Externalities of Education on Efficiency and Production Uncertainty of Maize in Rural Malawi

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Abstract

The paper looks at the existence, nature and form of intrahousehold and interhousehold externalities of education on efficiency and production uncertainty of maize in rural Malawi. Data from the Third Integrated Household Survey are used. I find statistically and economically significant positive intrahousehold and interhousehold externalities of education on both efficiency and production uncertainty, and that the intrahousehold externality effects are larger than interhousehold externality effects. Community level schooling is found to substitute for household level schooling in the sense that farmers who reside in households where members are not educated have relatively higher efficiency and lower production uncertainty on account of living in communities where some inhabitants are educated. The paper also finds that the intrahousehold and interhousehold externality effects are more pronounced for the least efficient farmers, and that they are monotonic, and largest when schooling is relatively low.

Keywords: intrahousehold; interhousehold;externality; Malawi

1 Introduction

The level of schooling within and between households may act like a public good in that the literate household or community members may confer a positive externality on the illiterate members in the household or community (Basu & Foster, 1998; Basu et al., 2002). The presence of these positive within and between household education externalities imply that an individual's education has far larger benefits which go beyond the individual. The extent of schooling within a household and a community can have a positive externality effect on agricultural productivity and technical efficiency. Such education externalities might arise for instance as uneducated farmers learn from the superior production choices of educated farmers in the community. The education externality could also arise when educated farmers are early innovators and are copied by those with less schooling (Knight et al., 2003; Weir & Knight, 2004). External benefits of education may also accrue within

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households and communities by one person taking decisions on behalf of another person (Dreze & Saran, 1995).

A number of household level studies have found evidence of education externalities on agricultural productivity and technical efficiency. There are two strands of literature on the presence of education externalities in agriculture; one strand examines the role of education externalities on productivity only, while another strand looks at the role of education externalities on both productivity and technical efficiency. Appleton & Balihuta (1996) study the relationship between the mean level of education of other farmers in the same enumeration area on agricultural production in Uganda. They find a statistically significant and substantial externality effect of education. Weir & Knight (2007) investigate the externality effect of site level education on productivity and efficiency using Ethiopian data. They find a statistically significant externality effect of education on productivity, but they fail to find a significant effect on technical efficiency. Asadullah & Rahman (2009) examine the role of within household and neighbourhood education on rice productivity and technical efficiency in Bangladesh. They fail to find any evidence of an external benefit of schooling, however they find that household education raises rice productivity, and reduces technical inefficiencies. Gille (2012) investigates the presence of inter-household education externalities on agricultural productivity in rural India, and finds that education spillovers do exist; specifically, holding other things constant, one additional year in the mean level of education of neighbors increases households' farm production by 2%.

This paper uses Malawian data on smallholder maize production in rural areas to make four contributions to the literature on technical efficiency in agriculture and within and between household education externalities. First, the existing literature has focused on the relationship between education externalities and technical efficiency but has provided no evidence of the relationship between education externalities and agricultural production uncertainty or risk. Crop production faces inherent uncertainty caused by variations in weather, disease, insects, and other biological pests. It is quite plausible to expect that farming households where some members have high levels of schooling or reside in communities with high levels of schooling would be better able to cope with production uncertainty and risk through for example learning or copying good crop husbandry from the educated. Here, I assess how education within and between households affects production uncertainty and the relative magnitudes of the two externalities. Second, the existing studies on efficiency have focused on the directions of the externality effect on technical inefficiency while overlooking the magnitudes of the partial effects. As noted by Liu & Myers (2009), this makes it impossible to quantify the magnitude of the intrahousehold and interhousehold externality effects, and to compare the sizes of the two effects. Knowledge of which effect is larger can be useful for policy in the sense that it makes it possible to determine which type of policy intervention will have the largest impact on inefficiency and uncertainty.

The third contribution relates to an understanding of who benefits more from education externalities. The existing literature assumes that the education externality at the village or community level is the same for all households regardless of the extent of schooling within a household. One would expect the inter-household education externality to be relatively more pronounced for those households with little or no schooling than for those with high levels of schooling. Pooling all households together provides a misleading picture of the size of the external benefits provided by education on technical efficiency and production uncertainty. Related to this, previous studies have not examined how the education externality effect varies with different levels of efficiency. The implicit assumption made in the literature is that the intrahousehold and interhousehold externality is the same for the most efficient farmers and the least efficient ones. And again by lumping all farmers together, the existing literature does not help in understanding who benefits more from education spillovers. A final contribution of this paper is that it assesses whether or not the externality effect of education on both technical efficiency and production uncertainty is positive or negative for all levels of schooling. Previous studies implicitly assume that the intrahousehold and interhousehold externality is constant over all levels of education. This is obviously quite restricted as it ignores the possibility that the externality effect can be non-monotonic: the returns to education can be increasing at low levels of education followed by diminishing returns at high levels of education. A failure to capture non-monotonicity can render estimation results imprecise at best and misleading at worst (Wang, 2002). By allowing a more flexible externality effect, the results can be more informative for the purpose of policy analysis.

The remainder of the paper is organized as follows. Section 2 provides a maize production and education profile for Malawi. In Section 3 the methodology is presented, and the variables and data used are discussed. This is followed by the empirical results in Section 4. Section 5 concludes.

2 Maize Production and Education in Malawi

Malawi's economy is agrobased, with the agricultural sector accounting for about 30% of GDP over the period 2005-2011. Over the same period, the agriculture sector was by far Malawi's most important contributor to economic growth, with a contribution of 34.2 percent to overall GDP growth (NSO, 2012a). Maize is a staple food in Malawi, and accounts for more than two-thirds of caloric availability (Ecker & Qaim, 2011). As a result of low food diversification, national food security continues to be defined in terms of access to maize. Smallholder agriculture is dominated by maize production, for instance, NSO (2012b) found that 85% of households in Malawi cultivated maize (69% in urban areas, and 88% in rural areas). Further to that, rain-fed smallholder maize production accounts for around one quarter of agricultural GDP. Hence, the relatively large size of the maize sector means that increases in maize production lead to significant and strong increases in overall agricultural GDP growth.

