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PRODUCTIVITY AND EFFICIENCY DIFFERENCE AMONG KENTUCKY GRAIN FARMS

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PRODUCTIVITY AND EFFICIENCY DIFFERENCE AMONG KENTUCKY GRAIN FARMS

THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Science in the
College of Agriculture, Food and Environment at the University of Kentucky
By

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ABSTRACT OF THESIS

PRODUCTIVITY AND EFFICIENCY DIFFERENCE AMONG KENTUCKY GRAIN FARMS

This paper attempts to estimate productivity and efficiency for Kentucky grain farms by applying a two-stage Date Envelopment Analysis (DEA) and DEA-based Malmquist method. The study covers the years 1999-2015. Also, productivity and efficiency testing hypotheses among different farm sizes and years are estimated. In the first step, productivity and efficiency indices are estimated through deterministic DEA. In the second stage, a panel regression is run with exogenous variables to explain the productivity and efficiency variation. In general small farms were found to be the least scale efficient compared to mid-sized and large farms, even though the results show overall productivity gain and technological improvements during the study. Therefore, small farms need to diversify their scope to survive due to a lack of scale efficiency.

KEYWORDS Data envelopment analysis, Malmquist efficiency index, technical efficiency, scale efficiency, grain farms.

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11/09/2021

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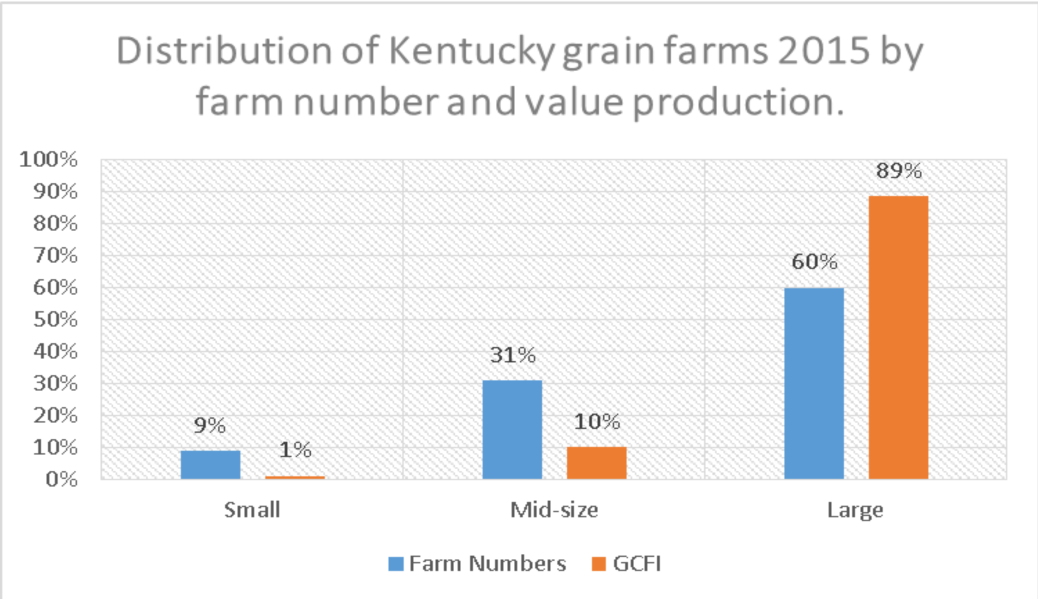
Table of Contents

List of Tables

List of Figures

Chapter1: Introduction

There are over 2 million farms in the United States, of which 88 percent are small farms with less than ($350,000) gross farm cash income (GFCI). The rest of the reminder, Twelve percent were mid-size and large farms (USDA, 2016). Farm sizes have shifted toward larger farms over the decades. This made it difficult for smaller family farms to survive and compete with mid-size and large farms. As for Kentucky's grain farms, over half were large farms with the biggest share of farm income, as shown in figure 1.



. Figure 1. Farm and production values for farm sizes of Kentucky grain farms 2015.

The distribution of U.S. farms across commodities is based on farm sizes. According to (USDA, 2017), farm sizes are based on annual Gross Cash Farm Income (GCFI), in which a farm with GCFI of less than $350,000 is considered small. A mid-size farm will have a GCFI of $350,000-$999,999 and large farms with GCFI of

$1,000,000 or more. We can also look at farms sizes and commodities distribution production values based on Figure 2. Small farms of the U.S. comprise about 26% of the agricultural sector and are comparable to mid-size farms with 23%. Small family farms dominate the production of certain commodities, including poultry and hay, with a share of 60% and 73%, respectively. On the other hand, large farms lead the way in producing cotton, dairy, and high-value crops (i.e., fruits and vegetables), and making up shares of 55%, 68%, and 56%, respectively (USDA 2016).

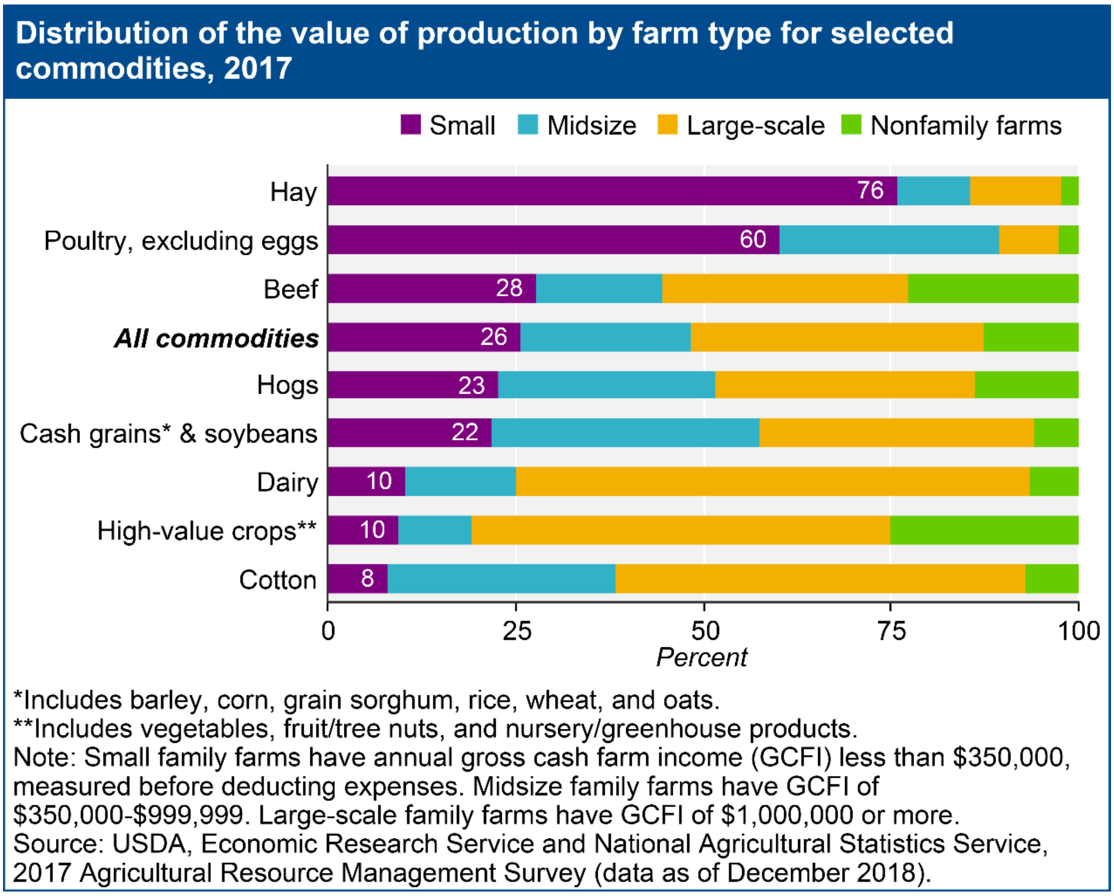


Figure 2 Distribution of the value of production by farm types for commodities. (Source: USDA, Economic Research Service, and National Agricultural Statistics Services, Agricultural Resource Management Survey)

Since small farms lack the benefits of economies of scale and competitive markets, the economic viability for small farms and farm sizes have been trending toward larger farms (C. Paul, Nehring, Banker, & Somwaru, 2004). Therefore, for small farms to be efficient and economically viable, input reduction is one of the ways to reduce operating costs.

U.S. agriculture transformed considerably in the last eighty years. During the 1920s, one out of three Americans were working on farms. However, in 1977 that number decreased to one out of twenty-eight, roughly 3.6 percent of 216 million people. From 1920 to 1977, there was 48.7 million net migration, and from 1920 to 1960, the farm work population reduced from 15.6 million to 8 million and with the same farming area. The average farm size increased from 150 acres to 440 acres by 1979 (Vogeler, 2019).

In general, farms fluctuate in operating profit margin (OPM) according to farm sizes based on their (GCFI). Larger farms are more efficient than smaller farms due to economies of scale (Hoppe, 2015). In our study, Kentucky grain farms over 60% of the small farms have an operating profit margin of less than 10%, which shows a higher chance of financial issues, the (OPM) is greater for mid-size and large farms and fewer farm operations in the red zone as shown in figure 7. The operating profit margin increases once the farm gross cash farm income GCFI passes ($150,000) (Hoppe, 2015).

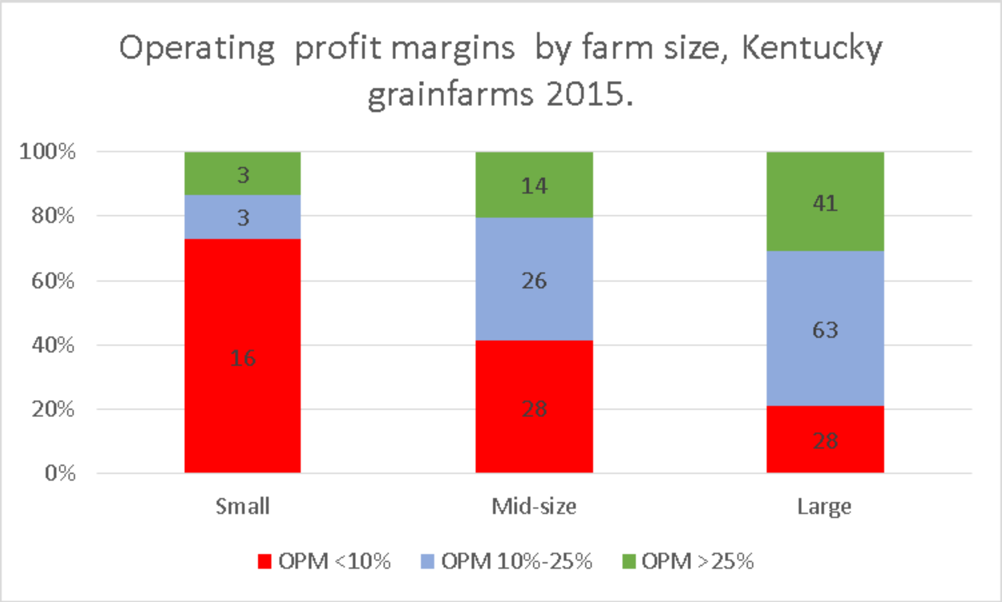


Figure 3. Kentucky grain Farm types and operation margins, 2015.

