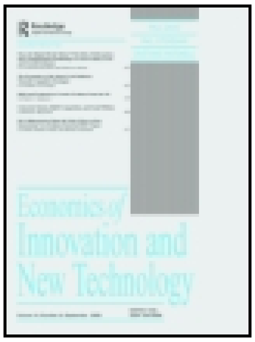

Economics of Innovation and New Technology

ISSN: 1043-8599 (Print) 1476-8364 (Online) Journal homepage: https://www.tandfonline.com/loi/gein20

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https://doi.org/10.1080/10438599.2019.1669331

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ABSTRACT

This paper aims to analyze the impact of improved maize adoption on farmers' welfare in Benin, using a random sample of 356 maize farmers. We provide a rigorous estimation by addressing selection bias and endogeneity issues. First, we applied a double-hurdle model to identify factors that inform farmers' decision to adopt improved maize. Second, we used the instrumental variable model to assess the impact of improved maize on farmers' income, poverty status, and poverty gap. For this, we used the predicted area under improved maize from the double-hurdle model as an instrument for the observed area under improved maize. We found that farm size, extension services, training on improved seed, and farmers' location are key variables that affect both farmers' decision and the amount of land under improved maize. We also found evidence that adoption of improved maize is positively associated with yield, income, and poverty reduction. Finally, we found no heterogeneous impacts of improved maize among poor and non-poor farmers. Adoption of improved maize favors small landholding farmers but did not have a significant impact on income for those who own large farms size. Overall, our results suggest that improved maize variety is important for rural development.

ARTICLE HISTORY
Received 13 March 2019
Accepted 9 September 2019

KEYWORDS
Adoption; improved maize; impact; welfare; Benin

JEL CLASSIFICATION
I32; O13; Q16

1. Introduction

Benin's economy depends heavily on agricultural sector which contributes about 32.7% to gross domestic product (GDP), and constitutes a primary livelihood source for about 70% of the active population (Ministère de l'Agriculture, de l'Elevage et de la Pêche [MAEP] 2017). Rain-fed production dominates in Benin, exposing the country to climate change and variability. Less than 10% of the irrigation potential in the country are used, covering only 0.8% of the total cropping land (Food and Agriculture Organization (FAO) 2014; Nonvide 2018). As a result, agricultural production is insufficient to meet the national consumption needs. About 20% of household in Benin are food insecure and 34% are at the risk of food insecurity (World Food Programme [WFP] 2014; Enquête Modulaire Intégrée sur les Conditions de Vie des Ménages [EMICoV] 2015). Poverty remains high in Benin, particularly in rural area with 43.6% of people being poor in 2015 (EMICoV 2015).

Maize is the main staple food for Benin, and is one of the food crops on which the government is focused to reduce food insecurity and poverty (MAEP 2017). It is grown by the vast majority (85%) of the farmers, covering 52.6% of the total cultivated land, and accounted for 78.3% of cereal production in Benin (MAEP 2017). Besides, the maize yield in Benin remains low and is decreasing from 1.4 tons per hectare (ha) in 2011 to 1.2 tons/ha in 2015 (MAEP 2017). This poor performance reflects, in

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general, the profile of the agricultural sector in Benin. The use of agricultural technology is still not widespread. For example, in 2013, a report by WFP (2014) indicated that 51% of farmers in Benin did not use any agricultural inputs including herbicide, insecticides, fertilizers, and improved seeds. The same report suggests that agricultural production decline in Benin is due to the insufficient use of farm inputs. Technology adoption is, therefore, important for the development and transformation of farming systems in Benin. A new technology is often introduced in agriculture by non-economic factors, such as government or non-governmental organization (NGO), while the adoption depends on the economic return derived from it (Griliches 1957; Dinar and Yaron 1992). This is in accordance with the theories of expected utility and economic rationality.

Governments and agricultural policy makers' interest in promoting high-quality seed increased as a result of climate change and variability, declining crop yield and the 2008 food crisis. Since then, the government of Benin has undertaken major reforms to increase production and productivity. These reforms include improvement in extension services, better organization of the production sectors, progressive mechanization of agriculture, distribution of subsidized quality inputs, and promotion of storage technology. Despite many efforts by the government and donors in promoting improved maize varieties, traditional varieties are widely grown. Only 47% of the total maize area in Benin are devoted to improved maize (MAEP 2016). However, previous studies in developing countries indicated high expectations from using improved seed. Adoption of good quality seed contributes not only to a high productivity but also to the improvement of farmers' welfare (Just and Zilberman 1988; Minten and Barrett 2008; Asfaw et al. 2012; Ghimire, Wen-chi, and Shrestha 2015). Higher crop productivity leads to lower food prices for the net food buyers, while unskilled workers benefit from higher real wages (Minten and Barrett 2008; Bezu et al. 2014). Zeng et al. (2015) found an increase in yield between 47.6% and 63.3% for farmers using improved maize seed in Ethiopia. The use of improved maize contributed to the decrease in the probability of falling into poverty by 19–31% among Mexicans farmers (Becerril and Abdulai 2010).

With 550,000 farmers producing maize in Benin (MAEP 2017), a small change in productivity is likely to affect the welfare of many people in the country. Moreover, the development and diffusion of improved seed is very costly. This calls for the need to justify the importance of such investment in developing countries. In line with this, the present study analyzes the impact of improved maize adoption on smallholder famers' welfare in Benin. It contributes to the growing knowledge by providing answers to the following empirical research questions: (1) What are the factors that influence the adoption of improved maize in Benin? (2) What are the impacts of improved maize adoption on farmers' welfare in Benin? An in-depth knowledge of the factors that inform the adoption decision, as well as the impact on smallholder farmers' welfare, is crucial to understand how policy intervention could help improve welfare among farmers in Benin.

This study adds knowledge to the literature. First, it provides support for future policy interventions, promoting improved maize to enhance the productivity and welfare in Benin. This comes at an important time, as domestic maize production estimated at 1,265,348 metric tons in 2015 is below the target of 1, 286,060 metric tons expressed in the 'Plan Stratégique de Relance du Secteur Agricole' of Benin 2011–2015. Also in the context of a new challenge of climate change and variability coupled with rapid population growth in Benin, the use of high yielding drought-tolerant varieties becomes essential. Second, while informative, empirical evidence on the impacts of improved maize varieties in Africa is limited (Khonje et al. 2015), for instance, in Benin, studies (Toukourou et al. 2004; Mahoussi et al. 2017) that have analyzed the impact of improved maize in Benin focused more on the factors affecting the intensity of improved maize adoption, and the performance of improved maize seed in terms of productivity improvement and profitability, which relates only to the effect of improved seed on production and may not necessarily translate into higher welfare. So the past studies in Benin neglect the link between improved maize adoption and welfare. Therefore, little is known on how the adoption of improved maize affects farmers'welfare. Our paper contributes to fill this gap in the existing literature by examining the link between improved seed adoption and welfare at individual maize farmer level in Benin.

The data used in this study come from a survey of 356 maize producers conducted in 2016 in Benin by the 'Programme d'Analyse des Politiques Agricoles de l'Institut National des Recherches Agricoles du Bénin (PAPA/INRAB)'. From a large body of empirical studies (Heckman 1979; Mendola 2007; Becerril and Abdulai 2010; Amare, Asfaw, and Shiferaw 2012; Asfaw et al. 2012; Bezu et al. 2014; Smale and Mason 2014; Zeng et al. 2015; Nonvide 2017; Verkaart et al. 2017; Nonvide 2018) on the impact of agricultural technology adoption, the major problems encountered are self-selection and endogeneity since technology adoption is not random. Because of some observables or unobservable characteristics (farmers' motivation, ability, among others), the decision by Benin farmers to grow improved maize seed could be endogenous in the outcome equation. Therefore, any estimate of the impact of improved maize adoption may be biased if this does not control the endogeneity problem.

