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Economic impacts of smallholder farmers' adoption of drought-tolerant maize varieties

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ABSTRACT

Drought and high temperatures are major threats to sustainable food production and consequently the livelihoods of the majority of Africans who depend on fragile agricultural systems. As a response to these threats, climate-smart agricultural technologies, such as drought-tolerant maize (DTM) varieties, have been developed and promoted on the continent. It is well-known that the adoption of improved technologies generally impacts positively on the wellbeing of adopters. Nevertheless, the magnitude of the impact of any technology or intervention is always an empirical question. Therefore, this study sought to determine the factors that influence the adoption of DTM and subsequently estimate how yield, commercialization intensity, and farm income are affected by adoption. To establish causation, we relied on observations from 200 farm households in the Northern Region of Ghana and estimated an instrumental variable regression. Consistent with findings reported in the literature, we found that DTM adoption is primarily driven by access to seed, extension service, labor availability, and location of farm households. In addition, we found that DTM adoption positively impacts on yield and commercialization intensity. The magnitude of impact is not trivial. For example, the yield of farm households increased by more than 150% (936 kg/ha) following DTM adoption. These results imply that policymakers and development practitioners must support research and promotion of climate-smart agriculture to improve adoption and welfare indicators, such as yield and commercialization.

1. Introduction

The northern part of Ghana is characterized by smallholder agriculture in which 80% of the population engages in subsistence farming dominated by very low farm productivity and farm income (Ministry of Food and Agriculture, MoFA, 2017). The low levels of productivity are attributable to such constraints as the low use of improved seeds, inadequate soil amendments, poor crop management practices, inadequate extension services, weak research-extension linkages and limited access to credit (MoFA, 2017). Over the years, the government of Ghana and its development partners have implemented several projects and programs aimed at addressing these constraints. Despite these interventions, the region remains subject to high poverty levels (Ghana Statistical Service, 2014), as agricultural remains rain-fed and highly sensitive to changes in the climate (MoFA, 2017).

An obvious area in Ghana that can be targeted for the dissemination of climate-smart technologies, such as drought-tolerant maize (DTM) varieties, is the northern part of the country, as the region is already subjected to harsh weather conditions and is the most vulnerable part of the country (Ghana Statistical Service, 2014; Ministry of Environment, Science, Technology and Innovation, 2013).[1] Therefore, developed DTM varieties have been promoted in most of the maize growing communities in northern Ghana through several mediums, such as radio, farmer field fora, farm demonstrations, bulletins and farmer-based organizations (Wiredu et al., 2010). DTM has several appealing traits, including tolerance to drought and striga infestation, as well as high yields that can potentially increase production and enable farmers to commercialize to improve their welfare (Tambo and Abdoulaye, 2012; Tambo, 2016). According to Fisher et al. (2015), DTM has no genetic modification, contain high protein content and is highly

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[1] Northern Ghana, just as the remainder of Africa, has limited capacity and thus is unable to effectively employ strategies to mitigate the effects of drought and high temperature (Antwi-Agyei et al., 2012; Collier et al., 2008). Nevertheless, some adaptation mechanisms are being used by smallholder farmers to address the effects of climate change including mixed farming, crop switching, tree planting, varying planting dates and more recently the cultivation of drought tolerant varieties (Tambo, 2016).

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efficient in terms of nitrogen utilization. La Rovere et al. (2014) shows that DTM is likely to build resilience by increasing production and reducing vulnerability.

The extent to which DTM varieties impact farm level performance and welfare is not well-documented. Previous studies have tended to focus on adoption, production and seed system characterization, economic analysis, and farmers' preference (Fisher et al., 2015; Tambo and Abdoulaye, 2012; Wiredu et al., 2010; Legese et al., 2009; Tahirou et al., 2009). The studies that analyze economic impacts have yielded varying results. Makate et al. (2017) found that DTM adoption in rural Zimbabwe significantly enhances overall maize productivity, market participation and household consumption. Holden and Fisher (2015) showed that DTM adoption in Malawi is largely driven by drought and risk aversion. These researchers also demonstrate that other improved maize varieties perform better than DTM. Cenacchi and Koo (2011) used the Decision Support Systems for Agrotechnology Transfer (DSSAT) tool to simulate the effects of DTM varieties under different climatic conditions. These researchers found that DTM is effective in reducing the yield gap in the most food insecure African countries. In all of the reviewed studies, an evaluation of DTM adoption effects on welfare outcomes using a more rigorous econometric technique is scarce. Common methods applied by previous studies are economic surplus and propensity score matching (La Rovere et al., 2014; Makate et al., 2017).

This research engaged 200 subsistence maize farmers in northern Ghana to determine the factors influencing DTM adoption. Beyond the level of adoption, we evaluated the impact of adopting DTM on yield, income, and maize commercialization intensity using the instrumental variable estimation technique. We found that DTM adoption is influenced by seed access, extension service, labor availability, and the residence of farm households, which consequently increase the yield and commercialization intensity. This study contributes to the literature in three main ways. First, we used the instrumental variable (IV) estimation technique to calculate the local average treatment effect (LATE) given the circumstances by which the project was implemented and the seed distribution mechanism. To the best of our knowledge, this study is the first in Ghana to use such an approach to identify the causal impact of DTM adoption. We computed two different IV regressions, that is, a direct two-stage least squares (2SLS), and a probit regression followed by a 2SLS. The latter regression provided a better estimate of the yield equation. Secondly, we demonstrated that access to improved technology is both a necessary and sufficient condition to adopt. Finally, commercialization intensity as an outcome has been less explored with respect to the adoption of improved technologies, such as DTM. Our study highlights the important role commercialization plays in the adoption of climate-smart technologies, such as DTM.

The remainder of the paper is structured as follows: the background of the DTM project follows immediately after this introduction. Section 3 presents the methodology followed by a description of the results in section 4. Section 5 discusses the results, and section 6 presents the concluding remarks.

2. Drought-tolerant maize adoption in Ghana

Table 1 presents the theory of change or logic underlying the DTMA project. The project began in 2007 and was jointly implemented by the International Maize and Wheat Improvement Center (CIMMYT) and International Institute of Tropical Agriculture (IITA). The project was designed to ultimately improve the livelihoods of millions of smallholder maize farmers in Africa. The project sought to achieve this goal through some intermediate results and outcomes. Using funding from the Bill and Melinda Gates Foundation (BMGF), the project was able to identify, advance, and screen maize germplasm for drought tolerance and other additional features, such as striga resistance, quality protein, and high yields. Promising lines were selected for multilocational trials in all of the participating project countries across a wide range of

Table 1
Project logic.

