Too poor to afford soaring fertilizer prices: does input substitution enhance Maize productivity in Malawi's smallholder farming sector?

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Abstract
Policymakers in low-income countries, such as Malawi, are facing a crucial choice on whether to boost investment in the input subsidy program to make fertilizers more affordable and accessible for poor farmers or to promote the use of cheaper, environmentally friendly organic fertilizers. Worth noting, the rising cost of fertilizers has put poor farmers and those who do not benefit from the input subsidy program in danger of food insecurity and malnutrition. Despite this, some farmers have turned to alternative soil fertility management methods, such as organic manure and legume intercropping, in response to the increase in fertilizer prices. Therefore, this study was conducted to examine the impact of substituting organic manure for fertilizers on maize productivity. The study used 2019 nationally representative agricultural household data collected by the National Statistical Office of Malawi in partnership with the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) project. The study findings indicated that there is a substitution effect between organic and inorganic fertilizers. Furthermore, the cost of maize production is lower when using organic manure compared to inorganic fertilizers, but average maize productivity is negatively impacted. The study recommends using both organic manure and inorganic fertilizer to maximize maize productivity, which can be achieved by leveraging agricultural extension interventions and effective targeting of the input subsidy programs.

Keywords: input elasticities of substitution, maize productivity, organic fertilizers, inorganic fertilizer prices

1. INTRODUCTION

Increasing agricultural productivity is considered as very vital for food security and economic development in most of Malawi's rural settings where there is an overreliance on rainfed agriculture. One of the critical challenges, however, associated with the smallholder farming sector is limited and declining soil fertility. This is one of the major causes of crop failure such as Maize. On the other hand, most of the farmland in Malawi is allocated to the cultivation of Maize crops (MoAIWD, 2018). This is so because Maize is a staple food crop among most households in rural and urban areas. As a result, the government of Malawi over the years have been implementing the input subsidy programme in order to boost maize productivity and improve soil fertility (Kanyamuka, 2017). The successive implementation of the input subsidy programme has enabled access to key inputs such as chemical fertilizers which have been increasing the productivity of Maize. Furthermore, there has been an improvement in food security, wages and rural incomes (Holden and Lunduka, 2010; Dorward and Chirwa, 2011).

On the contrary, it has also been noted that the input subsidy programme has been posing a fiscal burden on the national budget of Malawi thereby limiting public investment in other sectors. For instance, over 45 percent of the national budget has been allocated to the input subsidy programme (Devex, 2022). Whereas Dorward and Chirwa (2011) further alluded that the input subsidy programme in recent years has been affected by increased international prices and import outlays. This has led to soaring prices in the domestic fertilizer markets thereby causing the unaffordability of fertilizers among poor farmers. Due to these high costs, the government have also been reducing the number of targeted beneficiaries of the input subsidy programme. On the other note, there have also been concerns regarding poor targeting of the input subsidy programme to an extent that most affluent farmers benefit the most at the expense of resource-constrained households (Kanyamuka, 2017).

Other researchers have also emphasized that although input subsidy programs have promoted access to inorganic fertilizers, fertilizer's nutrient absorption by crops is dependent on the soil's biophysical properties (Fairhurst, 2012). In addition, excessive use of inorganic fertilizers could lead to further soil fertility depletion. As a result, there have been campaigns for sustainable ways of improving soil health which can make the chemical fertilizers in the input subsidy package more beneficial to smallholder farmers. Such sustainable options have included the intensification of the usage of organic manure or the adoption of integrated soil fertility management technologies.

Integrated soil fertility management technologies are regarded as a complementary application of inorganic fertilizers, organic manure, improved seed varieties, legume-intercropping, zero tillage and agroforestry whilst including the knowledge on how to use these techniques in the local settings of the farmer (Place et al., 2003; Vanlauwe et al., 2015; Hörner and Wollni, 2020). Unfortunately, there is low or partial adoption of integrated soil fertility management technologies especially due to the high initial investment costs, labour and knowledge constraints ((Jayne et al., 2019; Hörner et al., 2019; Takahashi et al., 2019). Worth noting, in the instances of soaring prices of fertilizers as well as lack of knowledge on the joint use of integrated soil fertility management practices; smallholder maize farmers are likely to substitute organic manure for inorganic fertilizers in order to replenish soil fertility on their farmland. Considering the aforementioned context, the following research questions can be posed: to what extent do maize farmers in Malawi use organic manure as substitutes for chemical fertilizers whenever prices of fertilizer have soared in the input markets? does intensification in the use of organic manure affect maize productivity in the smallholder farming sector?