The methods widely used to account for the selection bias include the propensity score matching (Becerril and Abdulai 2010; Amare, Asfaw, and Shiferaw 2012; Magrini and Vigani 2014; Zeng et al. 2015), endogenous switching regression model (Amare, Asfaw, and Shiferaw 2012; Khonje et al. 2015), and instrumental variable techniques (Bezu et al. 2014; Mathenge, Smale, and Olwande 2014; Smale and Mason 2014; Zeng et al. 2015). These methods are complementary and rely on assumptions. However, when unobserved characteristics (motivation, ability, or risk attitude) determine the adoption of improved maize variety, matching approach, therefore, is not an appropriate method as it does not account for endogeneity. To solve this endogeneity problem, the instrumental variables (IV) model is commonly used (Khandker, Koolwal, and Samad 2010; Cerulli 2014). Applying the IV model requires the availability of at least one instrumental variable assumed to be correlated with the treatment and uncorrelated with the outcome. These concerns might be minimized if appropriate instruments are found (Zeng et al. 2015). Various instruments were used in the literature to deal with the endogeneity of the improved maize adoption. Some authors used the cumulative adoption rate (Mathenge, Smale, and Olwande 2014; Smale and Mason 2014). Another instrument used is the predicted improved maize area (Bezu et al. 2014). Zeng et al. (2015) used a broad range of instruments including the distances to the nearest seed dealer, agricultural extension office, farmer cooperative and main market, and quality of roads to the main market.

Randomized evaluation would be better to estimate the impact of improved maize adoption. In the absence of this evaluation and baseline data, the result of this study should be interpreted with caution when it comes to any causal relationship between adoption and welfare. We employed a double-hurdle model to analyze the adoption decision of improved maize, and an instrumental variable (IV) technique to estimate the impact of improved maize on maize famers' welfare. We also check for the robustness of our results to the changes in the specification. Finally, we analyzed the distributional impacts of improved maize adoption across poverty status and farm size. A disaggregated analysis of poor farmers versus non-poor farmers, and smallest landholding farmers versus largest landholding farmers permits to identify who benefits more from the adoption of improved maize.

The rest of the paper is organized as follows. Section 2 presents a synthesis of the literature on the adoption and impact of improved maize. Section 3 describes the methods of analysis, and Section 4 presents the data and descriptive statistics. Section 5 reports and discusses the results. Finally, Section 6 concludes and highlights the policy implications of the findings.

2. Literature review

The early contributions of Griliches (1957, 1960) have aroused economists' devotion to determinants and consequences of the adoption of new technologies. Two schools of thoughts debate whether supply or demand factors are more relevant in the adoption process. In the demand side, studies give emphasis to choice models and game theoretic models (Stoneman 1981; Zettelmeyer and Stoneman 1993; Liu 2013). The interest was also on risk preference and information accumulation (Feder 1980; Binswanger 1980; Stoneman 1981; Just and Zilberman 1983) education (Huffman

2001; Duraisamy 2002), and access to extension services (Nkonya, Schroeder, and Norman 1997). Other literature have advanced the concept of social learning resulting from interactions among producers (Stoneman and Toivanen 1997; Stoneman 2013). Farmers are informed about new technologies as they are introduced either by the private sector or farmers by their own experiences, or through intervention in the formal sector, and the social learning process facilitates their dissemination (Marra, Pannell, and Ghadim 2003; Koundouri, Nauges, and Tzouvelekas 2006; Stoneman 2013).

Besides the demand side, the adoption process is determined by changes in the supply of the new technology (Hellegers, Zeng, and Zilberman 2011; Chang and Tsai 2015). Such changes may consist in the reduction of market price due to the imitative entry of competitors that erode the monopolistic rents of innovators or by the introduction of incremental innovations that widen the scope of application and use of the product innovation. Along this line, Chang and Tsai (2015) found that producers respond to the set of price signals for products and inputs employed in the production process, given the available technology. Large-scale adoption of technology may also affect market prices of both outputs and inputs, which, in return, affect adoption decisions and output supply (Hellegers, Zeng, and Zilberman 2011).

Empirically, various studies have shown that investing in modern technology is one of the most effective ways to improve crop productivity. For example, in Benin, a study by Toukourou et al. (2004) concluded that the use of improved maize contributes to an increase in the maize yield to about 740 kg/ha which makes the improved maize more profitable than the traditional varieties. Mahoussi et al. (2017) indicated that factors increasing the intensity of adoption of improved maize in Benin include experience in maize production, training on improved seed, and share of maize income in farm income. Using a bivariate probit model, Tura et al. (2010) found that human capital (adult workers, off-farm activity, and hiring labor), asset endowment (size of land owned), and institutional variables (membership in cooperatives and access to credit) strongly affect farmers' decision to adopt improved maize in Ethiopia, while the continuous use of the variety is affected by the proportion of area allocated to maize, literacy of the farmer, engagement in off-farm activities, extension visits, farmers' experience, farm size, and the use of fertilizer. Zeng et al. (2015) found a yield improvement of 47.6–63.3% for the improved maize seed compared to traditional varieties. Using instrumental variables and propensity score-matching methods, their results also show that the adoption of improved maize varieties led to a 0.8–1.3% drop of poverty incidence. Accounting for the heterogeneous effects of adoption, Zeng et al. (2015) found that poor farmers benefit less from the adoption because of the smallness of their farm size.

In Tanzania, the decision to allocate farmland to improved maize is positively correlated to family size, total farm size, land quality, membership of farmers' groups, ownership of radio, and livestock (Kassie, Jaleta, and Mattei 2014). Using a generalized propensity-score matching and Tobit selection model, Kassie, Jaleta, and Mattei (2014) found that an increase in the area planted with improved maize reduces the probabilities of chronic and transitory food insecurity between 0.7% and 1.2% and between 1.1% and 1.7%, respectively. This agrees with Magrini and Vigani (2014) who, using a propensity-score matching (PSM) method, have shown that the use of improved seeds has a positive effect on food availability, accessibility and utilization. Similar methodology was used by Amare, Asfaw, and Shiferaw (2012) but completed with the switching regression techniques. Results from both techniques (PSM and switching regression) indicate a significant impact of improved maize on household income and consumption expenditure. Khonje et al. (2015) also employed the propensity-score matching and endogenous switching regression models to estimate the causal impacts of improved seed adoption in Zambia. They showed that the adoption of improved maize leads to significant gains in crop incomes, consumption expenditure, and food security. Khonje et al. (2015) also concluded that improved maize varieties have significant poverty-reducing impacts in Zambia. Applying the control function approach to test for the endogeneity of hybrid seed adoption, Smale and Mason (2014) showed that the use of maize hybrids in Zambia is correlated with higher values of household income, assets, and less deprivation. Similar results were obtained by Mathenge, Smale, and Olwande (2014) who found that the use of hybrid maize seed in Kenya contributes to improve household welfare measured by total income, assets, inequality, and poverty. However, the larger effect was observed in the major maize growing areas. This confirms the previous study by Karanja, Renkow, and Crawford (2003), suggesting that technologies developed for high agricultural potential areas in Kenya are likely to have more profound aggregate impacts on maize production and lead to greater reductions in import demand (if prices are controlled) or maize prices (if prices are flexible).

