Government Expenditures, Social Outcomes, and Marginal Productivity of Agricultural Inputs: A Case Study for Tanzania

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Abstract

Using the most recent data from Tanzania, we investigate the impacts of district-level health and education expenditures on marginal productivities of agricultural inputs and overall production. We use a covariance structural model combined with a mixed linear model to account for the endogeneity of social outcomes and technological heterogeneity across districts. Our results confirm the significance of government social expenditures in human capital formation as measured through health and education indicators and their effects on agricultural productivity. Indeed, the marginal productivities of inputs (labor in particular) respond significantly and positively to health and education outcomes, especially considered jointly. The impacts also seem to be a function of the type of health constraint, with short-term health factors such as malaria and diarrhea impacting productivity from seeds and fertilizer while longer-term health constraints seem to have greater impacts on labor quality and land productivity. Our results also confirm the importance of considering intra-country heterogeneity as well as climate-related constraints, as the results show that annual precipitation has a signification impact on production for all specifications.

Key words: Tanzania, health, education, precipitation, marginal productivity, social expenditures, state variable

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I. Introduction

Global attention to the causes of poverty in Least Developed Countries (LDCs), especially sub-Saharan Africa, has increased. However, efforts to build upon the ongoing economic recovery and accelerate long-term economic development in much of Africa can be hindered by the need to use scarce resources to address the immediate symptoms of poverty rather than making investments that would increase income and production (Badiane and Ulimwengu 2009). Therefore, it is important that countries design programs that are able to meet short-term social needs while harnessing the growth effect of social service investments, particularly their impact on labor productivity.

Farmers in developing countries often do not have the resources or options that would allow them to reduce their risk of (or vulnerability to) health shocks. In general, poor households are more reliant on public services than wealthier households, which can mean that public spending on health may play a more important role in the lives of the poor and in low-income countries (Gupta, et al. 2003). However, it is difficult to draw conclusions on the impacts of particular social expenditures in rural areas as information on use of social services is not often available. In addition to limited data availability, there is also the concern that estimating the impacts of particular policies on productivity is complicated by endogeneity (Headey, et al. 2010).

Studies relying upon the data that does exist have not confirmed the linkages between social expenditures and outcomes in sub-Saharan Africa. For example, previous studies note that while health *capital* indicators can increase growth rates in Africa by 22 to 30 percent, results have been mixed when looking at health care *expenditures* and outcomes (Anyanwu and Erhijakpor 2007). Still, there are a few studies that have found that an increase in education spending by 1 percent of the country's Gross Domestic Product (GDP) can be linked to an average of an additional 3 years of schooling and that an increase in health spending of 1 percent of GDP can be associated with an increase in 0.6 percentage points in under-five child survival, especially in low-income countries (Baldacci et al. 2004). Many of the studies that have been done evaluate differences in income growth across countries (Hall and Jones, 1999; Fan and Rao, 2003) or evaluate only the impacts of expenditures on mortality or morbidity (see Anganwu and Erhijakpor 2007 for a detailed review). This can miss some important linkages, as it has been suggested that the relationship between health conditions and productivity can be more consistent than those between health conditions and income (McNamara et al. 2010). The mechanisms of this relationship have not been analyzed in detail, especially for sub-Saharan Africa.

Addressing this knowledge gap is important as even beyond direct mortality effects, health constraints can impact income in multiple ways. Time spent sick can detract directly from the quantity of labor available for agriculture, but can also lower the quality of agricultural labor as workers may not be as productive due to illness. Health problems and associated costs incurred can also impair farmers' willingness and ability (financially or physically) to incorporate new technologies, as well as lead to a loss of productivity due to the time needed to care for sick family members (Asenso-Okyere et al. 2011 and Drimie 2002). For example, the likelihood of adoption of new agricultural technology at the household level was greatly reduced by time spent sick or caring for sick household members in Ethiopia (Ersado, et al. 2004). This can impact productivity, both in the short- and long-term. Health issues, particularly malaria, but also unsafe drinking water and undernourishment, have been found to have a negative and significant impact on Total Factor Productivity (TFP), particularly in Africa (Cole and Neumayer 2006) and have been shown to lead to a shift in cropping patterns (Asenso-Okyere et al. 2009).

In addition to the impacts from health constraints, agricultural productivity can be impacted through educational expenditures and services. Unlike with health, however, the effects on agricultural productivity from increased education are not always straightforward. For example, an increase in secondary education may open up opportunities into non-agricultural activities that can provide more income, and therefore, may not necessarily improve agricultural productivity. However, an increase in primary education or vocational training may increase the pool of informed labor force that, in turn, can influence on-farm decision-making. In this way, additional education can lead to an increase in the efficiency of agricultural inputs (Phillips and Marble 1986).

A few different methods have been used in an attempt to empirically estimate the impacts of health and education on productivity. They include augmenting the human capital portion of the production function or/and allowing changes to labor efficiency (Teal 2011), using social indicators as determinants of an unobservable latent variable (Baldacci, et al. 2003), and estimating government expenditures as direct determinants of agricultural growth and poverty (Fan, et al. 2002). Despite data constraints, these studies have found that government expenditures in sectors such as agricultural research and development, irrigation, education, and infrastructure have contributed to agricultural productivity growth as well as reduced rural inequality and poverty in China and India (Fan, Hazell, and Haque 2000 and Fan, Hazell, and Thorat 2000). We expand empirically on these estimation methods to address some of their limitations using detailed data recently made available for Tanzania.

As with previous attempts to model the relationship between public expenditures on social services and productivity, we are limited by the data as we do not have actual utilization of social services or how these expenditures were allocated at the local level. However, we are able to draw some relevant conclusions regarding the role of expenditures in agricultural productivity in Tanzania using general information on health and education expenditures, disaggregated to the district level as well as social indicators at the household level. Specifically, we analyze the role of overall health and education expenditures on health and education indicators as well as their impacts on the marginal productivity of labor and other inputs for rural households in Tanzania. This research, in addition to using the most recently available agricultural production data for Tanzania[2], is novel in that it implements a covariance structural model to account for the underlying socio-economic environment and the difficultly in capturing the overall health of a population. In addition, unlike many previous approaches, it allows for technological heterogeneity at the district level by implementing a mixed linear model.

The paper is outlined as follows: Section II provides an overview of government expenditures and agricultural productivity in Tanzania; Section III includes the empirical background; Section IV provides a discussion of the data used; and Section V provides empirical results, together with additional tests of the modeling framework. The final section presents conclusions and resulting policy implications.

II. Social Expenditures and Agricultural Production in Tanzania

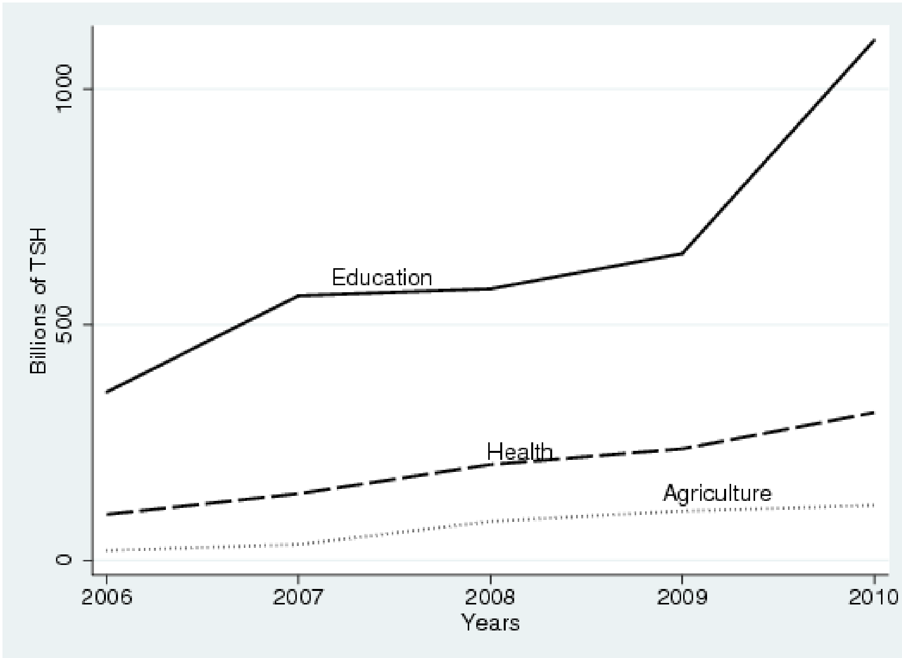
Although disaggregated data by the type of social service provided is not available, we are able to analyze the impact of particular categories of expenditures on social outcomes and agricultural productivity at a district-level. This type of analysis for one country rather than