The body of empirical literature in Malawi shows that the use and intensity of the use of organic manure are correlated with exposure to dry spells (Katengeza, Holden and Fisher, 2019). Whereas the study by Holden and Lunduka (2012) reported that the use of organic manure positively correlates with the use of chemical fertilizers and prevailing average fertilizer prices in the markets. Moreover, other researchers have highlighted that application of organic manure is linked to land tenure security (Kassie et al., 2015), knowledge of the production of manure (Kilcher, 2007; Mustafa-Msukwa et al., 2011) and availability of labour (Chatsika, 2016; Mustafa-Msukwa et al., 2011; Snapp et al., 2002). In terms of maize productivity studies in Malawi and other countries, evidence has depicted that conservation agriculture (Pedzisa, 2016), adoption of integrated soil fertility management (Kanyamuka, 2017), effective targeting criteria of Farm Input Subsidy Program (Asfaw et al., 2017), climate-smart technologies (Pangapanga-Phiri and Mungatana, 2021), drought tolerant maize and organic manure (Lunduka et. al., 2019; Katengeza and Holden, 2020; Gebre et al., 2021) have a positive impact on the maize production.

Building on the current body of knowledge, this paper makes novel contributions in two main ways: First, this paper uses nationally representative data from Maize farmers and input price data to test the degree of substitutability between organic manure and inorganic fertilizers. Previous studies have determined the degree of substitutability by using non-price data and those studies were not even country-wide analyses hence making their results none generalizable. Furthermore, some studies that have modelled adoption determinants of organic manure paid much focus on the sign of the coefficient of fertilizer price variable only in order to establish the elasticity of substitution. Nonetheless, it is vital to examine how a cost-minimizing producer would respond to changes in its economic environment. In light of this, the study would determine how the changes in both input prices affect input allocation decisions and consequently crop productivity. Second, this paper analyzes the effect of organic manure on maize productivity by considering the causal inference framework when the treatment variable is continuous. Worth noting, most of the previous studies have used the binary treatment effect which does not account for the heterogeneity effects of a treatment variable.

The remainder of the paper is structured as follows: section 2 will outline the theoretical framework, estimation strategy specification, and data used in the analysis, section 3 will present and discuss the results and section 4 will provide conclusions, implications for policy and future research.

2. METHODOLOGY

2.1 Theoretical Framework

The study is based on the cost minimization theory of the firm. The theory postulates that firms or producers choose the combination of inputs to produce a certain level of output at a minimum outlay. Therefore, the smallholder maize farmers will be aiming at lowering their production costs given their respective level of output.

The production function of a maize farm is expressed as follows:

$$f(x) = Y = y(x, z) \quad (1)$$

where; Y denotes the farmer's production quantity (i.e., amount of maize output per hectare), x represents vectors of purchased input quantity and z signifies the maize farmer's specific characteristics. Assuming that the production function is twice differentiable, the first-order condition is presented as follows:

$$\frac{\partial y}{\partial x} > 0 \quad (2)$$

The second-order condition is expressed in the following way:

$$\frac{\partial^2 y}{\partial x^2} < 0 \quad (3)$$

On the other note, the cost of purchased input is denoted as follows:

$$C = px \quad (4)$$

where p is a vector of input prices. The study assumes that maize farmers lower production costs subject to a given level of maize output. The cost-minimizing way of producing maize is expressed as follows:

$$C(p, y) = \underset{x \geq 0}{min}\{p(x). x | x \in V(y)\} \quad (5)$$

where p is defined as a vector of factor prices, x represents the factors of production, $V(y)$ is the input requirement set defined as convex, closed bounded and non-empty for all $y > 0$. The input requirement set is a set of all input bundles that produce a given level of maize output. The set is denoted as follows:

$$V(y) = \{x \ in \ R_+^n : (y, -x) is \ in \ Y\} \quad (6)$$

Setting up the Lagrangian function upon assuming that this is a constrained optimization case:

$$\mathcal{L}(\lambda, x) = px - \lambda(f(x) - y) \quad (7)$$

Differentiating the Lagrangian function with respect to the input variables and the Lagrangian multiplier will yield the following first-order condition:

$$p = \lambda \boldsymbol{Df}(\boldsymbol{x}^*) \text{ for } i, j = 1, \ldots, n \quad (8)$$

Therefore, dividing the ith condition by the jth condition will yield the following:

$$\frac{p_i}{p_j} = \frac{\frac{\partial f(x^*)}{\partial x_i}}{\frac{\partial f(x^*)}{\partial x_j}} \quad (9)$$