Increased agricultural productivity is one of the key focus areas of the Malawi Growth and Development Strategy (MGDS), an overarching medium term national development framework. This priority has seen the formulation of a number of sectoral strategy documents which include: a National Agricultural Policy (NAP) for the period 2010-2016, and an Agricultural Sector Wide Approach (ASWAp). The most significant productivity enhancing policy intervention in recent years has been the Farm Input Subsidy Program (FISP), which provides low-cost fertilizer and improved maize seeds to poor smallholders. Implementation of the FISP started in the 2005/6 cropping season, and in the 2012/13 financial year, the programme represented 4.6% of GDP or 11.5% of the total national budget (World Bank, 2013).

To get a sense of how maize productivity has evolved before and after this major policy intervention, Figure 1 shows maize production in millions of tonnes, area cultivated in hectares, and maize yield per hectare for the cropping period 1999/2000-2011/12. The land area dedicated to the growing of maize has remained fairly unchanged, however, it is evident that the maize yield per hectare rose sharply following the subsidy. For instance, the season preceding the subsidy (2004/05), the yield per hectare was 0.8 metric tonnes per hectare, and for the cropping season 2006/07, the yield per hectare was 2.7 metric tonnes per hectare. It should be pointed out that the bumper harvests following FISP coincided with good rains. There is therefore an obvious attribution problem here which has not yet been resolved, however, it is reasonable to assume that the FISP played a part in boosting maize yields. Although, the maize productivity has risen to an average yield per hectare of 2.1 between 2006 and 2012, it is still significantly lower when compared with other countries. For instance, the average maize yield over the same period was 4.1 metric tonnes per hectare, and 9.3 metric tonnes per hectare for South Africa and the United States of America respectively.

Despite recognizing the problem of low maize productivity, the MGDS does not explicitly identify education and its potential spillovers as one of the factors that could improve maize productivity in Malawi. The relevant strategies to increase maize productivity in the MGDS include: strengthening linkages of farmers to input and output market; promoting appropriate technology development, transfer and absorption; improving access to inputs; and promoting contract farming arrangements (GOM, 2011). By examining the nature of intrahousehold and interhousehold education spillovers in maize production, this paper provides useful insights into the relationship between maize productivity and education. The formal education system in Malawi is composed of three levels namely; primary, secondary, and post secondary. Education at all three levels is not compulsory. The Malawi government cognizant of the crucial role that human capital accumulation and development plays in fostering economic growth among other benefits introduced free primary education (FPE) in 1994. With FPE parents no longer have to pay fees for the primary education of children who attend government schools. Private primary schools however continue to charge fees. Increasing access to primary and secondary education is one of the main priority areas identified in the MGDS.

To assess if there have been improvements in education indicators in Malawi between 2004 and 2011, Table 1 reports the levels and trends in: a) adult literacy rates, b) primary enrolment rates, and c) primary school dropout rates. The proportion of the population aged 15 years and over that is literate increased marginally from 64% in 2004 to 65% in 2011; suggesting that there has been very little progress in improving adult literacy in Malawi. The proportion of adults who can read and write is higher in urban areas than in rural areas. Besides, the literacy rate for rural areas has remained almost unchanged while it has increased by about 3 percentage points between 2004 and 2011. For both years, significant progress has been made in increasing primary net enrolment rates. However, primary enrolment levels in rural areas are lower than those for urban areas. The internal efficiency of primary school system as measured by the dropout rate seems to have improved over the five year period. These statistics thus point to two milestones that Malawi has achieved; increased primary enrolment, and improved internal efficiency.

3 Empirical Strategy

3.1 A Stochastic Production Frontier with Non-Monotonicity

This paper uses a stochastic production frontier to measure technical efficiency. I adopt a stochastic frontier model developed by Wang (2002). The advantage of the Wang (2002) model is that it nests two modeling approaches as special cases. The first approach focuses on factors affecting the mean of technical inefficiency (see for example Kumbhakar et al. (1991), Huang & Liu (1994), and Battese & Coelli (1995)). The other approach deals with factors that influence production uncertainty i.e. the variance of the inefficiency effect (see for example Caudill et al. (1995), and Hadri (1999)). Using the Wang (2002) model, this paper is therefore able to investigate the presence of externality effects of schooling on both efficiency and production uncertainty.

The production structure for maize field i belonging to household j which is in community l is specified using a single-output, multi-input Cobb-Douglas production frontier given as follows

$$
\begin{aligned}
\ln q_{ijl} &= \ln q^*_{ijl} - u_{ijl} \\
&= \beta_0 + \sum_{k=1}^{5} \beta_k \ln x_{ijlk} + E\pi + v_{ijl} - u_{ijl} && (1) \\
v_{ijl} &\sim N\left(0, \sigma_v^2\right) && (2) \\
u_{ijl} &\sim N^+\left(\mu_{ijl}, \sigma^2_{u_{ijl}}\right) && (3) \\
\mu_{ijl} &= \alpha_w s_{ijl} + z_{ijl}\alpha && (4) \\
\sigma^2_{u_{ijl}} &= \exp\left(\theta_w s_{ijl} + z_{ijl}\theta\right) && (5)
\end{aligned}
$$

where; q_{ijl} is rainfed maize output, q^*_{ijl} is unobserved frontier/potential output, β_0 is an intercept, β_k $(l = 1..5)$ are output elasticities with respect to inputs x_{ijl}. There are five inputs; land measured in acres, own and hired labour measured in man days, capital measured as the total monetary value in Malawi Kwacha of farm implements (hoes, slashers, axes, oxcarts, oxploughs) owned by a household, seed measured in kilograms, organic and inorganic fertilizer measured in kilograms. E is a vector of agro-ecological zone dummies which capture zone level fixed effects, and π is the corresponding coefficient vector. There are eight rural agro-ecological zones. Agro-ecological zones control for differences in climate, soils, and market access conditions in an area[1]. Sherlund et al. (2002) show that failure to control for environmental conditions may lead to omitted variable bias in the estimated parameters of the production frontier, and biased estimated coefficients in the technical inefficiency model. v_{ijl} is a two sided random variable representing random variations in the economic environment facing production units, reflecting luck, weather, measurement errors, and omitted variables from the model. $u_{ijl} = \ln q^*_{ijl} - \ln q_{ijl} > 0$ is a technical inefficiency effect which is a non-negative truncation of a normal random variable. It represents deviations from potential output that reflect inefficiency such as farm-specific knowledge, the will and skills of farmers, and other disruptions to production. The notation "+" means that the underlying distribution is truncated from below at zero so that realized values of the random variable u_{ijl} are positive. It is assumed that v_{ijl} and u_{ijl} are independent of each other.