[2] The National Bureau of Statistics of the United Republic of Tanzania provided data from the 2008 agricultural census and advance data for the 2008 household budget survey for this study, for which the authors are grateful.

across very heterogeneous countries may allow a better understanding of the impacts of particular social expenditures on social outcomes and agricultural productivity. The heterogeneity even within a country is particularly important to consider for countries that have transferred expenditures to lower levels of government (Gupta, et al. 2002), as in Tanzania. In addition, using available data, we are able to evaluate the impacts of particular groups of public expenditures, which can be interesting from a policy perspective. For example, previous studies have found that the expenditures on social services and public goods can have a greater impact on agricultural incomes than nonsocial subsidies (Allcott, et al. 2006).

Tanzania includes 21 administrative regions and 133 councils (both district and municipal) with 10,342 villages (MOHSW 2009). Local Government Authorities (LGAs) at the district-level are responsible for delivering public health services, primary education, agricultural extension, water supply systems, and local road maintenance (Republic of Tanzania 2006). This transfer of responsibilities to LGAs has contributed to higher-quality health services (Denmark, Ministry of Foreign Affairs 2007). Figure 1 shows national spending (in millions of Tanzanian shillings (TSH) on health and education at the district level.

Figure 1: Tanzania Health and Education Spending, District Level



Source: Local Government Finance Working Group 2011.

As in many sub-Saharan African countries, the majority of the poor population in Tanzania is located in rural areas and is dependent upon agriculture for their livelihood. In Tanzania, around 80 percent of people are employed in agriculture (Cleaver, et al. 2005). Unfortunately, Tanzania appears to have very low poverty-growth elasticity over time, and economic growth has not translated into a steep decline in poverty (Pauw and Thurlow 2010). The government has striven to address poverty through investments in various social services including public health and education, agricultural extension, and infrastructure and it appears some changes have taken place. For example, the Primary Health Care Service Development Programme increased primary health service provisions through staff and supply increases and upgraded facilities (MOHSW 2009). The Centre for Research on Poverty Alleviation (REPOA), a Tanzanian nongovernmental organization (NGO), noted that according to census and

Demographic and Health Surveys data, from 1978 to 2005, infant mortality was reduced from 137 per 1,000 live births to 68, with similar reductions in under-five mortality, partially as a result of prevention and treatment of malaria, increased Vitamin A supplementation, immunization, and better nutrition (REPOA 2006). In terms of education initiatives, the Primary Education Development Plan 2002–2006 abolished primary school fees, increased teachers by 50 percent, and built more than 41,000 new classrooms (Mamdani et al. 2009). Despite these advances, there are still challenges in terms of staff, funds, and infrastructure. There also remain large differences in education between rural and urban areas (REPOA 2006).

There have been a few analyses that have addressed the impact of government services on rural incomes in Tanzania. In particular, Fan, et al. (2005) estimated the role of expenditures by estimating access to capital and infrastructure as a determinant of household welfare and then, linking expenditures to access variables. However, this analysis was limited by the data available at the time and focuses on poverty impacts rather than agricultural productivity. Temu, et al. (2002) also conducted a regional analysis for Tanzania, linking access to infrastructure and services, inputs, and other fixed factors to farm-level production. Taking this idea further with more recent datasets and further disaggregation, we use household-level agricultural production and indicators of health and education outcomes as well as public expenditure data at the district level to investigate the possible impacts of public expenditures on health and education indicators, and through this, on agricultural productivity.

III. Empirical Strategy

As mentioned previously, several studies have explicitly modeled the relationship between health and agricultural productivity by incorporating a health variable into the utility function (Pitt and Rosenzweig 1986) and modeling public expenditures and productivity using a system of equations (Benin, et al. 2009). Others have used stochastic frontier analysis (SFA) to estimate the relationship between agricultural efficiency and health measures or farmer education (Ulimwengu 2009; Phillips and Marble 1986). While calculating efficiency in production can provide additional information about the production constraints, there are some weaknesses associated with these approaches, regardless of the empirical specification. The models require either specification of a restrictive functional form or can be very sensitive to measurement error (in the case of nonparametric approaches) (Saradifis 2002). Frontier analysis can also ignore important farm-level differences between production possibilities and technological options and choices by assuming the same production frontier for all households (Mundlak 1988).

Taking a different approach, Fan, Hazell, and Haque (2000) and Fan, Hazell, and Thorat (2000) used a simultaneous structural equation framework to describe the impact of government spending on growth and poverty in India. They found that public expenditures reduce rural poverty through their effects on total factor productivity and incomes. This framework was designed to analyze the multiple channels through which government expenditures can affect agricultural productivity as well as account for endogeneity and possible interactions between variables. The authors later modified their approach by adding variables such as urban growth, institutions, and policies (Fan, et al., 2002). However, while empirically appealing, this framework is limited in its ability to identify the underlining economic behavior that may drive the results as well as indirect impacts through other agricultural inputs. Building on the structural modeling framework, we include fixed effects to allow for district heterogeneity as well as latent variables in an attempt to better explain the link between social expenditures and social outcomes as well as their impacts on marginal productivity of inputs.

Government expenditures on social services are expected to have direct effects on agricultural production but also indirectly through decisions regarding inputs and technology. To try to capture both, we first adopt the framework developed by Mundlak, et al. (1997) used to model farmers' decision processes. Mundlak, et al. (2008) argue that the wide variation in the estimation results of agricultural production functions may be partially due to the exclusion of factors representing the political, economic, or physical environment ("states") which have both direct and indirect effects on farm production and decisions. To implement this state-variable approach, input elasticities can either be calculated from observed factor shares (assuming allocative and technical efficiency) or from fitting a production function that is simultaneously determined by both observed inputs and state variables (Fulginiti and Perrin 1993). As the assumption of efficiency is likely too restrictive for rural households in Tanzania, we take the second approach, discussed in more detail below.

Following Mundlak, et al. (1997), each farm chooses a technology subject to its constraints under the prevailing socioeconomic environment and jointly determined with the variable inputs. A production function $F_j(X)$ is estimated for all production techniques (*j*) where X is a vector of constrained (*k*) and unconstrained (*v*) inputs so that $F_j(X) \ni v, k$ (Mundlak, et al. 1997). Depending on the choice of *(j)*, each farm selects the optimal level of inputs (*X)* for each technique (*j)* according to the assumption of profit maximization. However, as we assume that this function is conditional on the state variables *(s)*, any changes in *s* will imply changes in the optimal level of inputs (*x*)* as well as the chosen technology *F(x*,s)*. Therefore, the production function $F_j(X, s)$ assumes that the slope (β) and intercept *(Γ)* are both determined by *(s)*, as shown in Equation 1, where the dependent variable *(y)* is estimated as value-added per worker in their example and *u* represents the stochastic component (Mundlak, et al. 1997).

$$ln\, y = \Gamma\,(s) + \beta(s, x)\ln x + u \qquad (1)$$

In addition, recognizing the importance of allowing for heterogeneity described in Mundlak (1988), we further assume that production technologies are heterogeneous across districts. Our empirical implementation of this approach is outlined in more detail in the following sections, which address the issue of heterogeneity, the endogeneity of technology and inputs, and the challenges of finding appropriate social outcome variables.

