ASSESSING TECHNICAL EFFICIENCY OF WHEAT FARMERS IN PAKISTAN: A COMPARISON TO PRIOR PRODUCTIVITY ANALYSES OF PAKISTANI AGRICULTURE

By

Joshua Gill

A THESIS

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agriculture, Food and Resource Economics – Masters of Science

2015

ABSTRACT

ASSESSING TECHNICAL EFFICIENCY OF WHEAT FARMERS IN PAKISTAN: A COMPARISON TO PRIOR PRODUCTIVITY ANALYSES OF PAKISTANI AGRICULTURE

By

Joshua Gill

Agricultural production in Pakistan doubled during the green revolution, averting food crises and spurring an era of agricultural and economic growth. However, agricultural sector growth has decelerated to just 3.1 percent per annum during the past 10 years. There is a significant yield gap between progressive and average farmers in Pakistan, furthermore the national average yield of important crops such as wheat, cotton, rice, and sugarcane also lag behind both regionally and globally. Attention needs to be paid to issues pertaining to the prioritization of public investments and the design of public policies best suited to simultaneously accelerate productivity growth and reduce poverty. The paper specially evaluates wheat efficiency using a stochastic production frontier approach, since it is the staple diet and is grown extensively throughout the country. The results indicate that there is significant technical inefficiency with mean score of 78 percent. However, the major factors affecting the efficiency of farmers are no longer years of schooling, visits by extension agents, and land size as most prior studies have suggested. I find that land degradation and weather shocks are major sources of inefficiency. These findings suggest that effort is needed to improve the extension system so that farmers are better informed about alternate technologies, cropping systems, and sustainable practices.

ACKNOWLEDGEMENTS

This paper uses data collected by International Food Policy Research Institute (IFPRI) as part of a Pakistan Strategy Support Program (PSSP) in collaboration with Innovative Development Strategies (IDS). The contribution of Andrew Dillon, Thomas S. Jayne, and Russell Freed are gratefully acknowledged.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Introduction

Agriculture is still a very pivotal sector in the developing country context as it provides a source of livelihood to the majority of the populace and is a major contributor towards GDP. As Mellor & Lele (1973) pointed out it also has significant forward, backward, consumption and financial linkages and hence a productive and efficient agricultural system can provide the economy with the requisite stimulus to achieve economic growth. Pakistan is a case in point where agriculture holds immense importance as it accounts for 21.4 percent of the country's GDP and provides employment to 45 percent of its workforce (Pakistan Economic Survey, 2013). Pakistan's rural areas are home to 62 percent of the population, the majority of who derive their livelihoods from agriculture either through farming or through non-farm rural activities. Importantly, the agricultural sector is also a major contributor in exports earnings, a supplier of raw materials to agro-based industries, and a market for industrial outputs like fertilizer and tractors.

During the 'Green Revolution' of the 1960s and 1970s, Pakistan demonstrated that the combination of strategic development policies and appropriate agricultural technologies could be harnessed for growth and development. Agricultural production doubled during an approximately 20-year period, averting food crises and spurring an era of agricultural and economic growth. Partly as a result of these policies and investments, Pakistan's economy grew by 6 percent per annum during the 1980s, driven substantially by agriculture sector growth on the order of 4.1 percent (World Bank). In subsequent years, however, agricultural sector growth has been characterized by a prolonged but irregular deceleration punctuated by occasional booms and busts. Growth in the agricultural sector has decelerated to just 3.1 percent per annum during the past 10 years (Pakistan Economic Survey, 2013). This has given rise to food self-sufficiency concerns as well the ability of the economy to grow at a healthy rate and achieve its development and poverty reduction goals.

A report compiled by the Sustainable Development Policy Institute (SDPI) of Pakistan in 2012 revealed that almost 58.7 million (32 percent) people in Pakistan are living in poverty based on a multidimensional poverty index. The index took into account five areas namely education, health, water supply, sanitation and household assets. In addition people earning less than $1.25 a day were also taken to be below the threshold. Furthermore, the report also disclosed that 46 percent of the rural population falls below the poverty threshold and the issue is further compounded by the fact that those who suffer the most are small or landless farmers. Since most of these people rely on agriculture for income, improving their agricultural productivity and efficiency would address the issue of poverty by augmenting their income.

There is a plethora of literature that provides econometric evidence from country and cross-country studies that supports the theory that agricultural growth has a greater effect on reducing poverty than other sectors because it augments the incomes of the most marginalized that happen to live in rural areas and derive their income from agriculture. Datt and Ravallion (1996) in their study of India show that growth in agricultural productivity led to a reduction of absolute and relative poverty. Fan and Hazell (2001) also suggest that the government should invest in agricultural research to address the issues of poverty. Similarly, Christiansen and Demery (2011) suggest that a 1 percent per capita agricultural growth rate reduces poverty 1.6 times more than corresponding growth in the manufacturing sector and 3 times more than growth in the service sector. A number of studies have also been done on Pakistan which validate the hypothesis that there is an inverse relationship between agricultural growth and the incidence of rural poverty (Ahmad and Ludlow, 1989; Anwar, 1998; Arif et al., 2000; and World Bank, 2002) while Hussain and Khan (2011) used time series data of Pakistan spanning over forty years from 1961-2007 showed that there is a positive correlation between agricultural and GDP growth rate in Pakistan which is significant at the 1 percent level.

Traditional production theory suggests that growth in output can be achieved by increasing input use and moving along the production function or by adopting a better technology that shifts the frontier. Historically, adoption of new technologies has been at the core of discourse regarding improving agricultural productivity to increase the income of farmers (Schultz, 1964; Kuznets, 1966; and Hayami and Ruttan, 1971). Productivity growth has been generally thought of as the difference between the output and input growth rate, thus assuming that technical change is the sole driver of productivity growth. However, adoption of new technologies is not the only path that can result in an increase in production, as the differences among farmers realized and potential yields could also be due to their ability to use new technology and their motivation. Improvements in production efficiency is also an important determinant and can have huge potential benefits not merely in terms of higher output and productivity but also resource conservation. It is often cited in literature that a major source of yield gap among farmers in developing countries is due to the difference in their management practices which then present as technical inefficiency (Fan, 1991; Lin, 1992; Thirtle et al., 1995; and Kalirajan, Obwona and Zhao, 1996). One can observe a variation in yields even among farmers that have land in the same location, similar soil type, access to irrigation, grow same crop varieties and apply similar level of fertilizer. Pingali and Heisey (1999) postulate that such technical inefficiencies can eat away the positive gains from switching to a better technology and a number of studies have found similar results in Pakistan where the advantages of technological improvements were smoothed away due to increasing technical inefficiency (Ahmad and Ahmad, 1998 and Ahmad, 2001). Therefore total production growth can also be attributed to improvement in efficiency in addition to increased output and technological change. This means that it is also important to improve the knowledge base, education, and management skills of farmers along with developing the infrastructure and institutions that assist agriculture to achieve sustained growth (Pingali and Heisey, 1999; Ghura and Just, 1992).The objective of this study is to mea-sure the extent of inefficiency in Pakistan and also determine the factors that drive this inefficiency after controlling observables such as demographics, resource quality, and input technologies.

Pakistan has two primary cropping seasons called 'Kharif' and 'Rabi'. Sowing for kharif starts in April-June and harvesting is done during October-December. Rabi season kicks o_ with sowing starting in October-December and harvesting being done in April-May. Major kharif crops are rice, sugarcane, and cotton while the major rabi crop is wheat. These major crops account for 25.6 percent of the value added in agriculture and 5.4 percent of the GDP (Pakistan Economic Review, 2013). Wheat is the leading cereal crop in Pakistan and contributes about 10 percent to the value added in agriculture and 2.2 percent to GDP. It is also very important as it is the staple diet of the population, and various FAO reports state that it provides about 50 percent of the caloric and protein requirements and 8 percent of the total fat consumed by the people.

This paper looks specifically at wheat to examine technical inefficiency, since it is pivotal to meet the food requirements of a growing population that currently stands at 180 million. Moreover, food items make up 50 percent of the consumption expenditure of rural households and the share of wheat and wheat _our ranges between 9 to 20 percent (Household Integrated Economic Survey, 2012). Therefore, a well performing wheat economy would help prevent price volatility, keep prices affordable, and ensure sufficient supplies of the commodity.

The government normally announces a support price for the crop in order to maintain incentives for producers to expand production and maintain self-sufficiency. This is in confluence with Abbot (1962) who emphasized the need for farmers to have confidence in prices so that they may engage in additional investments that would raise their output and productivity. There is dire need to increase output in order to ensure food self-sufficiency and safeguard the populace from price volatility which was experienced during the 2008 food crisis. Moreover, frontier based expansion models cannot be pursued due to scarcity of arable land and water resources coupled with increasing pressure on land due to a burgeoning population that is growing at 2 percent per annum (Pakistan Economic Survey, 2013).

Table 1 below shows the wheat yield trend for Pakistan over the last 50 year. Even though yield has improved over the years and Pakistan is among the top ten wheat producers of the world but the yield per hectare is still below than that of other neighboring countries and pales in comparison to other top ten countries such as France and United Kingdom.

Table 1: Wheat Yield Trend (kg/ha)

Year	Bangladesh	China	India	Pakistan
1961	570	560	850	820
1970	870	1150	1210	1170
1980	900	1890	1440	1570
1990	1500	3190	2120	1820
2000	2210	3740	2780	2490
2010	2400	4750	2840	2550
2013	3010	5050	3150	2790

Source: FAO STAT

Nevertheless, it would be wrong to assume that the farmers in Pakistan are unambiguously inefficient based on these figures. The yield gaps among these countries could be solely due to factors such as technology, cultivars, management practices, and climatic conditions. However, there is also a significant difference among the yields of farmers and the yields that have been achieved in field demonstrations and experiments. According to Pakistan Agricultural research council (PARC) the improved varieties of wheat available in Pakistan have a genetic yield potential of around 6 to 8 tons per hectare and progressive farmers in irrigated parts of the country have been able to harvest 6 to 7 tons per hectare, while the average farmer's yield lags behind at roughly 3 tons per hectare (as shown in Table 1 above).

This study aims to update the existing literature on efficiency studies in Pakistan. Moreover, there is a dearth of studies that have tried to estimate efficiency of farmers at a national level as most of the studies have been limited to a few districts within a province. The only studies (that I am of aware of) that have aimed to rank the efficiency of farmers across the provinces and compare their sources of efficiency were based on an IFPRI panel that was collected from 1986-91. However, this study was also limited as the data was collected from four poorest districts; one district from each of the four provinces. The current study adds to the existing literature by carrying out an efficiency analysis that can be considered to be more representative of the farmers in the country as it uses data from 19 districts from all over the country (sampling detail is in the data section). The study will rank the wheat growing farmers across the provinces and also estimate the sources that are driving this inefficiency. This would be helpful in designing targeted policy that aims to improve the efficiency of farmers instead of solely focusing on reducing the cost of production by subsidizing inputs and providing incentive to adopt new technology. Another objective of this study is to identify the major sources of technical inefficiency and compare them to the findings of prior studies conducted in Pakistan (Ali and Flinn, 1989; Battese et al., 1993; Parikh and Shah, 1995; Battese and Broca, 1997; Ahmed et al., 2002). This would inform us whether the institutional, resource, or infrastructure constraints faced by farmers over the years have remained the same or the issues hampering growth have evolved and a change of policy is needed. This can also be thought of as an indirect measure of the efficacy of the agricultural policies being adopted by the government. However, one must be careful in interpreting this comparison as this study does not track the same household that were surveyed earlier which would be an ideal way to analyze the success of government policy. However, one can safely conjecture whether the problems faced by the farmers are on average similar to those that they have been facing over the years. This study also attempts to address the concerns regarding the reliability of the results given by stochastic frontier analysis. A major concern regarding the soundness of the results is their sensitivity to functional forms, distributional assumptions, and the input/output measure used. This partly stems from the fact that most of the analysis done using this methodology has been done at an aggregated level, however this study is based on data collected at plot level which allows me to carry out the analysis at a more micro level and overcome the problem to some extent.

The rest of the paper is structured as follows: section 2 provides a brief literature review of the stochastic frontier methodology followed by the findings and methodology of previous frontier production studies on Pakistan; section 3 gives a brief overview of prior studies; section 4 explains the survey and data collected; section 5 discusses the econometric model used; section 6 states the empirical results; and section 7 provides the conclusion.

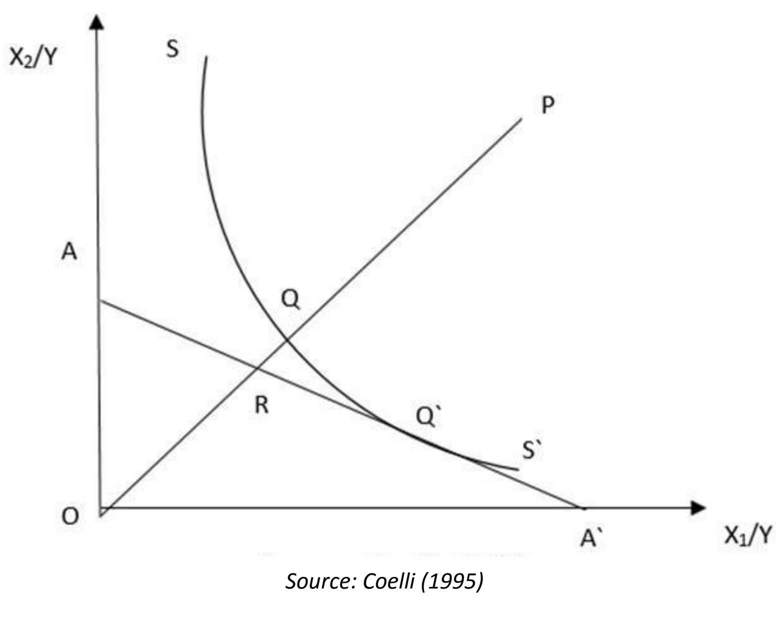
Literature Review

There are numerous studies that have aimed to measure production efficiency and attempted to identify bottlenecks that limit production efficiency of farmers. When it comes to literature on efficiency, stochastic frontier analysis is the main methodology which uses econometric estimation to analyze production relation-ships. Most of these frontier models are based off the seminal paper written by Farrell in 1957.