Impact Pathway	Description	Objectively Verifiable Indicators	Means of verification	Assumptions
Impact	Improve maize yield, commercialization, and income	Yield, sales and income of maize farmers increased	Impact assessment report	● Favorable weather ● Adoption of post-harvest technologies
Outcomes	Promote utilization of DTM	Farmers plant DTM seeds	Adoption monitoring report	● Availability of reliable extension partners (e.g., AEAs and seed co) ● Favorable weather
Outputs	Release several varieties of DTM	Newly improved DTM varieties released	Annual reports	Effective collaboration with national varietal release committees
Activities	Develop DTM varieties with additional traits such as striga tolerance, protein quality, and high yield	Multilocational breeding experiments established	Quarterly and annual reports	● Availability of trained and retooled national partners ● Political stability
Inputs	Source donor funds (i.e., BMGF)	Project activities commenced	● MoU ● Inception report	Timely release of funds

agroecological environments. Multilocational trials were established using the participatory 'mother and baby' approach in which researchers and farmers manage the mother and baby trial, respectively. This approach allowed the researchers to assess farmers' preferences for the different maize lines evaluated and consider that feedback in the advancement of the preferred lines. This process tended to facilitate adoption as farmers were involved in the selection and development of the varieties. Superior lines are eventually certified by national variety release committees as proven varieties that can be made widely available to maize farmers.

As can be anticipated, released varieties require vigorous promotion to meaningfully affect farmers' awareness, adoption, and livelihood improvement. Therefore, the DTMA project devoted substantial resources to the promotion of released DTM varieties. Promotion of DTM varieties is particularly important because farmers already have access to their own saved seeds and therefore need to be convinced to switch to DTM varieties. Switching to the cultivation of DTM varieties was expected to positively impact maize yield, commercialization, and income. The true impact of DTM varieties will likely be biased if we fail to consider farmer and farm characteristics thus we controlled for these variables in our model. The DTMA project was premised on some assumptions including timely release of funds, availability of trained and retooled national partners, political stability (e.g., in the Taureg/northern region of Mali), effective collaboration with national varietal release committees, favorable weather, and adoption of post-harvest technologies to avoid a glut and consequently low prices.

The DTMA project was implemented in Ghana and 12 other African countries. In Ghana, the project was implemented throughout the country, as there was no compelling reason to prefer one agroecology or region over another. According to Ghana's Ministry of Food and Agriculture (2014), maize is cultivated and consumed throughout the country.[2] DTMA collaborating partners for Ghana were strategically chosen to ensure that project activities were implemented nationwide. MoFA was the main public institution partnered to promote DTM varieties. MoFA has an office in every district of the country where agricultural extension officers are assigned to various communities. Similarly, Ghana's Council for Scientific and Industrial Research, CSIR (its national agricultural research council), has been mandated to develop agricultural commodities for every region of the country and was the institution partnered with to develop DTM varieties for Ghana. The Council's Savanna Agricultural Research Institute was responsible for conducting multilocational trials in northern Ghana, while its Crops Research Institute was responsible for the remainder of the country. Other local implementing partners were selected to reflect the national character of the DTMA project. Several private seed companies and agro-input dealers operating in different parts of the country were engaged and tasked to promote DTM in specific geographical areas. As part of the strategy to ensure wide adoption of the technology, over 33,000 MT of seeds were distributed to farmers in the participating sub-Saharan African (SSA) countries (CIMMYT, 2014).

CSIR was tasked to produce foundation seeds whereas private seed growers multiplied the foundation seeds into certified seeds. Several approaches were used to promote and disseminate DTM varieties, including farm demonstrations, print media, radio, and farmer field schools. Agricultural extension agents were also employed to out-scale the technologies to various districts within the regions. Placement of the intervention was non-randomly assigned in the target areas. The population units had no control on the placement of the intervention. As part of the dissemination efforts, farmers within the intervention districts were randomly provided seed to influence adoption. Compliance with regard to farmers' use of DTM seed was supervised by extension agents. For more information on the development and dissemination of DTM in Africa and Ghana, see Badu-Apraku et al. (2013); CIMMYT (2013); Etwire et al. (2013); Fisher et al. (2015); La Rovere et al. (2014) and Tambo and Abdoulaye (2012).

3. Materials and methods

3.1. Conceptual framework and hypotheses

Partial adoption of a new technology among smallholder farmers can be analyzed within the context of risk and uncertainty, market imperfections and input fixity (Sadoulet and De Janvry, 1995; Smale et al., 1994). Similarly, the adoption of new technologies and the imperfect knowledge about management practices may lower yields or increase yield variability (Foster and Rosenzweig, 2010). Technology adoption typically passes through experimental stages at the farmer level. New and old technologies may be applied together to facilitate comparison of performance, which then serves as the basis for determining the final adoption decision. Across subsistence farm households, adoption of new practices varies with socio-demographic characteristics given their production objective (Sadoulet and De Janvry, 1995).

According to Morduch (1995), production choice reflects the tradeoff between risk aversion and expected profit maximization. For example, farmers can engage in contract farming and participate in credit and insurance markets in order to hedge against risk and smoothen consumption. Regarding contract farming, transaction costs, information asymmetry (moral hazard) and lack of legal enforcement of contracts limit their effectiveness. Secondly, most credit and insurance markets are missing or non-functional even if they exist. Incompleteness of insurance and credit availability may delay adoption of profitable new agricultural technologies and constrain the levels of inputs necessary to exploit the new technologies, especially among resource-poor farmers (Foster and Rosenzweig, 2010). Foster and Rosenzweig (2010) further argue that the adoption of new technologies require investment in complementary inputs such as fertilizer, which may increase the overall risk given that farmers may not correctly estimate the full uncertainty ex post. For example, if the uncertainty in yield just occurred at harvest, one can reduce the labor force allocated to harvesting of the crop but the fertilizer and other complementary inputs cannot be reduced ex post. These factors expose resource-poor farmers to a high risk of low returns on their investment. Lack of guaranteed output market further increases the risks of farmers especially where there is lack of good storage facility and the crops are highly perishable. Rosenzweig and Binswanger (1993) establish that poor farmers facing increased rainfall variability invest in less risky portfolio leading to lower profits while wealthy farmers exhibit changing portfolios of investments. Poor farmers may cultivate less risky crops relative to wealthier farmers (Murdoch, 1990).