Of interest in this paper is the technical inefficiency model (equation (4)) and the production uncertainty model (equation(5)). The inefficiency model captures how the average years of schooling in a household s_{jl}, and other exogenous farm-specific control variables, z_{ijl}, influence inefficiency. Similarly, the production uncertainty model represents the relationship between production uncertainty- as measured by the variance of the inefficiency effects- and the average years of schooling in a household and other control variables. In both models, average years of schooling in a household capture the intra-

[1] Alternatively, community level fixed effects can be used here, however, since there are 624 communities after data cleaning, this means estimating too many fixed effects, and a loss of degrees of freedom.

household externality of education. The empirical analysis also uses the maximum years of schooling in a household as a robustness check. The production uncertainty model presents a more technical advantage over a model which assumes that the inefficiencies are homoscedastic. Explicitly modeling the exogenous factors ensures that the estimation of the production frontier model and the level of technical inefficiency is not biased, hence, policy conclusions are premised on valid results (e.g. Caudill et al. 1995; Hadri,1999). α_w and θ_w are coefficients of schooling on efficiency and production uncertainty, and α and θ are the corresponding coefficient vectors of the control variables. The inefficiency and production uncertainty models and the stochastic frontier production function in equation (1) are estimated jointly using maximum likelihood estimation to achieve both efficiency and consistency. Farm-specific estimates of technical efficiency are obtained via the conditional expectation $E[exp(u_{ijl}|v_{ijl})]$ (Battese & Coelli, 1988).

In order to capture the interhousehold externality effect of schooling on efficiency and uncertainty, I decompose the average years of schooling in a household s_{jl} into a between-community component, $\tilde{s}_l$, and a within-community component, $s_{jl} - \tilde{s}_l$, and then modify equations (4) and (5) to get

$$\begin{aligned} \mu_{ijl} &= \alpha_w \left(s_{jl} - \tilde{s}_l\right) + \alpha_b \tilde{s}_l + \alpha z_{ijl} \\ &= \alpha_w s_{jl} + \left(\alpha_b - \alpha_w\right) \tilde{s}_l + \alpha z_{ijl} \end{aligned} \tag{6}$$

and

$$\begin{aligned} \sigma^2_{u_{ijl}} &= \exp(\theta_w \left(s_{jl} - \tilde{s}_l\right) + \theta_b \tilde{s}_l + \theta z_{ijl}) \\ &= \exp\left(\theta_w s_{ij} + \left(\theta_b - \theta_w\right) \tilde{s}_l + \theta z_{ijl}\right) \end{aligned} \tag{7}$$

where α_b and θ_b represent the between-community effect, and the difference $\eta = \alpha_b - \alpha_w$ and $\gamma = \theta_b - \theta_w$, represents the externality effect i.e. the additional effect of schooling at the community level that is not accounted for at the household level. As a robustness check, I also use the maximum years of schooling in a community.

I use marginal effects to test for the presence of externality effects of schooling on inefficiency and uncertainty. The marginal effect of $\tilde{s}_l$ on the conditional expectation of u_{ijl} is given as (Wang, 2002; Liu & Myers, 2009)

$$\frac{\partial E\left(u_{ij}|\ln x_{ij}, s_{ij}, \tilde{s}_j, z_{ij}\right)}{\partial \tilde{s}_l} = \eta\left(1 - A_1 A_2 - A_2^2\right) + \frac{\gamma \sigma_u}{2}\left[\left(1 + A_1\right) A_2 + A_1 A_2^2\right] \tag{8}$$

where $A_1 = \frac{u_{ij}}{\sigma_{u_{ij}}}$ and $A_2 = \frac{\phi(A_1)}{\Phi(A_1)}$. ϕ and Φ are the probability and cumulative density functions of a standard normal distribution respectively. Thus, a test of the hypothesis that $\frac{\partial E\left(u_{ijl}|\ln x_{ijl}, s_{jl}, \tilde{s}_l, z_{ijl}\right)}{\partial \tilde{s}_l} = 0$, amounts to testing that there are no externality effects of schooling at the community level on efficiency. The sign and magnitude of $\frac{\partial E\left(u_{ijl}|\ln x_{ijl}, s_{jl}, \tilde{s}_l, z_{ijl}\right)}{\partial \tilde{s}_l}$

respectively indicate the direction and size of the externality effect. A positive (negative) externality effect of community level schooling on efficiency holds if $\frac{\partial E\left(u_{ijl}|\ln x_{ijl},s_{jl},\tilde{s}_l,z_{ijl}\right)}{\partial \tilde{s}_l} < 0 \left(\frac{\partial E\left(u_{ijl}|\ln x_{ijl},s_{jl},\tilde{s}_l,z_{ijl}\right)}{\partial \tilde{s}_l} > 0\right)$. Since $\frac{\partial E\left(-u_{ijl}|\ln x_{ijl},s_{jl},\tilde{s}_l,z_{ijl}\right)}{\partial \tilde{s}_l} = \frac{\partial E\left(\ln q_{ij}|\ln x_{ijl},s_{jl},\tilde{s}_l,z_{ijl}\right)}{\partial \tilde{s}_l}$, the marginal effect is also the semi-elasticity of output with respect to $\tilde{s}_l$.

Similarly, the marginal effect of $\tilde{s}_l$ on the conditional variance of the inefficiency term u_{ijl} is expressed as (Wang, 2002; Liu & Myers, 2009)

$$\begin{aligned}\frac{\partial V\left(u_{ijl}|\ln x_{ijl},s_{jl},\tilde{s}_l,z_{ij}\right)}{\partial \tilde{s}_l} &= \frac{\eta}{2\sigma_u}A_2\left(m_1^2-m_2\right) \\ &+\gamma\sigma_u^2\left\{1-\frac{1}{2}A_2\left[A_1+A_1^3+\left(2+3A_1^2\right)A_2+2A_1A_2^2\right]\right\}\end{aligned} \tag{9}$$

