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Plot size and maize productivity in Zambia: is there an inverse relationship?

Ayal Kimhi*

The Hebrew University of Jerusalem, Agricultural Economics Department, Faculty of Agriculture, P.O. Box 12, Rehovot 76100, Israel

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Abstract

This article examines the relationship between maize productivity and plot size in Zambia. It offers a unique empirical approach. First, it focuses on maize, which is the major crop on small and medium size farms in Zambia, but also accounts for the endogenous determination of the size of the plot devoted to maize. Previous studies have used total farm size or harvested area. Second, it corrects for selectivity in maize cultivation. Third, it controls for differences in land quality and weather conditions across districts. Finally, it offers a structural interpretation of the above framework by modeling farm decisions as a sequential, two-stage process, in which land is first allocated to the different crops based on the information set of the farmers at the time of planting, and the yield is affected by subsequent application of inputs, the quantities of which may depend on additional information that is revealed after planting. We use this recursive structure and the differences in the information sets over time to identify the model.

The results show that the endogeneity of plot size is very important in this analysis. When considering plot size as an exogenous explanatory variable, we find a monotonic positive relationship between the yield of maize and plot size, indicating that economies of scale are dominant throughout the plot size distribution. However, when we correct for the endogeneity of plot size, we find that the inverse relationship dominates the economies of scale in all plots up to 3 ha, which constitute 86% of our sample. These results suggest that market imperfections should be targeted by any policy aimed at increasing maize productivity in Zambia.

JEL classification: O1, Q1

Keywords: Maize yield; Plot size; Inverse relationship; Recursive decisions; Two-stage estimation; Two-sided tobit; Selectivity correction

1. Introduction

The "inverse relationship" puzzle is an empirical observation that agricultural productivity decreases with farm size in many developing countries.[1] Theoretically, economies of scale in production and lumpiness of some modern inputs such as machinery are supposed to favor larger farms (Binswanger et al., 1995). Attempts to explain the inverse relationship mostly rely on market imperfections. For example, when rural labor markets are not functioning, the surplus labor of family members is available for farm work at a very low shadow price (Sen, 1966). In small farms, therefore, the labor to land ratio would be higher than in large farms, and the output to land ratio would also be higher. The coexistence of imperfections in land, labor, and capital markets generates ambiguous conclusions about the relationship between farm size and productivity (Feder, 1985). Eswaran and Kotwal (1986) show that this could lead to yields that are decreasing with farm size for relatively small farms and increasing with farm size above a certain size threshold.

The inverse relationship has attracted the attention of many researchers over the years, mainly because it serves as a motivation for land redistribution from large to small farmers (Cornia, 1985; van Zyl et al., 1995): if smaller farms are more productive, a transfer of a hectare of land from a large farm to a small farm would increase aggregate land productivity. As a result, many empirical attempts have been made to support or refute its importance. The conclusions have been mixed. Results of positive effect of size on productivity have been explained by price and other policy distortions that are lower in larger farms (Kumbhakar and Bhattacharyya, 1992; Sawers, 1998), more intensive use of mechanization on larger farms (Zaibet and Dunn, 1998), insurance and financing constraints faced by poorer farm households that lead them to adopt less profitable strategies of cultivation (Kevane, 1996), and subsistence concerns of small farms that lead them to specialize in less profitable crops (Dorward, 1999; Fafchamps, 1992; Omamo, 1998).

*Corresponding author: Tel.: +972 8 9489376; fax: +972 8 9466267.
E-mail address: kimhi@agri.huji.ac.il (A. Kimhi).

[1] Note that we, as in most of the literature surveyed here, measure productivity as output per unit of land. Elsewhere (e.g., Thirtle et al., 2003), more sophisticated measures of total factor productivity and production efficiency are analyzed.

Results of negative effect of size on productivity (the inverse relationship) have been mostly explained by imperfect land and labor markets (Bardhan, 1973) and in particular family labor surplus on small farms that increases labor input per land and subsequently output per land (Carter, 1984; Mazumdar, 1965; Newell et al., 1997; Reardon et al., 1996), and advantages in hired labor supervision (Yotopoulos and Lau, 1973). Additional theoretical explanation of and empirical support for the inverse relationship is based on higher land conservation efforts on small farms (Byiringiro and Reardon, 1996), food price risk that creates food security stress that induces small farms to utilize more farm labor (Barrett, 1996), and the possibility that high-ability farmers self-select into small farms (Assuncao and Ghatak, 2003).

The ambiguity of the effect of size on productivity was demonstrated by Deolalikar (1981), who found evidence for productivity advantages for small farms in districts in which traditional technologies dominate, and the opposite in districts in which modern technologies dominate. This motivated studies that showed a U-shaped effect of farm size on outcomes (Carter and Wiebe, 1990; Heltberg, 1998). Dorward (1999) suggests that the inverse relationship may be observed in land-scarce areas while a positive relationship would dominate in land-abundant areas.