Smallholder farmers employ several innovative mechanisms to manage production risks including the adoption of climate-smart crop varieties that can withstand erratic rainfall, diseases and pests, and are high yielding. Given the general good characteristics of climate smart maize varieties, we anticipate that their adoption will impact positively on welfare outcomes. Therefore, we propose the following three testable hypotheses.

Hypothesis 1. *Adoption of drought tolerant maize variety increases maize yield*

Bucher et al. (2019) demonstrate the economic importance of DTM among smallholder farmers. In their study, they find that DTM effectively maintained yields even in times of moderate to severe droughts. Joint adoption of DTM and insurance enable farmers to recover their losses and return production to higher levels. Compared to traditional maize varieties, adoption of DTM variety performs better in terms of effectively maintaining average yields. In northern Ghana, on-farm and on-station demonstrations of DTM variety have shown a stable yield

[2] Note that even though DTM varieties have been bred to tolerate drought, they also perform very well under optimal conditions.

over traditional varieties (Savanna Agricultural Research Institute, 2017). Despite the possibility of DTM to perform below expectation in times of prolonged drought, we expect even higher losses for traditional varieties. In this regard, we expect the adoption of DTM to have a positive average impact on maize productivity.

Hypothesis 2. *Adoption of drought tolerant maize variety increases intensity of maize commercialization*

As indicated in the first hypothesis, adoption of DTM will likely result in higher output when compared traditional maize varieties (Barrett, 2008; Govereh et al., 1999; Von Braun, 1995, 2004). The surplus output generated from the use of DTM varieties will likely encourage smallholder farmers to participate or increase participation in maize output markets.

Hypotheses 3. *Adoption of drought tolerant maize variety increases crop income*

Finally, commercialization of surplus production will generate crop income[3] assuming market conditions are favorable (relatively high output price and large number of buyers are available) which can be reinvested in high-yielding technology to generate more surplus production (Asfaw et al., 2011; Fafchamps, 1992).

3.2. Estimation strategies

Following Ali and Abdulai (2010), the technology adoption decision is modeled within the random utility framework. Let T^* denote the difference between the utility from DTM adoption (U_A) and non-adoption (U_{NA}). A utility-maximizing farmer j will adopt DTM if the utility derived from adoption is greater than the utility from non-adoption such that $T^* = U_A - U_{NA} > 0$. Given that utility is unobservable, it can be expressed as a function of an observable element in the latent variable as follows:

$$T_j^* = \delta Z_j + \mu_j,\ \text{with} T_j = \begin{cases} 1\ if\ T_{ij}^* > 0 \\ 0\ otherwise \end{cases} \tag{1}$$

where T is a binary indicator variable that equals 1 if a farmer adopts DTM and zero otherwise, δ is a vector of parameters to be estimated, Z is a vector of explanatory variables associated with adoption, and μ is the random error term. Eq. (1) is the well-known probit model.

The probability of adopting[4] DTM is expected to be influenced by household, farm level, social network, and institutional factors. Education is expected to increase the probability of technology adoption. We expect adoption to be more associated with males than females. Access to extension services and market information are also expected to positively influence adoption. Subsidy and level of input use among smallholder farmers have been shown to influence DTM adoption (Carter et al., 2016; Holden and Fisher, 2015). We include subsidy to capture the effect of government support in the implementation of technologies. Membership of Farmer Based Organization (FBO) is included to ascertain how social network influences farm household decisions. Farmers that belong to an association are more likely to obtain financial support and a guaranteed market, thus increasing their technology adoption probability (Asfaw et al., 2011). The location of farm households also captures the agro-ecological differences (rainfall, altitude, infrastructure, resource endowment and farming conditions) that might influence the type of investment decisions made and subsequently yield and welfare outcomes (Asfaw et al., 2011). The role of transaction cost associated with marketing of agricultural inputs and outputs is captured by the distance to the local market. Transaction cost is expected to negatively influence DTM adoption. A detailed description of the explanatory variables is provided in Appendix 2.

DTM adoption is expected to increase yield, commercialization intensity, and crop revenue (outcome variables). If the outcome variables are a linear function of the adoption decision, along with a vector of other explanatory variables X, district dummy variables D_v, then the following equation holds:

$$Y_i = \varnothing X_i + \beta T_i + D_v + \varepsilon_i \tag{2}$$

where Y_i is the outcome variable, T_i represents an indicator variable for adoption, $\varnothing$ and β are parameter vectors to be estimated, and ε_i is an error term. The parameter β accurately measures the impact of adoption on the outcome variable under the condition that farmers are randomly assigned to treatment and non-treatment groups (Faltermeier and Abdulai, 2009). The estimation of β will be biased given that participation in the DTM program was not random.

The adoption decision is likely to be influenced by unobservable characteristics (e.g., innate abilities/motivation, managerial skills, and innovativeness) that may be correlated with the outcome variables. An upward bias will occur if the most skilled or motivated farmers choose to adopt. Within the context of our regression framework, ε will be correlated with adoption T and μ_j in Eq. (1). Conversely, farmers make the adoption decision based on anticipated benefits associated with the technology. In such a situation, the estimated effects of adoption on welfare outcomes will be biased using the OLS estimation procedure. This potential endogeneity problem can be addressed using the Instrumental Variable (IV) estimation technique. The first stage estimation is modeled such that the decision to adopt is determined by a set of exogenous covariates and instruments as follows:

$$T_i = \delta + H_i \vartheta + \mu_i \tag{3}$$

where $H_i = [X_i, X_i^*]$ is a vector of explanatory variables including the instrument X_i^* (access to DTM seed), δ and ϑ are parameters to be estimated, and μ_i is the random error term.

