DISSERTATION

THREE ESSAYS ON WHEAT PRODUCTION EFFICIENCY IN IRAQ:

COMPARISON BETWEEN MENA COUNTRIES AND INTERNAL COMPARISON OF DISTRICTS

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In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Spring 2019

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ABSTRACT

THREE ESSAYS ON WHEAT PRODUCTION EFFICIENCY IN IRAQ:
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Wheat is an important staple of the Iraqi diet, as it is for all the nineteen Middle East North African (MENA) countries. Wheat is also an important crop for farmers in the rural areas of these countries. Yet, all the MENA countries import wheat, and the gap between growing demands and local supplies is widening. This gap is prompting general concerns of food security and driving interest in wheat productive efficiency. The focus of this dissertation is examining the technical efficiency of wheat production with a goal of informing policy decisions in Iraq.

In this research, a conceptual approach of wheat productive efficiency is developed based on existing models and is translated into an empirical framework. The approach evaluates the relationships between different kinds of inputs such as human capital, financial capital, operational capital, imports and sociodemographic factors and the resulting wheat output. Inputs related to temperature, humidity and irrigation pattern also included.

Technical efficiency (TE) scores and factors affecting TE are explored with two empirical methods: Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). These methods are applied in two essays: panel data exploring Middle East North African countries and a cross sectional data of wheat producing districts in Middle and South of Iraq. A third essay synthesizes the result of the two empirical explorations.

In the first essay factors that affected productive efficiency are:

- Human capital: population (positive relationship with wheat production per unit of land).

- Operating capital: harvested area (negative relationship), number of tractors (negative relationship), number of harvesters (negative relationship), pesticides (positive relationship), urea (positive relationship), seeds (negative relationship).
- Financial capital: net national income (positive relationship).
- Import effect: imported quantity (negative relationship).

Also, factors that explained variation in TE are:

- Human capital: farmers with access to electricity (negative relationship), ratio of farmers population to urban population (negative relationship), extension specialist per 100,000 farmers (positive relationship), employment of female workforce within agriculture (positive relationship).
- Financial capital: credit to farmers (positive relationship).
- Energy used in agriculture effect: aggregated energy (negative relationship).
- Other agricultural competing activity: Livestock density (negative relationship).
- Politics effect: political instability (negative relationship).
- Surface irrigation effect: availability of the flow of surface water (negative relationship).
- Elevation effect: elevation (positive relationship).

In the second essay, factors affecting technical efficiency are:

- Human capital: ratio of farmers population to urban population (positive relationship),
- Financial capital: producer price index (negative relationship).
- Surface irrigation effect: distance to the flow of surface water (negative relationship).

The SFA and DEA indicate contradictory results. This might due to the randomness in SFA the DEA does not incorporate.

Average technical efficiency score for MENA countries adopting SFA equals 62% while it equals 97% when DEA is used. In the second essay, TE equals 63% while it equals 88% when DEA is adopted.

Results obtained from essay 1 and essay 2 used to obtain policies showed in essay 3. Those policies may not only have their positive effect on increasing TE but also on enhancing yield per unit for MENA countries and Iraq in particular.

Policies mentioned in essay 3 suggested a strong attention has to be paid to extension role in agriculture. Policy lever that Iraq can use to improve TE is investing in the quality of human capital through increasing the level of education for farmers.

ACKNOWLEDGEMENTS

I was really lucky to get this combination of committee members. I am indebted to them for their guidance and mentorship while working toward completing my degree program. In the Preliminary defense and in the formal meeting, I was getting a plethora of constructive critique. I'm particularly grateful to my advisor, Dr. James Pritchett, for all that I have learned from him. I learned from him how to be patient, calm, and productive. This man is very busy, but he still accepted to be my advisor. I just want to say thank you. I am also appreciative of the Iraqi Government especially the Higher Committee for Education Development in Iraq for funding me while pursuing my Ph.D.

The efficiency analysis utilized in this dissertation, especially in the first essay, would not happened without data. Thank you Food and Agriculture Organization (FAO) of the United Nations for the open access of data and the organization of the website. Thank you also, to my beloved brother Dr. Azher Altaie from University of Wasit/ College of Agriculture in helping me with getting the data from my second chapter. I was in a badly need for someone on ground available in Iraq to help me since going to Iraq and back to the US is impossible given all the complications accompanied that. This data is the backbone of chapter two and without you this would not be happening.

I must also thank the people who inspired, helped, encouraged me through finishing my Ph.D. in the Department of Ag. And Resource Economics; Dr. Marco Costanigro, Dr. Rebecca Hill, Dr. Gregory Graff, Dr. Chris Goemans, Dr. Stephan Kroll. Thank you also to my classmates and friends from CSU: Aron, Jason, Shiquin, Anders and Samad, and a lot of friends and family members who helped me in some way. I've been lucky to have a great family and such friends. Thank you

DEDICATION

I dedicate this work to my mom, Fahemma Altaie, who sacrificed a lot only to make me happy. She is my mum and Dad and thank you is not enough. Also, my patient, supportive, loyal, caring wife, Noor Alkanaani. Without you, none of this would be happening. In addition, I cannot forget my shiny stars, my kids, Fadhouli, Banen, and Yousif. Just seeing your eyes would recharge my batteries. A big appreciation would go to my pace maker, my brother Azher altaie. Your encouragement will be unforgettable. My other brothers, Ali, Esraa, and Sura, I cannot find words that show my appreciation. Thank you. I cannot describe how grateful I am for the infinite support that you provided toward competing my degree. This would not have accomplished without your support. Thank you

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1.1. Introduction

Agriculture is an important base industry for countries found in the Middle East and in North Africa (MENA) where rural areas have few employment alternatives. Food purchases take up a large portion of national disposable income in this area. Wheat is an important staple food comprising, on average, about 37% of the daily caloric need in the MENA population.

MENA countries do not produce a sufficient amount of wheat to meet domestic demand. According to Wright and Cafeiro (2010), 58 million metric tons of cereal grains is estimated to be imported collectively by this region, and in particular, wheat imports to the MENA region comprises 27% of all globally traded wheat (FAO, 2013). High dependency on international imports of wheat, strong local demand, and limited wheat production have led to stakeholders' interest in improving domestic wheat productivity in order to aid in food security and rural economic development. This is particularly true in Iraq, which suffers from insufficient wheat supplies relative to growing demand.

Improvements are possible by examining the policies and production of wheat throughout the MENA region, and perhaps mimicking those that are effective leads to improvements. The domestic productivity of wheat is highly variable across the MENA region. Egypt has the highest yield per unit area of the MENA countries with 61,000 (hg/ha), and this places Egypt as the 18th highest producer in a global ranking of wheat producing countries. In contrast, Iraq ranks 16th among the 19 MENA countries with 14,000 (hg/ha) and ranks 62 worldwide.

The technical efficiency of wheat production influences food security because improving efficiency can improve total wheat production. Wheat production is the result of total harvested area and yield per unit of land. Turkey leads total wheat production the MENA countries, while Iraq is the 7th. Iran is the country with the greatest harvested area of wheat, while Iraq is 5th (FAO, 2017). Relative to nearby countries in the MENA region, it may well be the case that Iraq can improve its total wheat production and wheat productive efficiency, which will assist with overall food security.

Macroeconomic policies, climate, land quality, and other factors may give rise to the differences in the total production of wheat and the efficiency of wheat production. The purpose of this research is to uncover the differences in efficiency and to shed light on the potential causes of these differences. Attention is focused on Iraq, where the government has an interest in improving wheat production as a way of promoting food security and economic viability in rural areas.

In Iraq, the gap between local production and domestic consumption fuels fears of food security. Based on the US Department of Commerce (2016), Iraq imports 65% of its yearly needs of wheat spending about $5 billion annually. Domestic wheat is planted heavily in the area between Tigris and Euphrates river valleys in an area called the Fertile Crescent where wheat originated more than 10,000 years ago (Kansas Wheat, 2015). Between 1991 and 2016, 53% of arable land was used for wheat in Iraq (FAO, 2017) and in 2016, 71% of arable land was devoted to wheat (FAO, 2017). In this way, wheat is an important crop to Iraqi farmers. Wheat is also an important element of the Iraqi diet providing 60% of daily caloric needs as reported by Ahmed and Ibrahem (2012).

The gap between domestic consumption and production of wheat is growing. In Figure 1, harvested wheat area and wheat production are illustrated alongside population growth for the years between 1961-2016. Ceteris paribus, it appears that the growth in wheat demand is greater than the rate of growth of wheat production and the gap is increasing. The increasing gap fuels policy makers' concerns of Iraqi food insecurity because local supply is not sufficient to meet the domestic needs on a consistent basis, if at all.

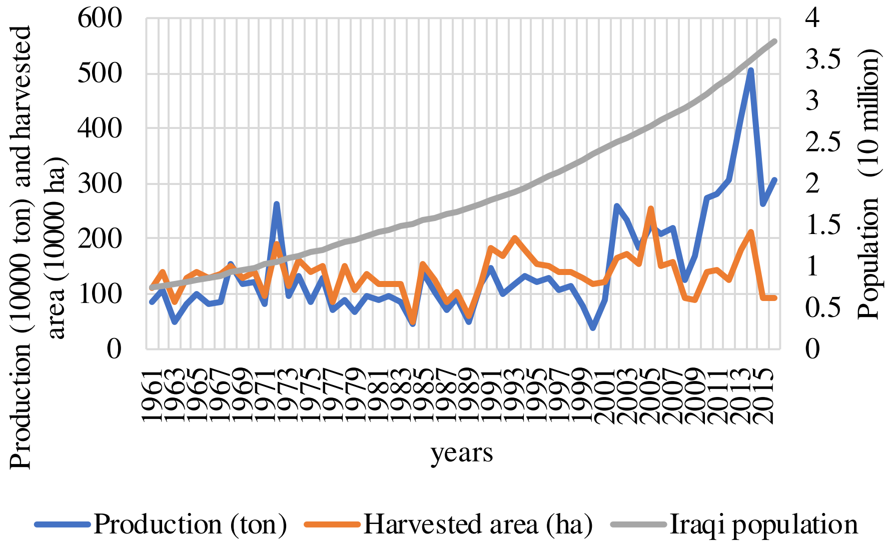


Figure 1. Wheat production, harvested area and population in Iraq (1961-2016)

Improving wheat production efficiency is one way to improve Iraqi food security. Comparing Iraqi wheat productive efficiency to other MENA countries may uncover strategies to enhance domestic supplies. The research objectives of this study are designed to uncover the sources of wheat productive efficiency in a macroeconomic context. The objectives include:

1. Measuring the efficiency of each MENA country's wheat productivity by:
    a. Creating a 26-year country dataset for the MENA region that includes data series for annual wheat produced, important factors of production and relevant socioeconomic data series.

b. Evaluating wheat productivity by completing Data Envelop Analysis (DEA) on this data using an output-based model and the Hicks-Moorsteen Productivity Index (HMI). In this sub-objective, distance functions are calculated for individual countries relative to the efficient frontier of wheat production, and the distance function is the basis for technical efficiency scores. After obtaining the technical efficiency scores, they will be regressed against important factors representing human capital, financial capital, infrastructure, policy, and climate. The regression is used to better understand the sources of variability in wheat production technical efficiency.

c. Completing a stochastic frontier analysis (SFA) using the original data set. In this analysis, non-stochastic residuals (i.e. errors in optimization) are captured from an initial regression of wheat productivity on factors of production. The errors in optimization are converted to a technical efficiency score, and these scores are regressed on important production factors and sociodemographic variables.

2. Interpreting and utilizing DEA and SFA results to better understand differences in technical efficiency for the MENA countries over the observed dataset.
3. Comparing the results of the DEA and SFA analyses to generalize what might be the source of (in) efficiency for Iraqi wheat production relative to the rest of the MENA region.

Two types of empirical analyses are used: Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). The separate analyses are used to provide robust inquiry into the research problem, and the comparison of results may provide additional insights.

To the author's best knowledge, no study has considered wheat productivity and efficiency in the MENA region by combining parametric and non-parametric methods. The analysis will be particularly useful to policymakers exploring initiatives to improve food security. The study adds to the growing literature in efficiency economics by demonstrating the application of standard tools to an empirical agricultural problem.

1.2. Literature Review

Economists seek to understand macroeconomic differences in agricultural production efficiency primarily with two empirical approaches: a parametric, statistical framework in which an efficient frontier is estimated, and a non-parametric optimization approach in which the economic distance of a country's production relative to a hypothetical efficient frontier is measured. Both methods are utilized in this study.

Farrell (1957) provides a seminal context for economic efficiency by defining efficiency as the ratio of best practice input usage to actual usage at a constant output level. Farrell's approach is conceptual, and his work catalyzed the development of the parametric and non-parametric empirical approaches for measuring efficiency and examining the sources of inefficiency.

1.2.1. Stochastic Frontier Analysis (SFA)

Stochastic frontier analysis (SFA) is the standard for economic efficiency research that uses a parametric approach. SFA generally involves estimating parameters that describe how the variation in factors of production and sociodemographic variables contribute to the variation in measures of technical efficiency, such as yield per acre. Pioneers in developing the parametric approach build on the work of Farrell (1957) and include Aigner and Chu (1968), Timmer (1971), Duggar (1974), Schmidt (1976), Aigner, Amemiya, and Poirier (1976) and Aigner, Lovell, and Schmidt (1977). These authors first argued that errors in optimization and random shocks cause an individual firm's production to deviate from an efficient frontier. Battese and Coelli (1992, 1995) then further advanced the approach by developing a model that incorporates firm specific characteristics that may influence efficiency in addition to factors of production. Examples of these factors include socioeconomic variables such as the age of farmers and their education level. In the specification of Battese and Coelli (1995), non-negative technical efficiency effects are calculated in the first stage of analysis. In the second stage, these non-negative technical efficiency effects are regressed against firm specific variables to uncover the relative contribution of each factor as a source of inefficiency. This general approach is the foundation of parametric methods in this dissertation.

1.2.2. Data Envelopment Analysis (DEA)

The family of non-parametric optimization approaches to efficiency studies also extends Farrell, and was first defined by Charnes, Cooper, and Rhodes (1978) known as CCR. This approach is labeled as data envelop analysis (DEA) and involves solving an individual optimization problem for all decision-making units. The optimal allocation of inputs is determined in this way, and this allocation is compared against a benchmark of an optimal allocation at the frontier of production. The original CCR model assumes constant returns to scale (CRS) in output with increases in input quantities, which is not desirable because of an implicit assumption that all firms are operating at the optimal scale. Banker, Charnes, and Cooper (1984); known as BCC, introduce a variable returns to scale (VRS) production technology with a piecewise linear specification for the production relationship that mimics decreasing returns to scale. Based on the CCR and BCC approaches, Charnes et al. (1985) developed the seminal approach of DEA that has been replicated in many different contexts.

Coelli (1995), reviews the strength and weaknesses of SFA and DEA to better understand the efficiency of each methodology in addressing specific research objectives. A strength of SFA is that it incorporates stochastic noise into decision making. This approach allows for errors in optimization by decision makers as well as the impact of exogenous shocks. However, specifying a functional form for the technology and explicit distributional assumption for the inefficiency error term are the limitations of SFA. In some sense, SFA methods restrict the relationship between efficiency indicators and factors of production by an assumption of a functional form, which might lead to incorrect inference of production relationships. DEA does not assume an explicit functional form about the technology; however, DEA is deterministic, and the modeling approach attributes all deviations from the optimal frontier to errors in optimization. Un this way, stochastic shocks do not enter into the calculation of the distance from the actual input allocation decision to the optimal input allocation decision.

The literature is not conclusive on the preferred methodology. As examples, Ferrier and Lovell (1990), Sharma, Leung, and Zaleski (1999), Vu (2007), Johansson (2005), Wadud (2003), Bravo-Ureta et al. (2007) applied both techniques to their empirical analyses. In some studies, SFA was preferred because of the added stochastic component. In other studies, DEA was preferred because it is less restrictive. Without a firm recommendation from the literature, the current study uses both SFA and DEA and compares the results of each.