where $m_1 = \sigma_u\left(A_1A_2+A_2\right)$ and $m_2 = \sigma_u^2\left(1-A_1A_2-A_2^2\right)$ is the mean and variance of u_{ij} respectively. To test whether or not community level schooling affects production uncertainty involves testing the hypothesis that $\frac{\partial V\left(u_{ijl}|\ln x_{ijl},s_{jl},\tilde{s}_l,z_{ij}\right)}{\partial \tilde{s}_l} = 0$. A positive (negative) externality effect of community level schooling on production uncertainty holds if $\frac{\partial V\left(u_{ijl}|\ln x_{ijl},s_{jl},\tilde{s}_l,z_{ij}\right)}{\partial \tilde{s}_l} > 0 \left(\frac{\partial V\left(u_{ijl}|\ln x_{ijl},s_{jl},\tilde{s}_l,z_{ij}\right)}{\partial \tilde{s}_l} < 0\right)$. Since $\frac{\partial V\left(u_{ijl}|\ln x_{ijl},s_{jl},\tilde{s}_l,z_{ij}\right)}{\partial \tilde{s}_l} = \frac{\partial V\left(\ln q_{ij}|\ln x_{ijl},s_{jl},\tilde{s}_l,z_{ij}\right)}{\partial \tilde{s}_l}$, the marginal effect is also the semi-elasticity of the output variance with respect to $\tilde{s}_l$.The marginal effects for the intrahousehold externality of education, $\frac{\partial E(u_{ij}|\ln x_{ij},s_{ij},\tilde{s}_j,z_{ij})}{\partial \tilde{s}_{jl}}$ and $\frac{\partial V\left(u_{ijl}|\ln x_{ijl},s_{jl},\tilde{s}_l,z_{ij}\right)}{\partial \tilde{s}_{jl}}$ are analogously derived.

To assess how the community education externality effect on efficiency and production uncertainty varies with household average years of schooling, I use equations (8) and (9) to calculate marginal effects of community level education for different quartiles of household average years of schooling. Similarly, the heterogenous effect of community and household level schooling on different levels of efficiency is captured by calculating the corresponding marginal effects for different quartiles of estimated efficiency. As has been shown by Wang (2002), equations (8) and (9) accommodate non-monotonic effects of $\tilde{s}_l$; implying that the marginal effects can be both positive and negative in the sample, and their signs do not necessarily coincide with the signs of either of the slope coefficients η and γ. The ability to capture non-monotonicity enables this paper to investigate whether the household and community level schooling externalities switch signs across the distributions of household and community level schooling. It thus, for example, allows the demonstration of directional differences in the externality effects between households and communities with low or no schooling and those with high levels of schooling.

3.2 Model specification tests

To ensure that the modeling structure as represented by equations (1) to (5) is valid, the paper tests a number of hypotheses sequentially using the Wald test (hypotheses 1,2, 4, and 5), and a third-moment test developed by Coelli (1995) (hypothesis 3). The third moment test is a skewness test, and seeks to determine if ordinary least squares residuals are significantly negatively skewed by using the standard normal distribution.

1. $H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \pi = 0$, this null hypothesis means that all variables included in the frontier production function are jointly insignificant.

2. $H_0 : \pi = 0$, the null hypothesis specifies that there are no agro-ecological zone fixed effects.

3. $H_0 : \mu = 0 = \sigma_u^2 = 0$, the null hypothesis implies that there is no inefficiency component. If the null hypothesis is true, then the truncated-normal model reduces to a linear regression model with normally distributed errors.

4. $H_0 : \alpha_w = \alpha = \eta = 0$, the null hypothesis specifies that the included exogenous determinants of technical inefficiency are jointly insignificant. A rejection of this null implies that the the included exogenous factors together influence technical inefficiencies.

5. $H_0 : \theta_w = \theta = \gamma = 0$, the null hypothesis specifies that the technical inefficiency effects are homoscedastic. Failure to reject this null implies that the variance of technical inefficiencies cannot be parameterized to capture determinants of production uncertainty.

3.3 Data and descriptives

The data used in the paper come from the Third Integrated Household Survey (IHS3). It is statistically designed to be representative at national, district, urban and rural levels. The survey was conducted by the National Statistical Office from March 2010 to March 2011. The survey collected information from a sample of 12271 households; 2233 (representing 18.2%) are urban households, and 10038 (representing 81.8%) are rural households. A total of 768 communities (clusters) were selected across the country. In each district, a minimum of 24 communities were interviewed while in each community a total of 16 households were interviewed. The survey collected socio-economic data at the household level and on individuals within the households. It also collected data on farming activities including crop output, land, labour and other inputs. This paper focuses on rural households as they are more involved in maize production. After data cleaning, I end up with non-missing maize production data for 4863 fields belonging to 3765 households in 624 rural communities. Since all fields are nested in households and communities, this feature of the data enables the paper to examine the internal (within the household) and external (outside the household) effect of schooling on maize production efficiency and uncertainty.

Some of the maize fields are mixed stand fields with more than one crop planted in a season. Since most inputs (land, fertilizer and labor) are at the field level, and cannot be uniquely assigned to maize production only, I follow Liu & Myers (2009), and generate a maize output index. The dependent variable, maize yield, is therefore measured as follows

$$q_{ijl} = \begin{cases} \frac{\sum_m p_m q_{ijlm}}{p_1} & \text{if intercropped field} \\ q_{ijl1} & \text{if monocropped field} \end{cases} \tag{10}$$

where q_{ijl} is the maize output index, p_m is the market price of crop m, q_{ijlm} is the yield of crop m in field i for household j in community l, and crop 1 is maize. Thus, for monocropped fields, maize yield is simply the actual yield. In addition to the independent variables already discussed, the following variables are used included. I control for the age of the principal farmer measured in years. A principal farmer is defined as a household member who makes decisions concerning crops to be planted, input use and the timing of cropping activities on a field. Age proxies for experiences which are helpful in improving production efficiency. According to Coelli & Battese (1996) older farmers are likely to have more farming experience and hence be less technically inefficient. I capture gender effects by including a dummy variable for sex of the principal farmer defined as one for male and zero for female. Female farmers tend to have a lower efficiency level and higher uncertainty of efficiency (Liu & Myers, 2009). One possible explanation for this is that female farmers do not have the same inheritance rights as males, and this reduces the incentive to work hard.

Secure land tenure may lead to more investment such as soil conservation and tree planting (see for example Deininger & Jin (2006)), and this may increase farm productivity. I capture security of land tenure by including a dummy variable which is one if the land for maize is owned by a household and zero if not. A land is considered owned if it was inherited or was purchased with a title deed. Binar et al. (2007) notes that agricultural extension services may speed up the diffusion process and the adoption of new varieties and technologies as well as leading to the efficient utilization of existing technologies by improving farmers' know-how. I therefore control for the effect of extension services by including a dummy variable which is equal to one if the household was visited by an extension agent during the growing season, and zero if not.