Like, Tura et al. (2010), a study by Idrisa, Ogunbameru, and Shehu (2012) employed a bivariate probit model and showed that the contact with extension agents, education, and access to credit significantly affected the decision of improved maize adoption in Nigeria. Furthermore, the study found that the adoption of improved maize varieties is associated with a significant reduction of food insecurity among producers. Using the double-hurdle model, the work of Bezu et al. (2014) indicated that the decision of adopting improved maize is negatively associated with age, female adult labor, maize price prior planting and fertilizer price, and positively correlated with education, household size, farm size, and farm credit organization. The intensity of improved maize increases with education, male adult labor, farm size, and access to subsidy. Furthermore, Bezu et al. (2014) used the control function approach and the instrumental method to test for endogeneity in evaluating the causal impact of improved maize adoption on household welfare. The results show the strong impact of improved maize adoption on household income, asset, and maize consumption. Results from a PSM estimates showed a positive impact of improved maize adoption on household welfare and poverty reduction in Mexico (Becerril and Abdulai 2010). Their study revealed that improved maize adoption helped increase household per capita expenditure by an average of 136–173 Mexican pesos, while reducing their probability of falling into poverty by 19–31%.

3. Empirical approach

This study is based on a non-separable model of farm household, in which farmers organize their labor to maximize utility over the consumption goods and leisure in an economic and institutional environment constrained by the prevalence of market failures in developing countries (de Janvry, Fafchamps, and Sadoulet 1991; Mathenge, Smale, and Olwande 2014; Verkaart et al. 2017). As a consequence, farmers are simultaneously engaged in both production and consumption decisions. Farmers produce goods for consumption or sale and credit constraints are relaxed through farm sales and off-farm income (Smale and Mason 2014; Mathenge, Smale, and Olwande 2014; Verkaart et al. 2017).

The objective of this paper is: (1) to analyze the adoption decision of improved maize, and (2) its impact on maize famers' welfare.

3.1. Adoption decision model

In addition to the production factors, our model of improved adoption includes farmers' characteristics and institutional variables as key determinants. Let A denote the area of land planted with improved maize:

$$A = f(P,\ X,\ I,\ R), \tag{1}$$

where P is a vector of input prices, while X represents farm and farmers' characteristics, and I is a vector of institutional variables. R represents region level dummies.

Since some farmers did not grow improved maize, our dependent variable is censored and model (1) is best expressed under the framework of a corner solution model. In such a model, the decision not to adopt improved maize is optimal for some farmers (Wooldridge 2010; Bezu et al. 2014; Verkaart et al. 2017). Therefore, A*i* is given as follows:

$$A_i = \max\,(0,\ A_i^*), \tag{2}$$

where the latent variable A_i^* referring to improved maize adoption equation, is given by

$$A_i^* = \alpha_0 + \alpha_1 P_i + \alpha_2 X_i + \alpha_3 I_i + \alpha_4 R_i + \varepsilon_i. \tag{3}$$

We expect inputs prices (P_i) negatively correlated with improved maize planting decision. To reduce the magnitude of the coefficients of input prices, they were included in the model in a logarithm form. In line with the microeconomic theory, a study by Bezu et al. (2014) found that input prices reduce the probability of improved maize planting. X_i includes age, gender, experience in maize production, training on improved maize and farm size. Following the works of Tura et al. (2010) and Kassie, Jaleta, and Mattei (2014), we expect that these variables increase the probability of adopting improved maize. The institutional variables (I_i) include education, extension services, and access to credit. Previous studies by Tura et al. (2010), Idrisa, Ogunbameru, and Shehu (2012) and Bezu et al. (2014) have shown that more educated farmers have more likelihood to adopt improved maize. Also frequent contact with extension agents increases the probability of improved maize planting. These studies also indicated that access to credit is positively correlated to improved maize adoption. The term R_i refers to region-level dummies. We expect significant region-level effect on improved maize decision.

We follow Bezu et al. (2014) and Verkaart et al. (2017) by using a double-hurdle model developed by Cragg (1971). This model relaxes the restrictions of Tobit model by assuming two independent hurdles in the process of adoption of improved maize. The double-hurdle model is expressed as follows:

$$A_{i1}^* = \beta_0 + \beta_1 P_i + \beta_2 X_i + \beta_3 I_i + \beta_4 R_i + \varepsilon_{i1} \quad \text{Adoption decision,} \tag{4}$$

$$A_{i2}^* = \alpha_0 + \alpha_1 P_i + \alpha_2 X_i + \alpha_3 I_i + \alpha_4 R_i + \varepsilon_{i2} \quad \text{amount of land planted decision,} \tag{5}$$

where A_{i1}^* represents the likelihood of adoption of improved maize, and A_{i2}^* the quantity of land under improved maize. The first hurdle relating to the farmer’s decision to adopt improved maize follows a probit model, while the second hurdle on the decision on the intensity has a truncated normal distribution.

3.2. Welfare impact model

Various indicators have been used to measure welfare in the literature. Consumption expenditure has been commonly used (Becerril and Abdulai 2010; Amare, Asfaw, and Shiferaw 2012). Other measures of welfare include income (Karanja, Renkow, and Crawford 2003; Bezu et al. 2014; Mathenge, Smale, and Olwande 2014; Verkaart et al. 2017), poverty (Becerril and Abdulai 2010; Mathenge, Smale, and Olwande 2014; Verkaart et al. 2017), and assets (Bezu et al. 2014; Mathenge, Smale, and Olwande 2014; Smale and Mason 2014). A more suitable measure of welfare would have been consumption expenditure, but the PAPA/INRAB surveys do not collect data on consumption expenditure. For the purpose of this study, indicators of welfare used are total income, farmers’ poverty status, and poverty gap measuring the depth of poverty, as defined by Foster–Greer–Thorbecke (FGT). The poverty gap refers to the amount of income needed to get farmers out of poverty. We choose this because it is more useful for policy purposes than is the headcount ratio and the severity of poverty (Mathenge, Smale, and Olwande 2014).

To calculate poverty indices, we employed the Foster–Greer–Thorbecke (FGT) index given by

$$P_\alpha = \frac{1}{n}\sum_{i=1}^{q}\left[\frac{Z - Y_i}{Z}\right]_\alpha, \tag{6}$$

where Z is the poverty line value of \$1.25 which was converted into CFA, the Benin currency, using the exchange rate when the data were collected. The resulting poverty line per year was CFA 272, 823.8. Y_i are farmers’ incomes, n is the size of the respondents, q the total number of poor in the sample, and α is the poverty aversion parameter. When $\alpha = 0$, $P_0 = q/n$ which is the poverty incidence, the proportion of farmers falling below the poverty line. When $\alpha = 1$, $P_1 = 1/n \sum_{i=1}^{q} [Z - Y_i/Z]$ is known as the poverty gap measuring the depth of the poverty. When $\alpha = 2$, $P_2 = 1/n \sum_{i=1}^{q} [Z - Y/Z]^2$ is the squared poverty gap index, indicating the severity of poverty.

Separate regressions were estimated for each indicator of welfare used for the analysis. The model estimated is as follows:

$$Y_i = \beta_0 + \beta_1 A_i + \beta_2 X_i + \beta_3 I_i + \beta_4 R_i + \varepsilon_i, \tag{7}$$

where Y_i are the outcome variables. The other variables are as previously defined. In line with previous studies (Becerril and Abdulai 2010; Amare, Asfaw, and Shiferaw 2012; Bezu et al. 2014; Smale and Mason 2014; Zeng et al. 2015) we postulate that adoption of improved maize has a positive effect on welfare among maize farmers through increased yield and income.