Previous studies of agricultural efficiency inform methodology and inform the choice of data for analysis. The next section highlights previous work in agricultural efficiency that is particularly relevant.

Bravo-Ureta and Pinheiro (1993) perform a review of frontier function literature that includes 30 studies. Most of these studies seek to explain farm level variation in TE. The variables most frequently used to explain the variation in TE are farmer education and experience, contact with extension service, access to financial credit, and farm size. Both DEA and SFA are used in these studies. Also, Bravo-Ureta, Rivas, and Thiam (2001) conduct a meta-analysis focusing on the variation in average TE in the agricultural sector. The authors examine 126 studies of developing and developed countries. In each study, TE is calculated using SFA and/or DEA. A general finding is that the mean TE calculated in DEA studies are greater than mean TE calculated in SFA studies due to the lack of randomness in DEA model. In terms of the magnitudes of estimates, SFA provide estimates for explaining TE variation that are typically lower when compared to DEA estimates. A general finding is that lower income countries have lower mean TE compared to higher income countries. In addition to that, T. J. Coelli and Rao (2005) used Malmquist productivity index (MPI) for the DEA analysis in order to compare the agricultural output and productivity of 93 developed and developing countries. The author's aim was to examine the plausibility of MPI and the trend over the study period. Finally, Bravo-Ureta et al. (2008) and Moreira and Bravo-Ureta (2010) compared the agricultural productive efficiency in three countries in South American based on technological change and technical efficiency using SFA. The average TE for each country is reported.

The previous studies inform the approach that will be used in the current work. Specifically, a key relationship exists between various forms of capital (human, financial, land) and productive efficiency. A version of the MPI is also used in the current study as an effective way to address TE within the context of DEA as it is helpful in examining changes over time.

Prior studies of agricultural productivity in the MENA region are relevant. Examples are Jemaa and Dhif (2005), Jansouz, Shahraki, and Shaeri (2013), Zamanian, Shahabinejad, and Yaghoubi (2013), and Belloumi and Matoussi (2009). These studies investigate technical efficiency in agriculture, but not using in DEA and SFA, and wheat productive efficiency is not addressed.

In summary, previous studies guide the empirical approach examining wheat productive efficiency in the MENA countries, and these studies highlight the key factors of production and sociodemographic variables that influence wheat productive efficiency. A knowledge gap exists in applying these techniques and knowledge to the MENA countries. Based on that, and to the author's best knowledge, this study will be the first in utilizing both DEA and SFA by applying it to these countries and determining factors affecting wheat technical efficiency levels. In addition, this study is unique in the way of combining standard inputs used in the wheat production process and socioeconomic variables believed to be country specific as a way of investigating factors affecting technical efficiency scores.

In the section that follows, the conceptual approach of Stochastic Frontier Analysis and the Data Envelopment Analysis is described.

1.3. Stochastic Frontier Analysis (SFA) – Conceptual Model

In this subsection, the general approach of Stochastic Frontier Analysis (SFA) is described. This discussion will introduce how the model has evolved over time to the form used in this study.

Initial research proposed a general production relationship for the i-th decision making unit (DMU) which may be written as:

$$y_i = f(x_i;\beta) \tag{1}$$

Where y_i is a single output, wheat, obtained from x_i, a vector of non-stochastic inputs used by the i[th] firm. β is a vector of unknown parameters describing the relationship between inputs and the single output.

Specifying a production function for equation 1 results in deterministic specification violating the regularity conditions of maximum likelihood estimation (MLE). This violation results in estimators being inefficient, and the model itself is misspecified.

Schmidt (1976) added a one-sided error distribution to equation (1) to resolve issues of assigning a deterministic production function. This approach relates output (y_i) to inputs (x_i) as in equation 1, but also has the ε_i, which represents an error distribution for the i[th] decision maker as in:

$$y_i = f(x_i;\beta) + \varepsilon_i \tag{2}$$

Based on the specification of Schmidt in equation 2, MLE will produce efficient estimates given a distributional assumption about ε_i. Schmidt did not specify a source of error, and regularity conditions of MLE are still violated.

Aigner et al. (1977) address the difficulties of violating the regularity conditions. In their model, they provide a more sophisticated specification of the error term. They decompose the error term as the summation of symmetric normal and non-negative half normal random variables. The new specification is:

$$y_i = f(x_i;\beta) + \varepsilon_i \text{ where } \varepsilon_i = v_i + u_i \tag{3}$$

Where v_i is a random variable that accounts for a stochastic error distributed independently and identically with $N(0,\sigma_V^2)$, while u_i reflects the non-negative random variable accounting for a decision maker's technical inefficiency distributed as truncation at zero of $N(\mu_i,\sigma_U^2)$. It is suggested that u_i may occur because a decision maker may misallocate inputs and be suboptimal in the resulting output.

In other words, technical inefficiency is attributed to errors in optimization by the decision maker and v_i is a stochastic error that might occur because of any number of exogeneous factors.

Technical efficiency scores are calculated as

$$TE_i = \exp(-\, u_i) \tag{4}$$

The technical efficiency scores are firm specific based on the i[th] decision making unit (DMU). Battese and Coelli (1995) seek to understand how conditions influence the variation of TE by incorporating sociodemographic factors that may influence the efficiency in producing output in addition to the application of inputs.

$$TE_i = f(z_i; \beta) + W_i \tag{5}$$

Where z_i are firm specific variables, and W_i is a random variable defined by the truncation of the normal distribution with zero mean and variance σ^2. Equation (5) is a "second stage" analysis in which the causal effect of factors of production and sociodemographic variables might be explained.

This research will use equation 3 in estimating a hypothetical efficiency frontier from 26 years for 19 countries of the MENA region. Technical efficiency (TE) for each country in each year is calculated using equation 4. Factors and sociodemographic variables believed to be affecting TE are investigated via equation 5.

1.4. Data Envelopment Analysis (DEA)-Conceptual Model

Data envelopment analysis (DEA) is a second approach used to measure efficiency in this study. In contrast to SFA, it is a non-parametric approach applied without specifying a functional form to the production relationship. Deviation from the efficient frontier is attributed solely to inefficient resource allocation decisions made by the decision-making units (DMUs), and no stochastic shocks are modeled. In some sense, this implies that the DMU has a perfect knowledge and foresight in agricultural production.

The seminal work on DEA is Charnes et al. (1978), who used linear programming to compare inefficient DMUs with the efficient ones. This specification is based on CRS and described by the following optimization problem:

$$\max_{\theta_i \ \lambda} \boldsymbol{\theta_i^{CRS}}$$

The above maximization problem is maximizing θ_i^{CRS} which is a ratio outputs y_i to inputs x_i that are weighted by a choice variable $\lambda_k \in \lambda$ as in:

$$\boldsymbol{max\ \theta_i} \ = \frac{\sum_{k=1}^{m} \lambda_1 y_1 + \lambda_2 y_2 + \dots \dots \dots + \lambda_m y_m}{\sum_{k=1}^{m} \lambda_1 x_1 + \lambda_2 x_2 + \dots \dots \dots + \lambda_m x_m}$$

Subject to

$y_i \ \geq \sum Y \lambda$	weighted sum of the outputs of the other DMUs is greater than or equal to the DMU being evaluated
$\theta_i^{CRS} x_i \ \leq \sum X \lambda$	weighted sum of the inputs of the other DMUs is less than or equal to the inputs of the DMU being evaluates (6)
$\lambda \ \geq 0$	non-negativity of weights

where θ_i^{CRS} is a TE measure of the *i*th DMU if constant returns to scale (CRS) is assumed. This TE can be described as the ratio of the sum of weighted outputs to the sum of weighted inputs (Cooper, Seiford, & Tone, 2006).

λ is a vector of weights attached to each of the efficient DMU allocation decisions with nx1 dimensions. X is the input vector for all DMUs and X_i is a vector of inputs for the ith DMU. To get the TE score for the *i*th DMU in the sample, a separate linear programming (LP) problem is conducted for each DMU. TE will depend on the value of θ_i^{CRS} as shown in equation 6, and if it equals 1, this means that the *i*th DMU is on the frontier under CRS, which also means that this DMU is technically efficient. The value of θ_i^{CRS} is bounded between 0 and 1. If $\theta_i^{CRS} < 1$, then the DMU lies below the efficiency frontier and this DMU is technically inefficient. (Charnes et al., 1978); (Färe & Grosskopf, 1985; Färe, Grosskopf, Lindgren, & Roos, 1994).

Banker et al. (1984) developed the BCC model to allow for greater usage of input-output relationship. This model is similar to CCR, but it differs in introducing an additional constraint, so the production frontier is piecewise linear and then has concave characteristics. This allows the variable returns to scale to be introduced in the model and allows the model to allow for non-optimal scale. This constraint is added to the optimization problem number 6 and is written as:

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{7}$$

Over time, literature studying technical efficiency began to make use of indices including the Malmquist Productivity Index (MPI). The MPI is particularly useful in panel data analysis in which distance functions are defined to describe a multi-output, multi-input production technology over time. The index does not have a behavioral (i.e., cost minimization or profit maximization) assumption. In this index, an input distance function specifies a production technology that captures the saving in inputs given an output level, while the output distance function increases a firm's output given the level of inputs. In this study, an output distance function approach is adopted by applying Malmquist TFP (MTFP) since output-oriented wheat production optimization is assumed.

The MPI index uses distance functions to calculate changes between two data points (in our case, a country's distance function in two adjacent time periods) by calculating the ratio of the distances of each data point relative to an efficient outcome benchmark. Adopting this approach is an opportunity to check the performance within the country across time and also a comparison of performance between countries.

Färe et al. (1994) expressed the MPI index between period t (the base period) and period t+1 as:

$$MPI_0^{t,t+1} = \left[\frac{D_0^t(x^{t+1}, y^{t+1})\, D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)\, D_0^{t+1}(x^t, y^t)}\right]^{1/2} \tag{8}$$

In the current study distance functions need be defined with respect to two different time periods in order to calculate the MTFP index. For instance, $D_0^t(x^{t+1}, y^{t+1})$ measures the maximal proportional change in outputs required to make (x^{t+1}, y^{t+1}) feasible in relation to the technology at time *t*. Also, $D_0^{t+1}(x^t, y^t)$ can be defined as a measure of the maximal proportional change in output required to make (x^t, y^t) feasible in relation to the technology at *t+1*. The distance function $D_0^{t+1}(x^{t+1}, y^{t+1})$ measures the maximum proportional change of output y^{t+1} given input x^{t+1} in given the technology in period *t+1*. Finally, $D_0^t(x^t, y^t)$ measures the maximum proportional change of output y^t given input x^t in the technology followed in period *t*. A value of $MTFP_0^{t,t+1}$ greater than one will indicate a positive TFP growth between the two periods. Equation 8 is the geometric mean of the two TFP indices, where the first is evaluated taking into account period t and the other t+1.

Equation 8 can be written in equivalent way as:

$$MPI_0^{t,t+1} = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \sqrt{\left(\frac{D_0^t(x^{t+1}, y^{t+1})\, D_0^t(x^t, y^t)}{D_0^{t+1}(x^{t+1}, y^{t+1})\, D_0^{t+1}(x^t, y^t)}\right)} \qquad (9)$$

where the expression outside the square root symbol measures the change in the output-oriented technical efficiency between period t and t+1. The expression inside the square root symbol represents technical change. It is a geometric mean of the shift in technology between the periods t and t+1 evaluated at x^t and x^{t+1}.

The MPI approach assumes constant returns to scale, which may not be appropriate for wheat production that can range between very small levels of input/output and larger scales of production. As a result, the Hicks-Moorsteen Index (HMI) is used to accommodate variable returns to scale (VRS) in the current study. Grifell-Tatjé and Lovell (1995) argue that the VRS is more flexible and generalizable for production technologies, and Glass and McKillop (2000) argue that MPI results may be infeasible where the more flexible VRS can result in optimal solutions. HMI is free from any assumptions concerning the optimization behavior such as the structure of the market, and VRS can be applied to decompose efficiency changes into three different measures such as technical, scale, and mix efficiency (O'Donnell, 2008). This current study constructs HMI to identify the sources of improvement or deterioration in the efficiency and therefore, the productivity level of MENA countries in wheat production.

In the specification proposed by O'Donnell (2012), TFP indices can be expressed as aggregate quantities. The Hicks-Moorsteen (HMI) is a TFP index that can be computed without price data. HMI is actually a ratio of Malmquist output and input quantity indices, and the index originated with Hicks (1961) and Moorsteen (1961). This index is calculated as:

$$HMTFP^{t,t+1} = \left[\frac{D_0^{t+1}(x^{t+1},y^{t+1})\,D_0^{t}(x^{t},y^{t+1})}{D_0^{t+1}(x^{t+1},y^{t})\,D_0^{t}(x^{t},y^{t})}\;\frac{D_I^{t+1}(x^{t},y^{t+1})\,D_I^{t}(x^{t},y^{t})}{D_I^{t+1}(x^{t+1},y^{t+1})\,D_I^{t}(x^{t+1},y^{t})}\right]^{1/2} \tag{10}$$

Where $D_0\ (x,y)$ and $D_I\ (x,y)$ are output and input distance functions, respectively. Also, *t* is the base period and *t+1* is the next period. In the formulation of equation 10, HMTFP will give both TE in the output and input oriented model. So, the left part of the right-hand side of equation 10 will give technical change and technical efficiency adopting output oriented model and the right part of the right hand side will give the same outcomes but this time by utilizing input oriented model.

1.5. Data

The purpose of the two empirical approaches is to uncover the impact of various forms of capital on wheat productive efficiency in the MENA countries. The conceptual framework is defined by equations 1-5 for the analysis of SFA and equations 6-9 for DEA. In order to describe this conceptually expressed relationship, a description of the data is needed and follows in this section.

In this study, 19 MENA countries are examined for 26 years. The MENA countries are Algeria, Bahrain, Djibouti, Egypt, Iran, Iraq, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Qatar, Saudi Arabia, Syria, Tunisia, Turkey, United Arab Emirates (UAE), and Yemen (TheWorldBank, 2017). MENA countries are typically large importers of wheat, and wheat price increases can have significant detrimental impacts on consumer wellbeing. The wheat industry is an important contributor to the local food supply, as well as farm income to all of the MENA countries. Of particular interest is Iraq, one of the 19 MENA countries.

Literature in agricultural economics suggest various forms of capital that are important determinants of productive efficiency. Table 1 summarizes some articles investigating the production efficiency of wheat in different countries. The * sign indicates variables that will also be used in the current study. The direction, + or -, of the variables on efficiency are found in parenthesis, and variables in bold are statistically significant.

