A STOCHASTIC PARAMETRIC ANALYSIS OF EFFICIENCY OF MILLET AND SORGHUM PRODUCTION IN NIGER

by

CHEN YANG

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Major Professor
Timothy J. Dalton

Abstract

Millet and sorghum are major crops in Niger, West Africa. Improving the productivity of millet and sorghum is important to fight against poverty and malnutrition in this country. This study contributes to this objective by conducting efficiency level of millet, sorghum farmers, and the factors that influence efficiency.

To reach this goal I applied a stochastic parametric frontier analysis using a cross-sectional data set collected by The Living Standards Measurement Study (LSMS) in 2011. I obtained 216 observations of plots that plant millet and 364 observations of plots that plant sorghum from 2011 to 2012 over the country. I employed Cobb–Douglas and Translog functional forms along with the half normal error distribution to estimate the production frontier. I also conducted a statistical test to choose the most appropriate functional form that fits the data for different crops.

It was found that the mean technical efficiency of millet farmers is 38.44 percentage and sorghum farmers is 58.22 percentage. Lastly, I analyzed the correlates of technical inefficiency, I employed two-step approach. I found that the inefficiency of farmers is related to managerial factors such as education level or farming method.

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Chapter 1. Introduction

Niger is a landlocked, Sub-Saharan nation, whose economy centers on subsistence crops and livestock. Agriculture contributes about 40% of GDP and provides livelihood for about 90% of the population in this country. However, as a developing country, Niger is consistently one of the lowest-ranked in the United Nations' Human Development Index, with about 59.5 percent population living below national poverty line in 2007 (according to statistics from the World Bank).

In order to help increase crop yield and to reduce poverty, the U.S Agency for International Development (USAID) sponsors The Feed the Future Collaborative Research on Sorghum and Millet Innovation Lab to produce innovations such as climate-resilient crop varieties and more profitable market approaches for the sorghum and millet farmers in Niger. The goal of this study is to estimate efficiency levels of millet and sorghum farmers and identify factors affecting the efficiency of millet and sorghum production to increase food supply in Niger.

The outline of this chapter is as following. Section a) presents the motivation of the study. Section b) and c) provide background information on socio-economic characteristics of the region and conditions of millet and sorghum production. Section d) presents the objectives of my study.

a) Motivation

Niger has a Gross Domestic Product (GDP) per capita in Parity Purchasing Power (PPP) terms of $771 in 2011, one of the lowest in Africa. Based on Gross Domestic Product per capita from 2009 to 2013, Niger is also the 7th poorest country in the world. Oxford University's Multidimensional Poverty Index (MPI) shows 92 per cent of Niger's population is trapped in "multi-dimensional" poverty, the highest among the 109 countries investigated.

However, the population of this poor country is still rapidly growing: Niger’s Institute for National Statistics (INS) calculates the current rate of population growth is 3.3 percent every year, which means there will be 56 million people living in Niger by 2050, compared to 16.9

million in 2013.

In order to help decrease the gap between food production and consumption, in 2013, the USAID sponsored The Feed the Future Innovation Lab for Collaborative Research on Sorghum and Millet to help increase food supplies and end poverty in semiarid Africa - making Niger one of their focus countries. The initiative uses research, education and outreach to advance solutions to hunger, poverty and malnutrition in low-income countries making use of collaborative research on millet and sorghum to improve farmers' productivity in sub-Saharan Africa. It is therefore important to figure out the efficiency situation for millet and sorghum production in these countries. By conducting an analysis of the efficiency of the farmers first, this study aims to provide guidance in designing solutions to improve yield.

b) Socio-Economic Characteristics of Niger

West Africa has a total population of 290 million and with GDP grew at a rate of 5.89% annually over the past 10 years. However, half of West Africans live on less than $1.25 per day.

Niger is one of the landlocked countries locate in the heart of West Africa. It is bordered by Algeria and Libya on the north, Mali on the west, Burkina Faso and Benin on the southwest, Nigeria on the south and Chad on the east. It has a total area of 1,267,000 km^2, but only half of this is habitable due to adverse climatic or soil conditions.

The population of Niger is about 16.9 million, growing at average rate of 3.3 percent. According to the data from World Bank, in 2007, 59.5% of the population in Niger under the national poverty line and in 2010, 83% of the population still lived rural area. Nearly 17 % of the children in Niger were malnourished in 2010. (UN World Health Organization, 2010).

c) Millet and Sorghum Production in Niger

Agriculture in Niger inevitably takes place under harsh environmental conditions. According to the agroecological zone report by Food and Agriculture Organization (FAO), many of the regions under agricultural activity in Niger are situated in the semi-arid tropics and its possible cropping period is 75-120 days, and the average monthly temperature is over 18℃

throughout the year. The mean annual rainfall is 300-400 mm which is very low. In addition, yearly change of rainfall is very large and the region is prone to drought.

Farms average 7 hectares which is very small for marginal rainfall regions. Households are a mixture of single and multiple families averaging 7 members (World Bank, 2001). All adults-above 14 years old labor on the communal fields. Most adults also are given small areas (as 0.1 hectares) for private fields in which they can work after their joint responsibilities on the communal fields are fulfilled.

Niger is one of the largest millet producing countries in West Africa. In 2012, Niger produced 3.86 million tons millet sharing 30 percent of Western Africa's millet production. Although harvested areas of millet production were keep growing and achieved 7 million hectares in Niger, but the yields were still below world's average.

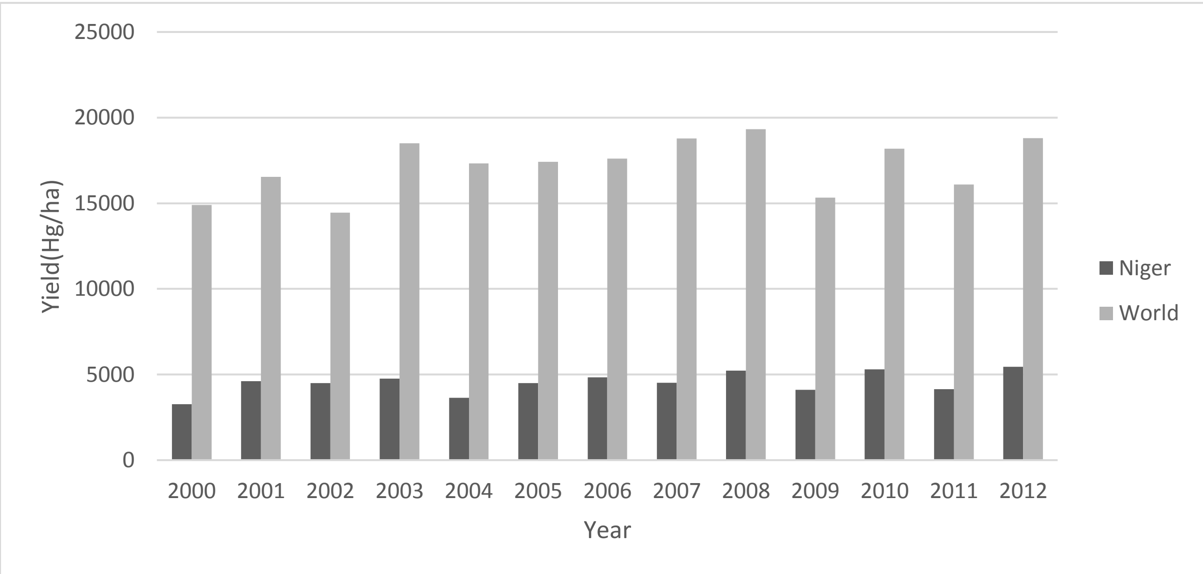

Figure 1-1 Comparison of millet yield between Niger and World's average

Niger is also the fifth largest sorghum cultivating country in the world. In 2012, the harvest areas of sorghum in Niger were beyond 3 million hectare and the production of sorghum was about 137 million tons, but the yield of sorghum production is far below world's average.

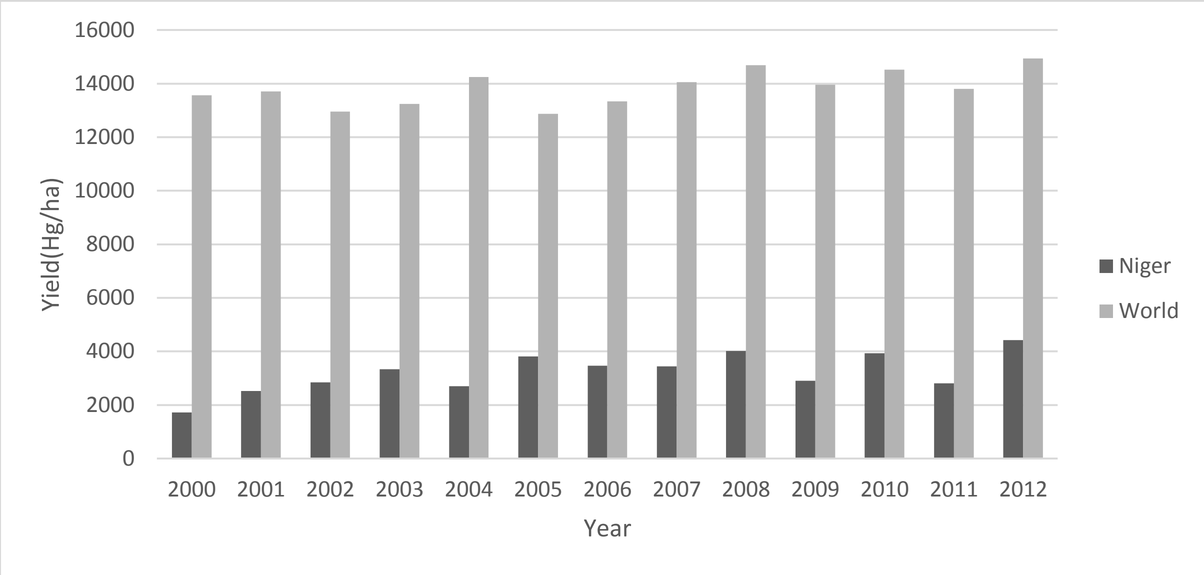

Figure 1-2 Comparison of sorghum yield between Niger and World’s average

As staple crops, millet and sorghum are very important for both Niger and West Africa’s food security. The yield of these two crops shows there may be a large potential to increase farmers’ efficiency in this country. So, in my study, I will focus on efficiency of millet and sorghum production in Niger.

d) Objectives

The goal of this research is to provide useful information for further researchers by developing more effective ways to increase the millet and sorghum production in Niger. To reach this goal, the first question that needs to be addressed is whether millet and sorghum production in Niger is efficient. The next question that needs to be addressed is what factors affect farmers’ efficiency.

To answer these questions, I will apply a stochastic frontier approach to determine the efficiency of farmers. I will then employ Cobb-Douglas and Translog production frontiers for millet and sorghum production with half-normal distributional assumption of inefficiency. Lastly, I will take two-step approach to determine the sources of inefficiency. The sub-objective of the study is to illustrate the effects of modeling on policy implications.