This expression $\frac{p_i}{p_j}$ denotes the rate at which factor j can be substituted for factor i while maintaining a constant cost. Whereas $\frac{\frac{\partial f(x^*)}{\partial x_i}}{\frac{\partial f(x^*)}{\partial x_j}}$ signifies the rate at which factor j can be substituted for factor i while maintaining a constant level of maize output. Worth noting, the first-order conditions for cost minimization are that the first derivative of the Lagrangian function is equal to zeros. On the other hand, the second-order conditions involve the bordered Hessian matrix of the Lagrangian;

$$D^2\mathcal{L}(\lambda^*, x_1^*, x_2^*, x_3^*, x_4^*, x_5^*) = \begin{pmatrix} 0 & -f_1 & -f_2 & -f_3 & -f_4 & -f_5 \\ -f_1 & -f_{11} & -f_{12} & -f_{13} & -f_{14} & -f_{15} \\ -f_2 & -f_{21} & -f_{22} & -f_{23} & -f_{24} & -f_{25} \\ -f_3 & -f_{31} & -f_{32} & -f_{33} & -f_{34} & -f_{35} \\ -f_4 & -f_{41} & -f_{42} & -f_{43} & -f_{44} & -f_{45} \\ -f_5 & -f_{51} & -f_{52} & -f_{53} & -f_{54} & -f_{55} \end{pmatrix} \quad (10)$$

The f_{ij} denotes $\partial^2 f/\partial x_i \partial x_j$, and $x_1^*, x_2^*, x_3^*, x_4^*, x_5^*$ represents the factors of production such as land, seed, fertilizer, organic manure and labour respectively.

The *first proposition of the study* is to estimate the elasticity of substitution among inputs in maize production. According to Maganga, Edriss and Matchaya (2013), the factor cost share equations have to initially be differentiated from the Translog cost function. The Translog cost function takes the following form:

$$InTC_i = \propto_0 + \sum_{k=1}^{5} \beta_k lnp_{ki} + \theta_i lny_i + \frac{1}{2}\sum_{k=1}^{5}\sum_{l=1}^{5} \beta_{k=1} lnp_{ki} lnx_{li} + \frac{1}{2}\theta_2 y^2 + \sum_{k=1}^{5} \beta_{ky} lnp_k lny + v_i + u_i \quad (11)$$

where $InTC_i$ is the total factor cost of the individual maize farm, p_1 is the mean price of organic fertilizer (manure) (MK per Kg), p_2 is the mean price of inorganic fertilizer (MK per Kg), p_3 is the mean price of seeds (MK per Kg), p_4 is the mean wage rate of man days per day per hectare, p_5 is the mean price of herbicides (MK per Kg) and y_i denotes maize output per acre. The $\propto_0$ represent the intercept term while β_k and θ_i are slope coefficients to be estimated. The cost share equation for input i is derived by differentiating the Translog cost function. Therefore, the derivative of the Translog cost function with respect to input prices yields the Shepard Lemma:

$$\frac{\partial lnC}{\partial lnP_i} = \frac{P_i x_i}{C} = S_i \quad (12)$$

where S_i denotes the cost share of the input factor. Hence, the cost share equation is expressed as follows:

$S_i = \propto + \sum \beta_{kj} lnp_j + \beta_{ky} y$ (13)

Moreover, the responsiveness of the change in factor i relative to a change in the price of factor j will be presented as follows:

$x_i = \frac{C}{w_i} s_i$ (14)

$\lambda_{kj} = \frac{\partial log x_i}{\partial log w_j} = \frac{w_j}{x_i} \frac{\partial}{\partial w_j} (\frac{C}{w_i} S_i)$ (15)

$= \frac{w_j}{x_i} \left(\frac{C\beta_{kj}}{w_k w_j} + \frac{x_j S_i}{w_k} \right)$ (16) applying Shephard's Lemma

$= \frac{\beta_{kj}}{S_i} + S_i \left(\frac{w_j x_j}{C} \right) \left(\frac{C}{w_i x_i} \right)$ (17)

$\lambda_{kj} = \frac{\partial log x_i}{\partial log w_j} = \frac{\beta_{kj}}{S_i} + S_j$ (18)

The Allen Elasticity of Substitution will be expressed as follows:

$\sigma_{ij} = \frac{\beta_{ii}}{S_i S_j} + 1$ (19)

A constant Allen Elasticity of Substitution arises when $\beta_{ij} = 0$. Furthermore, Binswanger (1974) noted that the own elasticity of input demand can be presented as follows:

$\lambda_{kk} = \frac{\beta_{ii}}{S_i S_i} + S_i - 1$ (20)

Whereas an equivalent Allen Elasticity of Substitution is:

$\sigma_{ii} = \frac{\beta_{ii}}{S_i S_i} + 1 - S_i$ (21)

On the other note, the Morishima cross-price elasticities of substitution between factors i and j are determined as $M_{ij} = \varepsilon_{ij} - \varepsilon_{ii}$ and $M_{ji} = \varepsilon_{ij} - \varepsilon_{jj}$ (Obare, Omamo and Williams, 2003).