Table 1.Variables utilized by literatures studied efficiency production in wheat in different countries

Authors	Variables
Battese, Malik, and Broca (1993) in Pakistan. Panel data of 4 years of 4 districts on wheat farmers highlighting the level of inefficiency in each district. Thus, technical efficiency for each farmer is estimated in each year. This study highlights the importance of analysis at the disaggregate level to pay attention in research and policy formulation in conducting such research.	**-total amount of land (+)** * **-total amount of labor (family)* (+)** -total amount of labor (hired)*(+) **-amount of fertilizer* (+)** -total hours of land preparation (-) **-number of ploughings* (+)** **-quantity of seeds (+)** -dummy variable indicating if the fertilizer was applied (-) -dummy variable indicating if the farmer used mechanical traction in wheat production (-) -dummy variable indicating if the farmer was owner or tenant of the land (+).
G. E. Battese, Malik, and Gill (1996) in Pakistan. Panel data of wheat farmers in 4 districts. New single stage model in obtaining technical inefficiencies over time was performed in this study. This new model applied a single stage analysis incorporating “standard’ inputs as well as factors believed affecting technical efficiency.	**-total amount of land* (+)** **-total amount of labor (family)* (-)** -total amount of labor (hired)* (+) **-amount of fertilizer* (+)** **-total hours of land preparation (-)** -number of ploughings* (-) **-quantity of seeds (+)** **-dummy variable indicating if the fertilizer was applied (+)** **-dummy variable indicating if the farmer used mechanical traction in wheat production (-)** -dummy variable indicating if the farmer was owner or tenant of the land (+) They also regressed the technical efficiency score against the firm specific characteristics. These characteristics are **-age of farmers (-)** **-maximum years of formal schooling* (-)** - ratio of adult males to the total household size (-)

G. E. Battese and Broca (1997) in Pakistan. Panel survey of wheat farmers of 1 district in 4 years as an attempt to identify the technical inefficiency levels and scale efficiency under different model specification.	**-total amount of land* (-)** **-total amount of labor* (+)** -amount of fertilizer* (-) **-quantity of seeds* (+)** -dummy variable indicating if the fertilizer was applied (-) The second stage of DEA which is regressing against firm specific characteristics included the following variables **-age of the farmers (-)** **-years of formal schooling* (-)** -dummy variable indicating if the farmer is owner or tenant of the farm (+) **-dummy variable indicating if the farmer constrained by credit availability (+)**
Ahmad, Chaudhry, Iqbal, and Khan (2002) in Pakistan. Survey covers 18 district in 3 provinces were used to know factors affecting wheat production as well as factors affecting technical inefficiency score adopting the model proposed by G. E. Battese et al. (1996).	**-area under wheat* (-)** **-amount of fertilizer* (+)** **-ration of phosphorous to NPK (+)** **-quantity of seeds* (+)** -quantity of yard manure (+) **-ratio of area under rice to the total cultivated area (-)** -ratio of area under cotton to the total cultivated area (+) **-dummy variable indicating a positive amount of fertilizer applied (+)** -dummy variable indicating positive amount of manure applied (+) **-dummy variable indicating if the canal alone is source of irrigation (+)** **-dummy variable indicating if the tube well is source of irrigation (+)** **-dummy variable indicating if the canal+tubewell is source of irrigation (+)** **-district dummies assuming one if the farm is located in specific district (+)** Second stage of regressing the efficiency scores against firm's specific characteristics. These characteristics are: **-age of farmer (+)** **-credit obtained by farmer* (-)** **-farm size (acres)* (-)** **-dummy variable indicating if education is up to primary schooling (-)** **- dummy variable indicating if education is up to middle schooling (-)** **- dummy variable indicating if education is up to matric schooling (-)** **- dummy variable indicating if education is greater than matric schooling (-)**

	- dummy variable indicating if education is up to middle schooling (-) **-dummy variable is the farmer was owner or tenant of the farm (-)** **-dummy variable indicating if the farmer consulted an extension agent (-)** **-distance of farm to main market town in (in kilometers)* (+)**
Hasan and Islam (2010) in Bangladesh. Farm level cross section data of 293 wheat farms in 3 districts to identify and analyze the inefficiency and yield gap.	-area under wheat* (+) -age of farm operator (-) **-years of formal schooling* (-)** -experience in wheat farming (years) (-) -household size of farm operator (-) -dummy variable indicating if the farmer has an extension linkage (+) -dummy variable indicating if the farmer has a training in wheat cultivation (-)
Tleubayev, Bobojonov, Götz, Hockmann, and Glauben (2017) in Kazakhstan. Cross section data of 200 farms benefiting from a farm survey conducted in 2015. Four districts were adopted in this study in order to understand policy effects on productivity and efficiency.	-production variables -farm characteristics variables -educational characteristics variables -supply characteristics variables **Production variables are** **- total cost of labor (+)** **- total cultivated area (hectare)* (+)** **- cost of raw materials such as seeds, fertilizers, and pesticides (+)** - **cost of machinery, advisory services from outside suppliers and depreciation (+)** **Farm characteristics variables** **- total farm area (ha)* (+)** - number of years the farmer operating so far* (+) **- total number of machines that the farms are using* (-)** **- distance from the most distant crop land and the farm* (-)** **- dummy variable showing if the farmer is belonging to an agricultural cooperation (+)** **- dummy variable if the farmers had insurance to secure their agricultural activities (-)** **- dummy variable if the farmer had access to credit* (-)** **- the amount of subsidies received by farmers (+)** **Educational characteristics variables** **- dummy variable used to identify if the farm's manager has a specialized agricultural education (-)** **- dummy variable used to show if the farm manager has a college level degree* (-)** **Supply characteristics variables** **- dummy variables indicating if the farmer market his output to agro-processing site (-)**

	- dummy showing if the farmer is marketing his output to procurement enterprises (-) - dummy variable showing if the supplies are conducted under special contractual agreements (-)
Tavva, Aw-Hassan, Rizvi, and Saharawat (2017) in Afghanistan. Survey distributed through 200 farmers in 7 districts of 5 provinces to assess factors influencing low wheat productivity and large gaps in production.	**- amount of capital used for inputs other than labor and seed in the wheat cultivation process (US $)* (+)** **- labor days per hectare* (-)** **- seed rate (kg/ha) used by the farm (+)** Second stage DEA used the following variables - family size* (-) **- total wheat area* (+)** **- ratio of wheat area to the total cultivated area (+)** - age of the farmers (-) - technology adoption score in wheat cultivation* (+) **- dummy variable captures the fact that if the farmer is using improved variety of wheat (+)** - dummy variables indicating that if the farmer is the owner of the farm (-) - dummy variable capturing the education level of the farmer (1= if the farmer literate, 0 otherwise)* (+) **- dummy variables showing the production system in which wheat cultivated (1= if wheat is cultivated under irrigated production system, 0 otherwise) (+)**

The previous studies rely on survey data of farmers to determine productive efficiency. The highlighted variables focus, in particular, on human capital, education, irrigation, area under cultivation and markets. The current study uses a similar approach, and macroeconomic panel data series are used in the analysis rather than survey data. This data is primarily obtained from the FAO (FAO, 2016) with supplements from USDA and the World Bank. The data can be obtained from the author on request.

1.6. Data Series in the Empirical Approach

The purpose of this section is to develop an empirical model of wheat productive efficiency. Following previous studies such as Battese et al. (1993), G. E. Battese et al. (1996), G. E. Battese and Broca (1997), Ahmad et al. (2002), Hasan and Islam (2010), Tleubayev et al. (2017), and Tavva et al. (2017), the wheat productive efficiency model begins with a production relationship as in:

$$yield\ (kg/acre) = f(har_{it}, pop_{it}, nep_{it}, nes_{it}, hav_{it}, tra_{it}, pes_{it}, ure_{it}, npk_{it}, qsed_{it}, net_{it}, impq_{it}) \quad (11)$$

where Table 2 defines pop_{it}, nep_{it}, $and\ nes_{it}$ as human capital variables. The variable representing financial capital is net_{it}. Operational capital variables are har_{it}, hav_{it}, tra_{it}, pes_{it}, ure_{it}, npk_{it}, $and\ qsed_{it}$. Variable that representing the imports of wheat is $impq_{it}$. This production relationship expressed in equation 11 adopted in the first stage of DEA and SFA.

1.7. Model Specification

We specify the production relationship as:

$$y_{it} = f(har_{it}, pop_{it}, nep_{it}, nes_{it}, hav_{it}, tra_{it}, pes_{it}, ure_{it}, npk_{it}, qsed_{it}, net_{it}, impq_{it}) \quad (12)$$

And the following equation is the second stage analysis adopted in both DEA and SFA.

$$te_{it} = f(cre_{it}, ppi_{it}, acc_{it}, rrtu_{it}, asti_{it}, enrg_{it}, emp_{it}, doms_{it}, dlaglsu_{it}, beingonwater_i, Exportingcountry_i, Politicalystablecountry_i, elevation_i, temperaturechange_{it}) \quad (13)$$

There variables are defined as:

Table 2. Definition of variables used in 1st and 2nd stage of wheat productive efficiency analysis

Variable name	Definition	
First stage analysis variables		
y_{it}	is the dependent variable. It is the yield of wheat per unit of land for country *i* in time *t (hg/acre).*	Dependent variable
pop_{it}	is the population of country *i* in time *t*.	Human capital variables
$nep_{it,}$	is the net enrolment of women in primary education in country *i* in time *t* (%).	
nes_{it}	is the net enrolment of women in secondary education in country *i* in time *t* (%).	

$net_{it,}$	is the net national income of country *i* in time *t* (USD).	Financial capital variable
har_{it}	is the area harvested of wheat for country *i* in time *t*.	Operational capital variables
hav_{it}	is the number of mechanical harvesters in country *i* in time *t*.	
tra_{it}	is the number of tractors in country *i* in time *t*.	
pes_{it}	is the quantity of pesticides in tons in country *i* in time *t*.	
$ure_{it,}$	is the quantity of urea applied in tons for country *i* in time *t*.	
$npk_{it,}$	is the quantity of a complex fertilizer composed from nitrogen (N), Phosphorus (P), Potassium (K) for country *i* in time *t*.	
$qsed_{it}$	quantity of wheat seeds planted in country *i* in time *t* (1000 ton).	
$impq_{it}$	quantity of wheat imported by country *i* in time *t* (tons).	Imports variable
Second stage analysis variables		
te_{it}	is the dependent variable obtained by the 1st stage analysis. It is the technical efficiency score obtained from 1st stage.	Dependen t variable
acc_{it}	is the percentage of rural area with access to electricity in country *i* in time *t*.	Human capital variables
cre_{it}	the amount that paid to the farmers as a credit in country *i* in time *t*.	
emp_{it}	is the percentage of women work in ag related labor in country *i* in time *t*.	
$asti_{it}$	agricultural science and technology indicators in country *i* in time *t*.	
$rrtu_{it}$	ratio of rural population to urban population in country *i* in time *t*.	
ppi_{it}	producer price index of local wheat (USD per ton) in country *i* in time *t*.	Financial capital variable
exp_t	Dummy variable equal 1 if the country is a wheat exporting country, 0 otherwise.	Imports, exports, domestic variables
$doms_{it}$	Domestic production of wheat in country *i* in time *t*.	

$dlaglsu_{it}$	Density of livestock in ag (livestock unit/ha)	
$enrg_{it}$	energy consumption in agricultural purposes in country i in time t.	Livestock competition, energy usage, political effect variables
$psav_{it}$	political stability and absence of violence/ terrorism in country i in time t.	
wat_i ,	Dummy variable equal 1 if the country has a surface irrigation (i.e. river), 0 otherwise.	
$temp_{it}$	Temperature change in country i in time t.	Irrigation, temperatu re, and elevation variables
$elev_i$	Elevation of country i.	

1.7.1. Description of variables

1.7.1.1. First Stage Analysis of Yield Productivity Variation

In the first stage of analysis, the yield of wheat per dunam is regressed on important factors of production and sociodemographic variables for the 26 countries and 19 years of analysis. The first stage variables are used to determine a measure of technical efficiency (TE). The TE is the foundation of the second stage of analysis. The variables in the first stage of analysis are specific variants of differing forms of capital: human capital, natural capital, financial capital, and operating capital.

1.7.1.1.1. Human Capital Variables

Population (pop_{it}): the population variable indicates the availability of labor force for agricultural production in this study. In general, an increasing population increases production of agricultural goods (Azadeh et al., 2011), perhaps because a greater quality of skilled labor and a larger number of unskilled laborers that is beneficial to agriculture (Battese et al., 1993).

Percentage of women work in agriculture (emp_{it}): this variable is included as a human capital variable to determine if this variable improves technical efficiency. Women are a large portion of the agricultural workforce in the MENA countries and the incremental contribution of women may enhance the overall TE score. A more educated population likely will increase technical efficiency. Farmers who are literate can read and benefit from recommendations that they can get from experts.

Net Enrolment of Women in Primary and Secondary School Education ($nep_{it,}$ and nes_{it}): Gender dynamics are important. A more highly educated female workforce is a key source of specialized labor in agriculture. The variables $nep_{it,}$ and nes_{it} are an indication of the quality of labor as an increased enrollment of women in primary school signals a long run investment in an educated workforce and increased labor force participation (Udoh, 2005). A potential policy recommendation can be inferred if female education is positively associated with yield per dunam.

1.7.1.1.2. Harvested Acres, Mechanical Capital, and Operating Capital

Harvested acres (har_{it}), machinery inputs ($hav_{it,}$ tra_{it}) and operation capital inputs pes_{it} ,ure_{it} ,npk_{it},$qsed_{it}$ are used here due to the hypothesis that using these inputs can increase productivity, if they are applied optimally at appropriate scales of production. Economies of scale likely exist for these inputs, where firms are trying to minimize cost by increasing their production from a given resource base, and that can be done by acting more efficiently. Financial capital is an important factor of wealth which is represented by net national income. In this case, increasing wealth means more funds are available to invest in agricultural business and operations related to agriculture.

Finally, imported quantities of wheat is included to understand how increasing dependency on imports is correlated with a high relative cost of domestic production.

1.7.1.2. Second Stage Analysis of TE Variation

The first stage of the analysis is used to calculate technical efficiency. In the second stage, the focus is to uncover how variations in technical efficiency are explained by variations in factors of production and sociodemographic factors.

In the second stage, macroeconomic policies and politics can explain differences in TE. Variables used in the 2nd stage are listed in table 2 and described below.

1.7.1.2.1. Human Capital-2nd stage analysis

Percentage of Farmers with access to electricity (*acc*): macroeconomic policies in education and infrastructure can influence TE. This is why the population of farmers relative to urban population is included as a second stage explanatory variable along with availability of electricity in rural areas. Electricity has a key role in powering irrigation pumps and post-harvest threshing and seed cleaning. Other variables related to the quality of human capital is the employment of women in agriculture related duties (*emp*). Including this variable is aiming to know if increasingly number of women joining agricultural workforce can increase efficiency.

Another variable referring to the quality of human capital is agricultural science and technology indicator, $asti_{it}$. In the FAO website, it is listed under the ASTI R&D Indicators, which is agricultural science and technology indicators relating to research and development. This index is calculated based on data on number of researchers in agriculture that are nationally employed either within the government, nonprofit, or higher education agencies for each 100,000 farmers. It is key assessing allocation and utilization of the existing resources in research and knowledge transfer (FAO, 2016).

Rate of rural population to urban population (*rrtu*): is adopted here as another human capital variable. This variable is used here to test if the increasing the availability of workforce within agriculture is explaining the differences in TE across MENA countries.

1.7.1.2.2. Financial Capital

Producer Price Index (*ppi*): this variable is used here as an indication about the financial capital that farmers have because it measures the prices received by farmers for agricultural goods. It is believed that producer price index in different countries may explain variation in TE because it provides the level of capital available for inputs in growing agricultural commodities such as wheat. The other financial capital variable is credit to farmers (*cre*). Increasing access to credit improves productive efficiency as it permits the purchase of higher quality inputs in greater abundance.

1.7.1.2.3. Imports, Exports, and Domestic Production Variables:

Cereal import dependency ratio ($cedr_{it}$): this ratio is calculated as the ratio of cereal grains imported relative to those that are exported. Ceteris Paribus, imports increase when the domestic production is costly relative to the cost of production outside the country's borders. This variable then becomes a proxy for the systematic differences in production that lead to less efficient and higher cost

Exp_i is a dummy variable if the country is exporting wheat. The theory here is if the country is exporting wheat then it has an advantage in technical efficiency vis a vis other countries at least for that year. It can be case that a MENA country both imports and exports wheat due to proximity of trading partners and availability of infrastructure.

Another variable included is the domestic production of wheat ($doms_{it}$) in each country i in each period t. it may be the case that if the domestic production increases, the TE might increase also. It is hypothesized that once the production of wheat crosses a certain threshold, then economies of scale begin as a sufficient demand exists for wheat production factors of production.

1.7.1.2.4. Livestock Competition, Energy Usage, and Political Stability:

Other factors that might affect efficiency is the density of livestock ($dlaglsu_{it}$) in MENA countries. The hypothesis here is it might be the case that livestock raising is more lucrative than producing wheat so countries with high density of livestock might be less technically efficient in the production of wheat. This hypothesis based on the assumption that wheat is not typically a fed grain, and that livestock production may compete for farm resources that might otherwise be available for wheat.

Energy availability ($enrg_{it}$): is a proxy for industrialization which can add value to labor inputs, so this variable is included and measured as energy per unit of time. It is an aggregate measure aggregating all sources of power from gas to electricity to coal.