Chapter 2. Literature Review

In this chapter, I present a brief summary of the production theory and a review of the literature of the stochastic parametric frontier models. I also review the developments in the methodology of frontier estimation for cross-sectional data and some empirical studies in agricultural economics.

The outline of this chapter is as following. Section a) presents definitions of the production and efficiency. Section b) introduces the general properties of the functional forms that I employ in this study. Section c) presents the methods of the determination of the sources of inefficiency and the modeling of the inefficiency term. Section d) shows a brief review of the empirical examples of the stochastic parametric frontiers in agricultural economics.

a) Production and Productive Efficiency

Production is defined as the process of combining and coordinating two or more materials and forces (inputs, factors, resources, or productive services) in the creation of some good(s) or service(s) (Beattie, Taylor, Watts, 2004). This transformation is subject to the available production technology that determines and restricts what is possible in combining inputs to produce output.

All possible combinations of output that the economy can possibly produce can be shown by a set described as the production possibility set. A convenient description of the production possibility for single output-multiple input is the production function. For instance, consider a firm that uses amounts of inputs (e.g. labor, machinery, materials) to produce a single output. The technological possibilities of such a firm can be summarized using the production function.

$$Q = f(X)$$

Where Q represents output and $X = (X_1, X_2, ...)$ is a N x 1 vector of inputs.

As the above formula, a production function is a quantitative or mathematical description of the various technical production possibilities faced by a firm (Beattie, Taylor, Watts, 2004). Production functions are assumed to be monotonic and strictly quasi-concave. The monotonicity means non-decreasing that implies employing more of every input does not cause less output. Monotonicity is satisfied if the first derivative of production function with respect to each input is positive. Formally, if $\partial Y / \partial X_i > 0$, for $i = 1, \dots . J$, the production function will be satisfied the monotonicity. Any monotonic function is both quasi-concave. The strictly quasi-concavity means that any convex combination of two input vectors can produce at least as much output as one of the original two. It is usually assumed for simplicity to assure a local maximum.

The production function also describes a frontier representing the limit of output obtainable from each feasible combination of inputs. This boundary of the production technology is characterized by production frontier function.

$$f(X) = \max\{Y : Y \in P(X)\} = \max\{Y : X \in L(Y)\};$$

Where P(X) describes the sets of output vectors that are feasible for each input vector. $X \in R$ and L(Y) describes the sets of input vectors that are feasible for each output vector $Y \in R$ (Kumbhakar and Lovell, 2000). Production frontiers denote the standard against which the performance of decision making units (DMUs) is evaluated. As definition, one can observe input-output combinations on or below the production frontier but no combinations can lie above the production frontier.

Productive efficiency happens when the economy is employing all of its resources efficiently. The concept is illustrated on a production frontier where all points on the curve are points of maximum productive efficiency. Equivalently, it occurs when the highest possible output of one good is produced, given the production level of the other good(s). Productive efficiency requires that all DMUs using best-practice technological and managerial processes.

Debrue (1951) offered the definition of input-oriented technical efficiency as the ability of a firm to use minimal inputs to produce a given set of outputs. It can be formulated as,

$$TE(Y, X) = \min(\omega : \omega X \in L(Y));$$

Where ω is scalar and stands for an equiproportionate contraction of all inputs.

By definition the input vector is said to be technically efficient if no equiproportionate contraction of all inputs is feasible. Similarly, Farrell(1957) proposed the definition of output-oriented technical efficiency as reflecting the ability of a firm to obtain maximal output from a given set of inputs. It can be formulated as,

$$TE(Y,X) = [\max(\psi: \psi Y \in P(X)]^{-1};$$

Where ψ is a scalar and stands for an equiproportionate expansion of all outputs.

By definition, the output vector is said to be technically efficient if no equiproportionate expansion of all outputs is feasible. The vast majority of efficiency analyses is measured radially, using isoquants as standards. These two measures are equal only if the production technology exhibits constant returns to scale, CRS, (Färe and Lovell, 1978)

Output oriented technical efficiency is measured as the ratio of actual output, Y, to potential output f(X). The estimates of the ratio $\mathrm{Y}/\mathrm{f}(\mathrm{X})$ will take values between zero and one indicating the degree of technical inefficiency. A firm will be considered technically efficient if Y=f (X).

The technical measurement of efficiency simply implies no wasteful use of resources that can be provided without price information and without having to impose a behavioral objective on producers. A more comprehensive measure of efficiency is economic efficiency. Economic efficiency reflects the ability of a firm to use factors of production in optimal proportions, in view of their respective prices. Economic efficiency can correspond to cost, profit or revenue efficiency. In each case, efficiency is measured by the ratio of the observed outcome to potential outcome, which is represented by corresponding frontier.

In this study, I will examine the technical efficiency of the millet and sorghum farmers in Niger. Because the data set does not provide enough information about prices of inputs and outputs, the word “efficiency” in this study alone refers to the technical efficiency.

b) Functional Forms

A mathematical representation of the production function must be specified to apply the theory to the data in any empirical study. One difficulty is the choice of functional form to show a good illustration of the unknown true technology.

In empirical literature, the most generally used functional forms to estimate production functions are Cobb-Douglas (CD), the generalized quadratic (GQ), the transcendental logarithm (TL), the generalized Leontief (GL), and the constant elasticity of substitution (CES).

In my study, I applied CD and TL forms first, then I use a likelihood-ratio test to choose best suitable function for each. I also evaluate the effect of the functional forms on the parametric estimation of production frontiers.

A CD production function can be written as:

$$ln(Y) = \alpha_0 + \sum_{i=1}^{k} \alpha_i \ln X_i$$

Where, α_i is the constant technology parameter and αis the K∗1 vector of parameters to be estimated.

The CD production function satisfies the regularity conditions globally. It has unitary elasticity of substitution by construction. Thus it does not allow for technically independent or competitive factors. The function is homogeneous of degree $\sum_{k=1}^{K} \alpha_k$ and the technology exhibits constant returns to scale if $\sum_{k=1}^{K} \alpha_k$ =1.

The CD form is a first-order Taylor series approximation to the true production frontier, hence it is a relatively simple form and easy to manipulate analytically. Nonetheless, the very simplicity and restrictive nature of CD form prevents it to model fairly sophisticated technologies. Instead TL form generally used as a more flexible production function where the flexibility is defined as the ability to represent production technology without placing any prior restrictions on the full set of elasticity of substitution and returns to scale.

The TL production function can be written as:

$$ln(Y) = \alpha_0 + \sum_{i=1}^{k} \alpha_i \ln X_i + \frac{1}{2}\sum_{i=1}^{K} \sum_{j=1}^{K} \beta_{ij} \, lnX_i \, lnX_j \; ;$$

Where β is the K∗K matrix of parameters to be estimated together with α, and $\beta_{ij} = \beta_{ji}$ imposed by symmetry for$i \neq j$.

The TL production function satisfies the regularity conditions locally but its global properties are ambiguous. The function is homogeneous of degree θ if $\sum_{i=1}^{K} \alpha_i = \theta$ and $\sum_{i=1}^{K} \beta_{ij} = 0$. The degree of return to scale depends on the input levels and measured by $\sum_i \frac{\partial \ln f(X)}{\partial \ln X_i}$, where $\ln(.)$ is the natural logarithm function. The technology exhibits constant returns to scale if the function is homogeneous and θ=1.

In empirical literature, there are two major approaches on how to make frontiers. One is a non-parametric approach that uses mathematical programming techniques and the other is a parametric approach that employs econometric techniques. In my study, I use the parametric approach, so I just briefly review this approach.

Stochastic frontier models, (SFM), originated with two path-breaking papers. These papers are published simultaneously and independently by Aigner, Lovell and Schmidt, (1977) (ALS) and Meeusen and van den Boeck, (1977) (MB). Early effects at specifying frontiers had a direct effect on the development of SFM models. A summary of these work is necessary to establish the SFM models.

Farrrell (1957) provided the definitions and empirical framework for both technical and allocative efficiency. By assuming constant returns to scale, Farrell used linear programming techniques to construct the convex hull of the observed input-output ratios. The efficient unit isoquant, presented in above section is estimated from a sample where the relationship between observations and the frontier is not based on an explicit functional form. The subsequent studies of the theory mainly focused on two limitations of Farrell's model: the assumption of CRS and the extreme sensitivity of the estimated frontier to outliers and measurement error.

Aigner and Chu (1968) suggested a parametric deterministic frontier model by imposing a Cobb-Douglas functional form on the frontier. Their model can be written as,

$$y_i = f(x_i; \beta)$$

They suggested the estimation of β by either linear programming or quadratic programming based on a cross section of N firms within a given industry. Formally they suggest minimization of;

$$\sum_{i=1}^{N} |y_i - f(X_i; \beta)| \text{ or } \sum_{i=1}^{N} |y_i - f(X_i; \beta)|^2 \text{ subject to } y_i \le f(X_i; \beta)$$

The ability to characterize the frontier technology in a simple mathematical form is the principal advantage of this approach. It also allows accommodating non-constant returns to scale into the model.

They allow some output observations lie above the estimated frontier. In his probabilistic frontier approach, Timmer (1971) took this suggestion, and he also allow some observations to be deleted until the model's parameters converged. Timmer's approach was considered as a desirable method to solve outlier and measurement error problems in estimating production frontiers by using linear programming methods. However, it was never fully exploited by the literature due to lack of any statistical or economic rationale. The estimates have no statistical properties such as standard errors or t ratios manly because the model does not include any statistical assumptions.

Although it was implicit in Aigner and Chu's study, Afriat (1972) was the first to explicitly propose the deterministic statistical model by including a one sided error-component. Afriat's model can be written as,

$$y_i = f(X_i;\beta)\exp(-u_i)$$

Where u_i is a non-negative random variable associated with the technical inefficiency of the firm. Afriat assumed a two-parameter beta distribution for the inefficiency of the inefficiency term and proposed the maximum likelihood, ML, method to estimate unknown parameters.

Richmond (1974) proposed the corrected ordinary least squares, COLS, method to estimate the model and he assumed that u_i has gamma distribution. This approach involves a correction for the constant term to provide consistent estimates of all the parameters of the frontier. However, the proposed correction is dependent on the distributional assumption on inefficiency term. Thus different distributional assumptions lead to different corrections of the constant term which in turn leads to different technical efficiency.

Schmidt (1976) stated that the linear and quadratic programming procedures in Aigner and Chu correspond to ML method if the assumed distribution if u_i is exponential or half-normal respectively. However, Schmidt noted a bounded range problem in ML estimation due to the dependence of the dependent variable on the parameters to be estimated. That is, the output vector is bounded by production function and the production function involves the unknown parameters to be estimated. This leads to inconsistent and inefficient estimates so that any statistical inference is invalid.