Table 2 presents summary statistics of the variables used in the study. Land holdings are small with the average log of land of -0.091. Levels of schooling are also low; the average years of schooling is about 3.8 years within households, and 3.6 years at the community level. These years of schooling correspond to junior primary education. The averages of maximum years of schooling are 7.5 and 8.1 years at the household and community levels respectively. These years of schooling are equivalent to senior primary education in Malawi. The table also shows that 76% of the principal farmers are male, and the average age of the principal farmer is about 43 years. Land tenure security is high, with 77% of the households saying they own the land they use for growing maize. The penetration of extension services is low; only 29% of the households said they were visited by an extension agent during the cropping season.

4 Results

4.1 Model specification results

In order to examine the validity of the modeling assumptions made in this paper, a number of model specification tests are conducted, and the results are reported in Table 3. The Wald test results show that all the variables included in the Cobb-Douglas production frontier are jointly statistically significant, and that there are statistically significant agro-ecological zone fixed effects. The third-moment test results lead to the rejection of the null hypothesis of no inefficiency component, and this means that technical inefficiency effects are present. Given the presence of the technical inefficiency effect, the mean of the inefficiency term can be modeled as a linear function of a set of covariates. The Wald test results indicate that the determinants of inefficiency included in the technical inefficiency model are jointly significant. Finally, Wald test results show that the technical inefficiency effects are heteroscedastic; and this implies that the estimation of a production uncertainty model is justified. I now turn to a discussion of the results for the production frontier, technical inefficiency and production uncertainty models.

4.2 Econometric results

The Cobb-Douglas production frontier results are reported in Table 4. They indicate that the Cobb-Douglas production frontier is well-behaved and satisfies all regularity conditions. Specifically, monotonicity conditions are satisfied since marginal products are all positive. Additionally, all the five inputs have statistically significant effects on output. Maize seeds as an input have the smallest effect on maize output; fertilizer on the other hand has the largest effect on maize output. The output elasticity of fertilizer implies that a 1% increase in fertilizer increases maize production by 0.42%. As mentioned earlier, the government of Malawi has been implementing a farm input subsidy programme (FISP) since the 2005/6 growing season. FISP provides provide low-cost fertilizer and improved maize seeds to poor smallholders. The frontier results offer some interesting insights on how the FISP can be altered to increase maize productivity. The combined effect on maize output of a 1% increase in seed and fertilizer is 0.47% while the combined effect on maize output of a 1% increase in land and fertilizer is 0.76%. This means that a land redestribution exercise which is implemented together with a fertilizer subsidy would have a 1.6 times larger effect on maize production that the current practice under FISP. The sum of the coefficients of all the inputs, a measure of returns to scale is 1.14, suggesting that maize production in rural Malawi exhibits increasing returns to scale. A Wald test ($\chi_1^2 = 24.94$) confirms that indeed there are increasing returns to scale in maize production. This result is however not in conformity with findings by Weir & Knight (2007) and Asadullah & Rahman (2009) who found evidence of decreasing returns to scale in cereal production by Ethiopian and Bangladesh farmers, respectively.

Figure 2 shows the distribution of the Battese and Coelli efficiency estimates for the sample. The efficiency scores are skewed to the left implying that few maize farmers are inefficient. Average technical efficiency is estimated to be at 0.66. The average technical efficiency of 0.66 means that maize production in rural Malawi can be increased by 34% by simply improving technical efficiency alone without increasing input usage. The most efficient maize field has a technical efficiency of 0.90 while the least efficient has a technical efficiency of 0.00. I now turn to the interpretation of the efficiency and production uncertainty results. Table 5 shows marginal effects for the inefficiency (i.e marginal effects on $E\left(u_{ij}|\ln x_{ij}, s_{ij}, \tilde{s}_j, z_{ij}\right)$ and production uncertainty models (i.e marginal effects on $V\left(u_{ijl}|\ln x_{ijl}, s_{jl}, \tilde{s}_l, z_{ij}\right)$. For the technical inefficiency model, positive marginal effects indicate relative technical inefficiency while negative marginal effects suggest relative technical efficiency. For the production uncertainty results, positive marginal effects imply an increase in uncertainty while the reverse holds when the marginal effects are negative. The magnitude of the marginal effects indicate the strength of this inefficiency and production uncertainty. All the five control variables are statistically significant in the two models. The results are generally in conformity with a priori expectations and previous literature. Interestingly, the marginal effects on inefficiency and production uncertainty seem to be qualitatively similar.

An interesting pattern for all the variables which is consistent with Bera & Sharma (1999), and Wang (2002) is that when a farmer moves toward the production frontier by having higher efficiency, it also reduces production uncertainty at the same time. Relative to female farmers, the results indicate that male farmers are more efficient, and they have lower production uncertainty. This result is similar to and consistent with the findings of Liu & Myers (2009). The results suggest that other things being equal, an older farmer is likely to achieve higher and more stable maize output. Since the marginal effects are also the semi-elasticities of output and output variance; holding other things constant, an increase in a farmer's age on average leads to a 0.01% increase in maize output, and a 0.02% increase in the stability of maize production. These effects though statistically significant, are clearly economically insignificant. The negative relationship between age and efficiency conforms to an assertion by Coelli & Battese (1996) that older farmers are likely to be more efficient because they have more farming experience. In contrast to the finding of this paper, Wang (2002) finds that older farmers have less stable output. Secure land is beneficial as it leads to higher efficiency and more stable maize production. These findings could possibly be due to the fact that secure land tenure may lead to more investment in soil conservation and tree planting which may lead to high and more stable production. Consistent with Binar et al. (2007), the paper also finds that extension services lead to higher efficiency. Additionally, farmers who were visited by extension agents have more stable maize output.

I now turn to the main focus of this paper, and discuss results on the existence, nature and form of intrahousehold and interhousehold externalities of education. The results in Table 5 show that there are statistically significant and positive intrahousehold and interhousehold externalities of education on both efficiency and production uncertainty of maize production in rural Malawi. In addition, the results also show that education externalities are quantitatively large. The results indicate that the positive spillover effect of schooling within a household on both efficiency and production uncertainty is larger than the positive externality effect of schooling at the community level. Since the marginal effects are also semi-elasticities of output; *ceteris paribus*, an additional year of schooling within a household translates into an increase in output of 2.9%, and one more year of schooling at the community level leads to an increase in output of 1.8%. The difference in the two externality effects on efficiency is statistically significant with a t-statistic (p-value) of 39.6 (0.00). In terms of production uncertainty, holding other things constant, a unit increase in average schooling within a household leads to a 3.4% increase in the output variance, and a unit increase in community level average schooling leads to an increase in the output variance of 1.9%. This difference is also statistically significant with a t-statistic (p-value) of 26.8 (0.00).