$Psav_i$ is a dummy variable adopted from the political stability and absence of violence (PSAV) data. This variable measures the likelihood that the government will be overthrown by unconstitutional means including politically- motivated violence and terrorism (FAO, 2016). It is one of the Worldwide Governance Indicators (WGI) project by Kaufmann, Kraay, and Mastruzzi (2011). The WGI project utilized 200 countries and territories measuring six dimensions and PSAV is one of them. Roughly, this variable is calculated based on a survey targeting public, private, and NGO sector experts worldwide containing data reflecting views on governance performance. The WGI also reports margins of error accompanying each studied country estimate. These error margins are basically reflecting the difficulties inherent in measuring governance.

1.7.1.2.5. Irrigation Pattern, Temperature, and Elevation

Another dummy variable is the availability of surface water (wat_i), indicates if country has access to surface water suitable for agricultural irrigation. Surface water includes lakes and rivers suitable for irrigation water storage and direct diversion respectively. The next variables are focused on natural capital as they are closely linked to growing conditions and climate. $Elev_i$ is a proxy for growing conditions as in the MENA countries a higher elevation is often associated with cooler growing conditions and improved precipitation, water infiltration and potentially soil water holding capacity. Another technical variable is $temp$. It is included to see if temperature variation across years has an effect on technical efficiency. Those elevation and temperature variables are important especially at the wheat ripening stage. For elevation, Thomson et al. (2002)indicate that elevation is important at the final stage of seed formulation especially at elevations below 4000 ft and with relatively cool maximum temperatures 30c^0 (86 F^0).

1.7.2. Summary and Descriptive Statistics of the Data Set

The variables listed in table 2 are collected from a variety of resource including USDA, FAO, and World Bank. The descriptive statistics for these data series are presented in table 3 and table 4. The data series collected for this study show high variation when viewed across time and countries.

Table 3 focuses on variables in the 1st stage of the analysis, and Table 4 lists variables used in the 2nd stage.

Table 3. Summary statistics for the variables used in the efficiency analysis 1st stage for wheat producing MENA countries from 1991 to 2016.

Variable	Units	Variable name	Mean	Coefficient of variation	Minimum	Maximum
Domestic harvested area	(1,000 acres)	*har*	868,236	1.74	2.00	7,222,311
Domestic population	(1,000 People)	*pop*	21,412	1.11	487.49	95,689
Net enrolment of women in primary education	percentage	*nep*	81	0.20	15.29	112
Net enrolment of women in secondary education	percentage	*nes*	68	0.34	8.00	111
Tractors used in each country	number	*tra*	89,934	2.38	53.00	1,079,894
Harvesters used in each country	number	*hav*	4,956	2.99	2.00	111,917
Quantity of pesticide used	ton	*pes*	4,619	1.81	1.10	48,716
Quantity of Urea used	ton	*ure*	275,832	1.97	113.00	2,832,831
Quantity of NPK used	ton	*npk*	105,038	1.73	2.00	995,375
Quantity of seeds used	(1000 ton)	*qsed*	206	1.87	2.00	1,960
Net National Income	(USD)	*net*	94.4 billion	1.43	1.50 billion	765 billion
Quantity of wheat imports	(tonnes)	*impq*	1,679,917	1.24	2.00	11,428,301

Table 4. Summary statistics for the variables used in the 2nd stage analysis for wheat producing MENA countries from 1991 to 2016.

Variable	Unit	Variable name	Mean	Coefficient of variation	Minimum	Maximum
Credit to farmers	Millions of USD	*cre*	40,501	1.93	11.29	497,962
Cereal import dependency ratio	Percentage*100	*cedr*	73	0.39	-4.80	100
Producer price index	(USD per ton)	*ppi*	118	0.58	0.19	662
Percentage of farmers with access to electricity	percentage	*acc*	86	0.31	1.60	100
Rural to urban population	percentage	*rrtu*	0.58	1.05	0.01	3.65
Agriculture science and technology indicator	(1 ag specialist for each 100000 farmer))	*asti*	38	1.47	3.50	276
Energy consumption for ag use	(Terajoule)	*enrg*	1,827	1.31	6.51	10,620
Women work in ag	percecntage	*emp*	22	1.12	0.00	89.20
Domestic of wheat production	(1000 ton)	*doms*	4,103	1.29	50.43	20,228
Density of livestock	(animal per hectare)	*dlag*	0.18	1.25	0.00	1.31
If a country has a surface water	Dummy variable	*wat*	0.47	1.06	0.00	1.00
Export value	(1000 US$)	*exp*	10,475	3.46	0.00	340,853
political stability and absence of violence/ terrorism	Dummy variable	*psav*	0.31	1.51	0.00	1
elevation	ft	*elev*	1,911	1,268.73	91.86	4,282
Avg. temperature change	Celsius	*temp*	0.98	0.67	-1.36	2.99

In summary, the previous studies typically focus on the following categories of variables:

- Operational inputs such as fertilizers.

- Land asset including its size and quality.
- Human capital including education and work force participation.
- Infrastructure such as tractors or irrigation.
- Financial capital as credit availability and governmental support such as subsidies.

This essay will examine the efficiency with which these inputs are used in wheat production. Similar to the previous studies, wheat production per unit land is the efficiency measure and includes factors of production, such as wheat land quantity, human capital, and other factors as the key inputs. Technical efficiency is calculated and regressed on characteristics to explore relative importance of each factor.

1.8. Results from SFA methods and DEA methods

The results are divided into two sections and each section has two stages of analysis. In the first stage, the technical efficiency scores are determined, and the second stage of analysis seeks to understand how the variation in technical efficiency is correlated with factors of production. Stochastic Frontier Analysis (SFA) is used as the first empirical approach followed by Data Envelopment Analysis (DEA).

Before implementing SFA, a simple examination of multicollinearity is performed using Variance Inflation Factor (VIF). VIF is a simple attempt to investigate the existence of multicollinearity in an econometric model (Kutner, Nachtsheim, & Neter, 2004). In this procedure, one of the explanatory variables is regressed against other explanatory variables. If one explanatory variable predicts the other covariates well, then multicollinearity exists which may lead to a poor goodness-of-fit and a poor understanding of the factors that most influence inefficiency. Taking the R^2 obtained by this regression, the VIF is calculated by using the formula $\frac{1}{1-R^2}$. The calculated value in this study equals to 1.7 which is less than 5, a general level of concern about for multicollinearity based on VIF (Wooldridge, 2000)

Tables 5 and 6 indicate the correlation between right hand side (RHS) variables.

Table 5. Correlation matrix of variables exists in the first stage of analysis

	lnhar	*lnpop*	*lnnep*	*lnnes*	*lntra*	*lnhav*	*lnpes*	*lnure*	*lnnpk*	*lnqsed*	*lnnet*	*lnimpq*
lnhar	*1*											
lnpop	*0.76*	*1*										
lnnep	*-0.10*	*0.04*	*1*									
lnnes	*-0.30*	*-0.16*	*0.44*	*1*								
lntra	*0.83*	*0.86*	*0.03*	*-0.15*	*1*							
lnhav	*0.78*	*0.80*	*0.09*	*-0.20*	*0.88*	*1*						
lnpes	*0.53*	*0.64*	*0.24*	*0.23*	*0.76*	*0.65*	*1*					
lnure	*0.24*	*0.55*	*0.13*	*-0.21*	*0.40*	*0.50*	*0.29*	*1*				
lnnpk	*0.22*	*0.45*	*0.37*	*0.10*	*0.48*	*0.42*	*0.47*	*0.37*	*1*			
lnqsed	*0.26*	*0.50*	*0.04*	*-0.24*	*0.40*	*0.52*	*0.15*	*0.60*	*0.25*	*1*		
lnnet	*0.05*	*0.49*	*0.50*	*0.35*	*0.34*	*0.42*	*0.43*	*0.54*	*0.70*	*0.35*	*1*	
lnimpq	*0.35*	*0.50*	*0.16*	*0.08*	*0.45*	*0.33*	*0.28*	*0.06*	*0.32*	*0.24*	*0.26*	*1*

Table 6. Correlation matrix of variables used in the second stage of analysis

	lncre	*lnpi*	*lnimpv*	*lnacc*	*lnrrtu*	*lnasti*	*lnenrg*	*lnemp*	*lndoms*	*lndlag~u*	*Beingo~r*	*Export~y*	*Politi~y*	*elevat~t*	*temper~e*
lncre	*1*														
lncedr	*-0.24*	*1*													
lnppi	*0.07*	*0.47*	*1*												
lnacc	*0.57*	*-0.03*	*0.04*	*1*											
lnrrtu	*-0.28*	*-0.24*	*-0.22*	*-0.34*	*1*										
lnasti	*0.17*	*-0.06*	*0.07*	*0.13*	*-0.04*	*1*									

lnenrg	*0.12*	*-0.28*	*0.02*	*-0.09*	*0.24*	*-0.19*	*1*								
lnemp	*-0.39*	*-0.38*	*-0.22*	*-0.39*	*0.79*	*0.03*	*0.21*	*1*							
lndoms	*0.09*	*-0.55*	*-0.20*	*0.19*	*0.54*	*0.10*	*0.47*	*0.59*	*1*						
lndlaglsu	*0.52*	*-0.03*	*0.08*	*0.40*	*-0.55*	*0.30*	*-0.33*	*-0.41*	*-0.19*	*1*					
Beingonwater	*0.01*	*-0.45*	*-0.17*	*-0.27*	*0.45*	*0.00*	*0.32*	*0.51*	*0.42*	*-0.02*	*1*				
Exportingc~y	*0.26*	*-0.12*	*0.08*	*-0.06*	*0.03*	*-0.16*	*0.14*	*-0.06*	*-0.03*	*0.12*	*0.10*	*1*			
Politicaly~y	*0.06*	*0.24*	*0.14*	*0.00*	*-0.42*	*0.03*	*-0.24*	*-0.49*	*-0.62*	*0.11*	*-0.35*	*-0.04*	*1*		
elevationft	*0.06*	*-0.40*	*-0.23*	*0.07*	*0.36*	*-0.08*	*0.18*	*0.29*	*0.53*	*-0.19*	*0.28*	*0.05*	*-0.62*	*1*	
temperatur~e	*0.01*	*0.15*	*0.43*	*-0.02*	*-0.12*	*0.03*	*-0.07*	*-0.07*	*0.02*	*0.09*	*-0.04*	*0.10*	*0.03*	*-0.06*	*1*

In table 5, the high correlation between harvested area and tractors is an indication of the availability of mechanical capital and the use of tractors is a joint input with land. Another high positive correlation is found between tractors, harvesters and population. It might be that as population grows, more people need to employ mechanical capital. Another high correlation is found between tractors and harvesters indicating their importance as a complementary capital in the production process.

1.8.1. SFA Parameter Estimates, TE and Interpretation

The logarithmic transformation of SFA parameter estimates from equation 12 are obtained by regressing wheat production on the explanatory variables in table 6. The error distribution is decomposed into an error in optimization and a stochastic portion. For this study, the estimates are obtained by using Stata v. (14) and the "frontier" command developed by Kumbhakar and Lovell (2000).

Results of the first stage SFA are shown in table 7. The individual standard error for each variable is indicated and overall equation statistics.

Table 7. Estimated parameters for the first stage SFA regression of wheat yield per unit land on explanatory variables (n=494)

Variable Type	Variable Name	1st stage output
Harvested area	$lnhar_{it}$	-0.0565***
		(0.0145)
Population	$lnpop_{it}$	0.464***
		(0.0502)
Net enrolment of women in primary education	$lnnep_{it}$	-0.0264
		(0.0765)
Net enrolment of women in secondary education	$lnnes_{it}$	0.0226
		(0.0404)
Number of tractors used	$lntra_{it}$	-0.0959***
		(0.0288)
Number of harvested used	$lnhav_{it}$	-0.125***
		(0.0210)
Amount of pesticide used	$lnpes_{it}$	0.0511***
		(0.0126)
Amount of urea used	$lnure_{it}$	0.0551***
		(0.0103)
Amount of NPK used	$lnnpk_{it}$	-0.00961
		(0.0110)
Amount of seeds used	$lnqsed_{it}$	-0.0925***
		(0.0217)
Net national income	$lnnet_{it}$	0.117***
		(0.0218)
Imported quantities of wheat	$lnimpq_{it}$	-0.0295***
		(0.00947)
	Constant	5.593***
		(0.431)
	Observations	494

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

$$LR\ chi^2(12) = 1593, \text{Prob} > chi^2 = 0.001, \text{Log Likelihood} = -158.481$$

Before interpreting the coefficient estimates in table 7, it is worthwhile to consider goodness of fit for these empirical results. One way to view goodness of fit is to consider if the explanatory variables are jointly different than zero. In this case, a likelihood ratio test is performed, and a Chi square statistic is calculated. The likelihood ration test is a test of the omnibus null hypothesis that all the coefficients in the model are zero (except the constant). The chi-square statistic equals 1,593. Thus, the null hypothesis that the coefficients are jointly equal to zero is rejected. In general, the model exhibits a suitable goodness of fit for explaining variation in wheat productive efficiency.

The 1st stage results indicate 9 out of 13 variables were statistically significant at the 95% significance level. Variables that showed a positive relationship with yield per unit of land are population, pesticide, urea and net national income. Variables that are negatively related to yield per unit of land are harvested area, number of tractors, number of harvesters, seeds quantity and the wheat import quantity. Variables were not significantly different than zero are net enrolment of females in primary and secondary school, and NPK fertilizer.

1.8.2. Interpreting the Coefficient Estimates for Explanatory Variables in the First Stage SFA

The estimated coefficients of Table 7 are useful in understanding the relative importance and direction that explanatory variables have on the variation in wheat productive efficiency. As an example, if the harvested area increases by 1% for all the MENA countries, it will be associated with yield decreases of 0.05% ceteris paribus. The negative relationship may be a sign of diminishing marginal returns to management's contribution when acres increase so that productive efficiency is not improved. The impact of population, as expected, is positive indicating a population increase of 1% is associated with a 0.5% increase in wheat productive efficiency ceteris paribus. Interestingly, this variable has the largest coefficient, and consequently the largest explanatory power, on the yield per unit dunam. The estimate relationship of women's enrolment not statistically different from zero and this was unexpected.

Mechanical capital is represented by the number of tractors and harvesters present in the countries, these variables have a negative relationship with wheat TE. This is unexpected since these mechanical capital components are expecting to affect yield per unit positively. This might be due to the inefficient use of this capital so adding more mechanical capital may decrease TE.

Pesticides and urea usage affect yield positively. More specifically, a 1% increase in pesticide use from the sample means will be associated with a 0.05% increase in wheat production ceteris paribus. For urea, adding more by 1% is associated with increasing yield by 0.05%. So, increasing the usage of urea and pesticides may affect yield per unit dunam positively. The parameter estimates for NPK was not found to be statistically different than zero.

Another surprising result is found in the analysis. The amount of seed allocated to wheat production has a negative relationship with the yield per dunam of the harvested crop. Perhaps this is due to a lack of precision in planting wheat with techniques that lead to poor germination and eventually affecting harvested yield. It might also be a sign of re-planting of a lost crop, and/or the result of low wheat prices in 2016, so the wheat is used as seed in 2017. A farmer has a choice, either to sell wheat today or use it as a seed in the future, and the choice to hold wheat may be in response to poor prices today.

Net national income, as an indicator of the availability of investment capital for loans and /or more capital that can be directed in operations is positively related with yield productivity. As expected, more imports have a negative relationship with yield per dunam. Increasing imported wheat quantities by 1% is associated with a yield reduction of 0.02%. Governments might increase the imports due to the lack of supply or the poor quality of the current product. Higher production costs might play a significant role here.

1.8.3. Calculating and Comparing TE Scores from the SFA Estimation Procedure

Now, after performing the first stage of analysis and capturing residuals, TE scores are obtained using equation 11 and then compared across countries and time. Each country has a TE score in each year, so the 26 countries have 19 TE scores for analysis.