The *second proposition* is to determine the influence of intensifying the usage of organic manure on maize output per hectare. This will be determined using the maize production function in Equation (1).

2.2 Estimation strategy specification

2.2.1 Iterated seemingly unrelated regression model

A Translog cost function is to be estimated simultaneously with cost shares of the factors of maize production using an iterated seemingly unrelated regression model. The model has been chosen in order to assist in computing elasticities of substitution among inputs for maize production in Malawi's smallholder farming sector. According to Greene (2018), the optimization conditions of economic theory for production suggest that a producer faces a vector of factor prices "$\boldsymbol{p}$". Then, its set of cost-minimizing factor demands for producing maize output Y will be a vector of K equations of the form $x_K = g_m(Y, p)$. As such, the empirical model is expressed as follows:

$w_1 = g_1(Y, P|\beta) + \varepsilon_1$ (22)

$w_2 = g_2(Y, P|\beta) + \varepsilon_2$ (23)

………..

$w_K = g_K(Y, P|\beta) + \varepsilon_K$ (24)

where β is a vector of parameters which are included in the production function and ε_K depict disturbance terms in optimization. Worth noting the covariance of the disturbance terms has to be non-zero.

In the context of this study, the entire model is expressed as follows:

$lnTC = \propto_0 + \beta_Y lnY + \sum_{K=1}^{K} \beta_K lnP_K + \varepsilon_i$ (25)

$S_K = \beta_K + \varepsilon_K,\ K = 1, \dots \dots, K$ (26)

where $lnTC$ is the log of the total cost of maize production, $\propto_0$, β_Y, β_K represent estimated coefficients, lnY denote the log of maize output, lnP_K depict a set of the log factor prices and ε_i is the residual term assumed to have a zero mean and constant variance. The cost share equations are captured by S_K reflecting a vector of share equations, β_K is the estimated parameter and ε_K is an error term which assumes normal distribution and $(0, \sigma^2)$. Furthermore, the following model is consequently obtained after expanding $lnTC(p)$ in a second-order Taylor series at the point where $\ln(p) = 0$;

$lnTC \approx \beta_0 + \sum_{K=1}^{K} \left(\frac{\partial lnTC}{\partial lnP_K}\right) + {}^1\!/_2 \sum_{K=1}^{K} \sum_{M=1}^{K} \left(\frac{\partial^2 lnTC}{\partial lnP_K lnP_M}\right) lnP_K lnP_M$ (27)

These derivatives are obtained at the expansion point. On the other note, capturing these derivatives as estimated parameters, the Translog cost model is expressed as follows:

$lnTC = \beta_0 + \beta_1 lnP_1 + \dots + \beta_K lnP_K + \vartheta_{11}({}^1\!/_2\, ln^2 P_1) + \vartheta_{12} lnP_1 lnP_2 + \vartheta_{22}({}^1\!/_2\, ln^2 P_2) + \dots + \vartheta_{KK}({}^1\!/_2\, ln^2 P_K)$ (28)

Then, the cost shares are depicted in the following way:

$$S_K = \frac{\partial lnTC}{\partial lnP_K} = \gamma_1 + \beta_{11} lnP_{K1} + \beta_{12} lnP_{K2} + \cdots + \beta_{KK} lnP_K \quad (29)$$

In addition, Young's theorem has emphasized that the matrix of second-order derivatives for continuous functions must be symmetric. It also imposes several conditions on the estimated coefficients. These are the restrictions for a vector of cross-equations:

$$\varphi_{KN} = \varphi_{NK} \text{ (Symmetry) } (30)$$

$$\sum_{K=1}^{K} \beta_K = 1 \text{ (Linear homogeneity) } (31)$$

$$\sum_{K=1}^{K} \varphi_{KN} = \sum_{N=1}^{K} \varphi_{KN} = 0 \quad (32)$$

Greene (2018) indicated that these restrictions are necessary to solve the problem of the singularity of the disturbance covariance matrix of the cost share equations for the factors of production. The parameters obtained from the Translog cost function enable derivation of the elasticities of substitution,

$$\omega_{KN} = \frac{\varphi_{KN} + S_K S_N}{S_K S_N} \quad (33)$$

$$\omega_{KK} = \frac{\varphi_{KK} + S_K (S_N - 1)}{S_K^2} \quad (34)$$

The factor-specific demand elasticities are then derived as follows: $\tau_K = S_K \omega_{KK}$ (Greene, 2018).