Several researchers claim that the inverse relationship is a statistical artifact resulting from unobserved variables and/or measurement errors. For example, suppose large farms have lower quality land than small farms. This could be because large farms rely more on rented land which tends to be of lower quality, or because high-quality land is subdivided more often. In this case productivity on small farms might seem to be higher even if the opposite is true. Assuncao and Braido (2004), Benjamin (1995), and Bhalla and Roy (1988) find that the inverse relationship weakens considerably after differences in land quality are taken into account. Lamb (2003) shows that the inverse relationship could not be explained solely on grounds of unobserved land quality differences or rural market imperfections, but after instrumenting farm size (assuming it is measured with error) the inverse relationship is washed away almost entirely. Assuncao and Braido (2004) show that the inverse relationship could be explained by either privately observed plot features or measurement errors in plot size, but could not distinguish between the two explanations.

This survey of the literature demonstrates that there is no uniform conclusion about the validity of the inverse relationship. Moreover, any empirical study that aims to test for the existence of an inverse relationship should account for (a) nonlinear effects of size on productivity; (b) differences in land quality across farms; and (c) measurement error in observed plot size. This study, which examines the presence of an inverse relationship on Zambian maize plots, accounts for all these issues. In addition, it accounts for an additional difficulty that has not received adequate treatment in the existing empirical literature, the possible bias caused by crop composition effects. If small farms are more heavily involved in the cultivation of high-valued crops than large farms, using total crop production as a measure of output may result in an artificial inverse relationship that is essentially nothing but a crop composition effect. This is why Bardhan (1973) recommends concentrating on "... farms in nearly monocrop regions or on cropwise production where input and output data are available separately for each crop" (p. 1375). Binswanger et al. (1995) add that "... focusing on a single crop is inappropriate except in monocrop farming systems. Individual crop studies are therefore not relevant to the farm size-productivity relationship problem" because "... part of the adjustment to incentive problems and other market imperfections is to vary the output mix so as to save on the factors with the highest scarcity value" (p. 2702). Several studies have indeed focused on relatively homogeneous farms in order to avoid the crop composition bias (Adesina and Djato, 1996; Bardhan, 1973; Barnum and Squire, 1978; Townsend et al., 1998), while many others have used total farm output as a dependent variable (e.g., Assuncao and Braido, 2004; Carter, 1984; Dorward, 1999; Heltberg, 1998; Kevane, 1996; Lamb, 2003). Barrett (1996) shows that cropping patterns are responsible for part, but not all, of the observed inverse relationship. Byiringiro and Reardon (1996) control for the crop composition effect by adding the share of high value crops as an explanatory variable in a production regression. However, they fail to recognize that this variable may be endogenous, to the extent that unobserved (to the econometrician) determinants of production may affect crop composition if they are foreseen by the farmer (Vavra and Colman, 2003). Similarly, Benjamin (1995) focuses on rice plots, claiming that it is rare that farmers would switch to other crops from rice, but also included a dummy variable for the use of high-yielding rice varieties without worrying about its endogeneity. Focusing on single-crop plots (see also Kumbhakar and Bhattacharyya, 1992) may invoke selectivity bias concerns, to the extent that the decision to grow a single crop may be related to farm productivity or may be affected by the same unobserved factors as farm productivity. None of these studies have attempted to correct this selectivity bias or at least test for its importance.[2]

The present study overcomes the crop composition obstacle by (a) measuring productivity on plots devoted to a single crop (maize); (b) correcting for selectivity in the sample of farms engaged in maize cultivation; and (c) correcting for endogeneity of the land devoted to maize, as in Weersink and Rozelle (1997). Selectivity correction is important because it could be that farms with a comparative disadvantage in maize cultivation will devote none of their plots to maize. If these farms are not distributed randomly with regard to size, one would obtain a biased estimate of the association between size and productivity. Likewise, the correction for endogeneity of land devoted to maize is important because farms with a comparative disadvantage in maize cultivation will devote relatively smaller

[2] We ignore the issue of intercropping here, simply because our data set does not provide any indication that this is relevant for Zambia.