Table 8 lists the summary TE scores for each of the countries. The mean score is a measure of a country's average technical efficiency in wheat production for the period 1991-2016 as reported in the second column. Average TE ranges from 0.28 (Yemen) to 0.92 (Egypt) with Iraq's TE of 0.52. Within the time period, a subset of countries exhibits wheat TE that varies substantially as illustrated by the coefficient of variation (CV) in Table 8 fourth column, and as represented graphically in Figure 2.

Table 8. Summary Statistic of the Obtained TE scores by SFA for Data Spanning 1991-2016.

	Mean	Median	CV	Minimum	Maximum
Technical Efficiency Algeria	0.43	0.43	0.17	0.31	0.53
Technical Efficiency Egypt	0.92	0.93	0.03	0.83	0.95
Technical Efficiency Iran	0.51	0.51	0.13	0.35	0.62
Technical Efficiency Israel	0.58	0.58	0.35	0.16	0.95
Technical Efficiency Iraq	0.52	0.53	0.40	0.14	0.93
Technical Efficiency Jordan	0.33	0.31	0.39	0.15	0.61
Technical Efficiency Kuwait	0.77	0.79	0.17	0.52	0.95
Technical Efficiency Lebanon	0.88	0.90	0.07	0.67	0.96
Technical Efficiency Libya	0.54	0.51	0.23	0.40	0.93
Technical Efficiency Morocco	0.60	0.61	0.36	0.23	0.92
Technical Efficiency Oman	0.74	0.73	0.17	0.35	0.92
Technical Efficiency Qatar	0.54	0.55	0.33	0.28	0.85
Technical Efficiency Saudi Arabia	0.83	0.86	0.11	0.59	0.95

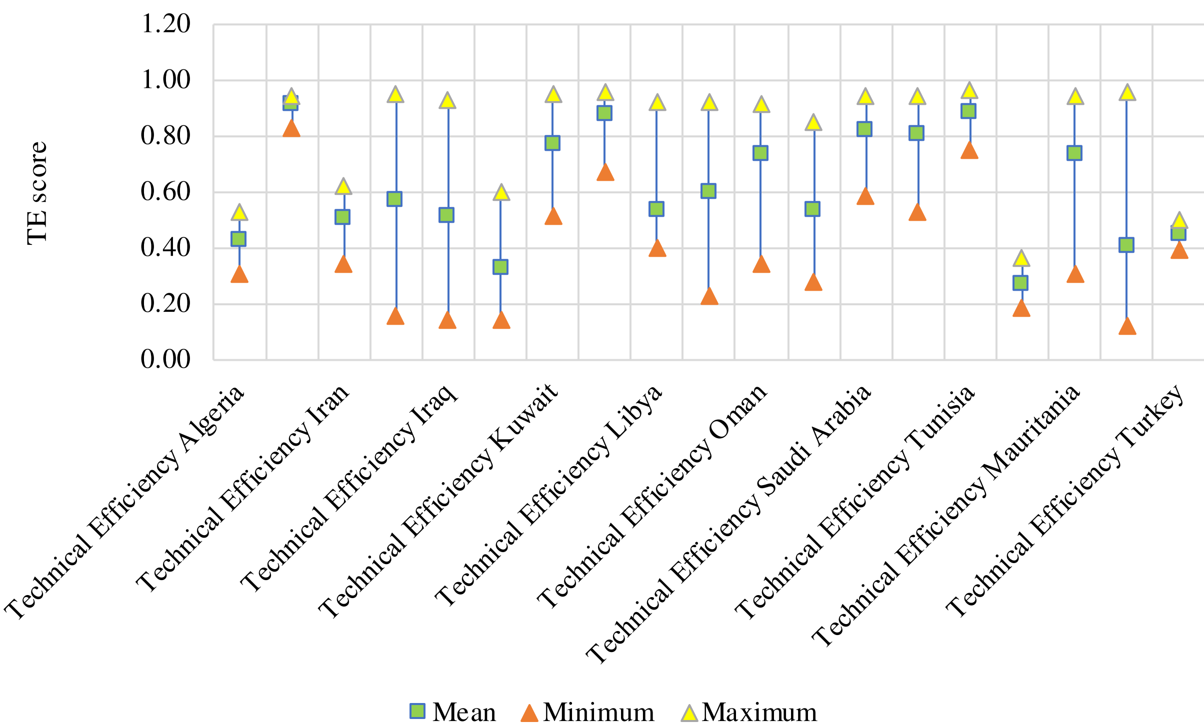
Technical Efficiency Syria	0.81	0.86	0.15	0.53	0.95
Technical Efficiency Tunisia	0.89	0.90	0.07	0.75	0.96
Technical Efficiency Yemen	0.28	0.28	0.16	0.19	0.37
Technical Efficiency Mauritania	0.74	0.82	0.23	0.31	0.94
Technical Efficiency UAE	0.41	0.34	0.54	0.12	0.96
Technical Efficiency Turkey	0.45	0.45	0.07	0.40	0.50

The median value is the median of 26 individual TE for each country across the years of analysis. Yemen has the lowest median recorded while Egypt got the highest. For Iraq, it came in the 12th rank before Qatar. When the median is larger than the mean, we surmise that some of the poor TE years were quite poor and tended to decrease the mean score. When the median is lower than the average, a year(s) of exceptionally high yields may be overwhelming "typical" year.

Coefficient of variance (aka relative standard deviation) is calculated as the ratio of the standard deviation to the mean. While not always true, those countries with the highest median TE have the lowest CV, which is not entirely surprising. The implication is important. The countries that have the lowest efficiency in producing wheat (TE) also have the widest dispersion of the yield per unit area. This fact means that domestic production and rural incomes may also vary widely from one year to the next. Egypt's CV is the lowest among the countries sampled, while UAE has the highest CV. Iraq is of particular interest in this study, and it receives a relatively higher CV equaling 0.4 making It the country with the 2nd highest CV in the study period.

With this information, more is known about the Iraqi challenge-- it's mean TE and the variation of TE is poor relative to MENA countries. This is further reinforced by Figure 2, which depicts a frequency of calculated technical efficiency (TE) scores of MENA countries across 19 years using SFA. The variation in TE within a country and across countries is apparent given the relative length between the maximum (top) and minimum (bottom) of the TE line. The mean of the TE score is also inscribed on the TE line. Of interest is the relative position on the mean TE to the maximum TE and the minimum TE. For some countries, the mean lies near the maximum (e.g. Egypt) suggesting TE is relatively high nearly every year on record, but a substantial TE shortfall might occur, perhaps due to drought. In other countries, the mean TE is close to the minimum suggesting the TE is generally low in most years with the occasional strong TE (bumper crop) in some years, perhaps due to a very good precipitation year. When a country's maximum TE and mean are similar, it may be that they have sufficient capital, infrastructure, and labor quality to sustain efficiency.

Figure 2. Distribution of TE Scores of MENA Countries From (1991- 2016) as estimated by SFA.



When examining Figure 2, it is clear that wide variation exists in the mean level (green boxes) of TE and dispersion about the mean. This dispersion is of interest to policy makers as they consider domestic wheat production and its contribution to food security. Specifically, leaders may be interested in policy that increases the mean TE and narrows the dispersion. Iraqi policy makers might seek a TE more like Egypt (second line graph from the left) than their own (fifth line graph from the left).

A test of the TE means is needed to determine if the observed cross-country differences are actual in a statistical sense. Hotelling's T-square statistic is used to compare TE means with a null hypothesis of no difference between means. The Hotelling's T-squared is a test of bivariate hypothesis (Hotelling, 1931). The null hypothesis is that the TE mean for each country is equal. The output of Hotelling's T-squared statistic is in table 8. Based on the output of table 9, a null hypothesis of equal means is rejected.

Table 9. Test of Mean TE difference across MENA Countries

H0: Vector of means is equal to a vector of zeros	
Hotelling T2	314,854
Hotelling F (19,7)	4639.96
Prob > F	0.0001

1.8.4. Examining Factors Determining Variation in TE Scores

The next stage of analysis considers if the variation in TE across all countries can be explained by the variation of important factors of production such as human and financial capital. Parameter estimates are listed in Table 10.

Table 10. Parameter estimates of factors influencing wheat production technical efficiency in MENA countries using the SFA method (n=494)

Variable type	Variable Name	2nd stage output
Credit to farmers	$lncre_{it}$	0.227***
		(0.0553)
Cereal import dependency ratio	$lncedr_{it}$	-0.310**
		(0.155)

Producer price index	$lnppi_{it}$	0.00862
		(0.110)
Percentage of farmers with access to electricity	$lnacc_{it}$	-0.587***
		(0.146)
Rural to urban population	$lnrrtu_{it}$	-0.965***
		(0.174)
Agriculture science and technology indicator	$lnasti_{it}$	0.251***
		(0.0727)
Energy consumption for ag use	$lnenrg_{it}$	-0.132**
		(0.0611)
Women work in ag	$lnemp_{it}$	0.544***
		(0.0833)
Domestic of wheat production	$lndoms_{it}$	-0.106
		(0.128)
Density of livestock	$lndlaglsu_{it}$	-0.761***
		(0.126)
If a country has a surface water	$beow_{it}$	-1.849***
		(0.245)
If a country is an exporter country	$expc_{it}$	0.0534
		(0.175)
political stability and absence of violence/ terrorism	$pols_{it}$	-1.049***
		(0.286)
elevation	$lnelevf_{it}$	0.000180*
		(9.29e-05)
Temperature change	$lntempc_{it}$	0.0198
		(0.135)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In this analysis of TE determinants, 11 out of 15 factors have effects that appear to be statistically different than 0. Factors that enhanced technical efficiency of wheat in the MENA region are credit for agricultural purposes ($lncre_{it}$), ASTI index ($lnasti_{it}$), employment of females within agriculture ($lnemp_{it}$), and elevation ($lnelevf_{it}$). Factors that affect technical efficiency negatively are cereal import dependency ratio ($lncedr_{it}$), percentage of rural population with access to electricity ($lnacc_{it}$), rate of rural to the urban population ($lnrrtu_{it}$), energy consumed for the agricultural purposes ($lnenrg_{it}$), the density of livestock in the agricultural area ($lndlaglsu_{it}$), being exposed to surface water or the availability of seasonal water flow for purpose of irrigation ($beow_{it}$) and being a stable country ($pols_{it}$).

Factor that did not affect the technical efficiency score are producer price index ($lnppi_{it}$), domestic supply of wheat ($lndoms_{it}$), being an export country ($expc_{it}$), and temperature change ($lntempc_{it}$).

Diving deeper into the parameter estimates, credit to agriculture ($lncre_{it}$), as expected, affects TE positively. Increasing agricultural credit by 1% is associated with 0.23% increase in wheat productivity TE of the MENA countries ceteris paribus. Additional credit at the same or lower cost is incentive to invest in wheat productive capacity assuming it has previously been a binding constraint on investment se. Increasing access to credit might mean a lower interest rate, less collateral, and governmental role providing insurance to the banks that they will get their money back if anything risky happened.

Producer price index ($lnppi_{it}$) did not seem to affect TE. This might be because price had been set by the government and the farmer has no channel to market his product except the government. As a result, the ppi is a poor measure of profitability, and perhaps profits are too low to encourage efficiency improvements.

Another variable related to the quality of the human capital is the percent of rural population with access to electricity ($lnacc_{it}$). It is surprising that this might have a negative impact on efficiency. One reason may be that farmers are not using electricity to irrigate their wheat; rather this is being used in other enterprises. If these enterprises receive more sources vis-à-vis wheat, then the wheat productive efficiency may be negatively impacted.

Ratio of rural to urban population ($lnrrtu_{it}$) is negatively associated with TE. A more urbanized population often implies better educated population overall. Increasing education levels tend to favor increasing wheat productive TE. In this case, a possible explanation is that if rural population is large, a greater labor supply is inexpensive then it will be substitute for capital such as tractors and harvesters where tractors and harvesters tend to increase TE, ceteris paribus. Larger rural populations may be less educated as well, that the quality of human capital applied to wheat farming might suffer. In addition, large rural populations sometimes imply households farming smaller and smaller wheat acreage per household, and this may result in diseconomies of scale.

The other variable is agricultural science and technology indicators ($lnasti_{it}$), which is simply the availability of an agricultural researcher expert for 100,000 farmers. This variable came positive indicating that if the proportion of those researchers increased by 1%, yield would increase by 0.25% ceteris paribus.

Energy for power irrigation ($lnenrg_{it}$) came negative and statistically significant indicating that more energy means less technical efficiency in wheat production another surprising result. This might be related, again, to the incremental cost of energy that will increase wheat production cost relative to its value, and wheat may be a lower value crop relative to others such as vegetable row crops. The higher cost might be in the cost per unit of energy or the cost of transporting and delivering the type of energy to the rural areas. Ultimately, the energy may not be devoted to wheat production, and hence the negative sign if increasing energy for power bids irrigation resources away from wheat.

Employment of females within agriculture in the MENA countries ($lnemp_{it}$) came statistically positive indicating the important role that females in wheat production process. More specifically, increasing females work force by 1% is associated with increases in technical efficiency by 0.54% ceteris paribus. Net increases in female participation have a net positive increase in production especially when labor is scarce.

The coefficient on the domestic supply of wheat variable ($lndoms_{it}$) for each country in each year is not statistically different from 0. The hypothesis of this variable is that increasing production past a threshold may lead to positive economic spillovers and the potential for increasing returns to scale that may exist as a result of industry-wide access to factors of production once a critical supply threshold is crossed. This appears not to be important in the context of the current data.

The parameter estimate for the density of livestock in the agricultural area is found to have a negative association with wheat TE at a statistically significant level. This is an indication that the pattern the MENA countries farmers are following is directed toward livestock and crops supporting livestock are replacing inputs that might otherwise be used for wheat.

The availability of irrigation water in MENA countries is represented by a dummy variable for a seasonal water flow for irrigation purpose ($beow_{it}$). The impact is statistically significant affecting wheat TE negatively. This means that even though there is a water flow, it is not associated with an increase in wheat TE. This might be due to using the old means in the irrigation process or it might be due to the higher salinity level in the water. Or, if wheat is grown primarily as a dryland crop, and then it may be that irrigation is of less importance in determining TE.

Controlling for a political stability or terrorism in MENA countries ($pols_{it}$) came statistically significant affecting TE negatively. So, if the regime in these countries is politically instable and/or it has politically-motivated violence, including terrorism, TE is likely to decrease. The consequence of less stability is less investment in agricultural improvements since the regime in these countries is more susceptible to chaotic change, where 1 is given when the country is stable in that year and 0 otherwise.

Dummy variable controlling for elevation ($lnelevf_{it}$) of the country had a positive and statistically significant impact on wheat TE. This is indicating that, to certain elevation level, the more elevation the country has, the higher wheat TE obtained. Most of the literature indicates that any elevation below 4000 ft is well suited for wheat. As elevation increases then so too does the TE perhaps due to their growing conditions. (FAO, 2016).

Finally, variable controlling for temperature change ($lntempc_{it}$) is not statistically different than zero. This might be due to a measurement error since this variable is measuring the average temperature through the year and calculate the difference between two adjacent year. Were it available, a measure of growing degree days might be a better approach to take the effect of temperature into account.

1.8.5. Calculating the TE results from the DEA procedure

The previous results calculate TE using a parametric approach, SFA. This section examines the same question but with non-parametric method. DEA is applied using HMI as a formulation for an objective function in a series of linear programming problems. Table *11* indicates the mean, median, CV, minimum and maximum of the TE scores.

Table 11. Summary statistics of TE scores for MENA countries obtained by DEA from data spanning 1991-2016.