How robust is the evidence of the existence of intrahousehold and interhousehold externalities of education to the way schooling is captured? The above results are based on the average years of schooling within and between households. It can be argued that the externality of schooling can best be captured by the highest level of education among all household or all community members. The one who receives the highest education in the household or at the community can help other household and community members in making production decisions. I therefore re-estimated the above models, and replaced household average years of schooling with the maximum years of schooling in a household, and average years of schooling in a community with the maximum of years of schooling in a community. The results are qualitatively similar to the ones seen before. Specifically, I find statistically and economically significant intrahousehold and interhousehold externalities of education. The marginal effects (standard errors) of maximum years of schooling in a household on inefficiency and production uncertainty are -0.0127 (0.0003) and -0.0145 (0.0004) respectively. Further to this, the marginal effects (standard errors) of maximum years of schooling in a community on inefficiency and production uncertainty are -0.0102 (0.0003) and -0.0107 (0.0005) respectively[2]. Thus, the pattern observed earlier that the intrahousehold externality effects are larger than the interhousehold externality effects

[2] A complete set of results is available from the author upon request.

remains unchanged even when this new definition is adopted. All this implies that the finding that there are positive education spillovers is not sensitive to how schooling is measured. The rest of the analysis is therefore based on average years of schooling at the household and community levels.

Do farmers who reside in households where there is little or no education benefit more from living in communities where some inhabitants are educated? I answer this question by looking at how the interhousehold externality effect varies across different quartiles of household level schooling. It is possible to estimate quartile-specific marginal effects because the marginal effects are observation-specific. The results are reported in Table 6. On efficiency, the results indicate that the externality effect of community level schooling is highest for households where members have no or little education while it is smallest for households with highly educated members. Specifically, the interhousehold externality effect in the first household schooling-quartile (i.e. the least educated households) is -0.0197. This effect translates into an increase in maize output of 2%. On the other hand, for households in the last household schooling-quartile, the interhousehold externality effect is 0.0164; implying that maize output increases by 1.6%. The interhousehold externality effects for all the quartiles are both statistically and economically significant. Turning to production uncertainty, a similar pattern is observed. The marginal effects of community level schooling are -0.0253 and -0.0152 for the first and last quartiles of household schooling respectively. This means that, *ceteris paribus*, the maize output variance decreases by 2.5% and 1.5% for farmers in the least educated and most educated households respectively. These results suggest that in terms of both efficiency and production stability of maize production, community level schooling substitutes for household level schooling in the sense that farmers who reside in households where members are not educated benefit more from living in communities where some inhabitants are educated.

Do less efficient farmers benefit more from household and community level schooling? Similar to the preceding analysis, I estimate the intrahousehold and interhousehold education externalities for different quartiles of estimated efficiency. The results of this analysis are reported in Table 7. All the marginal effects for the different quartiles are both statistically significant and quantitatively large. There is a decreasing trend of both the intrahousehold and interhousehold education externality effect on efficiency and production uncertainty from low to high quartiles of efficiency. Looking at the relationship between average household schooling and efficiency, the marginal effects are -0.0367 and -0.0245 for the first quartile and last quartiles respectively. This implies that an additional year of education at the household level leads to an increase in maize output of 3.8% and 2.5% for the least efficient and most efficient farmers respectively. The interhousehold externality effect on efficiency in the first quartile is -0.0184 and it is -0.0172 in the last quartile; suggesting that holding other things constant, farmers in the first and last quartiles experience an increase in maize output of 1.7% and 1.8% on account of an additional year of schooling in the community. This means that maize farmers with lower efficiency levels benefit more from increased education within and between households than the ones with higher efficiency levels. In keeping with a pattern observed earlier, the results also show that the intrahousehold externality effect on efficiency and production uncertainty is larger than the interhousehold externality across all quartiles.

The final problem addressed in this paper concerns whether or not the education externalities vary with level of schooling. Put differently, do the education externalities remain the same both in terms of sign and magnitude no matter the level of schooling? Evidence of nonlinearities would suggest that the externalities have a turning point. I divide the average years of schooling at the household and community levels into quartiles, I then use box plots of the estimated marginal effects of the average years of schooling across the four quartiles. Figures 3 and 4 shows the box plots which capture the evolution of intrahousehold and interhousehold externality effects on efficiency and production uncertainty across the quartiles. The marginal effects do not switch signs across the quartiles, implying the intrahousehold and interhousehold education externalities are monotonic. The results also show a negative but declining trend in the magnitudes of the externality effects as one moves from the first quartile to the last quartile, which means that education is most valuable with respect to reducing inefficiency and production uncertainty when schooling is relatively low, and the benefit is smaller at the higher education level.

5 Conclusion and policy implications

The paper has looked at the existence, nature and form of intrahousehold and interhousehold externalities of education on efficiency and production uncertainty of maize in rural Malawi. Data from the Third Integrated Household Survey are used. The results indicate that there are statistically and economically significant positive intrahousehold and interhousehold externalities of education on both efficiency and production uncertainty. These effects are insensitive to how schooling is captured; the results are qualitatively and quantitatively similar whether the externalities are measured using average years of schooling or maximum years of schooling. It has been found that the intrahousehold externality effects are larger than the interhousehold externality effects. The paper has found that community level schooling substitutes for household level schooling in the sense that farmers who reside in households where members are not educated have relatively higher efficiency and lower production uncertainty on account of living in communities where some inhabitants are educated. The intrahousehold and interhousehold externality effect of education is more pronounced for the least efficient farmers. The education externalities are found to be monotonic, and largest when schooling is relatively low.

