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Productivity impact of drought tolerant maize varieties under rainfall stress in Malawi: A continuous treatment approach

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Abstract

Drought tolerant (DT) maize varieties have received massive support in sub-Saharan Africa because of their potential to protect smallholder farmers against drought-related maize yield losses. Using four waves of household farm panel data from six districts in Malawi, we examine the impact heterogeneity of this technology on maize productivity using a continuous treatment approach. We find strong evidence of positive correlation between maize yield and adoption of DT maize varieties. On average, an increase by one hectare in the area allocated to DT varieties increases maize yield by 547 Kg/ha representing a 44% increase from the average maize yield of 1,254 Kg/ha for our sample. Our findings give evidence that DT maize technology has potential to protect smallholder farmers against drought-related production losses. Policies that promote increased allocation of maize area to DT maize hold potential to enhance food security. Smallholder farmers especially in drought-prone areas should be encouraged to allocate at least one-third of the maize plot to DT varieties while breeders continue with the efforts of breeding a DT variety that is not only drought tolerant but also adapted to all weather conditions. More importantly, the government should ensure provision of timely ex ante weather information to guide farmers on decision-making with respect to maize varietal choices.

KEYWORDS
dose–response function, drought tolerant, maize, productivity, rainfall stress

JEL CLASSIFICATION
D13, O13, O33, Q18, Q56

1 | INTRODUCTION

Maize is the single most important food crop in Malawi whose availability equates to food security (Smale, 1993). Annual maize consumption per capita in Malawi is one of the highest in Africa, estimated at 129 kg and makes approximately 90% and 54% of total cereals and caloric per capita intake, respectively (Derlagen, 2012). Maize takes over 90% of productive land under cereals and is dominated by smallholder farmers where about 97% of them grow maize (Denning et al., 2009). The crop is heavily dependent on rainfall during a single rainy season which covers at least 4 months from November/December to March (Nicholson, Klotter, & Chavula, 2014), and this rainfall is erratic and unpredictable (Jayne & Rashid, 2013; Kassie, Teklewold, Marenya, Jaleta, & Erenstein, 2015b).

The rainfall variability includes frequent dry spells and can reduce maize productivity by close to half and hence exacerbates the country's food insecurity problems (CIMMYT, 2013).

In a country characterized by poor and/or missing markets for credit, insurance and off-farm employment, investing in agricultural technologies that reduce vulnerability and risks of yield loss due to weather related shocks is an important alternative option (Davies, Guenther, Leavy, Mitchell, & Tanner, 2009; Kassie, Teklewold, Jaleta, Marenya, & Erenstein, 2015a; Pangapanga, Jumbe, Kanyanda, & Thangalimodzi, 2012). Drought tolerant (DT) maize varieties is one potential technology that has been developed to help smallholder farmers cope with drought and drought-related constraints. It is estimated that DT maize can produce up to 30% of their potential yield after 6 weeks of water stress, before and during flowering and grain-filling (Magorokosho, Vivek, & MacRobert, 2009). On-farm field experiments conducted across several countries in Southern Africa indicate that DT maize varieties can give a yield advantage of up to 40% over other maize varieties under severe drought environments (Tesfaye et al., 2016).

Given potential relevance of this technology to Malawi and several countries in sub-Saharan Africa (SSA), empirical evidence beyond ex ante analysis, and on-farm and on-station experiments is of particular importance. This paper adds to the body of literature by examining the impact of DT maize varieties on maize productivity in Malawi. This analysis is necessary because the increase of dry spells in the region is one of the major causes of low maize production and productivity besides low levels of nitrogen intake and soil depletion (Weber et al., 2012). Investment in appropriate technologies with hedging effect against dry spells has potential to increase yield or reduce yield loss. Thierfelder et al. (2017) for example reported that investment in conservation agriculture has a yield impact of 38–66% when a drought occurs while Arndt, Pauw, and Thurlow (2015) reported double dividends of improved yield and drought tolerance when DT maize seed was included in Farm Input Subsidy Program (FISP) in Malawi.

There have been some studies on this subject across countries in SSA and the results are mixed. For example, Holden and Fisher (2015) and Fekadu and Endeshaw (2016) found insignificant yield advantage of DT maize over other improved maize varieties except for local maize in Malawi and Uganda, respectively. On the other hand, Cenacchi and Koo (2011) reported positive impact of DT maize adoption on yields across all agroecological zones in several countries in SSA. Idrisa, Abdoulaye, Mohammed, and Ibrahim (2014), Radda (2015), and Awotide, Abdoulaye, Alene, and Manyong (2016) observed that adoption of DT maize significantly reduced food insecurity, increased crop yield and household welfare among farmers in Nigeria. In Zimbabwe, Makate, Wang, Makate, and Mango (2017) and Lunduka, Mateva, Magorokosho, and Manjeru (2019) reported that adoption of DT maize significantly enhanced overall maize productivity and consequently market surplus and household consumption. These findings indicate that the yield advantage of the DT maize is present primarily in drought years and such varieties may on average perform better in areas with higher frequency of droughts.

We investigate this further in this paper and make novel contributions to the body of literature in two main ways. First, our paper uses household farm panel data capturing important rainfall variation over time and space to examine the impact of DT maize on maize yield. The reviewed studies have used cross-sectional data that fails to capture unobserved heterogeneity. Our data spans 9 years from 2006 to 2015 and is of interest to this particular study as it captures three different rainfall scenarios, namely, normal-to-average rainfall in 2006 and 2009, early droughts in 2012, and early floods with late droughts in 2015. Second, we apply a continuous treatment approach (Cerulli, 2015), unlike the studies reviewed that have used binary treatment variable. The continuous treatment method allows assessment of dose–response function (DRF) and marginal treatment function (MTF) across different DT maize adoption levels. The DRF is synonymous to average treatment effect on the treated (ATET) while the MTF is equivalent to marginal treatment effect on the treated (MTET). The dose in our case captures the intensity of DT maize adoption in terms of acreage of land in hectares (ha) planted with DT maize varieties relative to total maize area while the response refers to the maize productivity in kg/ha. Thus, the dose is captured as a proportion of maize area allocated to DT maize varieties.