	Mean	Median	CV	Minimum	Maximum
Technical Efficiency Algeria	0.88	0.89	0.03	0.84	0.94
Technical Efficiency Egypt	1.00	1.00	0.00	1.00	1.00
Technical Efficiency Iran	0.91	0.91	0.03	0.86	1.00
Technical Efficiency Israel	0.95	0.96	0.04	0.82	1.00
Technical Efficiency Iraq	0.97	1.00	0.05	0.86	1.00
Technical Efficiency Jordan	0.99	1.00	0.02	0.89	1.00
Technical Efficiency Kuwait	1.00	1.00	0.00	1.00	1.00
Technical Efficiency Lebanon	1.00	1.00	0.00	1.00	1.00
Technical Efficiency Libya	0.94	0.92	0.06	0.86	1.00
Technical Efficiency Morocco	0.97	0.98	0.04	0.88	1.00
Technical Efficiency Oman	1.00	1.00	0.00	1.00	1.00
Technical Efficiency Qatar	1.00	1.00	0.00	1.00	1.00
Technical Efficiency Saudi Arabia	1.00	1.00	0.00	1.00	1.00
Technical Efficiency Syria	0.98	1.00	0.02	0.92	1.00
Technical Efficiency Tunisia	0.99	1.00	0.02	0.93	1.00
Technical Efficiency Yemen	1.00	1.00	0.00	1.00	1.00
Technical Efficiency Mauritania	1.00	1.00	0.00	0.98	1.00
Technical Efficiency UAE	1.00	1.00	0.00	1.00	1.00
Technical Efficiency Turkey	0.95	0.94	0.03	0.92	1.00

In Table *11*, the mean, median, CV, maximum and minimum are reported from the 26 TE scores that have been calculated. This mean ranges from 0.88 (Algeria) to 1 (Egypt, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Yemen, Mauritania, and UAE). Mean TE score for Iraq is 0.97.

As is obvious immediately, the TE scores calculated using DEA are greater and less dispersed than those reported in the SFA results, which is consistent with prior literature (Bravo-Ureta et al., 2001). Since the TE scores are high and the difference between years is small, the CV is very small and sometimes it is zero. In addition, the mean TE scores in each country are statistically different than one another as indicated by Hotelling-t square test as indicated by Table *12* .

Table 12. Hotelling T Square Test for Differences in Mean TE across the MENA countries

H0: Vector of means is equal to a vector of zeros	
Hotelling T2	446,423
Hotelling F (18,8)	446,000
Prob > F	0.001

In the second stage, the TE scores for each country are regressed against factors hypothesized to explain the variation in efficiency using a tobit approach and a maximum likelihood procedure. Results are reported in Table *13*.

Table 13. Output of the 2nd stage analysis by using DEA and Tobit analysis (n=494)

Variable type	VARIABLES	
Credit to farmers	$lncre_{it}$	0.00145
		(0.000957)
Cereal import dependency ratio	$lncedr_{it}$	-0.00397*
		(0.00227)
Producer price index	$lnppi_{it}$	-0.00601**
		(0.00236)
Percentage of farmers with access to electricity	$lnacc_{it}$	0.000440
		(0.00274)
Rural to urban population	$lnrrtu_{it}$	0.0143***
		(0.00243)
Agriculture science and technology	$lnasti_{it}$	0.00752***

indicator		
		(0.00146)
Energy consumption for ag use	$lnenrg_{it}$	-0.000350
		(0.00103)
Women work in ag	$lnemp_{it}$	-0.00659***
		(0.00141)
Domestic of wheat production	$lndoms_{it}$	-0.0172***
		(0.00215)
Density of livestock	$lndlaglsu_{it}$	-0.00256
		(0.00186)
If a country has a surface water	$beow_{it}$	0.0173***
		(0.00399)
If a country is an exporter country	$expc_{it}$	0.00379
		(0.00351)
political stability and absence of violence/ terrorism	$pols_{it}$	-0.00962*
		(0.00498)
elevation	$lnelevf_{it}$	-7.99e-06***
		(1.67e-06)
Temperature change	$lntempc_{it}$	0.000473
		(0.00253)
	Constant	1.137***
		(0.0224)
	Observations	494

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
$LR\ chi^2(15) = 274.01, \text{Prob} > chi^2 = 0.001, \text{Log Likelihood} = -999.267$

Second stage estimation of coefficients for DEA measure of wheat TE indicates different quantitative and direction results compared to the second stage analysis results obtained by SFA. In the second stage obtained by DEA, producer price index ($lnppi_{it}$) is statistically significant affects wheat TE negatively meaning that the higher prices farmer receives for agricultural product, the lower wheat TE score obtained.

Ratio of farmers to urban population ($lnrrtu_{it}$) is statistically significant and positively related to TE, where the higher the ratio, the higher the TE score. The same is true for indicator of agricultural science and technology indicator ($lnasti_{it}$) where the more specialists available the more efficient the country is in the production of wheat because farm managers have better access to information that improves decision making. The coefficient on employment of women in agricultural sector is statistically significant and very small. Domestic production of wheat had a negative, statistically significant impact on wheat TE. Since those countries are big consumers of wheat, increasing domestic production may increase TE rather than decreasing it. The dummy variable for seasonal water flow for purpose of irrigation indicating that countries with surface water are getting higher TE scores. Finally, for the elevation, the more elevated the country, the less TE would be which is contrary to the literature that reported in SFA results. Next step would be comparing the output of the TE obtained and comparing the output result of the second stage obtained in both DEA and SFA.

One thing worth mentioning is that the LHS variable (i.e. TE score) obtained by DEA is very close to 1 in terms of value. This might be due to the missing stochastic component that SFA has. Table *14* is comparing second stage results obtained by SFA and DEA.

Table 14. Comparing results of stage 2 analysis obtained by SFA and DEA

Variable	SFA estimates	DEA estimates
$lncre_{it}$(credit to farmers)	0.227***	0.00145
$lncedr_{it}$ (cereal import dependency)	-0.310**	-0.00397*
$lnppi_{it}$(producer price index)	0.00862	-0.00601**
$lnacc_{it}$(access to electricity)	-0.587***	0.000440
$lnrrtu_{it}$(farmers to urban)	-0.965***	0.0143***
$lnasti_{it}$(specialist to farmer)	0.251***	0.00752***
$lnenrg_{it}$(energy in ag)	-0.132**	-0.000350
$lnemp_{it}$(employment of women in ag)	0.544***	-0.00659***
$lndoms_{it}$(domestic production)	-0.106	-0.0172***
$lndlaglsu_{it}$(Livestock density)	-0.761***	-0.00256
$beow_{it}$ (if the country has a water flow for irrigation purposes)	-1.849***	0.0173***

$expc_{it}$ (if the country exports wheat)	0.0534	0.00379
$pols_{it}$ (political instability)	-1.049***	-0.00962*
$lnelevf_{it}$ (avg. elevation)	0.000180*	-7.99e-06***
$lntempc_{it}$ (Avg. temp change)	0.0198	0.000473

It is interesting that such large differences and impacts exists when comparing the SFA estimates and the DEA estimates. The models agree on the impact of:

- Access to credit (positive).
- Extension specialist (positive).
- Energy in agriculture (negative).
- Total domestic wheat production (negative).
- Livestock density (negative).
- Political instability (negative).

It is also true that the parameter estimates (aka coefficients) for SFA are larger than the DEA estimates. The difference may be in the stochastic element that is captured by SFA and not by DEA as is described by Coelli (1995).

One question worth asking, can the difference in the two columns be explained by the stochastic element? As an example, electricity may have positive value in DEA because all things being equal, electricity will enlarge the production based on DEA, which does not account for the random shocks such as drought. However, overtime, SFA estimate of electrical power in explaining TE may be negative because if a drought occurs, the electricity access is a cost that the firm might otherwise not have encountered if electricity is not used in irrigation. So SFA estimates over time take into account this fixed cost of electricity and DEA did not.

The impact of women's labor force participation in agriculture has a large, positive impact on wheat TE when the SFA estimates are considered, but a very small, negative impact when DEA estimates are considered. Perhaps this is because when stochastic events are considered, women participation in agriculture plays a large role in mitigating the negative effects of a stochastic event or perhaps allows for greater wheat TE when the stochastic event is positive. DEA does not explicitly model the stochastic nature of producing wheat, and the risk mitigating and/or opportunistic attribute of women in the labor force participation are not considered modeled.

Comparing results of the two approaches across countries reveals an interesting outcome. Nine countries out of nineteen showed a very close mean wheat TE scores forming 48% of the studied sample of the MENA countries. Those countries with similar mean wheat TE scores are Egypt, Kuwait, Lebanon, Oman, Saudi Arabia, Syria, Tunisia, Mauritania, and Turkey. Figure 4 is depicting these TE scores graphically. These countries are geographic neighbors, so it may be that wheat production in these countries is simply less impacted by stochastic events compared to other countries due to an endowment of natural capital.

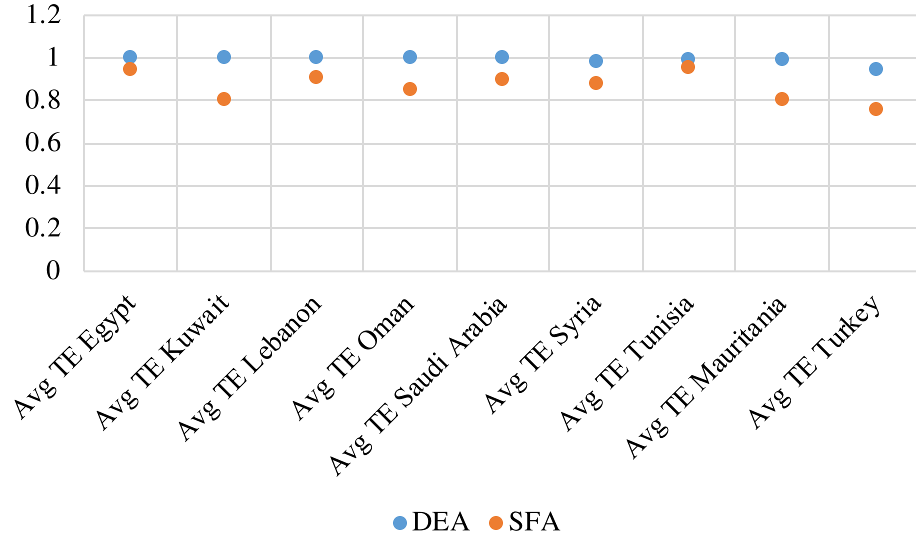


Figure 3. Countries with similar mean wheat TE scores when DEA and SFA are used to estimate TE.

Figure 4 is a side by side comparison of the outcome of minimum, maximum, and mean wheat TE obtained by DEA and SFA from each country. Differences exist among the countries. Egypt, for example, average TE obtained by DEA and SFA did not differ a lot. For Iraq, the range from the minimum to maximum is quite large for SFA when compared to DEA.

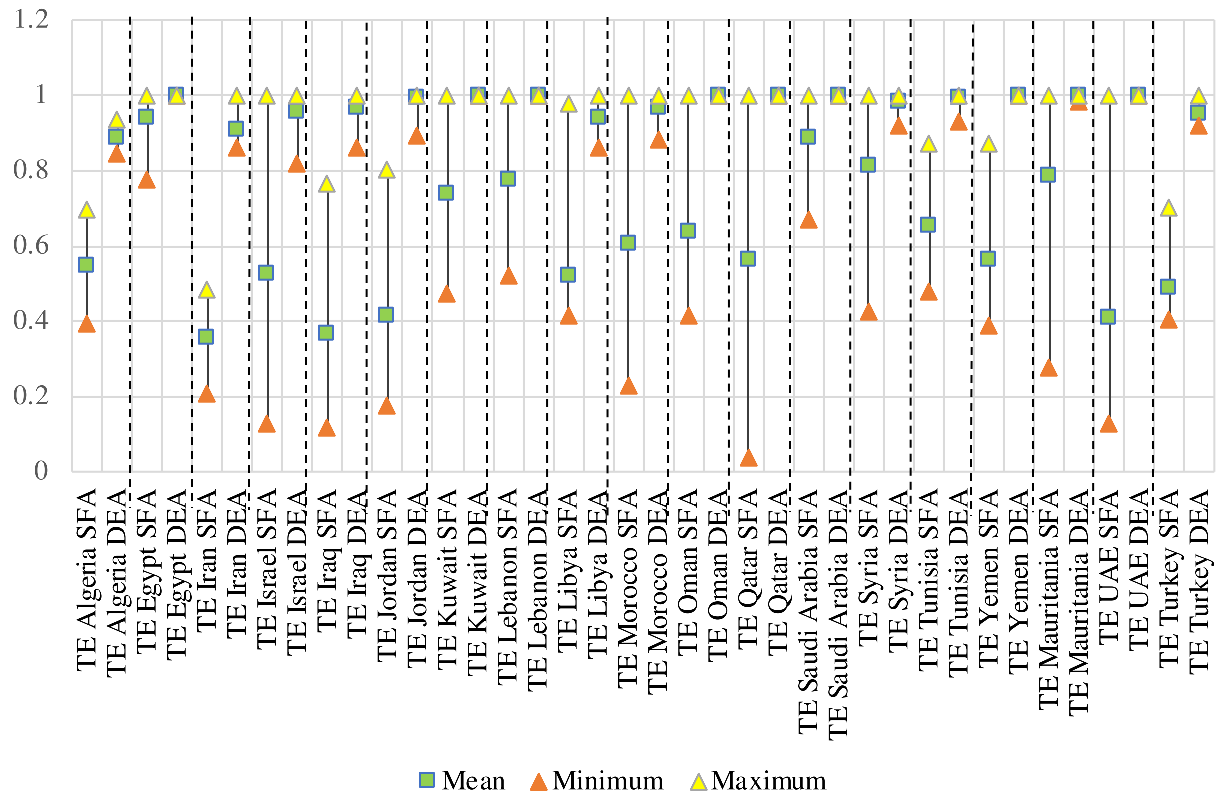


Figure 4. Distribution of TE Scores of MENA Countries From 1991-2016 estimated by DEA and SFA

DEA implicitly assumes that stochastic events do not occur, so the countries with the highest yields per unit of land are managing inputs optimally. The SFA approach allows for the fact that bounded rationality exists and even the best managed wheat production is suboptimal because stochastic events cannot be anticipated and managed.

Countries that showed different TE scores for DEA and SFA are forming 52% of the studied sample. Those countries are Algeria, Iran, Israel, Iraq, Jordan, Libya, Morocco, Qatar, Yemen, and UAE. Figure 5 indicates how these scores are differ across those countries.

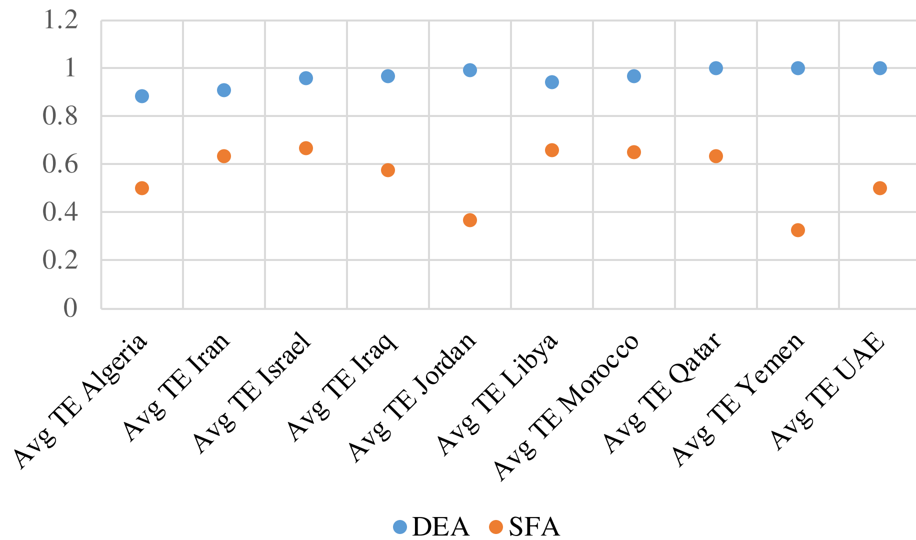


Figure 5. Countries with different TE scores when DEA and SFA adopted.

Again, as can be inferred from the above figure, DEA mean wheat TE scores are larger when compared to the TE scores obtained by SFA.