Due to observables and unobservable factors which induce some farmers to adopt improved maize than other, Equation (7) may suffer from selections bias and endogeneity problem. To control for this, we estimated Equation (7) employing an IV technique. Therefore, we follow Bezu et al. (2014) and Verkaart et al. (2017) by using the predicted values of area planted to improved maize as an instrument for observed values area under improved maize. The procedure is as follows: first, we estimate improved maize adoption decision using the double-hurdle model as outlined above, second, we calculate the unconditional expected values of adoption using the predicted values from the double-hurdle model, and finally we estimate the welfare equation by instrumenting the observed values of area under improved maize with its expected values. Previous studies (Wooldridge 2003; Bezu et al. 2014; Verkaart et al. 2017) indicated that this procedure is more efficient than the standard two stages least squares (2SLS).

3.3. Endogeneity issues

Due to the possible reverse causality some explanatory variables could be endogenous in the adoption decision model. In this study, we discuss the endogeneity of FBO membership, access to extension services, and participation in a training session. These variables are likely to increase the adoption of improved seed, but the training sessions, extension agents, and FBO would maximize their impact by targeting farmers who have already adopted improved maize or other agricultural technologies. These arguments suggest we should control for the potential endogeneity of FBO membership, access to extension services, and participation in the training session in order to identify their causals effects. Following Lampach, Nguyen Van, and To-The (2017) and Sinyolo, Mudhara, and Wale (2017), we test for the endogeneity of FBO membership, access to extension services and participation in the training session following two steps. First, we make a probit regression for FBO membership, access to extension services, and participation in the training session on the exogenous explanatory variables. This step allows us to calculate the generalized residuals. Second, the generalized residuals were added in the structural equation. A t-test of the generalized residual tests the null hypothesis of exogeneity (Wooldridge 2012; Smale and Mason 2014; Lampach, Nguyen Van, and To-The 2017; Sinyolo, Mudhara, and Wale 2017). Therefore, a statistically significant coefficient of the generalized residuals means endogeneity, and a statistically insignificant coefficient means exogeneity. The coefficients associated with the generalized residuals of FBO membership (p-value = .946), extension services (p-value = .668), and training (p-value = .895) are not significant. Thus, we conclude that the variables, FBO membership, access to extension services, and participation in the training session are exogenous.

4. Data and descriptive statistics

Data used in this study come from a survey of 356 maize producers conducted in 2016 in Benin by the 'Programme d'Analyse des Politiques Agricoles de l'Institut National des Recherches Agricoles du

Table 1. Distribution of improved maize users in Benin.

Improved maize	Benin	Region		
		Northern	Central	Southern
Adopters (%)	57	75	42	29
Non-adopters (%)	43	25	58	71
Sample size	356	191	95	70

Bénin (PAPA/INRAB)'. The survey covers 49 municipalities out of 77 in Benin. The municipalities selected belong to the eight (8) agro-ecological zones in Benin, particularly regions with conditions favorable to maize production. Prior to data collection, a census of maize producers was conducted in each municipality. Farmers were randomly selected based on the list of maize producers in the selected municipalities. The extension agents provided a list of well-known improved maize varieties in the country. Improved maize adopters are classified as farmers who planted improved maize varieties, while non-adopters are those who planted traditional varieties. It is important to note that, in Benin, farmers can get improved maize seed from various sources including own production, extension offices, local markets, or from neighboring countries such as Nigeria. As shown in Table 1, about 57% of farmers adopted improved maize in Benin. The analysis by location indicates that 75% of farmers in the Northern region adopted improved maize against only 42% and 29% in the Central and Southern, respectively. This suggests that farmers in Northern Benin are more likely to adopt improved maize compared to those in the Central and Southern Benin. Perhaps, this is due to the fact that a higher proportion of farmers in Northern Benin (65%) has access to extension services compared to 59% and 54% in the Central and Southern Benin, respectively. Similarly, a higher proportion of farmers in the Northern region belongs to farmers-based organization (FBO). These figures support the idea that technology adoption may occur through extension services and farmers' interactions (Conley and Udry 2010; Nonvide 2017). Also, note that farmers in northern Benin are more oriented to commercialization, while those in the central and southern consume more maize.

Table 2 presents the summary statistics of the socio-economic characteristics of improved maize adopters and non-adopters. Non-significant differences were observed among the two groups of farmers regarding variables such as age, gender, education, and inputs prices. This may be possibly because these variables cannot be affected by maize adoption or are outside of the farmers' control. Furthermore, we find that improved maize adopters have a significantly higher yield and total income

Table 2. Socio-economic characteristics of improved maize adopters and non-adopters.

Variables	All	Adopters	Non-adopters	*t*-test/ Khi-2
Yield (kg/ha)	1605.80	1722.749	1448.84	−2.61***
Income (in CFA)	584,482	721,527	400,552	−4.39***
Age (in years)	52.05	51.51	52.76	1.11
Gender (male = 1)	96.62	97.54	95.39	1.24
Education (yes = 1)	50.28	47.05	54.60	1.98
Farm size (in ha)	2.24	02.49	01.90	−6.25***
Experience (in years)	30.23	29.51	31.18	1.38
Extension services (yes = 1)	61.23	71.56	47.36	21.48***
FBO (yes = 1)	33.70	41.66	23.02	13.54***
Access to credit (yes = 1)	24.71	31.37	15.78	11.36***
fertilizer (kg/ha)	198.83	220.20	170.14	−4.70***
Herbicide (Liter/ha)	5.39	5.69	5.05	0.036
Price of urea (in CFA)	250.45	250.17	250.82	0.17
Price of NPK (in CFA)	251.25	251.43	251.06	−0.05
Price of herbicide (in CFA)	1426.75	1388.36	1478.30	0.45
Maize as main crop (yes = 1)	88.48	89.70	86.84	0.70
Training (yes = 1)	48.31	53.92	40.78	6.01**
Sample size	356	204	152	–

Note: CFA is Benin currency. Average exchange rate in 2016: USD 1 = CFA 597.97.

Table 3. The use of improved maize by poverty status.

Poverty index	All	Adopters	Non-adopters	Statistical tests
Poverty incidence (%)	0.38	0.32	0.47	7.58***
Poverty gap	0.17	0.14	0.20	4.66***
Poverty severity	0.11	0.10	0.12	−2.20**

***, **Significant at 1% and 5%, respectively

than the non-adopters. This suggests that the use of improved maize is associated with higher income through improved yield and sales of surplus. Farmers planting improved maize have significantly large farms compared to non-adopters, implying that improved maize adopters devoted more land to maize production. About 42% of improved maize adopters belong to FBO. In addition, improved maize adopters have more contact with extension agents and access to credit. This is in line with the need for institutional measures to support farmers. Table 2 also indicates that improved maize adopters applied higher dosage of fertilizer, indicating a positive correlation with farms' technologies. A significantly higher proportion of farmers (54%) that have participated in training on improved seed adopted improved maize. This suggests that participation in improved seed training is likely to increase the improved maize adoption rate.

The relationship between improved maize adoption and poverty status is presented in Table 3.

The proportion of maize farmers falling below the poverty line is significantly higher for farmers who did not adopt improved maize relative to adopters. The poverty gap is also higher for farmers who did not adopt improved maize compared to adopters. Similarly, the severity of poverty is less for improved maize adopters compared to non-adopters. This suggests that income inequality among the poor is significantly higher for farmers who did not adopt improved maize relative to adopters.