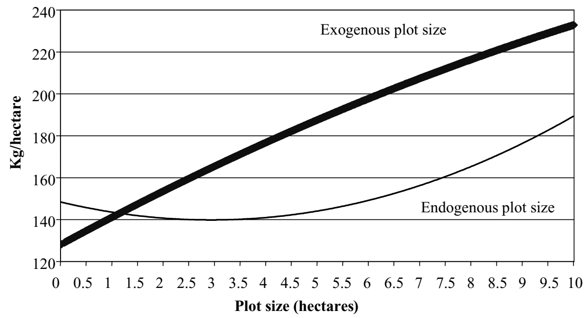

Fig. 1. Calculated yield as a function of plot size.

plots to maize cultivation, and in this case the association between size and productivity would be biased toward zero. In addition, correcting for endogeneity of plot size also corrects for measurement errors in this variable that were found to be important by Benjamin (1995) and Lamb (2003). Indeed, our results justify the correction for endogeneity of plot size. Fig. 1 shows that without correcting for endogeneity, the effect of size on yield is always positive, while it becomes negative for smaller plots after correcting for endogeneity.

Zambia provides a suitable case study for demonstrating the suggested empirical methodology. First, most farms, but not all, cultivate maize, giving rise to the sample selectivity issue. Second, most of the farms that cultivate maize devote land to other crops as well, giving rise to the plot size endogeneity issue. In addition, our data set includes a large number of observations on small and medium farms using relatively homogeneous production technology, allowing for productivity comparisons across the size distribution. However, the methodology developed here is not specific to either Zambia or this particular data set, and could be applied to other case studies as well.

Our methodology offers a structural interpretation of the above framework, by modeling sequential farm decisions in two recursive stages, as in Antle (1983), McGuirk and Mundlak (1992), Smale et al. (1995), and Weersink and Rozelle (1997). In the first stage, which is associated with the planting season, land is allocated to the different crops based on the information set available to the farmers at that time. The yield is determined in the second stage by subsequent application of inputs, the quantities of which may depend on additional information that is revealed after planting. We view farmers as operating within imperfect factor markets. The relatively high uncertainty prevailing in large parts of rural Zambia, not only with regard to input availability and prices, but also with regard to rainfall, highlights the importance of information in this context. We use this recursive structure of the decision process and the evolvement in the information set over time to identify the model.

The following section outlines the theoretical framework that underlies this analysis and the empirical approach. The data set is described next, followed by the empirical results. Conclusions are presented in the last section.

2. Analytical framework and empirical approach

Our analytical framework is based on the McGuirk and Mundlak (1992) framework, which relies on the sequential nature of decisions on a farm in the spirit of Antle (1983): "... Initially, farmers decide, given information at planting time, how to allocate land among different crops. Farmers then can change output only by influencing yield" (p. 133). Specifically, we assume that the production function for the *j*th crop is $y_j = F_j\ (x_j, k_j, e)$, where y is quantity of output, x is a vector of quantities of variable inputs, k is a vector of quantities of quasi-fixed inputs, and e is a vector of environmental variables (constraints, policy indicators, weather, soil type, location, etc.). The farmer's objective in the short run is to maximize the farm's net cash flow: $R = \Sigma p_j y_j - w' \Sigma x_j$, over choices of x_j and k_j, subject to the constraints on the availability of the quasi-fixed inputs $\Sigma k_j = K$, where p is the vector of output prices, w is a vector of variable input prices, and K is a vector of total farm-level quantities of quasi-fixed inputs. "Short run" in this sense means that decisions are conditional on the predetermined levels of the quasi-fixed inputs K. If all relevant information is known prior to planting, the results of farmer's optimization are vectors of conditional (on K) input demands $x_j(p, w, e, K)$, $k_j(p, w, e, K)$ and output supplies $y_j(p, w, e, K)$.

Note that we consider the farm-level quantities of the quasi-fixed inputs K as conditioning variables, as opposed to Weersink and Rozelle (1997) who treat them as endogenous in a dynamic framework, because many previous studies have found that farmers in Zambia are often subject to input availability constraints. Holden (1993) cites the highly imperfect labor markets as the main problem in Zambian agriculture. Wichern et al. (1999) attribute part of the labor shortage to poor health and education of hired workers, as well as to social norms that restrict the optimal allocation of labor. Jha and Hojjati (1993) show that credit is the most limiting factor in their study. Kimhi and Chiwele (2002) also find that shortage of funds for buying inputs is the major constraint reported by farmers. Jha (1990) mentions animal traction (oxen and implements) as a major constraint in the Eastern Province, while Foster and Mwanaumo (1995) claim that "more emphasis is needed on support systems such as extension education, agricultural research, infrastructure, and marketing." Wanmali (1990) also mentions the need for investments in various rural services. Alwang et al. (1996) claim that market liberalization cannot benefit remote households without improvements in infrastructure and market access. They also show that lack of male labor for land preparation is a major constraint in poor households. Seshmani (1998) adds, on top of all these constraints, the inadequate availability of on-farm storage facilities.