A. Consideration of District Heterogeneity

To account for heterogeneity among districts, we use a two-stage estimation of the production function in which the first stage estimates the production function for each district and the second stage explains the variation in these estimated parameters using exogenous covariates (following Verbeke and Molenberghs 2000). In their framework, Y_i is defined as the n_i-dimensional vector of repeated measurements of production for the household *(i)*, satisfying the following linear relationship:

$$Y_i = x_i\beta_i + \varepsilon_i \qquad (2)$$

Here, x_i is an (n_i*q) matrix of exogenous variables, β_i is the q-dimensional vector of unknown individual-specific regression coefficients, and ε_i represents the residual components. This uses the normal assumptions for ε_i: iid~N(($\sigma^2 I_{n_i}$), where I_{n_i} is a n_i-dimensional identity matrix (Verbeke and Molenberghs 2000). The second stage uses a matrix of exogenous covariates(Z_i) to explain this observed heterogeneity between households with respect to their specific (unknown) regression coefficients β_i as shown in equation *(3)* where the residual, $b_i \sim N(0, D)$:

$$\beta_i = Z_i\gamma + b_i \tag{3}$$

Equations *(2)* and *(3)* are combined to yield the generalized mixed-effects model (allowing both the fixed-effect (γ) and the random, individual-specific effect (b_i)):

$$Y_i = K_i\gamma + x_i b_i + \varepsilon_i \tag{4}$$

In Equation *(4)*, $K_i = x_i Z_i$ and is a $(n_i * p)$ matrix of exogenous covariates. This builds upon the assumptions that the model satisfies the following conditions: b_i ~N(0,D), $\varepsilon_i \sim N(0, \sum_i)$, and $b_1, \dots . b_N, \varepsilon_1, \dots \varepsilon_N$ are independent (Laird and Ware 1982). We apply this model at the district-level to capture heterogeneity within Tanzania.

B. Social Expenditures and Social Outcomes

Other studies have noted the difficulty in estimating impacts to the overall health of a population due to related factors that are difficult to disentangle and the fact that the nature of health problems may change and overall health is difficult to sufficiently measure using only a few indicators (Jack 1999). To address this and generate efficient estimates of the impacts of expenditures on social outcomes, Baldacci, et al. (2003) suggest modeling social outcomes as partially determined by the institutional and individual environment using a latent variable approach. Their approach estimates latent variables for health and education using a general covariance structure model:

$$S = \Lambda M + \delta \tag{5}$$

where Λ is the matrix of covariances between the latent (unobserved) variable M and the observed social variables (S). In the case of two observable variables (S_1 and S_2) for each household (i), assuming exogenous latent variables (M) and endogeneous latent variables *(N)* are uncorrelated with the error terms, Equation 5 can be written as:

$$s_{1i} = \Lambda_x M + \delta \text{ and } s_{2i} = \Lambda_y N + \varepsilon \tag{6}$$

and the structural equation model (Baldacci, et al. 2003; StataCorp 2011) is specified as:

$$N = \vartheta N + \Gamma M + \zeta \tag{7}$$

The variable ϑ are the regression coefficients for the endogenous latent variables (N) and Γ are parameters of the exogenous latent variables (M) with respect to *(N)*, with ζ specified as random disturbances (Baldacci, et al. 2003). We then utilize our social indicator variables (S) from Equation *(6)* as state variables in our specification of agricultural production, outlined in more detail below.

C. Application

Following Mundlak, et al. (1997), the aggregated agricultural output (Y_i) for household (*i)* is conditioned on state variables *(S)* for each district *(d)*, capturing district-level constraints through input quantities (*x)* alone. As discussed above, we first estimate the state variables (measures of health and education status) as functions of district-level government expenditures for health and education while controlling for household characteristics and district fixed effects as follows:

$$S_{id} = f(z_{id}, g_d) \tag{8}$$

where *i* and *d* represent the household identifier and district location, respectively, and *S*= (*education, health*), *z*: household member characteristics, and *g*: district-level government expenditures on education and health.

The district-level expected values of health $\left(\hat{S}_{hd}\right)$ and education $\left(\hat{S}_{ed}\right)$ outcomes were then plugged into equation *(10)* to estimate marginal productivities of each input (*l*) as (β_{il}) from the following production function where *p* is total precipitation, discussed in more detail in the following section:

$$Y_i = \beta_0 + \sum_l \beta_{il} x_{il} + \beta_d p_d + \varepsilon_i \quad (9)$$

$$\beta_{il} = \gamma_{0l} + \gamma_{1l}\hat{S}_{hd} + \gamma_{2l}\hat{S}_{ed} + u_{il} \quad (10)$$

IV. Data and Summary Statistics

For this analysis, we rely upon agricultural production data from the 2007/08 Agricultural Census, a nationally representative survey covering 52,594 households in Tanzania for the agricultural year that ran from October 1, 2007 to September 30, 2008 (NBS 2010). Given the variety of crops produced in Tanzania, weighted production is calculated as in Equation *(11):*

$$Y_i = \sum_{c=1}^{n} (y_{ic} \cdot a_{ic}) \quad (11)$$

Here, Y_i is the aggregate production amount (in kilograms) for household (i), y_{ic} is the production of crop *c*, and a_{ic} is the share of land allocated to crop *c*. In our case, value measurements were not possible given a lack of disaggregated price data. We assume that aggregate agricultural output as defined here is a function of typical agricultural inputs (chemical and physical) and constraints in the natural environment (such as precipitation).

For inputs, we include labor (the number of adult household members that are involved in agriculture as their main activity), the use of animals for traction, the amount spent on seeds, the quantity of chemical fertilizer used in kilograms, and the size of land planted in acres. Precipitation data are also included to control for weather variations. These data are satellite-collected daily precipitation (in millimeters per day) that has been averaged over the district observation points from the Climate Prediction Center of the US National Weather Service (NOAA 2010). These are the most accurate data available for these purposes, and have been calculated as precipitation amounts for the agricultural year. The specification was also done using a measurement of organic fertilizers, but inorganic fertilizers proved to be a better determinant of productivity differentials. This is not surprising given the relatively low levels of inorganic fertilizer use on small-scale farms.

In addition to the agricultural variables, data is taken from the 2008 Household Budget Survey (NBS 2011). This data is used to control for the rural location of households (the population of interest) and households headed by females (as we would expect that female-headed households might have different levels of access to public services in education) (UN Economic Commission for Africa 2008). For implementation of the latent-variable approach, the numbers of household members not affected by malaria, diarrhea, or long-term illness within the household over the past month were used as health indicators. These illnesses are in line with the most documented illnesses in this dataset as well as in previous studies for Tanzania (Koestle 2002). Education indicators included the number of household members who have completed secondary school, those who are literate in English, and those who are literate in Swahili. While accounting for adult education would have been interesting, this variable was not observed in enough households and data on professional and vocational training was not available. The summary statistics for these household-level variables are presented in Table A.1 in the Appendix.

Data on district expenditures for a range of expenditure categories is compiled and available online from the National Bureau of Statistics (Local Government Finance Working Group 2011). In Tanzania, past research has estimated that 57 percent of the “other charges” category for education is being diverted and 88 percent of these charges are diverted in health (Sundet 2004). Therefore, we account for the structure of expenditures by analyzing categories of these expenditures that are likely to include fewer leakages (personal salaries and development grants). Unfortunately, expenditure data for agriculture, roads, and other types of social expenditures were missing for a large majority of the sample.

We calculated the mean of expenditures for 2005 and 2006 to capture lagged effects (as much as possible given data limitations). This average allows a more consistent representation of district expenditures. As districts vary greatly in size, we calculated the expenditures per capita[3] at a district-level using population data from the Population Census for 2002/03, the most recent compiled source of population data for Tanzania (NBS 2006). Although in the estimations, we use billions of TSH per capita for scaling purposes and interpretation, Table 1 presents the amounts in TSH per capita.