Background

Farrell (1957) introduced a simple two input frontier model that made use of the efficient unit isoquant to measure economic efficiency. He suggested that the economic efficiency of a firm was composed of two factors technical and allocative efficiency. Technical efficiency reflected the firm's ability to produce the maximum output given a set of inputs and technology. Allocative efficiency on the other hand depicted the ability of a firm to utilize inputs in optimal ratios that is where the ratio of marginal product of two inputs should equal the ratio of their prices. The unit isoquant of the most efficient firm was given by SS' and the input price ratio by AA', shown in Figure 1.

Figure 1: Technical and Allocative Efficiency



Source: Coelli (1995)

A firm using inputs in the line segment QP to produce a unit of output is inefficient because the same output can be produced with lower levels of input. Similarly if the price ratios of the inputs are known then allocative efficiency can be calculated, if a firm is at the point Q then it is technically efficient but allocatively inefficient as the same output can be produced at a lower cost by substituting the two. Hence economic efficiency in Farrell's framework was a product of both technical and allocative efficiency. However, the production function of the fully efficient firm is not known in practice and the efficient isoquant has to be estimated from the sample data. Farrell proposed two options (i) a non-parametric approach which required the construction of linear convex isoquants such that all observed data points were to the left or below it or (ii) a parametric approach whereby a Cobb-Douglas function was fitted on data such that no observed point is to the left or below it.

Farrell's work was later on extended and developed by a number of authors who made a number of adjustments in the original model. Aigner and Chu (1968) introduced deterministic parametric methodology and estimated a Cobb-Douglas production function through linear programming for a sample of N firms:

$$\ln y_i = F(x_i; \beta) - u_i \quad , i = 1 \dots N \tag{1}$$

where y_i is the output of the i-th firm, x_i is the vector of inputs, β is a vector a parameters which have to be estimated, F(•) is the specified function (Cobb-Douglas in this case), and ui is a non-negative variable denoting inefficiency.

$$TE = \frac{y_i}{\exp(F(x_i; \beta))} = \exp(-u_i) \tag{2}$$

Technical efficiency of a firm was derived by calculating the ratio of the observed output of a firm relative to the maximum that could be achieved given a set of inputs, as suggested by the frontier. TE=1 if the producer achieves maximum possible output and TE<1 otherwise. A major difference in this approach compared to Farrell's was that this was output based approach rather than input based. That is instead of stating how much input can be reduced to produce a given output it focused on what was the maximum that could be produced with given inputs and technology.

Afriat (1972) also developed a model similar to Aigner and Chu but the inefficiency term was assumed to have a gamma distribution and the parameters were estimated using maximum likelihood (ML). Richmond (1974) suggested that the model proposed by Afriat could also be estimated by corrected ordinary least squares model. This was done by using the moments of distribution error to adjust the downward bias in the intercept estimate produced by simple OLS regression. Schmidt (1976) further contributed on the use of ML suggesting that the linear programming technique suggested by Aigner and Chu was in fact a ML estimation provided the disturbance term had a half normal or exponential distribution.

A major drawback of the above mentioned deterministic models is that they attribute all deviation from the frontier to inefficiencies. They do not account for measurement errors or factors that are beyond the control of the _rm. This is particularly relevant in the case of agriculture where output does not only depend on the ability of the farmer and the choices he makes but also on the external shocks like flood, pest attack, drought, etc. Another factor to be considered is the choice of parametric or non-parametric techniques. Non-parametric techniques tend to be extremely sensitive to outliers which can lead to incorrect efficiency estimates. Conversely, parametric frontiers models use specific functional forms but they run the risk of being overly restrictive. However, the crucial advantage that parametric techniques have over non-parametric is that they allow for statistical inference and one can run tests for various efficiency hypotheses and also validate functional specification fitted on data.

Timmer (1971) tried to overcome the deficiencies in deterministic models by developing a probabilistic frontier model. This method involved dropping of extreme values at each stage and re-estimating the model until the estimates stabilized. However, this technique has not been widely followed as the observations dropped at each step are selected arbitrarily without any economic or statistical reasoning. An alternative method called stochastic frontiers, however, has been adopted as a solution which accounts for statistical noise.

Cross-Section Data Stochastic Frontiers

Stochastic frontier model was independently proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). The model is given as follows:

$$\ln y_i = F(x_i; \beta) + v_i - u_i \quad , i = 1 \ldots N \tag{3}$$

where $F(x_i; \beta) - u_i$ is the deterministic part, v_i is the symmetric, identically and independently distributed term, u_i is a non-negative distribution independent of v_i denoting inefficiency, both v_i and u_i are independent of x_i.

Aigner, Lovell, and Schmidt assumed that v_i had a normal distribution as $N(0, \sigma_v^2)$and u_i could be either half-normal or exponential. This extension was developed based on the idea that output of a firm depends on two distinct disturbances. The one-sided u_i assumes that a firm ought to be operating on the frontier and any deviation is due to inability of the producer to use his factors of production efficiently. However, the frontier on the other hand can vary between firms or for the same firm over time due to external factors which are beyond the control of the firm. Hence $v_i \lesseqgtr 0$captures exogenous random shocks, measurement errors and other statistical noise. Therefore technical efficiency should now be measured by the following ratio:

$$TE = \frac{y_i}{F(x_i; \beta) + v_i} \tag{4}$$

Stochastic frontiers not only resolved the issue of statistical noise but allowed estimation of standard errors and confidence intervals which could not be performed with deterministic models as they violated some ML regulatory conditions (Schmidt, 1976). However, this does not imply that this methodology does not have any shortcomings. One critique is the a priori selection of a distribution term for u_i, this can be addressed to an extent by opting for more general forms such as truncated normal or gamma but the efficiency measures can still be affected by the distribution chosen. Another critique is regarding the choice of the functional form used in the models- this will be discussed in detail later.

An important feature of stochastic frontiers is the assumption that u_i is one sided which can make the total error term $[\varepsilon_i = (v_i - u_i)]$ asymmetric and not normal. This means that the OLS estimator will be inefficient. Given the assumptions that both disturbance terms are independent of x_i. estimation by OLS will give us consistent estimates for the $\beta_i' s$ except for the intercept. Moreover it will also not give us producer specific efficiency measures. However, we can test the skewness in the total error term using the OLS residuals. Schmidt and Lin (1984) proposed a test statistic

$$(b_1)^{1/2} = \frac{m_3}{(m_2)^{3/2}} \tag{5}$$

where m_2 and m_3 are the second and third moments of the OLS residuals.

A negative m_3 represents presence of technical inefficiency while a positive value suggests that the model is incorrectly specified. Coelli (1995), however proposed an alternative test as the distribution of $(b_1)^{1/2}$ is not widely published.

$$(b_1)^{1/2} = \frac{m_3}{(6m_2^3/N)^{1/2}} \tag{6}$$

This test statistic is asymptotically distributed as standard normal distribution and N is the number of observations. Asymmetry is a vital component of this model and its magnitude is measured by the relative variability of the two disturbance terms.

$$\lambda = \frac{\sigma_u}{\sigma_v} \tag{7}$$

A value of $\lambda \to 0$ implies that either $\sigma_u \to 0$ and/or $\sigma_v \to \infty$,, this suggests that the symmetric error term dominates the distribution of ε and we have an OLS model. On the other hand if $\lambda \to +\infty$ it implies that either $\sigma_u \to \infty$ and/or $\sigma_v \to 0$ in which case we have a deterministic model. It would be appropriate to test the hypothesis that the deviation from the frontier is entirely due to noise $\lambda = 0$, entirely due to technical inefficiency $\lambda = 1$ or a mixture of both $0 < \lambda < 1$. Hypothesis testing can be done using the Wald or likelihood ratio tests.

Estimation Methods

Corrected Ordinary Least Squares (COLS) and Maximum Likelihood (ML) estimation are the two most common methods used for estimating frontier functions. ML method is used if the distribution of the error term is explicitly assumed because it takes into account the distribution terms and is therefore more efficient at least asymptotically (Greene, 1980). An overview of both methods is presented below.

Corrected Ordinary Least Squares

As described above estimation of a stochastic frontier requires a set of strict assumptions regarding the distribution of inefficiency term and the statistical noise term. In addition, it also requires that the inefficiency term is independent of the input variables which is an unrealistic assumption as purported by Schmidt and Sickles (1984). According to them if a firm is aware of their technical inefficiency they will subsequently select their inputs in a manner which ameliorates the scenario. Nevertheless, given the set of assumption OLS regression will produce BLUE estimates for the slope parameters but the intercept would be biased. Winsten (1957) in his review of Farrell's paper suggested that this problem could be correct using a two-step approach. In the first step OLS can be used to estimate $\beta' s$ and the consistent but biased intercept. The intercept can then be corrected by shifting it upwards so that no data point is beyond the frontier. This is done by adding the maximum value of the OLS residual to the estimated intercept $\widehat{\alpha^*} = \hat{\alpha} + \max_i(\hat{u}_i)$. Afriat (1972) and Richmond (1974) suggested a slight variation of this method and proposed that the intercept be correct with the expected value $\hat{\alpha}^{**} = \hat{\alpha} + E(\hat{u}_i)$.

This procedure is relatively easy but it does not guarantee that the new frontier will shift enough that all data points are bounded from above. Nevertheless, a major drawback of both these fixes is that the adjusted frontier is parallel to the original OLS as only the intercept has been changed. This means that the structure of the best firm is the same as the one on average, which is a highly unrealistic constraint. In addition, even though the parameter estimates obtained from the methods above are consistent but they are still inefficient.

Maximum Likelihood

The maximum likelihood (ML) on the other hand takes into account the distribution terms and is more efficient at least asymptotically (Greene, 1980). The log-likelihood function was derived by Ainger et al. (1977) and the estimates of $\beta, \sigma^2, \text{and } \lambda$ are calculated by the following equations.

Under half normal distribution of $u_i \sim N^+(0, \sigma_u)$

$$\ln L\,(y|\alpha, \beta, \lambda, \sigma^2) = N\ln\frac{\sqrt{2}}{\sqrt{\pi}} + N\ln\sigma^{-1} + \sum_{i=1}^{N}\ln[1 - \Phi(\varepsilon_i\lambda\sigma^{-1})] - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\varepsilon_i^2 \qquad (8)$$

where λ is the ratio defined in (7), $\sigma = \sigma_u^2 + \sigma_v^2$, and Φ is the standard normal cumulative distribution.

Under truncated normal distribution of $u_i \sim N^+(\mu, \sigma_u)$

$$\ln L\,(y|\alpha, \beta, \lambda, \sigma^2) = -\frac{N}{2} - N\ln\sigma - N\Phi\left(\frac{-\mu}{\lambda\sigma}\right) + \sum_{i=1}^{N} \ln \Phi\left(\frac{-\mu\lambda^{-1} - \varepsilon_j\lambda}{\sigma}\right) - \frac{1}{2\sigma^2}\sum_{i=1}^{N} \varepsilon_i^2 \quad (9)$$

Under exponential distribution $u_i \sim Ex(\theta), \theta = \sigma_u^{-1}$

$$\ln L\,(y|\alpha, \beta, \lambda, \sigma^2) = -N\left(\ln\sigma_u + \frac{\sigma_v^2}{2\sigma_u^2}\right) + \sum_{i=1}^{N} \ln \Phi\left(\frac{-\varepsilon_i}{\sigma_v} - \lambda^{-1}\right) + \sum_{i=1}^{N} \frac{\varepsilon_i}{\sigma_u} \quad (10)$$

Coelli (1995) conducted a Monte Carlo analysis to investigate the _nite sample properties of ML and COLS and found that ML is considerably better than COLS especially when the one-sided component dominates the total error term. He recommends using ML estimator over COLS and using one-sided likelihood ratio test instead of Wald test or tests based on the third moment of OLS residuals due to the correct size and superior power of one-sided likelihood ratio test.

Measurement of Technical Efficiency

The next matter of interest is to use the stochastic frontiers to obtain producer level inefficiency estimates. This initial problem was overcome by the work of Jondrow et al. (1982) using the conditional distribution of u_i given ε_i. He showed that if u_i followed a $N^+(0, \sigma_u)$ distribution then $(u_i|\varepsilon_i)$ was distributed as $N^+\left(u^*, \sigma^{*2}\right)$ and the mean of this distribution could be used as point estimate. Once these estimates are calculated technical efficiency of each producer can be derived.

$$TE_i = \exp(u_i) \quad (11)$$

where $u_i = E(u_i|\varepsilon_i)$.

Battese and Coelli (1988) suggest an alternate point estimate for TE

$$TE_i = E[\exp(u_i)|\varepsilon_i] = \frac{[1 - \Phi(\sigma^* - u_i^*/\sigma^*)]}{[1 - \Phi(-u_i^*/\sigma^*)]} \exp\left[-u_i^* + \frac{1}{2}\sigma^{*2}\right] \tag{12}$$

where $u_i^* = \varepsilon\sigma_u^2/(\sigma_u^2 + \sigma_v^2)$ and $\sigma^{*2} = \sigma_u^2\sigma_v^2/(\sigma_u^2 + \sigma_v^2)$

The estimate suggested by Battese and Coelli performs better when u_i is not close to zero. But whichever method is used the estimates produced are inconsistent because the variation in $(u_i|\varepsilon_i)$ is assumed to be independent of i. It is possible to calculate confidence intervals but Kumbhakar et al. (1998) in their Monte Carlo study find that there is a negative bias in the estimated efficiencies and intervals. However, he reports that this bias decreases as the number of observations increase and that the point estimates perform better than interval estimates.

The efficiency measures discussed above are based on the assumption that the inefficiency term follows a half-normal distribution. This distribution is commonly used as it is both practical and reasonable. But this raises the question that do the efficiency scores generated change when different distributions are assumed and which one is correct. There is ample literature which shows that the efficiency estimates are sensitive to the distributional assumption of u_i. Greene estimated frontiers for U.S. electric utilities and used four one-sided distributions- gamma distribution, truncated normal, exponential, and the half normal. He finds out that even though the efficiency scores change but the efficiency ranking of producers is not sensitive to the distributions assigned to the efficiency term. Hence, he suggests using simple half-normal or exponential distributions rather than flexible and complicated ones such as gamma.

Meesters (2014) shows that exponential and half-normal distributions are captured by the truncated normal distribution. Moreover, the paper shows that one can run into non convergence of the optimization if the inefficiency component is defined as a truncated normal but the underlying data is exponentially distributed. Meester suggests that this means assuming truncated normal or exponential distribution is more a matter of convergence rather than the distribution of the inefficiency component.

Panel Data Stochastic Frontiers

Three major constraints of the stochastic frontiers discussed above are:

1. Assumption regarding the distribution of statistical noise and the inefficiency term.
2. Technical efficiency error to be independent of the regressors.
3. In ability to measure producer level technical efficiency consistently.