2.2.2 Dose response function model

The dose response function model (DRF) has been adopted to assess the causal impact of organic fertilizer (manure) on maize productivity. This model has been adopted following researchers such as Cerulli (2014), Katengeza and Holden (2020) who employed a continuous causal treatment technique in their studies. In this study, the underpinning reason for choosing this approach is that the level or dose of applying inputs among farmers varies significantly. As a result, relying on a binary treatment variable may mask crucial evidence since maize yield response varies with the level of inputs used by maize farmers. According to Katengeza and Holden (2020), the previous impact assessment studies have emphasized that DRF is similar to the average treatment effect (ATE) conditional on the treatment intensity (t), such that (t) is the continuous treatment variable. Whereas Cerulli (2014) further alluded that the dose of treatment is the term very useful in epidemiology to an extent that DRFs are estimated to monitor the response of patients to varying doses of drug administration. Based on this study, the level of organic fertilizer (manure) utilized by the maize farmers is captured as the quantity of organic fertilizer applied on the maize plot (Kg per hectare) and maize productivity is quantified as Kilograms per hectare. More noteworthy, the DRF is the conditional expectation of variations in maize productivity. Furthermore, the DRF model is specified as follows:

$Z = 1: y_1 = \eta_1 + f_1(x) + g(t) + \mu_1$ (35)

$Z = 0: y_0 = \eta_0 + f_0(x) + \mu_2$ (36)

where y_1 and y_0 are dependent variables representing maize productivity – Kilograms per hectare for the individual maize plot i conditional on treatment (Z_1) and without treatment (Z_0), x denotes the set of exogenous independent variables, $f_1(x)$ and $f_0(x)$ are response functions related to and not related to the application of organic fertilizer (manure) respectively, η_1 and η_0 are intercept parameters, μ_1 and μ_2 represent the two independently and identically distributed (iid) error terms with $(0, \sigma^2)$. Whereas $g(t)$ is an inherent response function of an observed treatment intensity (t).

With respect to equation (35), the treatment effect is denoted as $TE = y_1$ - y_0. Relying on the assumption of linearity in parameters for the functional forms such as $f_0(x) = x\psi_0$ and $f_1(x) = x\psi_1$, an Average Treatment Effect (ATE) conditional on x and t can thereby be expressed as follows:

$ATE(x, t, z) = z * [\eta + x\psi_1 + g(t)] + (1 - w) * [\eta + x\psi_0]$ (37)

where $\eta = \eta_1 - \eta_0$ and $\psi = \psi_1 - \psi_0$. Therefore, the following regression method is employed in order to estimate ATE.

$y_1 = \eta_0 + z_i * ATE + x_i\psi_0 + z_i * (x_i - \bar{x})\psi_1 + z_i[g(t_i) - g] + \phi_i$ (38)

where $\phi_i = \varepsilon_{0i} + z_i * (\varepsilon_{1i} - \varepsilon_{0i})$ (38)

Lastly, the identification of the ATE and DRF in this study is based on the strong assumption that the treatment variable is exogenous or that the Conditional Mean Independence (CMI) assumption is met. This is so because the study assumes that there is no nonrandom self-selection in the utilization of organic fertilizer (manure). For instance, most maize farmers are motivated even without skills to make their organic fertilizers from wastes, crop residues, livestock and poultry dung. In other instances, maize farmers utilize their incomes to purchase organic fertilizers (manure). In particular, they are driven by the need to maximize production regardless of the capability or inability to purchase inorganic fertilizers. Therefore, an assumption that there are no confounding factors associated with the continuous treatment variable (organic fertilizers or manure) is justifiable.

2.3 Data

The data used in this study comes from the Fifth Integrated Household Survey (IHS5). The IHS5 is a nationally representative survey administered to 12,288 randomly selected households from 32 districts in Southern, Central and Northern regions of Malawi. The two-stage stratified sampling design was used for the IHS5 survey. Furthermore, the data was collected by the National Statistical Office (NSO) in the period between April 2019 and March 2020. This was conducted in partnership with the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) project. Although the IHS5 data are primarily collected to provide information on several facets of household welfare in Malawi through its household, fisheries and community questionnaires, they also include data from separately administered agriculture questionnaires which, among other things, capture detailed information on cropland allocation, crop production, crop selling prices, inputs access and prices, and the socio-economic and institutional factors. Worth noting, for this study, the sample size is reduced to 7742 which represents the number of agricultural households that grew maize in Malawi within the study period.

3. RESULTS AND DISCUSSIONS

3.1 Descriptive analysis

Table 3.1 below shows that on average 92.3 percent of maize farming households reside in rural areas. On average, there are 31.7 percent of female-headed households and 70.9 percent of maize farming household heads are married. A typical maize farmer is 45 years old with 6 years of the highest education level. In addition, maize farming households have almost 5 household members. On the other note, 55.3 percent of the maize farming households had access to agricultural extension on average. Furthermore, 30 percent of maize farmers had access to credit on average. Finally, the mean maize productivity of the study sample is 1275.53 Kilograms per hectare.