5. Results and discussion

To achieve the objectives of this paper, we first estimate the double-hurdle model (Table 4) by assuming that the decision to adopt improved maize and the area planted are governed by separate processes. We believe famers' decision process is characterized by two processes which are different in their nature. A farmer takes first the decision to adopt improved maize or not and then a second decision regarding the quantity of land to be allocated to each variety of maize. This intuition is supported by our results which showed that different set of variables affect the decision to adopt and area under improved maize. Secondly, we estimate the instrumental variable regression model (Table 5) to assess the impact of improved maize adoption on our welfare variables. Finally, we disaggregate our results to explore the heterogeneous effects.

5.1. Results of the double-hurdle estimates

Overall, our model has a good fit with the exogenous variables, as indicated by the significance of the Chi-square statistic at 1% (Table 4). Results indicated that adoption and farmland allocated to improved maize depend on the location. Compared to the farmers in the Northern region, those in the Central and Southern regions are less likely to adopt improved maize, and allocate less land to improved maize. These results can be explained by the fact that the Northern region is known as the grain basket of the country. Furthermore, farmers in this region have more large farm size with an average of 2.6 ha against 1.9 and 1.7 ha in the Central and Southern region, respectively. Khonje et al. (2015) argue that if producers have more land, they can allocate more to improved maize.

The land under improved maize, but not adoption, is strongly and negatively correlated with producer's age up to 63 years beyond which the correlation is positive. Unlike Bezu et al. (2014) and

Table 4. Double-hurdle model estimates of improved maize adoption.

Variable definition	Probability of adopting improved maize (Hurdle 1)		Land under improved maize (Hurdle 2)	
	Coeff	Bootstrap s.e	Coeff	Bootstrap s.e.
Age (years)	0.067	0.062	−0.085***	0.031
Age square	−0.0006	0.0005	0.0007***	0.0002
Gender (Male = 1, Female = 0)	−0.093	0.481	−0.227	0.418
Education (0 = None, 1 = at least primary school)	−0.066	0.168	0.179*	0.100
Farming experience (Number of years)	−0.007	0.011	0.0017	0.065
Farm size (number of ha)	0.265***	0.127	0.170**	0.074
Extension services (Yes = 1, No = 0)	0.363**	0.170	0.662***	0.131
FBO (Yes = 1, No = 0)	0.082	0.184	−0.087	0.094
Credit access (Yes = 1, No = 0)	0.286	0.211	0.240***	0.089
Training on improved seed (Yes = 1, No)	0.401**	0.177	−0.211*	0.111
Maize as main crop (Yes = 1, No = 0)	0.470	0.236	0.192	0.176
Log improved maize price prior to planting (Price in CFA)	−0.725***	0.283	0.107	0.154
Log Urea price (Price in CFA)	0.286	0.444	−0.020	0.544
Log NPK price (Price in CFA)	0.003	0.055	0.072	0.046
Log herbicide price (Price in CFA)	−0.008	0.035	−0.011	0.028
Location (reference Northern region)	−0.664***	0.246	−0.396**	0.186
Central region	−0.936***	0.263	−0.494**	0.188
Southern region	−0.024	3.247	2.118	3.061
Constant	0.067	0.062	−0.085***	0.031
Sigma	–	–	0.626	0.035
Log likelihood	−184.968		−183.625	
χ^2	67.83		96.03	
Bootstrapping replication	1000		1000	

***Significant at 1%, **Significant at 5%, and *Significant at 10%.

Table 5. Impact of improved maize adoption on income and poverty.

	(1) Ln total income	(2) Poor (<$1.25)		(3) Poverty gap
	Coeff	Coeff	dydx	Coeff
Ln (improved maize area)	0.524**	−0.951***	−0.078**	−1.641***
	(0.248)	(0.338)	(0.158)	(0.512)
Gender	−0.246	0.475	0.122	0.331
	(0.231)	(0.436)	(0.127)	(0.594)
Education	0.016	0.053	0.019	−0.080
	(0.107)	(0.168)	(0.047)	(0.243)
Farming experience	0.024***	−0.015**	−0.004**	−0.024***
	(0.004)	(0.007)	(0.0019)	(0.008)
Farm size	−0.159**	0.211**	0.054*	0.168
	(0.067)	(0.105)	(0.029)	(0.146)
Extension services	0.110	−0.027	−0.041	0.170
	(0.239)	(0.378)	(0.108)	(0.506)
FBO	0.276**	−0.232	−0.073	−0.291
	(0.115)	(0.189)	(0.053)	(0.254)
Credit access	0.321**	−0.564*	−0.174**	−0.010
	(0.154)	(0.291)	(0.081)	(0.451)
Training on improved seed	0.107	−0.302*	−0.104**	0.185
	(0.102)	(0.173)	(0.045)	(0.249)
Maize as main crop	−0.204	−0.007	−0.001	0.055
	(0.142)	(0.242)	(0.067)	(0.220)
Constant	12.10***	0.216	–	0.023
	(0.363)	(0.634)	–	(0.815)
Log likelihood	-	−547.95		-
χ^2	133.85***	69.40***		80.53***
Bootstrapping replication	1000	1000		1000

Significance levels: *10%, **5%, ***1%.

Note: Values in parenthesis are robust bootstrapped standard errors. dydx denotes marginal effects. For models 1 and 3 coefficient and the average marginal effects are not different. In all models, Ln improved maize area is treated as endogenous and instrumented with the predicted area under improved maize obtained from the double-hurdle model (hurdle 2) of Table 4.

Verkaart et al. (2017), the effect is nonlinear. This result reveals that while the age of the farmer may not affect adoption, young farmers allocated less land to improved maize, suggesting that when the old farmers adopt improved maize, they allocate more land than the young farmers. This reflects the fact that in Benin the young have less access to land and other inputs than the older. Education does not influence the decision to adopt improved maize, but more educated farmers allocated more land to improved maize, confirming previous study (Asfaw et al. 2012; Bezu et al. 2014; Nonvide et al. 2018) which suggested that educated farmers are more receptive to new technologies than the non-educated farmers. In line with Bezu et al. (2014) and Kassie, Jaleta, and Mattei (2014), farm size is positively associated with both adoption and farmland allocated to improved maize. This suggests that farmers who own large farm size can allocate more land to improved maize than the smallest landholding farmers.

The probability of planting improved maize and the amount of land allocated increase with access to extension services, indicating that learning about new technologies occurs through extension services, as noted by Conley and Udry (2010). Regular contact with extension agents enhances farmers' knowledge on good agricultural practices and modern technologies. Farmers with access to credit allocate more land to improved maize than those who did not have credit. As suggested by previous findings (Bjornlund and Pittock 2017; Mdemu et al. 2017; Nonvide et al. 2018) access to credit allows farmers to purchase farm inputs and to operate the activities of firms in time. As expected, farmers who had participated to improved seed training have a higher likelihood to adopt improved maize. But they allocate less land to improved maize compared to those who did not participate to improved seed training. This negative correlation arises because farmers who participated in training on improved seed have a significantly higher yield (1.8 t/ha against 1.3 t/ha for those who did not participate) due to good practices learnt from the training. Therefore, expanding land area is no longer an option for them since they can intensify their production. Farmers who grow maize as the main crop have a higher probability of adopting improved seed, but this does not significantly increase the land planted to improved maize, while the sign off the coefficient (positive) is as expected.