Turning to the aspect of information availability, we assume that at the time of planting, the farmer has a partial information set s_1, including last year's prices, early weather conditions and forecasts, other environment characteristics (soil conditions, market situation, policy, etc.), and certain elements of K. Hence, planting decisions, that is, land allocated to each crop (land is assumed to be one of the quasi-fixed inputs), are made according to this information set only, and the land allocated to crop j can be specified as $a_j(s_1)$.[3] Between planting and harvest, more information is revealed, such as current prices and updated weather conditions, additional elements of e and K, and of course the vector of land allocations (a) which has been determined at the planting stage (Antle, 1983). These, in addition to the previous information, are included in the new information set, s_2. Based on the new information set, farmers choose levels of other inputs: $x_j(s_2)$, $k_j(s_2)$.

If production exhibits constant returns to scale in all inputs, then output can be expressed as a product of land input and yield: $y_j = a_j Y_j(x_j, k_j)$, where Y (yield) is crop output per unit of land. Since the allocation of inputs to crops is not observed, we can substitute optimal inputs into the yield functions and obtain the yield as a function of the information set: $Y_j(s_2) = Y_j[x_j(s_2), k_j(s_2)]$. This specification leads to the following two-stage estimation procedure. In the first stage one estimates the land allocation equations $a_j(s_1)$. The yield equations $Y_j(s_2)$ are estimated in the second stage, after substituting the calculated value (from the first stage) of a_j in s_2, to avoid simultaneity bias.[4]

More formally, this procedure implies specifying two linear recursive simultaneous equations for each crop, one for the land allocated and the other for the yield:

$$a = \alpha_0 + \alpha_A A + \mathbf{X_a}\boldsymbol{\alpha}_\mathbf{x} + u_a, \tag{1}$$

$$Y = \beta_0 + \beta_a a + \beta_{aa} a^2 + \mathbf{X_Y}\boldsymbol{\beta}_\mathbf{x} + u_Y. \tag{2}$$

For simplicity, we focus here on a single crop and therefore omit the subscript j. In (1), A is total land and a is land allocated to this specific crop. In (2), Y is the yield. a^2 is included as an explanatory variable in order to allow a nonlinear effect of plot size on yield. $\mathbf{X_a}$ and $\mathbf{X_Y}$ are matrices of explanatory variables that are assumed to be included in the relevant information sets s_1 and s_2, respectively. Hence, $\mathbf{X_a}$ is a subset of $\mathbf{X_Y}$. The error terms u_a and u_Y are assumed to be correlated due to common elements in the information sets that we do not observe but are known to the farmers. This causes simultaneity: estimating (2) alone will result in inconsistent parameter estimates because a and u_Y are correlated. However, the equations are recursive because (1) can be consistently estimated on its own.

In addition to the simultaneity problem, we face the problems of censoring and sample selectivity. Note that these problems are not relevant for the models of McGuirk and Mundlak (1992) and Weersink and Rozelle (1997), who use regional rather than individual farm data. Censoring is relevant for the estimation of (1), because the observed land allocation must be between zero and total land. Correcting for this problem is complicated by the fact that total land is farm specific. Therefore, for econometric reasons alone, we specify the dependent variable in Eq. (1) as a/A, the fraction of total land devoted to this specific crop. This way a/A is between 0 and 1. Note that leaving A as an explanatory variable implies that unlike in (1), the dependence of a on A is nonlinear. In fact, we do not have any reason to assume linearity in this case. In addition, we normalize the quantitative elements of $\mathbf{X_a}$ by A, to avoid scale biases.

Assuming normality of u_a, the likelihood function used for estimating (1) is:

$$\begin{aligned}&\prod_{a/A=0}[1-\Phi((\alpha_0+\alpha_A A+\mathbf{X_a}\boldsymbol{\alpha}_\mathbf{x})/\sigma_a)]\\&\quad\times\prod_{0<a/A<1}[\varphi((a/A-\alpha_0-\alpha_A A-\mathbf{X_a}\boldsymbol{\alpha}_\mathbf{x})/\sigma_a)/\sigma_a]\\&\quad\prod_{a/A=1}[1-\Phi((1-\alpha_0-\alpha_A A-\mathbf{X_a}\boldsymbol{\alpha}_\mathbf{x})/\sigma_a)],\end{aligned}\tag{3}$$

where Φ and φ are the cumulative distribution function and the probability density function, respectively, of a standard normal random variable, and σ_a is the standard deviation of u_a. Note that multiplication is over observations, but the index of observation is omitted for simplicity of exposition.

