is strongly correlated with adoption decision but that does not directly affect productivity). Following Krishnan and Patnam (2013) and Ma and Abdulai (2016), we use neighbours and friends' adoption decisions as an identifying instrument.[3] However, adoption status can be misclassified and such misclassification is non-classical and endogenous. To overcome such biases, we re-estimate our empirical specification using DNA-fingerprinted adoption status (T_i^d) instead of T_i.

[3]We checked the relevance of our instruments, that is, to test whether the instruments are correlated with the adoption status. The results (first stage regression) are reported in the online supplementary material. The coefficients on both the instruments are statistically significant at 1%, suggesting that they are relevant IVs.

$$Y_i = \alpha_0 + \theta^d T_i^d + \vartheta X_i + \varphi W_j + U_i \tag{3}$$

The size and direction of θ^d and θ determines the bias caused by endogenous misreporting of adoption status ($\theta^d = \theta$ no bias, $\theta^d > \theta$ downward bias and $\theta^d < \theta$ upward bias). Given the nature of the endogenous variable, we implement a two-stage procedure that explicitly takes into account the binary nature of the endogenous treatment variable, first using a probit model to predict the probability of adoption, then using the predicted probabilities from the first stage as an identifying instrument in the productivity equation in the second stage (Wooldridge, 2010).[4]

However, the productivity gain from adoption (θ^d and θ) is more likely to be heterogeneous conditional on adopters' observed and unobserved characteristics. To capture this heterogeneity, we extend the above average treatment effect model and estimate marginal treatment effects (MTEs) (Heckman and Vytlacil, 2005; Carneiro *et al.*, 2017). As explained above, let the observed productivity level (Y_i) of adopters and non-adopters be Y_i and Y_0, respectively. The potential outcome is then specified as follows:

$$Y_1 = \alpha_1 + \vartheta X + \varphi W + U_1 \tag{4}$$

$$Y_0 = \alpha_0 + \vartheta X + \varphi W + U_0 \tag{5}$$

Given the above potential outcome framework and the adoption decision model in equation (2), heterogenous expected gains conditional to observed and unobserved characteristics of farmers can be specified as follows:

$$Y_i = TY_1 + (1 - T)Y_0 \equiv Y_0 + T(Y_1 - Y_0) \tag{6}$$

Which is equivalent to:

$$Y_i = \theta_0(X_i) + T[\theta_1(X_i) - \theta_0(X_i) + U_{1i} - U_{0i}] + U_{0i} \tag{7}$$

This specification clearly shows that the return from adoption varies across farmers based on observable characteristics ($[\theta_1(X) - \theta_0(X)]$) and idiosyncratic individual-specific gains ($U_{1i} - U_{0i}$) (see, Heckman and Vytlacil, 2005, 2007; Carneiro *et al.*, 2017).[5]

The above framework provides consistent treatment effects at the farm level. However, estimating market-level impacts (poverty reduction) requires including indirect effects by taking into account the different pathways through which adoption may affect welfare of cassava producers. Generally, there are three pathways through which adoption may affect poverty: (i) effects through output price changes due to increased sp from adoption, affecting net-food buyers; (ii) effects through farm profits, where adopters may generate higher profits: (iii) effects through rural wages as a general equilibrium effect through wage adjustment. We focus on the first two cases,

[4]The same empirical approach was used to estimate treatment effects for cost of production.

[5]We estimated equation (7) using both self-reported and DNA-fingerprinted adoption status to recover MTEs with and without measurement error, respectively. MTEs were estimated using local instrumental variables (LIV-semiparamteric model). The LIV approach, allows for more flexible functions for the MTE and imposes no distributional assumptions on the unobservables of the model.

ignoring the effect of wage adjustments as most farmers use family labour for cassava production.[6] We estimate the aggregate effects of adoption using the following steps: (i), estimate farm-level treatment effects (yield and cost changes) due to adoption; (ii) estimate income effects (producer and consumer surplus changes) based on yield and cost treatment effects and allocating the resulting income changes to appropriate households; (iii) estimate the counterfactual income distribution based on changes in producer and consumer surplus and calculating impacts that can be attributed to adoption. To allocate adoption induced income changes to farm households, we first identify the type of market (open/closed) and the market position of a given farmer (net buyer/seller). Given that cassava is a non-tradable food staple, we use a closed economy model to estimate the income changes following adoption.