Kentucky has over 76,000 farms, which places it on 6th rank nationally in farm count in 2013. Kentucky ranks 16th nationally, accruing $2.74 billion in net farm income and $5.7 in the total value of cash receipt for commodities in terms of farm income. Kentucky ranks 25th in total agricultural exports in 2013 and 2nd in unprocessed tobacco. The top exported agricultural products for 2013 were soybeans, livestock products, wheat, poultry, and other plant products (USDA, 2014, 2015).

In 2013, Kentucky farmers spent $3.9 billion on inputs. These expenditures include $953 million on feed, $462 on fertilizer, $436 million on labor, $304 million on fuel and oil, $263 million on seeds, $164 million on chemicals, and $77 million on seeds electricity (USDA, 2014, 2015).

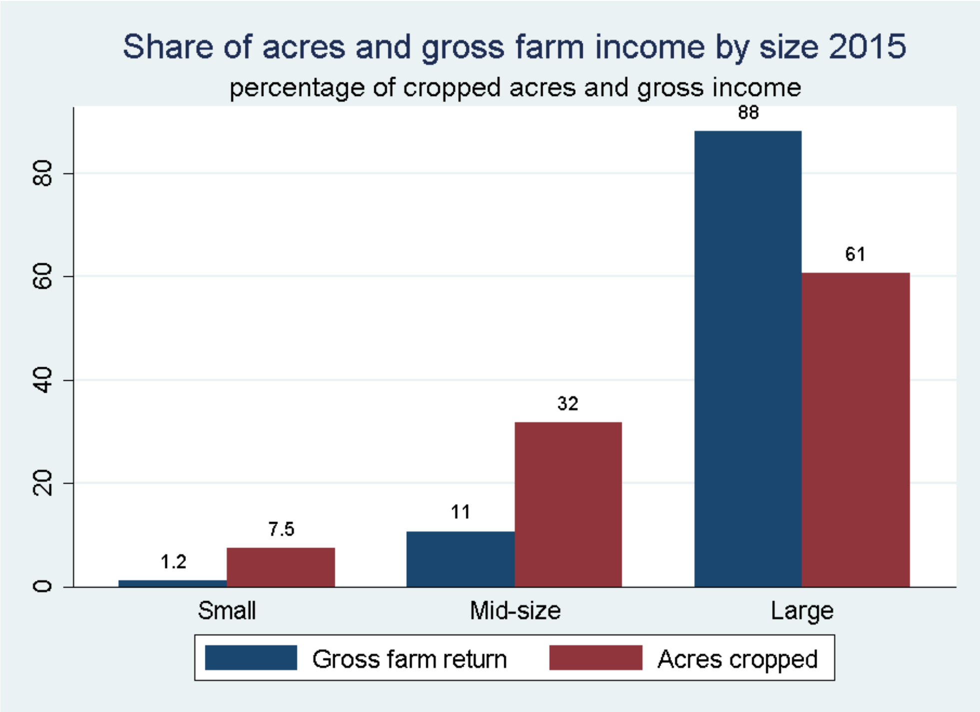


Figure 4 Kentucky Grain farms percentage share of acres cropped and gross farm return by size 2015 . (source:KFBM 2015 farm data set)

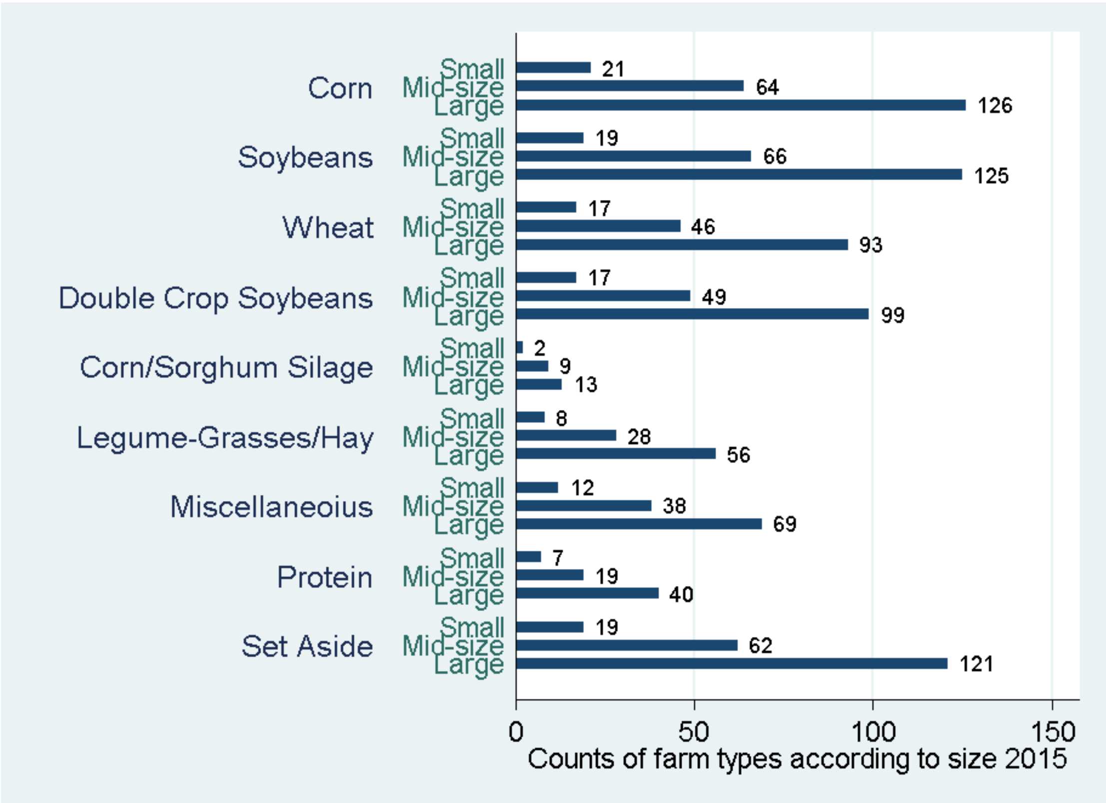


Figure 5. Kentucky farm types and sizes 2015.

In this study, we focus on the grain farms in Kentucky, and grain farms are defined as the value of feed fed is less than 40% of crop return, and the value of feed to dairy is less than one-sixth of crop return (Jenkins, 2014). Kentucky grain farms are scattered over four geographical areas: Purchase, Pennyroyal, Central Kentucky, and Ohio Valley. Kentucky's grain farms for the year 2015 in the dataset were 222 farms with average tillable acres of 2,440. When it comes to farm expenditures, there are six groups of expenses. These six types of expenditures are crop cost(seeds, fertilizers and pesticides), power and machines, building, labor, land, and other expenses. Other expenses are divided into veterinary expenses, medicine, livestock supplies, insurance, diverse and non-land charges, while non-cash costs entail depreciation, non-land interest, and interest on owned lands (KFBM 2014). An accrual adjustment was made for both cash and non-cash costs. The accrual adjustments were made for variations in prepaid expenditures and accrual interest and expenses.

Comparing the cost of non-feed farms based on farm size, the large farms had the highest percentage crop expense amongst the three group farm sizes. Meanwhile, small farms had a low crop expense and land charges, yet they incurred a higher expenditure for equipment, power, and labor costs than the other farm group sizes. As for labor costs (paid and unpaid), the larger farms had lower labor expenditures than small farms. This can partly contribute to a higher land utilization percentage, especially for tobacco, compared to mid-sized and large farms. Another explanation for the difference in labor cost is the opportunity cost of unpaid labor costs for the operator's own and unpaid family labor on the farm, leaving small farms a few acres to divide the cost over, as presented in Figure 5. The non-feed cost components are in percentage, while farm size is defined based on acres rather than gross income in the figure mentioned above.

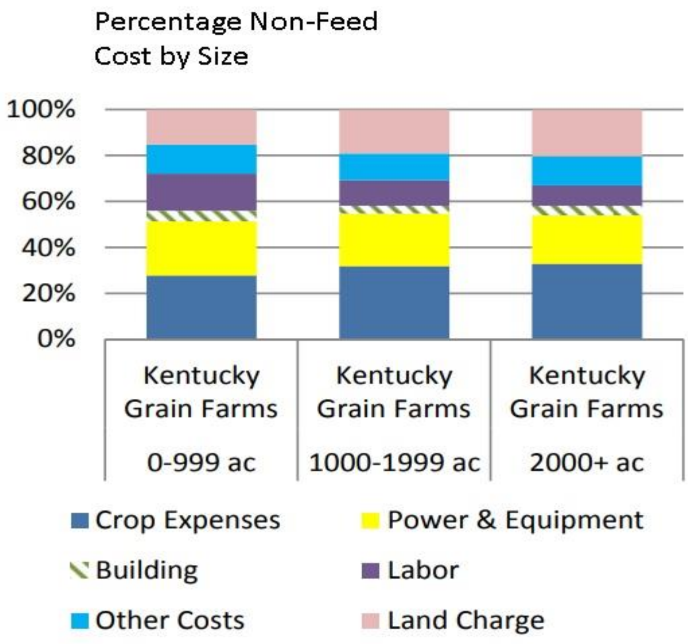


Figure 6. Percentage of non-feed cost by farm sizes in Kentucky.

On the other hand, land cost entails land equity charges, lease cost, cash rent, interest on non-cash tillable acres, and property taxes. Insurance cost includes crop, liability, and property insurance on farm assets (KFBM 2014).

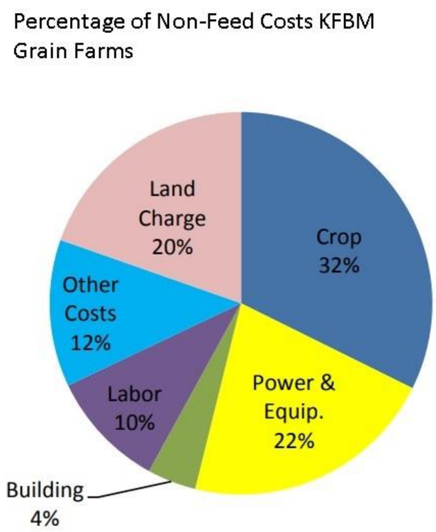


Figure 7. Percentage of non-feed cost KFBM Kentucky grain farms.

Efficiency and productivity improvement are vital for farms, more specifically for small-scale or small farms. In general, productive farms can study in business for longer with the chance to expand in the future (Key, 2018). The improvement of efficiency can have many spillovers, and may be agricultural productivity progression is essential in poverty reduction (Mellor, 1999). Devkota and Upadhyay (2013) found that agricultural productivity growth drastically reduces poverty among rural Nepalese households. Gollin, Lagakos, and Waugh (2014) research shows enormous productivity discrepancies for three grains, maize, rice, and wheat, among countries based on macro and micro evidence and refute that hypothesis that productivity differences are due to measurement error. Thus, productivity improvement can be the catalyst for an array of direct and indirect conduits to poverty mitigation (Thirtle, Lin, & Piesse, 2003). However, agricultural productivity lags in developing countries compared to other non-agricultural sectors by almost double even after considering sector differences (Gollin et al., 2014). even though the developed countries have led the way in terms of the highest yield in agricultural per worker and land, despite the lag for developing countries, there has been an improvement in agricultural productivity in recent decades. Yet, the current productivity is still at the same level as the industrialized nation in 1960 (Fuglie & Wang, 2012).