Sample selectivity is relevant for the estimation of (2), because we only observe Y if $a > 0$. As has been shown by Heckman (1979), one cannot estimate (2) by ordinary least squares using the subsample in which $a > 0$, because the sample selection rule depends on $\mathbf{X_a}$ and u_a, and therefore the expectation of u_Y in the selected sample is a function of $\mathbf{X_a}$ (due to the correlation between u_a and u_Y) resulting in inconsistent parameter estimates. We employ the selectivity correction procedure suggested by Heckman (1979), by adding to Eq. (2) the conditional expectation of u_Y in the selected subsample, which, assuming joint normality of u_a and u_Y, equals $\sigma_{aY}/\sigma_Y\varphi(Z)/[1-\Phi(Z)]$. Here, Z is equal to $(\alpha_0 + \alpha_A A + \mathbf{X_a}\boldsymbol{\alpha}_\mathbf{x})/\sigma_a)$, σ_{aY} is the covariance between u_a and u_Y, and σ_Y is the standard deviation of u_Y. The yield equation we estimated is, therefore,

$$\begin{aligned}Y = {}&\beta_0 + \beta_a a' + \beta_{aa} a'^2 + \mathbf{X_Y}\boldsymbol{\beta}_\mathbf{x} + \sigma_{aY}/\sigma_Y\varphi(Z')/\\&[1-\Phi(Z')] + u_Y \qquad \text{if } a > 0,\end{aligned}\tag{4}$$

where primes indicate variables that are calculated by substituting parameters estimated in the first stage for the relevant coefficients in (1). Note that identification of the coefficients of (4) that does not rely solely on functional form assumptions requires that Z include a variable that does not appear independently in (2). Total land (A) serves this purpose in our model.

[3] Hassan (1996) shows that both socioeconomic factors and agroclimatic conditions explain a significant proportion of the variability of maize planting decisions in Kenya, in addition to access to extension and machine services. Weersink and Rozelle (1997) also use yield expectations to explain planting decisions, but this requires panel data, which we do not have for Zambia.

[4] Smale et al. (1995) observe the allocation of fertilizer among the crop varieties and hence are able to use an empirical framework, which extracts more information from the sample. Weersink and Rozelle (1997) estimate a three-stage model, the middle stage being the allocation of labor and fertilizer among the crops, which they observe.

Table 1
Variables used in the estimation

Name	Description	Sample mean
Total land	Total land used for seasonal field crops (ha)	1.780
Maize land	Fraction of land used for maize	0.654
Maize yield[a]	Yield of maize (100 kg/ha)	1.420
Female	1 = female head of household	0.212
Age	Age of head of household (years)	44.89
Higher education	1 = head of household with higher than primary education	0.188
Distant road	1 = nearest road is more than 5 kilometers away	0.179
Distant market	1 = distance to nearest output market is more than 20 kilometers	0.116
No market access	1 = household has no access to output markets	0.274
Extension	1 = exposed to at least one kind of extension service	0.547
Irrigation	1 = some of the land is irrigated	0.117
No irrigation-know	1 = not irrigating more due to lack of knowledge	0.294
No irrigation-funds	1 = not irrigating more due to lack of funds for equipment	0.263
Hired workers perm[a]	Number of permanent hired workers	0.011
Family male workers[a]	Number of male family members employed on the farm	2.659
Family female work[a]	Number of female family members employed on the farm	3.117
Draught animals[a]	Number of draught animals used on the farm	0.203
Machines[a]	Number of animal-drawn implements	0.246
Credit received[ab]	Amount of credit received (10,000 Kwacha)	0.986
Chemical fertilizer[ab]	Total amount of chemical fertilizers used (100 kg)	1.122

[a]These variables are expressed as per hectare of land total.
[b]These means are based on the 3,973 "clean" observations who reported maize output.

3. Data and descriptive statistics

We use data from two separate surveys that were conducted in Zambia within several months during the crop year of 1993–1994. Both surveys were conducted by the Central Statistical Office in Zambia, and were administered over the same sample of farmers. The sample was designed to be representative for Zambia as a whole. The population from which the sample was drawn was defined as small- and medium-scale farm households. Large commercial farms were excluded from the survey.

Farm categories in Zambia are defined on the basis of the technologies applied (Government Republic of Zambia, 1994). Commercial farmers are characterized by extensive mechanization, use of modern technology and management, and heavy reliance on hired labor. They number less than 1,500 and are concentrated in the narrow railroad corridor. Small-scale farmers, on the other hand, depend mostly on hand-hoe cultivation and unpaid family labor, and use low levels of modern farm inputs which, when used, consist mostly of chemical fertilizer and hybrid seeds on maize cultivation. There are about 600,000 farm households classified as small-scale farmers in the country. Medium-scale farmers, also called emergent farmers, who number about 100,000 farm households, fall in between these two categories but are mostly distinguished by their use of animal power. This is a transitional phase prior to commercial farming. Small- and medium-scale farmers contribute between 40% and 60% of the agricultural output in Zambia.

