Does heterogeneity in goals and preferences affect allocative and technical efficiency? A case study in Northern Nigeria.

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Abstract

Household characteristics are commonly used to explain variation in smallholder efficiency levels. The underlying assumption is that differences in intended behavior are well described by such variables, while there is no a priori reason that this is the case. Moreover, heterogeneity in farmer goals and preferences, in relation to the role of the farm enterprise, are not well documented in developing countries. This paper makes a contribution to fill this gap, by empirically determining heterogeneity in farmer goals and attitudes in Nigeria through a pair-wise ranking, supplemented with Likert scales. Factor analysis is used to reduce these data into behavioral factors. We estimate technical and allocative efficiency levels and analyze how these are related to farm characteristics and the identified behavioral factors. The models in which both intended behavior and farmer characteristics are included give a significantly better fit over models in which only household characteristics are included. These regression results suggest that the socio-economic environment affects efficiency levels both directly and indirectly, through changes in goals and attitudes. Additional research in rural areas of developing countries should establish how agricultural policies should account for this heterogeneity.

1. Introduction

A large body of literature analyses, both through parametric and non-parametric methods, farm production behavior in rural areas of developing countries. The majority of non-parametric approaches aims to simulate farmer production decisions under various assumptions and scenarios (e.g., Hazell and Norton, 1986). While these provide useful insights in a potential efficient response to exogenous changes, the results are strongly conditional on the assumptions made by the researcher on farmer behavior. For example, several studies explain observed variation in technical and allocative efficiency levels from household and socio-economic characteristics (e.g., Alene and Manyong, 2006), while other studies estimate household factor demand as a function of prices and household characteristics (e.g., Singh *et al.*, 1986)). These studies thereby circumvent further explicit assumptions on the shape of the utility function. However, these studies make an implicit assumption that the relationship between farmers' production goals and preferences and household characteristics is homogenous in the area of study, while there is no clear reason why this should be the case. While some studies acknowledge the importance of attitudes and production goals, very few actually attempt to quantify these at the micro level.

Risk attitudes, starting from Binswanger (1980); time preferences; and preferences related to cooperation and trust have received considerable attention in field experiments in developing countries (e.g., Cardenas and Carpenter, 2008). On the other hand, very few other attitudes have received attention in empirical research. For example, poorly functioning agricultural markets undoubtedly explain a considerable part of the strong subsistence production-orientation found amongst many smallholder farmers. That said, such imperfections can influence production decisions both in a direct and indirect way. While economic circumstances limit farmers from market-oriented production, farmers might view the production of sufficient subsistence staple crops as their duty. The latter belief can be reinforced by social, natural and economic factors.

The identification and quantification of farmer goals has received considerable attention in developed countries. Van Kooten *et al.* (1986) documented farm goals in Canada, Willock and Deary (1999) in Scotland, while Basarir and Gillespie (2006) documented and quantified differences in attitudes and goals between beef and dairy producers in Louisiana. To determine the effects of these "human factors" several studies have linked farm productivity measures and production choice with farmer attitudes. Penning and Leuthold (2000) found important relationships between farmer attitudes and usage of future contracts in the Dutch hog sector. Amongst Dutch dairy farmers, Bergevoet *et al.* (2004) found that farmers' objectives and attitudes explain variation in farm size and milk quota. Hence, heterogeneity in farmer attitudes clearly matters in developed countries, while it has received, except for risk attitudes, preciously little attention in developing countries.

A few exceptions are Costa and Rehman (1999) who found that goals do affect farm decisions on herd size in Brazil, while Solano *et al.* (2006) related farmer decision-making profiles to farm performance in Costa Rica. Some studies focusing on African smallholder agriculture in relation to productivity explicitly acknowledge the presence and relevance of multiple, sometimes conflicting goals (e.g., Tittonell *et al.*, 2007), while others have ventured to determine farmer attitudes in relation to specific farm management practices (e.g., Okoba and De Graaff, 2005; Brown, 2006). None to our knowledge have empirically determined and quantified goals and attitudes related to the farm enterprise in general in Sub-Saharan Africa.

The objective of this research is twofold. First, we quantify heterogeneity in farm production attributes empirically amongst smallholder farmers in a rural African setting. Second, we investigate if heterogeneity in these attitudes and goals indeed results in different production strategies. In particular, variation in different measures of productivity and efficiency –profit allocative, food allocative and technical efficiency– are likely to be a partial result of heterogeneity in these attitudes, something we determine empirically.