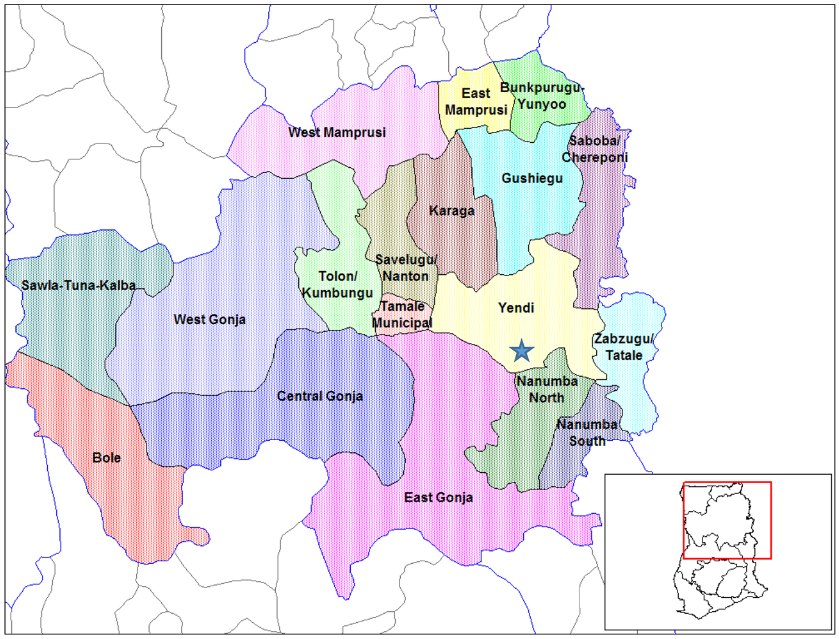
We use Durbin (1954), Wu-Hausman (Wu, 1974; Hausman, 1978) and Wooldridge (1995) robust score tests[5] to formally evaluate the hypothesis that DTM adoption is exogenous. A significant test statistic implies that the binary treatment variable is endogenous, thereby justifying the use of IV regression.

The potential endogeneity bias in the adoption decision is addressed by using access to DTM seed, which was randomly distributed to farmers in the target areas, as an instrument. A farmer with access to the seed is likely to be influenced to adopt it, thus creating a sub-population of adopters and non-adopters. Some studies have explored access to information as an instrument for adoption (Khonje et al., 2015; Sanglestsawai et al., 2015; Asfaw et al., 2012a, b; Di Falco et al., 2011; Dontsop-Nguezet et al., 2011). However, we argue that access to information alone is insufficient for technology adoption. Therefore, we propose access to DTM seed as an alternate instrument given the circumstances under which the DTM program was implemented. DTM seed was randomly assigned to farmers and was envisaged to act mainly as an instrument during the design of the experiment. That is, the principal means of identifying causal effect is through receipt of seed. The validity of this instrument is based on satisfying two core assumptions: (1) Relevance and (2) Exogeneity. The instrument should be relevant such that adoption is conditional on access to seed which may translate to an outcome effect. Access to DTM seed is highly significant in the first stage result which indicates the relevance of the proposed instrument. The strength of our instrument (access to DTM seed) is

[3] We acknowledge that the intervention could have an equilibrium effect, that is, if adoption is widespread and yields increase broadly in the economy, this could lower output prices and mitigate some of the positive impacts on incomes.

[4] See Negatu and Parikh (1999) for detailed discussion of agricultural technology adoption and the justification for choice of the explanatory variables influencing adoption.

[5] The Woodridge robust score test is associated with a 2SLS estimation where a robust standard error is specified.



Note: ★ represents Mion district

Fig. 1. Administrative map of the Northern Region of Ghana.

tested based on the F-statistic test proposed by Stock et al. (2002). Our results show that the F-statistic value is greater than 10 which indicates that the proposed instrument is not weak. Secondly, the instrument should satisfy the exogeneity condition based on the random assignment of seed. To check for the randomness of the instrument, we perform a balance test on all the explanatory variables. Results of the balancing test is reported in the appendix (Table A1). The results indicate that all the explanatory variables are balanced except for access to fertilizer subsidy which is significant at the 1% level. The fertilizer subsidy program is a national intervention targeted at smallholder farmers to boost productivity. However, fertilizer use is complementary to the DTM seed therefore, farmers who use the seed were encouraged to take advantage of the subsidy program. Thus, it is not surprising that access to DTM seed and the fertilizer subsidy program are correlated. From the foregoing, it can be assumed that our instrument is random and thus appropriate for identifying the causal effects of adoption.

We expect access to randomly assigned DTM seed to impact our outcome variables only through a change in adoption status. That is, we do not expect farmers' circumstances (yield, maize commercialization intensity, and income) to change just because they have access to seed unless they indeed adopt the seed. Therefore, we hypothesize that access to DTM seed will increase the chance of adoption although there may be issues of non-compliance (Awotide et al., 2016). Given that the DTMA Project was implemented throughout the country, we do not expect a strong correlation between our variables of interest and access to seed. Table A2 in the appendix shows the relationship between access to seed and adoption of DTM seed. Out of the 42 farmers who were randomly given the seed, 39 (93%) planted the seed while 3 (7%) did not.

3.3. Study area

The Northern Region (Fig. 1), one of the three regions that comprise northern Ghana, is the largest region in Ghana in terms of land mass covering a mostly low-elevation area of approximately 70,384 square kilometers. The region shares boundaries with the Upper East and the Upper West regions to the north, the Brong Ahafo and Volta regions, to the south, Togo to the east, and Cote d'Ivoire to the west. Generally, the climate of the region is relatively dry, with a single rainy season that begins in May and ends in October. The crops cultivated by the majority of agricultural households include maize, yam, millet, sorghum, rice, groundnuts, soybean and cowpea.

3.4. Data

The data used for the analysis were based on a farm survey of maize farmers conducted in August 2014. Two major maize-producing districts (West Gonja and Mion) in the Northern Region[6] of Ghana were surveyed. A multistage sampling technique was used in the districts, communities and households. The target districts and communities were purposively sampled, whereas households were randomly sampled. During the first stage, two districts were purposively selected within the Northern Region based on their volume of maize produced. During the second stage, 10 communities each were purposively selected based on accessibility, and availability of functional farmer groups from a list of communities in the two districts. Finally, 10 maize producers were randomly selected from a list of maize producers within each of the selected communities. A total of 200 households were sampled from 20 communities. The simple random sampling employed to select the maize farmers in the communities is a probability sampling approach. Therefore, concerns regarding non-randomness of the sample are minimized. We also conducted a power test for the sample used. The power test is the chance to reject the null hypothesis given that the null hypothesis is false. It is the process of determining the sample size for a study. Given the intended sample size, we can derive the resulting power of the sample. Following Yamane (1967): $n = (N/1+Ne^2)$, where N denotes the total population of farmers in the Northern Region of Ghana, 2,479,461 (Ministry of Food and Agriculture (Ministry of Food and Agriculture, MoFA, 2011); e denotes the margin of error of the sample, and n denotes the sample size. The derived margin of error of the sample is 7% (given the sample size of 200 maize farmers used in this study) which is considerable in social science research. This implies that we are 93% confident in the results obtained from the sample.

[6] In 2019, two new administrative regions (i.e. North East and Savannah) were carved out of the Northern Region. Mion is still in the Northern Region while West Gonja now falls under the Savannah Region.