These short coming can be overcome if panel data is used as it has more observations about the same unit over a period of time. We can now relax the strong distributional assumptions regarding the error term as the repeated observations of a unit allows us to substitute that requirement. In addition, independence of technical efficiency from the regressor terms is also not required. Moreover, availability of multiple observations on a single unit also helps to obtain more consistent and precise inefficiency estimates.

The general panel stochastic frontier model is of the form

$$\ln y_{it} = F(x_{it}; \beta) + v_{it} - u_{it} \quad , i = 1 \dots N; \;\; t = 1 \dots T \tag{13}$$

There are two common variants of this model; one assumes the inefficiency for individual producers to be fixed over time while the other one allows for inefficiency to vary. The former makes sense if the panel is not long. However, long panel data is usually not available for developing countries and hence it is more relevant.

Time In-Variant Technical Inefficiency

A general model for time variant efficiency can be written as

$$lny_{it} = \alpha + \beta lnx_{it} + v_{it} - u_i \quad ,i = 1 \dots N; \; t = 1 \dots T \tag{14}$$

Fixed Effects Model

The simplest panel data model is the fixed effects model and the above general model can be adapted to it by assuming that $\mathrm{v_{it}}$ to be i.i.d. $(0, \sigma_v^2)$ and not correlated to the inputs. No restriction is imposed on the distribution of the inefficiency term and it is allowed to be correlated with the regressors. Since we are holding the inefficiency to be constant for each time period the model can be defined as

$$lny_{it} = \alpha_i + \beta lnx_{it} + v_{it} \tag{15}$$

where $\alpha_i = \alpha - u_i$ is the producer specific intercept and the model is estimated by OLS and the fixed effects estimator is derived which is consistent if either N or T go to infinity.

The frontier is then normalized with the best fixed effects estimator $\hat{\alpha} = max_i(\hat{\alpha}_i)$ and the technical efficiency estimated as $\hat{u}_i = \hat{\alpha} - \hat{\alpha}_i$. However a problem with this approach is that $\hat{u}_i$ along with capturing the time-invariant technical efficiency across producers also captures all other factors that vary among producers and shows it as inefficiency. This problem can be overcome by using a random effects model.

Random Effects Model

Unlike the fixed effects model under this framework we allow the inefficiency term to vary randomly but we assume that it is uncorrelated with the regressors and the statistical noise term. We maintain the assumption that $\mathrm{v_{it}}$ is i.i.d. $(0, \sigma_v^2)$ and no distribution is imposed on the error terms. The model can be written as

$$\ln y_{it} = \alpha^* + \beta \ln x_{it} + v_{it} - u_i^* \tag{16}$$

where $\alpha^* = \alpha - \mu$, $\mu = E(u_i)$, and $u_i^* = u_i - \mu$.

This model is estimated using the two step Generalized Least Square (GLS) estimator. In the first step OLS is used to estimate all parameters after which the two variance components are estimated. The second step is to use the variances to re-estimate the parameters using feasible GLS which gives us consistent estimates as if both N and T are large. Measurement of technical efficiency is done using the average values of FGLS residuals and the estimator is $\hat{u}_i = \hat{\varepsilon}_i^* - \hat{\varepsilon}_i$ and $\hat{\varepsilon}_i^* = \max(\hat{\varepsilon}_i)$.

Maximum Likelihood

The above methods show that using panel data one can either relax the distribution assumption or the independence assumption. However, if the two restrictions are reasonable then we can carry out maximum likelihood estimation. Moreover, since we are using panel data the estimated parameters will be more efficient. Battese and Coelli (1988) estimator given in equation (12) can be generalized for panel data under the assumptions taken for cross-sectional data.

The three methods detailed above impose very different properties and restrictions on the data. One can choose amongst the three based on data, for instance if N is large and T is small one should prefer the random effects model over the other two. Similarly, if it is reasonable to assume that the error terms are independent of the regressors, then ML estimation will be more efficient as it makes use of the distribution densities imposed. There have been a few studies where the three approaches have been compared empirically, for example Ahmad and Bravo-Ureta (1996) compared 17 fixed effects and ML models on dairy farms and found that the two approaches yield similar results in terms of efficiency correlation and efficiency ranking.

Time Variant Technical Inefficiency

A general model for time variant efficiency can be written as

$$\ln y_{it} = \alpha_{it} + \beta \ln x_{it} + v_{it} \quad (17)$$

where $\alpha_{it} = \alpha_t - \mu_{it}$ and $\mu_{it} \geq 0$ and the inefficiency terms can be computed by $\hat{u}_{it} = \hat{\alpha}_t - \hat{\alpha}_{it}$ and $\hat{\alpha}_t = \max_i[\hat{\alpha}_{it}]$

Fixed and Random Effects Model

Similar to the time invariant model, fixed and random effects approach can be used to estimate the time varying model. Cornwell et al. (1990) proposed a model in which the intercepts depended on a number of observables ω_t and δ_i fixed effects.

$$\alpha_{it} = \delta_i \omega_t = (\delta_{i1}\ \delta_{i2}\ \delta_{i3}) \begin{pmatrix} 1 \\ t \\ t^2 \end{pmatrix} \quad (18)$$

However, since time-invariant regressors cannot be included in a fixed effects model a GLS random effects estimator was developed by Cornwell et al. (1990) that could incorporate time-invariant regressors in the time varying efficiency model. However, this model produced inconsistent results if the technical efficiency was correlated to the independent variables. Lee and Schmidt (1993) proposed an alternative in which the term μ_{it} in equation (17) is defined as $\mu_{it} = (\sum_{t=1}^{T} \beta_t d_t)\mu_i$ where d_t is a dummy variable for time. This formulation is more flexible than the one proposed by Cornwell et al. as it does not restrict the temporal pattern of μ_{it} but it does require the t to be the same for all producers. This model is preferable if the panel is short and once the t and μ_{it} have been estimated one can form the expression

$$\mu_{it} = \max_i\{\hat{\beta}_t \hat{\mu}_i\} - (\hat{\beta}_t \hat{\mu}_i) \quad (19)$$

Technical efficiency can be calculated as $TE_{it} = \exp -\mu_{it}$

Maximum Likelihood

If the independence and distribution restrictions can be imposed on the error terms then ML method can be used. Kumbhakar (1990) proposed that the inefficiency term be defined as

$$\mu_{it} = \mu_i \left(1 + \exp(\delta_1 t + \delta_2 t^2)\right)^{-1} \quad (20)$$

Battese and Coelli (1992) recommended an alternative

$$\mu_{it} = \mu_i \left(\exp\left(-\delta(t - T)\right)\right) \quad (21)$$

Kumbhakar's functional form required the estimation of δ_1 and δ_2 which determine whether β_t increasing/decreasing and concave/convex. The value of β_t lies between zero and one and a test of null hypothesis for time-invariant technical efficiency can be done by making $\delta_1 = \delta_2 = 0$.

Battese and Coelli only require one additional parameter to be estimated and β_t can take any positive value if $\delta > 0$ and the function decreases at an increasing rate. If $\delta < 0$ then β_t increases at an increasing rate. Battese and Coelli (1992) model was further generalized by Cuesta (2000) who allowed all producers to follow their own temporal inefficiency pattern where the producer specific parameters ξ_i are allowed to vary with time and

$$\mu_{it} = \mu_i \times \exp[-\xi_i(t - T)] \quad (22)$$

However, a major drawback of this model is the difficultly to estimate it, especially when the number of firms is large (Carroll et al., 2011). Another variant of technical efficiency was given by Kumbhakar and Hjalmarsson (1991)

$$\mu_{it} = \alpha_i + \xi_{it} \quad (23)$$

The technical inefficiency term ξ_{it} is assumed to be distributed as half normal, producer specific errors are given by α_i (random or fixed). Estimation is carried out in two steps, the first step involves obtaining all parameters of equation. In the next step distributional assumptions on the error terms are imposed and the fixed effects $\alpha_i + \beta_0$ along with the parameters v_{it} and ξ_{it} are estimated using a maximum likelihood using the estimation from the first step. This model splits time-invariant heterogeneity α_i from time varying inefficiency ξ_{it} but the heterogeneity term would capture elements of inefficiency if they are also time invariant (Kumbhakar and Lovell, 2003).

The true fixed and random effect models given by Greene (2005) also aim to address the issue of heterogeneity being captured in the inefficiency term. The concept is similar to that of Kumbhakar and Hjalmarsson (1991) but the estimation procedure is different. Under the fixed effects model the unobserved heterogeneity is directly captured in the production function by using a producer specific dummy variable

$$\ln y_{it} = a_i + \sum_{k=1}^{K} \beta_{ik} \ln x_{kit} + v_{it} - u_{it} \tag{24}$$

where a_i is the producer specific dummy and the efficiency term varies with time.
The model is estimated using a one-step maximum likelihood approach, however, whether the term captures time invariant heterogeneity is still a matter of contention. For example if some of the some of the factors which result in poor efficiency are time invariant(skill of the plot manager) then that effect might be captures by a_i and the inefficiency effect for such a firm will be downward biased and vice versa. The true random effects model is similar but the only difference is that the heterogeneity is assumed to be uncorrelated with the input variables.

$$\ln y_{it} = (\alpha_i + \theta_i) + \sum_{k=1}^{K} \beta_k \ln x_{kit} + v_{it} - u_{it} \tag{25}$$

Carroll et al. (2011) estimate the inefficiency and productivity of Irish farms using the Greene's true effects models and compare it with those of Battese and Coelli (1992). They find significant differences between the mean and distribution of the inefficiency scores but all models showed similar trends in total factor productivity. They try to identify the most apt approach and test for theoretical consistency of the models and prefer the true effect models as they had less violations and produced a greater percentage of significant parameters.

Determining Sources of Inefficiency

Once it has been identified that inefficiency exists in a production process the next most important consideration is the identification of factors which lead to this inefficiency, in order to advice relevant policy interventions. A number of studies have done this in two stages where the predicted inefficiencies derived in the first stage are regressed with firm specific factors. This approach has serious drawbacks and Schmidt (2011) highlights three problems with two stage estimation:

1. The estimated frontier is biased if x and z are correlated and z matters

This is because of the potential omitted variable bias because we estimate the frontier and derive the inefficiency term assuming that it is independent but then it is regressed on a number of variables assuming that it depends on them.

2. We underestimate the effect of explanatory variables on u

This can be explained by the fact that $\hat{u}_i$ is a shrinkage of $\varepsilon_i = y_i - x_i'\hat{\beta}$ and that depends on the relative variance of u and v. We need to shrink more when the variance of the inefficiency term is relatively small to the variance of the stochastic term. However, if we shrink all the observations by the same variance then $\hat{u}_i$ would be under dispersed and we would under estimate the effect of the explanatory variables.

3. Testing whether the distribution of u is independent

These issues can be overcome by specifying functions that explicitly include firm specific effects in the inefficiency equation, and estimating the parameters simultaneously (Battese and Coelli, 1995). This is achieved by the following expression

$$\mu_{it} = \delta z_{it} + \omega_{it} \tag{26}$$

where z_{it} is a vector of explanatory variables associated with technical inefficiency, δ is a vector of unknown coefficients and ω_{it} is a random variable truncated with zero mean and variance σ_u^2 such that the point of truncation is $-\delta z_{it}$.

Distance Functions

Distance functions are a useful tool to characterize the structure of multi-input multi-output production technologies. An important aspect of distance functions is the application of the duality theory as under certain assumptions an input distance function is the dual to a cost frontier and an output distance function is the dual to a revenue frontier. Hence they are useful in cases where we do not have information on prices or we cannot impose behavioral assumptions such as cost minimization or revenue maximization (Coelli et al., 2005). Distance functions can be classified into two major categories, namely, Input distance functions and output distance functions. Input distance functions describe the input set and illustrate the extent to which a firm can reduce inputs without affecting its output. Output distance functions on the other hand describe the output set and explain the extent to which output can be increased without changing input. Input distance functions are preferred over output distance functions when the producer has more control over inputs and vice versa. Coelli & Perelman (1996) have discussed both input and output distance functions in adequate detail.

An input distance function for N inputs and M outputs can be described as

$$\mathrm{d}_i^I = \mathrm{d}^I(x_{1i}, x_{2i}, x_{3i} \dots \dots, x_{Ni}; q_{1i}, q_{2i}, q_{3i} \dots \dots, q_{Mi}) \tag{27}$$

where x_{ni} is the n-th input and q_{mi} is the m-th output of firm i, $d_i^I \geq 1$ is the max that the input vector can be contracted equiproportionality without reducing the output and vice versa.

The techniques of estimating stochastic production functions described earlier can be extended to distance functions. However, it is not as easy it seems because there is no natural dependent variable, another issue may be the correlation of independent variables with the error term which would violate one of the basic tenets of stochastic frontier theory and lead to biased estimates. The issue of endogeneity of regressors and failing to satisfy the regulatory conditions of concavity and quasi-concavity still holds as well. However, a range of options are available through which one could overcome these problems as the regulatory conditions can be imposed using the beysian technique suggested by O'Donnell and Coelli (2005). We can also normalize the inputs which would allow us to compare the returns for different inputs, for example if we opt for a cobb-douglas model then the distance function can be written as

$$\ln d_i^I = \beta_0 + \sum_{n=1}^{N} \beta_n \ln x_{ni} + \sum_{m=1}^{M} \varphi \ln q_{mi} + v_i \tag{28}$$

where v_i captures statistical noise and measurement error.

The above model is nondecreasing, linearly homogenous, and concave in inputs if all $\beta's > 0$ and $\sum_{n=1}^{N} \beta_n = 1$. Then by rearranging we can get

$$\ln x_{Ni} = \beta_0 + \sum_{n=1}^{N-1} \beta_n \ln\left(\frac{x_{ni}}{x_{Ni}}\right) + \sum_{m=1}^{M} \varphi \ln q_{mi} + v_i - u_i \tag{29}$$

This function can now be estimated using the maximum likelihood method discussed earlier and an input-oriented technical efficiency term can be derived by

$$TE = \frac{1}{d_i^I} = \exp(-u_i) \tag{30}$$

Distance functions have a variety of applications and Coelli & Perelman (2000) deliberate on the various methods to estimate stochastic frontier distance functions. Distance functions have a range of applications and parametric distance functions have been used to measure firm specific technical efficiency (Coelli and Perelman 2000) and decompose growth over time (Fuentes et al., 2001). In addition to these distance functions have also been used to investigate shadow prices (Swinton, 1998) and substitutability of outputs (Grosskopf et al., 1995). Most applications of distance functions have used translog production functions imposing monotonicity and homogeneity. However, many researches have not made an attempt to impose curvature conditions due to its complexity. This violation of economic theory leads to incorrect shadow prices and elasticities. Depending on the extent of departure from the true values these one may end up making incorrect conclusions and perverse policy recommendations regarding efficiency and growth.