Table 1: District Expenditure Data

District Expenditures (TSH) per Capita (Mean 2005 & 2006)		
Expenditure Category	**Mean**	**Standard Deviation**
Education Personal Salaries	22,841	48,400
Education Development Grants	6,357	15,013
Education Total Spending	34,482	72,574
Health Personal Salaries	5,179	9,559
Health Development Grants	1,719	4,180
Health Total Spending	9,893	22,657

Source: Local Government Finance Working Group 2011

V. Results

A. Estimation of Social Outcomes

As mentioned previously, indicators of health and education outcomes often used in traditional approaches may not be appropriate proxies given that the health of a population is difficult to accurately measure. We first specify tobit models to estimate our expected state variables for health and education using both development and personal salary expenditures in the education and health sectors. The results were shown to vary with the choice of indicator,

[3] On October 30, 2011, TSH 1,724.35 = $1 (OANDA, 2011).

supporting the use of a latent-variable approach as discussed earlier and as per Baldacci, et al (2003). Therefore the latent variables approach was implemented using the structural equation model specified in Equation *(7)*. These results are presented in Tables 2 and 3 for health and education, respectively. The models, as specified, fit a measure of “good” health and the “stock” of education at the household level. Indicators of household health status include the numbers of household members without the common illnesses of malaria and diarrhea, but also long-term illnesses. These longer-term diseases have been found to have negative effects on income and livelihoods in Tanzania (Koestle 2002; Adhvaryu and Beegle 2010).

As shown in Table 3, all of the indicators are positively and significantly correlated with the health status variables. Results also suggest a quadratic relationship between health status and expenditures on salaries in the health sector.[4] These results suggest the existence of a minimum amount from which health expenses start improving farmers’ health status in all types of illness. For example, at the household level, this minimum for long-term health is estimated at TSH 53,510 per capita (approximately US$31[5] per capita per year).

[4] The maximum/minimum is the value of x that solve $\frac{dy}{dx} = 0$.
In this specification (y=a+bx+cx*x), the solution is given by $x = -\frac{b}{2c}$.

[5] All dollar amounts are in US dollars. On October 30, 2011, TSH 1,724.35 = $1 (OANDA, 2011).

Table 2: Health Expenditures and Health Outcome

Variables	No Long-Term Illness	No Malaria	No Diarrhea
Health Development/capita	5.454	4.063	5.5473
Health Development/capita²	-143.48	-110.00	-150.00
Health Salaries/capita	-14.100***	-10.637***	-14.519***
Health Salaries/capita²	135.294**	102.239**	139.555***
Rural	0.174***	0.136***	0.186***
Health Indicators			
Member without long-term health problems	1.00	1.291***	0.946***
Members without fever	0.775***	0.845***	0.619***
Members without malaria	0.654***	1.000	0.733***
Members without diarrhea	1.057***	1.3648***	1.000
Variances			
Health	0.978***	0.586***	1.091***
Without long-term health problems	0.095***	0.094***	0.094***
Without fever	0.283***	0.282***	0.282***
Without malaria	0.261***	0.259***	0.259***
Without diarrhea	0.003*	0.003*	0.003***
chi²(21)=	1701.05	1715.69	1715.69
Log Likelihood	16106.8	168892.7	168892.7
N	9725	9846	9846

**p<0.10, **p<0.05, ***p<0.01*

With respect to education, the number of household members with secondary education, those with literacy in Swahili, and those with literacy in English were used as indicators of the household stock of education. Unfortunately, as mentioned, information on vocational training is not available and therefore, the following analysis is focused on secondary education. In his review of public expenditure and education outcomes in Africa, Al-Samarrai (2003) concluded that increased resources for education alone are unlikely to be sufficient for achieving education goals and that the composition of resources and the institutions that govern the use of these resources are crucial. As shown in Table 3, both English literacy and literacy in Swahili are significant determinants of our education indicator (secondary education); while English literacy is positively associated with the stock of education, literacy in Swahili has a reducing effect on the stock of education. This may be due to the fact that completion of secondary education (constrained to be equal to the stock of education in our setting) requires knowledge of English. Unlike health, both salary and development expenditures in education significantly affect the stock of education, but in different ways. Indeed, while development expenditures require a minimum amount (TSH 285,034 per capita per year—or approximately $165) from which a positive effect can be observed, there seems to be a maximum amount (TSH 281,163 per capita per year—or $163) of salary expenditures beyond which no positive effect is observed.

Table 3: Education Expenditures and Education Outcome

Variables	Secondary Education
Education Salaries/capita	1.615***
Education Salaries/capita²	-2.872**
Education Development/capita	-2.156***
Education Development/capita²	3.783*
Rural	-0.122***
Male Household Head	-0.032***
Education Indicators	
Completed Secondary	1.00
English Literacy	0.412***
Swahili Literacy	-0.304**
Variances	
Education	0.06***
Completed Secondary	0.132***
English Literacy	0.167***
Swahili Literacy	3.215***
chi²(12)=	222.94
Log Likelihood	75690
N	9819

*Note: *p<0.10, **p<0.05, ***p<0.01*

B. Estimation of Production Function

Moving onto the estimation of the production function (first without the consideration of state variables), Ordinary Least Squares (OLS) estimates, with and without precipitation are compared to random effects (RE) estimates. All inputs and outputs are logged values and estimates can be interpreted as elasticities. The results reported in Table 4 show that all input elasticities are significant and positive. Compared with other inputs, elasticity of production with respect to land and seeds are the highest, ranging from 0.445 to 0.577 for land and from 0.466 to 0.522 for seeds. The value of land elasticity seems to support the idea that agricultural growth in sub-Saharan Africa has often been driven by land expansion (Dethier and Effenberger 2011). The elasticity with respect to labor is modest and only significant when we account for precipitation and district heterogeneity.

Precipitation appears to have a nonlinear relationship with production as too much precipitation in one area during a season can be detrimental to crop production. The results suggest a tipping point of 638.5 millimeters of precipitation[6] when using the RE model and 777.2 millimeters with the OLS specification, beyond which additional precipitation begins to decrease agricultural production. This nonlinear and significant relationship between climatic variables and agricultural productivity has been documented in the literature (Maddison, et al. 2006; Gommes 1999). The results here highlight the necessity of controlling for agro-climatic conditions as well as other sources of heterogeneity when estimating input elasticities.

[6] Tipping point is the value of rainfall/temperature for which agricultural production reaches its maximum level. It is the value of x that solve $\frac{dy}{dx} = 0$. In our specification (lny=a+blnx+clnx*lnx), the solution is given by $x = e^{\frac{-b}{2c}}$.

Table 4: Production Estimation

Variable	OLS	OLS with Precip	RE Model
Land	0.577***	0.520***	0.445***
	(0.011)	(0.012)	(0.030)
Labor	-0.015	0.050***	0.074**
	(0.013)	(0.015)	(0.032)
Seeds	0.522***	0.499***	0.466***
	(0.003)	(0.004)	(0.008)
Fertilizer	0.020***	0.014***	0.042***
	(0.002)	(0.003)	(0.008)
Animals	0.206***	0.182***	0.118***
	(0.009)	(0.010)	(0.020)
Precipitation		19.621***	25.165***
		(0.685)	(2.568)
Precipitation²		-1.474***	-1.948***
		(0.051)	(0.190)
Constant	0.094***	-64.80***	-80.219***
	(0.027)	(2.310)	(8.661)
Obs.	51174	41313	41313
Groups			113
Adj R²	0.562	0.521	
Chi²/F	13110.7	6424.9	9396.7
Log Likelihood			66050.3

*Note: Std errors in parentheses, *p<0.10, **p<0.05, ***p<0.01*

C. Social Indicators and Productivity

Moving forward with the inclusion of state variables as discussed previously and following Equation *(4)*, the agricultural production function at the household level was estimated using a generalized mixed linear model, for which the results are presented in Table 5. This incorporates the expected values of education and health measures estimated from equation *(8)*, with the intercepts and indirect effects for health and education. To allow for comparison, the results without state variables (the RE model from Table 4) are also presented.