All of the models proposed in studies mentioned above were either non-stochastic of questionable statistical or economic rationale, or contrary to the usual maximum likelihood regularity conditions. These arguments lie behind the stochastic frontier model of ALS (1977) and MB (1977). This approach involves the specification of the error term as being made up of two components, one normal and the other from a non-negative one-sided distribution. This model can be represented as:

$$y_i = f\ (X_i; \beta)\exp(\varepsilon_i)$$

Where $\varepsilon_i = v_i - u_i$, v_i is assumed identically and independently distributed as $N\ (0, \sigma_v^2)$ and the non-negative error component, u_i is assumed to be distributed independently of v_i. As in the deterministic models, the non-negative error component reflects the fact that each firms' output must lie on or below its production frontier. Thus any deviation from the frontier due to this component is regarded as technical inefficiency because deviations are the result of factors under the firm's control. On the other hand, the normal distribution component of error term reflects the fact that the frontier itself can vary randomly across firms, or over time within a firm. There are possible measurement errors and/or external factors such as climate that are not under the control of firm. These factors can contribute to the deviations from the frontier that are not an actual inefficiency of the firm. Thus the normal error component is introduced to count for this fact and isolate the inefficiency factors that are under firm's control from external ones. Also it should be noted that the presence of symmetric error component v_i solves the bounded range problem encountered in estimation of deterministic models.

Formally, under this approach the productive efficiency,$\exp(-u_i)$is measured by the ratio $y_i/[f(X_i, \beta) + v_i]$, rather than the ratio $y_i/f(X_i, \beta)$.

Since the ALS (1977) and MB (1977) approach was first introduced there has been a substantial amount of progress in both modeling and estimating the stochastic frontiers. In this study, I present a selective reviews of the literature focusing on the developments in cross-sectional data modeling and estimation techniques. I also present brief survey of empirical applications in agricultural economics.

The stochastic frontier model is generally estimated by either ML or COLS methods by usage of either method we can directly get the estimates of the frontier parameters β, nonetheless, to estimate the productive efficiency of each producer, distributional assumptions about the one-sided error component is required. The most widely used distributional assumptions about u_i are the half-normal (ALS, 1977) and the exponential (MB, 1977). Both of these distribution specifications have a pre-determined shape for the distribution of the disturbances with a mode at zero. This causes the technical inefficiency scores to be in the neighborhood of zero, which in turn might provide incorrectly high technical efficiency levels. Stevenson (1980) and Greene (1990) proposed free shape distributions to allow for a more flexible representation. These specifications include the estimation of the mode of distribution together with the inefficiency scores.

Generally there is no good economic or statistical a priori for the choice of the distribution of inefficiency, and there is some evidence that mean efficiency scores can be sensitive to alternative specifications. Thus, Lee (1983), and Schmidt and Lin (1984) provided the empirical framework to examine the appropriateness of these various distributions by employing Lagrange Multiplier tests. Nonetheless, Kumbhakar and Lovell (2000), stated that neither rank nor decide compositions of individual efficiency scores are particularly sensitive.

In general, the use of fixed-shape models has dominated the empirical literature. This is because the additional complexity in the estimation of free shaped models is believed to outweigh their benefits. Ritter and Simar (1997) state that flexible distributions may not form the basis of a valid measurement unless the sample data is large enough that includes several thousand observations. They roundly suggest that the use of relatively simple distributions such as half-normal and exponential is more convenient than more flexible distributions for small or medium sized samples. Also, Battese and Coelli (1988&1992) have tested half-normal models against the truncated normal ones and the latter have not rejected the former.

Under the assumptions of $v_i \sim N(0, \sigma^2)$ and $u_i \sim N|0, \sigma^2|$ the relevant log-likelihood function can be formed as,

$$\ln L(y_i|\beta,\lambda,\sigma^2) = Nln\frac{\sqrt{2}}{\sqrt{\pi}} + Nln\sigma^{-1} + \sum_{i=1}^{N} ln[1-\Phi(\varepsilon_i\lambda\sigma^2)] - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\varepsilon_i^2$$

Where σ^2 and λ are the distribution parameters to be estimated together with the technology parameters β, and $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \frac{\sigma_u}{\sigma_v}$. λ is interpreted as an indicator of the relative variability of the two sources of random error.

If $\lambda < 1$, the symmetric error dominates the determination of ε.

If $\lambda > 1$, the one-sided error becomes the dominant source of random variation in the model. It is worthy to note that, at the extremes.

If $\lambda \to 0$, the model collapse to an OLS production function with no technical inefficiency.

If $\lambda \to \infty$, the model represents a deterministic production frontier with no noise.

The maximization of the log likelihood function provides the ML estimates of the distribution parameters λ and σ sigma along with the estimates of the technology parameters β. In their empirical example ALS (1977) estimated a stochastic frontier CD function using U.S agricultural data for six years and the 48 contiguous states. They assumed a normal exponential distribution of the error term of the stochastic frontier model, and compared the results to the OLS estimates of the average response function. They found that the variance of the one-sided error term was less than one percent of total variance. Therefore, the estimates of the stochastic frontier were not significantly different from the average response function.

Mean technical efficiency of all producers can be calculated by the formula proposed by Lee and Tyler (1978)

$$\mathrm{E}(exp\{-u\}) = 2[1-\Phi(\sigma_u)]exp\{\sigma_u^2/2\}$$

Where $\mathrm{E}(.)$ is the expectation operator and$\Phi(.)$ is the standard normal cumulative function. It was initially believed impossible to derive the firm specific efficiency scores.

Soon after Jondrow (1982) provided a solution to predict $exp\{-u\}$ by extracting the information on u_i from the conditional expectation of u_i, given the estimates of the random variable ε_i. Formally, Jondrow defined the expected firm-specific technical inefficiency component for normal-half-normal case as,

$$E[u_i/\varepsilon_i] = -\left(\frac{\sigma\lambda}{1+\lambda^2}\right)\left[\frac{\Phi(\varepsilon_i\lambda/\sigma)}{\Phi(-\varepsilon_i\lambda/\sigma)} - \left(\frac{\varepsilon_i\lambda}{\sigma}\right)\right]$$

Where$\Phi(.)$ is the standard normal density function and $\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}$

Unfortunately, with cross-sectional data their estimate of technical efficiency are inconsistent; however it is the best that can be achieved. (Kumbhakar and Lovell, 2000)

Similarly, the point estimates of u_i for normal-exponential and normal-truncated normal cases can be derived by the following formulas respectively.

$$E[u_i/\varepsilon_i] = (\varepsilon_i + \theta\sigma_v^2) - \frac{\sigma_v\Phi[-(\varepsilon_i + \theta\sigma_v^2)/\sigma_v]}{\Phi[-(\varepsilon_i + \theta\sigma_v^2)/\sigma_v]}$$

Where θ is the estimated parameter from exponential distribution.

$$E[u_i/\varepsilon_i] = -\left(\frac{\sigma\lambda}{1+\lambda^2}\right)\left[\frac{\sigma_v\Phi[-(\varepsilon_i + \theta\sigma_v^2)/\sigma_v]}{\Phi[-(\varepsilon_i + \theta\sigma_v^2)/\sigma_v]} - \left(\frac{\varepsilon_i\lambda}{\sigma} + \frac{\mu}{\sigma\lambda}\right)\right]$$

Where μ is the mode of the distribution to be estimated together with other distributional parameters σ^2 and λ. Note, if $\mu = 0$ then the truncated normal distribution collapses to half-normal.

The frontier function model proposed by Farrell used the efficient unit isoquant as a standard to measure all types of efficiencies. Farrell also suggested that the efficiency of a firm consists of two main components. The first component, technical efficiency (TE), reflects the ability of firms to obtain the maximum output from a given set of inputs. The second component, allocative efficiency (AE) or price efficiency (PE) refers to the ability of firms to use inputs in optimal proportions, given their respective input prices. Multiplying these two measures together yields total (overall) economic efficiency (EE) or simply economic efficiency.

No matter what type of methodologies is chosen; the estimation of technical efficiency is obtained in terms of inputs and outputs. When we examine efficiency in isoquant space, using input-oriented measures, we address the following question: can input use be decreased proportionally without changing the output quantity produced? Alternatively, we may want to know how we could expand the quantity of output produced without changing the quantity of input used. In this case, our focus is within an output-output space, or an output-oriented measure. We do not obtain the same result if we estimate technical efficiency using either input or output oriented measures except when the production technology exhibits constant returns to scale (Fare and Lovell, 1978).

We can also classify frontier functions by how we interpret the deviation of a group of firms from the best performing firm in the sample. In this sense, frontier functions are either deterministic or stochastic frontiers. In a deterministic production frontier model, output is assumed to be bounded from above by a deterministic (non-stochastic) production function. However, the possible influence of measurement errors and other statistical noise upon the shape and positioning of the estimated frontier is not accounted for. In other words, deterministic models assume that any deviation from the frontier is solely due to inefficiency.

On the contrary, in a stochastic frontier model, output is assumed to be bounded from above by a stochastic production function. Therefore, the error term in stochastic frontier models has two parts: one representing randomness or statistical noise, and the other representing technical inefficiency.

c) Sensitivity of Efficiency Scores

The stochastic frontier model proposed in the previous section provides the empirical framework to analyze the efficiency of the producers. The primary motivation of these analyses is to obtain the efficiency scores to guide possible policies to enhance production. If producers are efficient the policies should be directed towards improving the existing technology. However, the estimated efficiency scores have little to say if the producers are inefficient. In this case, the determination of the sources of inefficiency is necessary to spot the problem and design the pertinent policy to correct it. This concerns the incorporation of exogenous variables that are specific to each producer and characterize the environment in which production occurs. These variables can indicate the managerial characteristic of producer such as experience and education level, or the technological characteristics of production; such as the infrastructure and the quality of inputs.

There are two competing approaches in the empirical literature to identify the sources inefficiency: one-step and two-step procedures.

In the first procedure the exogenous variables are assumed to influence output directly by influencing the structure of the production frontier (Kumbhakar, Ghosh and McGukin, 1991; Huang and Liu 1994). Formally, the frontier model is represented as

$$y_i = f(X_i, Z_i\beta)\exp(\varepsilon_i)$$

Where, $\mathrm{Z} = \mathrm{Z}(Z_1, \ldots, Z_n)$ denotes $\mathrm{N} * \mathrm{K}$ matrix of exogenous variables that capture the features of environment in which production takes place. Accordingly, Z_i is the $1 * \mathrm{K}$ vector of exogenous variables that are beyond the control of i^{th} DMU.

And all other variables have been previously defined. In this formulation, similar toX_i, The exogenous variables are also assumed to be uncorrelated withε_i. Thus, they influence the performance by influencing the structure of the production rather than influencing the efficiency of producer. This can be considered as a disadvantage of one-step approach since the variation in inefficiency is left unexplained. Another disadvantage of the approach is the substantial decrease in degrees of freedom especially when estimating a flexible functional form such as TL or GL. As in the conventional stochastic production frontier model, ML or COLS methods can be used to obtain the estimates of the frontier parametersβ. Differently, the parameter vector β now consists of both technology and environmental parameters.