As mentioned earlier that one can also derive shadow prices which can then be compared with observed prices to determine allocative efficiency-regarding the mix of inputs and outputs. This information can also be used to decompose productivity growth into its components. Brummer et al. (2002) disaggregated productivity growth using total differential method into four components namely technical change, technical and allocative efficiency, and scale efficiency. Elasticities and shadow share information can also be obtained from distance functions, however, one must be certain of the fact that estimated distance function satisfies the monotonicity and curvature conditions. Monotonicity violations can result in incorrect elasticities and curvature violations can lead to the frontier being convex to origin, furthermore the shadow prices could also be incorrectly signed. O'Donnell & Coelli (2005) show how Beysian approach can be used to impose these constraints on the parameters of a translog output distance function.

Cost and Revenue Frontiers

If information on input and output prices is available and we can impose a behavioral of cost minimization then we can achieve measures of economic efficiency against which the performance of a firm can be measured. When input prices are available we can measure the cost efficiency of producer, we assume that the producer faces a vector of strictly positive input prices given by w and he aims to minimize the cost of producing and output vector y using an input vector x.

Then an input set or an input distance function can be used to develop a cost frontier. The cost frontier represents the minimum cost of producing a scalar quantity of output given input prices and hence is the standard against which cost efficiency is measured. It is given by the ratio of the minimum cost to observed cost, however, all cost inefficiency cannot be attributed to technical efficiency as it is the product of allocative and technical efficiency as stated by Farrell. For example if we assume two input vectors $\hat{x}$ & $\tilde{x}$ represent the technically efficient and cost minimizing vector to produce a given output. Then

$$\text{Cost Efficiency} = {}^{w\tilde{x}}/_{wx} \;\; ; \;\; \text{Allocative Efficiency} = {}^{w\tilde{x}}/_{w\hat{x}} \, ;$$

$$\text{Technical Efficiency} = {}^{w\hat{x}}/_{wx}$$

Under certain properties the cost frontier is a dual to the input distance function and the two are equivalent representations of the same production technology assuming cost minimization behavior and exogenously given prices (Coelli, 2005). Similarly when information in output prices is available and one can assume the behavioral assumption of revenue maximization then economic efficiency is measured against the revenue frontier. The structure is essentially the same as cost frontier where in this case p is a vector of output prices and $q, \hat{q}$ & $\tilde{q}$ represent the observed output, technically efficient and the revenue maximization output vector. Then

$$\text{Revenue Efficiency} = {}^{pq}/_{p\tilde{q}} \;\; ; \;\; \text{Allocative Efficiency} = {}^{p\hat{q}}/_{p\tilde{q}} \,;$$

$$\text{Technical Efficiency} = {}^{pq}/_{p\hat{q}}$$

Profit Frontier

Stochastic frontier techniques based on production functions to estimate technical and allocative efficiency under the primal and dual settings have some limitations. They assume that inputs are exogenous and independent of inefficiency. This issue can be addressed by imposing the behavioral assumption of profit maximization were both inputs and outputs are considered endogenous. This approach is better than assuming cost minimization as the latter also assumes output to be exogenous.

Kumbhakar (2001) uses a profit maximizing framework assuming that the producer is unable to attain to maximum profit due to technical inefficiency or allocative efficiency or both. It is shown that when one uses profit functions where producers are inefficient as compared to profit frontiers the input demands, output supplies, elasticities, and returns to scale are not the same. This is because the frontier is not a neutral transformation of the augmented inefficient production function. It is also shown that in general total profit efficiency is not a product of technical and allocative profit efficiency, however, there might be cases where this decomposition still holds.

The profit function in the presence of both technical and allocative efficiency can be written as $\pi(w, p, u, \theta) = \pi(w^s, pe^u)$ where $w^s = \left(w_1^s, \ldots., w_j^s\right)$ is the shadow input price vector. The production function is given by $f(x) = ye^{-u}$ and the first order condition of profit maximization can be expressed as $f_j(\cdot)pe^u = w_j^s$ where the shadow price of input j is described as $w_j^s = \theta_j w_j$.

Hotelling's lemma can be applied to derive the input demand and output supply functions and their elasticities and returns to scale can also be calculated by taking derivatives of the share equations. Actual profit π^a can be expressed as $\pi^a = py - wx \equiv \pi(w^s, pe^u) \cdot H\,(w, p, u, \theta)$ and it can be shown that this is less than the maximum $\pi(w, p)$ due to the presence of technical and allocative efficiency.

In order to estimate the profit function stated above we need to have a parametric specification on $\pi(w^s, pe^u)$ and a translog form is preferred and it imposes minimal a priori restrictions. If we assume producers to be only technically inefficient then the profit function can be written as

$$\ln\left(\frac{\pi^a}{p}\right)\pi = u + \beta_0 + \sum \beta_j \ln\left(\frac{w_j}{pe^u}\right) + \frac{1}{2}\sum_j \sum_k \beta_{jk} \times \ln\left(\frac{w_j}{pe^u}\right)\ln\left(\frac{w_k}{pe^u}\right) \qquad (31)$$

Using Hotelling's lemma one can derive share cost equations from the profit function. Under the panel setting if we assume that technical efficiency is time invariant, then we can estimate it without making any distributional assumptions. We can use the system consisting of the profit function and the cost share equations to estimate technical efficiency using the non-linear iterative seemingly unrelated regression method. The approach can be easily extended to cases where producers are both technically and allocatively inefficient.

Latent Models

When investigating technical efficiency of firms it is generically assumed that they operate under a similar production technology. However, it might be the case that different production units have different production technologies and these are then erroneously interpreted as inefficiency. These issues can be addressed by estimating a latent class stochastic frontier in a panel framework. Some researchers have tried to avoid this problem by categorizing sample observations based on exogenous sample information. Earlier Caudill (2003) introduced an expectation-maximization (EM) algorithm to estimate a mixture of two stochastic cost frontiers in the presence of no sample separation information and Greene (2002) proposed a maximum likelihood latent class stochastic frontier model using sample separation information and allowing for more than two classes. However, both of these techniques assume that the efficiency term is independent of time. This assumption is restrictive if one is interested in a productivity growth study. Orea and Kumbakhar (2004) overcomes this problem by developing a panel data latent class stochastic frontier approach in both efficiency and latent class components. To determine efficiency, the technology of each class must be modeled and they assume that the technology can be characterized by a dual cost function, and the cost function of class j is of the translog for

$$\ln(\mathrm{C_{it}}) = \ln\left(\mathrm{y_{it}}, \mathrm{w_{it}}, \mathrm{t}, \beta_{\mathrm{j}}\right) + \mathrm{u_{it}}|_{\mathrm{j}} + \mathrm{v_{it}}|_{\mathrm{j}} \tag{32}$$

where i = 1,…,N; t =1,…,Ti; and j =1,…,J stand for firm, time and class. C_{it} is actual total cost; y_{it} and w_{it} are vectors of outputs and input prices; and β_j is the vector of parameters to be estimated for class j.

A two-sided random error term $v_{it|j}$ and a non-negative cost inefficiency term are added to each class of frontiers to make them stochastic. The two terms are assumed to be independent of each other. In order to estimate the model by MLE method it is also assumed that the noise term follows a normal distribution with mean zero and constant variance σ^2_{vj} and the inefficiency term is a non-negative truncated distribution with mean zero and variance σ^2_{uj}. The inefficiency term is modeled as a product of time invariant firm effect and a function of time, λ_{it}.

MLE techniques will give asymptotically efficient estimates of all the parameter, given the assumptions stated about. An important consideration when estimating latent class models is that the sample is generated by different technologies which are known. If the assumed number of classes is more than the true number it would lead to an over specified model. The estimated parameters can be used to compute the conditional posterior class probabilities by following the steps outlined in Greene (2002). This lets us classify the samples into groups even when sample-separating information is not available-goodness of fit of each estimated frontier is used to identify groups.

Once frontiers for different classes have been estimated the next step is to compute the efficiency level of each individual firm. This can be done by assigning each firm a class and then determining its efficiency from the relevant frontier. This method is rather adhoc in nature and can be avoided by using an alternate method

$$\ln \mathrm{EF}_{\mathrm{it}} = \sum_{\mathrm{j}=1}^{\mathrm{J}} \mathrm{P}(\mathrm{j}|\mathrm{i}) * \ln \mathrm{EF}_{\mathrm{it}}\,(\mathrm{j}) \tag{33}$$

where P(j|i) is the posterior probability to be in the jth class for a given firm i and $EF_{it(j)}$ is its efficiency using the technology of class j as the reference technology. This method does not consider a specific frontier as a reference to measure inefficiency against, instead it considers technologies from all classes. For an application of this methodology on Spanish Banks one can refer to Kumbakhar et al. (2003).

The need for theoretical consistency

Another criticism of stochastic frontiers which has resurfaced is the choice of production functions. Since the estimates obtained from these models are used to advice policy interventions it is imperative that the estimates are robust and well founded on economic theory. Sauer and Hockmann (2006) highlight that since the focus of these studies is now on measuring relative efficiencies between different units it is important that the economic theory should hold at all data points. They show that production frontiers which are not consistent with economic theory i.e. they violate the regulatory conditions of monotonicity, concavity and convexity they can produce elasticities that are incorrectly signed and lead to counterproductive policies.

There is no specific guideline in economic theory which prescribes the choice of certain forms of functional relationship over the other. However, some essential criteria that need to be met ex ante.

1. Theoretical Consistency: In the case of production functions, it should be monotonic as well as quasi-concave.
2. Domain of Applicability: It is the set of values of the independent variables over which the functional form maintains theoretical consistency.
3. Flexibility: This is the ability of the function to represent unbiased but theoretically consistent economic behavior through appropriate choice of parameters.
4. Computational Facility: This implies 'linearity in parameters', input demand functions should be in linear in parameters and in closed form, and the function should be parsimonious in terms of the number of independent variables required to achieve a certain degree of flexibility.
5. Factual Conformity: The function should be consistent with the conventional econometric facts.

The notion of flexibility is of key concern to us as an ideal production function should be flexible enough that its shape is determined by economic theory rather than other restrictions imposed a priori. A flexible function has the ability to provide local second order approximations for a given functional relationship. Cobb-Douglas is by far the most common production function used in productivity analysis despite its well-known limitations. Sauer and Hockmann (2006) show that Cobb-Douglas even though can be theoretically consistent globally but fails when it comes to flexibility due to lack of free parameters. They suggest that Cobb-Douglas production functions should not be used any further for stochastic efficiency estimations as it cannot be restricted to regularity conditions at all.

Translog is the other most common functional form used for production analysis. This form has the advantage of being flexible as compared to Cobb-Douglas but maintaining global monotonicity is impossible without losing flexibility. Sauer and Hockmann (2006) examined a number of studies that have used Translog due to its superiority as a flexible function that is also linear in parameters. However, they find that the regulatory conditions of monotonicity and quasi-concavity are not met by most of these studies on at least one parameter. They conclude that a Translog flexible function is adequate as it meets the basic requirements of economic theory but one needs to check for regulatory conditions posteriori. If these conditions do not hold then they need to be imposed a priori, however that can lead to significant bias in the results and a loss of flexibility.

Hence, there is essentially a tradeoff between theoretical consistency and flexibility, with translog and other flexible functions. The solutions proposed to this issue are:

- Imposing theoretical consistency locally and maintaining functional flexibility
- Choose functional forms that are globally consistent and flexible

Stochastic production frontiers also face the same problem of endogeniety which production functions that use data on inputs and outputs to estimate productivity. The case has been pointed out in literature (Marschak and Andrews, 1944; Griliches and Mairesse, 1995) and arises due to the fact that the output of a _rm depends on the optimal mix of inputs which are chosen jointly. Standard approaches to overcome this problem are using fixed effects or input prices as instruments, however, they have been unsatisfactory (Griliches and Mairesse, 1995; Ackerberg et al., 2006). Relatively new approach to handle this issue has been to use lagged values of the inputs as instruments but it also has its limitations as some inputs are flexible and the decision is static rather than dynamic, hence using lagged values is not very useful. It makes more sense to view the production function as a purely technical relationship and the parameters as a correlation rather than a causal relationship.

Strengths and Limitations

Since Farrell's original work a number of frontier efficiency models have been developed based. They can be divided into two main categories namely parametric and non-parametric. Non-parametric methods involve use of linear programming and do not require any functional form to be imposed on the data. Parametric frontiers models on the other hand are econometric estimates and use specific functional forms such as Cobb-Douglas which are then imposed on data. Another important classification would be that of deterministic and stochastic frontiers models. Deterministic models assume that all deviation away from the frontier is due to inefficiency whereas stochastic frontiers account for measurement errors and exogenous random shocks which are beyond the control of the firm. These models have then been later extended to incorporate panel data.

It is recommended to use stochastic methods if one is using agricultural data, as one would be expected to run into problems such as measurement errors and missing values. Moreover, random shocks such as rain, wind, etc. can also have a significant effect on efficiency. This method also has the advantage that it allows statistical inference and one can run hypothesis tests regarding the extent of inefficiency. Depending on what the research question is, one can opt from among the score of models which look at both technical change and efficiency, time varying and time invariant technical efficiencies.

However, like every other econometric method this approach also has its own drawbacks such as compliance with regularity conditions and economic theory, the issue of heterogeneity and endogeniety. These problems to an extent have been overcome by new development where the regulatory conditions can be imposed and heterogeneity can be controlled for.

Earlier Studies

There have been numerous studies using the frontier function to measure agricultural efficiency in developed and developing countries. However, this section focuses on studies that have been conducted in developing countries using a parametric approach. This section provides a summary of the findings and highlight factors that can be attributed to the prevalence of inefficiency. Most of the early efficiency studies were mainly focused on determining the technical efficiency of farmers using simple measures of efficiency such as yield indices and estimation of production functions. However, over time the methodology shifted to Stochastic Frontier Analysis (SFA) and Data Enveloping Analysis (DEA). Stochastic frontiers have been the most prevalent econometric estimation method used as they accommodate for statistical noise such as measurement error and we can specify a parametric specification which allows us to conduct statistical tests. Majority of the studies showed that small farmers are less efficient due to limited access to financial resources which limit their ability to invest in better technology. However, Schultz's (1964) 'poor but efficient hypothesis' challenged this widely accepted belief and claimed that small farmers utilized their limited resources in an efficient manner. However, there have been mixed results which support both points of view and has the interest of development economists trying to improve the efficiency of farmers as majority of the farmers in developing countries are small.