In the closed economy case, local supply changes will necessarily affect local market prices. To capture aggregate benefits of adoption through aggregation of farm-level effects we use the economic surplus model (ESM, hereafter). The ESM captures adoption induced supply responses (per unit cost reductions) through a simple shift in the supply function of producers (Alston *et al.*, 1995). Estimating the aggregate poverty reduction effect of adoption in ESM requires an estimate of the counterfactual price and quantity (P^{ct} and Q^{ct}), which are not observable but can be calculated algebraically based on observed price (P^{obs}), observed production (Q^{obs}), extent of supply shift (cost reduction per unit of output, commonly referred as the k-shift parameter), the size of supply elasticity (ε) and demand elasticity (η) (Zeng *et al.*, 2015; Kassie *et al.*, 2017). The k-shift parameter measures adoption induced cost reduction per unit of output (the extent of outward shift in the supply curve). Following Alston *et al.* (1995) and Zeng *et al.* (2015) the k-shift parameter is calculated as follows:

$$k = \left(\frac{\theta_y}{\varepsilon} - \frac{\theta_c}{1+\theta_y}\right) \times \pi \tag{8}$$

where θ_y and θ_c are the treatment effects for yield and cost of production, respectively. π measures current adoption rate of improved cassava varieties. Using the estimated k-shift parameter, P^{obs}, Q^{obs}, ε and η the counterfactual price level (P^{ct}) that would have existed without adoption of improved cassava varieties is derived as follows (Zeng *et al.*, 2015):

$$P^{ct} = P^{obs}\left(\frac{\varepsilon+\eta}{\varepsilon+\eta-k\varepsilon}\right) \tag{9}$$

Counterfactual production level (Q^{ct}) is calculatedy subtracting aggregate production gains of adoption from observed cassava production (Q^{obs}). Once the k-shift parameter, Q^{ct} and P^{ct} are determined, adoption induced changes in producer and consumer surplus can be calculated following Alston *et al.* (1995) as follows:

$$\Delta PS = P^{ct}Q^{ct}(k-Z)(1+0.5Z\eta) \tag{10}$$

$$\Delta CS = P^{ct}Q^{ct}Z(1+0.5Z\eta) \tag{11}$$

[6]Capturing wage adjustments is also beyond the scope of this paper. However, as a robustness check, we followed the approach of Kassie *et al.* (2017) and calculated effects using empirically estimated poverty elasticities.

where Z equals the proportional reduction of market price $((P^{ct} - P^{obs})/P^{ct})$. Following Zeng *et al*. (2015), we allocate producer and consumer surplus changes to appropriate farm households to measure welfare changes due to adoption. The estimated producer surplus changes are allocated to individual households as adoption and price effects. In particular, producer surplus changes associated with lower market prices (i.e. income losses) among net-sellers are allocated as price effects using their sales quantities from total production as a weight. Adoption effects are then calculated as the difference between total producer surplus and price effect. Similarly, consumer surplus related changes are allocated to households using their expenditure on cassava (both purchased and home consumption from own production) as a weight.

3.1. Descriptive statistics

3.1.1. Adoption rate of improved cassava varieties

Previous studies (Zeng *et al*., 2015; Kassie *et al*., 2017) used household survey data to measure adoption rates with the assumption that farmers' self-reported data correctly reflect their adoption status. We use both DNA-fingerprinted and self-reported adoption data to measure adoption rates. Figure 1 shows adoption rates based on DNA-fingerprinted and self-reported adoption data as well as misclassification rates from the household survey at the plot level. The household survey result shows 54% adoption rate while the DNA-fingerprinting result shows about 68% adoption rate at the plot level. In addition, the misclassification rates (both false negatives and positives) are non-trivial, with farmers identifying improved varieties as landraces on 25% of the plots, and reporting landraces as improved varieties on 10% of the plots.