Sustainable agriculture practices depend on applying fewer inputs to attain optimal efficiency and reduce negative externalities such as; environmental pollution due to excessive chemicals and economic cost. Sadiq and Isah (2015) claim that well-informed practices and management of ecological resources are essential to transition from intensive input-use practice toward sustainability. Sadiq et al. (2015) and Sanusi (2015) claim that overproduction and excessive-input use in agriculture is one of the many factors responsible for environmental degradation and lack of economic stability.

The structure of agriculture has changed over the decades, starting in the 1920s in Europe and the United States. In this period, agriculture transitioned towards higher application of chemicals, pesticides, and energy consumption, mainly derived from fossil fuels. During the 1960s and 1970s, the agricultural green revolution program had exported the intensive application of inputs and advanced technologies to developing countries (Sadiq et al., 2015). This improved crop yields considerably per unit of cultivated lands in tropical and temperate areas, and this practice seemed profitable during the 1970s. However, nowadays, sustainable agriculture is emphasized for various environmental and economic factors. Conventional and intensive-input agriculture use is criticized for short-term maximum yield without prospects for future stable production (Sadiq et al., 2015).

Meanwhile, sustainable agricultural practices force more long-term steady production and less ecological damage than maximum out compared to conventional agriculture (Sadiq et al., 2015). This cannot merely be achieved by less input use but also with innovation and new technology adoption to agriculture (Sadiq et al., 2015). Despite some farmers' slow adoption of precision agriculture technologies, there is a potential to reduce input costs through access to information and application control (Schimmelpfennig & Ebel, 2016). In their study, Van Evert, Gaitán-Cremaschi, Fountas, and Kempenaar (2017) showed that precision agricultural herbicide and fungicide applicators increased the profitability and reduced input cost in Greece olive vines, and increased sustainability on potato farms in the Netherlands.

There are two exchangeable terminologies used to define a production performance of a firm: efficiency and productivity. In general, efficiency is determined by how a firm's decision-making unit (DMU) can utilize and coordinate production inputs. Although there is a difference between productivity and efficiency, productivity is considered a more descriptive measure of performance while efficiency is normative (Ray & Desli, 1997).

Two commonly used approaches to estimate the efficiency and productivity of firms or Decision Making Units (DMU) are the non-parametric method Data Envelopment Analysis (DEA) and the parametric Stochastic Frontier Analysis (SFA). This study uses DEA and Malmquist-based DEA for our farm data analysis and compares our results to those in the literature for both (DEA) and (SFA).

The two main approaches that have been used in the analysis of financial or production efficiency are stochastic frontier analysis (SFA) and data envelopment analysis (DEA). In the first case, the production function consists of a random component and production inefficiencies, including errors for both. The latter approach (DEA) does not require a functional form production assumption since the efficient frontier is derived from all data points (Bauman, Thilmany, & Jablonski, 2017). Instead, production functions are considered production frontier; any deviation from the function is viewed as inefficiency (Greene, 2012).

Data Envelopment Analysis (DEA) measures firms' efficiency through linear programing. This method allows the efficiency analysis of firms that convert multiple inputs into multiple outputs. Thanassoulis, Portela, and Despic (2008) defined DMU’s efficiency as a ratio of its weighted outputs to weighted inputs. Each DMU’s efficiency score is estimated relative to an efficiency frontier. The DMUs operating on the frontier will have a score of 1 or (100% efficient) compared to their peers, and those operating under the frontier will have an efficiency score of less than one. An efficiency score of less than 1 suggests that the DMU is inefficient. The efficient firms (i.e., with scores equal to 1) will serve as a benchmark for the rest of the sample's inefficient firms.

Charnes, Cooper, and Rhodes (1981) applied linear programing to estimate efficiencies. The first of one assumes Constant-Return to Scale technologies, which is known as (CRS) or (CCR) or (OTE) Overall technical efficiency. Charnes, Cooper, and Rhodes 1978 also suggested a measure of overall technical efficiency (OTE). OTE is comprised of two different components, known as Pure Technical Efficiency (PTE) and Scale Efficiency S.E. The partitioning of efficiency measures assists in identifying the source of the inefficiencies.

The second assumption is Variable-Return to Scale technology (VRS). PTE is obtained under variable returns to scale measures the inefficiencies due to managerial practices. Unlike CRS, it omits SE The model was proposed by (Banker, Charnes, & Cooper, 1984) and is also known as the (BCC) model. The S.E. can be derived from the OTE through PTE.

For comparing efficiencies over time, a widely implemented method has been the Malmquist Productivity Index (MPI) which measure productivity changes over time with similar DEA nonparametric approach. MPI underpinnings developed by Caves, Christensen, and Diewert (1982) and further described by R. Färe, Grosskopf, Lindgren, and Roos (1994) to estimate the index using linear programing. The productivity index MPI is decomposed into efficiency change and technological change. A firm is considered technically efficient when a level of output is achieved with minimum input. If a firm falls under its production possibility frontier, then deemed inefficient(Figure.6). While increased output occurs over time due to technological change given the same input combination level for the same firm, these changes can shift the production possibility frontier upward (Tim J Coelli & Rao, 2005). When the value of Malmquist total factor productivity is greater than one (MPI> 1) shows progress in productivity when (MPI <1), this means the status quo or regress in productivity. The two components of the total factor productivity, which are known as efficiency change and technological change. The efficiency change shows the DMUs efficiency change over time and catching up to the frontier. The technological change reflects the shift in the technology frontier over time.

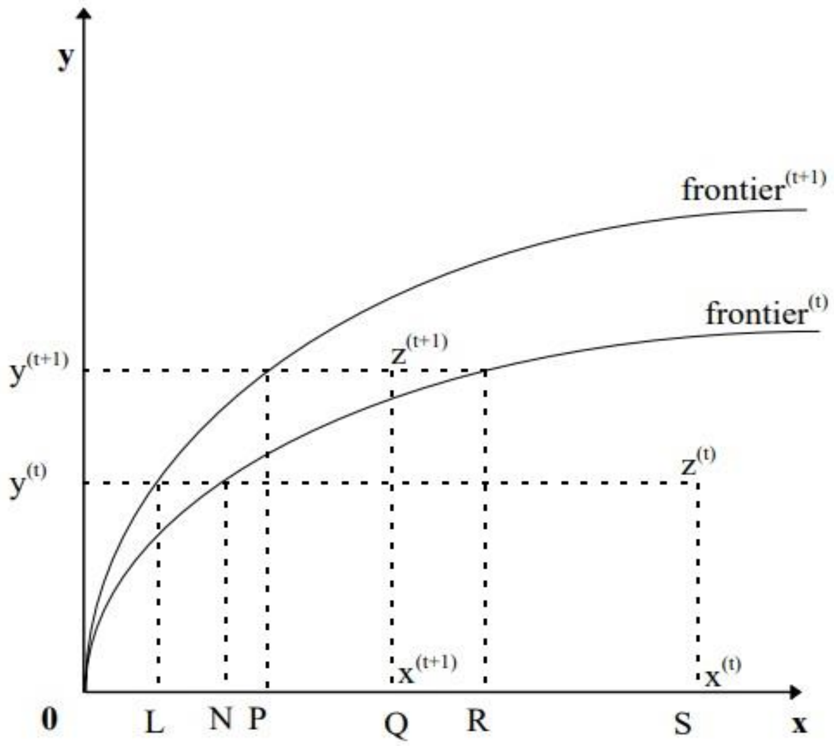


Figure 8. Productivity Change over time. (source:(Worthington 2000)

This thesis aims to measure the efficiency and productivity change of grain farms in Kentucky from 1999-2015. In the first stage, efficiency measures, overall technical efficiency, pure technical efficiency, and scale efficiency are estimated.

Also, measures over productivity were calculated, including total factor productivity, efficiency change, and technological change. In the second stage, we run a regression model on some efficiency and productivity measures and test the regression coefficient among the farm sizes for the independent variables.

Chapter 2: Literature Review

Relative efficiency measurement is generally obtained through two main methods parametric and non-parametric. Stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are the primary examples for each method. SFA was introduced by Aigner, Lovell, and Schmidt (1977) and Meeusen and van Den Broeck (1977). DEA was proposed by Charnes, Cooper, and Rhodes (1978).

In SFA, there is a functional relationship between the input and output; the production parameters are estimated through a statistical technique (Mukhtar, Mohamed, Shamsuddin, Sharifuddin, & Iliyasu, 2018). According to (Tim J Coelli, 1995), one advantage of SFA is hypothesis testing. On the other hand, one of SFA's shortcomings is the assumption of functional form for the frontier and error term distribution. DEA is distinct in the utilization of linear programming to build a piecewise frontier for the data. Since DEA is non-parametric and deterministic, it does not require an assumption about functional form or error term distribution. Instead, it calculates the inefficiencies for the DMU by deviation from the efficiency frontier (Tim J Coelli, 1995).

DEA is an approach to evaluate relative efficiencies of entities named as DMUs (decision-making units). Each DMUs efficiency is defined in terms of the ratio of the sum of output to input weighted (Thanassoulis et al., 2008).

$$T.E._k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \qquad \textit{Equation 1}$$

In which the following means:

TE_k: technical efficiency of firm k., using (m) inputs to produce (s) output.

y_{rk} :output amount of r produced by firm k:

x_{ik}: input amount of i used by firm k:

u_r: weighted output of r;

v_i: weighted input of i.

n: number of DMUs .

s: number of outputs

m: number of inputs

SFA comes with different prerequisites: functional form for the production frontier, normal distribution of random errors, and non-negative technical efficiency of random variables (half-normal or truncated normal distribution) (Timothy J Coelli, Rao, O'Donnell, & Battese, 2005). SFA is a parametric approach that theorizes a functional form that sets a frontier or a boundary for the production, and any nonconformities can be interpreted as inefficiency. The most widely used functional forms used in research studies are Cobb-Douglas and translog cost function. However, the translog functions proved to be more malleable in a way that can provide a second-order differential approximation and any arbitrary function any point. Despite this flexibility with translog function, multicollinearity may occur (Timothy J Coelli et al., 2005). SFA also assumes that some unit deviation from the production frontier could not solely be attributed to technical inefficiencies. Instead, it could be due to measurement errors, non-systematic factors, or statistical noises.

Distributional assumptions have to be made to separate stochastic noise from efficiency effects (Bauer, 1990). Even though half-normal is considered to have proper formulation, the truncated-normal allows for more flexibility in modeling (Battese & Coelli, 1995; Jondrow, Lovell, Materov, & Schmidt, 1982). The distributions assumed for inefficiencies are half-normal, truncated, exponential, and gamma when the error term is one-sided. With the distributional assumptions for both error terms, the model is estimated via maximum likelihood. For cross-section models, the inefficiency is estimated indirectly from the combined error term and conditional on the value of composite residual (Katharakisa & Katostaras, 2016). sometimes theoretical considerations affect the choice of distributional specification. For instance, when the mode is zero, the half-normal and exponential distribution is avoided, meaning most inefficiency would center around the value of zero, while technical efficiency value of one, meanwhile truncated normal and gamma model permit wider range (Timothy J Coelli et al., 2005). Another difference between SFA with DEA is that the latter allows for multiple input and output simultaneously. This is plausible with (DEA) approach(Scippacercola & Sepe, 2014).