One of the earliest studies in the developing world was done by Kalirajan (1981) using a cobb douglas production frontier. He estimated the technical efficiency of paddy farmers using a random sample from an Indian state and found that technical efficient was the major driver for the difference in yield amongst farmers. He found that a major cause of technical inefficiency was the lack of contact that farmers had with the extension agents. He suggested that this meant that farmers had inaccurate knowledge about production technology which was leading to inappropriate use of inputs. Another frontier study using a Cobb-Douglas specification and maximum likelihood approach was done by Ekanayake (1987) where a sample of Srilankan rice farmers was divided into two groups based on whether the farm was located at the head or tail of the watercourse. It was observed that farms at the head of the watercourse did not have significant technical inefficiency while those at the tail were operating at a technical efficiency of about 50 percent. Other factors such as education, experience and credit were also found to have a significant impact on technical efficiency.

Lau and Yotopoulos (1971) used a dual profit function approach to estimate both technical and allocative efficiency of farmers in India. They found that farms less than 10 acres were more efficient as compared to bigger farms. However, when Huang and Bagi (1984) used a translog production frontier to estimate technical efficiency using a sample of farmers from two states in India they found that there was no difference between small and large farms. Similar results were also found by Bravo-Ureta and Evenson (1994) in eastern Paraguay for cotton and cassava growers. They observed average technical efficiency to be 58 percent for cotton growers and 59 percent for cassava growers. However, they found a weak linkage between farm size, manager's age and education, extension and credit and efficiency.

Ali and Flinn (1989) used the frontier methodology to estimate farm level profit efficiency of basmati rice producers in Gujranwala district of Punjab, Pakistan. They found that mean profit inefficiency level was 28 percent and ranged from 5 to 87 percent. They found that the variation in profits was largely driven by socioeconomic factors (education, tenancy, off-farm employment, credit) which were responsible for more than half of profit loss with education being highly significant. Resource base (farm size, tube well ownership, tractor use) issues had a small impact on profit levels while institutional factors factors (water constraint, late planting, late fertilizer application) explained 25 percent of the variability in profit loss.

Kalirajan (1990) estimated firm specific technical and allocative efficiency of 103 rice farmers in Philippines using a translog production frontier. He found technical efficiency scores that ranged between 64 to 92 percent whilst the average was 79 percent. In addition, all firms were found to be allocatively inefficient in all inputs. Ali and Chaudary (1990) carried out a study in four different cropping regions of Pakistan. They used cobb-douglas specification and measured the technical and allocative efficiency of farmers across these regions using a probabilistic production frontier. They found technical efficiency to range between 80 to 87 percent while the overall allocative efficiency ranged between 53 to 69 percent. Battese and Coelli (1992) used a stochastic frontier approach in a panel setting where efficiency was allowed to vary over time. They used data on 15 paddy farmers from 1975 to 1985 and estimated five different specifications of Cobb-Douglas models. They found technical efficiency ranged between 67 to 88 percent in 1975-76 and 88 to 96 percent in 1984-85.

Parikh and Shah (1995) conducted a study to measure the technical efficiency of farmers in North-West Frontier Province of Pakistan using a cross-sectional data collected in 1988-1989. They found very high efficiency levels with mean efficiency level at 96.2 percent and ranging between 91-98 percent. Their analysis considered factors such as tenancy, education, and demographic characteristics to explain the variation in technical efficiency across farmers. They found that households with bigger families were more efficient, education had a positive effect on technical efficiency, credit improved efficiency levels as well, and small land holdings were seen to be less efficient. Other factors such as age, non-farm income, extension, and farm and non-farm assets did not have a statistically significant impact on efficiency in their study. Another study in Pakistan was done by Battese, Malik and Gill (1996) using a single stage stochastic frontier model to estimate the technical efficiency of wheat farmers in 4 districts of Pakistan. They found that technical efficiency played a significant role in the model, however inefficiencies of production decreased with experience and years of formal schooling. The study used panel survey household data which was initiated in 1986 and collected data from four districts which were selected based on various production and infrastructure indices. The mean technical inefficiencies of farmers growing wheat the four districts namely, Faisalabad, Attock, Badin, and Dir were 0.79, 0.58, 0.57, and 0.78 respectively. They found substantial variation in the individual efficiency levels which could have also been due to the inadequacies of the model such as absence of data regarding socioeconomic or resource variables. This could also explain why the coefficients on the explanatory variables in the inefficacy models turned out to be insignificant.

Since the 2000's researchers have been primarily interested in using different methodologies to determine efficiency. Most authors experimented with various forms of production function, distributions of the error term, estimation techniques, and sample sizes. They were focused on comparing the efficiency of different agricultural systems and evaluating how government policies impact efficiency. Javed et al. (2008) study the efficiency of rice-wheat systems in Punjab using the DEA approach and find mean technical efficiency of 0.83. They also find that farm size, age of manager, education, extension services, and access to credit along with distance from market were major determinants of technical efficiency. Baksh et al. (2006) use a stochastic frontier to study technical efficiency and its determinants for potatoes in two districts of Punjab and found mean efficiency of 0.84. They found that extension, farm size and experience were the factors which significantly impacted inefficiency. Table 2 below provides a summary of some of prior studies and their findings.

Table 2: Studies of Technical Efficiencies of Farmers

Study	Crop	Country	Methodology	Sources of Inefficiency
Ahmed et al. (2002)	Wheat	Pakistan	Stochastic Production Frontier	Farm size, Credit, Distance from Market, Irrigation, & Extension
Ali and Finn (1989)	Rice	Pakistan	Stochastic Profit Frontier	Education, Credit, Irrigation, Off-Farm Employment, & Fertilizer
Bakesh et al. (2006)	Potatoes	Pakistan	Stochastic Production Frontier	Extension, Age, & Scale of Production
Battese et el. (1993)	Wheat	Pakistan	Stochastic Production Frontier	Extension, Ownership, & Seed Type
Battese and Broca (1997)	Wheat	Pakistan	Stochastic Production Frontier	Age, Education, & Credit
Bravo-Ureta and Evenson (1994)	Cotton & Cassava	Paraguay	Stochastic Production Frontier	No clear relationship between efficiency and socioeconomic factors
Ekanayake (1987)	Rice	Srilanka	Stochastic Production Frontier	Irrigation, Education, Credit, & Non-Farm Income.
Huang and Bagi (1984)	All Crops	India	Stochastic Production Frontier	N\A
Hussain, Coelli and Simmons (1999)	Cotton	Pakistan	Stochastic Production Frontier	No clear relationship between efficiency and socioeconomic factors
Javed et al. (2008)	Rice-Wheat System	Pakistan	Data Envelopment System	Farm Size, Education, Credit, Age, Extension, & Distance to Market
Lau and Yotopoulos (1971)	All Crops	India	Profit Function & Factor Share Equations	Farm Size
Kalirajan (1990)	Rice	Philippines	Production Frontier & Factor Share Equations	Non-Farm Income & Method of Crop Establishment.
Parikh and Shah (1995)	All Crops	Pakistan	Stochastic Production Frontier	Education, Credit, & Land Size

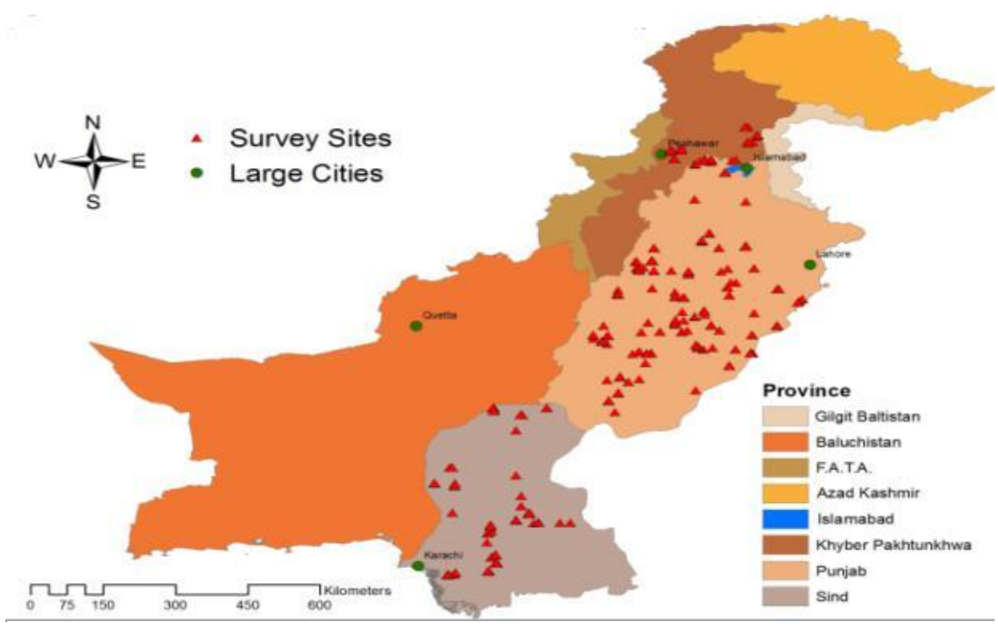
Majority of the studies listed above have found farm size, extension, education and credit to be major determinants of technical efficiency. This suggest that the inefficiency is driven primarily by institutional factors where farmers have difficulty accessing credit which hampers their ability to buy inputs in adequate quantity and of appropriate quality. The case is further exacerbated by the fact that average farm size is very small in Pakistan and banks might be reluctant to provide credit to farmers with less or no collateral. In addition to having an indirect impact on technical inefficiency, small farm size also makes the adoption of new technologies economically unviable as they require economies of scale and hence small farmers tend to be more inefficient. However, it is also possible that small farmers owing to their limited resources are more prudent in their choices and are at least as efficient as a big farmer. A lot of inputs such as fertilizers, seeds, and pesticides are divisible and the adoption of such technology is not constrained due to small farm size, moreover the introduction of small tractors has made mechanization of small farms possible as well. Hence, the assumption that small farmers might not be as inefficient once we control for such factors. Extension is another factor which has repeatedly showed up in studies which suggests that farmers need advice for farming and more effort needs to be put into strengthening the institutions that are responsible for the dissemination of research. The fact that this information is not available to farmers across the board suggests that these institutions have not been able to achieve their objectives. This could be due to poor infrastructure such that it is not possible to reach all farmers, the amount of money allocated to such institutions is not sufficient which limits their ability to reach a larger group of farmers, or that the quality of human resource available is diverse and even though farmers might be interacting with the extension agents but their usefulness is very limited. The ability of the farmer to understand and adopt new technology is not just contingent on the extension agents but also the capability of the farmer and education plays a very important role in developing competence. This suggests that the more than just direct interventions in the agricultural system is needed to improve agriculture productivity and sustain it.

However, most of these studies have been conducted on a very small scale and have been limited to a few districts. This has meant that the results from these studies cannot be assumed to hold true for the entire country or province due to the ecological diversity of the country. This study aims to bridge that gap by using a more representative sample. In addition, most of the studies have taken the household as the unit of analysis and the input and output measures used in the analysis have suffered from aggregation bias, compromising the quality of data. For example a household might be cultivating more than a single plot of land, and it possible that the plots are in different location with one being at the head of an irrigation canal while the other being at the tail or that due to financial constraints the farmer rations resources among plots and applies the optimal mix of inputs on one plot and not on the other. This issue is addressed in this study by using micro level data which is available at the plot level. In addition, the study also undertakes a series of sensitivity tests by altering the specification of the production frontier, using different distributions for the inefficiency term, and using alternate measures for the input and output variables where possible.

Data

The data for this study is based off a Rural Household Panel survey that was conducted under the Pakistan Strategy Support Program (PSSP) and implemented by International Food Policy Research Institute (IFPRI) and its partner Innovative Development Strategies (IDS). This was a comprehensive survey in which production data was collected in detail at the plot level along with various other topics such as income sources, employment, consumption patterns, time allocation, assets and savings, credit, and education. This paper uses one round of that data that was carried out during 2012 in the rural areas of three provinces: Sindh, Punjab, and Khyber-Pakhtunkhwa (KPK) while the fourth province Balouchistan was dropped from the sample due to security concerns.

Figure 2: Survey Sites



Source: IFPRI

A multistage stratified sampling technique was used to select the sample. Pakistan is divided in four provinces namely Sindh, Punjab, Balouchistan and Khyber-Pakhtunkhwa (KPK). These provinces are further divided into 114 districts and according to the census of 2008 there are 27,059 mouzas(revenue villages) in Punjab, 5,983 in Sindh, 7,480 in Balouchistan and 11,854 in KPK. In the _rst stage a probability proportionate to size was used to select the districts as this ensured that districts with a higher number of households had a greater propensity to be chosen. The number of districts selected from each province was based on the proportion of households that reside in each province. Accordingly a total of 19 districts were selected; 12 belong to Punjab, 5 to Sindh, and 2 to KPK. The mouzas were then chosen from among these districts with each mouza having an equal probability of being chosen irrespective of its population. These mouzas were then separated into enumeration units and each unit consisted of a maximum of 200 households. An enumeration unit was then randomly selected and then 28 households were randomly selected from among the unit for survey. Figure 2 above shows the location of the mouza level data that was collected.

Pakistan has a very diverse ecology and is divided into ten agro ecological zones by the Pakistan Agriculture Research Council based on physiography, climate, rainfall, soil type and land use. The ten zones are as given below and Figure 3 provides a graphical representation of these zones.

I. Indus Delta

This is in the south of the country and the climate is arid with mean temperature ranging between 30 to 40 degree Celsius in summers and 19 to 20 degree during winter. Average monthly summer rainfall is 75 mm and winter rainfall is less than 5 mm. Soil type is clayey and silty with the main Kharif crops being rice, sugarcane and cotton while the main rabi crop being wheat.

II. Southern Irrigated Plain

The lower Indus Plain makes up this region and the climate is arid with hot summers and mild winters. Temperature during summer is around 40 to 45 degree Celsius and falls to as low as 8 degree during winter in the north whereas in the southern regions summer temperature is 38 to 43 degree Celsius and 8 -12 degree winter. There is hardly any rainfall in this zone during winters, however, average monthly summer rainfall is close to 50 mm in the south and 18 mm in the north. Soils in this zone can be classified as silty and sandy loam but the areas to the north are loamy and clayey. Important crops grown in this region are wheat, cotton, rice, and sugarcane.