1.1 | DT maize varieties in sub-Saharan Africa

Drought tolerant maize seed has been a vital component in breeding programs since late 1990s across countries particularly in SSA because of recurrent droughts (Bänziger, Setimela, Hodson, & Vivek, 2006). In mid 2000s, the International Maize and Wheat Improvement Centre (CIMMYT) and the International Institute of Tropical Agriculture (IITA) launched a Drought Tolerant Maize for Africa (DTMA) project to support development and dissemination of DT maize varieties in SSA. Since then over 200 DT maize varieties have been released across 13 DTMA countries (Angola, Benin, Ethiopia, Ghana, Kenya, Malawi, Mali, Mozambique, Nigeria, Tanzania, Uganda, Zambia, and Zimbabwe) reaching over 43 million smallholder farmers. The DTMA project was jointly implemented among National Agricultural Research Systems (NARS) by CIMMYT and IITA and concluded in December 2015 (Wawa, 2016, unpublished report by CIMMYT).

In Malawi, DT maize has received enormous support from the government, private and other public institutions where among other avenues, the seed has been an integral component in the Farm Input Subsidy Program (FISP). FISP effectively enhances availability and affordability of the seed (Holden & Fisher, 2015). As of December 2015, 18 DT maize varieties (15 hybrids and three open pollinated varieties [OPV]) were released under the DTMA project (Abate, 2015). Adoption has since been increasing over the years (Fisher et al., 2015; Holden & Fisher, 2015; Holden & Quiggin, 2017; Katengeza, Holden, & Lunduka, 2019). In addition to the FISP, exposure to recurrent droughts has been another important factor driving adoption. This could be related to the varieties' better performance under rainfall stress assuming farmers are able to observe and compare yield of different maize varieties under drought growth conditions.

1.2 | Distribution of DT maize seed varieties in Malawi

DT maize varieties in Malawi are either hybrids or OPVs (Abate et al., 2017; Lunduka, Fisher, & Snapp, 2012) whose development, regulation and certification across the country is greatly managed by the public sector. The varieties are then made available to seed companies for multiplication and are provided to smallholder producers via agrodealers (KIT, 2016). For the past 15 years, distribution has been influenced by FISP where both hybrid and OPV seeds are provided to farmers at subsidized rates. The beneficiaries are entitled to either a 2-kg bag of hybrid seed or a 4-kg bag of OPV (Ricker-Gilbert & Jones, 2015) of which some are DT varieties. The deliberate inclusion of DT maize varieties in the FISP package has seen an increase in availability of the seed across the country and are easily accessible by smallholder farmers. Holden and Fisher (2015) for example reported that 69–82% of input subsidy beneficiaries redeemed DT maize seed varieties. It is however uncertain whether the demand of the DT seed will remain outside FISP.

DT OPV varieties include ZM309 and ZM523 while hybrid DT include SC403 as reported in Table A4. OPVs are however not popular among the farmers in Malawi despite being widely available (KIT, 2016). For instance, Lunduka et al. (2012) found that 98% of input subsidy beneficiaries who redeemed DT maize seed, redeemed hybrid seed. A focus group discussion by KIT (2016) collaborated this finding by reporting that farmers prefer hybrid to OPV varieties due to the greater discount. Hybrid maize varieties are relatively more expensive in Malawi than other varieties hence farmers take advantage of the subsidies to access the seed. KIT (2016) reported an average price of 362 Malawi Kwacha (MK)/kg for a hybrid seed compared to MK254 for OPV and MK301 for local. Without subsidies, the average hybrid seed price was MK563/kg while with subsidies it was reported as MK273/kg. It should however be noted that the major varietal price variations are between hybrids, OPVs and local and not necessarily between DT and non-DT.

2 | THEORETICAL FRAMEWORK, EMPIRICAL MODEL, AND ESTIMATION STRATEGY

2.1 | Theoretical framework

Production under uncertainty where different states of nature are possible but not known to the producer at planting time can be presented as a state-contingent production framework (Chambers & Quiggin, 2000; Quiggin & Chambers, 2006). The state-contingent model assumes x different inputs, s possible states of nature and y distinct outputs. Input $x \in \Re_{+}^{X}$ allocation decision and the choice for a state contingent output $y \in \Re_{+}^{S*Y}$ are made ex ante (that is before the state of nature is revealed). Inputs are then fixed and output produced ex post (Quiggin & Chambers, 2006). The technology can then be summarized as $T = [(x, y) : x \text{ can produce } y]$. Given output price (p_y) and input price (p_x), the technology can be expressed as a cost function $C\ (p_{x,}y) = \min[p_x x|(x, y) \in T]$ or as a demand function $x\ (p_{x,}y) = \operatorname{argmin}[p_x x|(x, y) \in T]$.

Assuming two states of nature (s_1 & s_2) of which state one (s_1) is unfavorable, the farmer's interest is to maximize output (y). The farmer's problem is choice under uncertainty whereby s_1 is unfavorable if and only if $y_1 < y_2$. In this case, a farmer can decide to adopt more risk-substituting or risk-complementary inputs. Holden and Quiggin (2017) noted that an increase in probability of s_1 will lead to an increase in adoption of risk-substituting inputs for a given expected output. In the context of this paper, farmers in Malawi are more likely to adopt risk-substituting maize varieties in order to adapt to frequent dry spells. An input x_j is a risk-substituting (complementary) at y^0 (state-contingent output) if $y^0 \precsim y' \Rightarrow x_j(p_x, y') \geq x_j(p_x, y^0)(x_j(p_x, y') \leq x_j(p_x, y^0))$ where y' is a riskier output. This implies that for a given expected output, less risk-averse producers will choose more risky state-contingent output plan while more risk-averse producers will use more risk-substituting than risk-complementary inputs (Chambers & Quiggin, 2000).

Given that the farmer's objective is to maximize expected utility [EU(.)] from output y, the adoption decision of alternative inputs can be modeled as an optimal land allocation problem (Ding, Schoengold, & Tadesse, 2009). If we assume p_x and p_y are nonrandom and that smallholder farmers are price takers, the only source of uncertainty is climatic risks. An individual farmer will allocate a mix of inputs (X) to maximize expected utility from output (y). We can therefore specify the farmer's optimal land allocation problem as $\max_X E\ [U(\pi)] = \max EU[p_y y - p_X(X)]$. Thus, farmers will adopt DT maize variety if and only if $[EU(\pi_1^{DT})] >$ $[\mathrm{EU}(\pi_1^{nonDT})]$. Our interest in this paper is to examine whether maize yield under drought stress (y_1) is greater for DT maize adopters than those who grew other maize varieties such as other improved non-DT maize (OIM) and local maize (LM) varieties. If yield for DT maize is higher than other maize varieties under rainfall stress growth conditions, then DT maize variety is a risk-substituting technology, otherwise it is risk-complementary. Given that the majority of smallholder farmers in Malawi adopts a portfolio of maize varieties due to differences in consumption, drought tolerance and production traits (Lunduka et al., 2012), we are more interested in the level of adoption as opposed to whether one adopts DT maize or not. We therefore adopt the dose–response function (DRF) (Cerulli, 2015) to examine the impact of DT maize varieties on maize yield.