The results in Tables 5 demonstrate the impact of the inclusion of social outcomes on the magnitude and significance of input elasticities, both separately and when interacted with state variables. They appear to provide evidence that education (secondary education) significantly impacts the productivity of inputs both directly (land, seeds, fertilizer, and animals) and indirectly as complements to other inputs (seeds and land). For health, similarly, it appears that all indicators have direct and indirect effects on productivity. The results also suggest that compared to long-term diseases and diarrhea, malaria has the greatest impact on productivity for all inputs other than animals. The results would suggest that the return to additional investment in malaria prevention on agricultural productivity of labor in Tanzania might be higher compared to similar interventions on other diseases.

We also analyze the interactions of health and education indicators as increased health capital has been shown to be positively associated with education capital in developing countries (Baldacci, et al. 2008). Table 6 provides interaction between health and education variables and the results confirm that when the interaction between education and health (especially malaria) is considered, the role of education in productivity changes. These results will be tested further using additional metrics in the following discussion.

Table 5: Production Estimation with and without State Variables

Variable	NoState	Secondary Education	Long Term Health	Diarrhea	Malaria
Land	0.445***	0.425***	0.436***	0.435***	0.433***
	(14.96)	(13.06)	(14.54)	(14.42)	(14.28)
Labor	0.0742**	0.0858**	0.0925***	0.0929***	0.0930***
	(2.3)	(2.5)	(-2.85)	(2.85)	(2.84)
Seeds	0.466***	0.481***	0.469***	0.470***	0.471***
	(58.56)	(56.92)	(59.88)	(59.78)	(59.72)
Fertilizer	0.0421***	0.0460***	0.0449***	0.045***	0.046***
	(5.47)	(5.52)	(5.85)	(5.88)	(5.89)
Animals	0.118***	0.126***	0.115***	0.114***	0.116***
	(6.01)	(4.99)	(4.84)	(4.76)	(4.78)
Precipitation	25.16***	25.85***	27.36***	27.38***	27.41***
	(9.8)	(10.21)	(-10.81)	(10.81)	(10.83)
Precipitation²	-1.948***	-1.987***	-2.091***	-2.092***	-2.095***
	(-10.25)	(-10.61)	(-11.16)	(-11.17)	(-11.18)
Education Intercept		-11.61***			
		(-14.38)			
Land*Education		-1.512**			
		(-2.22)			
Labor*Education		-0.235			
		(-0.33)			
Seeds*Education		1.114***			
		(6.38)			
Fertilizer*Education		0.225			
		(1.29)			
Animals*Education		0.591			
		(1.01)			
Health Intercept			4.425***	4.192***	5.964***
			(14.33)	(14.30)	(14.45)
Land*Health			0.699**	0.661	0.945**
			(2.43)	(2.42)	(2.47)
Labor*Health			-0.0387	-0.048	-0.055
			(-0.13)	(-0.17)	(-0.14)
Seeds*Health			-0.432***	-0.407***	-0.583***
			(-6.16)	(-6.14)	(-6.25)
Fertilizer*Health			-0.163**	-0.157*	-0.219**
			(-2.32)	(-2.36)	(-2.34)
Animals*Health			-0.0651	-0.0556	-0.113
			(-0.22)	(-0.20)	(-0.30)
Constant	-80.22***	-83.24***	-88.61***	-88.67***	-88.77***
	(-9.26)	(-9.75)	(-10.37)	(-10.38)	(-10.39)
District Fixed Effects	YES	YES	YES	YES	YES
N	41313	41313	41313	41313	41313
Log Likelihood	-66050	-65938	-65942	-65943	-65939
Wald Chi²	9397	9999	10280	10267	10268

*Note: *p<0.10, ***p<0.05, ***p<0.01; t stats in parentheses*

Table 6: Interactions between Health and Education

Variable	NoState	Long Term Health& Education	Diarrhea & Education	Malaria & Education
Land	0.445***	0.433***	0.432***	0.432***
	(14.96)	(-12.61)	(12.74)	(12.85)
Labor	0.0742**	0.0806**	0.0814**	0.082*
	(2.3)	(2.23)	(2.28)	(2.30)
Seeds	0.466***	0.475***	0.476***	0.476***
	(58.56)	(-53.7)	(54.50)	(54.83)
Fertilizer	0.0421***	0.0401***	0.0408***	0.0412***
	(5.47)	(-4.64)	(4.78)	(4.88)
Animals	0.118***	0.134***	0.1323***	0.1312***
	(6.01)	(-5.13)	(5.10)	(5.07)
Precipitation	25.16***	26.64***	26.644***	26.712***
	(9.8)	(-10.5)	(10.50)	(10.53)
Precipitation²	-1.948***	-2.040***	-2.041***	-2.046***
	(-10.25)	(-10.87)	(-10.87)	(-10.90)
Education Intercept		-5.958***	-6.051***	-5.560***
		(-3.47)	(-3.58)	(-3.20)
Land*Education		0.46	-0.607	-0.439
		(-0.73)	(-0.42)	(-0.29)
Labor*Education		-0.347	-0.971	-1.036
		(-0.58)	(-0.70)	(-0.72)
Seeds*Education		-0.274	0.518	0.454
		(-1.99)	(1.57)	(1.34)
Fertilizer*Education		-0.315	-0.427	-0.455
		(-2.26)	(-1.29)	(-1.33)
Animals*Education		0.969*	2.463*	2.347
		(-1.43)	(1.77)	(1.64)
Health Intercept		2.438***	2.287***	3.481***
		(-3.71)	(3.72)	(3.91)
Land*Health		-0.542	0.409	0.677
		(-0.37)	(0.69)	(0.79)
Labor*Health		-0.971	-0.330	-0.499
		(-0.69)	(-0.60)	(-0.62)
Seeds*Health		0.489*	-0.248*	-0.385*
		(-1.45)	(-1.95)	(-2.09)
Fertilizer*Health		-0.435*	-0.297**	-0.432*
		(-1.28)	(-2.30)	(-2.31)
Animals*Health		2.396	0.958	1.223
		(-1.74)	(1.46)	(1.32)
Constant	-80.22***	-86.10***	-86.11***	-86.35***
	(-9.26)	(-10.06)	(-10.06)	(-10.08)
District Fixed Effects	YES	YES	YES	YES
N	41313	41313	41313	41313
Log Likelihood	-66050	-65928	-65928	-65925
Wald Chi²	9397	10188	10183	10188

*Note: *p<0.10, ***p<0.05, ***p<0.01; t stats in parentheses*

D. Additional Metrics for Interpretation

To further interpret the results in Tables 5 and 6, we employ a series of metrics developed by Fulginiti and Perrin (1993). The first metric is the average production elasticities with respect to inputs which correspond to Equation *(9)* and is shown in Table 7. These elasticities simply compile the results from Tables 5 and 6 and are reported for only those districts in which they were significant for each model specification. As mentioned previously, the focus is on secondary education due to a lack of information on vocational training. As can be seen in Table 7, labor elasticity is estimated at 0.053 (with education), 0.064 (with long-term health), and 0.066 (with both education and malaria considered) compared to the baseline of 0.031. The production elasticity with respect to land decreases once education and health are considered, implying that higher health and education stocks increase land productivity.