III. Sandy Desert (a & b)

These regions have xerophytic vegetation and the annual rainfall is around 300 to 350 mm. Soil in this region is mostly sandy and is mostly used for grazing, however there are strips of land which are clayey or loamy where wheat, rice, cotton, mustard, pulses, vegetables and other fodder crops are grown.

IV. Northern Irrigated Plains (a & b)

Region 'a' is the flood plain along the rivers and the climate is semi-arid to arid with summer temperatures of up to 40 degree Celsius and winter temperatures as low as 6 degree. The annual rainfall is about 300 to 500 mm in the east and 200 to 300 mm in the south west. Soil types are sandy, loam-clay, and loam while the important irrigated crops in this area are wheat, rice, and sugarcane in the north while wheat, cotton, sugarcane are grown along with citrus and mangoes towards the center and south. Region 'b' is composed of alluvial valleys where the soil is silty clay and clay loam and the climate is semi-arid with mean monthly rainfall of 20 to 30 mm. The important crops grown here are wheat, sugarcane, maize and tobacco along with orchards.

V. Barani Lands

This region has a humid climate with maximum summer temperature of 39 degree Celsius and average monthly summer rainfall of 200 mm and about 50 mm during the winter. The southern part of this zone has a semi-arid climate with maximum summer temperature of 38 degree Celsius and average monthly summer rainfall of 85 mm and 30 to 45 mm in the winter. Soil type here is mostly calcareous and the agriculture is dependent upon rainfall. Important crops grown here are wheat, rice, maize, pulses, and sugarcane.

VI. Wet Mountains

This zone comprises of high mountains and plateaus. Winters tend to be very cold here and the mountain tops are usually covered with snow till spring. The summers are generally mild and average monthly rainfall in summers is 236 mm and 116 mm in winters. Soil type is silty loam to silty clayey and roughly 25 percent of the land is used for agricultural purposes while the rest is forest area. Major crops grown here are wheat and maize.

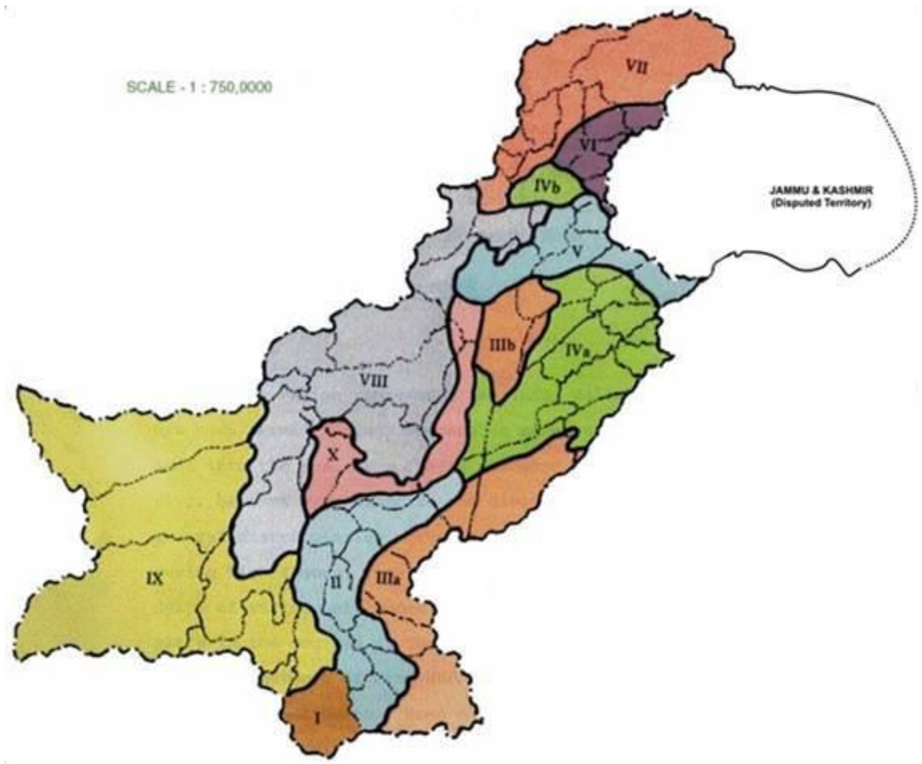
VII. Northern Dry Mountains

This region is composed of valleys which are fed by water from the glaciers. The zone has mild summer and cold winters, the mountain tops are covered with snow for the most part of the year and average monthly rainfall during summer is 10 to 20 mm and 25 to 75 mm during the winter. Soil type in the valleys is mostly clayey and most of the land is used for grazing purposes, however, wheat and maize are grown in parts of it.

VIII. Western Dry Mountains

This zone has barren hills and the climate is mostly semi-arid. Temperature is around 30 to 39 degree Celsius during summers and goes below freezing during winters, the average monthly rainfall is around 30 to 35 mm. The north western part of this zone has a sub humid climate and the summer temperature is around 32 degree Celsius and the winter temperature is 2 degree Celsius. Average monthly summer rainfall is 95 mm while winter rainfall ranges between 63 to 95 mm. Soil type is loamy and land is mostly used for grazing except for some portion that is irrigated and where wheat, maize, and fruits are grown.

Figure 3: **Agro Ecological Zones**



Source: Pakistan Agricultural Research Council (PARC)

IX. Dry Western Plateau

This is a mountainous area and has arid climate. The summer temperature goes up to 40 degree Celsius in summer while the winter temperature is around 3 to 6 degree in the north. Summer temperature in coastal region is 34 degree and 11 to 15 degree during winter. Rainfall is sparse and soils are silty loam with most of the land used for grazing along with cultivation of melons and sorghum.

X. Sulaiman Piedmont

This zone comprises the Sulaiman Range and the climate is arid and hot with summer temperatures of about 40 to 43 degree Celsius in summer and 7 degree in winter. Soil types are loam and clay with wheat, millets, and gram being the main crops grown.

As described above, the ecology of Pakistan is very diverse but wheat is grown almost throughout the country. However, due to the conducive weather conditions and availability of water through an irrigation network the central and Southern parts of Pakistan are known as the bread basket of the country where the most of the wheat production takes place. Table 3 below provides summary statistics of the wheat farmers in our sample which is composed of data from 70 villages. 62 percent of these observations are from the province of Punjab which is a major wheat production zone, 19 percent observations are from Sindh and the rest from KPK.

Table 3: Wheat Output, Input Utilization, and Farm Characteristics (Plot Level)

Variable	Observations	Mean	Standard Dev.
Wheat Yield (kg/acre)	862	1131	436
Wheat Output	862	3640	4770
Total Hired Labour (hr)	862	113	229
Total Family Labour (hr)	862	130	141
Share of Hired Labour	860	0.35	0.35
Total Operated Farm Size (acre)	862	5.76	7.06
Area Wheat Planted (acre)	862	3.08	3.54
Tractor (hr)	860	9.21	10.87
Fertilizer Indicator	833	0.98	0.15
Nitrogen Used (nutrient kg)	833	147	188
Phosphorous Used (nutrient kg)	833	57	77
Seed Quantity Used (kg)	862	168	174
Cost of Pesticide Used (Rs.)	862	2091	2678
Education Indicator	858	0.57	0.49
Irrigation Indicator	862	0.86	0.35
Extension Indicator	862	0.22	0.41
Natural Disaster Indicator	862	0.21	0.41
Land Ownership Indicator	862	0.66	0.47
Water Logging Indicator	862	0.10	0.31
Salinity Indicator	862	0.05	0.23
Household Head Age	858	48	13

Wheat yield of farmers in our sample is around 1100 kg per acre which is equivalent to 2700 kg per hectare and falls in line with the statistic reported in other studies. However, there is significant variation in this measure as the high standard deviation suggests. The maximum yield reported in our sample is 2500 kg per acre while the lowest is 80 kg per acre. If we disaggregate this national yield we find that Punjab has the highest yield of 1280 kg per acre followed by Sindh with 990 kg per acre and KPK with 770 kg per acre. Family and hired labour hours are the number of labour hours spent on a plot of land and the share of hired labour is the proportion of hours spent by hired labor on the plot. This number is fairly big which suggests that the labor market is present, however we cannot make any conjecture regarding its efficiency. Total operated farm size is the sum of all plots that the family operates and we observe that the average farm size is 5.7 acres for a household which highlights the fact that majority of farmers in Pakistan are small. Thee agriculture census of Pakistan (2008) further shows that the distribution of land is very skewed as it reveals that 64 percent of the farms are less than 5 acres but they only account for 19 percent of the total farm area, whereas only 11 percent of the farms are more than 12.5 acres but they make up for 53 percent of the total farm area.

Tractor hours is the total number of hours that a tractor was used on a plot at different stages of the production cycle. Fertilizer indicator is a binary variable which is equal to 1 if the farmer applied nitrogen or phosphorous on his plot. The high statistic of 0.98 suggests that the use of chemical fertilizers is very common. However, we do see that the use of nitrous fertilizer is more common and that the use of fertilizers is very unbalanced as the ratio of phosphorous to nitrous fertilizer is very low. The education indicator is a proxy for the ability of the household head who is also the plot manager in our data. The variable is equal to zero if the household head never went to school but is equal to one otherwise. The table shows that 57 percent of the plots were managed by someone who had received some form of education.

The irrigation indicator is also a binary variable which measures accessibility to irrigation. The variable is equal to one if either canal or ground water irrigation was applied on the plot in the previous year.

We find that a very high number of plots in our sample had access to some form of irrigation. This is expected as Pakistan has a very extension network of canal irrigation system and the use of tube wells is also very common. Natural disaster is a binary variable which is equal to one if sort of climatic shock in the form of flood, drought, heavy rain, or winds was experienced on the plot. Land ownership measures tenancy and we find that 66 percent of the plots in our sample were managed by their owners. Access to an extension agent is measured by the extension indicator, the variable takes the value of one if there was any interaction with an extension agent. We find that this number is very low as only 20 percent of plot managers' report having access to an extension officer. Water logging and salinity are proxies for soil quality and we observe that 5 percent of the plots suffer from salinity and 10 percent are waterlogged.

The dependent variable in the model specification is kilograms of wheat per plot. The inputs are labor which includes both family and hired labor and are measured in term of number of labor hours expended per plot. Nitrogen and phosphorus are in terms on nutrient kg applied per plot, this number was computed by multiplying the nutrient content in a kilogram of fertilizer with the total quantity used. There is potential of measurement error here as the amount is self-reported and the nutrient content is assumed to be similar across all fertilizers. Pesticide is the amount of money spent on pesticides, insecticides and weedicides and is measures in term of Rupees spent on chemical sprays on each plot by the household. Tractor is measured in terms of number of hours it was used on each plot and the frontier is run with village level fixed effects. The variables used in the inefficiency term are farm size which is the sum of the plots the household cultivates, extension is an indicator variable which is 1 if the household was visited by an extension agent and zero otherwise. Tenancy status is given by the indicator variable owner which is equal to 1 if you own the plot and zero otherwise, age is used as a proxy for experience, ratio of hired labor to total labor is also included to see if hired labor is more efficient, and finally resource base is measures by number of indicator variables such as salinity and water logging which are 1 if the plot suffers from these issues and zero otherwise, best, moderate and worst quality soil indicator variables are also included where the soil is categorized as best if it is clay loam or loam. Moderate if it is sandy loam or clay and worst if it is sandy. An indicator for weather related shocks is also included and it is equal to one if the plot was affected by flood, heavy rains, drought, high winds and frost.

Econometric Model

Quadratic and translog specification for the production function have been used to explain the production relationship due their well-known advantages over other commonly used functions such as the Cobb-Douglas. These functional forms are preferred as they are more flexible and realistic allowing for it allows for decreasing returns and interactions between inputs. However, as part of robustness check I also run the cobb-douglas specification and use different measures for the inputs/output where data permits.

The quadratic function is defined as follows

$$\ln y_i = \alpha + \sum_j \beta_j \ln x_{ji} + \sum_j \sum_k \beta_{jk} \ln x_{ji} \ln x_{ki} + \sum_l \beta_l D_{li} + v_i - u_i \qquad (34)$$

where the subscript i stands for the ith firm in the sample of N firms, y is the quantity of crop harvested from a plot in kilograms, x's are the inputs, and D is the dummy for fixed effects.

The production frontier is determined by capital (farm machinery), inputs (seeds and fertilizers), farm size and quality (soil quality), hired and household labour, and natural disasters such as floods and drought.

v_i is the stochastic component of the error which accommodates for statistical noise and exogenous random shocks. It is assumed to be identically and independently distributed as a normal distribution $N(0, \sigma_v^2)$.

u_i is the non-negative error component which represents technical inefficiency. It is assumed to be independently distributed between itself and the stochastic error component. It is given as the non-negative truncation of the normal distribution as $N^+(\mu_i, \sigma_i^2)$

$$\mu_i = \delta_0 + \sum_m \delta_{mi} z_{mi} + \sum_j \delta_{ji} x_{ji} \tag{35}$$

The specification of the inefficiency term as function of explanatory variables is done to estimate the model in one step and avoid the serious biases that can arise through two stage estimation (Wand & Schmidt, 2002). The inefficiency term is expected to be dependent upon factors such as access to credit, tenancy status, education, soil quality, natural disasters, time of crop establishment, and water constraints. It is also assumed that the inefficiency term is affected by the technology such as use of fertilizer and pesticides along with years of experience. The production function coefficients will give us the production elasticities due to the log-log specification and the coefficients of the inefficiency component will give us a measure of how much inefficiency is correlated with these variables and whether this relationship is statistically significant.

One of the main concerns when estimating a production relationship is the choice of a functional form. Producer theory suggests that the functional form should be quasi-concave but there are many functional forms that meet that criteria such as linear production functions. However, a linear functional form would be unrealistic as we expect the marginal product of inputs to decline with higher application rates. Quadratic and Translog specifications are the two most specifications used in literature. Translogs are considered more flexible but are a good choice if there are no zeros in the data, hence in this case we opt for a quadratic specification.