The latter approach proceeds in two steps. In the first step, one estimates the conventional stochastic frontier model and efficiency levels of each producer by ignoring Z. Then, in the second step, the analyst regress the estimated measure of inefficiency Z, to explore the variation in efficiency levels with Z, (Kalirajan and Shand, 1985). Formally, the model in the first step is represented exactly same as the conventional stochastic frontier model,

$$y_i = f(X_i, \beta)\exp(\varepsilon_i)$$

Then, in the second step the model to be estimated can be represented as,

$$\mathrm{E}\left[\frac{u_i}{\varepsilon_i}\right] = \mathrm{g}(Z_i; \delta) + \tau_i$$

Where $\mathrm{E}\left[\frac{u_i}{\varepsilon_i}\right]$ is a measure of producer specific efficiency proposed by Jondrow et al,(1982), δ is the environmental parameters to be estimated, $\mathrm{g}(.)$ represents the assumed functional relationship between exogenous variables and the efficiency of the producer, and τ is the error term. This model is generally estimated by Tobit technique since the dependent variable is limited between zero and one.

The two-step approach overcomes the disadvantages of the one-step approach. First, the two-step approach explains the variation of the producer performance by influence of Z_i.on the efficiency of producers. This requires, in contrast to the one-step, the exogenous variables, Z_i assumed to be correlated with u_i. Also, the two-step approach provides the estimates of all variables without any decrease in degrees of freedom. Theoretically, the first step is subject to the omitted variable bias since in the second step it is assumed that the predicted inefficiencies have a functional relationship with Z_i. On the other hand, if there is no omitted variable bias in the first step, then the assumption in the second step to explain the variation in efficiency will remain invalid. So as the estimates of the second-stage regression. In my study, I will use the two-step approach.

d) Empirical Studies

Stochastic frontier models have been estimated in a considerable number of empirical studies in agricultural economics. In this section I present a review of the empirical studies that employed a stochastic parametric approach to construct the frontier.

Ongore (2011) studied the technical efficiency among smallholder farmers in Kenya. He used a random sample of 211 bulrush millet-growing households and specified a Cobb-Douglas stochastic production function to measure the technical efficiency. The result implies that given the level of technology and inputs, the output could be increased by 28 to 56 percent through better use of available resources thus farmers should be trained to enhance their capacity to efficiently use the available resources.

Ogundari, Ojo and Ajibefun (2006) studied on economies of scale and cost efficiency in small scale maize production using stochastic frontier cost function in Nigeria. A Cobb-Douglas functional form was used. The empirical evidence indicates the existence of relative economies of scale despite the fact that the farms operate at small scale level.

Linton and Miller (2011) estimated a stochastic production frontier using cross-sectional farm-level data. They estimate profits for sweet sorghum and competing crops from stochastic models for both Bolivar County and Monroe County, Mississippi.

Boubacar (2012) used a Just-Pope stochastic production function to access crop yields responses to persistent drought spells in eight countries of Sahel. The results suggest that changes in climate variables show a similar pattern across all of the three major crops cultivated in Sahel.

Kirmi and Swinton (2004) estimate the cost efficiency of maize producers in Kenya compared to Uganda. They estimated a TL cost function using a cross-sectional data of 581 maize producing household in Kenya and Uganda in April-May 2003. They found that on average the 95 percent of costs could be avoided without any loss in total output employing a two-step procedure they identified recycled maize seed, late planting and cultivated area as the major determinants of the cost inefficiency.

Battese and Broca (1997) estimated TL and CD stochastic frontiers using a panel data set of wheat farmers in Pakistan, for the period 1986-1990. They modeled three different technical inefficiency effects proposed by Battese and Coelli (1992, 1995) and Huang and Liu (1994) to highlight possible differences of estimates under different specifications. They found that the predicted efficiency of the farmers and the statistically significant functional inefficiency conducting generalized likelihood-ratio tests the authors concluded that for the sample under study, the non-neutral specification of the inefficiency effects, proposed by Huang and Liu (1994) was the preferred model.

Chapter 3. Frontier Analyses for Millet and Sorghum Production in Niger

This chapter presents the analysis of stochastic parametric frontier model to determine the millet and sorghum farmers' efficiency.

I formulate two different functional specifications of technology, CD and TL along with half-normal distribution of the inefficiency term. Section a) introduces the study area and the data. Section b) includes a representation of the methodology of the analyses employed in this chapter. Sections c) through j) present the results of the estimates of each functional form and show the statistical tests to choose the most appropriate functional form that fits the data. Section k) compare the results between millet and sorghum.

a) Study Area and the Data

The data I used in this study was collected by The Living Standards Measurement Study (LSMS)[1]. LSMS survey questionnaires cover a range of topics, from demographics to education, health, labor, consumption, finance, farm production, and non-farm activities. The survey has also been designed to have national coverage, including both urban and rural areas in all the regions of Niger, including the rural areas, agricultural zones, agro-pastoral zones and pastoral zones.

The target population of this survey is drawn from households in all eight regions of the country with the exception of certain strata found in Arlit (Agadez Region). The portion of the population excluded from the sample represents less than 0.4% of the total population of Niger. The total estimated size of the sample is 4,074 households. The eight regions in this research are shown by their names in the boxes below figure 3.1.

[1] The Living Standards Measurement Study (LSMS) was established by the Development Research Group (DECRG) to explore ways of improving the type and quality of household data collected by statistical offices in developing countries.

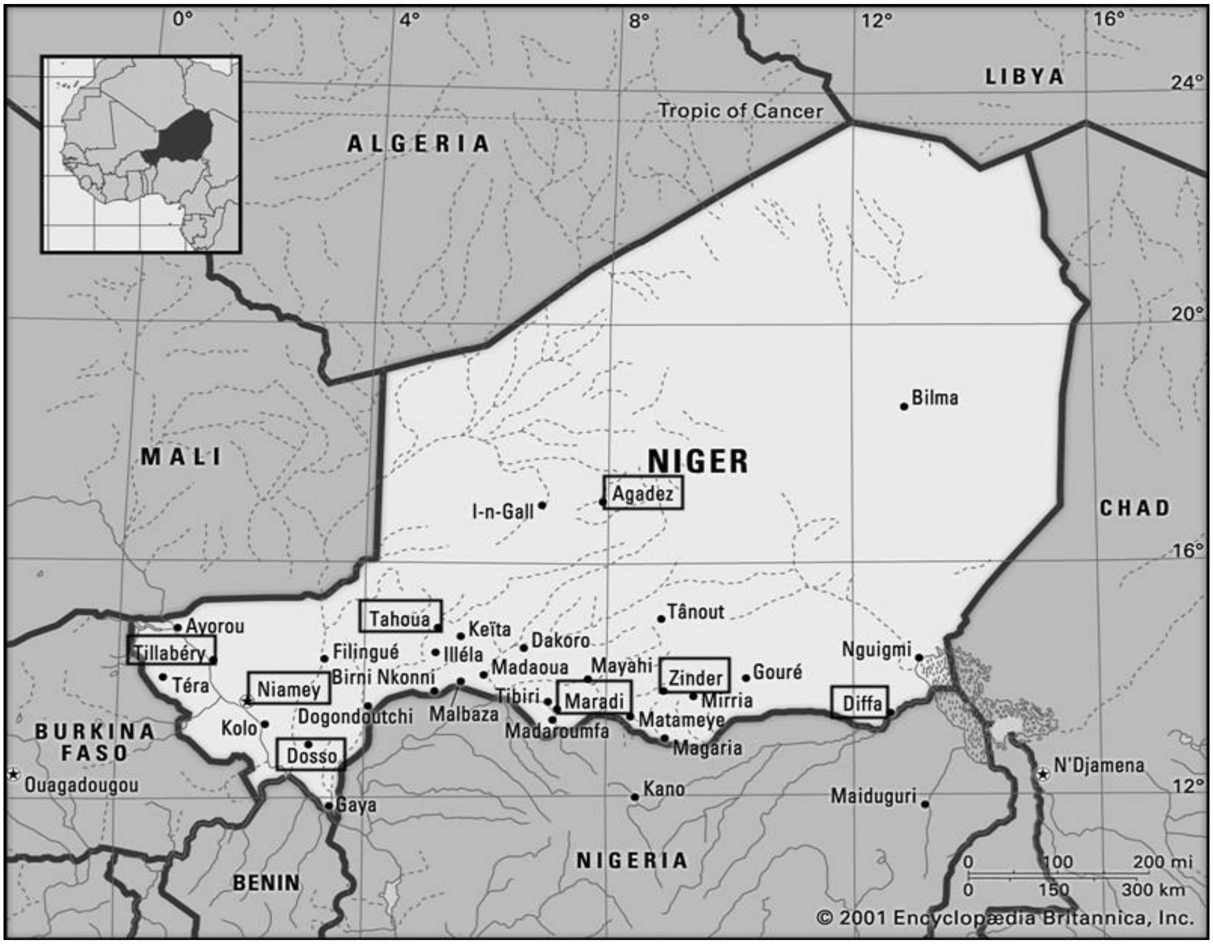

Figure 3-1 Map of study areas

In my research, I focus on the questions related to socio-economic and agronomic information on household’s demographic characteristics and the farm-specify situation of millet and sorghum production. From the data set, I choose 216 plots that plant millet in 2011 to 2012 over the country. Similarly, I choose 364 plots that plant sorghum in the same time period. Table 3-1 shows the distribution of observations of millet and sorghum in this study. Notice, there are no observation for sorghum in Niamey, which is different from millet distribution, so the region dummy variables are different between production frontier models.

Table 3-1 The distribution of observations by different regions

State	Millet	Sorghum
Diffa	32	32
Dosso	40	36
Maradi	22	93
Tahoua	34	72
Tillaberi	57	28
Zinder	27	103
Niamey	4	0
Total	216	364

The list of the variables and their descriptions are the following:

Total Production: The aggregate amount of output of millet or sorghum from each plot in kilograms.

Land Area: The acreage of each plot in hectares.

Labor: The amount of family labor and the amount of non-family labor for soil preparation, planting, maintenance and harvest in unit of hours.

Water: Total rainfall in wettest quarter within 12 month period measured in millimeter.

Seed: The amount of seed used in each plot measured in kilograms.

Fertilizer: The amount of organic and inorganic fertilizer used in each plot measured in kilograms. I add 0.01 to data set of sorghum observations to avoid the zero values.

Age: The age of household head measured in years.

Education: The years of education received by household head measured in years.

Family size: The number of family members.

Modern dummy: Takes value of one modern seed used on each plot.

Farming method dummy: Takes value of one pure farming method used on each plot.

State Dummy: In millet production, takes value of zero for Niamey and value of one for Tillaberi, Zinder, Diffa, Dosso, Maradi and Tahoua. In sorghum production, takes value of zero for Tillaberi and value of one for Zinder, Diffa, Dosso, Maradi and Tahoua.