The Crop Forecast Survey included 7,269 farmers, 87% of whom were defined as small-scale farmers, and the other 13% as medium-scale farmers. In the survey, farmers were asked about their access to particular services such as extension, credit, and marketing channels, and about their irrigation practices. Demographic information about the household was also collected. The Crop Forecast Survey was matched to the Post Harvest Survey, in which detailed input–output data were collected, and from which knowledge of and access to modern production techniques such as improved seed varieties and chemical fertilizers can be inferred. The post-harvest survey included 6,469 farms. We do not know for sure why the numbers of observations in the two surveys are different.

The merged data set was checked for consistency of the cropping information by checking whether a farmer who indicated that he grows a certain crop also reports a positive amount of land allocated to that crop. A total of 5,903 farms (91%) passed this test for all crops reported. The two data sets were then merged, resulting in 5,329 matched observations (90% of the consistent observations in the post-harvest survey). Some other observations were excluded due to missing explanatory variables. The estimation procedure eventually used 5,280 observations. Table 1 presents the definitions of the variables used in the analysis and their sample means.

The major crop in the sample farms is maize, which is grown by 84% of the farmers in the merged data set, and accounts for 78% of the cultivated land in the farms that do grow maize, and 65% of all cultivated land. We therefore treat, for the purpose of estimation, all other crops as a composite crop.[5] This means that we only estimate the maize land fraction and yield equations,

[5] We also tried to treat other crops individually, but the results were disappointing due to the small numbers of observations for each crop other than maize.

as in the model described in the previous section. About one-third of the farmers grow nothing but maize. This justifies the need to account for censoring from above of the fraction of land devoted to maize.

Among the quantitative variables in the data set, we treat total land, credit, fertilizers, draught animals, machines, and family and hired workers as quasi-fixed inputs, whose quantity is given in the short run. We observe the total quantity of each quasi-fixed input used by the farm but not the allocation among crops (except for the land allocation). These inputs are considered fixed in the short run because they are either predetermined (land, animals, machines, family workers) prior to the planting season, or affected by quantity constraints due to imperfect markets (credit, fertilizers, hired labor). We assume that the available quantities of credit and fertilizers are not known to the farmer prior to planting. This is a reasonable assumption given the imperfect nature of the relevant markets. Credit applications made by farmers take a long time to process, and the availability of fertilizers depends on various bottlenecks in the distribution process. Hence the quantities of these quasi-fixed inputs cannot affect planting decisions, and they are included as explanatory variables in the yield equation only.

Other explanatory variables include infrastructure indicators (distance to road and access to market),[6] exposure to extension services through direct and indirect channels, an irrigation dummy, and the reasons for not irrigating. We also include the gender, age, and education of the household head as explanatory variables. In addition, each stage of the estimation procedure includes district dummies, which control for land quality and weather differences across districts. We have tried to use land-quality indicators and rainfall data directly instead of the district dummies, but we did not have rainfall data for all districts and the difference between districts with and without rainfall data was statistically significant, hence we decided to stick with the district dummies.

4. Estimation results

The results of the censored regression of the fraction of land allocated to maize are reported in Table 2. In addition to the variables shown in the table, the regression included district dummies, which were found to be jointly statistically significant. The importance of the district dummies can be explained in part by the fact that different species of maize may be advantageous in different climatic areas (Chipanshi, 1989). In addition, environmental variables such as land quality and rainfall, which vary across districts, can increase both expected and actual yields within species. Other than extension, irrigation, and family labor, all explanatory variables affect the fraction of land allocated to maize significantly. In particular, the fraction of land allocated to maize is negatively associated with the total size of land used for field crops.[7] This means that farms with larger plots of field crops tend to have a more diversified crop mix than smaller farms. Female-headed households tend to devote smaller fractions of their land to maize. The fraction of land devoted to maize increases with the farmer's age and education, meaning that older and more educated farmers tend to be more specialized in maize cultivation. To the extent that age stands for farm experience, perhaps human capital enhances the economies of scale in maize cultivation. Distance from road or to market reduces the fraction of land devoted to maize. This indicates the use of maize, at least in part, as a cash crop. However, the fraction of land devoted to maize is higher when markets are inaccessible. The contradictory nature of the last two results hints at a nonmonotone effect of market accessibility on crop composition. Farms with no access to markets are those with the highest fraction of land devoted to maize, other things being equal. When markets become accessible but are relatively distant, farmers allocate more land to other crops. These might be cash crops that are not very useful for self-consumption. When markets become more accessible, the fraction of land devoted

Table 2
Results of the censored regression of the fraction of land allocated to maize