2.2 | Empirical model specification

We examine the impact of DT maize varieties on maize productivity using the dose–response function (DRF) following the approach by Cerulli (2015). We follow other authors such as Kassie, Jaleta, and Mattei (2014) who used a continuous treatment approach to evaluate the impact of improved maize varieties on food security in Tanzania. Shiferaw, Kassie, Jaleta, and Yirga (2014) also adopted the continuous treatment approach to assess the impact of improved wheat varieties on household food security in Ethiopia. In this approach, we consider the fact that in some instances what is important is not just whether one adopts a given technology or not but also the level (or dose) of adoption. Once farmers adopt a given technology, they differ in the intensity of adoption. The DRF therefore enables assessment of the impact heterogeneity of adoption. In our study, we expect both spatial and temporal variations in the level of adoption of DT maize varieties such that using intensity of adoption as a treatment variable, increases precision of results than just relying on binary treatment. While the binary treatment gives a value of zero to untreated group and one to the treated, the continuous treatment approach gives untreated group a dose of zero and the treated group a dose ranging from above zero to 100. In relation to epidemiology language where patients react differently to different levels of treatment, the maize yield response could be different at different levels of DT maize adoption of which the binary variable is unable to capture.

In the impact literature the DRF is equivalent to average treatment effect (ATE) given the level of treatment (t), where (t) is the continuous treatment variable. The dose (or treatment) in our case is the level of DT maize adoption measured as a share of total maize land allocated to DT maize varieties while the response is the maize yield measured in kilograms per hectare (kg/ha). The DRF represents the conditional expectation of maize yield variations given confounding variables. The derivative of the DRF stands for the Marginal Treatment Effect (MTE), which illustrates how the effects of DT maize on maize yield change as the intensity of DT maize use increases.

Let the level of treatment (t) range from zero to 100 where nonadopters of DT maize varieties take the value of zero while adopters take values greater than zero. Our interest is to examine the causal effect of treatment (t) on maize productivity (y) assuming adopters and nonadopters respond differently to both treatment and confounding factors (x). We are interested in estimating the DRF of y on t, where t is endogenous. The approach allows the treatment variable to be endogenous by applying instrumental variable (IV) estimation and facilitates assessment of the heterogeneity of impact.

Given these notations, let y_{1i} and y_{0i} be the outcome variable (maize productivity, measured in kilograms per hectare (kg/ha)) for individual plot i with treatment (w_1) and without treatment (w_0), respectively, where $i = 1, \ldots, N$. Note that w is a dummy treatment variable. N is the total number of plots where N_1 are plots with DT maize varieties and N_0 are nonadopted plots of DT maize varieties. We define $x = x_1, x_2, x_3, \ldots, x_m$ as a vector of M exogenous observable characteristics, $g_1(x)$ & $g_0(x)$ as response functions associated with and without DT adoption respectively and assume μ_1 and μ_0 as two scalars, and e_1 and e_0 as two random variables with zero unconditional mean and constant variance. The treatment (t) takes the continuous values in the range [0, 100] and we define $h(x)$ as the intrinsic response of a given level of treatment (t). The outcome equations for a given population is then expressed as:

$$\left[\begin{array}{ll} w = 1: & y_1 = \mu_1 + g_1(x) + h(t) + e_1 \\ w = 0: & y_0 = \mu_0 + g_0(x) + e_0 \end{array}\right. \tag{1}$$

The x variables included in the model include productive inputs, household and plot characteristics, and rainfall stress variables. Productive inputs include fertilizer use (kg/ha—natural log), farm size (ha—natural log), organic manure (kg/ha—natural log) and male and female family labor (adult equivalent/ha—natural log). These inputs are measured per plot where some plots had DT maize while others had non-DT varieties. We also include dummies for local maize varieties and access to seed and fertilizer subsidy. Household characteristics include age (years), sex, and education (years) of household head, household size (number of persons) and off-farm labor (adult equivalent/ha—natural log). At plot level, we control for observable plot characteristics such as plot size (ha—natural log), number of plots, plot distance (km) (i.e., distance from the farmer's home to the plot), soil type, slope, and soil fertility as reported by the farmer. The rainfall stress variables are longest early and late dry spells (days) and December average rainfall (mm). Notice that the December average rainfall coincides the planting time for the next year's harvest. The December rainfall is very critical in our setting because latest observations in Malawi show that maize planting is done in December in most parts of the country. In our computation of the dry spells we first considered the start date of normal rains. The early dry spell therefore coincides the period after first rains and we assume that during this period farmers are still planting and changes to the rains would affect germination and vegetative growth of the crop. The late-season dry spells coincide with flowering period of the crop. Other variables included are average distance to agricultural input markets (km) and year-specific and district-specific dummies. We also include averages of time-varying variables in order to control for unobserved heterogeneity in our model.

From Equation (1) we can then define the treatment effect (TE) as $TE = (y_1 - y_0)$. Assuming a linear-in-parameters parametric form for $g_0 \ (x) = \ x\delta_0$ and for $g_1 \ (x) = \ x\delta_1$, we can state Average Treatment Effect (ATE) conditional on x and t as

$$ATE \ (x, t, w) = \ w * [\mu + x\delta_1 + h(t)] + (1 - w) * [\mu + x\delta_0], \tag{2}$$

where $\mu = \mu_1 - \mu_0$ and $\delta = \delta_1 - \delta_0$.