2.1 Agriculture Efficiency and Productivity

2.2 DEA related studies

DEA been utilized across different fields of study. It can be applied in an output-oriented or an input-oriented configuration, depending on the type of research. For example, an input-oriented DEA is necessary for a farm setting since farmers have more control over short-term input than output (Williams & Shumway, 1998) (C. J. M. Paul & Nehring, 2005).

Deliktaş and Candemir (2007) measure production efficiency and total factor productivity of state-owned Turkish agriculture for 1999-2003. In the first stage, the results found that technical efficiency deteriorated while scale efficiency improved. Therefore, the result of technological regress causes a decline in total factor productivity for the study period. The second part of the study was a regression on the technical efficiency of relevant factors, amongst which irrigation rate, geographical factors, and tractor as technology were significant.

Candemir, Özcan, Güneş, and Deliktaş (2011) measured Turkey's Hazelnut Agricultural Sale Cooperative Union's total factor productivity growth and technical efficiency in Turkey for years 2004-2008 using DEA and Malmquist productivity index. Overall, the total factor productivity decreased, while there was a technical efficiency improvement on average and regressed in technological change, technical efficiency improvement.

The input-oriented DEA method with a variable return to scale specification was implemented by (Wang, Shi, Zhang, & Sun, 2017) to investigate agricultural efficiencies for irrigation districts in Northwest China. Only 30% of the irrigation districts were technically efficient, whereas 42% and 32% exhibited pure and scale efficiency. It is noticeable that input-reduction can be achieved with the agricultural practice in terms of irrigation area, green water, blue water, fertilizer, and machinery while maintaining the same output level.

Funk (2015) compares technical efficiency and productivity among farms that adopted BES (Biologically enhanced soybeans) for a panel of farms from 1993 to

2011. First, DEA method was used to estimate efficiencies and productivity, technical efficiency, and the Malmquist efficiency index with its two components, efficiency change, and technological changes. Five inputs and output factors were included; labor, general, direct inputs, maintenance, and energy. The output categories are corn, wheat, soybeans and sorghum, and other crops. Later, a Tobit regression analysis showed a positive impact of (biologically Enhanced Soybeans).

Energy efficiency for cucumber greenhouse in Iran was assessed by (Pahlavan, Omid, & Akram, 2012) with return-to-scale assumption data envelopment analysis. This was done for one period of cultivation, and the results found that energy consumption can be reduced with the same output level to be efficient.

Agricultural water efficiency use was measured using DEA for the Heihe River basin in China for 2004-2012. The index for efficiency measure was technical efficiency, pure technical efficiency, and scale efficiency. The results show a change in water utilization efficiency and technical and scale efficiency improvement (Wang et al., 2017)

Millet farm efficiency was estimated for farmers in Kano, Nigeria, 2013-2014 (Mukhtar et al., 2018). Since there is a potential to improve yield amongst the farmers, DEA was used to obtain the farm efficiency measures and an OLS regression to determine the significant factors influencing the technical efficiency.

The potential energy saving of maize farmers was investigated using DEA in Niger State, Nigeria, among small maize farms to determine the efficient farms and calculate the potential reduction of input use among inefficient farms to estimate greenhouse gas emissions and carbon sequestration. Only a portion of the farms were considered technically efficient. However, the results project 32% reduction in overall input if the efficiency of farms below the frontier rose to a higher level (Sadiq et al., 2015).

2.3 SFA and DEA comparison studies

Two federal milk policies that impact marketing policy and income loss have been analyzed on dairy technical efficiency using DEA and SFA (Murova & Chidmi, 2013). Logistic regression is applied to determine efficient farm probability. Both approaches significantly negatively impacted the marking policy, and similar results were obtained for regional impact and some encompassed variables. On the other hand, the income loss policy had a significant positive impact on technical efficiency. Efficiency for U.S. family farms was investigated by C. Paul et al. (2004) for 1996-2001. For the small farms to compete with larger farms and survive by fixing the source of inefficiency. The study applied the DEA and Stochastic Production Frontier (SPF). The results suggest that family farms were inefficient on a scale and technical level (C. Paul et al., 2004). A study by Ghorbani, Amirteimoori, and Dehghanzadeh (2010) investigated the efficiency of cattle feedlot farms in the Caspian for 2007-2008, applying three different techniques: The Stochastic Frontier Analysis (SFA), Data Frontier Analysis (DFA), and Data Envelopment Analysis (DEA). Both of the first two approaches produce lower estimates of the feedlot technical efficiency estimate than respectively compare to the non-parametric DEA approach.

2.4 Efficiency and Productivity in other sectors

Data Envelopment Analysis is versatile across sectors of the industries and not limited to a particular group. In this section, we explore DEA and Malmquist-based DEA studies in the financial sector. The productivity and efficiency of Australian Building society banks was measured for 1993-1997 using the DEA-based Malmquist productivity index. There was a productivity increase in building societies throughout the study; this contributed to technological progress rather than efficiency improvement. However, the efficiency gains were mainly due to scale efficiency (Worthington, 2000).

Camanho and Dyson (2006) applied DEA and Malmquist index to compare efficiency and productivity growth among different Portuguese commercial banks branches. The goal is to recognize the best practice branches and most of the banks use the same resources under different managerial and environmental conditions.

Gulati (2011) investigates efficiency among banks from the private and public bank sectors and different sizes from 2006-2007 in India. The relevant DEA efficiency results show that most domestic banks were inefficient, and only a handful form the efficiency frontier. The private sector banks lead the efficiency frontier, yet their efficiency between the public and private banks is not statically significant. Simultaneously, the difference between larger and medium banks is evident in terms of scale efficiency. In addition, the Tobit regression discloses profitability, and off-balance sheet activity had a significant impact on technical efficiency.

Using DEA, Yannick, Hongzhong, and Thierry (2016) compare technical efficiency between public and private sector banks in Côte d'Ivoire from 2008 to 2010. The challenge for some of the banks is in terms of the transformation of deposits into credit loans. While the foreign banks are efficient compared to the public banks, the Ivorian banks seemed inefficient in terms of loan allocations, and the source of inefficiency is the production scale.

A study by Raphael (2013) investigates the nature and extent of efficiency and productivity of a group of Tanzanian banks. The research applied a DEA-based

Malmquist productivity index. The goal is to compare three categories of banks, large domestic banks, large foreign banks, and small banks for years from 2005-2011. Overall, there was an improvement in most of the efficiency and productivity measures. The mean efficiency was higher for large domestic and small banks compared to foreign banks. While total factor productivity for small banks was higher than large domestic and international banks, there was technical change progress. However, the primary source of efficiency gains was due to technical efficacy rather than scale efficiency.

2.5 Comparing DEA and SFA

The objective of DEA and SFA is to estimate technical efficiencies for decision-making units. Therefore, results obtained from the different methods will have some discrepancies. Some of the literature covered in this study shows the different outcomes for efficiency estimates between the two methods used (C. Paul et al., 2004) (Li, 2009) (Sav, 2012). While in other studies, the inconsistent results indicate a higher efficiency estimate when using SFA (Abdulai, Nkegbe, & Donkoh, 2018) (Wadud & White, 2000).

C. Paul et al. (2004)

Analyzed the farming industry's structural change and traditional family farms' trajectory and fate. The farms were surveyed from the Corn-Belt region and for the years 1996-2001. The goals are to determine the economic performance of the small U.S. farms and their ability to compete with larger farms and subsist in a fast-changing market through applying determinist and stochastic frontier methods. There was a difference in scale and efficiency measurements of economic performance between the DEA and SFA. However, the results are compatible with USDA findings

Suggesting that small farms cost efficiency due to operation scale and diversity is a major contributor to their incapability to compete with larger farms.

2.6 Environmental Factors and Efficiency

There are exogenous factors that affect the performance of firms that are beyond managerial control. However, several DEA models consider external factors, such as Banker and Morey (1986a) utilize a categorical model and the non-discretionary variable model proposed by Banker and Morey (1986b) and Charnes et al. (1981). These models incorporate environmental factors into the DEA. The most appropriate approach is the two-stage method (Timothy J Coelli et al., 2005) (Pastor, 2002). The two-stage DEA starts with running a DEA model with the discretionary inputs and outputs factors; then, the estimated efficiency is regressed through either a Tobit or ordinary least squares against the exogenous variable (i.e., environmental or non-discretionary factors). However, some might argue that the ordinary least square regression might be suitable as a replacement for a tobit regression inf some cases (Hoff, 2007) .

Chapter 3: Methodology

3.1 Data

The data used in this study is prepared by the Kentucky Farm Business Management (KFBM). Financial and agronomic data for the farms were obtained from Ilinois program Farm Business Farm Management (FBFM) into a spreadsheet each year. Individual farm's financial data were pooled to represent the whole farm. In this study, we only use the certified data, which means data reviewed and verified by (KFBM) specialist. Annual precipitation data were obtained from UKAg weather center measured in inches while growing days for corn obtained from Useful to Usable (U2U) multi-year, multi-university integrated research and extension project. The input data for the DEA and MPI model are divided by the operational acres of the individual farms to normalize the data.

This study tries to assess Kentucky grain farm efficiency using a non-parametric method DEA. The data was obtained from the KFBM at the farm level from 1999 to 2015. The panel data is unbalanced for 499-grain farms for consecutive years with the total observation of 4078 for MPI data set and 2663 observations for DEA dataset. The farms are divided into three sizes according to their gross return the small, mid-sized and larger farms observations. Then measures of a farm’s relative pure technical efficiency (PTE), overall technical efficiency (OTE), scale efficiency S.E. were obtained through an input-oriented DEA. A panel data is used to determine input-oriented Malmquist total factor productivity (TFP), from a panel set data compiled from the same cross-section data set. TFP is decomposed into efficiency change (EFFCH) and technological change (TECH).

The DEA models require input and output for each farm, referred to as DMUs. The inputs of interest for grain productions are measured in U.S. dollars: fertilizer cost, pesticide cost, seed cost, hired labor cost, machinery repairs, and fuel and oil cost. These are considered the major inputs for grain farm operation's cost. The output variable is measured in gross farm return.

Table 1: Summary statistics.