Empirical Results

Production Structure and Determinants of Inefficiency

Estimates of the stochastic production frontier and the determinants of inefficiency are presented in Table 4. The primary variables of interest in this specification are the technology parameters such as machinery, fertilizers, pesticides and land. We observe that the coefficient on land is very close to 1 and statistically significant for the first three models, however there is variation in the magnitude of the coefficient. A wald test was performed to estimate if the difference is statistically significant and we failed to reject the null that the difference is zero expect between model 1 and model 3. The coefficients were also not statistically different from 1 suggesting that there are constant returns to scale. As expected first order parameters of most of the inputs have a positive coefficient, we find that irrigation has a positive impact on output which is statistically significant at 1 percent. Hired labor gives a negative sign under the cobb Douglas specification but when we incorporate interactions we see that hired labor is positive and statistically significant along with use of pesticides. The subsample with only irrigated plots we see that seed fertilizers have a statistically significant impact on output which highlights the importance of the complementary relationship between use of chemical fertilizers and timely availability of water. The coefficient on salinity is negative, however it is statistically insignificant. The coefficient on waterlogged plots is positive which is unexpected. Since these plot characteristics were self-reported it is possible that there is significant measurement error or the question was not asked properly from the respondents.

The second order parameters are negative for inputs (fertilizer and sprays) are negative which suggest diminishing marginal products. However, the coefficients of hired labor and hours of tractor use are positive across all models in both the full and restricted sample. This suggests that there is increasing returns to scale with more mechanization. The positive sign on hired labor might seem counter intuitive as we expect family labor to be more motivated and shirk less but it could be the case that farms on which hired labor is used are larger. The positive and statistically significant sign on the interaction between hired labor and area planted suggests the same. It is also interesting to note that the coefficients on tractor is not statistically significant which could be due to the fact that there is very less variation within the sample and mechanized farming in being practiced on most of the farms. However, the thresher is also not significant in the three models but this could be due to the small size of the plots where it is not feasible to use a thresher.

Table 4: Maximum Likelihood Estimates of Stochastic Production Frontier

	(1) Wheat Produced	(2) Wheat Produced	(3) Wheat Produced	(4) Wheat Produced
Wheat Produced				
Area Planted	0.875	1.561	1.212	1.018
	(6.40)	(3.00)	(8.25)	(1.26)
Family Labor	0.0253	0.125	-0.00123	0.0179
	(0.90)	(1.21)	(-0.04)	(0.13)
Hired Labor	-0.00666	0.168	0.000821	0.0875
	(-0.38)	(2.79)	(0.05)	(1.17)
Tractor	0.113	0.00998	0.107	-0.121
	(1.93)	(0.04)	(1.92)	(-0.42)
Thresh	0.156	0.449	0.0803	0.0619
	(2.72)	(1.60)	(1.45)	(0.20)
Seed	1.127	0.264	0.978	0.861
	(7.06)	(0.74)	(5.31)	(1.90)
Nitrogen	0.0641	-0.0994	0.130	0.354
	(1.71)	(-0.77)	(2.63)	(2.04)
Sprays	0.112	0.878	0.0199	0.216
	(1.89)	(3.00)	(0.34)	(0.73)
Irrigation	0.283	1.858	0	0
	(4.65)	(4.48)	(.)	(.)
Water Logging	0.107	0.105	0.0938	0.0940
	(2.52)	(2.54)	(2.39)	(2.40)
Salinity	-0.0558	-0.0910	-0.0670	-0.0837
	(-1.09)	(-1.88)	(-1.44)	(-1.82)
Area Planted sq	-0.0216	0.168	-0.0468	-0.100
	(-0.59)	(0.97)	(-1.13)	(-0.45)
Family Labor sq	-0.000842	-0.00542	0.00182	-0.000650
	(-0.19)	(-1.03)	(0.42)	(-0.12)
Hired Labor sq	0.00574	0.00794	0.00303	0.00540
	(1.79)	(2.14)	(1.03)	(1.48)
Tractor sq	0.0123	0.0245	0.00871	0.0312
	(0.89)	(1.04)	(0.66)	(1.33)
Thresh sq	-0.0249	0.0112	-0.00722	-0.000989
	(-1.41)	(0.54)	(-0.43)	(-0.05)
Seed sq	-0.0984	0.102	-0.0949	0.0164
	(-6.12)	(1.63)	(-5.10)	(0.25)

Table 4 (cont'd)

Nitrogen sq	-0.00137	-0.000927	-0.0108	-0.0126
	(-0.24)	(-0.10)	(-1.65)	(-1.23)
Sprays sq	-0.0412	-0.0218	-0.00304	-0.0322
	(-1.33)	(-0.63)	(-0.10)	(-0.96)
area x f_lab		0.0281		0.0188
		(0.55)		(0.30)
area x h_lab		0.0892		0.0694
		(2.84)		(1.98)
area x trac		-0.104		-0.151
		(-0.74)		(-1.11)
area x thresh		0.0316		0.0409
		(0.22)		(0.28)
area x seed		-0.413		-0.108
		(-2.47)		(-0.50)
area x seed		-0.413		-0.108
		(-2.47)		(-0.50)
area x nit		0.0197		0.168
		(0.31)		(1.88)
area x sprays		0.262		0.0326
		(1.66)		(0.21)
area x i_dum		0.441		0
		(2.07)		(.)
f_lab x h_lab		-0.00589		-0.00118
		(-0.87)		(-0.16)
f_lab x trac		-0.00405		-0.00720
		(-0.21)		(-0.35)
f_lab x thresh		-0.0127		0.00170
		(-0.95)		(0.13)
f_lab x seed		-0.0546		-0.0567
		(-1.66)		(-1.50)
f_lab x nit		0.0698		0.0533
		(4.94)		(2.51)
f_lab x sprays		0.00964		0.0247
		(0.43)		(1.08)
f_lab x i_dum		-0.130		0
		(-3.35)		(.)
h_lab x trac		-0.00387		0.000345
		(-0.33)		(0.03)
h_lab x thresh		-0.0438		-0.0460
		(-3.89)		(-4.19)
h_lab x seed		-0.0525		-0.0356
		(-2.83)		(-1.82)
h_lab x nit		0.0172		0.0126
		(1.98)		(1.14)
h_lab x sprays		0.0163		0.0150
		(1.49)		(1.43)
h_lab x i_dum		-0.0321		0
		(-1.25)		(.)
trac x thresh		-0.0583		-0.0401
		(-1.32)		(-0.95)
trac x seed		0.0734		0.0773
		(0.84)		(0.87)
trac x nit		0.0149		0.0111
		(0.45)		(0.30)
trac x sprays		-0.0239		-0.00147
		(-0.44)		(-0.03)
trac x i_dum		-0.122		0
		(-1.12)		(.)

Table 4 (cont'd)

thresh x seed		0.0291		0.0478
		(0.32)		(0.53)
thresh x nit		-0.0406		-0.0225
		(-1.20)		(-0.58)
thresh x sprays		0.0926		0.0923
		(1.88)		(1.98)
thresh x i_dum		-0.121		0
		(-1.19)		(.)
seed x nit		-0.0245		-0.142
		(-0.57)		(-2.52)
seed x sprays		-0.213		-0.119
		(-2.30)		(-1.32)
seed x i_dum		-0.207		0
		(-1.55)		(.)
nit x sprays		-0.0335		0.0177
		(-0.76)		(0.42)
nit x i_dum		-0.0464		0
		(-1.15)		(.)
sprays x i_dum		-0.146		0
		(-1.31)		(.)
Constant	2.822	3.470	3.433	3.335
	(8.14)	(5.64)	(8.56)	(3.70)
lnsig2v				
Constant	-3.175	-3.318	-3.394	-3.351
	(-23.14)	(-23.37)	(-22.17)	(-19.97)
lnsig2u				
Avg HH Education	0.241	0.254	-0.0893	-0.0479
	(2.16)	(2.16)	(-0.75)	(-0.36)
Farm Size	-0.538	-0.787	-0.257	-0.323
	(-3.93)	(-4.77)	(-1.63)	(-1.74)
owner	-0.0166	-0.0283	-0.161	-0.153
	(-0.11)	(-0.17)	(-0.95)	(-0.82)
Age	0.0246	-0.193	0.0325	-0.144
	(0.10)	(-0.75)	(0.12)	(-0.49)
Extension	-0.220	-0.229	0.0641	0.000166
	(-1.06)	(-1.01)	(0.31)	(0.00)
Natural Disaster	0.575	0.723	1.005	1.074
	(3.26)	(3.81)	(4.82)	(4.21)
Plant Date	0.110	0.439	1.464	1.260
	(0.31)	(1.14)	(1.73)	(1.29)
Best Soil	-0.931	-1.127	-0.385	-0.634
	(-3.11)	(-3.55)	(-1.15)	(-1.75)
Moderate Soil	-0.344	-0.627	0.0855	-0.108
	(-1.21)	(-2.10)	(0.27)	(-0.32)
Worst Soil	0	0	0	0
	(.)	(.)	(.)	(.)
Constant	-1.135	-0.286	-3.375	-2.509
	(-1.03)	(-0.25)	(-2.36)	(-1.59)
Sample	All	All	Irrigated	Irrigated
Fixed Effects	Yes	Yes	Yes	Yes
N	827	827	712	712

t statistics in parentheses

p < 0:05, p < 0:01, p < 0:001

As highlighted in the data section the ecology of Pakistan is very diverse and since the data was collected from different parts of the country, all the models were run with district level fixed effects to capture soil quality, rainfall distribution, temperatures, cropping systems and infrastructure.

The determinants of the inefficiency are also given in the table above and shed some light on what explains inefficiency among the wheat producing farmers of Pakistan. The average household education variable was created by adding the years of schooling of all male members of the household above sixteen years of age and then dividing that sum by the number of people that fall in this category. The positive sign on the variable when the model is run on the full sample is counterintuitive as it implies that the agriculture efficiency falls as the average education in the household increase. This inverse relationship between human capital and agricultural productivity can be explained by the fact that as individuals acquire education they move out of agricultural production. The migration out of this sector could be due to higher returns in alternative professions, this is more important for regions which lack complementary inputs such as irrigation or the other supportive infrastructure.

The results on the restricted sample corroborate with this conjecture as the sign on the education variable is negative once we only consider irrigated plots as these are expected to be more productive. However, to check the robustness of this result other measures of education such as the years of education of the household head and indicator variable for education were also used which showed similar results.

Farm size is shown to reduce inefficiency suggesting that plots managed by households that have larger holding are more efficient. This can be explained by along various dimensions as a larger farm size allows for economies of scale, in addition it is easier to acquire credit from banks, it provides better access to buyer as it reduces their transaction costs due to higher volumes, and it provides the household the flexibility to experiment on some plots. Hence we larger farmers are usually more progressive and are normally the _rst ones to adopt new technologies and coefficient on our full sample suggest that the impact of this variable is also statistically significant at the 1 percent level. However, the variable is no longer significant once we only consider irrigated plots which implies that at least some of the constraints mentioned earlier no longer hold true. This can be due to the fact that these plots are more valuable and hence have well defined property rights and as a result lenders might be more willing to offer credit. Secondly, access to irrigation improves productivity allowing the farmer to crop the land more intensively and helping him achieve production volumes that make it possible for him to access better markets.

Owner is a binary variable which indicates tenancy status and the results suggest that ownership of the plot being managed reduces inefficiency. The negative sign can be explained by contract theory and moral hazard where there is an information asymmetry and the principal cannot effectively observe the actions of the agent. This leads to the agent putting in less effort as compared to what the principal would exercise. However, we find that this is not a very important factor as it is not statistically significant. The age variable aims to capture the experience of the farmers in order to evaluate its relationship with efficiency. We would expect that there would be an inverse relationship where the more experienced farmers would be more efficient as they have a better information about their environment which they have learnt over time. However, one could also argue that more experienced or older farmers are also more risk averse and might not want to experiment or adopt new technologies. Our results are also ambiguous as the sign changes between the quadratic and translog specification but the coefficient is insignificant across these models.

Extension is measured by a binary variable which is equal to one if extension agent met with the plot manager. The results for the full sample suggest that having access to an extension agent reduces inefficiency even though the relationship is not statistically significant. However, the coefficient changes the sign once the sample is limited to irrigated plots but it is still statistically not significant.

These results suggest that the advice given by the extension agents is not very useful as it fails it register a significant impact. Another explanation could be that the advice of extension agents is not very timely or that the information provided is common knowledge and does not add value. The natural disaster variable is highly significant as expected and is measured as a binary variable which is equal to one if the was a natural disaster such as floods, drought, high winds, and frost. These factors increase inefficiency directly by destroying part of the output and also indirectly as these incidents impede the efficacy of input use such a fertilizer, seed, and labor. Delay in planting of wheat is also a source of inefficiency as it reduces the number of days that the crop needs to achieve it genetic potential. Sometimes the delay in planting is based on unavailability of water in the irrigation network. Late arrival of water subsequently also affects the timely application of fertilizers which means that the nutrients are not available to the plant at critical stages of growth. Agronomic factors such as soil quality also affect inefficiency as the negative signs on best soil and moderate soil imply that better the soil quality would result in an improved response to use of inputs such as fertilizer, water, and tractors.

The results suggest that farmers suffer the most due to weather change followed by land quality. These results suggest that extension, education, planting date, and tenancy are no longer that major determinants of inefficiency as a number of prior studies have postulated. The inefficiency results suggest that farmers are not well equipped to ameliorate the adverse impacts of weather. Information needs to be focused on how to change production systems or techniques that would make them less vulnerable to such weather shocks. The inefficacy of the extension service also raises an important question regarding the information that is being passed onto the farmers and whether it is relevant to the challenges they face. The finding that the soil quality is also restricting yield potential is important as it highlights the fact that the management practices of the farmers need to be improved or changed to ensure that soil health is maintained. Unlike weather change, soil health is something that the farmers have control over and they can address this by through management practices. The cropping systems need to be reevaluated and mono cropping systems that are extremely nutrient exhaustive system need to be changed.

Technical Inefficiency

The estimated mean technical efficiency of farmers is around 78 percent and ranges between 96 and 12 percent. The mean technical efficiency scores across the model and samples were compared using a t-test and the difference between the mean scores was found to be statistically significant. This is a shortcoming of stochastic frontiers where the results are prone to model specifications, however models suggest that there is a significant level of technical inefficiency.

Table 5: Technical Inefficiency Score

Stats	(Cobb Douglas)	(Translog)	(Cobb Douglas)	(Translog)
Mean	.768	.787	.785	.797
Standard Dev.	.127	.125	.131	.130
Min	.149	.172	.137	.174
Max	.955	.959	.960	.959
Sample	All	All	Irrigated	Irrigated

The distribution of the efficiency is given in Table 6 which suggests that about 45% of the farmers operate between 80 to 90 percent efficiency. This is encouraging from a methodological perspective because even though the mean efficiency score is different across the models the distribution of the farmers is similar across them. We observe that significant proportions of farmer operate at an efficiency level between 60 to 80 percent.