To our knowledge no other study has related farmer goals and preferences to efficiency levels in smallholder agriculture in Sub-Saharan Africa. In Section 2 we discuss the method of analysis and data collection; the main findings are presented and discussed in Section 3, which we discuss and from which we draw conclusions in Section 4.

2. Estimation approach and data

We relate observed efficiency levels to both household characteristics and heterogeneity in goals and attitudes. Common approaches start with determining various efficiency measures E^s, for example through Data Envelopment Analysis (DEA). These measures are commonly expressed on a scale between 0 and 1, with 1 reflecting full efficiency. Observed efficiency levels are then related to household characteristics as in (1)[4], with K a vector of household characteristics such as age, level of education and distance to markets. Due to the censored nature of the observations, (1) is estimated by a Tobit regression.

$$E^s = \beta_{0s} + \sum_{i=1}^{N} \beta_{is} K_i + \varepsilon_{1s} \tag{1}$$

In our approach we hypothesize that efficiency levels can be explained by household goals and preferences, in addition to household characteristics. We include these through "behavioral" variables z_j, and are interested whether equation (2) better describes the observed variation in efficiency levels.

$$E^s = \beta_{0s} + \sum_{i=1}^{N} \beta_{is} K_i + \sum_{j=1}^{M} \gamma_{js} z_j + \varepsilon_{1s} \tag{2}$$

It is possible that the behavioral variables z_j are related to the household characteristics K (3):

$$z_j = \alpha_{0j} + \sum_{i=1}^{N} \alpha_{ij} K_i + \varepsilon_{2j} \tag{3}$$

Hence if household preferences and goals indeed have a direct effect on efficiency levels, and if these preferences are fully described by household characteristics (3), then by substituting (3) into (2), equation (4) can be estimated directly.

$$E^s = \beta^*_{0s} + \sum_{i=1}^{N} \beta^*_{is} K_i + \varepsilon^*_{1s} \tag{4}$$

This reflects the commonly estimated case were z_j is unobserved. The parameter estimates of household characteristics K then capture both direct and indirect effects (through z_j), with $\beta^*_{is} = \beta_{is} + \sum_{j=0}^{M} \gamma_{js} \alpha_{ij}$ and $\varepsilon^*_{1s} = \varepsilon_{1s} + \sum_{j=1}^{M} \gamma_{js} \varepsilon_{2j}$.

[4] We suppress the farmer subscript in the formulas presented

Moreover, if household characteristics fully explain intended behavior (and ε_{1s} and ε_{2j} are uncorrelated), the variance explained in both regressions should be largely similar. This hypothesis is examined further in this paper. If the inclusion of behavioral factors in (2) does give a significantly better fit, compared to direct estimation of (4), we should conclude that household preferences and goals do give additional explanation to observed efficiency levels.

It is however not directly obvious if (2) and (3) can be estimated consistently. If the causality is postulated correctly as in (2) and (3), and if K and ε_{2j} are independent, then (2) can be estimated directly and consistently if the error terms ε_{1s} and ε_{2j} are uncorrelated (e.g., Greene, 1997, p.737). However there are several reasons why the error terms might be correlated. First, measurement errors in K would not only render consistent estimation of (3) impossible, but would also induce correlation between both equations as K enters both. Secondly, unobserved variables such as local climatic conditions might influence both behavioral factors and efficiency levels. This omitted variable bias then carries over to both equations. Furthermore, efficiency levels and intended behavior might suffer from simultaneity bias. We therefore test if endogeneity affects the estimated Tobit models. By estimating (3) variables are identified which correlate with z_j but not with efficiency levels E^s and serve as potential instruments. A Wald test on exogeneity is used to test if z_j need to be instrumented (e.g., Cameron and Trivedi, 2005, p. 561).

To determine whether household goals and preferences matter in estimating (2), data from a smallholder setting in Northern Nigeria is used. Data was collected in the 2006-cropping season from 230 farmers in seven villages. The village selection was based on differences in market access, population pressure and differences in soils and climate. In each village a list of inhabitants was established with village elders, from which 30 to 40 farm households were randomly selected. At this point all selected farmers were asked if they were willing to participate in the survey, which consisted of three different surveys administered at different moments in time. In the first survey general household characteristics (household composition, land ownership, livestock and asset holdings, other sources of income) are collected before the cropping season. A second survey served to obtain production data (output quantities, input use) shortly after harvest.