Table 3.2 presents the variables and summary statistics for millet and sorghum production. Means, standard deviations, minimum and maximum of the variables are presented.

Table 3-2 Variables and summary statistics for millet and sorghum production

	Millet				Sorghum			
Variables	Mean	SD	Min	Max	Mean	SD	Min	Max
Total Prod	234.89	326.14	1.00	2800.00	83.46	116.58	2.00	800.00
Land	2.65	2.59	0.16	20.10	2.17	4.73	0.10	85.50
Labor	407.47	345.53	18.00	1956.00	406.14	436.19	18.00	3960.00
Water	455.91	106.05	281.00	880.00	375.82	61.47	267.00	681.00
Seed	63.72	213.80	1.00	2500.00	0.55	2.55	0.10	25.10
Fertilizer	801.53	2759.73	0.10	28000.10	1804.27	4212.96	0.01	40050.01
Age	44.01	14.42	17.00	80.00	45.34	14.07	20.00	87.00
Education	0.61	0.60	0.00	8.00	0.73	0.79	0.00	8.00
Family Size	6.47	3.40	2.00	20.00	6.90	3.56	1.00	22.00
Modern Dummy	0.01	0.12	0.00	1.00	0.01	0.07	0.00	1.00
Farming Method	0.40	0.49	0.00	1.00	0.82	0.38	0.00	1.00
Diffa	0.15	0.36	0.00	1.00	0.09	0.28	0.00	1.00
Dosso	0.19	0.39	0.00	1.00	0.10	0.30	0.00	1.00
Maradi	0.10	0.30	0.00	1.00	0.26	0.44	0.00	1.00
Tahoua	0.16	0.37	0.00	1.00	0.20	0.40	0.00	1.00
Tillaberi	0.26	0.44	0.00	1.00	0.08	0.27	0.00	1.00
Zinder	0.13	0.33	0.00	1.00	0.28	0.45	0.00	1.00
Niamey	0.02	0.14	0.00	1.00	0.00	0.00	0.00	0.00

In the statistics results, we can find that the average cultivating land areas and labor use for millet and sorghum production are similar. Average water use for millet is higher than sorghum indicates that main planting places of millet are on the south side of sorghum in Niger. For both millet and sorghum farmers, the household heads' average age are around forty-five years old and they have low education level. Sorghum farmers are more likely to choose mono-cropping in their plots

b) Methodology of the Analyses of the Chapter

To use the ML method to estimate the stochastic frontier, one first needs to specify the relevant log-like hood function, $\ln L = \sum_{I=1}^{M} l_i$ (where l_i is the ith farmer's log-likelihood function).The log-likelihood function is the natural logarithm of the marginal density function of the composed error term over a sample of N producers. For convenience, it is worthy to reproduce ALS(1977) and MB(1977) model to describe the path of formulation of log-likelihood function. The stochastic parametric frontier model can be represented as:

$$y_i = f(X_i; \beta)\exp(\varepsilon_i)$$

Where $\varepsilon_i = v_i - \mu_i$, vi is assumed identically and independently distributed as N(0, σ_v^2)and the non-negative error component, u_i , is assumed to be distributed independently of v_i .The probability density function of the symmetric error can be written as:

$$f(v) = \frac{1}{\sqrt{2\pi}\sigma_v}\exp\{-v^2/2\sigma_v^2\}$$

The next step is to form the joint density function, $f(u,v)$. Given the independence assumption of u and v, the joint density function equals to the product of their individual density functions. Replacing v with its equivalent $\varepsilon + \mathrm{u}$ and integrating u out of the function provides the marginal density function $\mathrm{f}(\varepsilon)$ for the half normal case as:

$$\mathrm{f}(\varepsilon) = \int f(u, (\varepsilon + u)du = \frac{2}{\sigma}\Phi\left(\frac{\varepsilon}{\sigma}\right)\Phi\left(-\frac{\varepsilon\lambda}{\sigma}\right)$$

Finally, taking the natural logarithm of each marginal density function over a sample of N producers yields the log-likelihood function. The respective formulations for half normal is

$$\ln L\ (y_i|\beta,\lambda,\sigma^2) = A - Nln\sigma + \sum_{i=1}^{N} ln\Phi(\frac{\varepsilon_i\lambda}{\sigma}) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\varepsilon_i^2$$

Note that the parameter β to be estimated along with the distributional parameters of $\lambda, \sigma, \theta, \sigma_v,$ andμ/σ_u, is not explicit in the above formulations.

A specification of a functional form completes the formulation. As presented in the previous chapter, a CD functional form in natural logarithms takes form:

$$\ln y_i = \ln(A) + \sum_{i=1}^{K} \alpha_{ik} lnX_{ik} + \varepsilon_i$$

The TL functional forms can be represented as following respectively:

$$\ln y_i = \alpha_0 + \sum_{i=1}^{K} a_i lnX_i + \frac{1}{2}\sum_{i=1}^{K}\sum_{j=1}^{K}\beta_{ij} lnX_i lnX_j + \varepsilon_i$$

Where $\beta_{ij} = \beta_{ji}$ imposed by symmetry for i $\neq$ j.

Substituting $\varepsilon_i = lny_i - lnA + \sum_{k=1}^{K}\beta_{ik}X_{ik}$ into the log-likelihood function completes the specification. Then, the ML estimates of the parameters can be obtained by maximizing the respective log-likelihood function with respect to the parameters.

c) Estimates the Cobb-Douglas Production Frontier for Millet Production

Table 3-3 Cobb-Douglas production frontier estimates for millet

Variables	Unit	Coef.		Std. Err.
Constant	-	0.80		2.74
Land	Hectares	0.91	*	0.47
Labor	Hours	0.24	***	0.08
Seed	Kilograms	0.16	**	0.08
Water	Millimeter	0.76	*	0.45
Fertilizer	Kilograms	0.03	**	0.02
Region Diffa	1=Diffa	-0.70		0.54
Region Dosso	1=Dosso	-1.36	**	0.58
Region Maradi	1=Maradi	-1.40	**	0.57
Region Tahoua	1=Tahoua	-2.13	***	0.55
Region Tillaberi	1=Tillaberi	-1.26	**	0.55
Region Zinder	1=Zinder	-1.12	**	0.56
λ	-	3.13		0.21
σ_v	-	0.54		0.09
σ_u	-	1.68		0.14
ln L		-326.87		

The signs, *, **, ***, denote the significance levels of 10, 5 and 1 percent, respectively

As represented in the Table 3-3, most parameters are significantly different from zero. The indicator of the relative sources of inefficiency λ, equals to 3.13. The data suggest that the differences in performance of farmers are more related to the differences in their utilization of technology than the random effects that are not under their control.

The coefficient estimates on individual inputs represent the partial output elasticity of the respective input in regions.

The land area has an output elasticity of 0.91 percent. That is, one percent increase in cultivated land will increase the output by 0.91 percent. Land is the largest positive factor affecting the output.

The output elasticity of the labor is 0.24, hence, a one percent increase in use of manual labor induces more increase in millet output by 0.24 percentage points.

The output elasticity of the seed is 0.16, one percent increase in seed usage will increase the output by 0.16 percentage points.

The output elasticity of water is 0.76, one percent increase in water usage will increase the output by 0.76 percentage points. Water is the largest positive factor affecting the millet output.
The output elasticity of fertilizer is 0.03. One percent increase in water usage will increase the output by 0.03 percentage points.

From region part, Niamey, the capital of Niger has the highest yield level among the country. Compare to Niamey, region Tahoua has the lowest yield level for millet production.

Therefore, if CD form is the correct representation of the true technology, the use of land, labor, seed, water and fertilizer can be considered as the technological sources of inefficiency.

The CD production function exhibits constant returns to scale when $\sum_{i=1}^{K} \alpha_i = 1$. The Wald test statistics is 1.43. Comparing to the critical $\chi^2(.90,1)$ value 2.71, the constant returns to scale is rejected at the 10 percent significance level for this model. Parameters of the CD production function exhibits decreasing return to scale.

d) Estimates the Translog Production Frontier for Millet Production

As discussed in the previous chapter, applying different production function may cause different results. So I estimated more flexible function form using Translog model. Table 3-4 presents the estimates of TL production frontier for millet production.

Table 3-4 Estimates the Translog production frontier for millet production

Variables	Unit	Coef.		Std. Err.
Constant	-	60.96		55.81
Land	Hectares	-14.00		19.21
Labor	Hours	-0.36		2.33
Seed	Kilograms	0.56		2.42
Water	Millimeter	-18.53		17.85
Fertilizer	Kilograms	1.52	**	0.63
Land*Land	-	1.75		3.28
Labor*Labor	-	0.12		0.16
Seed*Seed	-	0.02		0.10
Water*Water	-	3.13		2.88
Fertilizer*Fertilizer	-	0.01		0.02
Land*Labor	-	-0.08		0.42
Land*Seed	-	-0.07		0.38
Land*Water	-	2.53		3.07
Land*Fertilizer	-	-0.24	**	0.11
Labor*Seed	-	-0.04		0.08
Labor*Water	-	0.02		0.38
Labor*Fertilizer	-	0.01		0.02
Seed*Water	-	-0.03		0.38
Seed*Fertilizer	-	0.00		0.02
Water*Fertilizer	-	-0.25	**	0.10
Region Diffa	1=Diffa	-0.79		0.59
Region Dosso	1=Dosso	-1.36	**	0.60

Table 3-4 Estimates the Translog production frontier for millet production (Continued)

Variables	Unit	Coef.		Std. Err.
Region Maradi	1=Maradi	-1.36	**	0.60
Region Tahoua	1=Tahoua	-2.08	***	0.57
Region Tillaberi	1=Tillaberi	-1.35	**	0.56
Region Zinder	1=Zinder	-0.99	*	0.56
λ	-	3.10		0.27
σ_v	-	0.52		0.12
σ_u	-	1.62		0.17
ln L	-	-318.94		

The signs, *, **, ***, denote the significance levels of 10, 5 and 1 percent, respectively

The indicator of the relative sources of inefficiency, λ, equal to 3.10. The data also suggests that the differences in performance of farmers are more related to the differences in their utilization of technology than the random effects that are not under their control like CD form.

Few variables are significant in the Table 3-4. However, due to the existence of the cross-economic effects the individual Z -test do not represent the significance of the individual inputs.

I used Wald test to test of the joint significance of the individual inputs. The null hypothesis that an individual inputs has no effect on output implies that the coefficient on any input is jointly equal to zero. These test statistics are compared to the critical $\chi^2(.90, 6)$ value of 10.6

The Wald test results imply that land, water and fertilizer are significant while labor and water are not in TL form. The results were shown at Table 3-5 below.