In order to know reasons behind these differences, a closer look at the data of the highest TE countries and the lowest TE countries is shown. The highest nine countries, which has a similar TE scores on the DEA and SFA, has a highest average yield (31,182.18 (hg/ha)), biggest average population (22,560.22 (1000 person)), larger number of average number of tractors (130,298.3 or 29 tractor per ha), highest average net national income ($107 billion), highest average percentage of women employed within agriculture (23.6%), biggest average amount of Urea fertilizer applied (376,784.8 ton or 0.84

(ton/ha)), biggest average amount of pesticides applied (5,722.824 liter or 0.2 (lit/ha)), and highest average percentage of women enrolled in the primary education (82.47%). However, those nine counties have the lowest average of harvested land (451574.2 ha), lowest average number of harvesters (2968 or 2 harvesters per ha), lowest average population with access to electricity (84.45%), lowest average amount of NPK fertilizer (69,015.04 ton or 1.5 (ton/ha)), lowest average credit for the agricultural purposes ($37,959.04), and lowest average temperature change (0.89 °C).

Since those nine countries have a relatively high yield and low harvested area, low credit to farmers and high net national income, this means that these countries are the wealthiest and higher level of technology is invested in their production.

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1.9. Conclusions

The purpose of this research is to examine wheat productive efficiency by comparing the wheat output per land unit in MENA countries from 1991-2016. A first objective was to create a conceptual model of technical efficiency and assemble a panel data of 19 countries across 26 years set using two empirical procedures; DEA and SFA.

The panel data is created utilizing FAO data for wheat production in the MENA countries including factors of production and socioeconomic data. After constructing the panel data, Data Envelopment Analysis (DEA) is applied here to the panel data mentioned above. DEA entails two stages: in the first stage technical efficiency (TE) score is computed using an optimization problem for each country, and in the second stage, TE is regressed on factors believed to explain differences of mean wheat TEs across MENA countries. In the DEA analysis, no functional form is imposed on the data, so the implicit assumption is that input choices and the resulting outputs are made in the absence of stochastic events. Also, Stochastic Frontier Analysis (SFA) is adopted here. SFA is a parametric approach that posits both stochastic and optimization errors on the part of wheat managers. The TE is derived from the optimization error and then regressed on explanatory variables. Results from DEA and SFA is interpreted and compared to better understand reasons behind differences in TE across MENA countries.

1.9.1. Political Stability and Wheat Productive Efficiency

Without any question, political stability and lack of terrorism had the greatest marginal impacts on wheat productive efficiency and the variation in mean wheat TE when stochastic events are modeled as part of the analysis. (-1.049 in the SFA estimates and 0.0962 in DEA). This type of instability significantly impacts food security. Some countries with the lowest TE in wheat production are Jordan, Yemen, Algeria, and Iraq, and with the exception of Jordan, these countries have all suffered from political instability during the study period.

1.9.2. Human Capital and Wheat Productive Efficiency

Human capital plays an important role in explaining the variation in yield per land area and in TE.

- Population ($lnpop_{it}$): was the largest, positive variable on yield per dunam in stage 1 analysis
- Rural to urban population ($rrtu_{it}$): was very important in explaining TE in both SFA and DEA.
- Women in agriculture ($lnemp_{it}$): had an important impact on mean TE variation in the SFA analysis
- Enrolment of women in primary school ($lnnep_{it}$): did not seem to impact yield, which is surprising and may be due to measurement error

The quality of the human capital can be improved through the use of technical expertise, and this research indicates that this can be effective ($the\ asti_{it}$variable has a positive significant impact on TE). All of these can be improved by country policies.

1.9.3. Financial Capital

Financial capital is positively associated with increasing wheat productive efficiency. This is inferred directly via access to credit (cre_{it}) which came positive and significant in SFA when explaining the yield per dunam variation., or indirectly as financial capital due to net national income (net_{it}) had a positive, statistically significant impact on yield per dunam in the stage one analysis of SFA. This capital needs to be deployed wisely, as it appears that additional tractors, harvesters, NPK and seeds all tend to reduce productivity ceteris paribus in this analysis.

1.9.4. Availability of Irrigation Water Resources

In terms of irrigation, results showed that availability of seasonal water flow for irrigation is negatively affects the wheat TE in the second stage of the SFA and a smaller, positive impact on the second stage DEA. This might be due either to the high level of salinity or due to the adaptation of dryland cultivation due to the lack of water flow in most of the MENA countries. More in-depth analysis is needed of the water resources, but it may be the case that promoting best practices in dryland cultivation techniques through bundling, strip cropping, summer fallow and mulches can increase the level of mean TE.

1.9.5. Comparing DEA and SFA for Policy Analysis

Looking at the TE scores obtained by DEA, one might ask why those scores are close to 1 with low variation comparing to SFA with high variation. Average mean wheat TE with DEA is 0.98 where the average of mean wheat TE using SFA is 0.62. This average is calculated for all the 19 countries through the 26 years. The difference appears to be in the explicit modeling of stochastic events in a data set that spans a large geographic area (MENA) and many years (1996-2016). Implicitly, the DEA approach does not recognize opportunities to expand the output based on the given level of inputs, perhaps because it mathematically cannot expand the frontier to account for successfully managing a stochastic event. In contrast, SFA creates a frontier that includes successful management of the stochastic event as demonstrated by countries that lie at or near the frontier of wheat production. Both approaches may be suitable for answering policy questions, and more in-depth investigation is needed to better understand the errors that occur form relying on one method. In general, a conservative approach might be to focus ion SFA estimates, as these allow for policies to be derived to account for the inherent risk of stochastic events disrupting wheat production, and ultimately food security.

1.10. Limitations of the Current Study

This study has some limitations. First, the data used in this study is at a macroeconomic level and relies importantly on consistent measurement of data across countries. Not all of this data may accurately represent the farm population. particularly the enrolment of women in primary school or the participation of women in agriculture. Likewise, the quality of inputs is difficult to measure with available data. For example, the access to irrigation water does not capture the quality of available water resources.

Given the potential for measurement error, perhaps the interpretation of the DEA and SFA estimates are best focused on the direction of the effect rather than coefficient values. As more data are available, estimated parameters can be validated and refined. The data used in this study is specific to MENA countries, and while I am confident in the modeling framework, it would be interesting to see how the results would be different with a different study area. An example would be expanding the analysis to

South African countries or Europe, and this research would benefit from the experience gained from analyzing efficiency there. It would be interesting to compare results based on different areas. Another example would be seeking a modeling framework combining DEA and SFA in the same model. In SFA, Cobb-Douglas production function were utilized. It would be interesting to use translog or quadratic and compare the results

CHAPTER 2: STUDYING WHEAT PPRODUCTIVE EEFFICIENCY IN SOME IRAQI DISTRICTS USING A CROSS-SECTION OF DATA

2.1. Introduction

Policy makers in Iraq are concerned about food security, and in particular, the role of wheat production in food security. The primary objective of this dissertation to better understand the wheat productive efficiency in Iraq using two related studies. The first study considers Iraq's wheat productivity relative to other MENA countries with a conceptual framework grounded in economic efficiency and empirical measures estimated with panel data. In doing so, likely macroeconomic and country specific reasons for wheat productivity differences are uncovered.

In this essay, attention is directed exclusively to the domestic wheat production of Iraq by comparing districts according to their wheat productivity. This study shares the conceptual framework of efficiency analysis with the previous study and applies two empirical methodologies grounded in a parametric and non-parametric method, but the analysis is tightly focused on Iraqi production districts and cross-sectional data. The intention is to provide additional site-specific insights in the absence of variability across national policies, culture and climate.

The study focuses on domestically available forms of capital (e.g. human, equipment, and infrastructure) and the use of production inputs (fertilizers, chemicals, district characteristics). More specifically, 105 districts with 8 wheat producing provinces are considered. The wheat production data is aggregated at the district level, and a measure of technical efficiency is defined and calculated. The model adopted here is an output-based model, and as such, the model seeks to increase efficiency by expanding output from an input level that is bounded.

Districts are likely to differ in technical efficiency of wheat production because of local conditions, culture, and infrastructure. An example of an inefficient use of inputs is applying more fertilizer than is profitable or may even be needed to achieve the maximum potential yield especially in dry seasons. Within a district, conventional practice may encourage over-application of fertilizer, while in a different district fertilizer is applied more conservatively due to differences in education, technical advice and/or experience. Thus, in two neighboring districts, one may be more efficient than the other in spite of sharing almost the same socioeconomic characteristics and the same levels of endowed inputs.

In general, differences in efficiency across districts may be related to education level, policy, farmer experience or training, and (or) access to inputs. Efficiency will be measured using two techniques: data envelopment analysis (DEA) and stochastic frontier analysis (SFA). Both approaches create a benchmark of efficient outcomes, and then an individual district's observations can be compared to these benchmarks. A second stage regression analysis will take the technical efficiency measures mentioned previously, and then explore how the variation in inefficient outcomes might be explained by the variation in factors of production and socioeconomic variables.

After performing these efficiency measurements, potential sources of inefficiency, if found, in wheat production will be investigated. Further investigation may suggest policies that these districts might potentially follow in order to become more technically efficient in wheat production.

In summary, the objectives of this study are:

1. Benchmarking technically efficient wheat producing districts in Iraq using two empirical methods (DEA and SFA);
2. Describing how technical efficiency differs across districts;
3. Investigating the source/causes of inefficiency, if present;
4. Examining where investments or policy initiatives might enhance wheat productive efficiency.

2.2. Literature Review

The previous essay in this dissertation examines the efficiency literature as it relates to agricultural production with a particular emphasis on country level studies over time. Scientists have also considered farming efficiency at a single point in time over smaller geographies such as farms and districts. Table 15 is a succinct listing of many prominent studies of this type, and the table includes the study objectives, methods and variables. Some variables, or similar types of variables, are used in the current study and these are identified with an asterisk.

Table 15. Examples from the economic literature that examine agricultural productive efficiency at a farm level.

Authors	Variables
Vu (2007) in Vietnam (Data from 595 farm households estimating technical efficiency employing DEA and SFA to explain differences in farm level efficiency).	-crop value (thousands at the current value) -seed expenditure (thousands at the current value) -fertilizer expenditure*(thousands at the current value) -pesticide expenditure*(thousands at the current value) -family hours for farming exp.*(thousands at the current value) -percent of crop from the overall cultivated area (%) -estimated family hours for crop production (hours) -cultivated land*(square meter) -fixed asset and equipment exp.*(thousands at the current value) -hired labor expenditure (thousands at the current value) -asset hire and maintenance (thousands at the current value)
Al-Niamy and Al-Rawi (2012a) in Iraq (53 farm in Mosul province- Telkif district in 2008-2009 season using DEA model to estimate technical efficiency)	-Urea fertilizer quantity applied (kg)* -DAP fertilizer quantity applied (kg)* -amount of herbicide (liter)* -mechanical capital used in irrigation purposes (horse power) -amount of water applied (cubic meter) -quantity of seed used (kg) -cultivated area (dunam)*
Al-Niamy and Al-Rawi (2012b) in Iraq (53 farm in Mosul province- Telkif district in 2008-2009 season employing SFA model estimating technical efficiency scores)*	-mechanical technology used (horse power) -hired labor (man/day) * -amount of water applied (cubic meter) -quantity of seed used (kg) -cultivated area (dunam)*
Ali (2015) in Iraq (23 farmer in Dyala province- Jalawla district using DEA to estimate economic, technical, allocative, and scale efficiencies) *	-cultivated area (dunam)* -family labor (hour)* -capital labor rented (hour) -fertilizer applied (kg)* -seed applied (kg)
Shafiq and Rehman (2000) in Pakistan (120 farms in southern part of Pakistan's Punjab by using DEA to estimate technical and allocative efficiencies)	-irrigated hectares (number of hectares) -Nitrogen fertilizer used (kg)* -Phosphate fertilizer used (kg)* -labor used (h/ha) *

	-pesticide costs (currency per hectare) * -tractor hours (h/ha)
Wadud (2003) in Bangladesh (two villages in Bangladesh in August-September 1997 season in order to estimate economic, technical, allocative efficiencies by using DEA and SFA approaches)	-cultivated area (hectare)* -price per acre of land ($) -family and hired labor (number of workers) * -wage per man day ($) -irrigation cost (price per acre) -fertilizers quantities (kg)* -average price of all fertilizers ($) * -pesticides quantities (milliliter/acre) * -price of pesticides ($) * After getting efficiency score, it regresses against -age of farmers (years) -land fragmentation -years of schooling (years)* -irrigation infrastructure dummy -land degradation dummy
Coelli, Rahman, and Thirtle (2002) in Bangladesh (406 rice farms in 21 village employing DEA in order to estimate cost, technical, allocative, scale efficiencies) TOBIT	-land cultivated (ha)* -animal power (pair-days) -fertilizer (kg)* -seed (kg) -labor (day)* -land rent (taka/kg) -fertilizer price (taka/kg) * -seed price (taka/kg) -labor wage (taka/day) -animal power cost (taka/kg) Inefficiency scores obtained is regresses against the following variables -education of household head (years)* -experience (years) -age (years) -family size (person) -working member (person) -infrastructure index (number) -soil fertility index (number)* -non-agricultural income share (%) -tenancy (%) -extension visit (%)* -training receipt (%) -number of rice plots (n)
Bravo-Ureta and Pinheiro (1997) in Dominican Republic (60 farms located in Dajabon estimating economic, technical, allocative efficiencies by using SFA approach)	-land* -labor (worker/days) * -fertilizer (100 lb) * -expenditure on tools -value of seed and draft power used in the production process After obtaining inefficiency scores, they were regressed against the following variables -dummy variable is the farmer producing under contract with an agribusiness firm

	-dummy variable if the farmer is agrarian reform beneficiary -dummy variable if the farm is medium size (51-100 tareas or 7.7-15.5 acre) -dummy variable if the producer has four or more years of schooling -dummy variable if the farmer is young (less than twenty five years) -number of people in the household including the household head
Mburu, Ackello-Ogutu, and Mulwa (2014) in Kenya (130 wheat farmer in Nakuru district to estimate economic, technical, allocative efficiencies and SFA is used)	-quantity of fertilizer used (kg/acre) * -quantity of seeds (kg/acre) -quantity of chemicals (kg/acre) * -quantity of foliar (liter/acre) -cost of hired labor (per acre) -cost of family labor (per acre) Factors that believed influencing efficiency are -dummy variable equal 1 for large scale farms and zero for small scale farm size -dummy variable equal one if the gender is male and zero otherwise -dummy variable equal 1 if the farmer is married and zero otherwise -dummy variable showing the educational level for the household* -dummy variable knowing if the farmer is self-employed or salaried. -dummy variable knowing if the farmer is belonging to farmer group or not -dummy variable showing land tenure -dummy variable showing if the seeds are from the farmer's previous year or purchased -distance to the nearest certified seed seller (km)* -distance to the nearest extension services (km)* -age of the household head
Alemdar and Oren (2006) in Turkey (farms in 2000-2001 growing season in Adiyaman province to study the determinants of technical efficiency of wheat farming by employing DEA approach) TOBIT	-seeds (kg/ha) -nitrogen fertilizer (kg/ha) * -phosphor fertilizer (kg/ha) * -labor (h/ha) -machinery (h/ha) * -pesticide cost (1000 TL/ha) * To know causes of inefficiency, the following variables has been used -age of farmer (years) -education of the farmer* -share of family labor (%) -number of plots -land size (ha)*

2.2.1. Themes from the Previous Literature Incorporated in the Current Study

The current study borrows from the previous literature by adopting similar variables that represent forms of human capital. As an example, the educational level of a farmer has been explained by many such as Coelli et al. (2002), Bravo-Ureta and Pinheiro (1997), Mburu et al. (2014), and Alemdar and Oren (2006). These studies have found a significant role of education in explaining differences in TE. In these studies, education is investigated as a dummy variable (i.e. educated or not), or a categorical variable assigning value for each level of education, or education in years. The current adopts the idea of farmers' education but with the actual number of farmers with no education, primary education, secondary education, high school education and college education as separate categories of data sources.

In terms of labor devoted to agriculture, literatures such as Vu (2007), Al-Niamy and Al-Rawi (2012a), Al-Niamy and Al-Rawi (2012b), Ali (2015), Shafiq and Rehman (2000), Wadud (2003), Coelli et al. (2002), Bravo-Ureta and Pinheiro (1997), Mburu et al. (2014), Alemdar and Oren (2006) investigate labor's effect on productivity and/or TE. Several approaches are used depending on data availability including worker per day, cost of labor per acre, family hours of labor, hours per hectare and number of workers as total. This study uses a ratio of farmers' population to urban population as indication of the pool of available labor.