The third survey was used to elicit farmer goals and preferences and consisted of a number of questions intended to construct scales on the relative importance of production attributes. This survey consists of two parts: a fuzzy pair-wise ranking and a set of Likert-scale questions[5]. Both parts were translated into the local language (Hausa) and its objective carefully explained to the farmer by an experienced enumerator.

Farmers were asked to indicate preferences in a fuzzy pair-wise goal ranking, which included five different goals. These are: getting the highest net benefits from farming; getting the highest subsistence food production; minimizing the risks of farming; safeguarding the soil for future generations and minimizing labor use in agriculture. Each possible combination of these attributes was visualized clearly to the farmer, whereby a line drawn between the attributes represents the relative preference. The farmer was then asked to indicate his relative preference by placing a cross on the line. A cross, placed in the center, signals indifference, while deviations from the center indicate a preference for one of them. We use the method described by Van Kooten *et al.* (1986) to obtain aggregated scores for each attribute, in which a higher score reflects a stronger preference for this attribute.

In addition to this ranking the farmer responded to 17 questions further measuring each of these attributes. The farmer was asked to state his opinion on each question and respond in the format Agree/ Neutral/ Disagree or Don't know. The enumerator wrote down the answer given. We did not opt to include a more extended scale; as such nuances would not be captured easily in the process of translation. Applying factor analysis reduced the dimensionality of these data, such that the set of variables z_j is the minimum set of variables describing most of the variance observed.

Data Envelopment Analysis (DEA) is used to measure efficiency levels (e.g., Ray, 2004). The advantage of using DEA, instead of commonly applied stochastic frontier analysis (SFA) (e.g., Kumbhakar and Knox Lovell, 2000) is the flexibility to account for multiple in- and outputs, whereas endogeneity problems plague multiple in- and output estimations in SFA. A major disadvantage of DEA is that the method is consistent, but biased in small samples. Simar and Wilson (2007) propose a method to improve the consistency. However some studies find only small differences between

[5] More information on the questions included can be obtained from the authors.

SFA and DEA estimates (e.g., Alene *et al*., 2006) or minor changes when applying the Simar and Wilson method (e.g., Afonso and St. Aubyn, 2006). These findings suggest the two methods are interchangeable for sufficiently large samples and we opt not to correct for this small sample bias.

Three different measures of efficiency are estimated, which are likely to capture the variety of goals, or trade-offs, different farmers aim for. First, input-oriented technical inefficiency is estimated[6]. Secondly, we estimate a measure of allocative food inefficiency, as the distance between actual food production and potential maximal food production, both of which are feasible given the observed input bundle used. This distance only reflects the potential gain in food production by shifting output quantities, not by removing technical inefficiency. The calculation of food efficiency is similar to the concept of revenue efficiency in which, instead of market prices, relative nutritional content of outputs in MegaJoules is used. Finally a measure of profit allocative inefficiency is estimated. For this we use the Färe decomposition (Ray, 2004, p. 233), estimating the amount of profits lost, divided by costs incurred, due to choosing a profit inefficient input-output combination.

We hypothesize that the measures of food and profit allocative efficiency reflect two extreme situations between which a farmer operates. A farmer who is excluded from, or chooses not to participate in markets, is likely to be relatively food efficient, while farmers fully integrated into input and output markets are likely to be more profit efficient.

In the area of study 22 different crops are grown (median per farmer: 3), and 8 different kinds of inputs are used (median per farmer: 5). To increase the efficiency of the DEA approach we aggregate outputs into three main groups: cereals, legumes and high-value crops (roots, tubers and vegetables). We include rice and sugarcane as separate outputs, since both of them require a special land input (riverbed fields) and their prices and nutritional values per unit output differ considerably from other cereal or high-value crops. On the input side only the different types of fertilizer are aggregated. Given the distinct roles of the other inputs no further input aggregation was carried out.