Variable	Coefficient	*T*-value
Intercept	0.9666	30.529**
Total land	−0.0146	−3.984**
Female	−0.0626	−3.868**
Age	0.0624	3.725**
Higher education	0.1516	8.626**
Distant road	−0.0764	−5.009**
Distant market	−0.1028	−4.807**
No market access	0.0435	2.408**
Extension	0.0019	0.129
Irrigation	−0.0276	−1.322
No irrigation-know	−0.0332	−1.884*
No irrigation-funds	0.0122	0.188
Hired workers perm.	0.1312	2.642**
Family male workers	−0.0043	−1.583
Family female workers	−0.003	−1.217
Draught animals	−0.0225	−2.046*
Machines	0.0523	4.225**
Sigma	0.5427[a]	
Number of cases	5,280	
Log likelihood	−4,273.99	

Notes: The model also included district dummies.
*Coefficient significant at the 5% level.
**Coefficient significant at the 1% level.
[a]The standard deviation coefficient was transformed prior to estimation to assure convergence; hence the standard error of the untransformed estimate is not reported.

[6] Jacoby (2000) showed that roads and access to markets were important for the welfare of Nepalese farmers. Smale et al. (2001) found that infrastructure affected land allocation among maize varieties in Mexico. Foster and Mwanaumo (1995) found that infrastructure was one of the most important determinants of maize productivity in Zambia.

[7] Fafchamps (1992) shows that farm size affects land allocation decisions in the presence of food price uncertainty. Omamo (1998) attributes this phenomenon to transport costs. Zulu et al. (2000) claim that market liberalization has lead to a downward trend in maize cultivation in Zambia.

Table 3
Results of the maize yield equation

Variable	Actual maize land		Predicted maize land	
	Coefficient	T-value	Coefficient	T-value
Intercept	9.6788	10.0739**	11.3500	11.3067**
Maize land	1.3486	7.6524**	−0.6094	−2.4300*
Maize land squared	−0.0288	−2.3330*	0.1013	4.2906**
Female	−0.4273	−0.9959	−0.9118	−2.0826*
Age	−2.7361	−2.3890*	−0.9763	−0.8371
Higher education	0.5412	1.2533	0.9814	2.2532*
Distant road	−0.3519	−0.7735	−0.2104	−0.4379
Distant market	0.5598	0.9594	0.5735	0.9589
No market access	0.0552	0.1257	−0.3701	−0.8248
Extension	0.4723	1.3410	0.5978	1.6580
Irrigation	−0.2127	−0.3194	0.0109	0.0161
No irrigation-know	0.1157	0.2616	−0.0107	−0.0238
No irrigation-funds	−0.5401	−1.2554	−0.4491	−1.0275
Hired workers perm.	2.6201	1.8720	3.0567	2.1574*
Family male workers	0.4711	7.3517**	0.4052	6.2123**
Family female workers	0.3259	5.8977**	0.3052	5.2160**
Draught animals	−0.2318	−1.1729	−0.1882	−0.9406
Machines	1.0100	4.2197**	0.9679	3.9926**
Credit received	0.3846	6.8329**	0.4867	8.5920**
Chemical fertilizer	0.0357	2.0076*	0.0362	2.0056*
Selectivity correction term			4.8091	1.8692
Sigma	9.86		9.98	
Number of cases	3,973		3,973	
R^2	0.207		0.188	
Adjusted R^2	0.193		0.173	
F-statistic	14.357		12.565	

Notes: Both models also included district dummies.
*Coefficient significant at the 5% level.
**Coefficient significant at the 1% level.

to maize increases again, but does not reach the same level as in farms without access to markets. It could be that with better market accessibility, farms can adopt maize varieties that make maize relatively more profitable.

Lack of irrigation knowledge has a negative effect on the fraction of land devoted to maize, and the same is true for the number of draught animals. The number of permanent hired workers and the number of animal-drawn implements have positive effects on the fraction of land devoted to maize, indicating that maize cultivation is labor intensive relative to the cultivation of other crops.

The results of the maize yield equation are reported in Table 3.[8] Two versions are reported: the version on the left-hand column using actual plot size as an explanatory variable, without correcting for its endogeneity, while the version on the right-hand column uses the predicted plot size instead. Other than that, the two versions are identical. We observe a nonlinear dependence of yield on plot size in both cases, but the patterns are opposite in sign. While the overall trend in both cases is positive, yield is first increasing and then decreasing with size when actual size is used, but is first decreasing and then increasing with size when predicted size is used.[9] Hence, we conclude that failing to control for the endogeneity of plot size in such analyses may lead to incorrect conclusions about the effect of plot size on crop yields.[10] The true association between size and productivity is nonlinear, first decreasing and then increasing, as in the theoretical model of Eswaran and Kotwal (1986) and the empirical findings of Carter and Wiebe (1990) and Heltberg (1998).