The estimates of TL production frontier are more difficult to interpret than the estimates of the CD form. Unlike the CD form, the first-order effects no longer represent the elasticity of output. In flexible functional forms the elasticity of output represents the combined effects of both first-order effects. In case of TL form this is calculated by the following formula:

$$\frac{\partial lnY}{\partial lnX_k} = \left(\frac{\partial Y}{\partial X_k}\right)\left(\frac{X_k}{Y}\right) = \beta_k + \sum_{j=1}^{K} \delta_{jk} lnX_j$$

Table 3-5 presents the elasticity estimates of the TL form that is calculated at the respective averages of each input.

Table 3-5 Wald test and elasticity estimates of millet for Translog from

Variables	Chi-square		Elasticity
Land	12.18	*	0.22
Labor	8.96		0.25
Seed	5.68		0.19
Water	10.6	*	0.13
Fertilizer	10.75	*	0.02

The signs, *, **, ***, denote the significance levels of 10,5 and 1 percent, respectively

Similar with CD form, land, labor, seed, water and fertilizer all have positive output elasticity. Land has the largest positive effect to output among significant variables.

The TL production function exhibits constant returns to scale when $\sum_{i=1}^{K} \alpha_i = 1$ and $\sum_{i=1}^{K} \beta_{ij} = 0$. The Wald test statistics is 1.43. Comparing to the critical χ^2(.90, 2) value 4.61, the constant returns to scale is rejected at the 10 percent significance level for this model.

e) Summary the Results of Different Frontier Models for Millet

In both models, land, water and fertilizer are significant. All of them have positive effect to millet production. Land is positive to production means millet output will increase when farmers farm more lands. The significance of the water is robust for both models. Water has the large positive effect to production among all inputs so this suggests that rainfall is the key factor to increase harvest. Even though fertilizer is significance in both models, the small estimated elasticity (0.03 (CD), 0.02(TL)) shows that using more fertilizer will not improve production substantially. From region part, we can find Niamey is the highest yield area among other states in Niger.

Lastly, the results show that most estimates are sensitive to the functional form used. Consequently, we can expect the measures of farm efficiency and the identification of the potential sources of inefficiency are sensitive too.

f) Choosing Between the CD and TL Forms for Millet Production Frontier Model

For further analyses, I applied the econometric test for choosing a suitable form. Note that CD form is nested in TL form, then I conduct a likelihood-ratio test to compare between these two models. Formally, the likelihood ratio statistics are calculated as:

$$\mathrm{C} = 2(L_2 - L_1)$$

Where L_2 is the log-likelihood function of the alternative model, TL form, which value -318.94. And the L_1 is the log-likelihood function of the null model, CD form, which value -326.87. Then get C = 15.86. This value it then compared to the critical χ^2(.90, 15) value 22.3, the coefficient of the values is not statistically significant, this result suggest that CD form is the most appropriate function for millet production.

g) Estimates the Cobb-Douglas Production Frontier for Sorghum Production

Table 3-6 Cobb-Douglas production frontier estimates for sorghum production

Variables	Unit	Coef.		Std. Err.
Constant	-	-2.23		3.10
Land	Hectares	1.07	**	0.50
Labor	Hours	0.19	**	0.08
Seed	Kilograms	0.00		0.07
Water	Millimeter	0.98	**	0.49
Fertilizer	Kilograms	0.01		0.01
Region Diffa	1=Diffa	0.13		0.26
Region Dosso	1=Dosso	-0.36		0.23
Region Maradi	1=Maradi	-1.59	***	0.18
Region Tahoua	1=Tahoua	0.00		0.20
Region Tillaberi	1=Tillaberi	-0.28		0.26
λ	-	0.72		0.95
σ_v	-	1.07		0.20
σ_u	-	0.78		0.75
ln L	-	-543.71		-

The signs, *, **, ***, denote the significance levels of 10, 5 and 1 percent, respectively

As represented in the Table 3-6, land, labor, water and region dummy Maradi are significantly different from zero. The indicator of the relative sources of inefficiency λ, equals to 0.74. The data suggest that the differences in performance of farmers are more related to the differences in their utilization of technology than the random effects that are not under their control.

The coefficient estimates on individual inputs represent the partial output elasticity of the respective input in states.

The land area has an output elasticity of 1 percent. Means one percent increase in cultivated land will increase the output by 1 percent. As similar result we got from millet production model, land is also the largest positive factor affecting output.

The output elasticity of the labor is 0.19, as a result, a one percent increase in use of manual labor induce more increase in millet output by 0.19 percentage points.

The output elasticity of water is 0.98, one percent increase in seed usage will increase the output by 0.9 percentage points. Water is another large positive factor affecting the sorghum output. As the only one significant region dummy variable, Maradi has lower yield level than Zinder. Similarly, if CD form is the correct representation of the true technology, the use of land, labor, water, can be considered as the technological sources of inefficiency.

The CD production function exhibits constant returns to scale when $\sum_{i=1}^{K} \alpha_i = 1$. The Wald test statistics is 1.61. Comparing to the critical χ^2(.90,1) value 2.71, the constant returns to scale is also rejected at the 10 percent significance level for this model. Parameters of the CD production function exhibits decrease return to scale.

h) Estimates the Translog Production Frontier for Sorghum Production

Table 3-7 Estimates the Translog production frontier for sorghum production

Variables	Unit	Coef		Std. Err.
Constant	-	44.93		66.04
Land	Hectares	-18.99		22.52
Labor	Hours	3.41		3.39
Seed	Kilograms	-5.29	*	2.77
Water	Millimeter	-18.95		21.75
Fertilizer	Kilograms	-0.50		0.42
Land*Land	-	4.65		3.99
Labor*Labor	-	-0.14		0.13
Seed*Seed	-	-0.68	*	0.27
Water*Water	-	4.17		3.66
Fertilizer*Fertilizer	-	0.01		0.01
Land*Labor	-	-0.57		0.55
Land*Seed	-	1.14	*	0.56
Land*Water	-	4.28		3.80
Land*Fertilizer	-	0.10		0.07
Labor*Seed	-	-0.19		0.13
Labor*Water	-	-0.49		0.54
Labor*Fertilizer	-	-0.01		0.01
Seed*Water	-	1.10	*	0.51
Seed*Fertilizer	-	0.00		0.02
Water*Fertilizer	-	0.09		0.07

Table 3-7 Estimates the Translog production frontier for sorghum production (Continued)

Variables	Unit	Coef		Std. Err.
Region Diffa	1=Diffa	-0.07		0.29
Region Dosso	1=Dosso	-0.49		0.26
Region Maradi	1=Maradi	-1.56		0.18
Region Tahoua	1=Tahoua	0.02	*	0.20
Region Tillaberi	1=Tillaberi	-0.39		0.27
λ	-	0.76		0.92
σ_v	-	1.03		0.20
σ_u	-	0.78		0.73
ln L	-	-531.79		

The signs, *, **, ***, denote the significance levels of 10, 5 and 1 percent, respectively

The indicator of the relative sources of inefficiency, λ, equal to 0.76. The data also suggests that the differences in performance of farmers are more related to the differences in their utilization of technology than the random effects that are not under their control.

Due to the existence of the cross-economic effects the individual Z -test do not represent the significance of the individual inputs, few variables are significant in the table.

I also used Wald test to test of the joint significance of the individual inputs for sorghum. The null hypothesis that an individual inputs has no effect on output implies that the coefficient on any input is jointly equal to zero. These test statistics are compared to the critical χ^2(.90, 6) value of 10.6

The Wald test results imply that Land, Seed and Water are significant while Labor and fertilizer are not.

Using the same method in previous analyses, I calculated the elasticity estimates of the TL form at the respective averages of each input in Table 3-8.

Table 3-8 Wald test and elasticity estimates of sorghum for Translog from

Variables	Chi-square		Elasticity
Land	12.8	*	0.92
Labor	11.37	*	0.13
Seed	10.58	*	1.59
Water	12.23	*	0.76
Fertilizer	2.77		2.04

The signs, *, **, ***, denote the significance levels of 10,5 and 1 percent, respectively

Land has positive output elasticity similar with CD form estimate. The number is 0.92. Seed has the largest positive effect to output among significant variables and it is larger than 1. Labor and water also has positive effect to production.

The TL production function exhibits constant returns to scale when $\sum_{i=1}^{K} \alpha_i = 1$ and $\sum_{i=1}^{K} \beta_{ij} = 0$. The Wald test statistics is 3.61. Comparing to the critical χ^2(.90, 2) value 4.61, the constant returns to scale is rejected at the 10 percent significance level for this model.

i) Summary the Results of Different Frontier Model for Sorghum

As same as millet, land is significant in two models and also the positive effect to output among other inputs. This suggests that farmers can get more production when they increase their plant areas. Using more labor can improve sorghum production for labor has positive effect to yield and it is significant in CD and TL forms. TL form shows that seed has a quite large effect for the estimated elasticity which is 1.59. Water is robust for both models. The estimated elasticity (.98 (CD) and 0.76(TL)) indicates that rainfall situation is critical to sorghum production. Fertilizer shows no influence to yield in both models.

.

j) Choosing Between the CD and TL Forms for Sorghum Production Frontier Model

Using the likelihood ratio statistics, L2 is the log-likelihood function of the alternative model, TL form, which value -531.79. And the L1, the log-likelihood function of the null model, CD form, which value -543.71, then get C = 23.84. This value it then compared to the critical χ^2(.90, 15) value 22.3, the coefficient of the values is statistically significant, this result suggest that TL form is the most appropriate function for sorghum production.

k) Compare Millet and Sorghum Production Frontier Estimate Results

Table 3-9 Millet and sorghum production frontier estimate results (CD form)

Variables	Unit	Millet		Sorghum	
Land	Hectares	0.91	*	1.07	**
Labor	Hours	0.24	***	0.19	**
Seed	Kilograms	0.16	**	0.00	
Water	Millimeter	0.76	*	0.98	**
Fertilizer	Kilograms	0.03	**	0.01	

The signs, *, **, ***, denote the significance levels of 10, 5 and 1 percent, respectively

From the Table 3-9 above, we notice that land, labor, water are significant variables for both millet and sorghum production in CD form. Results also suggest that land, labor, water are positive factors affecting output. Farmers will increase their production when they cultivate more lands, use more labor or have better rainfall situation no matter for millet or sorghum. Seed and fertilizer have positive effect to millet production, but fertilizer’s influence is very small. Notice water is a large positive factor affecting both millet and sorghum production, Harvest is largely determined by the rainfall situation of current year.

I also compare elasticity of TL production model for millet and sorghum in Table 3-10 below. Similar with CD form, in TL model, land and water are also significant and positive factors for both millet and sorghum production. Notices, labor and seed are significant and seed has a large influence to sorghum production.

Table 3-10 Millet and sorghum production frontier estimate results (TL form)

Variables	Unit	Millet		Sorghum	
Land	Hectares	0.22	*	0.92	*
Labor	Hours	0.25		0.13	*
Seed	Kilograms	0.19		1.59	*
Water	Millimeter	0.13	*	0.76	*
Fertilizer	Kilograms	0.02	*	2.04	

The signs, *, **, ***, denote the significance levels of 10, 5 and 1 percent, respectively

As a consequence, from two different forms of production frontier, we get land and water are determining factors, and labor, seed, fertilizer are all important inputs have positive influence to millet and sorghum production in Niger.