Table 3.1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.
Residence type =Rural	7742	.923	.267
Gender of the HH=Female	7742	.317	.466
Marital status of the HH=Married	7742	.709	.454
Age of the HH	7742	44.918	16.225
Household size	7742	4.605	2.043
Education of HH	7742	5.801	4.115
Access to extension=Yes	7742	.553	.497
Access to credit=Yes	7742	.3	.458
Maize productivity	7742	1275.534	43497.268

Note: Obs-observations, HH-Household head

3.2 Estimation results of an iterated seemingly unrelated regression

The estimated parameters of the Translog cost frontier are presented in **Table 3.2a**. The findings show that the price of organic fertilizer, price of inorganic fertilizer, price of seed, wage rate and price of herbicides have a positive and significant effect on the total cost of maize production. However, the price of seed highly increases the cost of production for maize. This is followed by the price of inorganic fertilizer. Considering the recent geopolitical tensions in Europe, the aforementioned trends are expected to change. Nevertheless, it is justifiable for the government of Malawi to be supporting the poor farmers with input subsidies so as to lessen the cost of producing the maize crop which is an important crop for food security. To reap more benefits input subsidies should be provided at a right time to the farmers. On the other hand, farmers can also be advised to switch to organic fertilizers in order to save the costs of maize production. However, agricultural extension workers have to play an active role in disseminating information on how to make organic fertilizers properly as well as the recommended applications on a maize plot. In consequence, maize farmers will be able to attain higher maize productivity.

Table 3.2a: Estimates of the Translog cost frontier obtained using iterated unrelated regression model seemingly

VARIABLES	lnTC
Log price of organic fertilizer	0.000545***
	(0.0001)
Log of price of inorganic fertilizer	0.011329***
	(0.0004)
Log of price of seed	0.020948***
	(0.0016)
Log wage rate	0.002240***
	(0.0002)
Log of price of herbicides	0.000228***
	(0.0000)
0.5* lnprc_organic_fert^2	0.001596***
	(0.0000)
0.5* lnprc_inorganic_fert^2	0.001656***
	(0.0000)
0.5* lnprc_seed^2	0.003724***
	(0.0002)
0.5* lnwage_rate^2	0.000722***
	(0.0000)
0.5* lnprc_herbicides^2	0.001113***
	(0.0000)
0.5*lnamountof_maize_output* lnamountof_maize_output	0.252731***
	(0.0076)
lnprc_organic_fert* lnprc_inorganic_fert	-0.000056***
	(0.0000)

lnprc_organic_fert* lnprc_seed	-0.000046***
	(0.0000)
lnprc_organic_fert* lnwage_rate	-0.000016
	(0.0000)
lnprc_organic_fert* lnprc_herbicides	0.000023
	(0.0000)
lnprc_organic_fert* lnamountof_maize_output	-0.000071***
	(0.0000)
lnprc_inorganic_fert* lnprc_seed	-0.000159***
	(0.0001)
lnprc_inorganic_fert* lnwage_rate	-0.000094*
	(0.0001)
lnprc_inorganic_fert* lnprc_herbicides	-0.000218
	(0.0002)
lnprc_inorganic_fert* lnamountof_maize_output	-0.002214***
	(0.0001)
lnprc_seed* lnwage_rate	0.000041
	(0.0002)
lnprc_seed* lnprc_herbicides	-0.000314
	(0.0009)
lnprc_seed* lnamountof_maize_output	-0.003597***
	(0.0003)
lnwage_rate* lnprc_herbicides	-0.000192**
	(0.0001)
lnwage_rate* lnamountof_maize_output	-0.000333***
	(0.0000)
lnprc_herbicides* lnamountof_maize_output	-0.000037***
	(0.0000)
Constant	2.604918***
	(0.1351)
Observations	7,742
R-squared	0.128
e(r2_1)	0.231
e(r2_3)	0.0747
e(r2_5)	0.187
e(chi2_1)	2352
e(chi2_3)	620.8
e(chi2_5)	1779
e(p_1)	0.000***
e(p_3)	0.000***
e(p_5)	0.000***

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
ISURE model presents normal standard errors, ln – Log and prc – price
lnTC – Total cost

Table 3.2b: Estimates of the cost share equations obtained using iterated seemingly unrelated regression model