Variables	**Variable symbols**	**Mean**	**Std. dev.**
Discretionary INPUTS			
X_1 Fertilizer		198384.1	328935
X_2 Pesticides		92188.88	121034.3
X_3 Seed		111458.4	152549
X_4 Machinery Repairs		63051.38	70771.19
X_5 Fuel and Oil		53212.97	82863.41
X_6 Hired Labor		98629.62	155416.7
OUTPUTS			
Y_1 Gross Farm Returns		1369466	1941115
Non-Discretionary inputs			
β_1 Age of oldest Dependent child	**Age**	5.16	9.1
β_2 Number of Household	**HHM**	2.17	2.35
Members	**SPR**	140.64	436.38
β_3 Soil Productivity Rating	**TA**	4535353	8455640
β_4 Total Assets	**GOV**	65638.84	86053.44
β_5 Government Payments			
β_6 Growing Degree Days	**AGDD**	2420.99	123.92

β 7 Annual Average Precipitation	**AP**	50.23	6.52

According to Golany and Roll (1989), the number of DMUs should be double the number of inputs and output. On the other hand, Bowlin (1998) emphasized that the DMUs should be three times that sum of input and output. Another recommendation regarding DMU size and input-output is that DMUs numbers should equal twice the product of inputs and outputs factors (Dyson et al., 2001). The number of DMUs included per each period is at least greater than the minimum numbers of what literature required; this increases the likelihood of capturing high-performing DMUs to form the efficient frontier.

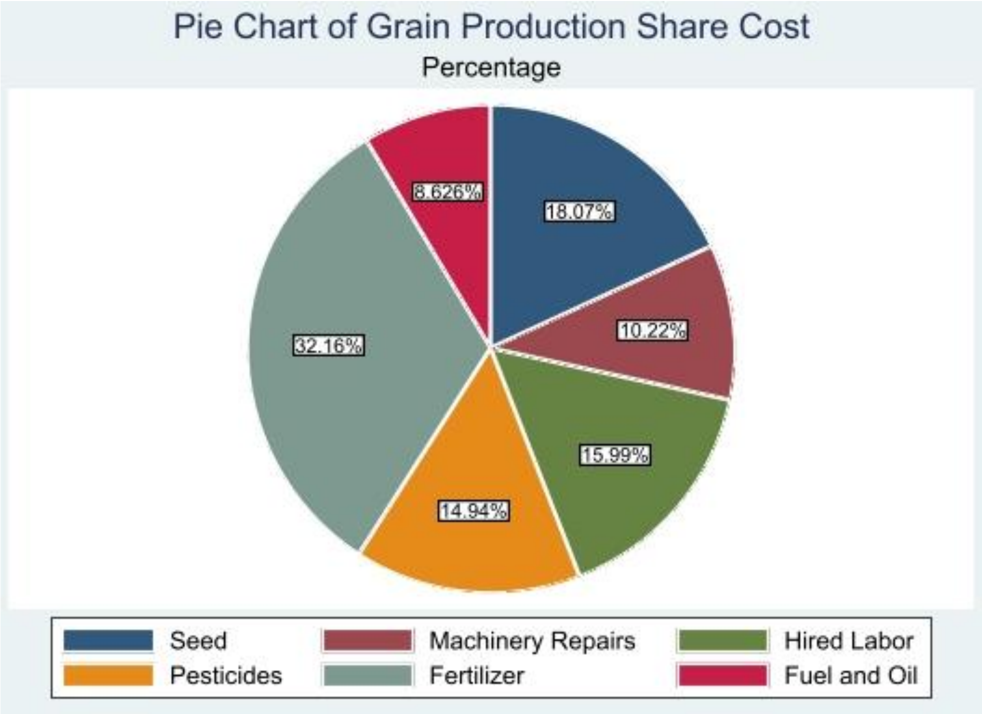


Figure 9. Grain production share costs.

DEA models can determine the efficiency score among DMUs more effectively irrespective of data size developed by (Andersen & Petersen, 1993; Doyle

& Green, 1994; Rousseau & Semple, 1995). DEA models can either be input-oriented or output-oriented. This study applies the input-oriented model to examine efficient inputs used by farmers. On the other hand, inputs utilization can be modified and controlled by the producer. This will reduce input/inputs for the inefficient DMUs to operate on the efficient frontier and then calculate the scale efficiency (S.E.) and whether it is increasing or decreasing. There are two assumptions for input-oriented DEA models, the Constant-Return-to scale (CRS) and Variable-Return to Scale (VRS).

The efficiency measurement unit range from 0 (inefficient) to 1 (efficient), and then the inefficient decision-making units (DMU) will be compared to efficient DMUs on the efficiency frontier to obtain (λ), to calculate the source of inefficiencies. Each inefficient DMUs will be compared to DMUs on the efficient frontier, which is also known as benchmarking. In this case, we can calculate input reduction for inefficient DMUs given the same level of output.

3.2 Theoretical Model

DEA has two main configurations, CRS and VRS, with either input or output orientation. Each of these configurations is used in this study, and scale efficiency is obtained from dividing CRS over VRS. Sometimes CRS is known as overall technical efficiency and VRS as pure technical efficiency; in other words, efficiency is due to no management. We show the specification of the CRS and VRS models as follows.

3.3 Constant Return to Scale (CRS)

The DEA's different models aim to identify the most efficient DMUs in converting inputs (X_1, X_2,…, X_n) into outputs (Y_1, Y_2,…Y_m). Then the DMUs are compared and ranked relative to the best performance DMU in the group. The Constant Return to scale (CRS) model, also referred to sometimes as (CCR) named after (Charnes, Cooper, and Rhodes). Efficiency is defined as the maximum ratio of weighted outputs to inputs, under a condition that every DMUs ratio of weighted outputs to inputs is less or equal to one(Charnes et al., 1978).

The Input-Oriented CCR is calculated as follows:

$$T.E._{k} = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \qquad \text{Equation 2}$$

In which the following means:

TE_k: technical efficiency of firm k., using (m) inputs to produce (s) output.

y_{rk} :output amount of r produced by firm k:

x_{ik}: input amount of i used by firm k:

u_r: weighted output of r;

v_i: weighted input of i.

n: number of DMUs .

s: number of outputs

m: number of inputs

The U_r and V_i denote weights applied to the Output (Y) and input (X) maximize efficiency score (TE_k) for the DMU and results in two things. First, the constraint makes the efficiency score not exceed 1.0 for any DMUs. Second, the applied, weighted outputs and input are always positive. Thus, the linear programming problem solution is solved as follows:

$$Maximize = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \qquad \text{Equation 3}$$

$$Subject\ to = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \qquad j=1 \ldots n$$

Equation 4

$U_r, V_i > 0 \qquad \forall r = 1, \dots, s; i = 1, \dots, m$ *Equation 5*

This linear programming equation can be solved in two different ways. Under the first approach, the weighted sum of the inputs is held constant, and the weighted sum of the outputs is maximized. This will result in (output-oriented CRS model). On the other hand, when the weighted sums of inputs are minimized and outputs weighted sums held constant, the second approach will produce the (input-oriented CRS model) used in our study.

CRS-output oriented model primal equation	CRS-input oriented model, primal equation
Minimize $\sum_{i=1}^{m} v_i x_{ik}$ Subject to $\sum_{i=1}^{m} v_i x_{ij}$ -$\sum_{r=1}^{ns} u_r y_{rj}$ ≥0 , j=1,..,n $\sum_{r=1}^{m} u_r y_{rk}$ =1 u_r, v_i >0, ∀r=1,..,s;i=1,…,m	Maximize $\sum_{r=1}^{s} u_r y_{rk}$ Subject to $\sum_{i=1}^{m} v_i x_{ij}$ -$\sum_{r=1}^{ns} u_r y_{rj}$ ≥0 , j=1,..,n $\sum_{i=1}^{m} v_i x_{rk}$ =1 u_r, v_i >0, ∀r=1,..,s;i=1,…,m

Since the model could have an infinite solution, there is a constraint added to deal with this problem:

$\sum_{i=1}^{m} v_i x_{rk}$ =1

$\sum_{r=1}^{m} u_r y_{rk}$ =1

Usually, the envelopment form is preferable to the multiplier form since it has fewer restrictions than the latter (i.e., s+m compared to n+1).

CRS-output oriented model dual equation	CRS-input oriented model, dual equation

Maximize $\emptyset_k$ Subject to $\emptyset_k\, y_{rk}$- $\sum_{j=1}^{n} \lambda_j y_{rj} \leq 0$, r=1,…,s x_{ik} -$\sum_{j=1}^{n} \lambda_j x_{ij} \geq 0$, i=1….,m $\lambda_j \geq 0$, ∀j=1,…,n	Minimize θ_k Subject to y_{rk}-$\sum_{j=1}^{n} \lambda_j y_{rj} \leq 0$, r=1,…,s $\emptyset_k\, x_{ik}$ -$\sum_{j=1}^{n} \lambda_j x_{ij} \geq 0$, i=1….,m $\lambda_j \geq 0$, ∀j=1,…,n

In which **(θ, ∅)** represent the technical efficiency of DMU (k) and **(λ_j)** is the weighted inputs and outputs of firm **j**.

3.4 Variable Return to Scale (VRS)

The application of the CCR model is appropriate in conditions where DMUs are working under an optimal scale, and it can be used in conjunction with the BCC model. While in reality, due to financial limitations, imperfect competition, government regulations, etc., will hinder firms from operating below the optimal level. Banker (1984) proposed the model-driven from the CRS model, which removes the scale efficiency effects. The BCC model is driven from the CRS model by relaxing constant return to scale and the addition of convexity constraint ($\sum_{j=1}^{n} \lambda_j$=1 in the dual equation):

VRS output-oriented model, primal equation	VRS input-oriented model, primal equation
Minimize $\sum_{i=1}^{m} v_i x_{ik}$ - c_k Subject to $\sum_{i=1}^{m} v_i x_{ij}$ -$\sum_{r=1}^{s} u_r y_{rj}$ - $c_k \geq 0$ j=1,..,n $\sum_{r=1}^{s} u_r y_{rk}$ =1 u_r, v_i >0, ∀r=1,..,s;i=1,…,m	Maximize $\sum_{r=1}^{s} u_r y_{rk}$ + c_k Subject to $\sum_{i=1}^{m} v_i x_{ij}$ -$\sum_{r=1}^{s} u_r y_{rj}$ - $c_k \geq 0$, j=1,..,n $\sum_{i=1}^{m} v_i x_{ik}$ =1 u_r, v_i >0, ∀r=1,..,s;i=1,…,m

VRS output-oriented model dual equation	VRS input-oriented model, Dual equation
Maximize $\emptyset_k$ Subject to $\emptyset_k\, y_{rk}$- $\sum_{j=1}^{n} \lambda_j y_{rj} \leq 0$, r=1,…,s x_{ik} -$\sum_{j=1}^{n} \lambda_j x_{ij} \geq 0$, i=1….,m $\sum_{j=1}^{n} \lambda_j$=1 $\lambda_j \geq 0$, ∀j=1,…,n	Minimize θ_k Subject to y_{rk}-$\sum_{j=1}^{n} \lambda_j y_{rj} \leq 0$, r=1,…,s $\theta_k\, x_{ik}$ -$\sum_{j=1}^{n} \lambda_j x_{ij} \geq 0$, i=1….,m $\sum_{j=1}^{n} \lambda_j$=1 $\lambda_j \geq 0$, ∀j=1,…,n

3.5 Scale Efficiency

The constant return to scale (CRS) model efficiency score can be decomposed into "pure" technical efficiency (VRS), which is a result of managerial practices and scale efficiency S.E. When there are discrepancies between technical efficiency obtained under (CRS) and (VRS) for a particular (DMU), this can be a result of scale inefficiency S.E. Therefore, the scale efficiency is derived by dividing (CRS) technical efficiency over (VRS) for a particular (DMU) as following:

$$SE=\frac{TE_{CRS}}{TE_{VRS}}$$

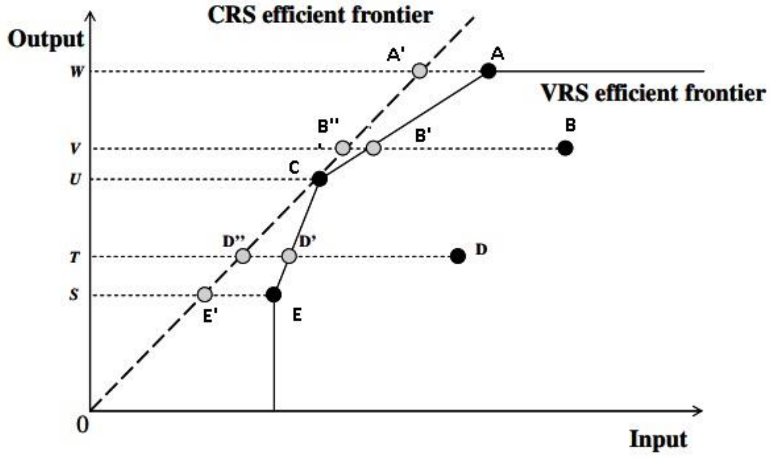


Figure 10. Comparison of constant return scale to Variable return to scale Efficient Frontier.