Prices and nutritional values (FAO, 2006) used for each of these aggregate outputs are a weighted average of prices of individual crops, in which the weights

[6] A measure of output oriented technical inefficiency was dropped from further analyses due to the large correlation with input-oriented technical inefficiency.

represent the share of production of a crop in total production of this aggregated output (in kg). In a similar way prices for the aggregated fertilizer variable are calculated. Moreover, it is noted that some inputs are fixed in the short-run (household labor available to agriculture, field and riverbed field size). Hence these variables cannot (in the short run) be purchased or sold on the market, and the DEA model is modified for this (Ray, 2004, p. 220).

3. Estimation results

Table 1 shows the aggregated scores from the fuzzy pair-wise ranking. It appears that staple food production and sustainability are the most important attributes to farmers in the area of study, followed by risk aversion, while gross margins and labor use minimization are relatively unimportant.

We further compared the ordering of the aggregated scores with the scores on the individual pairs. These are fully consistent for 77% of the sample, while for the remaining observations one to three of the individual pairs are inconsistent with the aggregated scores. Therefore we tend to believe the aggregated scores well reflect transitivity of the goals as implied by the ranking of the individual pairs.

Various rotations are used to facilitate easier interpretation of the factor loadings, though with largely similar results. The results and an interpretation of the observed factors are given in Table 2. We refer to these factors, i.e., variables z_j, as the behavioral factors in the remainder of the document. The results show that nine factors explain 68% of total variation observed.

The estimated efficiency levels are given in Table 3. A farm is considered technically, food or profit allocatively efficient (inefficient) when the related score takes the value of 1 (<1). The results show that, on average, farmers are relatively food efficient, but far from profit efficient, which seems to confirm the high scores on staple food production and low scores on gross margins obtained in the pair-wise ranking. At the same time a considerable part of the food inefficiency levels is attributable to technical output inefficiency. Furthermore, profit allocative efficiency levels are on average a low 0.23[7].

Table 4 shows the results of estimating equation (2) for the three different efficiency measures[8]. In all these estimations significant effects of some behavioral

[7] We use the log of Färe allocative profit efficiency in the regression analysis
[8] Using Stata 9.2

factors are observed. Especially the factors describing risk averting behavior and the minimization of labor use are highly significant in multiple estimations.

We formally test whether the inclusion of the behavioral factors does give a better explanation of the variation observed. In all three final models an F-test on the exclusion of the behavioral factors is rejected. Moreover the pseudo-R^2, adjusted-R^2 and Akaike's information criterion (AIC) indicate a better fit after including behavioral factors in all estimations (bottom rows Table 8). On the other hand, the drop in AIC, indicating an increased fit, is only moderate but significant.

We subsequently analyze whether the endogeneity of the behavioral factors affects the consistency of the estimation, by using a Wald-test on exogeneity. This analysis is however hindered by the availability of instruments. In regression A two behavioral factors appear significant, for which potential instruments are needed. Of the three village dummies not affecting technical efficiency levels, two strongly correlate with both behavioral factors (Table 5).

Furthermore, use of hired labor is likely to be endogenous to efficiency levels. First, farmers operating at low efficiency levels may benefit more from hiring labor thereby increasing the demand for it. Second, decisions on using additional hired labor may be influenced by favorable weather outcomes. Hence, the use of hired labor may be correlated with the error term. A potential instrument for hired labor use is the total value of assets, which does not correlate with technical efficiency levels.

Similarly, suitable instruments are identified for the behavioral factors with significant effects in regressions C and D, as well as engagement in wage labor. The identified instruments are shown in Table 5. Unfortunately the reduced form estimations for the factors 5 and 6 do not pass the rule-of-thumb for a strong instrument, as the F-value is smaller than 10 (Stock and Watson, 2003).

Subsequently, a test was carried out to examine whether the inclusion of behavioral variables z_j induces endogeneity bias in regressions A, C and D. The results of a Wald-test[9] –under the null hypothesis of exogeneity– using Newey's two-step estimator, does not lead to rejecting the null hypothesis in all cases (bottom rows Table 4). Unfortunately the likelihood function does not converge for the case in which all endogenous regressors are instrumented simultaneously. Nevertheless the negative effect of hired labor in regression A is suspect and we carried out a separate

[9] A Durbin-Wu-Hausman test was used in the OLS regression D.

regression in which only hired labor is instrumented. This led to a rejection of exogeneity of this parameter (p=0.03), for which we instrument (regression B). It shows that the partial effect of hired labor on technical efficiency levels is indeed positive as expected. Since none of the tests reject the exogeneity of the behavioral factors z_j, we conclude that including them does not affect the consistency of estimating (2).