To estimate the ATE, we can use the following regression approach:

$$\begin{aligned} y_i = \mu_0 \ + \ w_i{*}ATE + \ x_i\delta_0 + w_i{*}(x_i - \bar{x})\,\delta_1 \\ +w_i\left[h(t_i) - \bar{h}\right] + \eta_i, \end{aligned} \tag{3}$$

where $\eta_i = e_{0i} \ + w_i{*}(e_{1i} - e_{0i})$

Equation (3) is necessary for estimating the parameters of interest ($\mu_0, \mu_1, \ \delta_0, \ \delta_1, \ ATE$). However estimation of Equation (3) to identify ATEs and DRF in our context requires that the assumption of unconfoundedness or conditional mean independence (CMI) is met. CMI means that:

$$E \ \left(y_{ji}|w_i, t_i, x_i\right) = \ E\left(y_{ji}|x_i\right) \text{ with } j \ = \ [0, 1]. \tag{4}$$

This CMI assumption may not hold in our context because the treatment is endogenous due to nonrandom self-selection into adoption. We therefore, restate Equation (3) as follows:

$$\left[\begin{array}{l} y_i = \mu_0 \ + x_i\delta_0 + \ w_iATE + w_i\,(x_i - \bar{x})\,\delta_1 \\ \qquad + aw_iT_{1i} + bw_iT_{2i} + cw_iT_{3i} + \eta_i \ (4.1) \\ w_{i,}^{*} = x_{w,\ i}\beta_w + \epsilon_{w,i} \ (4.2) \\ t_{i}^{'} = x_{t,\ i}\beta_t + \epsilon_{t,i} \ (4.3), \end{array}\right.$$

where $T_{1i} = t_i - E(t_i)$, $T_{2i} = t_{2i} - (t_{2i})$, and $T_{3i} = t_{3i} - E(t_{3i})$. w_i^* is the latent treatment variable; t_i is fully observed only when $w_i = \ 1$ (and $t_i = t_i^*$); $x_{w,\ i}$ and $x_{t,\ i}$ are two sets of exogenous regressors explaining treatment while $\epsilon_{w,i}$, $\epsilon_{t,i}$, and η_i are error terms and are correlated with one another with zero unconditional mean. Equation (4.2) is the selection equation, which defines the regression explaining the treatment indicator w^* with the vector of covariates $x_{w,\ i}$ used to set treated and untreated groups. Equation (4.3) is the treatment-level equation that defines how the level of DT maize adoption is decided, and it only considers eligible treated units. The treatment level is determined by the vector of covariates $x_{t,\ i}$.

The terms w_i, T_{1i}, T_{2i}, and T_{3i} are endogenous and the latter three are functions of the endogenous t. Having two endogenous variables ($w_i^*$and t_i^*) would therefore require at least two IVs ($z_{w,i}$ and$z_{t,i}$) to identify Equations (4.1)–(4.3). These should be correlated with $w_i^*$and t_i^* but not with y_i to satisfy exclusion restriction and uncorrelated with $\epsilon_{w,i}$, $\epsilon_{t,i}$ and η_i for exogeneity to hold. In our case we identify the IV that is correlated with w_i^*as distance to agricultural markets while we take variables distance to agricultural markets and number of children (less than 12 years old) as IVs correlated with t_i^*. We justify the selection of these instruments in Section 2.3 below.

2.3 | Estimation strategy

Following the endogeneity assumption of the adoption of DT maize variable we made in Section 2.2, there is a need to conduct a test to examine whether the presumably endogenous variable in the model could in fact be exogenous. If the endogenous regressor is exogenous, then the OLS estimates are more efficient (StataCorp LP, 2014). We use the Durbin and Wu–Hausman test statistics as reported in Table A1. Our results show that the statistics are significant and we reject the null hypothesis of exogeneity and conclude that the variable is indeed endogenous and hence IV method is relevant. Using the OLS estimation in this setting would result in biased and inconsistent estimates of the parameters (Deaton, 2010).

Next, we identify the IVs and argue why we think they are exogenous in our model and therefore valid as well as relevant. Deaton (2010) describes an external variable as one "whose values are not set or caused by variables in the model" and that being external is not sufficient for a variable to be exogenous and therefore valid as an instrument. We use distance to agricultural markets and number of children (less than 12 years old) as instrumental variables. Summary statistics of these IVs are provided in Table A1, which include means and standard deviations. While these variables are likely to affect the access to inputs, we argue that they do not have any direct effect on output and are therefore exogenous and valid. Distance to agricultural markets can influence access to DT seed and hence adoption but should not directly influence maize yield. Number of children may influence access to farm input subsidies which in turn influences use of DT maize variety as the government of Malawi include the DT seed in the subsidy package. This is supported by findings in earlier studies (Holden & Lunduka, 2012; Katengeza et al., 2019) and statistical tests. Statistically, we use an F-statistic, the Sargan (score) and Basmann tests. The F-statistic measures the joint significance of the additional instruments other than those included in the model as exogenous variables. If the F-statistic is not significant, then the additional instruments have no significant explanatory power over an endogenous variable they are instrumenting. Our results in the Table A1 report a significant F-statistic ($F = 11.05 > 10$) and we therefore conclude that these instruments can be considered strong and sufficiently correlated with the endogenous variables. In addition, the Sargan (score) and Basmann tests show that the IVs are uncorrelated with the structural error term and hence we have no reason to assume that either one of the excluded exogenous variables should in fact be included in the structural equation.

Having identified the appropriate IVs, we then proceed to estimate Equations (4.1)–(4.3). Equations (4.2) and (4.3) are jointly estimated by the type-2 tobit model using a Heckman two-step procedure. The first step of this procedure involves a probit estimation of w_i^* on $x_{w,i}$ using only N_1 observations. The second step is the ordinary least squares (OLS) of t_i^* on $x_{t,i}$ utilizing the Mill's ratio from the first step and using all N observations. Having jointly estimated (4.2) and (4.3), we obtain the predicted values of w_i and t_i from the previous type-2 tobit estimation. We then perform a two-stage least squares (2SLS) to get consistent estimates of the parameters (μ_0, δ_0, ATE, δ_1, a, b, and c) in 4.1. Once these coefficients are consistently estimated, the causal parameters of interest (ATEs and DRF) are consistently estimated using the OLS.