The graph above explains the nature of pure technical efficiency (VRS), overall technical efficiency (CRS), and Scale efficiency S.E. as follows: firm B is inefficient under both VRS and CRS assumptions. In an input-oriented setting, firm B must move toward B' to be considered VRS efficient, and the score is B'/B. The VRS inefficiency for firm B is the distance B.B.'. To be CRS efficient, firm B needs to move further toward B" and the score would be B"/B. The input-oriented CRS inefficiency can be shown as the distance from B to B'' points. To be scale and technically efficient, B needs to scale down by B"/B' and only reduce by factor B'/B for technical efficiency. The ratio efficiency measures are between values from zero to one.

3.6 DEA Efficiency for panel data

Malmquist TFP was introduced by Malmquist (1953) and Caves et al. (1982) developed later by R. Färe, Shawna Grosskopf, Mary Norris, and Zhongyang Zhang (1994). The index is measured through a non-parametric DEA and can be applied to panel data to measure productivity change over time. The (TFP) consists of two parts, the first part is "catch-up," which is the efficiency change over time. The second component is known as technological change "frontier shift" which manifest measures of the changes in technology over time in other words, change in the efficiency frontier.

Technical efficiency in this context denotes the (DMUs) ability to utilize a minimum set of input to produce maximum output. In figure 11, each frontier level shows the maximum output (y) from the assumed level of input (x). The current frontier is (t), and the future frontier is named (t+1). The (DMU's) productivity variation over time is either due to change in position relative to the frontier (efficiency change) or frontier shit (technological change). If efficiency is not calculated, then the productivity change over time cannot be decomposed clearly either to efficiency change or to the frontier technological changes, a shift in the production frontier.

On the current frontier (t), with the input and output buddle denoted by z (t) and an Input-based efficiency measure can be driven from the horizontal distance ratio of 0B/0F, which means input reduction is needed to achieve technical efficiency on the current frontier (t). While for the future frontier (t+1), the producer's input needs to be multiplied by the proportion distance between (0E/0D) to achieve technical efficiency in like frontier (t). Since the frontier has changed in (t+1), the (0E/0D) is considered technically inefficient due to frontier change.

Malmquist productivity index can be obtained in either output or input-oriented settings. When input-orientated, the focus is on reducing input with a given level of output. For example, according to Färe, Fèare, Grosskopf, and Lovell (1994) an input-oriented Malmquist productivity index can be derived as follow:

$$M_I^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t) = \left[\frac{D_I^t(y^{t+1},x^{t+1})}{D_I^t(y^t,x^t)} \times \frac{D_I^{t+1}(y^{t+1},x^{t+1})}{D_I^{t+1}(y^t,x^t)}\right]^{1/2} \quad \textit{Equation 6}$$

The letter (I) corresponds to input-oriented model, and (M) stands for Malmquist total productivity for the current production points (x) and (y) in a period of (t+1) relative to previous term (t), and (D) is distance value for the input. A value greater than one shows positive growth in total factor productivity between the two time periods.

$$M_I^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t) = \frac{D_I^{t+1}(y^{t+1},x^{t+1})}{D_I^t(y^t,x^t)} \left[\frac{D_I^t(y^{t+1},x^{t+1})}{D_I^{t+1}(y^{t+1},x^{t+1})} \times \frac{D_I^t(y^t,x^t)}{D_I^{t+1}(y^t,x^t)}\right]^{1/2} \quad \textit{Equation 7}$$

The Malmquist Productivity index (M) is consists of the product of Efficiency Change (EFFCH) and Technological Change or progress (TECH):

$$M = EFFCH \times TECH \quad \textit{Equation 8}$$

$$EFFCH = \frac{D_I^{t+1}(y^{t+1},x^{t+1})}{D_I^t(y^t,x^t)} \quad \textit{Equation 9}$$

$$TECH = \left[\frac{D_I^t(y^{t+1},x^{t+1})}{D_I^{t+1}(y^{t+1},x^{t+1})} \times \frac{D_I^t(y^t,x^t)}{D_I^{t+1}(y^t,x^t)}\right]^{1/2} \quad \textit{Equation 10}$$

3.7 Regression Analysis

In the second stage of the study, we ran a regression analysis on some of the productivity and efficiency indices to evaluate the impact of other exogenous factors on the total factor productivity (TFP), efficiency change (EFFCH), and technological progress (TECH). The independent variables are: age of oldest Dependent child, number of household members, farm size in acres, soil productivity rating, and government payments.

$$TFP = \beta_0 + \beta_1 \text{Log Age} + \beta_2 \text{ Log HHM} + \beta_3 \text{ Log SPR} + \beta_4 \text{Log TA} + \beta_5 \text{Log GOV} + \beta_6 \text{Log AGDD} + \beta_7 \text{ Log AP} + \varepsilon_i$$

$$EFFCH = \beta_0 + \beta_1 \text{Log Age} + \beta_2 \text{ Log HHM} + \beta_3 \text{ Log SPR} + \beta_4 \text{Log TA} + \beta_5 \text{Log GOV} + \beta_6 \text{Log AGDD} + \beta_7 \text{ Log AP} + \varepsilon_i$$

$$TECH\ \beta_0 + \beta_1 \text{Log Age} + \beta_2 \text{ Log HHM} + \beta_3 \text{ Log SPR} + \beta_4 \text{Log TA} + \beta_5 \text{Log GOV} + \beta_6 \text{Log AGDD} + \beta_7 \text{ Log AP} + \varepsilon_i$$

Chapter 4: Empirical Results

The results shown are from the estimation of the DEA-based efficiency, and the Malmquist index of productivity results may be seen in table 2 . When the total factor productivity is greater than one, it signifies productivity growth. The total factor productivity is the product of efficiency and technological change, with a value greater than one showing efficiency gain or technological progress. Less than one exhibits deterioration of efficiency or technological regress. The efficiency change can be further decomposed into technical efficiency (pure technical efficiency) or scale efficiency improvement. The scale efficiencies are driven from CCR and BCC models, while efficiency change is derived from MPI estimations. From Table 2, we can see a regress in productivity across all the farms by -26.5 % (0.735-1.0)*100. When we compare farm sizes, we see that small farms, on average, are leading in terms of gains in total productivity, efficiency change, technological change, and pure technical efficiency, except for scale efficiency. Small farms are behind mid-sized and large farms.

Table 2: Efficiency and productivity means for different farms sizes between 1999 and 2015

DMU	Total Productivity Factor	Efficiency Change	Technological Change	Pure Technical Efficiency	Scale Efficiency
Small farms	0.974	1.134	0.860	0.620	0.894
Mid-size farms	0.777	1.086	0.716	0.582	0.928
Large farms	0.526	1.068	0.492	0.586	0.936
All farms	0.735	1.095	0.671	0.596	0.919

When a DMU's efficiency score is one, it operates at the full efficient level relative to the other farms within the same sample and period. The full efficient farms then form the efficient frontier and become the benchmark. Among the small farms, 25 % were overall efficient, 25% fully technically efficient, and only 65% were scale efficient, as shown in Table 3. As for mid-sized and large farms, the efficiency percentage was 10% OTE, 10% PTE, and 57% S.E. for mid-sized farms and large farms, the percentages were 6 % OTE, 6% PTE 58% S.E. as shown in Table 4 and 5.

Table 3: Small farms technical efficiency distribution 2015.

Statistic	OTE	PTE	SE
N	20	20	20
TE- < 0.40	5	4	0
0.40≤ TE < 0.50	5	6	0
0.50≤ TE < 0.60	2	2	0
0.60≤ TE < 0.70	0	0	0
0.70≤ TE < 0.80	1	0	0
0.80≤ TE < 0.90	1	2	1
0.90≤ TE < 1.00	1	1	6
TE = 1.00	5	5	13

Table 4: Medium farm Technical Efficiency distribution 2015.

Statistic	OTE	PTE	SE
N	66	66	66
TE- < 0.40	15	14	0
0.40≤ TE < 0.50	18	16	0
0.50≤ TE < 0.60	11	11	2
0.60≤ TE < 0.70	9	9	0
0.70≤ TE < 0.80	4	5	2
0.80≤ TE < 0.90	1	0	4
0.90≤ TE < 1.00	1	4	20
TE = 1.00	7	7	38

Table 5: Large farm Technical Efficiency distribution 2015.

Statistic	OTE	PTE	SE
N	131	131	131
TE- < 0.40	25	21	0
0.40≤ TE < 0.50	39	38	0
0.50≤ TE < 0.60	31	32	0
0.60≤ TE < 0.70	16	15	0
0.70≤ TE < 0.80	5	7	7
0.80≤ TE < 0.90	7	7	5
0.90≤ TE < 1.00	0	3	42
TE = 1.00	8	8	77

The annual efficiency and productivity mean (table 6) show the geometric mean of the indices for each year. There is, on average, loss in total productivity factor mean by 25 % (0.75-1.00)*100, in which 1.4 % (1.014-1.00)*100 was due to efficiency change and 26 % (0.740-1.00)*100 for technological regress. Thus, on average, the scale efficiency was higher than technical efficiency.