4. Discussion and conclusions

In the analysis presented we compare three different measures of efficiency, technical efficiency, profit allocative and food allocative efficiency. The two allocative efficiency measures used, are included as two extreme cases between which farmers operate: integration into all input and output markets and exclusion from these markets. The results from both efficiency measures suggest that most farmers are relatively food efficient and only few are profit efficient. Moreover, we find that the observed differences not only result from household characteristics directly, but also from personal goals and preferences.

Five of the nine identified behavioral factors do affect efficiency levels, although the significant effects of factor 8 disappear after correcting for endogeneity (regression B). The signs of the parameter estimates largely confirm intuition. Factor 3 strongly relates to the desire to minimize labor use (from the pair-wise ranking) and negatively affects technical efficiency levels.

Factor 1, resulting from questions expressing issues related to risk aversion, decreases (increases) levels of profit (food) allocative efficiency. This coincides with the common expected effects of risk aversion. For example, the analysis of profit allocative efficiency shows that households with relatively high asset ownership display higher levels of profit efficiency. Levels of profit efficiency are, however, lower for households facing higher levels of risk aversion, conditional on the asset level. Further reduced form estimations suggest that risk aversion levels in a household mainly depend on the location of the household, whereby risk aversion increases for decreasing levels of rainfall.

A second effect is found from the factor indicating the need to fulfill subsistence food demands from own production (Factor 6), which lowers levels of profit allocative efficiency. This behavioral factor is strongest in the most isolated location, contrary to a location close to the major urban center, Kano. Apart from age, no other household characteristics were found to relate to this factor, and the total observed variation remains largely unexplained from the variables included. Local believes and personal perceptions, such as status and pride, might further explain this finding.

Finally, a factor expressing a desire of being a successful farmer explains both food and profit allocative efficiency negatively. This is a somewhat puzzling effect and possibly farmers, for whom this view is strongest, aim for an objective other than food production or profits.

A number of variables describing socio-economic characteristics are dropped from the final models as no significant effects are found. In addition, village dummies are included to pick up both local climatic conditions, and the fact that not all crops can be cultivated in each location. The direct effects of the socio-economic variables retained are similar to those described in other efficiency studies in African smallholder agriculture. Technical efficiency levels increase with soil quality (e.g., Sherlund *et al.*, 2002), average age in the household and –after correcting for its endogeneity– with use of hired labor. There is a negative effect of schooling on technical efficiency levels, possibly due to an orientation for, and interest in, the non-farm sector. Farmers for which the distance to farms is larger, are less food allocatively efficient. This possibly reflects that riverbed fields, used for production of high-value crops, are commonly not found close to households due to risk of flooding. Furthermore, profit (food) efficiency increases (decreases) with other sources of income and increases (decreases) if farmers have received agricultural training.

In conclusion, both socio-economic characteristics and goals and preferences have direct effects on efficiency levels, in addition to some indirect effects of household characteristics through changes in goals and preferences. These findings confirm the growing body of research describing the relation between efficiency levels and heterogeneity in decision-making profiles in agriculture in developed countries (e.g., Ondersteijn *et al.* 2003, Bergevoet *et al.*, 2004). Clearly, such heterogeneity deserves more attention in farm-level research in an African setting as well.

That said, the approach followed in this research raises some additional issues. First, a large number of behavioral factors describe a complex combination of different nuances of attitudes, goals and preferences. This makes the design of empirical surveys, aimed at replicating similar research in other areas, difficult.

Furthermore, although these attitudes clearly play a role in explaining both technical and allocative efficiency, as such it is not yet of great use to policy-makers. Since village dummies qualify as potential instruments for behavioral factors, it suggests local conditions are strongly related to expressed attitudes and preferences. Hence, further analysis should identify the causal relationships between the different behavioral factors and socio-economic characteristics, and focus on how rural agricultural policies should account for this effectively.