Table 7: Marginal Productivity of Inputs

Model	Land	Labor	Seeds	Fertilizer	Animal
No State	0.459	0.031	0.468	0.042	0.137
Education Alone	0.451	0.053	0.472	0.042	0.137
Health Alone					
Long Term Health	0.440	0.064	0.471	0.044	0.124
Diarrhea	0.423	0.052	0.481	0.048	0.133
Malaria	0.423	0.052	0.481	0.048	0.133
Education & Health Combined					
Education & Long Term Health	0.431	0.061	0.475	0.044	0.116
Education & Diarrhea	0.435	0.062	0.475	0.045	0.114
Education & Malaria	0.425	0.066	0.478	0.473	0.111

Source: Author's calculations; Note: Square roots of variances for all elasticities presented are less than 0.005

The second metric from Fulginiti and Perrin (1993), is the elasticity of production with respect to state variables (health and education) and evaluated from Equations *9* and *10* where both y and s are in log form as:

$$\frac{\partial y}{\partial s} = \frac{\partial y}{\partial \beta}\frac{\partial \beta}{\partial s} = \sum_l \gamma_{ls} x_l + b_s \qquad (12)$$

The results are shown in Table 8, with components of Equation *12* broken out individually. The metric of interest (average production elasticities with respect to states) is estimated at -3.24 with respect to education, 5.31 with respect to the presence of a long-term disease, 0.13 with respect to diarrhea, and 0.16 with respect to malaria. This suggests that while increased health would be an advantage for agricultural production, increasing household stock of education (here secondary education) may decrease overall agricultural production as an increase in secondary education may open up opportunities into nonagricultural activities and thereby reduce available labor for farming activities.

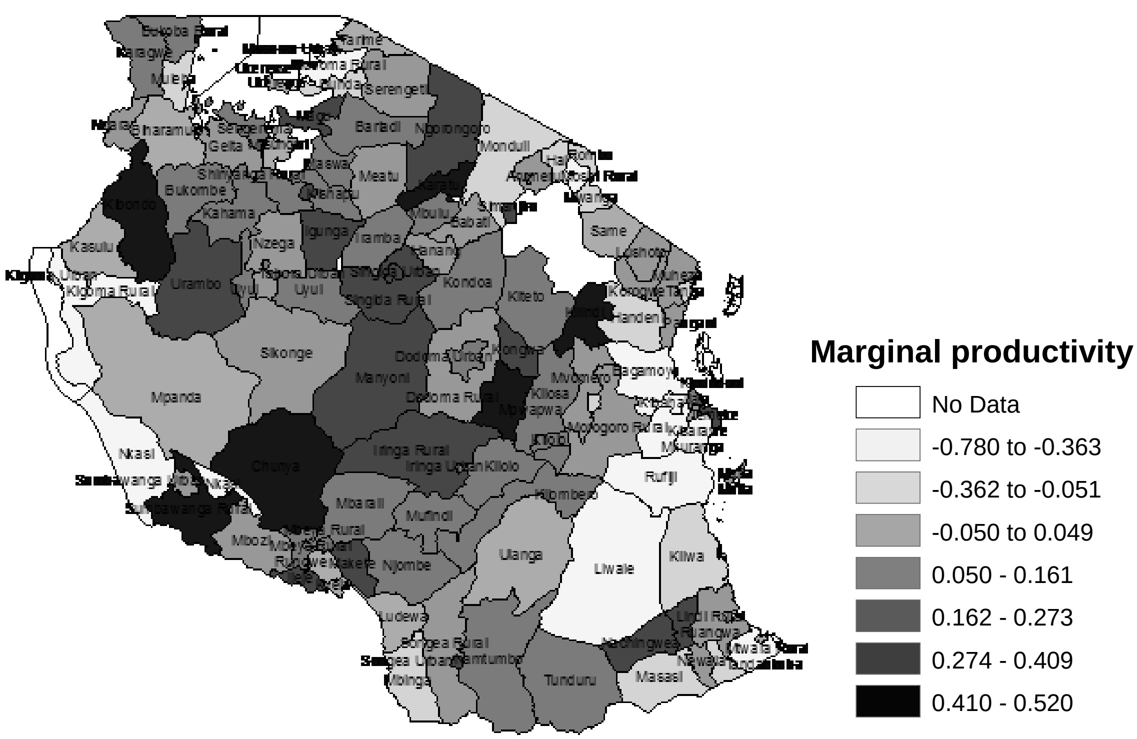
Table 8: Production Elasticities & Marginal Productivity of Inputs with Respect to States

	Elasticities of Marginal Productivity of Inputs with Respect to States						State own-elasticities	Elasticity of production with respect to states
	Total Elasticitiy (sum of MPs)	Land	Labor	Seeds	Fertilizer	Animals		
Secondary Education	0.2	-1.5	-0.2	1.1	0.2	0.6	-11.6	-3.24
No Long-term disease	0.9	-0.5	-1.0	0.5	-0.4	2.4	2.4	5.31
No Diarrhea	0.5	0.4	-0.3	-0.2	-0.3	1.0	2.3	0.13
No Malaria	0.6	0.7	-0.5	-0.4	-0.4	1.2	3.5	0.16

Source: Author's calculations

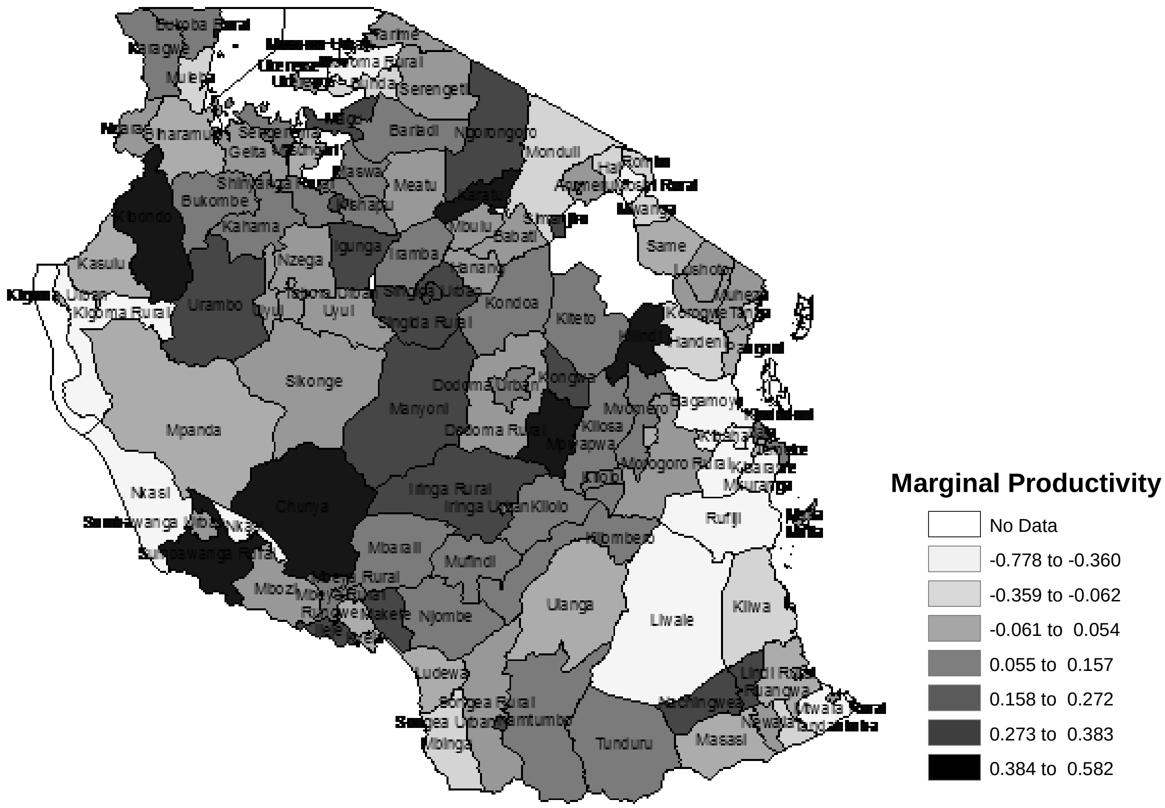
Total elasticities (summed across all inputs) are positive as overall production increases but there are significant differences in individual estimates and not all individual estimates are significant (as shown in Tables 5 and 6). These findings highlight the need for careful targeting in the implementation of social programs aimed at improving agricultural productivity. The variation in significance of the impacts associated with social variables among districts could indicate diversity in production technology across Tanzania. This is also captured through geographical distribution of labor productivity with respect to states, shown in Figure 2 for long-term health and Figure 3 for education. Additional figures showing district heterogeneity in marginal productivities for land and labor (both separately and combined) are included in the Appendix. This diversity highlights the shortcomings of the homogeneous technology assumption, and at least in the case of Tanzania, policy recommendations based on national averages are likely to miss the target in many districts.