To avoid the bias associated with misclassification, we used adoption status from DNA-fingerprinted data to measure productivity gain and poverty reduction effect for our main analysis.[7] We also estimate effects using self-reported adoption rate from the household survey to show the bias associated with misclassification.

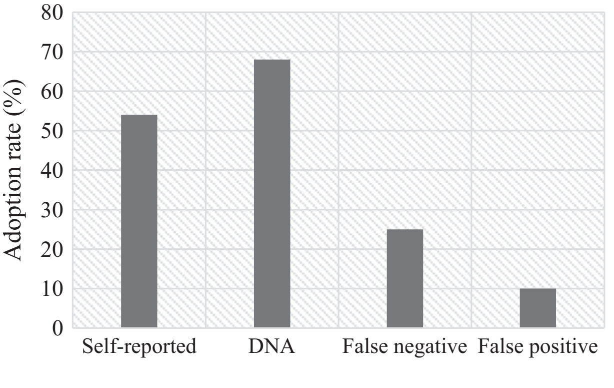

Figure 1. Adoption rate of improved varieties

[7]Wossen *et al*. (2018) provided a detailed treatment of the issue of misclassification in adoption studies.

3.1.2. Distribution of yield

Yield (output per ha) is calculated as the ratio of total output to GPS-measured plot size.[8] In our setting, GPS measures are taken for all cassava plots from all surveyed households. However, our production data are based on self-reported values.[9] Production data were collected using local measurement units as non-standard production units are used by the majority. Figure 2 shows that average cassava yield for our sample is reported as 14.7 t/ha, with, adopters reporting significantly higher yields than non-adopters irrespective of the way adoption status is measured.

3.1.3. Other socio-economic characteristics

Table 1 presents key socio-economic and plot-level variables used in our regression analysis. Household level controls include: age, household size, education, membership of different social groups and ownership of livestock. Plot level controls include: soil fertility indicators, plot management and the use of agricultural inputs. We hypothesise that both household level and plot level characteristics affect farmers' decision to adopt improved cassava varieties. As shown in Table 1 adopters and non-adopters tend to be significantly different in most of the socio-economic and plot level variables. Finally, our instruments, friend is an adopter and neighbour is an adopter are measured based on farmers' self-reports. When disaggregated by adoption status, 59% of adopter's friends and 67% of adopter's neighbours are adopters while the adoption level among neighbours and friends of non-adopters is quite low. These differences are also statistically significant at 1% significance level, suggesting that our instruments are sensible.

4. Results

4.1. Average treatment effects

Table 2 presents productivity and cost treatment effects at the farm level. Results are presented for self-reported and DNA-fingerprinted adoption status, respectively. The

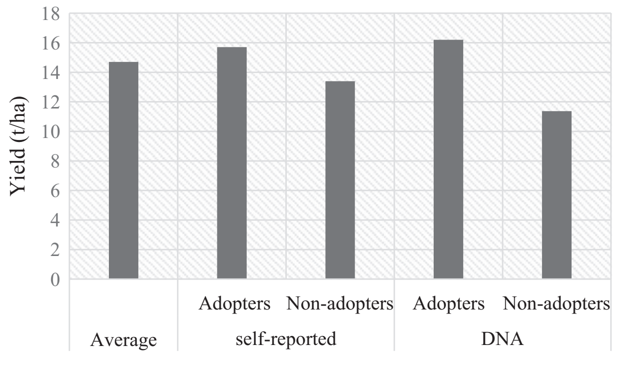

Figure 2. Cassava yield based on adoption status (DNA and self-reported)

[8]Comparison of GPS measured and self-reported plot size suggests that farmers overestimate the size of smaller plots and underestimate the size of bigger plots.

[9]Undertaking a full-crop cut to measure production is both costly and effectively impossible, since the crop is continuously harvested, though we recognise that self-reported values can also be prone to errors.