Table 6: Frequency Distribution of Efficiency

Efficiency	***(Cobb Douglas)***	***(Translog)***	***(Cobb Douglas)***	***(Translog)***
0-30%	***1.0%***	***0.8%***	***0.7%***	***1.0%***
31-40%	***1.3%***	***1.0%***	***1.3%***	***1.2%***
41-50%	***2.1%***	***2.3%***	***2.7%***	***1.9%***
51-60%	***5.7%***	***4.6%***	***5.1%***	***4.1%***
61-70%	***12.5%***	***9.4%***	***9.1%***	***8.6%***
71-80%	***26.5%***	***24.4%***	***21.5%***	***20.2%***
81-90%	***44.7%***	***46.4%***	***46.8%***	***47.9%***
91-100%	***6.3%***	***11.2%***	***12.8%***	***15.1%***
Sample	***All***	***All***	***Irrigated***	***Irrigated***

As mentioned above the efficiency of these farmers primarily is being affected by the ability of the plot manager to navigate through the challenges of weather change. The other significant factor was degrading land resource which can be significantly improved through farmer practices. There are about 10 percent farmers who have efficiency scores between 0 to 30 percent which is troubling as these farmers are extremely inefficient and can substantially improve their income levels through better farming practices and adoption of feasible technologies.

Conclusion

The objectives of this study were to measure technical efficiency of farmers using stochastic frontier method-ology, determine the factors that are driving this inefficiency and compare them to earlier studies. We found evidence of considerable technical inefficiency among the farmers in Pakistan and the results show that efficiency varies from 13 to 97 percent and the mean efficiency is 78 percent which suggests that given the existing technology and input usage output can be increased by 22 percent on average. In addition, we observe that natural disasters such as floods, drought, and untimely rains have an adverse impact on efficiency which is statistically significant at the 1 percent levels. We also observe that resource quality significantly affects the efficiency where better quality soil reducing technical efficiency as the results show that best quality soil is statistically significant at 1 percent level. The other statistically significant variable is land size and we observe that larger land size reduces technical efficiency. These results highlights the fact that the changing weather is one of the major reasons for poor performance of farmers and better quality land helps ameliorate the impact of this affect. Similarly wealthier famers would be better o_ at reacting to these shocks through better investment or adoption of technology which is less prone to such weather shocks such as drought. However, contrary to previous studies in which we see that education reduces technical inefficiency we see that this does not hold across all farmer types and that the impact is not statistically significant. The migration out of the agricultural sector could be due to its low productivity which translates into low return for farmers, as a result educated members of the household tend to leave this occupation as they have access to other more rewarding jobs. Another factor that we find no longer as significant is extension services which sheds light on the fact that the information that is being provided by agents is not very helpful which could mean that the information being shared with the farmers is either not relevant or has not improved over time. These findings suggest that targeted interventions that apprise the farmers about how they can improve and sustain the health of their soil through better management practices and less exhaustive cropping systems. At the same time effort must be made to inform farmers about methods through which they can safeguard themselves against the adverse impacts of weather shocks by adopting more resilient varieties or switching to other crops.

REFERENCES

REFERENCES

Abbott JC. The role of marketing in the development of backward agricultural economies. Journal of Farm Economics. 1962; 44(2):349_362.

Ackerberg D, Caves K, Frazer G. Structural identification of production functions. 2006;

Afriat SN. Efficiency estimation of production functions. International Economic Review. 1972; p. 568_ 598.

Ahmad E, Ludlow S. Growth, poverty and inequality in Pakistan. Pakistan Development Review. 1989; 28(4):831_48.

Ahmad M, Bravo-Ureta BE. Technical efficiency measures for dairy farms using panel data: a comparison of alternative model specifications. Journal of Productivity Analysis. 1996; 7(4):399_415.

Ahmad M, Chaudhry GM, Iqbal M, Khan DA. Wheat Productivity, Efficiency, and Sustainability: A Stochastic Production Frontier Analysis [with Comments]. The Pakistan development review. 2002; p. 643_663.

Aigner D, Lovell CK, Schmidt P. Formulation and estimation of stochastic frontier production function models. Journal of Econometrics. 1977; 6(1):21_37.

Aigner DJ, Chu SF. On estimating the industry production function. The American Economic Review. 1968; p. 826_839.

Ali M, Chaudhry MA, et al. Inter-regional farm efficiency in Pakistan's Punjab: A frontier production function study. Journal of Agricultural Economics. 1990; 41(1):62_74.

Ali M, Flinn JC. Profit efficiency among Basmati rice producers in Pakistan Punjab. American Journal of Agricultural Economics. 1989;71(2):303_310.

Andersson A. Maize remittances, smallholder livelihoods and maize consumption in Malawi. The Journal of Modern African Studies. 2011;49(01):1_25.

Anwar T. Absolute poverty in Pakistan: evidence and alleviating strategy. Journal of Rural Development and Administration. 1998;30:75_94.

Arif GM, Nazli H, Haq R, Qureshi SK. Rural Non-agriculture Employment and Poverty in Pakistan [with Comments]. The Pakistan Development Review. 2000;p. 1089_1110.

Bakhsh K, Ahmad B, et al. Technical efficiency and its determinants in potato production, evidence from Punjab, Pakistan. 2006;.

Battese GE, Broca SS. Functional forms of stochastic frontier production functions and models for technical inefficiency effects: a comparative study for wheat farmers in Pakistan. Journal of productivity analysis. 1997;8(4):395_414.

Battese GE, Coelli TJ. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical economics. 1995;20(2):325_332.

Battese GE, Coelli TJ. Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. Springer; 1992.

Battese GE, Coelli TJ. Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. Journal of econometrics. 1988;38(3):387_399.

Battese GE, Malik SJ, Gill MA. An investigation of technical inefficiencies of production of wheat farmers in four districts of Pakistan. Journal of Agricultural Economics. 1996;47(1-4):37_49.

Brümmer B, Glauben T, Thijssen G. Decomposition of productivity growth using distance functions: the case of dairy farms in three European countries. American Journal of Agricultural Economics. 2002;84(3):628_644.

Bravo-Ureta BE, Evenson RE. Efficiency in agricultural production: the case of peasant farmers in eastern Paraguay. Agricultural economics. 1994;10(1):27_37.

Carroll J, Newman C, Thorne F. A comparison of stochastic frontier approaches for estimating technical inefficiency and total factor productivity. Applied Economics. 2011;43(27):4007_4019.

Caudill SB. Estimating a mixture of stochastic frontier regression models via the EM algorithm: A multiproduct cost function application. Empirical Economics. 2003;28(3):581_598.

Christiaensen L, Demery L, Kuhl J. The (evolving) role of agriculture in poverty reduction: An empirical perspective. Journal of development economics. 2011;96(2):239_254.

Coelli T. Estimators and hypothesis tests for a stochastic frontier function: a Monte Carlo analysis. Journal of productivity analysis. 1995;6(3):247_268.

Coelli T, Perelman S. Technical efficiency of European railways: a distance function approach. Applied Economics. 2000;32(15):1967_1976.

Coelli T, Perelman S. Efficiency measurement, multiple-output technologies and distance functions: With application to European Railways. 1996;.

Coelli TJ, Rao DSP, O'Donnell CJ, Battese GE. An introduction to efficiency and productivity analysis. Springer Science & Business Media; 2005.

Cornwell C, Schmidt P, Sickles RC. Production frontiers with cross-sectional and time-series variation in efficiency levels. Journal of econometrics. 1990;46(1):185_200.

Cuesta RA. A production model with firm-specific temporal variation in technical inefficiency: with application to Spanish dairy farms. Journal of Productivity Analysis. 2000;13(2):139_158.

Darku AB, Malla S, Tran KC. Historical review of agricultural efficiency studies. CAIRN Research Network. 2013;.

Ekayanake S. Location specificity, settler type and productive efficiency: a study of the Mahaweli project in Sri Lanka. The Journal of Development Studies. 1987;23(4):509_521.

Fan S, Hazell P. Returns to public investments in the less-favored areas of India and China. American Journal of Agricultural Economics. 2001;p. 1217_1222.

Farrell MJ. The measurement of productive efficiency. Journal of the Royal Statistical Society Series A (General). 1957;p. 253_290.

Fuentes HJ, Grifell-Tatjé E, Perelman S. A parametric distance function approach for Malmquist productivity index estimation. Journal of Productivity Analysis. 2001;15(2):79_94.

Greene W. Fixed and random effects in stochastic frontier models. Journal of productivity analysis. 2005;23(1):7_32.

Greene W. Alternative panel data estimators for stochastic frontier models. Unpublished manuscript (September 1, 2002), Department of Economics, New York University. 2002;.

Greene WH. Maximum likelihood estimation of econometric frontier functions. Journal of econometrics. 1980;13(1):27_56.

Griliches Z, Mairesse J. Production functions: the search for identification. National Bureau of Economic Research; 1995.

Grosskopf S, Margaritis D, Valdmanis V. Estimating output substitutability of hospital services: A distance function approach. European Journal of Operational Research. 1995;80(3):575_587.

Hayami Y, Ruttan VW, et al. Agricultural development: an international perspective. Baltimore, Md/London: The Johns Hopkins Press; 1971.

Huang CJ, Bagi FS. Technical efficiency on individual farms in northwest India. Southern Economic Journal. 1984;p. 108_115.

Husain A, Khan AQ. Relationship between agriculture and GDP growth rates in Pakistan: An Econometric Analysis (1961_2007). Academic Research International. 2011;1(2):322_326.

Javed MI, Adil SA, Javed MS, Hassan S. Efficiency analysis of rice-wheat system in Punjab, Pakistan. Pak J Agri Sci. 2008;45(3):95_100.

Kalirajan K. An econometric analysis of yield variability in paddy production. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie. 1981;29(3):283_294.

Kalirajan KP. On measuring economic efficiency. Journal of applied econometrics. 1990;5(1):75_85.

Kalirajan KP, Obwona MB, Zhao S. A decomposition of total factor productivity growth: the case of Chinese agricultural growth before and after reforms. American Journal of Agricultural Economics. 1996;p. 331_338.

Kumbhakar SC. Estimation of profit functions when profit is not maximum. American Journal of

Agricultural Economics. 2001;83(1):1_19.

Kumbhakar SC. Production frontiers, panel data, and time-varying technical inefficiency. Journal of econometrics. 1990;46(1):201_211.

Kumbhakar SC, Hjalmarsson L. Estimation of technical efficiency and technical progress free from farm-speci_ed e_ects: an application to Swedish dairy farms. Memorandum-Department of Economics, Gothenburg University, School of Economics and Legal Science (Sweden). 1991;.

Kumbhakar SC, Löthgren M, et al. A Monte Carlo analysis of technical inefficiency predictors. Economic Research Inst.; 1998.

Kumbhakar SC, Lovell CK. Stochastic frontier analysis. Cambridge University Press; 2003.

Kuznets S, Murphy JT. Modern economic growth: Rate, structure, and spread. vol. 2. Yale University Press New Haven; 1966.

Lau LJ, Yotopoulos PA. A test for relative efficiency and application to Indian agriculture. The American Economic Review. 1971;p. 94_109.

Lee YH, Schmidt P. A production frontier model with flexible temporal variation in technical efficiency. The measurement of productive efficiency: Techniques and applications. 1993;p. 237_255.

Lin JY. Rural reforms and agricultural growth in China. The American economic review. 1992;p. 34_51.

Marschak J, Andrews WH. Random simultaneous equations and the theory of production. Econometrica, Journal of the Econometric Society. 1944;p. 143_205.

Meesters A. A note on the assumed distributions in stochastic frontier models. Journal of Productivity Analysis. 2014;42(2):171_173.

Meeusen W, Van den Broeck J. E_ciency estimation from Cobb-Douglas production functions with composed error. International economic review. 1977;p. 435_444.

Mellor JW, Lele UJ. Growth linkages of the new food grain technologies. 50. Department of Agricultural Economics, Cornell University; 1972.

O'Donnell CJ, Coelli TJ. A Bayesian approach to imposing curvature on distance functions. Journal of Econometrics. 2005;126(2):493_523.

Orea L, Kumbhakar SC. E_ciency measurement using a latent class stochastic frontier model. Empirical Economics. 2004;29(1):169_183.

Parikh A, Ali F, Shah MK. Measurement of economic efficiency in Pakistani agriculture. American Journal of agricultural economics. 1995;p. 675_685.

Ravallion M, Datt G. India's Checkered History in Fight against Poverty: Are There Lessons for the Future? Economic and Political Weekly. 1996;p. 2479_2485.

Richmond J. Estimating the e_ciency of production. International economic review. 1974;p. 515_521.

Sauer J, Frohberg K, Hockmann H. Stochastic e_ciency measurement: the curse of theoretical consistency. Journal of Applied Economics. 2006;9(1):139_165.

Schmidt P. One-step and two-step estimation in SFA models. Journal of Productivity Analysis. 2011;36(2):201_203.

Schmidt P. On the statistical estimation of parametric frontier production functions. The review of economics and statistics. 1976;58(2):238_39.

Schmidt P, Lin TF. Simple tests of alternative speci_cations in stochastic frontier models. Journal of Econometrics. 1984;24(3):349_361.

Schmidt P, Sickles RC. Production frontiers and panel data. Journal of Business & Economic Statistics. 1984;2(4):367_374.

Schultz TW, et al. Transforming traditional agriculture. Yale University Press. 1964;.

Swinton JR. At What Cost do we Reduce Pollution? Shadow Prices of SOâ„ Emissions. The Energy Journal. 1998;p. 63_83.

Thirtle C, Hadley D, Townsend R. Policy-induced Innovation in Sub-Saharan African Agriculture: A Multilateral Malmquist Productivity Index Approach. Development Policy Review. 1995;13(4):323_348.

Timmer CP. Using a probabilistic frontier production function to measure technical e_ciency. The Journal of Political Economy. 1971;p. 776_794.

Winsten C. Discussion on Mr. Farrellâ ™s paper. Journal of the Royal Statistical Society. 1957;120:282_ 284.

WorldBank. Poverty in Pakistan: Vulnerabilities, Social Gaps, and Rural Dynamics. World Bank Report. 2002;(24296-PAK).