2.4 | Data and descriptive statistics

The data in this paper comes from household panel surveys from six districts in Malawi, namely, Chiradzulu, Kasungu, Lilongwe, Machinga, Thyolo, and Zomba. The districts are located in different agroecological zones and receive different amounts of rainfall. Machinga and Zomba for example are partly located in a drought prone zone (Katengeza et al., 2012; Mangisoni, Katengeza, Langyintuo, Rovere, & Mwangi, 2011; World Bank, 2010) while Thyolo lies in the high plateau and hilly areas (Bunda College, 2008). The first round of the survey took place in 2006 where an initial sample of 450 households was drawn using a simple random sampling technique following the 2004 Integrated Household Survey Two (IHS2) (Lunduka, 2009). Data collection used a semistructured questionnaire on household and plot level characteristics with detailed plot-level information that include area measurements using the Global Positioning System (GPS). In 2009, 378 of these households were resurveyed and 350 households were resurveyed in 2012 and 2015, giving a four-round unbalanced household panel data. Our paper uses plot-level information from 449 households in 2006, 373 in 2009 and 345 in 2012 and 2015 with valid observations (Table 1).

Table 2 presents adoption of DT maize varieties in relation to other maize varieties grown by the farmer. As discussed in section two, DT varieties are both OPV and hybrids. Smallholder farmers in Malawi adopt a portfolio of maize varieties given different production and consumption attributes of the varieties (Lunduka et al., 2012). While DT maize is preferred for drought tolerant traits, other improved non-DT hybrids are high yielding under normal rainfall while local varieties have preferred processing and consumption characteristics. These varieties were identified based on the definition given by maize breeders from Chitedze research station, a government research institution. A list of maize varieties was provided and categorized as DT, local and other improved (OIM). Farmers were then asked what varieties were grown in a particular season. We provide some of the popular varieties in online Appendix Table A4 as reported by the famers and were accordingly categorized based on the list provided by the breeders.

Adoption of DT maize varieties is in this paper measured both as a binary variable (one if DT maize variety was planted on a given plot and zero otherwise) and

TABLE 1 Study areas and sample households by year

	2006		2009		2012		2015		Total	
District	**HHs**	**Plots**	**HHs**	**Plots**	**HHs**	**Plots**	**HHs**	**Plots**	**HHs**	**Plots**
Thyolo	61	94	47	100	47	98	47	91	202	383
Zomba	86	139	82	114	77	167	79	149	324	569
Chiradzulu	53	98	39	77	35	70	34	60	161	305
Machinga	56	77	43	84	46	85	43	65	188	311
Kasungu	97	122	90	183	79	141	79	99	345	545
Lilongwe	96	128	72	114	61	119	63	113	292	474
Total	449	658	373	672	345	680	345	577	1512	2587

Note: We present only maize plots.

TABLE 2 Maize type grown by year

Variable	2006	2009	2012	2015	Total
Maize type					
DT maize (1 = yes)	0.03	0.16	0.33	0.31	0.20
OIM (1 = yes)	0.54	0.29	0.31	0.33	0.37
Local maize (1 = yes)	0.45	0.55	0.37	0.36	0.43
DT maize area (ha)	0.01	0.07	0.17	0.15	0.10
OIM area (ha)	0.24	0.10	0.14	0.13	0.16
LM area (ha)	0.18	0.24	0.16	0.15	0.19

continuous variable captured in percentage of maize area (ha) allocated to DT varieties. Katengeza et al. (2019) reported an increase in adoption from 3% in 2006 to 43% in 2015. We use plot-level adoption in this paper and we find an increase from 3% of the plots in 2006 to 31% of the plots in 2015 for DT maize varieties while other improved non-DT maize varieties (OIM) have decreased from 54% of the plots in 2006 to 33% in 2015 with local maize decreasing from 45% to 36% of the plots, respectively (Table 2).

Next, in Table 3 we present summary statistics of the dependent variable (maize yield) and explanatory variables used in this paper. Roughly, the mean maize yield for an average individual in the area was 1,254 kg/ha. We control for household heterogeneity by including household characteristics such as age (years), education (years) and sex of household head, household size and *ganyu* (off-farm) labor. We further include household endowments such as operational farm size (ha), real asset value in Malawi Kwacha (MK) and tropical livestock unit (TLU). There is a slight decrease for farm size from 0.96 ha in 2006 to 0.85 ha in 2015 and we expect an increase in maize productivity as farm size decreases based on the inverse farm size productivity relationship assumption. We include asset value and livestock ownership in tropical livestock units (TLU) as proxy wealthy indicators and we assume that ownership of livestock and physical assets will enhance access to and use of agricultural inputs and technologies such as inorganic and organic fertilizer. Asset value increased from 2006 to 2015 in real terms but there is a decrease in TLU.

Access to FISP is measured by whether households accessed seed subsidy and/or fertilizer subsidy. We notice that seed subsidy access increased from 21% in 2006 to 64% in 2015 but there is a decrease from 2012 to 2015 for fertilizer subsidy. The dropping of fertilizer subsidy access may affect maize yield via reduced inorganic fertilizer use intensity. We could not include quantity of fertilizer subsidy because we assumed this is embedded in the quantity of fertilizer we used as a production input control. We also include distance to agricultural input market as a supply factor likely to influence access to drought tolerant maize seed and inorganic fertilizer.

Key inputs to maize production apart from seed are inorganic fertilizer, organic manure, male labor and female labor. Inorganic fertilizer use intensity increased from 2006 to 2009 but decreased in 2012 and 2015. We disaggregate male and female household labor to capture household heterogeneity effects. Availability of male labor endowment is key to maize production in Malawi (FAO, 2011). Plot-specific variables include plot size (ha), plot distance (km), number of plots, perceived soil fertility, slope, and soil type. These variables control for observable plot heterogeneity. We also include drought and rainfall stress variables constructed using daily rainfall data from the nearest weather stations to each sample community, obtained from the Department of Climate Change and Meteorological Services under the Ministry of Natural Resources, Energy and Mining. A dry spell is defined as a period of 10–15 days with a total rainfall of less than 20 mm following a rainy day of at least 20 mm. We include the longest dry spell periods (days) within the early (1 December to 15 January) and late rainy season (31 January to 15 March) and December mean rainfall in mm. We define these as early and late dry spells, respectively.