Chapter 4. Analyses of the Efficiency Scores and the Determination of Inefficiency

This chapter is organized as following: In section a) I represent the methodological framework of analyses. Section b) to c) presents the analyses of the efficiency scores of the millet farmers and gives the result of two-step approach. Section d) to e) presents the analyses of the efficiency scores of the sorghum farmers and gives the result of two-step approach. Section f) shows the comparison of efficiency scores for millet and sorghum.

a) Methodology of the Analyses of the Chapter

Having obtained the estimates of the production structure and the most convenient functional form to represent the technology. A natural next step is to analyses the technical efficiency of the farmers. Jondrow (1982) provided the formulations to predict the firm-specific technical efficiency. The idea is to extract informational on the technical inefficiency component of the error term u_i from its conditional expectation given the estimates of the composed error term, ε_i . Formally, the expected firm-specific technical inefficiency component for normal-half-normal, normal-exponential and normal-truncated normal cases can be defined respectively as:

$$\mathrm{E}\left(\frac{u_i}{\varepsilon_i}\right) = -\left(\frac{\sigma\lambda}{1+\lambda^2}\right)\left[\frac{\emptyset(\varepsilon_i\lambda/\sigma)}{\Phi(-\varepsilon_i\lambda/\sigma)} - \left(\frac{\varepsilon_i\lambda}{\sigma}\right)\right]$$

$$\mathrm{E}\left(\frac{u_i}{\varepsilon_i}\right) = -(\varepsilon_i + \theta\sigma_v^2) - \left[\frac{\sigma_v\emptyset[-(\varepsilon_i + \theta\sigma_v^2)/\sigma_v]}{\Phi(\varepsilon_i + \theta\sigma_v^2)/\sigma_v}\right]$$

$$\mathrm{E}\left(\frac{u_i}{\varepsilon_i}\right) = -\left(\frac{\sigma\lambda}{1+\lambda^2}\right)\left[\frac{\emptyset(\varepsilon_i\lambda/\sigma + \mu/\sigma\lambda)}{\Phi\left(-\frac{\varepsilon_i\lambda}{\sigma} - \mu/\sigma\lambda\right)} - \left(\frac{\varepsilon_i\lambda}{\sigma} + \frac{\mu}{\sigma\lambda}\right)\right]$$

All the distribution parameters, $\sigma, \lambda, \theta, \sigma_v, \mu, \varepsilon$ are estimated via the maximum likelihood method along with the parameters of the imposed production function. The estimated technical efficiency scores, $\mathrm{E}\left(\frac{u_i}{\varepsilon_i}\right)$ are defined in the $[0, 1]$ interval only if the output is in its aggregate form.

Once estimate of technical efficiency are obtained, the next step is to determine the sources of inefficiency. As described in the second chapter, this involves the incorporation of exogenous variables that are specific to each producer and characterize the environment in which production occurs. I search for the sources of inefficiency by making use of two different methods: The one-step approach and the two step approach. The estimated function in the one-step approach can be represented as:

$$\sqrt[2]{y_i} = \alpha_0 + \sum_{i=1}^{K} \alpha_k(\sqrt[2]{X_k}) + \frac{1}{2}\sum_{i=1}^{K}\sum_{j=1}^{K} \beta_{ij}(\sqrt[r]{X_i X_j}) + \sum_{i=1}^{Z} \psi_i(Z_i) + \varepsilon_i$$

On the other hand, I use OLS in the second-step of two-step approach, which can be formulated as:

$$\mathrm{T}E_i = \sum_{i=1}^{Z} \psi_i(Z_i) + \tau$$

b) Plot-Specific Efficiency Scores for Millet Production

The plot technical efficiency scores are calculated with respect to the estimates of CD form for millet. Also, recall that the estimated best practice frontier is the envelope of all producers. Hence, the calculated efficiency scores are comparable between farmers in whole country. The summary statistics of the technical efficiency scores (in percentage) are presented in the Table 4-1 below.

Table 4-1 Technical efficiency scores (In percentage) for millet farmers

Variable	Obs	Mean	Std. Dev.	Min	Max
Cobb-Douglas	216	38.44%	22.48%	1.32%	83.83%

The mean technical efficiency scores of the millet farmers about 38.44 in percent and range from 1.32 to 83.83 in percentage in Niger.

Around 27 percent of the farmers' efficiency scores are less than 20%. Note that crop failures are captured by the lower tail of the distribution of the efficiency scores. About 80 percent farmers' efficiency scores are around 60%. Very few farmers have efficiency scores more than 80% in Niger for millet production. The distribution results show in the Figure 4.1 below.

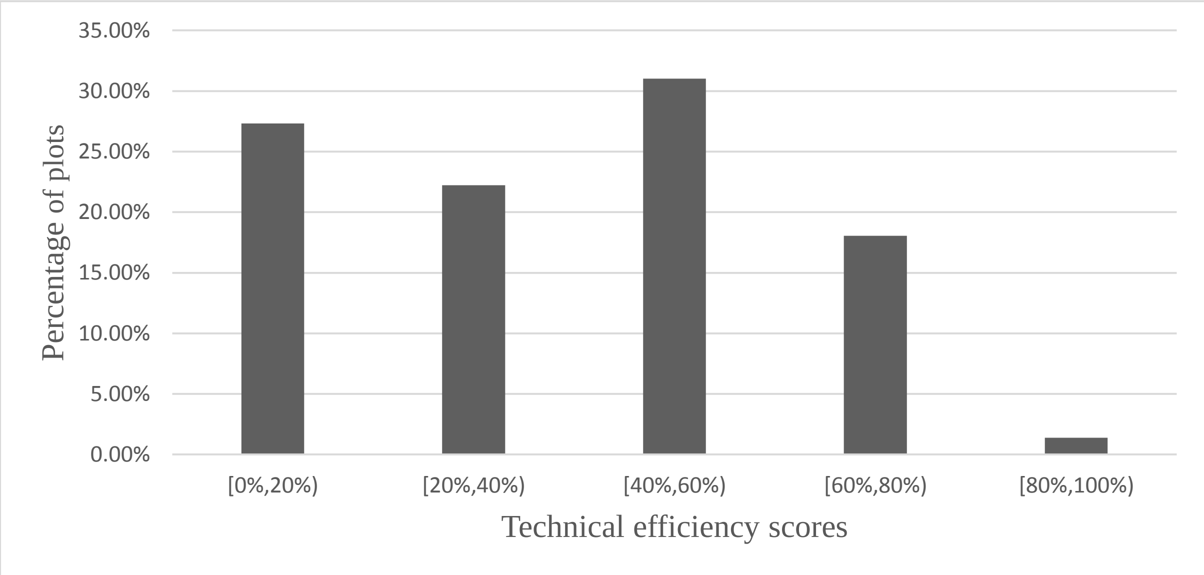

Figure 4-1 Distribution of technical efficiency scores for millet farmers

c) Estimates of the Two-Step Approach for Millet Production

I employed the CD form to determine the sources of inefficiency. Hence, in the following analyses I make comparisons only with the results of the CD form estimated in the previous chapter. Now I regress efficiency scores over the farm-specific variables to analyze the correlates of the inefficiency of the farmers. Table 4-2 shows the estimate results.

Table 4-2 Estimates of the two-step approach for millet production

Variables	Coef.		Std. Err.
Constant	0.60	***	0.16
Age	0.00		0.01
Age*Age	0.00		0.00
Education	-0.10	**	0.05
Education*Education	0.01	**	0.01
Family size	-0.03	*	0.02
Family size*Family size	0.00		0.00
Modern	0.11		0.13
Farming Method	-0.02		0.03

The signs, *, **, ***, denote the significance levels of 10, 5 and 1 percent, respectively

First I present the results of the tests of significance of these variables. I conduct tests for both significance on the individual variables and the joint significance of all variables. For individual variables, the tested null hypothesis is that the coefficient of a variable and the coefficient of its square term are jointly equal to zero. Modern and farming method do not have square terms in the model, the null hypothesis for the significance test of these variables includes only their respective coefficient. Lastly, the calculated statistics for the joint significance of all farm-specific variables. Table 4-3 presents the results of the significance tests.

Table 4-3 Significance tests of the farm specific variables (millet, Wald statistics)

Variables	Chi-square	
Age	1.04	
Education	2.51	*
Family size	1.90	
Modern	0.88	
Farming Method	-0.51	
Farm-specific	1.71	*

The signs, *, **, ***, denote the significance levels of 10, 5 and 1 percent, respectively

Besides education and farm-specific, other individual variables do not have an effect on efficiency. This result indicates that the inefficiency of millet farmers is related to the managerial factors such as education level.

d) Plot-Specific Efficiency Scores for Sorghum Production

The plot technical efficiency scores are calculated with respect to the estimates of TL form for sorghum. Also, the estimated best practice frontier is the envelope of all producers. Accordingly, the calculated efficiency scores are comparable between farmers in whole country. The summary statistics of the technical efficiency scores (in percentage) are presented in the Table 4-4 below.

Table 4-4 Technical efficiency scores (In percentage) for sorghum farmers

Variable	Obs	Mean	Std. Dev	Min	Max
Translog	364	58.82%	9.50%	32.07%	77.07%

The mean technical efficiency scores of the sorghum farmers about 58.82 in percent and range from 32.07 to 77.07 in percentage in Niger.

Less than 5 percent of the farmers' efficiency scores are between 30% and 40%. About 65 percent farmers' efficiency scores are around 50% to 70%. 10 percent farmers have efficiency scores more than 70% in Niger for sorghum production. The distribution results show in the Figure 4.2 below.