Table 2
Descriptive summary of selected variables.
Source: Authors' calculation using farm survey data

Variable	Full Sample (n = 200)		Adopters (n = 104)		Non-adopters (n = 96)		Difference	Prob.
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.		
Outcome variables								
Yield (kg/ha)	2441.16	3212.65	2737.8	2454.7	2119.8	3858.28	618.04	0.17
Intensity of maize commercialization	0.39	0.37	0.52	0.36	0.25	0.34	0.27	0.00
Maize income (GHS/ha)	1171.04	1529.09	1439.19	1461.44	880.55	1555.01	558.65	0.00
Household characteristics								
Age of household head	47.39	13.61	46.69	14.15	48.14	13.04	−1.44	0.46
Sex of household head	0.97	0.17	0.98	0.14	0.96	0.2	0.02	0.36
Formal education	2.99	5.35	4.15	6.06	1.73	4.12	2.42	0.00
Farm characteristics								
Farm size	3.241	5.66	1.33	1.07	1.65	2.98	−0.33	0.30
Access to labor	0.26	0.44	0.4	0.49	0.09	0.29	0.31	0.00
Knowledge of fertilizer	0.85	0.36	0.95	0.22	0.74	0.44	0.21	0.00
Contract farming	0.13	0.33	0.2	0.4	0.04	0.2	0.16	0.00
Cropping systems	0.46	0.5	0.64	0.48	0.27	0.45	0.36	0.00
Institutional factors								
Access to extension service	0.15	0.35	0.22	0.42	0.06	0.24	0.16	0.00
Subsidy	0.27	0.44	0.34	0.48	0.19	0.39	0.15	0.02
District	0.5	0.5	0.69	0.46	0.29	0.46	0.4	0.00
Distance to local market	5.37	7.15	5.42	4.23	5.31	0.96	0.11	0.92
Access to seed	0.76	0.43	0.84	0.37	0.68	0.47	0.16	0.00

Note: Difference is computed as the mean of adopters minus the mean of non-adopters. GHS represents Ghana cedi. 1 USD = GHS3.215 (Source: Bank of Ghana, 2016).

Therefore, the sample is highly representative, and the results can be generalized for the population of maize farmers in the 20 selected communities in the West Gonja and Mion districts in the Northern Region of Ghana.

The data collected captured household demographic and farm characteristics, soil improvement technologies, crop production, income and expenditure, household experience with credit and shocks, information and social interventions, commercialization and food security. Table A3 in the appendix shows how we defined and measured the variables used for the study. Note that the data that we utilized are self-reported farmer responses collected through administration of a semi-structured questionnaire. Even though farmer surveys and self-reported data have some limitations, the authors took steps to guarantee that the data were of high quality. Prior to the survey, enumerators with at least a Higher National Diploma (polytechnic degree) were recruited and trained for 3 days. The training included a thorough discussion of the questionnaire, definition of concepts, ethical issues in social research, field practice, and role playing using the major local languages. The authors also engaged supervisors who were tasked to backstop the enumerators during farmer interviews and check completed questionnaires daily for possible errors that were corrected before leaving the sampled communities.

Indicators for farm and welfare outcomes are yield (measured as the total maize output per hectare), intensity of maize commercialization (measured as the ratio of the value of maize sold to the value of total output) and crop income (i.e. the market value of a hectare of maize).

4. Results

4.1. Socioeconomic characteristics of the sample households

Table 2 shows the summary statistics and statistical significance tests of the equality of means for continuous variables and equality of proportions for binary variables for both adopters and non-adopters. The result shows that 52% of the sampled households adopted DTM varieties. Average maize yield is 2.4 tons per hectare. An average household sells approximately 40% of their maize produce which translates into GHS 1171.00. Adopters and non-adopters have no significant differences in yield, but the opposite holds for the maize commercialization intensity and income. All three outcome variables are higher for the adopters in comparison to non-adopters. For example, adopters recorded yield, commercialization, and income values of 2.7 tons per hectare, 52% and GHS 1439.00, respectively, while non-adopters recorded 2.1 tons per hectare, 25% and GHS 881, respectively (Table 2).

A statistically significant difference is observed in the means of all variables except for age, sex of the household head, farm size, and distance to local market. For all the significant observables, adopters have relatively higher values than non-adopters. Non-adopters have higher landholdings than adopters. DTM adopters who reside in the West Gonja District of the Northern Region are more likely to receive market information compared to non-adopters.

4.2. Determinants of drought-tolerant maize adoption

Table 3 presents the maximum likelihood estimates of the probit model (Eq. 1). The probit model was used to estimate the conditional probability of adopting DTM given observed household characteristics.

Table 3
Probit model estimates of adoption of drought-tolerant maize varieties.
Source: Authors' calculation using farm survey data

Variables	Marginal Effects	
	Coefficient	Robust Standard Error
Access to seed (1 = yes)	0.355***	0.088
Sex of household head (1 = male)	0.349**	0.152
Formal education (1 = formal)	0.004	0.005
Member of FBO (1 = member)	−0.046	0.077
Access to extension (1 = yes)	0.235**	0.097
Distance to local market	−0.003	0.003
Access to market information (1 = yes)	0.017	0.073
Access to subsidy (1 = yes)	0.105	0.066
Available labour (1 = yes)	0.259***	0.068
Location of farmer	0.222***	0.057
Number of observations	200	

Notes: ***Significant at 1% level, **Significant at 5% level, and *Significant at 10% level.

The coefficient and marginal effects are both reported in Table 3. DTM adoption is significantly and positively influenced by the sex of the household head, seed access, extension, labor and farmer location. Among these factors, seed access both statistically and numerically has the greatest effect on DTM adoption.

Farmers with access to seed are 36% more likely to adopt DTM relative to those without access. Several factors have been identified in the adoption literature as constraints to adoption. Notable among these factors is the lack of credit to facilitate implementation of improved technologies. Therefore, making seed available to farmers increases their adoption probability. The adoption probability is higher for male farmers than for female farmers. The probability of adopting DTM is 35% higher among male farmers than female farmers. Female farmers are typically resource-constrained, limiting their likelihood of technology implementation. In the study area, males tend to have more access to more productive farm land and other incentives that enhance their adoption decisions. The results show that the overwhelming majority of households are headed by males.

Access to extension service increases the probability of adopting DTM. Farmers with access to extension are 24% more likely to adopt DTM than those without. In Ghana and parts of Sub-Saharan Africa, the use of public extension agents is heavily relied upon to deliver technologies to farmers despite the inadequacy of personnel and logistics (Lamontagne-Godwin et al., 2017). Access to labor increases the probability of DTM adoption by 26%. Access to hired labor in northern Ghana is often limited during specific times of the production season. The use of family labor is common among farm households in the study area, particularly in locations where a larger household size is maintained. Nevertheless, there may be competing needs (on-farm and off-farm activities) among household members that may limit their engagement time on the field during peak times of the season when it is needed most. Therefore, labor availability will favor DTM adoption.