3 | RESULTS AND DISCUSSION

We start by presenting an overview of maize yield distribution for the three maize varieties (DT maize, OIM, and LM) in Figure 1 disaggregated by year. We acknowledge that the DT varieties in Malawi are either hybrids or OPVs and these varieties have different yield potential. The two types also follow different seed systems as OPVs could be recycled three times without much genetic potential loss, whereas farmers need to purchase hybrids each season (Abate et al., 2017; Lunduka et al., 2012). Our analysis would therefore benefit by comparing OPV-DT with OPV-OIM and hybrid-DT with hybrid-OIM. However in our sample, 95% of those who grew DT, used hybrid-DT while only 5% used OPV-DT (Table A2). Thus, we do not

TABLE 3 Summary statistics and definition of explanatory variables by year

Variable	2006	2009	2012	2015	Full sample
Maize yield (kg/ha)	925.99	1428.72	1469.72	1177.52	1254.12
Household characteristics and endowments					
Age of household head (years)	41	47	51	49	47
Sex of household head (1 = female)	0.24	0.21	0.22	0.34	0.25
Household size (# of persons)	5.27	5.39	5.55	5.83	5.51
Number of children	3.28	2.86	2.91	2.93	3.00
Off-farm labor (# of adults)	0.15	0.22	0.40	0.21	0.24
Asset value (Malawi kwacha)	4038	4059	4306	5717	4512
Tropical livestock unit	1.07	1.47	1.45	0.58	1.15
Farm size (ha)	0.96	0.87	0.79	0.85	0.87
Institutional variables					
Household accessed maize seed subsidy (1 = yes)	0.21	0.35	0.55	0.63	0.43
Household accessed fertilizer subsidy (1 = yes)	0.35	0.57	0.74	0.48	0.54
Distance to agricultural market (km)	4.00	4.28	4.34	4.18	4.20
Member of parliament from ruling party (1 = yes)	0.44	0.39	0.49	0.47	0.45
Inputs					
Fertilizer quantity (kg/ha)	178	218	206	212	203
Organic manure (kg/ha)	1181	1310	464	994	984
Male household labor (adult equivalent/ha)	2.35	3.29	3.28	4.10	3.25
Female household labor (adult equivalent/ha)	2.07	3.03	2.91	3.71	2.92
Plot characteristics					
Plot size (ha)	0.44	0.41	0.38	0.37	0.40
Plot distance (km)	0.96	2.86	2.81	3.29	2.48
Number of plots (#)	2.27	3.49	4.89	4.41	3.77
Sandy soil (dummy)	0.31	0.26	0.17	0.21	0.24
Loam soil (dummy)	0.53	0.49	0.64	0.65	0.58
Clay soil (dummy)	0.16	0.25	0.19	0.14	0.19
Flats slope (dummy)	0.62	0.56	0.73	0.51	0.61
Moderate slope (dummy)	0.32	0.37	0.23	0.41	0.33
Steep slope (dummy)	0.06	0.07	0.04	0.08	0.06
High soil fertility (dummy)	0.19	0.15	0.14	0.08	0.14
Medium soil fertility (dummy)	0.50	0.61	0.80	0.69	0.65
Low soil fertility (dummy)	0.31	0.23	0.05	0.23	0.20
Drought and rainfall variables					
December average rainfall (mm)	6.78	7.27	7.23	7.51	7.20
Longest early dry spell (days)	8.84	9.30	6.67	5.70	7.65
Longest late dry spell (days)	9.68	7.17	10.51	9.53	9.22

have statistical power to tease out the difference in performance between these, given our limited sample size. We therefore proceeded without disaggregating hybrid-DT and OPV-DT.

Our results in Figure 1 show that in 2006, maize yield was higher on plots with DT maize followed by OIM varieties. However, the plots for DT adopters were very few such that the yield difference between adopters and non-adopters of DT could be misleading. In 2009 and 2012, the mean yield is higher on plots with OIM varieties followed by DT. It was reported by Holden and Fisher (2015) that DT maize did not perform any better than OIM in 2012, a year characterized by early-season droughts but good late-season rains. In 2015, a year where most parts of the country were affected by floods early in the season and late-season droughts, mean maize yield is higher on DT plots. The 2012 and 2015 results are critical in our setting. Our findings indicate that average maize productivity is higher

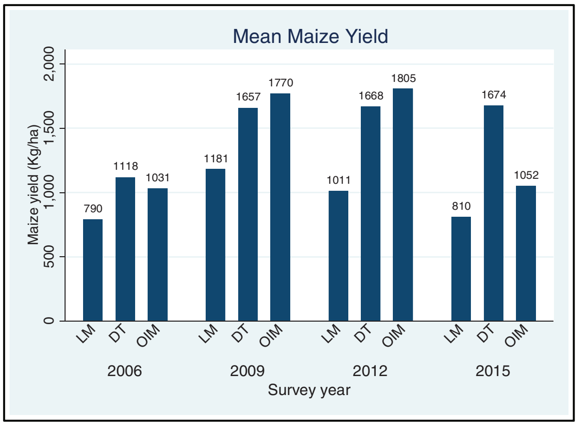

FIGURE 1 Maize yield distribution by variety and by year [Color figure can be viewed at wileyonlinelibrary.com]

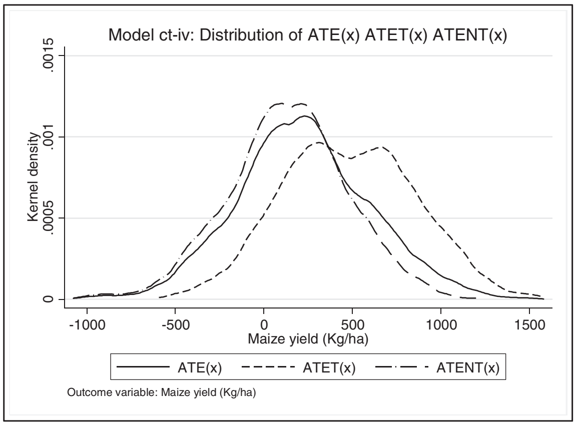

FIGURE 2 Average maize yield on full sample (ATE), treated (ATET), and nontreated (ATENT)

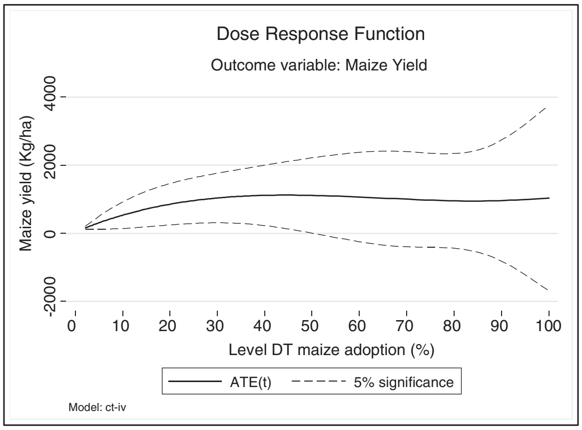

FIGURE 3 Estimated dose–response function (average DT maize impact)