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Tables

Table 1: Means (and standard deviations) of goals in pair-wise ranking

Goal	Gross Margin	Staple food production	Risk aversion	Labour use	Sustainability
Mean (standard deviation)	0.18 (0.14)	0.65 (0.28)	0.41 (0.20)	0.07 (0.09)	0.64 (0.28)

Table 2: Factor Analysis

Factor	Variation explained	Cumulative variation explained	Higher scores reflect:
1	11.27	11.27	Risk averting behaviour
2	10.02	21.29	Drive to invest in farm business
3	9.49	30.78	Minimize labour use, cannot invest in soils
4	7.57	38.35	Safeguard soil resources for future use
5	6.67	45.03	Wants to be a successful farmer in the future
6	6.28	51.30	Subsistence crop production is one's duty
7	6.03	57.34	Seeks exit from agriculture
8	5.58	62.92	Maximizing financial benefits from farming
9	4.84	67.75	Finds no pleasure in farming

Table 3: Efficiency levels

Efficiency measure	Technical (Input Oriented)	Food allocative	Profit allocative
Mean	0.67	0.84	0.23
Standard Deviation	0.34	0.15	0.23

Efficiency levels are expressed on a scale between 0 and 1 (1 = full efficiency).

Table 4: Relating variation in efficiency levels to characteristics and behaviour

	Regression	**A**	**B**	**C**	**D**
	Efficiency Measure:	Technical Efficiency	Technical Efficiency[2]	Food allocative	Profit allocative[3]
	Estimation method:	Tobit	IV-Tobit	Tobit	OLS
	Exogenous Variable[1]:				
Socio-economic variables	Farm size				
	Farm distance			-0.05***	
	Farm quality		0.35***		
	Household size				
	Other income source of household head (Dummy)			-0.08***	0.50***
	Average age household		0.14*		
	Achieved primary/koranic education(Dummy)	-0.24**	-0.13*		
	Achieved secondary/tertiary education (Dummy)	-0.22*	-0.24**		
	Distance to markets	0.16**			
	Total value of assets				0.17***
	Total livestock ownership (TLU)				
	Household has attended agricultural trainings (Dummy)			-0.13**	
	Household head engages in wage labour (Dummy)			-0.09***	
	Household head hires wage labour (Dummy)	-0.26**	0.44**		
Village Dummies	Bindawa				
	Kunchi				
	Warawa			0.13	-0.59**
	Kiru	0.47***		0.08	0.50**
	Hayin Dogo	0.41***	0.22***		
	Ikuzeh	0.19*	0.12*		-1.28***
Behavioural factors	Factor 1 Risk averting behaviour			0.02**	-0.28***
	Factor 3 Minimize labour use, cannot invest in soils	-0.13***	-0.08***		
	Factor 5 Wants to be a successful farmer in the future			-0.03*	-0.15**
	Factor 6 Subsistence crop production is a duty				-0.13*
	Factor 8 Maximizing financial benefits from farming	-0.09**			
	F-test on excluding behavioural factors (p-value)	0.00	0.00	0.05	0.00
	Wald test exogeneity[4]	0.99		0.98	0.61[5]
	With behavioural factors — Pseudo -R^2	0.30		2.41	0.38[6]
	With behavioural factors — AIC	185.64	89.60	3.96	413.25
	Without behavioural factors — Pseudo -R^2	0.27		1.38	0.34[6]
	Without behavioural factors — AIC	197.68	115.91	12.55	444.54

[1] * significant at 10%, ** significant at 5%, *** significant at 1%, only significant variables shown

[2] Tobit regression in which use of hired labour is instrumented for by total value of assets

[3] Dependent variable is log of profits lost due to allocative inefficiency multiplied by -1. Higher values reflect lower losses and higher levels of profit efficiency.

[4] p-value of a Wald-test on exogeneity is shown. The behavioural factors, use of hired labour, and engagement in wage labour are instrumented by using Newey's two-step estimator.

[5] Durbin-Wu-Hausman test

[6] Adjusted-R^2

Table 5: Identifying instruments

	Household hires wage labour	Household engages in wage labour	Factor 1	Factor 3	Factor 5	Factor 6	Factor 8
Household Size					0.25*		
Age household head						0.41	
Total value of assets	0.07***	-0.09***					
Livestock ownership					-0.13**		
Kunchi (Village dummy)			-0.61***	1.61***			0.63***
Warawa (Village dummy)				0.99***			-0.50***
Hayin Dogo (Village dummy)			-1.01***				
Ikuzeh (Village dummy)					-0.66***		
F-value	19.29	16.55	19.17	60.89	4.55	3.20	10.23

** significant at 5%, *** significant at 1%
Table shows reduced form estimations, explaining potential endogenous variables (top row) from exogenous variables not affecting efficiency levels.