Prices	Share of organic fertilizer	Share of inorganic fertilizer	Share of seed	Share of wage	Share of herbicides
Orga Fert	0.001596***	0.000085	-0.001460**	-0.000081	-0.000003
	(0.0000)	(0.0001)	(0.0006)	(0.0001)	(0.0000)
Inorga Fert	-0.000056***	0.001656***	-0.000851***	-0.000150***	-0.000016***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Seed	-0.000046***	-0.000159***	0.003724***	-0.000149***	0.000003
	(0.0000)	(0.0001)	(0.0002)	(0.0000)	(0.0000)
Wage	-0.000016	-0.000094*	0.000041	0.000722***	-0.000006
	(0.0000)	(0.0001)	(0.0002)	(0.0000)	(0.0000)
Herbicides	0.000023	-0.000218	-0.000314	-0.000192**	0.001113***
	(0.0000)	(0.0002)	(0.0009)	(0.0001)	(0.0000)

Note: Orga Fert – Organic fertilizer, Inorga Fert – Inorganic fertilizer

From the estimation results in **Table 3.2b**, it is shown that the price of inorganic fertilizer is significant at 1 percent with an inverse relationship on the cost share of organic fertilizer (manure). This suggests that there is substitutability between organic fertilizer and inorganic fertilizer. As such, it can be inferred that organic fertilizer is cheap and high prices of inorganic fertilizer influence the reallocation of resources from purchasing chemical fertilizer to organic fertilizer purchase. Furthermore, such type of results is consistent with the rest of the cross-price elasticities of inputs in maize production.

3.3 Estimation results of the dose response function model

The results from **Table 3.3** shows that the model perfectly fits the data with the R-squared value of 39.1 percent and the null hypothesis that the regression coefficients are equal to zero is rejected (Prob>F=0.0000***). As such, it can be concluded that the covariates jointly and significantly determine maize productivity. Moreover, the findings show a negative and significant ATE, equal to -0.07. This means that, on average, all the values taken by the organic manure variable are negative. In that regard, it can be inferred that households that applied organic manure decreased maize productivity by 7 percent and the p-value is less than 1 percent significance level. Furthermore, the Dose response function plot in **Figure 3.3** confirms that the relation is first weakly declining and then declines with a maximum around a dose level of 80. The relation is even highly significant at a 5 percent probability value.

Table 3.3: Estimates of the Dose response function model

VARIABLES	(1) Log of maize productivity
Organic manure	-0.07***
	(0.022)
Gender of the household head ==1(Female)	-0.05**
	(0.022)
Age of the household head	0.00***
	(0.001)
Household size	0.00
	(0.005)
Highest education level of the household head in years	0.03***
	(0.003)
access_to_credit==1	-0.04*
	(0.020)
access_to_extension==1	-0.02
	(0.020)
hh_mseed_subsi==1	0.05
	(0.050)
hh_fertilizer_subsi==1	-0.08**
	(0.038)
soil_type1==1	-0.05*
	(0.028)
soil_type2==1	0.11***
	(0.028)
soil_type3==1	0.08***
	(0.027)
good_soil==1	0.10***
	(0.020)
flat_slope==1	-0.08***
	(0.019)
Distance to a larger weekly market in Kilometres	0.00
	(0.001)
Log of total asset value in MK	0.02***
	(0.003)
Log of land size (hectare)	0.14***
	(0.018)
Log of maize plot size (hectare)	-0.39***
	(0.019)
Log of fertilizer applied (Kgs per hectare)	0.17***
	(0.006)
Log of labour used (Kg per hectare)	-0.00
	(0.013)

Log of seed applied (Kg per hectare)	0.22***
	(0.014)
Log of herbicides applied (Kg per hectare)	0.02
	(0.028)
Improvedseedvariety==1	0.13***
	(0.020)
_ws_organic_manure_qty2	0.07***
	(0.010)
Tw_1 = o,	-
Tw_2	-0.00***
	(0.001)
Tw_3	0.00***
	(0.000)
Constant	4.07***
	(0.079)
Observations	7,742
R-squared	0.391
Prob>F	0.0000***

Note: Robust standard errors in parentheses
****** p<0.01, ** p<0.05, * p<0.1***
Dose response function model presents robust standard errors