Figure 2: Marginal Productivity of Labor (Long-Term Health as State variable)



Source: Authors' calculation

Figure 3: Marginal Productivity of Labor (Education as State variable)



Source: Authors' calculation

VI. Conclusions

Combining the most recent nationally-representative data on agricultural production and household characteristics available for Tanzania, we evaluate the impact of district-level health and education expenditures on human capital and marginal productivity of agricultural inputs at the household level. This research allows more detailed analysis than some previous studies in that it analyzes the heterogeneity within one country, accounting for district-level expenditures and heterogeneity of production and climate. It also analyzes unique types of government expenditures and health constraints to the extent possible and their direct and indirect effects on agricultural productivity. This relies upon the combination of a generalized mixed-effects model (to capture heterogeneity) and a covariance structure that accounts for not only the underlying socio-economic environment driving farm-level decisions but also imperfect measurements of health and educational outcomes.

The results of the analysis confirm the significance of government social expenditures in human capital formation as measured through health and education indicators. Building upon this knowledge, we also show that these health and education indicators significantly impact agricultural productivity both directly and indirectly. The results show variation in effects across types of diseases as well as combined effects of both education and health across input productivities. Overall production elasticities respond positively to the absence of long-term disease and to a greater extent than to malaria or diarrhea. In terms of educational indicators, overall production elasticities respond negatively to an increase in secondary education, which may indicate a focus on off-farm sources of income. For particular inputs, the marginal productivity of land and labor are most affected by long-term disease incidence while seeds and fertilizer productivity is more affected by malaria and diarrhea. These results may highlight the difference in the short-term health factors that impact immediate on-farm investments and the longer-term health constraints which may be a sign of limited investments to restructure agricultural production.

The results also point to the importance of controlling for heterogeneity across sub-national entities as well as the overwhelming importance of precipitation as a constraint to agricultural production. The findings highlight the effects of different types of social expenditures, such as health versus education expenditures, as well as between expenditure allocations such as development expenditures and salary expenditures. In particular, we find a minimum level of expenses on health salaries from which farmers' health status improves across all types of illness. Likewise, our results show that there is a minimum level of expenditures needed to see changes in the stock of education. This result is in line with what has been documented in other regions and calls for careful targeting of social spending to achieve expected educational outcomes.

Overall, our findings support the idea that the level of productivity resulting from the use of various agricultural inputs is affected differently by changes in social outcomes and that these changes can be affected by government expenditures. They also highlight the existence of estimation bias when marginal productivities of inputs are assumed to be constant across locations or farming households. Geographical distribution of marginal productivities of inputs with respect to these state variables, even after controlling for district fixed effects and variation in precipitation, seem to confirm technology heterogeneity across districts. Ignoring this heterogeneity when implementing social or agricultural programs could result in inefficient use of limited government resources.

Findings from this paper are intended to provide research-based evidence to guide the formulation, implementation, and monitoring of agricultural strategies and their connection to social programs. This type of analysis could be improved by further disaggregating social expenditures by function or nature of targeted social issues. Such disaggregation will provide more visibility to policymakers in terms of appropriate and specific tools available for effective decision-making. Addition of a dynamic framework would also allow the capture of lagged effects in the relationship between social outcomes and social expenditures, and as well between social outcomes and marginal productivities of agricultural inputs. The major limitation of this study is the use of several datasets that were not necessarily designed to complement each other, thereby raising the risk of potential biases. To address this issue, we recommend the use of integrated household surveys where data on agriculture, budget, and social services are jointly collected. Regardless of these challenges, the results presented here combine novel approaches to address the research question and allow substantial room for discussion on public expenditures' role in agricultural development and guidance for future research and data collection.

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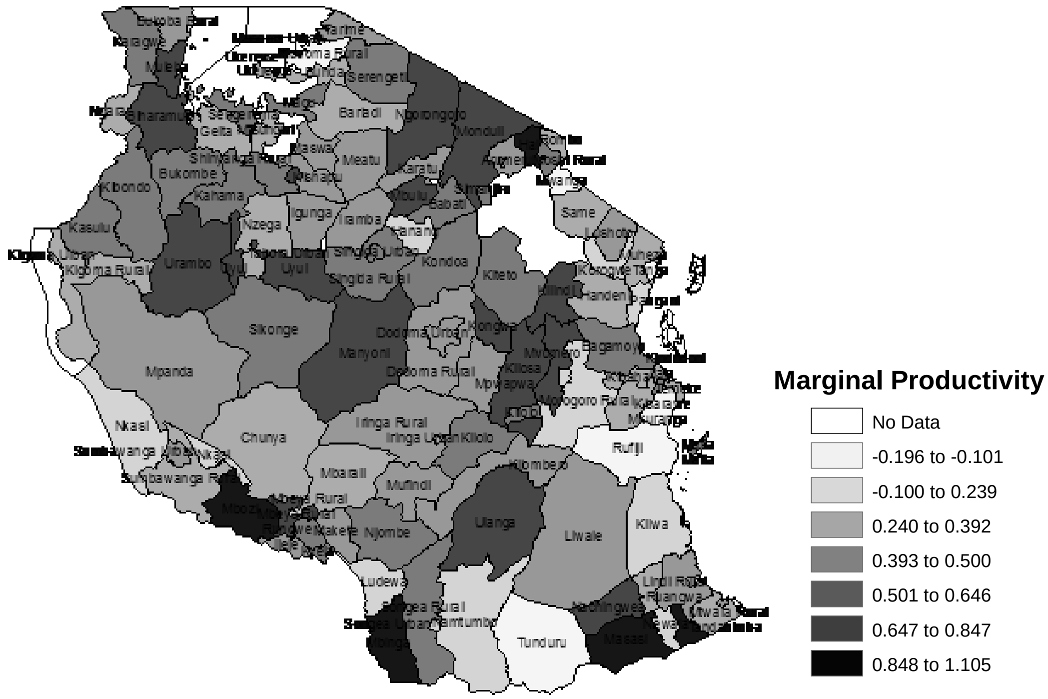
APPENDIX

Table A1: Summary Statistics

Production	**obs**	**mean**	**std dev**	**min**	**max**
production (area-weighted kg)	51534	1011	2956	0	224653
labor	52594	2.1	1.4	0	19
land (acres)	51534	3.9	5.1	0	160
fert (kg)	51534	586	10245	0	900950
animals	52594	0.25	0.43	0	1
seeds (tsh)	51534	30692	62025	0	3710010
animals	52594	0.25	0.43	0	1
Annual precipitation (mm)	42363	844	250	452	2115
Tobit Regressions (individuals)					
female	37938	0.52	0.50	0	1
rural	37938	0.35	0.48	0	1
No sickness	37896	0.78	0.41	0	1
No malaria	37938	0.86	0.35	0	1
years of education	37826	5.37	4.24	0	20
Latent Variables Equations (households)					
completed secondary	10972	0.14	0.44	0	5
English literacy	10972	0.07	0.42	0	9
Swahili literacy	10972	2.15	1.83	0	19
No malaria	10972	0.48	0.85	0	11
No fever	10972	0.53	0.93	0	11
No diarrhea	10972	0.72	1.07	0	13
No long term health problems	10972	0.69	1.06	0	14