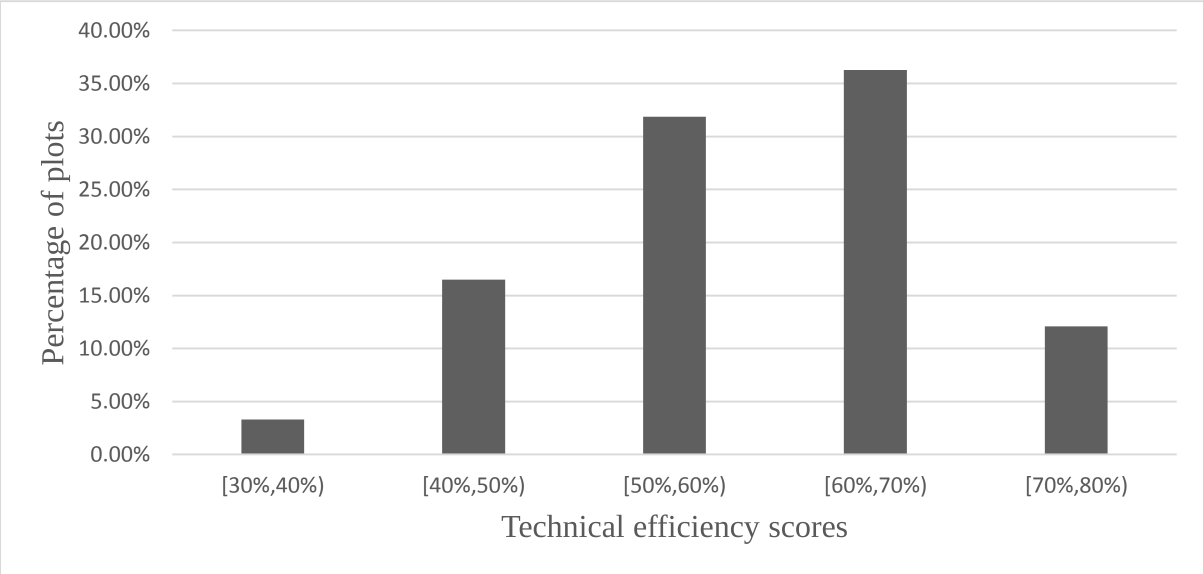

Figure 4-2 Distribution of technical efficiency scores for sorghum farmers

e) Estimates of the Two-Step Approach for Sorghum Production

I employed the TL form to determine the sources of inefficiency. Hence, in the following analyses I make comparisons only with the results of the TL form estimated in the previous chapter. Now I regress efficiency scores over the farm-specific variables to analyze the correlates of the inefficiency of the farmers. Table 4-5 shows the estimate results.

Table 4-5 Estimates of the two-step approach for sorghum production

Variables	Coef.		Std. Err.
Constant	0.63	***	0.05
Age	0.00		0.00
Age*Age	0.00		0.00
Education	0.01		0.01

Table 4-5 Estimates of the two-step approach for sorghum production (Continued)

Variables	Coef.		Std. Err.
Education*Education	0.00		0.00
Family size	0.00		0.00
Family size*Family size	0.00		0.00
Modern	0.02		0.07
Farming Method	-0.04	***	0.01

The signs, *, **, ***, denote the significance levels of 10, 5 and 1 percent, respectively

Similarly, I conduct tests for both significance on the individual variables and the joint significance of all variables. I also calculated the joint significance of all farm-specific variables. Table 4.6 presents the results of the significance tests.

Table 4-6 Significance tests of the farm specific variables (sorghum, Wald statistics)

Variables	Chi-square	
Age	0.02	
Education	0.62	
Family size	1.52	
Modern	0.02	
Farming Method	-0.04	***
Farm-specific (all variables)	1.58	

The signs, *, **, ***, denote the significance levels of 10,5 and 1 percent, respectively

Besides Farming method, other individual variables do not have an effect on efficiency. Farmers were inefficient if he/she plant mono-crop in their plots. This result do not have statistic significant evidences indicate that the inefficiency of sorghum farmers is related to the managerial factors.

f) Compare Efficiency Scores for Millet and Sorghum Production

Table 4-7 Efficiency scores for millet and sorghum

Variable	Obs	Mean	Std. Dev.	Min	Max
Millet(CD)	216	38.44%	22.48%	1.32%	83.83%
Sorghum(TL)	364	58.82%	9.50%	32.07%	77.07%

From Table 4-7, it’s easy to find that millet farmers have a lower average efficiency scores than sorghum farmers but the range of efficiency scores for millet farmers is larger. The minimum efficiency score of millet farmer is very low and the maximum of efficiency score are similar. This results imply that some millet farmers were suffering crop failures, but sorghum farmers have a better situation. Both millet and sorghum have a strong potential to increase production in Niger.

Table 4-8 Efficiency scores by different regions for millet and sorghum

State	Millet	Sorghum
Diffa	35.82%	59.17%
Dosso	37.51%	58.84%
Maradi	38.43%	59.15%
Tahoua	37.45%	58.39%
Tillaberi	40.46%	58.80%
Zinder	40.84%	58.71%
Niamey	31.99%	-

Separate by different regions, as the table 4-8 shows, we can see for millet production, Niamey has the lowest average efficiency score, but it also has highest standard deviation, for its observations are only four, it’s not right to say this region was suffering the lowest efficiency due to only small observations were adopt in this study. Diffa has the second lowest average efficiency score. Tahoua has the third lowest average and the lowest minimum efficiency score.

In production frontier estimates results, Tahoua also has lowest yield compare to Niamey among other regions.

For sorghum production, all regions have quiet similar average efficiency scores and also have high standard deviation. Zinder has the lowest minimum efficiency score while Tahoua has the highest among other regions.

There are some households that plant millet as well as sorghum in their plots. I figured out their average efficiency scores as the table 4-9 shows. From average efficiency scores, the results suggest that planting sorghum seems more efficient than millet, but also, because only 18 observations were found from the data set, it's not statistically significant to say planting sorghum was more efficient than millet in Niger.

Table 4-9 Efficiency scores for farmers who plant millet and sorghum

Variable	Obs	Mean	Std. Dev.	Min	Max
Millet(CD)	18	41.09%	16.81%	5.26%	64.02%
Sorghum(TL)	18	58.78%	9.46%	41.57%	68.69%

Chapter 5. Conclusion

The general objective of this study was to examine factors that influence the efficiency of millet and sorghum farming in Niger, West Africa.

I conducted a stochastic parametric frontier analysis using a cross-sectional data set collected by The Living Standards Measurement Study (LSMS). The analyses considered over 216 households of millet farmers and 364 households of sorghum farmers from 7 different regions in Niger.

I employed two different functional forms along with half-normal distribution of inefficiency term to derive the best-practice frontier for different crops. I used a two-step approach to determine the sources of inefficiency. I also employed a comparative analysis of two crops.

a) Summary of the Results

I used a stochastic parametric approach to estimate the best practice frontier. The results show that CD form is suitable for millet production and TL form is suitable for sorghum production.

The results of best practice frontier suggest that the land area and water are the major positive effect factors of production for millet and sorghum. Labor, seed and water also have positive effects on output.

Labor, seed and fertilizer are productive for millet planting, however fertilizer has a week influence to millet total production. Labor and seed are productive for sorghum planting, especially, seed has a strong influence to sorghum total production.

I also found that the technology for millet production exhibits decreasing returns to scale. The plot-specific technical efficiency scores ranged between .13 and .84 for millet farmers and .32 and .77 for sorghum farmers. Planting sorghum is more efficiently than millet for farmers who cultivated both crops. Lastly, I found that education levels of household heads influence millet production efficiency and farming method has a significant effect on efficiency scores of sorghum. The result point to that the inefficiency of millet farmers in Niger is related to the managerial factors.

b) Policy Implications and Recommendations

As this research has shown, water is an important factor influencing millet and sorghum production. As mentioned earlier, most agricultural area receives an average of 300 mm to 400 mm of rainfall annually. In such an environment, farmers are unlikely to adopt high-yielding technologies (Mazzucato and Ly, 1994). Decision makers need to center on improving irrigation schemes in all farming areas in Niger.

This analysis was shown that farmers in Niger practice low input in agriculture. From statistic results, we found that most farmers do not use any fertilizer for sorghum production, which maybe one reason of fertilizer shows not significant and very weak influence to production in my study. However, for sorghum production, seed is a quite big positive factor to production. All these evidence show that farmers need to use more inputs like fertilizer and seed to increase production. In order to achieve this, policy makers should consider about developing local inputs markets and try to make the prices of organic fertilizers are more affordable to millet and sorghum farmers in Niger.

Another implication of this research is that technical efficiency in millet production in Niger could be greatly increased through better use of available resources. The key to solving the problem is improving the education level for farmers. The training of agricultural knowledge such as Inter-planting technology will be helpful in improving sorghum farmers' efficiency in Niger.

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Appendix A – Statistic Results for Millet Production in Niger

Variables	Unit	Mean	SD	Min	Max	P50
Total Millet Prod	Kilograms	234.89	326.14	1.00	2800.00	140.00
Land	Hectares	2.65	2.59	0.16	20.10	2.10
Labor	Hours	407.47	345.53	18.00	1956.00	297.00
Water	Millimeter	455.91	106.05	281.00	880.00	436.50
Seed	Kilograms	63.72	213.80	1.00	2500.00	25.00
Fertilizer	Kilograms	801.53	2759.73	0.10	28000.10	0.10
Age	Years	44.01	14.42	17.00	80.00	41.50
Education	Years	0.61	0.60	0.00	8.00	0.00
Family Size	Number of family member	6.47	3.40	2.00	20.00	6.00
Modern Dummy	1=Modern seed	0.01	0.12	0.00	1.00	0.00
Farming Method Dummy	1=Pure	0.40	0.49	0.00	1.00	0.00
Region Dummy Diffa	1=Diffa	0.15	0.36	0.00	1.00	0.00
Region Dummy Dosso	1=Dosso	0.19	0.39	0.00	1.00	0.00
Region Dummy Maradi	1=Maradi	0.10	0.30	0.00	1.00	0.00
Region Dummy Tahoua	1=Tahoua	0.16	0.37	0.00	1.00	0.00
Region Dummy Tillaberi	1=Tillaberi	0.26	0.44	0.00	1.00	0.00
Region Dummy Zinder	1=Zinder	0.13	0.33	0.00	1.00	0.00
Region Dummy Niamey	1=Niamey	0.02	0.14	0.00	1.00	0.00

Appendix B – Statistic Results for Sorghum Production in Niger

Variables	Unit	Mean	SD	Min	Max	P50
Total Millet Prod	Kilograms	83.46	116.58	2.00	800.00	35.00
Land	Hectares	2.17	4.73	0.10	85.50	1.19
Labor	Hours	406.14	436.19	18.00	3960.00	282.00
Water	Millimeter	375.82	61.47	267.00	681.00	366.50
Seed	Kilograms	0.55	2.55	0.10	25.10	0.10
Fertilizer	Kilograms	1804.27	4212.96	0.01	40050.01	0.01
Age	Years	45.34	14.07	20.00	87.00	45.00
Education	Years	0.73	0.79	0.00	8.00	0.00
Family Size	Number of family member	6.90	3.56	1.00	22.00	6.00
Modern Dummy	1=Modern seed	0.01	0.07	0.00	1.00	0.00
Farming Method Dummy	1=Pure	0.82	0.38	0.00	1.00	1.00
Region Dummy Diffa	1=Diffa	0.09	0.28	0.00	1.00	0.00
Region Dummy Dosso	1=Dosso	0.10	0.30	0.00	1.00	0.00
Region Dummy Maradi	1=Maradi	0.26	0.44	0.00	1.00	0.00
Region Dummy Tahoua	1=Tahoua	0.20	0.40	0.00	1.00	0.00
Region Dummy Tillaberi	1=Tillaberi	0.08	0.27	0.00	1.00	0.00
Region Dummy Zinder	1=Zinder	0.28	0.45	0.00	1.00	0.00
Region Dummy Niamey	1=Niamey	0.00	0.00	0.00	0.00	0.00