Location plays a significant role in the adoption decision of farmers. Farmers who reside in the West Gonja District are 22% more likely to adopt DTM than farmers who reside in the Mion District. Farmers that reside in higher than normal temperatures and drought-prone areas are more likely to adopt DTM as an adaptation mechanism to erratic and harsh climatic conditions. The Mion district experience relatively higher rainfall than the West Gonja district, therefore, the higher the likelihood of the adoption of the climate smart technologies in the that district (CHIRPS, 2017)[7] .

4.3. Yield and welfare effects of drought-tolerant maize adoption

This section begins with a presentation of the estimated effects of DTM adoption on yield, commercialization intensity and crop income using two different estimation procedures (Tables 4 and 5). DTM adoption impacts positively on yield and commercialization intensity. Table 4 reports the results of the IV estimation procedure using direct 2SLS. Table 5 shows the results of the instrumental variable estimation technique in which a probit model was estimated during the first stage and then followed by a two-stage least squares (2SLS) estimation.

Columns (1), (3) and (5) represent the regression without district controls whereas columns (2), (4) and (6) includes the district controls. The estimation procedure allows for the estimation of DTM adoption on the treated group (ATET), untreated group (ATENT) as well as the average treatment (ATE). The coefficient of the instrument from the first stage regression is highly significant at the 1% level of significance with high F-statistic values across the different specifications. Following Stock et al. (2002), we can conclude that the instrument is not weak because all the F-statistic values are greater than 10. Second, the insignificance of the robust score chi-square value in the yield and crop income estimation indicates that the adoption of the DTM seed variable is exogenous (Tables 4 and 5). However, the variable is endogenous in the estimation of the commercialization intensity outcome making OLS estimation inconsistent. According to Wooldridge (1995), the 2SLS estimation is consistent even when the adoption variable is exogenous. Based on the test, we can conclude that the methods employed in this study are appropriate.

The impact of DTM is underestimated in the absence of the district level controls. Failure to consider the district level controls could lead to a biased estimate of the causal effect. The estimated effects of adoption on yield and commercialization intensity differ across models. However, crop income was not significant across the different specifications (Tables 4 and 5). The direct 2SLS results show that DTM adoption increases maize yield and commercialization intensity across the entire population by 193.4% (692 kg/ha) and 0.42 (Table 4), respectively, without considering district controls. However, the estimated effect increases to 207% (791 kg/ha) and 0.46 (Table 3), respectively, when the district variables are included in the regression. These results show that DTM adopters realize a yield effect of 2487.75 kg/ha (without district controls) and 2587.05 kg/ha (with district controls). Similarly, commercialization intensity increases by 0.67 (without district controls) and 0.71 (with district controls) among DTM adopters.

Results of the probit-2SLS show that DTM adoption increases yield and commercialization intensity by 174% (369 kg/ha) and 0.45, respectively, without district controls (Table 5). The yield and commercialization intensity increased by 224% (936 kg/ha) and 0.35, respectively, after including the district controls in the regression (Table 4). DTM adoption also impacts positively on crop income but is statistically insignificant. The average treatment effect on the treated (ATET) and untreated (ATENT) are both statistically insignificant for all columns.

Fig. 2 shows the distribution of the three sub-population units (ATE (x), ATET(x) and ATENT(x)) resulting from the probit-2SLS estimation. The figure also shows the distribution of yield, commercialization intensity and income. It can be observed that ATE(x) and ATET(x) of the yield outcome variable are more uniformly distributed with their highest modal value at 200% (739 kg/ha). ATENT(x) records the highest modal value of an approximately 100% (272 kg/ha) yield, thereby predicting that non-adopters would have recorded less yield if they had adopted DTM. For the commercialization intensity, the distribution of ATE(x) is dispersed in two peaks. The highest modal value is recorded at 50% which is consistent with the modal value of ATET(x). The ATENT(x) is slightly skewed to the left with a modal value of 30%. We also observed that ATET(x) is more uniformly distributed with a 50% modal value, followed by ATE(x) and ATENT(x) in that order at modal values of 50% and 35%, respectively. An overlap exists between the yield and production outcomes. Commercialization intensity seems to be more skewed towards the left with the highest modal value of 0.1 (10%) commercialization.

The skewed distribution for farmers with access to seed (ATET) is a confirmation that farmers with access to seed benefit more from DTM adoption. The reverse holds for farmers without access to seed (ATENT). Except for the level of kurtosis, the distribution of income does not markedly vary across access status (ATE, ATET and ATENT) as already indicated.

5. Discussion

This section begins with a discussion of the factors that influence DTM adoption and the impact of DTM adoption on yield, income and commercialization intensity using the IV estimation technique. The results provide empirical evidence of the relevant factors that influence DTM adoption in the Northern Region of Ghana.

5.1. Determinants of DTM adoption

DTM adoption is more likely for male farmers who reside in the West Gonja District and have access to seed, extension service, and

[7] Climate Hazard Infrared Precipitation with Station Data

Table 4
Direct-2SLS estimates of the impact of DT maize adoption.

	Direct-2SLS					
	Yield (log)		Intensity of commercialization		Crop income (log)	
	(1)	(2)	(3)	(4)	(5)	(6)
Adoption of DT Maize	1.934**	2.068**	0.418**	0.459**	0.534	0.583
	(0.773)	(1.092)	(0.163)	(0.219)	(0.703)	(0.644)
First stage -instrument						
Access to seed	0.374***	0.289***	0.374***	0.289***	0.314***	0.250***
	(0.069)	(0.075)	(0.069)	(0.075)	(0.070)	(0.075)
Mean of control group	1796.051	1796.051	0.248	0.248	997.532	997.532
Diagnostics						
F-stat	28.99	14.87	28.99	14.87	20.14	10.99
Robust score chi2 (1)	0.241	0.233	2.876*	2.401	0.648	0.397
District controls	No	Yes	No	Yes	No	Yes
Observation	200	200	200	200	200	200

Notes: Robust standard errors in parenthesis. ***Significant at 1% level, **Significant at 5% level, and *Significant at 10% level. Source: Authors' calculation using farm survey data.