Table 6: mean yearly Efficiency and Productivity scores.

year	Total Productivity Factor	Efficiency Change	Technological Change	Pure Technical Efficiency	Scale Efficiency
1999	0.430	1.012	0.425	0.647	0.998
2000	0.652	1.013	0.644	0.656	0.978
2001	0.648	0.903	0.718	0.686	0.950
2002	0.920	0.830	1.109	0.712	0.808
2003	1.450	1.204	1.204	0.695	0.969
2004	0.920	0.830	1.109	0.712	0.808
2005	0.905	0.961	0.942	0.629	0.975
2006	0.900	3.000	0.300	0.280	0.624
2007	0.942	0.833	1.131	0.560	0.967
2008	1.095	1.004	1.090	0.643	0.987
2009	0.652	1.013	0.644	0.656	0.978
2010	0.905	0.961	0.942	0.629	0.975
2011	0.942	0.833	1.131	0.560	0.967
2012	0.476	0.923	0.516	0.539	0.939
2013	0.475	1.256	0.379	0.675	0.965
2014	0.733	0.877	0.836	0.406	0.902
2015	0.433	0.823	0.527	0.539	0.967
Mean	0.750	1.014	0.740	0.588	0.921

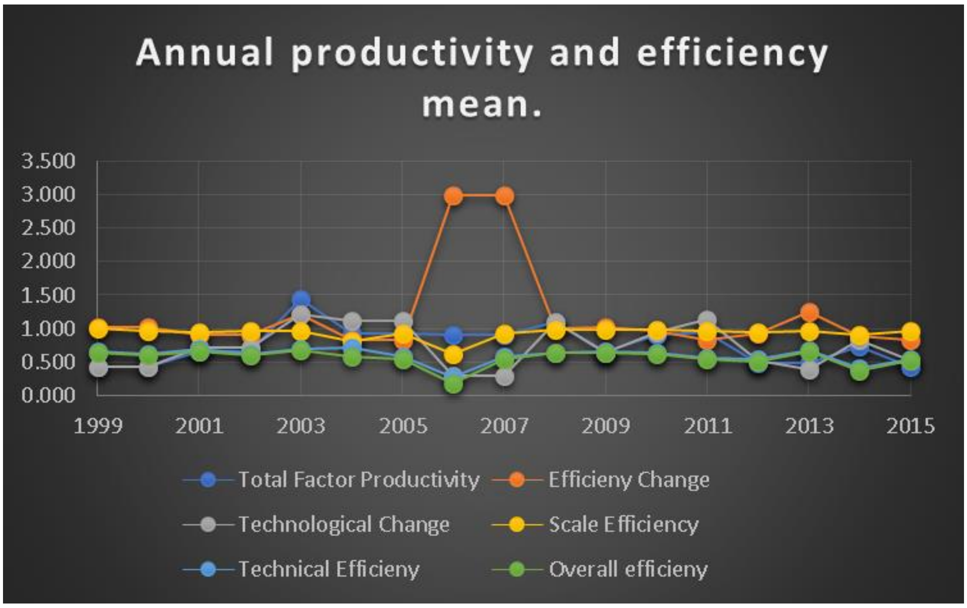


Figure 11. Mean productivity and efficiency for all farms.

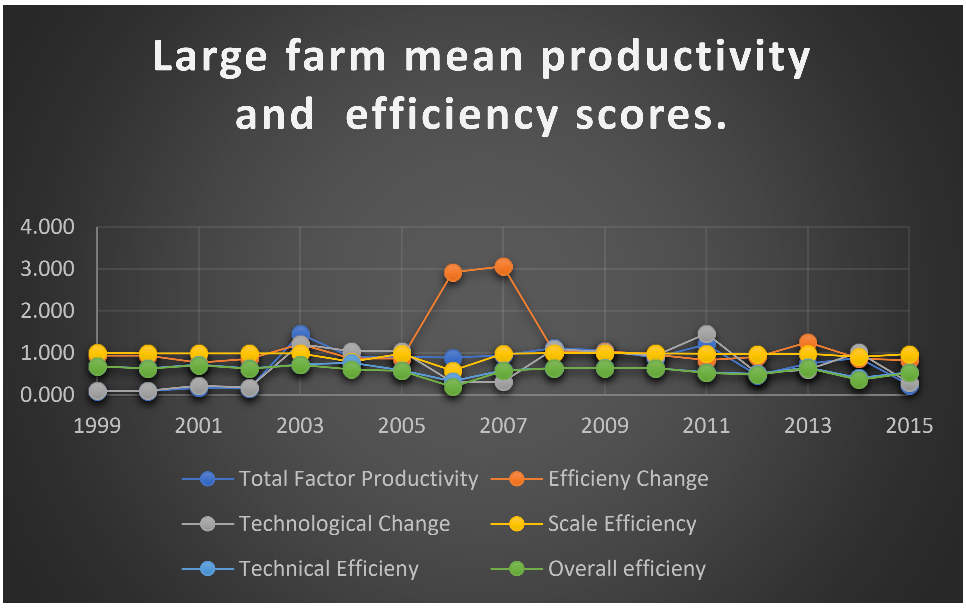


Figure 12. Mean productivity and efficiency for large farms.

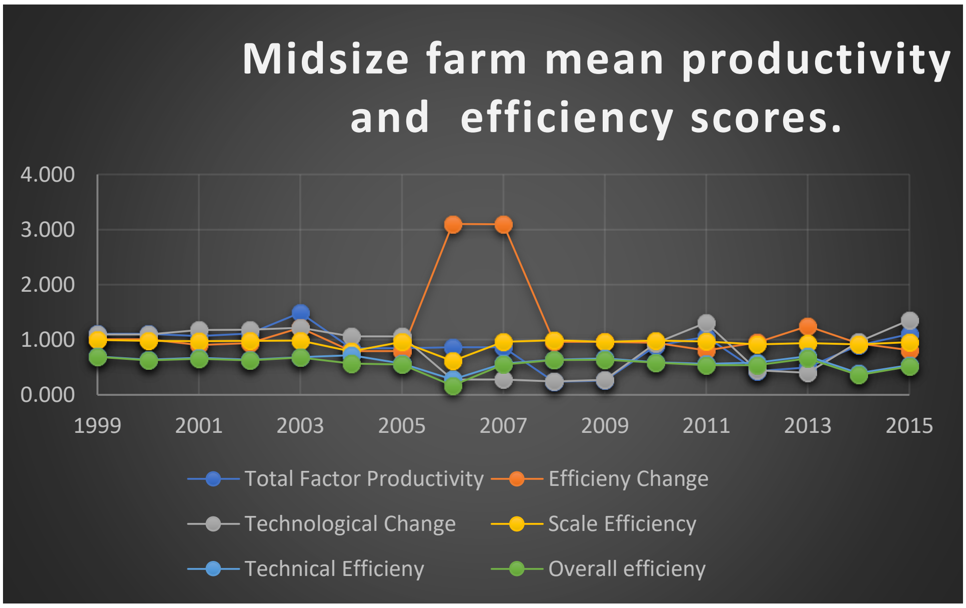


Figure 13. Mean productivity and efficiency for Mid-sized farms.

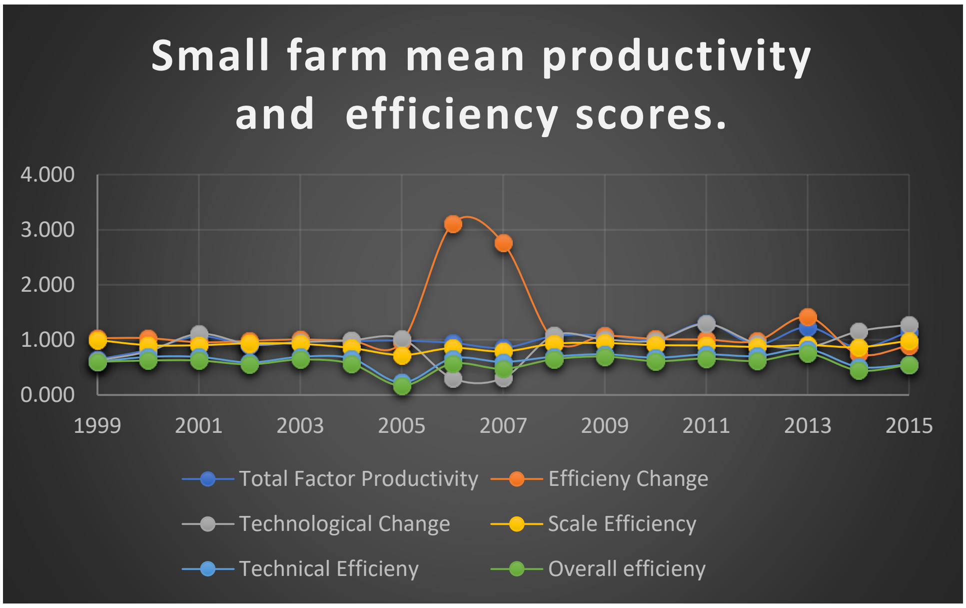


Figure 14. Mean productivity and efficiency for small farms.

In the second stage, a panel regression is run for the grain farms. The dependent variables are total factor productivity, efficiency change, and technological change. The independent variables of interest were non-discretionary factors such as the age of the oldest dependent child, the number of household members, soil productivity rating, government payments, total assets, and weather variables, including average annual precipitation measured in inches and aggregate growing degree days. The regression is run separately for each farm size and corrected for fix or random effect. A Hausman test is used to determine whether to choose a fixed effect or random-effect model. The full results for the Hausman test are included in the appendix page table.10 to table.17. The first two columns are the estimated coefficient and standard error and the regression coefficients' statistical significance level. The Hausman test did not show the difference between random and fixed effect for TFP and Efficiency change regression. Still, for technological change regression, the random effect model is chosen result table.12. In total, for small farm regression, there are seven statistically significant variables for efficiency and technological change regression table.7. For the efficiency change regression, the household member variable has the biggest value. In contrast, for technological change, the regression model was household numbers followed by average annual precipitation and government payments.

Table 7. Small farm regression results.

	Total Factor Productivity		Efficiency Change		Technological Change	
Variables	Coefficients	Std. error	Coefficients	Std. error	Coefficients	Std. error
Intercept	5.473e+27***	8.04E+14	-5.17E+27	0	5.90E+13	1.25E+14
Age	1.44E+12	5.08E+12	-0.052***	0.013	-1.02E+11	7.63E+11
HHM	1.97E+13	4.42E+13	0.593***	0.114	1.008e+13*	5.62E+12
SPR	-9.84E+11	9.08E+12	0.013	0.023	1.41E+10	1.21E+12
GOV	-2.16E+09	1.43E+09	-0.000***	0	7.096e+08***	2.43E+08
TA	3151237.195	30723402.89	0	0	-1313232.909	5122343.454
AGDD	1.35E+10	1.97E+11	-0.001**	0.001	1.17E+10	3.52E+10
AP	-3.77E+12	3.19E+12	-0.001	0.008	-1.50e+12***	5.74E+11

	Significance level *** p<0.01, ** p<0.05, * p<0.1	

All the regressions for the mid-size farm are random effect models based on the Hausman test table.12 through table.14. There is only one statistically significant for mid-sized farms for total factor productivity: the age of the oldest dependent child. On the other hand, we have four statistically significant variables for the efficiency change regression, while technological change regression only has one statistically significant variable, as shown in table.8.