Higher prices for improved seed reduce the probability of improved maize planting, but did not affect the decision on the land allocated. This shows that changes on the supply side may negatively affect the adoption decision. Indeed since farmers are price-takers, when the price increases, the demand for improved maize will decrease and therefore the adoption rate. Also, when the price decreases, due to the imitative entry of competitors that erode the monopolistic rents of innovators, or because of the introduction of incremental innovations that widen the scope of application and use of the product innovation, the adoption rate of improved maize would increase. However, large-scale adoption of improved maize may affect output and input prices which, in return, may negatively affect farmers' decisions regarding adoption, input demand, and output supply (Hellegers, Zeng, and Zilberman 2011; Chang and Tsai 2015). For instance, an increase in production due to the adoption of improved maize would reduce the output price and thus the mark-ups which may affect the pay-off and hence adoption decisions. This will reduce not only the rent of adopters but also that of non-adopters (Hellegers, Zeng, and Zilberman 2011).

5.2. Results of the instrumental variable regression models

Table 5 reports results from the IV models which provides evidence on the link between improved maize adoption and our welfare variables. An IV regression model was estimated for models 1 and 3, while for model 2 we estimated an IV probit model. The results are robust to the selected welfare indicators, presenting a positive and significant impact of adoption of improved maize on income (model 1), farmers' poverty status (model 2), and poverty gap (model 3). Keeping all other controls constant, a 10% increase in the area planted with improved maize is associated with a 5.24% increase in total income, a reduction of probability of being poor by 0.78%, and reduction of poverty gap by 16.41%. We conclude that adoption of improved maize contributes to move farmers out of poverty through increased income. These results are similar to the previous studies which have shown a positive relationship between farm technology and welfare. For instance, Verkaart et al. (2017) showed that increasing access to improved chickpea is a promising pathway for rural development in Ethiopia. Similarly, the adoption of improved maize in Malawi had a positive impact on household own maize consumption, income, and assets (Bezu et al. 2014). In the eastern Zambia, Khonje et al. (2015) found significant poverty-reducing impacts of improved maize adoption.

For robustness checks, we estimate different specifications of our model. This helps us to test the validity of the results (Verkaart et al. 2017). The results of the robustness checks are presented in Table 6. Row (1) reports, for comparison purposes, our primary estimation results are presented in Table 5. We present in row (2) results were we treat improved maize area as exogenous. In row (3) we present results where we replace our key variable of the extent of adoption (improved maize area) by the amount of seed planted. Across all these specifications we found that adoption of improved maize has a positive impact on farmer's income and a consistent negative impact on the probability of being poor and the poverty gap. These proved that our results remain consistent with the changes in the specification.

Other significant variables include maize farming experience, farm size, membership of FBO, access to credit, and training on improved seed (Table 5). Experience in maize farming was positively associated with income and poverty, suggesting that more experienced farmers have higher income and higher probability of moving out of poverty. Farm size is negatively correlated with income and positively correlated with the probability of being poor. This implies that farmers who have larger farm size have lower income and higher probability of being poor. Following previous studies (Bezu et al. 2014; Verkaart et al. 2017) we expected that farmers who have larger farm size will have higher income. This unexpected result showing a negative impact of larger farms' size on the welfare is an indication of the weak capacity of farmers in developing countries, and particularly maize farmers in Benin to efficiently manage large farms. In this study, we observe a negative correlation (−0.28) between yield and farm size. Perhaps, this is due to the market imperfection (Carletto, Savastano, and Zezza 2013; Ali and Deininger 2015) as most farmers in developing countries have poor access to farm inputs as well as to credit. FBO membership appears to be positively correlated with income, indicating that being a member of FBO contributes to improve farmers' welfare. Access to credit is positively and significantly associated with total income and negatively with poverty. This indicates that maize farmers who have access to credit have higher income and are likely to move out of poverty. Controlling for all other factors, the probability of being poor reduces by 0.17% when farmers have access to credit. Access to credit is the core cause of most constraints encountered in farming (Mdemu et al. 2017; Nonvide et al. 2018). While we observed the expected sign for the variable training on improved seed, the effect is only significant on the poverty status with a negative sign. This negative relationship indicates that participation to training on improved seed is likely to reduce farmers' probability of being poor by 0.10%.

Overall, our results provide rigorous evidence that improved maize adoption contributes to increase yield, income, and poverty reduction in Benin. This is in line with previous studies (Bezu

Table 6. Robustness checks of improved maize adoption impact.

	(1) Ln total income	(2) Poor (<$1.25)	(3) Poverty gap
(1) Primary results	0.524**	−0.951***	−1.641***
	(0.248)	(0.338)	(0.512)
(2) Improved maize area treated as exogenous	0.533***	−0.653***	−1.550***
	(0.082)	(0.147)	(0.228)
(3) Ln improved maize seed (kg)	0.119***	−0.068*	−0.266***
	(0.022)	(0.037)	(0.052)
Bootstrapping replication	1000	1000	1000

Significance levels: *10%, ***1%.
Note: Value in parenthesis are robust bootstrapped standard errors. Regressions include all explanatory variables used in Table 5.

Table 7. Comparison of estimations of income for poor and non-poor farmers, and small and large farms.

	Poor	Non-poor	Small farms ≤2.5 ha	Large farms >2.5 ha
Ln (improved maize area)	−0.721	0.700	0.777***	−0.117
	(0.310)	(3.464)	(0.170)	(1.149)
Education	−0.007	−0.025	−0.054	0.121
	(0.115)	(0.598)	(0.112)	(0.205)
Farming experience	0.031***	0.005	0.006	0.027***
	(0.005)	(0.007)	(0.004)	(0.008)
Farm size	−0.077	−0.025	–	–
	(0.095)	(0.642)	–	–
Extension services	−0.003	−0.146	−0.077	0.662
	(0.241)	(2.676)	(0.175)	(1.102)
FBO	0.285*	0.040	0.109	0.258
	(0.163)	(0.136)	(0.115)	(0.230)
Credit access	0.001	−0.156	−0.036	0.779
	(0.207)	(1.143)	(0.116)	(0.521)
Training on improved seed	0.221	−0.036	0.211**	−0.109
	(0.120)	(0.678)	(0.099)	(0.238)
Maize as main crop	−0.139	−0.104	0.177	−0.436
	(0.198)	(0.650)	(0.159)	(0.288)
Constant	10.996***	12.837***	12.052***	11.516***
	(0.320)	(0.454)	(0.230)	(0.339)
χ^2	39.51****	20.02***	116.09***	47.67***
Number of observations	137	219	151	205
Bootstrapping replication	1000	1000	1000	1000

Note: Significance levels: *10%, **5%, ***1%.

et al. 2014; Kassie, Jaleta, and Mattei 2014; Khonje et al. 2015; Zeng et al. 2015) which found similar positive impact of improved maize adoption. Other studies (Dercon and Christiaensen 2011; Verkaart et al. 2017) pointed out that some farmers may not be able to capitalize on the new technology. Thus, the impacts of technology adoption may differ among farmers. In line with this, the study aimed to analyze a disaggregated estimation of the welfare model (equation 7). Due to the low proportion of female farmers (3.4%) in our sample, we failed to conduct a more robust analysis by estimating equation (7) disaggregated by gender. However, a statistical significance test among farmers who adopted improved maize indicates no gender difference among adopters in terms of yield ($t =$ 1.222) and income (1.223). This suggests that all farmers have the potential to realize same benefits from the adoption of improved maize. This is an encouraging result in the sense that farmers are equally likely to benefit from the use of improved maize. Similar results were found by Bezu et al. (2014) in Malawi.