Table 1
Descriptive statistics based on self-reported adoption status

	Full sample (N = 5,180)	Adopters (N = 2,814)	Non-adopters (N = 2,366)	Mean diff
Household size (number of members)	4.60	4.85	4.30	0.55***
Education (years of schooling)	8.68	9.02	8.28	0.75***
Age (measured in years)	51.59	51	52.3	–1.30***
Sex (1 = male 0 = otherwise)	0.89	0.91	0.87	0.04***
Livestock ownership (TLU)	0.72	0.88	0.53	0.35
Access to extension (1 = yes, 0 = no)	0.36	0.46	0.25	0.21***
Access to credit (1 = yes, 0 = no)	0.45	0.50	0.39	0.11***
Mobile phone ownership (1 = yes, 0 = no)	0.967	0.98	0.95	0.03***
Membership in credit and saving groups (1 = yes, 0 = no)	0.34	0.37	0.31	0.06***
Membership in cooperatives (1 = yes, 0 = no)	0.25	0.30	0.19	0.11***
Membership in cassava growers' association (1 = yes, 0 = no)	0.21	0.27	0.14	0.13***
Plot with good soil fertility (1 = good, 0 = otherwise)	0.74	0.78	0.69	0.09***
Plot with medium soil fertility (1 = medium, 0 = otherwise)	0.24	0.20	0.29	–0.09***
Plot with poor soil fertility (1 = poor, 0 = otherwise)	0.02	0.02	0.02	–0.01
Plot managed by men	0.36	0.42	0.30	0.12***
Plot managed by women	0.49	0.47	0.51	–0.04***
Plot managed jointly	0.15	0.11	0.20	–0.09***
Plot is intercropped (1 = yes, 0 = no)	0.55	0.55	0.56	–0.01
Labour use (MD/ha)	108.4	100	118	–18.00
Fertiliser use (1 = yes, 0 = no)	0.34	0.30	0.37	–0.07***
Herbicide use (1 = yes, 0 = no)	0.47	0.54	0.38	0.16***
Pesticide use (1 = yes, 0 = no)	0.09	0.11	0.07	0.04***
Friend is adopter (1 = yes, 0 = no)	0.50	0.59	0.39	0.20***
Neighbour is adopter (1 = yes, 0 = no)	0.43	0.67	0.14	0.54***

Note: ***, ** and * refer to significance at 1%, 5% and 10% levels, respectively.

Table 2

Farm level yield and cost treatment effects

	Yield		Cost	
	Self-reported adoption status	DNA-based adoption status	Self-reported adoption status	DNA-based adoption status
Adoption	0.478***	0.584***	0.287**	0.312*
	(0.109)	(0.122)	(0.142)	(0.163)
Other controls	Yes	Yes	Yes	Yes
Location dummies	Yes	Yes	Yes	Yes
Input prices	No	No	Yes	Yes
N	5,180	5,180	5,180	5,180

Notes: Standard errors clustered at the enumeration area-level are reported in parentheses. ***, ** and * refer to significance at 1%, 5% and 10% levels, respectively. Other controls include use of fertiliser, herbicide and pesticide, plot management, intercropping, soil fertility status, ownership of mobile phones, access to extension, access to credit, membership in cassava growers' association, membership in informal saving and credit institutions, membership in cooperatives, livestock size in TLU, age, education, household size, and sex. Location dummies: North, South-West South-East and South-South.

results in Table 2 suggest that adoption increases yield by 60%–79% depending on the way adoption status is measured.[10] Our main result also shows that adoption has a positive and statistically significant effect on the cost of production.[11]

4.2. *Marginal treatment effects*

Marginal treatment effects are presented to show heterogeneity in returns to adoption. It does so by evaluating effects over the common support of the propensity score. If there is no sufficient overlap in the common support, MTEs will not reliably be estimated. Figure 3 shows the distribution of the propensity scores for adopters and non-adopters.

Results show that there is a significant overlap over the common support and hence MTEs can be recovered reliably. Figure 4 presents marginal treatment effects for yield using DNA-fingerprinted adoption status (mean and 95% confidence interval obtained through 1,000 bootstrap replications). The results suggest significant heterogeneity in returns to adoption.