Table 5
Probit-2SLS estimates of the impact of DT maize adoption.
Source: Authors' calculation using farm survey data

	Probit-2SLS					
	Yield (log)		Intensity of commercialization		Crop income (log)	
	(1)	(2)	(3)	(4)	(5)	(6)
Adoption of DT Maize						
ATE	1.735**	2.236**	0.492**	0.353**	0.193	0.534
	(0.875)	(0.907)	(0.224)	(0.170)	(0.714)	(0.644)
ATET	2.167	2.742	0.548	0.433	0.208	0.663
	(6.066)	(2.465)	(1.017)	(0.980)	(2.178)	(2.377)
ATENT	1.268	1.689	0.432	0.266	0.173	0.357
	(2.985)	(1.604)	(0.603)	(0.395)	(1.664)	(1.296)
Mean of control group	1796.051	1796.051	0.248	0.248	997.532	997.532
First stage -instrument						
Access to seed	1.528***	1.306***	1.528***	1.306***	1.364***	1.188***
	(0.348)	(0.356)	(0.348)	(0.356)	(0.358)	(0.366)
Diagnostics						
F-stat	28.99	14.87	28.99	14.87	20.14	10.99
Robust score chi2(1)	0.241	0.233	2.876*	2.401	0.648	0.397
District controls	No	Yes	No	Yes	No	Yes
Observation	200	200	200	200	200	200

Notes: Robust standard errors in parenthesis. ***Significant at 1% level, **Significant at 5% level, and *Significant at 10% level.

labor. The findings indicate that DTM adoption increases among farmers who have access to improved seed. Resource poor farmers typically rely on recycled seed for subsequent production seasons, thus exposing them to low yield and eventually low income and commercialization intensity. Making seed accessible to farmers through either direct support from NGOs or input subsidy programs from government can enhance adoption of improved technologies. Most of the development projects in Ghana have focused on breeding for new varieties, seed multiplication and financial assistance to input dealers (to make seed readily available to smallholder farmers). Some studies have also underscored the importance of facilitating seed access to farmers. For example, Wiredu et al. (2014) argued that enhancing seed access is necessary for adoption of technology that translates to a higher farm income. Buah et al. (2011) also emphasized that easy access to seed reduces operational costs and increases farm income. The implication of the result is that efforts to improve farm level DTM adoption and consequently welfare must include the provision of seeds.

Technological adoption in Africa tends to favor male farmers. Some technologies disseminated by agricultural development projects are not gender sensitive making it more difficult for females to adopt. In some cases, high labor requirements are complements to these technologies which subsequently increase the production cost. The high financial commitment is a challenge to most female farmers limiting their use of such technologies. There must be a conscious effort to invest in technologies that are gender sensitive and less costly to increase adoption across gender.

Access to extension services has been repeatedly shown to enhance adoption of improved technologies despite the limited support that extension service receives from African governments. Farmers are typically exposed to the benefits and inherent characteristics of improved technologies by extension officials through farmer field fora, field days and demonstration plots. Currently, the use of innovation platforms has also become a medium through which extension information is communicated to farmers. Khonje et al. (2015) showed that access to extension service increases the probability of adopting improved maize varieties in Eastern Zambia. Asfaw et al. (2011) also found that access to extension increases the probability of adopting pigeon pea in Tanzania and chickpea in Ethiopia by 14% and 8%, respectively. Extension delivery systems will continue to play critical roles in technological adoption if the needed support, such as logistics and funding, are provided on a regular basis. For effective communication and demonstration to smallholder farmers, it is also necessary for extension officials to be frequently trained to keep abreast with the latest technologies developed by research institutions.

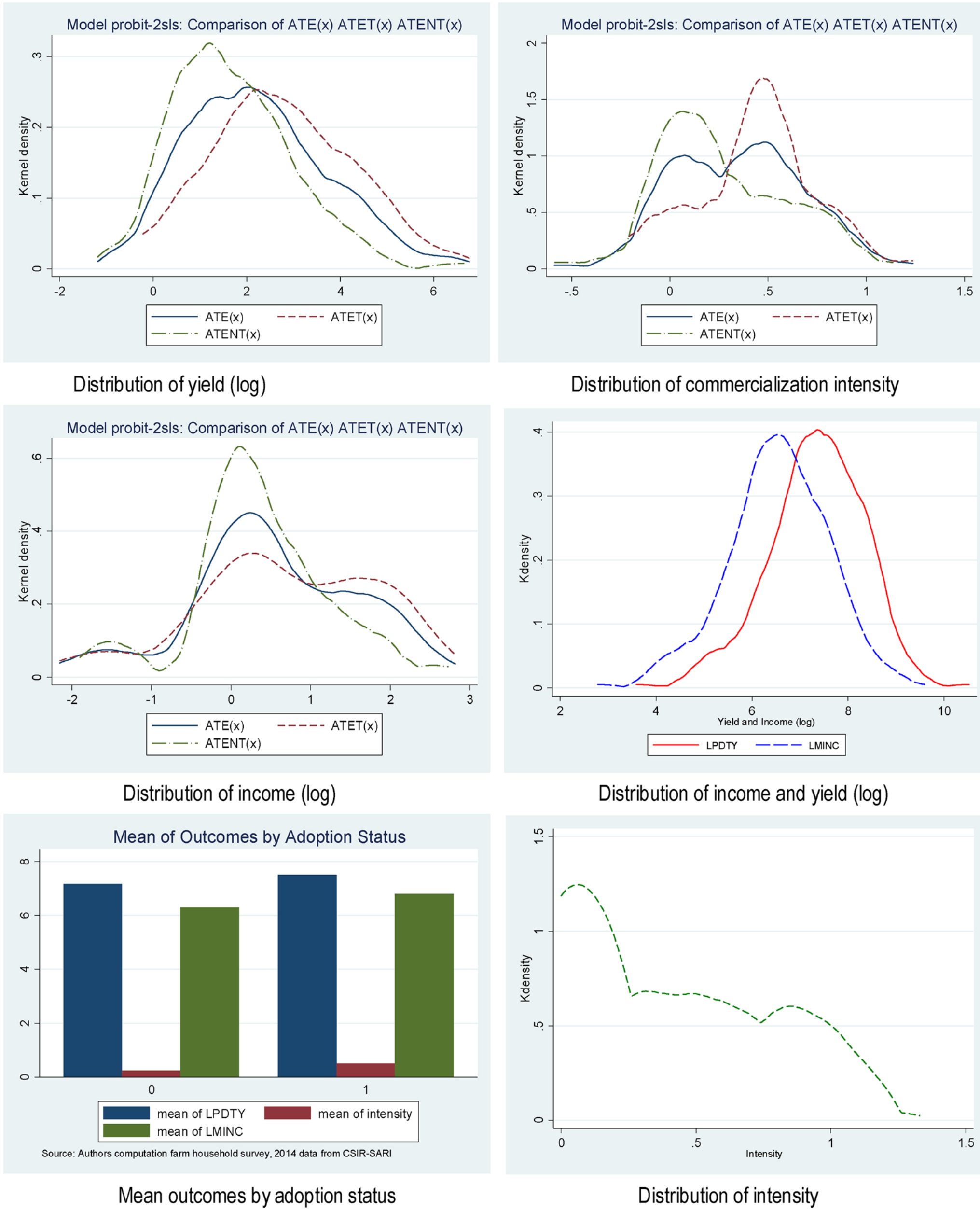


Fig. 2. Distribution of ATE(x), ATET(x) and ATENT(x) and outcomes.