This conclusion is reinforced by looking at Fig. 1, in which the dependence of yield on size is shown graphically for the two cases, with and without controlling for the endogeneity of plot size. We observe that without controlling for endogeneity, maize yield is monotonically increasing with plot size throughout the size distribution, despite the nonlinear relationship implied by the regression coefficients. However, when controlling for endogeneity of plot size, the yield is first decreasing with size and then increasing. The size in which the minimum yield is attained in this latter case is approximately 3 ha. About 86% of our sample is below 3 ha of land. Hence, we conclude that the inverse relationship between plot size and the yield of maize is in effect for most small- and medium-size farms in Zambia. This result is similar to Heltberg's (1998) findings for Pakistan.[11]

The statistically significant positive effects of family labor, machines, credit, and fertilizer on the yield of maize are fairly consistent across the two specifications of the yield equation, and confirm the earlier results of Holden (1993), Jha and Hojjati (1993), and Kumar (1994). However, several other coefficients change considerably after correcting for the endogeneity of plot size. For example, the yield of maize is lower in female-headed households and is increasing with education and with hired labor, but these intuitively appealing effects are statistically significant only when plot size is considered endogenous. On the other hand, age appears to have a statistically significant negative effect on yield when plot size is considered exogenous, which is also consistent with intuition, but this effect becomes insignificant after correcting for endogeneity. The infrastructure, extension, and irrigation variables are not statistically significant in any of the specifications, although extension is close to having a significant positive effect on yield. The coefficient

[8] We had to exclude a number of observations that apparently devoted land to maize but did not report the yield.

[9] We also estimated a third-degree polynomial in size but we could not reject the hypothesis that this specification is no different than the one reported in Table 3.

[10] We also estimated both models without correcting for selectivity, but this did not change that pattern of the size-yield relationship. Observe that the coefficient of the selectivity correction term is not statistically significant at the 5% level. Note that the Heckman (1979) procedure may be vulnerable to collinearity between the explanatory variables and the selectivity-correction term, yet an informal test revealed little, if any, collinearity in this case.

[11] It could be that the increase in yields above a certain size is due to the adoption of improved technologies. We tried to control for this effect by including machines among the explanatory variables, but it could be that the effect is more complex. Perhaps the yield-size relationship should be analyzed jointly with the choice of techniques. The data set is not sufficiently detailed to permit such an analysis.

of draught animals is also insignificant, perhaps because this variable is correlated with the machines variable. The district dummies were jointly statistically significant.[12]

The selectivity correction is not statistically significant at the 5% level. This could be due to multicollinearity. Note that a relatively large number of coefficient estimates are insignificant. The exclusion of the associated explanatory variables could improve the multicollinearity situation, and could also serve to validate that the significant coefficients and the resulting conclusions are not contaminated by multicollinearity. For this, the model was re-estimated with the exclusion of the personal variables, infrastructure variables, extension, and irrigation.[13] The results clearly indicate that all the significant results are robust to multicollinearity. In addition, the selectivity correction term is statistically significant in this case, indicating that controlling for selectivity into maize cultivation is practically important.

5. Conclusions

This article has demonstrated, for the case of maize cultivation in Zambia, that accounting for endogenous crop composition is crucial for estimating the relationship between productivity and plot size. In particular, we treat the size of the plot devoted to maize as an endogenous explanatory variable in the yield equation. Previous studies used total farm size or harvested area as an explanatory variable and treated them as exogenous. After accounting for the endogeneity of plot size, we found that the inverse relationship between size and productivity dominates the economies of scale in all plots up to 3 ha, which constitute 86% of our sample. In contrast, when considering plot size as an exogenous explanatory variable, we found a monotonic positive relationship between the yield of maize and plot size, indicating that economies of scale are dominant throughout the size distribution. This undermines the findings of previous studies in various countries that did not adequately account for endogeneity of crop composition.

The policy implications of our results are far reaching. The results imply that economies of scale in maize cultivation in Zambia become operative only above a certain plot size threshold, whereas the inverse relationship between size and productivity prevails on smaller plots. Therefore, the results suggest that the size distribution of farms in Zambia could be converging toward a bi-modal distribution, with a large number of small subsistence farms on one extreme and a small number of large commercial farms on the other extreme. This pattern has been identified in several other countries (e.g., Weiss, 1999). In a land-abundant country such as Zambia, the inverse relationship is likely to be a result of market imperfections (Kimhi and Chiwele, 2002). While further research on this topic is still necessary, targeting imperfections in the land market, in the credit market, and in markets for inputs and products emerges as a necessary condition for improving the prospects of small farmers in Zambia.

[12] It is possible to find the effects of district-specific variables on the yield when estimating the model with district dummies, by running a linear regression of the estimated district dummies on the set of district-specific variables (Borjas and Sueyoshi, 1994). We were not able to get interesting results from this last regression and hence it is not reported here. The reason is that we had very few observations due to the missing rainfall data.

[13] The results are not shown here. They are available from the author on request.

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