The slope of MTEs over U_t (the unobserved resistance to adopt improved cassava varieties) shows some interesting features. The estimated MTE is generally a

[10]The correct interpretation of log-linear estimates should be: 100 × (exp(coef) − 1). In most empirical applications of semi-log models, researchers often interpret the size of parameter estimates directly. However, this interpretation is approximately valid when the true parameter estimates are between −0.1 and 0.1. Failure to adjust parameter estimates in a log-linear specification will bias the estimated magnitude of outcome variables of interest (such as productivity). For example, in Table 2, the treatment effect of 0.478 should be interpreted as adoption increases yield by 60% instead of 47.8% and this has a huge implication on the poverty reduction impact of adoption.

[11]Results with the full list of controls are reported in the online supplementary material.

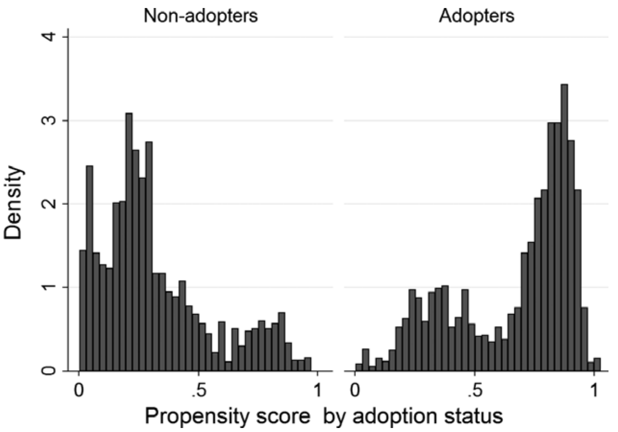

Figure 3. Distribution of propensity scores over the common support region

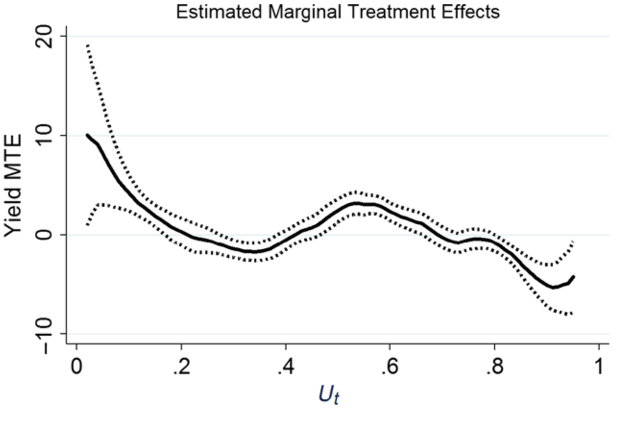

Figure 4. Distribution of yield marginal treatment effects (MTEs) based on DNA-based adoption status

decreasing function of U_t, where farmers with lower values of U_t are those who are more likely to adopt improved cassava varieties, suggesting that farmers self-select into adoption based on their comparative advantage, consistent with Suri (2011). As shown in the online Appendix S1, MTE results using self-reported adoption status show a similar decreasing relationship with U_t. The distribution of cost MTEs (Figure 5) suggests that farmers with the highest propensity to adoption face higher costs of production.[12] Reducing structural and technical barriers that make adoption expensive for these groups of farmers is, therefore, important to maximise the benefits from adoption.

[12]The MTE curve for cost of production based on self-reported data is quite similar to Figure 5 (see online Appendix S1).