Malawi like other developing countries is largely agrobased, with the majority of the population, especially the rural population, finding their livelihood in agriculture. The proportion of the population in wage employment is low. For instance, NSO (2012b) finds that only 13.4% of the labour force in Malawi in 2011 was in regular wage employment. Hence, the returns to education in the labour market though important are not very useful as a guide on public investment in education. In this context, returns to education in agriculture would be relevant. Further to this, and as pointed out earlier, the MGDS despite identifying strategies to increase maize productivity does not explicitly recognise the role that education can play in increasing maize productivity. The results in this paper underline the fact that education can play an important role in increasing maize productivity as well as ensuring that production risk or uncertainty is reduced. Crucially, the findings imply that farmers who are uneducated are not necessarily worse-off in maize production as they benefit from living in households or communities where some members are educated. The existence of social benefits arising from educating individual members of a society emphasises the fact that evaluation of the costs and benefits of investments in education should take into account the social returns; failure to do so may underestimate the benefits of education and lead to its underprovision.

The finding that the education externalities on both efficiency and production are most pronounced when schooling is low, further suggests that to increase maize productivity, investments in education should focus more on primary education. This is consistent with a large literature on social and private rates of return to education in developing countries which show that returns to primary education are high, relative to a discount rate and to returns to higher levels of education. Besides, the implication of the results to focus more on primary education offers some justification for the provision of free primary education in Malawi, and the magnitude of the intrahousehold and interhousehold externalities of education is a useful indicator of the productivity of this public investment in education.

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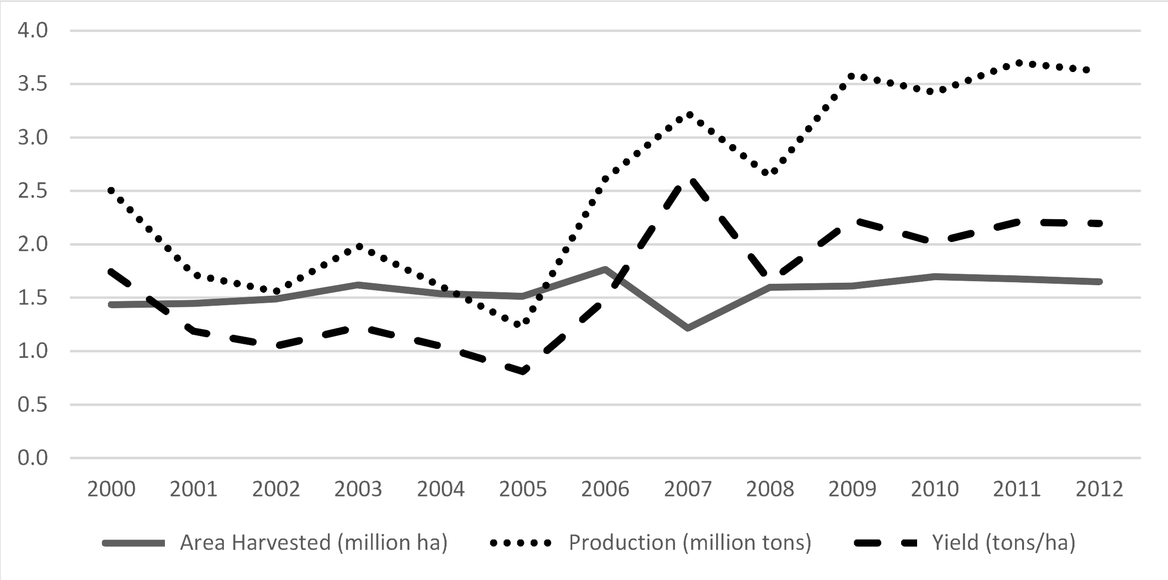
Figure 1. Evolution of maize yield, area harvested and production 2000-2012



Source: Author's computation using FAOSTAT database

Table 1. Trends and levels of some education statistics, 2004-2011

Indicator	Malawi		Rural		Urban	
	2004	2011	2004	2011	2004	2011
Adult literacy	63.9	65.4	60.9	60.7	85.6	89.0
Net primary enrolment rate	80.0	85.8	79.3	84.6	86.8	92.7
Gross primary enrolment rate	112.9	120.0	112.0	119.2	122.4	125.1
Primary dropout rate	5.1	1.3	5.3	1.4	4.1	0.9

Source: NSO (2005, 2012b)

Table 2. Descriptive statistics

Variable	Mean	SD
log of yield	6.396	1.205
log of seed	1.836	1.509
log of land	-0.091	0.783
log of fertilizer	4.208	0.712
log of labour	3.402	0.510
log of capital	6.567	1.112
zone1: Nsanje, Chikwawa districts	0.004	0.062
zone2: Blantyre, Zomba, Thyolo, Mulanje, Chiradzulu, Phalombe districts	0.172	0.378
zone3: Mwanza, Balaka, Machinga, Mangochi districts	0.124	0.330
zone4: Dedza, Dowa, Ntchisi districts	0.159	0.366
zone5: Lilongwe, Mchinji, Kasungu districts	0.203	0.402
zone6: Ntcheu, Salima, Nkhotakota districts	0.130	0.337
zone7: Mzimba, Rumphi, Chitipa districts	0.157	0.364
zone8: Nkhatabay, Karonga districts	0.051	0.219
average years of schooling in a household	3.822	2.268
average years of schooling in a community	3.576	1.071
maximum years of schooling in a household	7.496	3.330
maximum years of schooling in a community	8.056	2.206
male principal farmer	0.757	0.429
age of principal farmer	43.019	15.989
household visited by extension agent	0.290	0.454
land owned by household	0.770	0.421
Observations	4860	

Table 3. Model specification tests

No.	Hypothesis	Wald /Z statistic	DF	P-value	Conclusion
1	$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \pi = 0$	4203.10	12	0.00	Frontier variables jointly significant
2	$H_0 : \pi = 0$	1325.10	7	0.00	Significant agro zone fixed effects
3	$H_0 : \mu = 0 = \sigma_u^2 = 0$	-14.99[a]	-	0.00	Inefficiency effects are present
4	$H_0 : \alpha_w = \alpha = \eta = 0$	21.38	6	0.00	Efficiency variables jointly significant
5	$H_0 : \theta_w = \theta = \gamma = 0$	29.18	6	0.00	Heteroscedastic model is valid

[a] This is based on the standard normal statistic. DF is degrees of freedom.