Location of farmers plays a major role in the adoption of improved technologies such as DTM. Farmers in drier locations are more likely to adopt technologies that can withstand their harsh climatic conditions. This result is consistent with the findings of Makate et al. (2017) who suggested that farmers that reside in drier locations recognize the importance of adopting DTM varieties as an adaptation response to erratic and worsening climatic conditions. To ensure wide adoption at all locations, high volumes of DTM seed should be produced by research institutions and multiplied by seed producers and effectively marketed to enhance farmers' access.

5.2. Impact of DTM on yield, commercialization intensity and income

DTM adoption significantly increases yield and commercialization intensity among smallholder farmers in the Northern Region of Ghana. From the results, we can infer that the increase in maize productivity leads to a significant increase in commercialization and an insignificant increase in income. The results suggest that DTM may not necessarily increase income despite significant and positive levels of yield and commercialization intensity. The insignificant effect of DTM adoption on income is one result that requires further research. This could be attributed to the fact that non-adopters may have better marketing and negotiating skills, thereby obtaining higher prices for their products and consequently higher incomes. Market conditions such as low-price regimes because of a high supply may also significantly contribute to the reduction in economic gains from high commercialization intensity. This result is consistent with the findings of Makate et al. (2017) who showed that DTM adoption increases yield, sales and personal household consumption in rural Zimbabwe.

The Northern Region of Ghana is confronted with high temperatures and erratic rainfall which typically threaten food production and livelihoods. Farm households are the most affected unit of the population during the dry season. Most farm households, because of long dry period, migrate out of the region to seek better opportunities in the southern part of the country while others resort to collection of fruits and sale of livestock as coping mechanisms. Household food consumption is significantly reduced during this period exposing household members to several forms of illness and stunted growth, which can ultimately lead to death in some extreme cases. This study therefore underscores the importance of promoting climate-smart technologies such as DTM varieties among smallholder farmers. DTM adoption will be high if seed is readily accessible to farmers when most needed, particularly before the growing season. Finally, food availability, which is an integral component of food security, will be realized if there is a conscious and joint effort from both development practitioners and governments to support the development, promotion and marketing of DTM seeds.

6. Conclusions

This study investigated the determinants and impacts of adoption of drought-tolerant maize on yield, commercialization intensity and income in northern Ghana using data from 200 farm households. The causal impact of DTM adoption was estimated using an IV estimation technique with different model specifications. The probit model estimation suggests that DTM adoption is determined by seed access, extension service, labor availability, and location of farm households. Seed access both statistically and numerically had the greatest effect. This shows the practical significance of seed access on DTM adoption.

The IV estimation showed that adoption of DTM varieties led to significant gains in yield and commercialization intensity. The results further showed that the magnitude of the effect of DTM adoption on the outcome variables varied across the IV specifications. Compared to a direct-2SLS, a probit-2SLS provides a better estimate of the yield equation. These findings are important for understanding how smallholder farmers make decisions regarding the adoption of climate-smart agriculture and the subsequent welfare impacts. Despite the limitations in the use of cross-sectional data, and the instrument, this study significantly contributes to the adoption literature, particularly as it relates to the Northern Region of Ghana, where drought is a major challenge to smallholder agriculture. Agricultural productivity and commercialization intensity can be enhanced by implementing systems that increase seed access. The need to understand how DTM adoption changes over time (given the development of other improved maize varieties) under different seed policy systems remains an important topic for future research.

Author statement

The authors declare that this manuscript is original and there is no conflict of interest.

Declaration of Competing Interest

The authors declare that they have no competing interests, neither financial nor non-financial.

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Appendix A

Table A1
Balance test.

Variables	Access to seed Mean	Non-access to seed Mean	*p* value
Distance to local market	0.795	0.763	0.738
Sex	0.974	0.984	0.769
Access to extension services	0.231	0.227	0.972
Knowledge of fertilizer	0.974	0.974	0.986
Contract farming	0.256	0.182	0.433
Cropping system	0.590	0.644	0.629
Formal education	5.000	5.862	0.560
Age of household head	44.821	43.806	0.711
Farm size	2.988	3.285	0.676
Access to labour	0.436	0.388	0.673
Subsidy	0.462	0.186	0.009

Table A2
Compliance and non-compliance.

	Adoption of DTM seed		Total
Access to DTM seed	Non-adopt	Adopt	
Non-access	93	65	158
Access	3	39	42
Total	96	104	200

Table A3
Description of explanatory variables.

Variable	Description	Measurement
Yield	Quantity of maize produced per hectare	Kilogram per hectare
Commercialization intensity	Share of total production sold	Ratio
Maize Income	Market value of a hectare of maize (i.e., product of price and quantity)	Ghana cedi per hectare
Access to improved seed	Measures if a farmer receive a DTM variety	1 = Yes 0 = Otherwise
Sex of household head	Measures the sex of a farmer	1 = Male 0 = Female
Formal education	Number of years farmer was in school	Years
Member of FBO	Measures if a farmer belongs to an FBO	1 = Member 0 = Otherwise
Access to extension	Measures if a farmer had contact with an extension officer	1 = Yes 0 = Otherwise
Distance to local market	Distance to local market	Kilometers
Access to market information	Measures if a farmer has information on prices of commodities	1 = Yes 0 = Otherwise
Access to subsidy	Measures if a farmer benefitted from government's subsidy on fertilizer and seed	1 = Yes 0 = Otherwise
Available labor	Measures if a farmer faced some constraints in accessing farm labor	1 = Yes 0 = Otherwise
Location of farmer	Residence of farmer	1 = West Gonja 0 = Mion

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.landusepol.2020.104524.

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