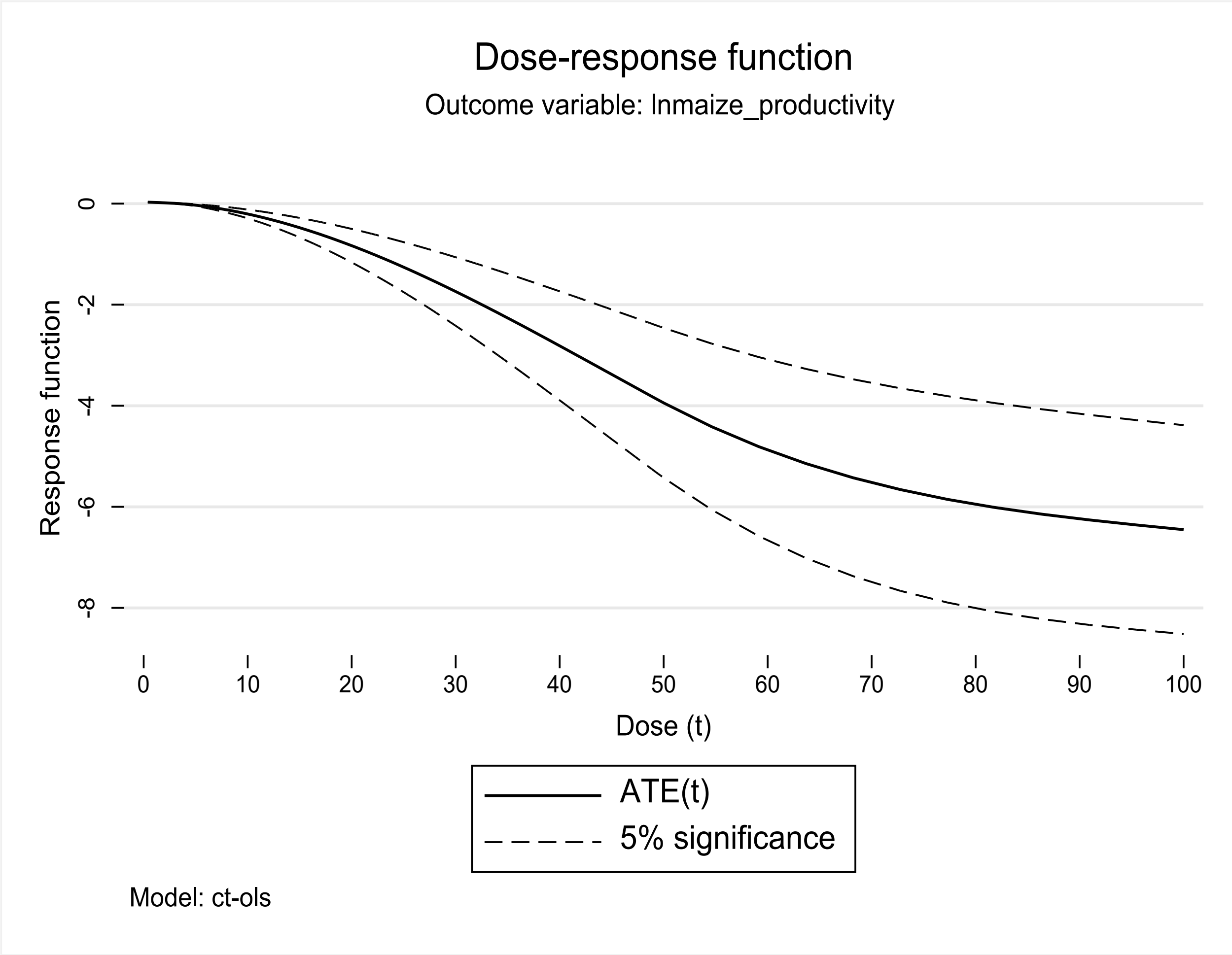

Figure 3.3: Dose response function of organic fertilizer on maize productivity. Exogenous treatment case

4. CONCLUSIONS, IMPLICATIONS FOR POLICY AND FUTURE RESEARCH

The study has analyzed input elasticities among maize farmers whereby a Translog cost function was jointly estimated with the factor cost shares using iterated seemingly unrelated regression model. In addition, the study assessed whether the intensification of organic manure has a causal effect on maize productivity by employing the dose response function. The findings provide evidence that there is a degree of substitutability between organic fertilizer and inorganic fertilizer whenever inorganic fertilizer becomes expensive to be purchased by maize farmers. Evidence also shows that the cost of maize production is minimal with the application of organic manure as compared to inorganic fertilizers. On the other note, the study has found strong evidence that average maize productivity is negatively and significantly associated with the intensity of organic fertilizer (manure) application on maize plots in Malawi.

Taking into account that the maize farmers are responsive to the price changes in the input markets and intensified use of organic manure only has less potential to raise maize productivity, the study in consequence recommends that maize farmers should be encouraged to use both organic manure and inorganic fertilizer especially by taking advantage of the agricultural extension interventions and effective targeting of the input subsidy programs. In particular, agricultural extension workers will play a crucial role in disseminating information on how to make organic fertilizers properly as well as advising farmers on the recommended applications of organic fertilizers on a maize plot. On the other hand, input subsidies will lessen the cost of producing the maize crop whilst enabling poor farmers to access chemical fertilizers which will be combined with organic fertilizers. Such input combination will ensure that there is high nutrient use efficiency considering that maize crop is a nutrient-demanding crop. Therefore, high benefits in terms of maize productivity will be achieved. Worth noting, future research should consider applying longitudinal data in order to analyze the dynamics of input elasticity substitution and maize productivity growth.

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