Table 4. Translog production function results

Variable	Coefficient
log of seed	0.0501***
	(0.0082)
log of land	0.3430***
	(0.0210)
log of fertilizer	0.4206***
	(0.0207)
log of labour	0.2439***
	(0.0261)
log of capital	0.0830***
	(0.0118)
Zone 2	0.4740**
	(0.2051)
Zone 3	0.7110***
	(0.2056)
Zone 4	1.7267***
	(0.2048)
Zone 5	1.3871***
	(0.2044)
Zone 6	1.1310***
	(0.2055)
Zone 7	0.5612***
	(0.2057)
Zone 8	0.5453***
	(0.2102)
Returns to scale	1.14
Chi2	4203.10
Observations	4860

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2. Kernel density estimate of technical efficiency estimates

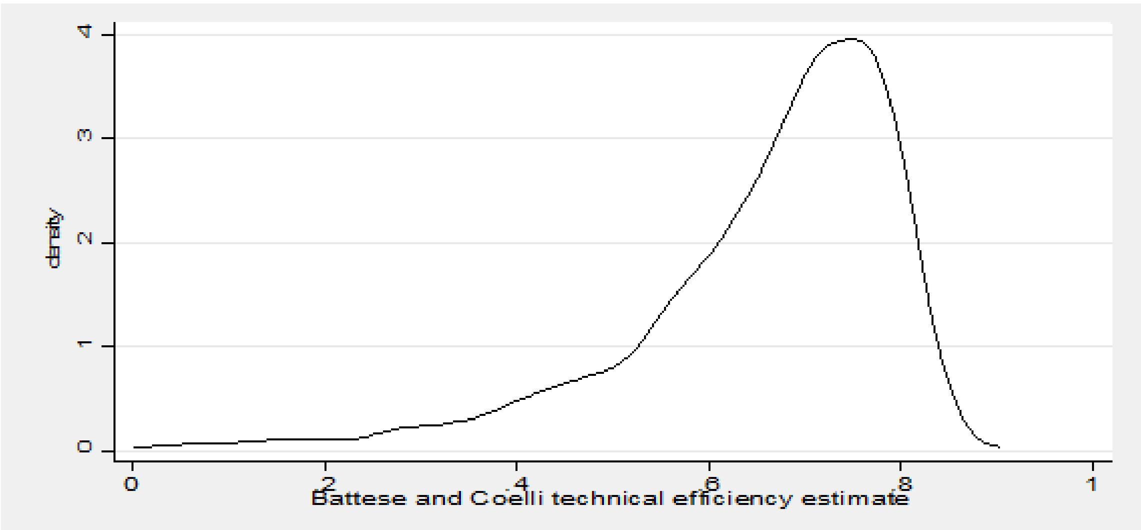


Table 5. Marginal effects of inefficiency

Variable	Inefficiency	Uncertainty
average years of schooling in a household	-0.0292***	-0.0339***
	(0.0004)	(0.0007)
average years of schooling in a community	-0.0177***	-0.0190***
	(0.0002)	(0.0001)
male principal farmer	-0.0734***	-0.0837***
	(0.0007)	(0.0012)
age of principal farmer	-0.0001*	-0.0002***
	(0.0002)	(0.0001)
land owned by household	-0.0891***	-0.1176***
	(0.0031)	(0.0052)
household visited by extension agent	-0.0176***	-0.0183***
	(0.0001)	(0.0001)
Observations	4860	4860

Bootstrapped (1000 replications) standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Marginal effects over quartiles of average household schooling

Variable	Quartiles			
	0-25	25-50	50-75	75-100
	Inefficiency			
average years of schooling in a community	-0.0197***	-0.0183***	-0.0173***	-0.0164***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	Uncertainty			
average years of schooling in a community	-0.0253***	-0.0203***	-0.0176***	-0.0152***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	945	1128	1321	1466

Bootstrapped (1000 replications) standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Marginal effects over quartiles of Battese and Coelli efficiency estimates

Variable	Quartiles			
	0-25	25-50	50-75	75-100
	Inefficiency			
average years of schooling in a household	-0.0367***	-0.0285***	-0.0270***	-0.0245***
	(0.0011)	(0.0006)	(0.0006)	(0.0005)
average years of schooling in a community	-0.0184***	-0.0178***	-0.0175***	-0.0172***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	Uncertainty			
average years of schooling in a household	-0.0474***	-0.0324***	-0.0301***	-0.0259***
	(0.0021)	(0.0010)	(0.0009)	(0.0006)
average years of schooling in a community	-0.0210***	-0.0191***	-0.0184***	-0.0176***
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Observations	1215	1215	1215	1215

Bootstrapped (1000 replications) standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3. Externality effect over quartiles of household average years of schooling

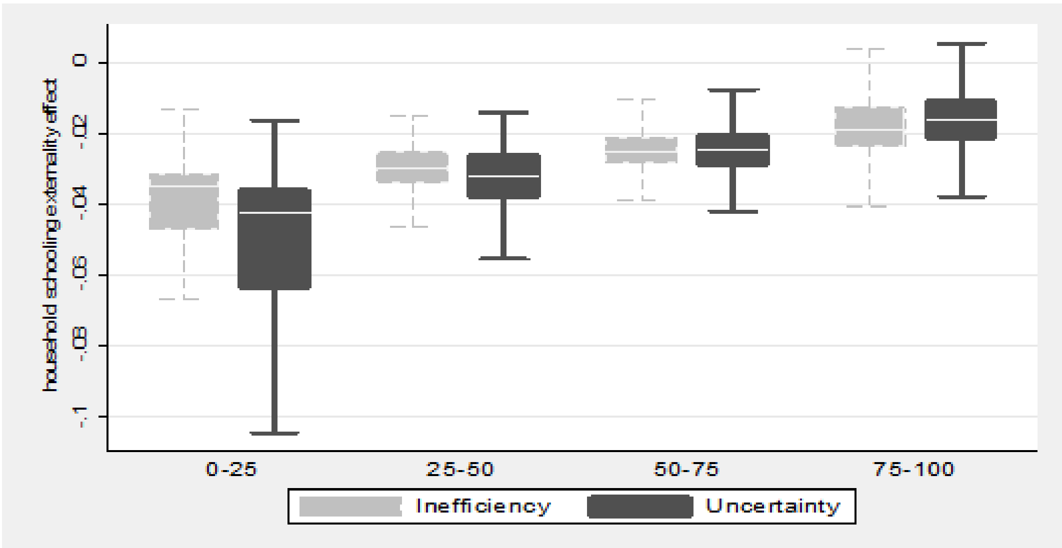


Figure 4. Externality effect over quartiles of community average years of schooling