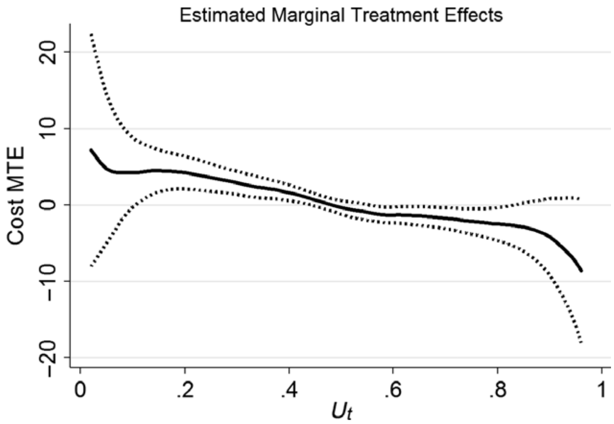

Figure 5. Distribution of cost marginal treatment effects (MTEs) based on DNA-fingerprinted adoption status

4.3. Impact of adoption on poverty

We follow the approach of Zeng *et al.* (2015) and use our yield and cost treatment effects along with supply and demand elasticities from the literature to estimate the poverty reduction effect of adoption. We used a demand elasticity of 0.46 (Tsegai and Kormawa, 2002) and a supply elasticity of 0.7 (Obayelu and Ebute, 2016). The average 2009–2014 market price (P^{obs}) per kilogram of cassava was US$ 0.14.[13] The corresponding total production of cassava for 2009–2014 was 46.5 million metric tons. Given these data, the k-shift is computed as a 51% cost reduction per kilogram of cassava which leads to a counterfactual price (P^{ct}) of US$ 0.20. We then calculate the counterfactual per-capita total expenditure by subtracting household-specific consumer and producer surplus changes from observed per-capita expenditure.[14] Poverty impacts are then estimated based on the differences between observed and counterfactual per-capita total expenditure distributions (Figure 6).

To enable comparison between counterfactual and observed *per capita* expenditure levels, we deflated nominal expenditure values to real values using the national consumer price index. In our case, the incidence of poverty was calculated using the international poverty line of 1.9 USD per day, evaluated at purchasing power parity (PPP). The distribution of the observed *per capita* expenditure always lies to the right of the counterfactual *per capita* expenditure, suggesting a reduction in poverty due to adoption. As shown in Figure 6, adoption has led to a 4.6 percentage point poverty reduction implying that 7.5% of the rural poor cassava producers have escaped poverty in the current year due to adoption of improved cassava varieties.[15] Such poverty

[13]This price is calculated as the average price of cassava from 2009 to 2014 from FAOSTAT.

[14]We used per-capita expenditure instead of income as we do not have complete income measures in our survey.

[15]The counterfactual poverty headcount ratio and poverty impact are 0.615 and 0.046, respectively. Thus, the percentage of the originally poor who have escaped poverty is 0.046/0.615 = 7.5%.

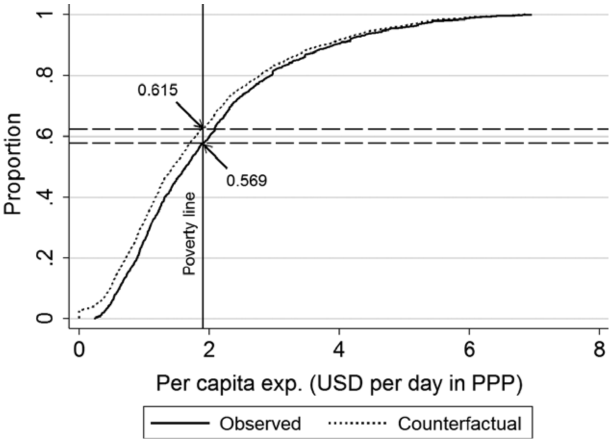

Figure 6. Distribution of observed and counterfactual *per capita* expenditure

reduction suggests about 1.62 million individuals per year have escaped poverty in Nigeria due to adoption of improved cassava varieties.[16]

4.4. Robustness checks

4.4.1. Robustness to the measurement of adoption status

As a robustness check, we also estimated the poverty reduction effect of adoption using self-reported adoption status from the household survey. As implicit in our farm-level adoption effects estimates, the aggregate poverty reduction effect is smaller when using self-reported adoption status from the household survey. Using self-reported adoption status, the poverty reduction impact of adoption becomes only 3.1% points, translating to 1.1 million individuals per year. This suggests that more precise estimates of adoption status are crucial to prioritise interventions and funding research in the agricultural sector.