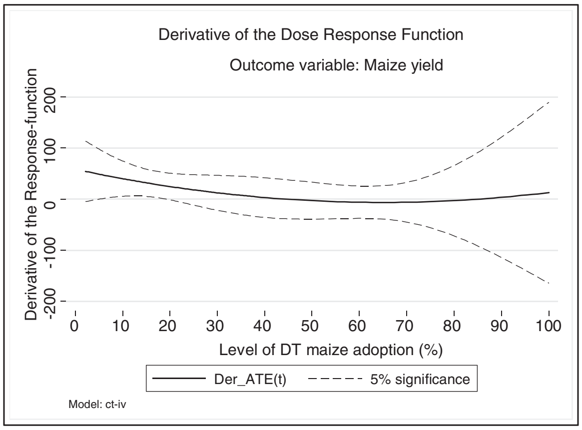

FIGURE 4 Marginal treatment effect of maize productivity

on OIM plots than DT during late-season good rains, but the situation reverses when late-season droughts occur.

Figure 2 shows average treatment effect (ATE), average treatment effect on the treated (ATET) and average treatment effect on nontreated (ATENT). We compare the average yield of DT maize varieties to the weighted average of OIM and LM varieties. The plots show that the peak of the ATET is on the right of both ATE and ATENT peaks suggesting that the mean of ATET lies on the right of ATE and ATENT. Thus, the mean maize yield on maize plots for adopters of DT maize is relatively above that of the average individual of maize producers in the study area and also above that of nonadopters assuming adoption. This is evidence of yield advantage of DT maize varieties over other maize varieties.

In Table 4 and Figures 3 and 4, we report the results of dose–response function (DRF) and marginal treatment effect (MTE). The regression results used to estimate the DRF and MTE are presented in Table A5. We show results for an IV approach with mean variables of time varying variables included as additional regressors to control for unobserved heterogeneity. These results show that maize yield is positive but insignificantly correlated with DT maize adoption but negative and significantly correlated with LM in reference to OIM varieties. We do not discuss these results in detail as the focus of our procedure is the DRF and MTE.

The DRF results show that maize yield increased with the level of DT maize adoption. Maize yield increased by 370 kg/ha at 5% DT maize adoption level to 1,139 kg/ha at 38% level of adoption. We observe a flat and declining graph after 38% level of adoption up to 100%. On average an increase of one hectare of land allocated to DT maize varieties increases maize productivity by 547 kg/ha. This represents 44% increase from an average maize yield of 1,254 kg/ha (Table 3) for all sample households. The results also imply heterogeneity of the impact of DT maize adoption on maize productivity. The MTE results show a weak and declining u-shape where at low levels of DT maize

TABLE 4 Predicted ATE and MTE at some specific DT maize adoption levels

DT maize adoption level (%)	Productivity (pooled)		Productivity (2009)		Productivity (2012)		Productivity (2015)	
	ATE	MTE	ATE	MTE	ATE	MTE	ATE	MTE
1	139.66	62.10	−1280.89	242.21	−1146.81	17.11	788.18	−35.95
5	370.47	52.87	−474.75	166.39	−1051.90	31.62	665.70	−25.16
10	607.98	42.25	137.24	84.94	−852.32	43.73	570.10	−12.89
20	937.09	23.86	337.15	−34.62	−379.74	42.01	545.93	7.12
30	1106.74	8.59	−381.47	−100.46	−103.23	6.57	777.62	25.01
38	1139.38	0.81			−208.57	−38.60		
52	1072.87	−8.71			−1694.87	−178.95		
69	906.56	−9.73	−1367.20	198.82				
87	811.26	1.53					1962.46	−7.98
100	923.44	17.08					1664.78	−40.17

Note: The yearly model results are not stable. This is mainly due to the small sample size for our model to reach stability unlike the pooled model that has used a full dataset and hence more stable results. A similar study with a large sample size would be required for more robust evidence.

adoption the MTE is significant and positive up to about 20% adoption of DT maize, and insignificant and positive above that (see graphs of DRF and MTE in Figures 3 and 4). No further improvement is observed at about 30–40% level of adoption, which implies that the change due to a unit change in DT maize is less than the change due to a unit change in OIM varieties at these levels. The implication is also that a portfolio mix of DT and OIM will give more stable production over time.

In Table 4 we also report results of year-specific models. We disaggregated the analysis based on survey year because different years have different rainfall pattern and this could have different implications on our results. We could however not include the year 2006 because DT maize adoption was too low to make a significant impact on their own. The findings show negative ATE for the years 2009 and 2012 where normal late-season rains were reported. We nonetheless, observed that in 2015 where late-season droughts were reported, ATE is positive and is highest at 87% level of DT adoption. These findings which are similar to the results reported in Figure 1 suggest that OIM varieties possess higher yield potential under good late-season rainfall conditions than DT maize varieties. On the other hand, DT maize varieties have yield advantage over OIM in late-season drought growth conditions.

In addition to the DRF estimates of MTE, we also added a quintile estimation of yield gain/loss based on maize area under DT varieties as reported in Table A3. The results show that about 95% of DT maize adopters were in the 1st quintile (< 25%) while only 0.3% allocated more than 75% of the maize area under DT maize varieties. The ATE increased from the 1st quintile to the second and the sample is too small to say much about higher levels of adoption. What is evident from the quintile regression is that adoption of DT maize varieties of up to the second quintile result in significant yield increase. This is in agreement with the DRF which found a maximum response of around 30–40% adoption level but we need to be cautious about what would happen with higher adoption levels as our sample is too small in this range.

There are several implications of the DRF and MTE results presented in Table 4 and Figures 2–4. First, results from a dummy treatment variable have limitations. We notice from the results presented in the Table A5 that the correlation between maize yield and adoption of DT maize is positive but insignificant using OIM varieties as reference varieties. One would be tempted to conclude that DT maize varieties have no yield advantage over OIM but local varieties as reported by Holden and Fisher (2015) and Fekadu and Endeshaw (2016). The DRF results however show that the impact of DT maize varieties is low at low levels of DT maize adoption but increases as adoption levels increase. Failure to find yield advantage of DT maize varieties could simply reflect low adoption levels. As adoption level increases, farmers are likely to realize higher and more significant yield increase.