Table 7 reports the results from the estimation of total income disaggregated by the poor and non-poor, and by farm size. We classified farm size into two categories. The small farms refer to farm size less than 2.5 ha, and those farms size greater than 2.5 ha were classified as large farms. This classification is consistent with the fact that the average farm size in Benin is 1.7 ha (MAEP 2017). The disaggregated analysis of poor versus non-poor farmers reveals no significant difference in impact. This suggests that poor and non-poor farmers derive similar benefit from the use of improved maize. Table 7 also shows a positive association of improved maize adoption and income for smallest landholding farmers, while the effect was not significant for the largest landholding farmers, indicating that smallholder farmers are able to realize the potential from adoption of improved maize. This confirms the findings by Asfaw et al. (2012) and Verkaart et al. (2017) who found a non-significant impact of adopting improved seed on income for the largest landholding household.

While our findings support a positive impact of improved maize adoption on farmers' welfare, the spillover impacts related to changes in food prices and non-farmers benefits were not explored in this study. Further studies must consider these economy-wide effects of improved maize adoption and use, for example, a panel data set to analyze these impacts in a more dynamic approach.

6. Conclusion

This paper analyzed the factors that influence farmers' decision to adopt improved maize varieties and its impact on welfare in Benin. We estimate the adoption of improved maize using a double-hurdle model and then the predicted value of area under improved maize, obtained from the estimation of the double-hurdle model, was used as instrument for the observed value to control for the endogeneity of area under improved maize in the welfare model. The selected indicators for welfare include total income, poverty status, and poverty gap and are based on data availability. The poverty variables were calculated following Foster, Greer, and Thorberke decomposition. The results from the double-hurdle model indicated that variables such as farm size, extension services, training on improved seed, and location affect both farmers' decision and the amount of land under improved maize. Improved maize price prior to planting has a positive effect on the adoption decision but not the land to be planted. Other variables including age, education, and credit affect only the area under improved maize. The estimation of the welfare equation revealed that adoption of improved maize significantly increases income and reduces poverty. There was no evidence of heterogeneous impacts among poor and non-poor farmers. Adoption of improved maize favors small landholding farmers but did not have a significant impact on welfare for those who own large-sized farms. The findings of this study suggest a need for additional support measures to lift farmers to move out of poverty. Policies that facilitate access to the inputs of farms, regular training and promote strong institutional support measures can significantly contribute to improving welfare in the rural area of Benin.

Disclosure statement

No potential conflict of interest was reported by the authors.

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References

Ali, D. A., and K. Deininger. 2015. "Is There a Farm Size–Productivity Relationship in African Agriculture? Evidence from Rwanda." *Land Economics* 91 (2): 317–343.

Amare, M., S. Asfaw, and B. Shiferaw. 2012. "Welfare Impacts of Maize–Pigeonpea Intensification in Tanzania." *Agricultural Economics* 43 (1): 27–43.

Asfaw, S., B. Shiferaw, F. Simtowe, and L. Lipper. 2012. "Impact of Modern Agricultural Technologies on Smallholder Welfare: Evidence from Tanzania and Ethiopia." *Food Policy* 37 (3): 283–295.

Becerril, J., and A. Abdulai. 2010. "The Impact of Improved Maize Varieties on Poverty in Mexico: A Propensity Score-Matching Approach." *World Development* 38 (7): 1024–1035.

Bezu, S., G. T. Kassie, B. Shiferaw, and J. Ricker-Gilbert. 2014. "Impact of Improved Maize Adoption on Welfare of Farm Households in Malawi: A Panel Data Analysis." *World Development* 59: 120–131.

Binswanger, H. P. 1980. "Attitudes Toward Risk: Experimental Measurement in Rural India." *American Journal of Agricultural Economics* 62 (3): 395–407.

Bjornlund, H., and J. Pittock. 2017. "Exploring the Productivity and Profitability of Small-scale Communal Irrigation Systems in Sub-Saharan Africa." *International Journal of Water Resources Development* 33 (5): 685–689.

Carletto, C., S. Savastano, and A. Zezza. 2013. "Fact or Artifact: The Impact of Measurement Errors on the Farm Size–Productivity Relationship." *Journal of Development Economics* 103 (1): 254–261.

Cerulli, G. 2014. "ivtreatreg: A Command for Fitting Binary Treatment Models with Heterogeneous Response to Treatment and Unobservable Selection." *The Stata Journal: Promoting Communications on Statistics and Stata* 14 (3): 453–480.

Chang, S. C., and C.-H. Tsai. 2015. "The Adoption of New Technology by the Farmers in Taiwan." *Applied Economics* 47 (36): 3817–3824.

Conley, T. G., and C. R. Udry. 2010. "Learning about a New Technology: Pineapple in Ghana." *American Economic Review* 100 (1): 35–69.

Cragg, J. G. 1971. "Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods." *Econometrica* 39 (5): 829–844.

de Janvry, A., M. Fafchamps, and E. Sadoulet. 1991. "Peasant Household Behaviour with Missing Markets: Some Paradoxes Explained." *The Economic Journal* 101 (409): 1400–1417.

Dercon, S., and L. Christiaensen. 2011. "Consumption Risk, Technology Adoption and Poverty Traps: Evidence from Ethiopia." *Journal of Development Economics* 96 (2): 159–173.

Dinar, A., and D. Yaron. 1992. "Adoption and Abandonment of Irrigation Technologies." *Agricultural Economics* 6 (4): 315–332.

Duraisamy, P. 2002. "Changes in Returns to Education in India, 1983–94: By Gender, Age-Cohort and Location." *Economics of Education Review* 21 (6): 609–622.

EMICoV. 2015. *Enquête Modulaire Intégrée sur les Conditions de Vie des Ménages*. Cotonou, Bénin: Institut National de la Statistique et de l'Analyse Economique (INSAE).

FAO. 2014. *Statistical Database (FAOSTAT)*. Rome: Food and Agriculture Organization.

Feder, G. 1980. "Farm Size, Risk Aversion and the Adoption of New Technology under Uncertainty." *Oxford Economic Papers* 32 (2): 263–283.

Ghimire, R., H. Wen-chi, and R. B. Shrestha. 2015. "Factors Affecting Adoption of Improved Rice Varieties among Rural Farm Households in Central Nepal." *Rice Science* 22 (1): 35–43.

Griliches, Z. 1957. "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica* 25 (5): 501–522.

Griliches, Z. 1960. "Hybrid Corn and the Economics of Innovation." *Science* 132 (3422): 275–280.

Heckman, J. 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 47 (1): 153–161.

Hellegers, P., D. Zeng, and D. Zilberman. 2011. "Technology Adoption and the Impact on Average Productivity." *Economics of Innovation and New Technology* 20 (7): 659–680.

Huffman, W. 2001. "Human Capital: Education and Agriculture." In *Handbook of Agricultural Economics*, 1, 1st ed. Amsterdam: Elsevier.

Idrisa, Y. L., B. O. Ogunbameru, and H. Shehu. 2012. "Effects of Adoption of Improved Maize Seed on Household Food Security in Gwoza Local Government Area of Borno State, Nigeria." *Agricultural Science Research Journals* 2 (2): 70–76.

Just, R. E., and D. Zilberman. 1983. "Stochastic Structure, Farm Size and Technology Adoption in Developing Agriculture." *Oxford Economic Papers* 35 (2): 307–328.

Just, R. E., and D. Zilberman. 1988. "The Effects of Agricultural Development Policies on Income Distribution and Technological Change in Agriculture." *Journal of Development Economics* 28 (2): 193–216.

Karanja, D. D., M. Renkow, and E. W. Crawford. 2003. "Welfare Effects of Maize Technologies in Marginal and High Potential Regions of Kenya." *Agricultural Economics* 29 (3): 331–341.