4.4.2. Considering other mechanisms – other considerations

In our main analysis, both productivity and price mechanisms were captured consistently by linking farm-level treatment effects with the economic surplus model. However, as pointed out by Kassie *et al.* (2017), adoption-induced productivity growth may provide additional income to poor households by creating marketing and job opportunities along the value chain. Therefore, we follow the approach of Alene *et al.* (2009) and Kassie *et al.* (2017) and measure a poverty reduction effect of adoption by using an empirically estimed poverty elasticity with respect to agricultural productivity growth. In this framework, the poverty reduction effect of adoption is estimated as follows:

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[16]This is calculated as 0.075 $\times$ number of cassava producers (i.e. according to FAOSTAT the total area under cassava that corresponds to our production and price value is about 5.2 million ha. With average cassava area of 1.09 ha, the number of cassava producers becomes about 4.7 million). Given average family size of 4.6, the total number of individuals becomes 21.6 million).

$$\Delta P_n = \left(\frac{CS + PS}{AgGDP} \times \varepsilon_p\right) \times N \tag{12}$$

where ΔP_n and N denote the number of people that escaped poverty due to adoption and the number of poor people in the country, respectively. CS and PS are consumer and producer surplus, respectively. $AgGDP$ is agricultural GDP and ε_p is the elasticity of poverty to agricultural productivity growth. According to the 2015 Nigerian Bureau of Statistics (NBS), the agricultural GDP of the country is US$ 8.5 billion (21% of the total GDP). In addition, Alene *et al.* (2009) and Thirtle *et al.* (2003) suggested a 0.72 elasticity of poverty to agricultural productivity growth for Africa. Using our results from the economic surplus model and ε_p of 0.72, the number of people lifted out of poverty due to adoption is estimated to be 2 million people.

5. Conclusions

In this article, we examined the key research question: Does adoption of improved cassava varieties have an effect on poverty? The poverty reduction effect of adoption of improved cassava varieties was estimated using DNA-fingerprinted adoption data. Using DNA-based adoption status, we show that 1.62 million individuals have been lifted out of poverty due to adoption of improved cassava varieties. Moreover, our results suggest that this estimate is sensitive to the measurement of adoption status. Therefore, proper measurement of adoption status is crucial for estimating the poverty reduction effect of technology adoption. Further, we found that adoption of improved cassava varieties has a heterogeneous impact. We found that farmers self-select adoption based on their comparative advantage: those with the highest yield gains have the highest propensity to adopt. However, farmers who are more likely to be adopters are also likely to face higher input costs. Addressing structural and technical barriers that make adoption expensive for these groups of farmers is, therefore, important to maximise the benefits from adoption.

Supporting Information

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

Appendix S1. Figure S. (1) Map of study area; (5) Distribution of yield MTEs based on self-reported adoption status; (6a) MTE's based on polynomial normal model using self-reported adoption status; (6b) MTE's based on polynomial normal model using DNA-fingerprinted adoption status; (7) Relationship between self-reported and GPS measured area. Table S: (2) First stage regression results; (3) Productivity estimates; (4) Cost estimates

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.

Alene, A. D., Menkir, A., Ajala, S. O., Badu-Apraku, B., Olanrewaju, A. S., Manyong, V. M. and Ndiaye, A. 'The economic and poverty impacts of maize research in West and Central Africa', *Agricultural Economics*, Vol. 40, (2009) pp. 535–550.

Alene, A. D., Khonje, M., Abdoulaye, T., Kulakow, P. and Manyong, V. M. *Adoption of Improved Cassava Varieties in Southwestern Nigeria* (IITA Technical report submitted for the DIIVA project, IITA-Ibadan, Nigeria, 2012).

Alston, J. M., Norton, G. W. and Pardey, P. G. *Science Under Scarcity: Principles and Practice for Agricultural Research and Priority Setting* (Ithaca, NY: Cornell University Press, 1995).