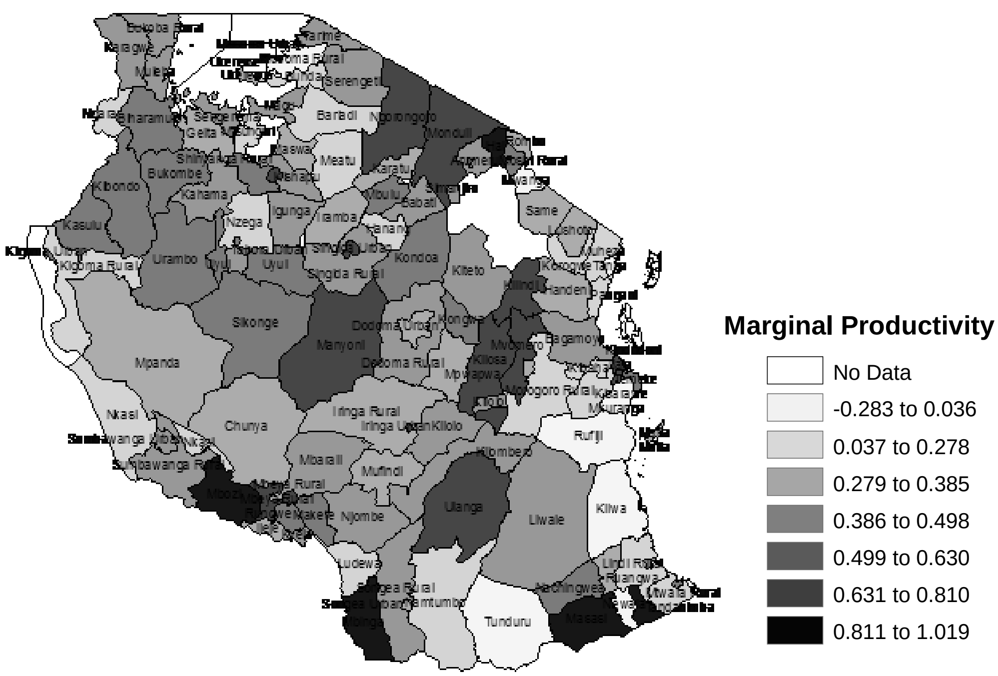
Source: Author's calculation from NBS 2010 and 2011

Figure A1—Marginal Productivity of Land (Education as State Variable)



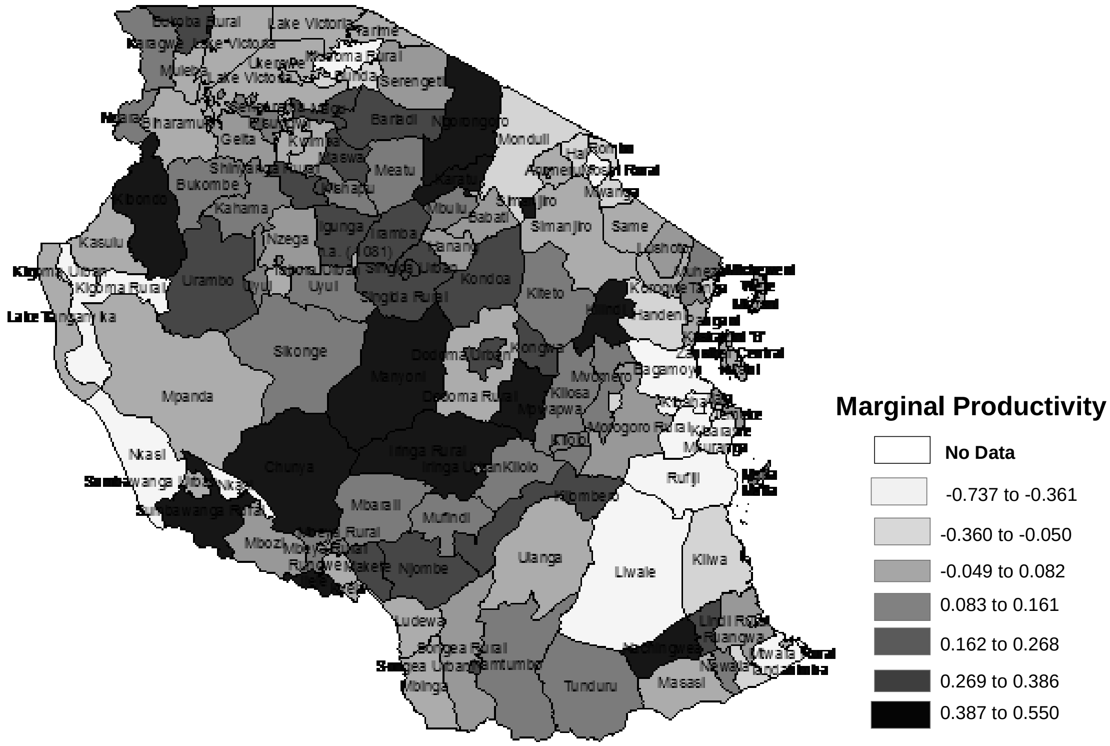
Source: Authors'calculations

Figure A2—Marginal Productivity of Land (Long-Term Health as State Variable)



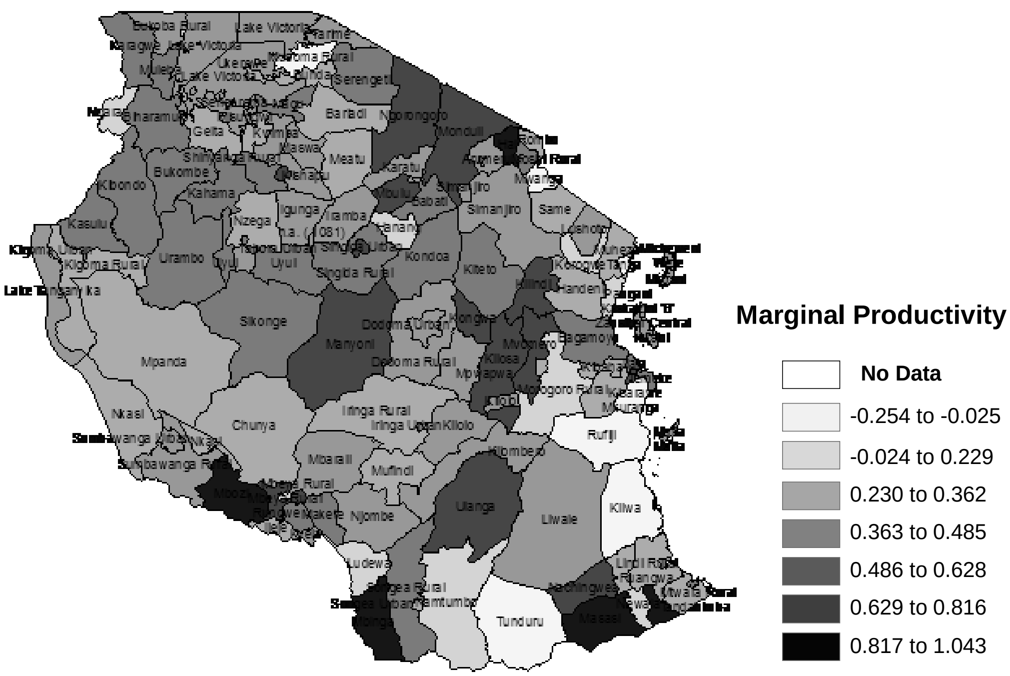
Source: Authors'calculations

Figure A3—Marginal Productivity of Labor (Education and Health as State Variables)



Source: Authors'calculations

Figure A4—Marginal Productivity of Land (Health and Education as State Variables)



Source: Authors'calculations