Second, and related to the first point above, we notice that the impacts of DT maize varieties on maize yield are heterogeneous. There is an increase in the impact from low levels of DT maize adoption up to 30–40% adoption level but our data limitations do not allow us to make any strong conclusions about the effect under higher adoption levels. The results indicate that a mixed stand, combining DT and OIM is recommendable to food insecure and risk averse farmers. The reason is that DT maize varieties are less yielding compared to OIM varieties under good rainfall conditions but drought-resilient and performing relatively better under drought conditions, especially when the drought occurs later in the rainy season. Since farmers face production uncertainty because of uncontrollable production factors such as weather, a decision to grow a particular variety is a gamble, as the state of nature is not known at the time of input decision-making. Full adoption of DT maize varieties (i.e., 100% allocation of maize area to DT maize) for example may result in loss of yield when a good state of nature (good rainfall) is revealed but may result in yield gains when a bad state of nature, especially a late drought occurs. The reverse is true with OIM varieties. In such situations, risk averse farmers are better off adopting a portfolio of maize varieties. Our results are thus, showing that allocating at least 30%–40% of land under maize cultivation to DT maize varieties would result in a reduction in risks and may even increase average yields over time for farmers facing frequent droughts. We, however, emphasize that providing farmers with timely weather/climate information would help them make appropriate maize variety portfolio choices to hedge against rainfall uncertainty that cannot be predicted with high certainty several weeks into the future. The best possible ex ante weather information should be provided to farmers before planting time. Potentially, this could maximize yield benefit given the predicted amount and distribution of rainfall in that season.

Third, DT maize varieties have no yield advantage relative to OIM varieties during good rainfall years. The impact is, however, very visible and significant in the year where late-season droughts occurred in our data. These results provide evidence that adoption of DT maize varieties result in substantial increase in maize yield under rainfall stress conditions. Thus, DT maize varieties hold potential to protect farmers against late-season droughts. Our results are a substantial addition to on-station and on-farm trials where adoption of DT maize increases maize productivity under weather stress conditions. Experimental evidence shows that DT maize varieties have yield advantage over other maize varieties when faced with droughts during grain formation, as they are developed to withstand late-season dry spells (Kostandini et al., 2015; La Rovere et al., 2010; Setimela et al., 2013; Tesfaye et al., 2016). Our results are consistent with the experimental evidence and, in particular, show how maize productivity changes at different levels of DT maize adoption. Our findings also add value to the *ex post* studies by Radda (2015) and Awotide et al. (2016) in Nigeria, by Makate et al. (2017) and Lunduka et al. (2019) in Zimbabwe and by Cenacchi and Koo (2011) in several countries in SSA. These studies used a dummy treatment variable and cross sectional data to examine the impacts of DT maize varieties. Our results using household farm panel data and with a continuous treatment variable authenticate the empirical conclusion that DT maize varieties have potential to increase maize productivity during rainfall stress conditions and hence improve household food security.

The overall significance of the results in this paper to smallholder farmers in Malawi and the SSA region who are consistently exposed to dry spells, is that the likelihood of poor harvests most of them get when dry spells occur can be minimized with adoption of appropriate technologies. Maize production is low in the presence of drought because majority of smallholder farmers lack alternative technologies to sustain production (Giller et al., 1997 in Chilimba et al., 2005). Thus, with proper use of agricultural technologies such as DT and other climate-smart agriculture (CSA) practices, farmers should be able to hedge against drought-related yield losses. Katengeza (2020) noted that CSA technologies have the capacity to enhance drought resilience as well as improving nutrient uptake. Such technologies could be complements or alternatives to other technologies such as irrigation with hedging effect against drought stress when such are not available or expensive to the farmer. Combining maize production with other drought-tolerant food crops such as cassava should be encouraged for more sustainable food security.

4 | CONCLUSION AND RECOMMENDATIONS

Weather extremes, especially recurrent droughts, threaten agricultural productivity and food security in Malawi whose population largely depend on maize for food. Drought tolerant (DT) maize is one potential technology to minimize the negative impacts of drought. During the last 10–15 years several DT maize varieties have been developed and disseminated across the country. Examining the impact of this promising technology in enhancing maize productivity under drought is increasingly becoming important. Building on the works of Holden and Fisher (2015) on the same household farm panel data, this paper has used a continuous treatment approach to understand the impact of DT maize in Malawi under rainfall stress. The data is from farm households in six districts collected in 3-year intervals between 2006 and 2015.

We have found strong evidence that average maize yield is positively and significantly correlated with adoption of DT maize varieties. Average maize yield increased by 370 kg/ha at 5% rate of DT adoption to 1,139 kg/ha at 38% DT maize adoption level. On average an increase by one hectare of maize area allocated to DT maize varieties increases maize yield by 547 kg/ha representing a 44% increase from a sample average of 1,254 kg/ha. The marginal treatment effect of the adoption rate is significant and positive up to 20% adoption rate and insignificant and positive above that. Our findings provide evidence that DT maize varieties have potential to hedge against negative effects of droughts on maize yield. A combination of DT and other improved maize varieties hold the potential to reduce yield losses in drought years and enhance average maize yields across good and bad years. Our findings indicate that farmers living in drought prone areas of Malawi should plant at least one third of their maize area with DT maize varieties to reduce the risk and enhance their food security. Smallholder farmers lack alternative technologies to hedge against drought-related yield losses (Giller et al., 1997 in Chilimba et al., 2005) such that adoption of climate-smart technologies such as DT could enable farmers to get better harvests, despite persistent dry spells.

The paper therefore recommends enhancement of policies that promote access to and availability of DT maize varieties particularly in drought prone areas. With FISP facilitating access to and use of DT maize seed, there is a need for deliberate efforts to increase allocation of DT maize varieties in drought-prone areas. The FISP package should be accompanied by extension messages to enhance awareness of DT seed and related benefits under rainfall stress growth conditions. Farmers in high rainfall areas with good access to inorganic fertilizer should be encouraged to grow high yielding hybrids under such growth conditions. We do not recommend DT maize in such areas as that could result in lower yields. Although weather information could be uncertain at times, we encourage the government through the Department of Climate Change and Meteorological Services to provide farmers with timely *ex ante* weather/climate information to guide their decision making with respect to maize varietal choices.

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DATA APPENDIX AVAILABLE ONLINE

A data appendix to replicate the main results is available in the online version of this article. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.

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SUPPORTING INFORMATION

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

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