Kassie, M., M. Jaleta, and A. Mattei. 2014. "Evaluating the Impact of Improved Maize Varieties on Food Security in Rural Tanzania: Evidence from a Continuous Treatment Approach." *Food Security* 6 (2): 217–230.

Khandker, S. R., G. B. Koolwal, and H. A. Samad. 2010. *Handbook on Impact Evaluation: Quantitative Methods and Practices*. Washington, DC: The World Bank.

Khonje, M., J. Manda, A. D. Alene, and M. Kassie. 2015. "Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia." *World Development* 66: 695–706.

Koundouri, P., C. Nauges, and V. Tzouvelekas. 2006. "Technology Adoption Under Production Uncertainty: Theory and Application to Irrigation Technology." *American Journal of Agricultural Economics* 88 (3): 657–670.

Lampach, N., P. Nguyen Van, and N. To-The. 2017. "Robustness Analysis of Organic Technology Adoption: Evidence from Northern Vietnamese Tea Production" September 15, 2017. SSRN. https://ssrn.com/abstract=3037389 or http://dx.doi.org/10.2139/ssrn.3037389.

Liu, E. 2013. "Time to Change What to sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China." *Review of Economics and Statistics* 95 (4): 1386–1403.

MAEP. 2016. *Evaluation de la production vivrière 2015 et des perspectives alimentaires pour 2016 au Benin. Rapport général volume 1. Office National d'Appui à la Sécurité Alimentaire (ONASA)*. Cotonou: Ministère de l'Agriculture, de la Pêche et de l'Elevage.

MAEP. 2017. *Plan Stratégique de Développement du Secteur Agricole 2017–2021*. Cotonou: Ministère de l'Agriculture, de la pêche et de l'élevage.

Magrini, E., and M. Vigani. 2014. "Technology Adoption and the Multiple Dimensions of Food Security: The Case of Maize in Tanzania." LICOS Centre for Institutions and Economic Performance. Discussion Paper 352/2014.

Mahoussi, F. E., P. Y. Adégbola, A. Zannou, E. F. Hounnou, and G. Biao. 2017. "Facteurs influençant l'intensité de l'utilisation des semences améliorées de maïs au Bénin." *Annales des sciences agronomiques* 21 (1): 37–52.

Marra, M., D. J. Pannell, and A. A. Ghadim. 2003. "The Economics of Risk, Uncertainty and Learning in the Adoption of new Agricultural Technologies: Where are we on the Learning Curve?" *Agricultural Systems* 75 (2–3): 215–234.

Mathenge, M. K., M. Smale, and J. Olwande. 2014. "The Impacts of Hybrid Maize Seed on the Welfare of Farming Households in Kenya." *Food Policy* 44: 262–271.

Mdemu, M. V., N. Mziray, H. Bjornlund, and J. J. Kashaigili. 2017. "Barriers to and Opportunities for Improving Productivity and Profitability of the Kiwere and Magozi Irrigation Schemes in Tanzania." *International Journal of Water Resources Development* 33 (5): 725–739.

Mendola, M. 2007. “Agricultural Technology Adoption and Poverty Reduction: A Propensity-Score Matching Analysis for Rural Bangladesh.” *Food Policy* 32 (3): 372–393.
Minten, B., and C. B. Barrett. 2008. “Agricultural Technology, Productivity, and Poverty in Madagascar.” *World Development* 36 (5): 797–822.
Nkonya, E., T. Schroeder, and D. Norman. 1997. “Factors Affecting Adoption of Improved Maize Seed and Fertiliser in Northern Tanzania.” *Journal of Agricultural Economics* 48 (1–3): 1–12.
Nonvide, G. M. A. 2017. “Effect of Adoption of Irrigation on Rice Yield in the Municipality of Malanville, Benin.” *African Development Review* 29 (2): 109–120.
Nonvide, G. M. A. 2018. “A re-Examination of the Impact of Irrigation on Rice Production in Benin: An Application of the Endogenous Switching Model.” *Kasetsart Journal of Social Sciences*. doi:10.1016/j.kjss.2017.12.020.
Nonvide, G. M. A., D. B. Sarpong, T.-M. G. Kwadzo, H. Anim-Somuah, and F. Amoussouga Gero. 2018. “Farmers’ Perceptions of Irrigation and Constraints on Rice Production in Benin: a Stakeholder-Consultation Approach.” *International Journal of Water Resources Development* 34 (6): 1001–1021. doi:10.1080/07900627.2017.1317631.
Sinyolo, S., M. Mudhara, and E. Wale. 2017. “The Impact of Social Grant Dependency on Smallholder Maize Producers’ Market Participation in South Africa: Application of the Double-Hurdle Model.” *South African Journal of Economic and Management Sciences* 20 (1): a1474. doi:10.4102/sajems. v20i1.1474.
Smale, M., and N. Mason. 2014. “Hybrid Seed and the Economic Well-being of Smallholder Maize Farmers in Zambia.” *The Journal of Development Studies* 50 (5): 680–695.
Stoneman, P. 1981. “Intra-firm Diffusion, Bayesian Learning and Profitability.” *The Economic Journal* 91: 375–388.
Stoneman, P. 2013. “The Impact of Prior use on the Further Diffusion of New Process Technology.” *Economics of Innovation and New Technology* 22 (3): 238–255. doi:10.1080/10438599.2012.708133.
Stoneman, P., and O. Toivanen. 1997. “The Diffusion of Multiple Technologies: An Empirical Study.” *Economics of Innovation and New Technology* 5 (1): 1–17. doi:10.1080/10438599700000005.
Toukourou, A. M., P. Y. Adegbola, C. G. Yallou, and G. Gbehounou. 2004. “Evaluation des variétés améliorées de maïs EVDT 97 STR C1 et TZEE-W SR (variété extra précoce) dans les zones infestées par Striga hermonthica au Sud-Bénin.” *Bulletin de la Recherche Agronomique du Bénin* 45: 37–46.
Tura, M., D. Aredo, W. Tsegaye, R. La Rovere, T. Girma, W. Mwangi, and G. Mwabu. 2010. “Adoption and Continued use of Improved Maize Seeds: Case Study of Central Ethiopia.” *African Journal of Agricultural Research* 5 (17): 2350–2358.
Verkaart, S., B. G. Munyua, K. Mausch, and J. D. Michler. 2017. “Welfare Impacts of Improved Chickpea Adoption: A Pathway for Rural Development in Ethiopia?” *Food Policy* 66: 50–61.
WFP (World Food Programme). 2014. *Analyse Globale de la Vulnérabilité, de la Sécurité Alimentaire et de la Nutrition (AGVSAN)*. Roma, Italy: République du Bénin.
Wooldridge, J.M. 2003. “Further Results on Instrumental Variables Estimation of Average Treatment Effects in the Correlated Random Coefficient Model.” *Economics Letters* 79 (2): 185–191.
Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. Cambridge, MA: MIT Press.
Wooldridge, J. M. 2012. *Quasi-maximum Likelihood Estimation and Testing for Nonlinear Models with Endogenous Explanatory Variables* (Working Paper). East Lansing, MI: Michigan State University.
Zeng, Di, J. Alwang, G. W. Norton, B. Shiferaw, M. Jaleta, and C. Yirga. 2015. “Ex Post Impacts of Improved Maize Varieties on Poverty in Rural Ethiopia.” *Agricultural Economics* 46 (4): 515–526.
Zettelmeyer, F., and P. Stoneman. 1993. “Testing Alternative Models of New Product Diffusion.” *Economics of Innovation and New Technology* 2 (4): 283–308. doi:10.1080/10438599300000009.