Table 8. mid-sized farm regression results

	Total Factor Productivity		**Efficiency Change**		**Technological Change**	
Variables	Coefficients	Std. Error	Coefficients	Std. Error	Coefficients	Std. Error
Intercept	3.98E+13	2.02E+14	4.270***	0.848	2.71E+13	1.02E+14
Age	-2.16e+12*	1.21E+12	0.003	0.004	-1.16e+12*	6.15E+11
HHM	9.34E+12	9.24E+12	0.029	0.027	5.30E+12	4.61E+12
SPR	3.01E+11	2.14E+12	0.001	0.007	1.26E+10	1.07E+12
GOV	-8.79E+07	1.68E+08	-0.000***	0	-7.39E+07	86177844.75
TA	-6035441.79	4331393.554	0	0	-3527871.58	2224664.995
AGDD	-1.24E+09	5.03E+10	-0.001***	0	4.47E+09	2.60E+10
AP	3.90E+10	9.05E+11	-0.024***	0.005	-1.43E+11	4.68E+11
	Significance level *** p<0.01, ** p<0.05, * p<0.1					

The Hausman test suggests that random effect is appropriate for TFP and technological change regression, as shown in tables 15 and 17, while efficiency change regression requires fixed effects. The only statistically significant variable in

TFP regression for large farms is the number of household members and average annual precipitation. As for efficiency change regression, there are four significant variables with a number of household members with greatest value followed by soil productivity rating. While for technological Change regression, only one statistically significant variable is average annual precipitation, as shown in table.9.

Table 9. Large farms regression results

	Total Factor Productivity		Efficiency Change		Technological Change	
Variables	Coefficients	Std. Error	Coefficients	Std. Error	Coefficients	Std. Error
Intercept	-1.80E+14	1.34E+14	-0.313	1.559	-1.28E+14	1.09E+14
Age	-1.03E+12	8.46E+11	0.001	0.007	-4.37E+11	6.76E+11
HHM	9.440e+12*	5.29E+12	0.179***	0.055	5.47E+12	4.38E+12
SPR	4.93E+11	1.44E+12	0.065***	0.021	1.95E+11	1.27E+12
GOV	11620599.59	47216892.42	0	0	-3605337.22	34848969.67
TA	164,977.89	381,486.71	0	0	237,100.82	277,128.88
AGDD	3.60E+10	3.15E+10	-0.001***	0	2.91E+10	2.27E+10
AP	1.133e+12*	6.28E+11	-0.018***	0.004	8.912e+11**	4.49E+11
	Significance level *** p<0.01, ** p<0.05, * p<0.1					

For the total productivity age of the oldest dependent child, the number of household members and average annual precipitation are significant for some of the different farm sizes. As for efficiency changes, number of household members, government payment, growing degree days, and average annual precipitation are statistically significant across farm sizes. While for technological change, regression age of oldest dependent child statistically significant for some of the farm sizes. It is also worth mentioning that more factors could have been included to explain some of the variations for productivity and efficiency but were not available. Such factors can be farmer's age, education, broadband access, and work-related experience.

Chapter 5: Conclusion

This study focuses on productivity and efficiency for grain farms in Kentucky across farms sizes and years for 1999-2015. The study has two components, the first DEA and Malmquist-based DEA approach, to determine the farms' productivity and efficiency measures. Moreover, the second part tries to analyze the productivity and efficiency measures through a panel regression to explain the underlying determinants for the productivity indices. In general, there was an improvement in total factor productivity, mainly due to efficiency. However, the efficiency gain was in big part due to scale enhancements rather than technical efficiency gain. When we look into the result among different farms size, small farms were least scale-efficient compared with the mid-size and large farms; this is consistent with (USDA 2001), which mentions the disadvantage of small farms due to cost inefficiency and lack of scale efficiency. The mean total factor productivity is higher for small size and was mostly due to technological improvements, while the efficiency gains were due to scale efficiency. For small and mid-sized farms, the total productivity was higher than the large farms. However, similarly, the gains were due to technological improvement. As for the efficiency gains, it mainly contributed to better scale efficiency.

Regardless of the statistically significant variables across farm sizes, the top factor affecting total factor productivity, efficiency change and technological change regression are; the age of the oldest dependent child, number of household members, soil productivity rating, average annual precipitation, and aggregate growing degree day. The results are consistent with the preivous study, which shows that small farms lack scale efficiency and trail behind mid-size and large farms. In summary, the study shows that even though small farms lead in terms of total factor productivity and technical efficiency, but still fall behind in terms of scale efficiency compared to mid-size and large farms.

Further studies can be done regarding farms efficiencies evaluations and potential improvement in cost and input minimization. This requires more detailed data on unit cost and amount of fertilizer and chemicals used for each crop type to facilitate efficiency comparison among different crop productions. Lack of Understanding crop type and available input may pose a restriction for the study application. Studies on farms in clusters based on climate, crop mix, geography might provide a more appropriate benchmark for productivity and efficiency analysis.

Appendix A:

Table 10: Hausman Test for MPI regression small farms.

	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fixed	random	Difference	S.E
Age	1.44E+12	1.44E+12	1.93E-02	.
HHM	1.97E+13	1.97E+13	-1.22E+00	.
SPR	-9.84E+11	-9.84E+11	-6.24E-01	.
GOV	-2.16E+09	-2.16E+09	-7.15E-06	.
TA	3.15E+06	3.15E+06	-1.13E-07	.
AGDD	1.35E+10	1.35E+10	-1.12E-02	.
AP	-3.77E+12	-3.77E+12	-1.00E-01	.
			.	
b = consistent under Ho and Ha; obtained from xtreg				
B = inconsistent under Ha, efficient under Ho; obtained from xtreg				
Test: Ho: difference in coefficients not systematic				
chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)				
= 0				
Prob>chi2 =				

Table 11: Hausman Test for Technologilca Change regression small farms.

	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fixed	random	Difference	S.E
Age	6.62E+11	-1.02E+11	7.64E+11	5.99E+11
HHM	1.50E+13	1.01E+13	4.92E+12	6.31E+12
SPR	-3.95E+11	1.41E+10	-4.09E+11	1.24E+12
GOV	-5.52E+08	-7.10E+08	1.58E+08	1.25E+08
TA	-2.66E+06	-1.31E+06	-1.35E+06	2858872
AGDD	-5.53E+09	1.17E+10	-1.72E+10	1.33E+10
AP	-1.35E+12	-1.50E+12	1.56E+11	2.01E+11
b = consistent under Ho and Ha; obtained from xtreg				
B = inconsistent under Ha, efficient under Ho; obtained from xtreg				
Test: Ho: difference in coefficients not systematic				
chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)				
= 6.83				
Prob>chi2 = 0.2335				

Table 12: Hausman Test for MPI regression mid-size farms.

	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fixed	random	Difference	S.E
Age	-1.92E+12	-2.16E+12	2.39E+11	6.35E+11
HHM	7.72E+12	9.34E+12	-1.62E+12	6.85E+12
SPR	5.57E+11	3.01E+11	2.56E+11	1.53E+12
GOV	9.41E+06	-8.79E+07	9.73E+07	5.93E+07
TA	-4.49E+06	-6.04E+06	1.54E+06	1.56E+06
AGDD	-2.00E+10	-1.24E+09	-1.88E+10	1.39E+10
AP	2.74E+11	3.90E+10	2.35E+11	2.33E+11

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg
Test: Ho: difference in coefficients not systematic
chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 3.94
Prob>chi2 = 0.5574

Table 13: Hausman Test for Efficiency Change regression mid-size farms.

	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fixed	random	Difference	S.E
Age	0.006132	0.0028965	0.0032355	0.0065881
HHM	0.123777	0.0289042	0.0948731	0.0605211
SPR	0.005807	0.0011689	0.0046379	0.0137121
GOV	-2.74E-06	-3.27E-06	5.26E-07	7.02E-07
TA	1.37E-08	2.16E-09	1.15E-08	1.82E-08
AGDD	-0.00046	-0.0007241	0.0002634	0.0001525
AP	-0.02026	-0.0243516	0.0040898	0.0023908

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg
Test: Ho: difference in coefficients not systematic
chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 9.81
Prob>chi2 = 0.0808

Table 14: Hausman Test for technological change regression mid-size farms.

	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fixed	random	Difference	S.E
Age	-9.78E+11	-1.16E+12	1.80E+11	3.64E+11
HHM	3.35E+12	5.30E+12	-1.95E+12	3.85E+12
SPR	4.07E+11	1.26E+10	3.95E+11	8.63E+11
GOV	-2.39E+07	-7.39E+07	5.00E+07	3.46E+07
TA	-3.06E+06	-3.53E+06	4.67E+05	909558
AGDD	-4.64E+07	4.47E+09	-4.52E+09	8.17E+09
AP	-7.33E+10	-1.43E+11	6.95E+10	1.38E+11

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)

= 1.35

Prob>chi2 = 0.9301

Table 15: Hausman Test for total productivity factor regression large farms.

	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fixed	random	Difference	S.E
Age	2.83E+11	-1.03E+12	1.31E+12	9.05E+11
HHM	2.58E+12	9.44E+12	-6.86E+12	7.71E+12
SPR	-3.18E+12	4.93E+11	-3.67E+12	3.23E+12
GOV	2.35E+07	1.16E+07	1.19E+07	2.65E+07
TA	2.27E+05	1.65E+05	6.18E+04	1.74E+05
AGDD	2.60E+10	3.60E+10	-1.00E+10	1.37E+10
AP	7.73E+11	1.13E+12	-3.60E+11	2.47E+11

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)

= 4.97

Prob>chi2 = 0.4201

Table 16: Hausman Test for efficiency change regression large farms.

	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fixed	random	Difference	S.E
Age	8.09E-04	-2.61E-03	3.42E-03	6.10E-03
HHM	1.79E-01	9.31E-03	1.70E-01	4.98E-02
SPR	6.48E-02	6.57E-03	5.82E-02	2.01E-02
GOV	5.67E-08	-7.31E-08	1.30E-07	1.97E-07
TA	-2.45E-09	-8.52E-10	-1.60E-09	1.27E-09
AGDD	-8.91E-04	-1.02E-03	1.25E-04	8.88E-05
AP	-1.79E-02	-2.15E-02	3.64E-03	1.50E-03

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg
Test: Ho: difference in coefficients not systematic
chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 26.56
Prob>chi2 =0.0001

Table 17: Hausman Test for technological change regression large farms.

	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fixed	random	Difference	S.E
Age	2.21E+11	-4.37E+11	6.58E+11	5.57E+11
HHM	2.23E+12	5.47E+12	-3.24E+12	4.95E+12
SPR	-2.51E+12	1.95E+11	-2.71E+12	2.16E+12
GOV	2.58E+06	-3.61E+06	6.19E+06	1.59E+07
TA	2.67E+05	2.37E+05	2.97E+04	105466.1
AGDD	2.25E+10	2.91E+10	-6.64E+09	8.71E+09
AP	6.81E+11	8.91E+11	-2.10E+11	1.60E+11

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg
Test: Ho: difference in coefficients not systematic
chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 4.23
Prob>chi2 = 0.5162

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- MS Agricultural Economics . (Expected) 2021

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Selected Papper/ Presentation

Hussein, Ahmed. Dr. Sayed Saghaian , U.S Broiler, turkey and total poultry supply response to corn feed prices." 2017 Annaul Meeting of the Southern Agricultural Economics Association. February 2017. Mobile, AL.