Carletto, C., Savastano, S. and Zezza, A. 'Fact or artifact: The impact of measurement errors on the farm size-productivity relationship', *Journal of Development Economics*, Vol. 103, (2013) pp. 254–261.

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

Dixon, A. G. O., Okechukwu, R. U., Akoroda, M. O., IIona, P., Ogbe, F., Egesi, C. N., Kulakow, P., semakula, G., Maziya-Dixon, B., Iluebbey, P., Yoweni, M. O., Geteloma, C., James, B., Eke-Okoro, O. N., Sanni, L., Ntawuruhunga, P., Tarawali, G., Mahungu, N., Lemchi, J., Ezedinma, C. I., Okoro, E., Kaniu, E., Adeniji, A. A. and Nwosu, K. *Improved Cassava Variety Handbook* (Unpublished report, International Institute for Tropical Agriculture, 2011).

Gollin, D., Stephen, P. and Richard, R. 'The role of agriculture in development', *American Economic Review*, Vol. 92, (2002) pp. 160–164.

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

Heckman, J. and Vytlacil, E. 'Econometric evaluation of social programs, part II: Using the marginal treatment effect to organize alternative econometric estimators to evaluate social programs, and to forecast their effects in new environments', in J. J. Heckman and E. E. Leamer (eds.), *Handbook of Econometrics* (Amsterdam: Elsevier, 2007, pp. 4875–5143).

Kassie, M., Marenya, P., Tessema, Y., Zeng, D., Jaleta, M., Erenstein, O. and Rahut, D. B. 'Measuring farm and market level economic impacts of improved maize production technologies in Ethiopia: Evidence from panel data', *Journal of Agricultural Economics*, Vol. 69, (2017) pp. 76–95.

Krishnan, P. and Patnam, M. 'Neighbours and extension agents in Ethiopia: Who matters more for technology adoption?', *American Journal of Agricultural Economics*, Vol. 96, (2013) pp. 308–327.

Ma, W. and Abdulai, A. 'Does cooperative membership improve household welfare? Evidence from apple farmers in China', *Food Policy*, Vol. 58, (2016) pp. 94–102.

Obayelu, A. O. and Ebute, S. *Cassava output supply response in Nigeria: A Vector Error Correction Model (VECM) approach*. (Ibadan: Department of Agricultural Economics, University of Ibadan, 2016).

Rabbi, Y. I., Kulakow, P., Manu-aduening, J. A., Dankyi, A. A., Asibuo, J. Y., Parkes, E. Y., Abdoulaye, T., Girma, G., Gedil, M. A., Ramu, P., Reys, B. and Maredia, M. K. 'Tracking crop varieties using genotyping-by-sequencing markers: a case study using cassava (Manihot esculenta Crantz)', *BMC Genetics*, Vol. 16, (2015) pp. 1–11.

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

Thirtle, C., Lin, L. and Piesse, J. 'The impact of research-led agricultural productivity growth on poverty reduction in Africa, Asia and Latin America', *World Development*, Vol. 31, (2003) pp. 1959–1975.

Tsegai, D. and Kormawa, P. 'Determinants of urban households' demand for cassava and cassava products in Kaduna, northern Nigeria: The application of AIDS model', Paper prepared for Conference on International Agricultural Research for Development, (Witzenhausen, 2002).

Wooldridge, J. M. *Econometric Analysis of Cross Section and Panel Data* (Cambridge, MA: The MIT Press, 2010).

Wossen, T., Abdoulaye, T., Alene, A., Feleke, S., Menkir, A. and Manyong, V. 'Measuring the impacts of adaptation strategies to drought stress: The Case of drought tolerant maize varieties', *Journal of Environmental Management*, Vol. 203, (2017) pp. 106–113.

Wossen, T., Abdoulaye, T., Alene, A., Nguimkeu, P., Feleke, S., Rabbi, Y., Haile, M. and Manyong, V. 'Estimating the productivity impacts of technology adoption in the presence of misclassification', *American Journal of Agricultural Economics*, forthcoming, (2018). https://doi.org/10.1093/ajae/aay017.

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.