Variables related to operational inputs such as fertilizer and herbicides are included in this study. Previous work such as Vu (2007), Al-Niamy and Al-Rawi (2012a) or Wadud (2003) incorporate similar variables, and they are measured either in terms of the cost of these inputs or collected at an aggregate level, which means mentioning the fertilizer without indicating which fertilizer. This study uses fertilizers, herbicides, and fungicides that are typically applied in the wheat producing districts in the middle and south of Iraq. For mechanical input, the literature considers mechanical capital in terms of available horsepower (Al-Niamy and Al-Rawi (2012a), hours per hectare (Shafiq and Rehman (2000). In the current study mechanical capital is proxied with an actual count data of sprayers, tractors, and harvesters.

Distance to extension center and the distance to water are important variables included in this study. Mburu et al. (2014) is the only study, as far as we know, that adopted this idea for farm level agricultural production in the MENA region, where they measured the distance to the nearest certified seed seller and the distance to the nearest extension center.

Per capita income is not typically used in efficiency studies. Coelli et al. (2002) adopted the idea of non-agricultural income share, as a percentage. This study adopted per capita income as a factor that might explain the differences in TE because of the availability financial capital for direct investment in a district.

2.2.2. Contributions to The Literature

As noted in Table 15, a series of studies consider the technical efficiency of farms. The current study adds to the literature in its study scope and use of data. As an example, data utilized here is a cross section of Iraqi districts and no study, as far as the current authors are aware, make use of district level data that extends over such a wide expanse spatially. New variables employed in this study relative to those in Table 1 include the distance to the water supply distance to the extension center. These data series are obtained using the QGIS software and primary measurement. This study introduces technical variables that may affect productive and technical efficiency scores such as temperature, rainfall amounts, and humidity level, and these are not present in the studies found in Table 15. Regarding the analysis tools, this study is the first one combining a DEA and SFA approach using Iraqi cross-sectional data. DEA relies on linear programming methods while an econometric/parametric approach is the crux of SFA. This study employs a second stage, tobit regression analysis estimation is examining local factors play in explaining variation in TE. This step is used elsewhere, but not in the studies of Table 15 that focus primarily on farm level production in ecoregions similar to Iraq.

This study will be useful to Iraqi policymakers who are grappling with strategies to improve wheat productive efficiency, food security and rural incomes. While not a complete accounting of the net economic costs and benefits of potential policy instruments, this study does lend insight into the efficacy of opportunities such as expanding education opportunities, access to credit and infrastructure investment.

2.3. Variable Definition and Data Description

Variables in this study represent various forms of capital that contribute to wheat productive efficiency in Iraq. Definition of the variables are shown in Table 16. This data is from unpublished data resources in the Iraqi Ministry of Agriculture (MOA) and from a published data from the Iraqi Central Statistical Organization (CSO) in Iraq.

Table 16. Definition of explanatory variables used in the DEA and SFA analysis. All variables are collected for the year 2016

Variable name	Definition
First stage analysis variables	
y_i	is the dependent variable. It is the wheat yield per unit of land ($i = 1\ to\ 105$ district observations)
$area_{\ i}$	is wheat cultivated area (dunam) in district i,
DAP_i	is DAP fertilizer (ton) in district i,
$urea_{\ i(ton)}$	is urea fertilizer (ton) in district i,
$Pallas_{\ i(liter)}$	is a herbicide used (liter) in district i,
$Raxil_{i(kg)}$	is a fungicide used (kg) in district i,
$spr_{\ i}$	is the number of sprayers in district i,
$tra_{\ i}$	is the number of tractors in district i,
$har_{\ i}$	is the number of harvesters in district i,
FP_i	is the ratio of the number farmers to the number of urban populations in district i,
$temp_i$	is the average temperature in district i,
Second stage analysis variables	
te_i	is the dependent variable obtained by the 1st stage analysis by a linear transformation of the optimization error term.

$distowat_{i(km)}$	is the distance to water supply (km) in district i,
$distext_{i(km)}$	is the distance to extension center (km) in district i,
pci_i	is the per capita income in district i,
bac_i	is the number of people with bachelor degree in district i,
$high_i$	is the number of people with high school degree in district i,
sec_i	is the number of people with secondary school degree in district i,
pri_i	is the number of people with primary school degree in district i,
non_i	is the number of people with no degree in district i,
$rain_i$	is the average cumulative rainfall in district i ,
$humd_i$	is the average of humidity in district i,

It's useful to understand the relative dispersion of the data and its levels. Table 17 and Table 18 shown the descriptive statistics of these data series with Table 17 focusing on variables used in the first stage of analysis and Table 18 focusing on the second stage analysis.

Table 17. Summary statistics for the first stage variables from the year 2016, n=105.

	Mean	Standard Deviation	Minimum	Maximum
area (dunam)	34,724	42,736	200	266,972
DAP (ton)	178	141	0.34	574
urea (ton)	1,251	1,267	6	7,800
Raxil (kg) (3gm/kg seed)	455	650	2	4,022
Pallas (lit) (0.26 lit/acre)	332	330	2	2,322
sprayers (number)	1,092	5,963	5	60,524
tractors (number)	3,019	19,850	20	202,547
harvesters (number)	4,907	23,475	50	237,277
Farmers to urban (percentage)	0.40	0.37	0	0.99
Average temperature (centigrade)	37	5	22	48

Table 18. Summary statistics for the second stage variables from the year 2016, n=105.

	Mean	Standard Deviation	Minimum	Maximum

distance to water supply (km)	16.32	15.42	2.2	68
distance to extension center (km)	61.55	62.31	2	272
per capita income (Iraq Dinar)	1310.81	1109.09	222	6243
Bachelor (number of farmers)	181.40	448.56	2	2354
high school (number of farmers)	345.87	257.07	22	2283
secondary school (number of farmers)	27.62	47.41	2	272
primary school (number of farmers)	124.72	168.78	2	962
non-educated (number of farmers)	779.47	3283.99	2	32527
rainfall amounts (millimeter)	40.16	20.44	0.2	87
relative humidity (percentage)	70.30	16.52	36	98

The data is obtained from 8 provinces located in the middle and south of Iraq, and the data series are reported at the district level. The overall number of districts included in the data is 105. The cross-sectional data provides information on operational, mechanical, and socioeconomic characteristics.

Overall, the average of planted area in wheat producing districts is (34,724) dunam (almost 8,580 acre) ranging from 200 dunam (about 49.5 acre) minimum and 266,972 dunam maximum (approximately 65970 acre). In this regard, the data series provides for varying scales of production.

Diammonium phosphate (DAP) is a widely used phosphorus fertilizer. This fertilizer provides a high nutrient content making it a favorite among other fertilizer providing phosphorus (Mosaic, 2019). Total DAP application is variable ranging from 0.34 ton (680 lbs.) to 573.8 ton (about 1,147,600 lbs. and 50 kg/dunam which equals 110.2 lb/dunam). Urea, another fertilizer, containing 46 percent nitrogen and has a significant effect in yield increment also varies in the data. Its application ranged from 6 ton (1200 lbs.) to (1.56lbs.), which equals 36.2 kg/dunam (79.8 lb/dunam). This amount per dunam is divided into two portions, the first one is added at the germination stage and the second one added at the stage of forming the seeds.

Raxil is a seed treatment fungicide used in the districts. Based on Bayer (2019), this fungicide has a strong role in the treatment of seedling disease and pest protection in cereals. This was offered by the Iraqi Ministry of Agriculture ranging from 2 kg (almost 4.4 lbs.) to 4,022 kg (approximately 8,867 lbs.).

The application per dunam is 20 grams. Herbicides are very important in wheat production. Most Iraqi farmers apply Pallas, a selective herbicide used to control a post emergence of certain weeds in wheat (DowAgroSciences, 2016). This herbicide also ranged from 2 liters (equals 0.52 gallon) to 2322 liters (approximately 613 gallon) with 125 ml per dunam.

In terms of mechanical capital, there is also a higher level of availability. The forms of mechanical capital in this study ranges from sprayers, tractors, to harvesters. For sprayers, the district level number of units ranges from 5 units to 60,524 units. Total number of tractors ranges from 20 units to 202,547 units. Also, total number of harvesters ranged from 50 units to 237,277 units. Numbers of harvesters, tractors, and sprayers per dunam are 3, 9, 14 respectively.

The ratio of farmer population to urban population indicates that on average 40% of the population of the samples are farmers. This is means that we are dealing with an agricultural society utilizing farming as their main source of income.

In terms of technical factors, temperature is used, as shown in chapter one, due to its role at the final stage of seed formulation. Average temperature in the growing season ranged from 22°C (equals 71.6°F) to 48.37°C (approximately 120°F) in 2016.

The second stage variables summary statistics also indicate interesting variation and levels for human capital. When it comes to education, the largest share of farmers falls into a category of no formal education degree attained. Farmers with bachelor's degree ranked third out of five educational categories. The distribution for farmers education is likely to influence wheat productive efficiency.

Distance to water supply ranged from 2.2 km (about 1.36 mile) to 68.4 km (approximately 42.5 mile). This variable was added to measure not only the distance to surface irrigation resources, but also might be an indicator of the efficiency of the irrigation system (e.g., in canal ditch systems less irrigation water is typically available the further the farmer's field is from the original source), and a proxy for the quality of water. It might be the case that the level of salinity in the water flow is relatively high by the time it reaches the fields the furthest away from the original surface water source.

The provincial or national government may choose to fund extension centers near farmers. These centers are useful for experts to meet with the public and/or demonstrate yield enhancing technical practices. To check if living close or far from extension centers can explain the difference in TE, distance in kilometers (km) is measured from the district to the nearest extension center. Minimum distance for a district to the extension center is 2 km (about 1.24 mile) while the maximum distance is 272 km (almost 169 mile).

Lastly, the natural capital is likely to vary across wheat producing districts. To this end, technical variables such as rainfall (ml) and relative humidity (%) are included due to their significant role in the final stages of germination as mentioned in chapter 1.

2.4. Stochastic Frontier Analysis: Empirical Procedure

Stochastic Frontier Analysis is used to investigate factors important in wheat yield efficiency in Iraqi districts by regressing yield (kg/dunam) against variables listed in Table 16. These variables are proxies for various forms of capital including natural capital, financial capital, human capital and operation capital. Equation 1 follows Coelli (1995) which is shown below:

$$y_{i\left(\frac{kg}{dunam}\right)} = B_0 + B_1 area_{i(dunam)} + B_2 urea_{i(ton)} + B_3\, DAP_{i(ton)} + B_4\, Pallas_{\,i(liter)} + B_5\, Raxil_{i(kg)} + B_6\, spr_i + B_7\, tra_i + B_8\, har_i + B_9\, FP_i + v_i + u_i \quad (1)$$

where:

v_i is a random error that captures stochastic events that influence wheat yield. The specification permits random variation along the output frontier and captures the effects of measurement error.

u_i is an error in optimization term that captures the effect of inefficiency relative to the stochastic frontier. This term is the technical efficiency (TE) and is calculated in equation 2 as:

$$TE = 1/\exp(u_i) \tag{2}$$

The differences in technical efficiency can be partially determined by a regression of effi

scores on important factors of production such as natural capital, human capital and infrastructure as shown in equation 3:

$$TE_{i\,(\%)} = B_0 + B_1 disw_i + B_2\, dise_i + B_3\, pci_i + B_4\, bac_i + B_5\, high_i + B_6\, sec_i + B_7\, pri_i + B_8\, non_i + B_9\, rain_i + B_{10}\, humd_i + \varepsilon_i \tag{3}$$

Battese and Coelli (1995) propose a statistical model that combines the first and second stage (i.e. equations 1 and 3 are estimated simultaneously) together in a one step by the 'frontier' command in Stata. Wang and Schmidt (2002) showed that the two-step procedure in efficiency studies will give a biased result due to the misspecification in the first stage. The solution is to perform a one-step procedure based on the model that correctly specifies the data generating process or the distribution of (y), which is the yield in our case, given (x), which are the 1st stage variables, and (z), the 2nd stage variables. Wang and Schmidt (2002) indicated that in the one step-procedure, the relationship between (z) and technical efficiency is imposed in the estimation procedure of technology (1st stage) and firms' (in our case, districts) efficiency levels not only at the 2nd stage of analysis.

2.5. Data Envelopment Analysis: Empirical Procedure

DEA is a non-parametric approach used to study factors affecting productive and technical efficiency. In the first stage, a linear programming method is used to obtain TE scores, rather than a regression approach that characterizes SFA. No stochastic component is specified in the optimization, and this is a key distinguishing characteristic between SFA and DEA. Any deviation of a district outcomes is attributed to inefficiency in the decision made at a district level.

The linear programming approach is based on Charnes et al. (1978):

$$\max_{\theta_i\ \lambda} \boldsymbol{\theta_i^{VRS}}$$

$Subject\ to$

$\theta_i^{VRS} y_i \geq \sum Y \lambda$ weighted sum of the outputs of the other Decision Making Units (DMUs) is greater than or equal to the DMU being evaluated (a)

$x_i \leq \sum X \lambda$ weighted sum of the inputs of the other DMUs is less than or equal to the inputs of the DMU being evaluates (b) (4)

$\lambda \geq 0$ non-negativity of weights (c)

$\sum_{j=1}^{n} \lambda_j = 1$ constraint allowing for VRS. (d)

In the output-oriented model, θ_i^{VRS}, is the ratio of weighted output to weighted inputs. An optimal level of θ_i^{VRS} is obtained by maximizing the weighted sum of output while keeping the weighted sum of inputs the same. The optimal allocation of inputs can be compared to the actual level of inputs to determine the efficiency of the district. If the optimal allocation of inputs and the actual level of inputs achieve the same level of output, then the district is said to lie on the wheat production frontier.

2.6. Stage 2 Estimation Procedure for Both SFA and DEA

This research makes use of two empirical methodologies: a nonparametric Data Envelopment Analysis (DEA) and a stochastic parametric Stochastic Frontier Analysis (SFA).

The first stage of non-parametric analysis uses DEA and follows the procedure of Coelli (1996) and using DEAP v (2.1). The DEA is implemented with a series of variable returns to scale optimization problems. A problem is solved for each district in which output is maximized for a given level of inputs. From this first stage of analysis, the technical efficiency measure of wheat production is derived for each district. The second stage of the analysis uses Tobit regression to examine factors that help explain variation in TE as in equation 3.

2.7. Results

2.7.1. Stochastic Frontier Analysis (SFA)

The initial estimation procedure in SFA entails regressing the productive efficiency measures (logarithm of yield per dunam) on the explanatory variables listed in Table 17 using maximum likelihood estimation (MLE). Multicollinearity may be presented among the input variables, so Variance Inflation

Factor (VIF) is calculated as an index to measure the variance of the estimated regression coefficient. VIF is performed recording a value of 1.2, which is less than 5, and a general rule is that a VIF of greater than 5 indicates a high level of multicollinearity (Sheather, 2009). Also, correlation coefficient between RHS variables both in the first and second stage is reported in Table 19 and Table 20.

In Table 19, there is a high correlation between the natural log of area and the natural log of Pallas, which is expected as insecticides are often applied at a rate that is consistent across land units. Sprayers and tractors are also highly correlated variables. This might be due to the nature of sprayers being attached to tractors, as well as the fact that farms of sufficient size and wealth that own one will have sufficient wealth to own both.

Correlation among second-stage variables is shown in Table 20. In that table, no correlation coefficient value considered high, above 0.8.

Table 19. Correlation coefficient between 1st stage analysis variables.

	lnarea	*lndap*	*lnure*	*lnrax*	*lnpal*	*lnspr*	*lntra*	*lnhar*	*lnfp*	*lntemp*
lnarea	1									
lndap	0.73	1								
lnure	0.75	0.78	1							
lnrax	0.59	0.55	0.49	1						
lnpal	0.86	0.68	0.72	0.44	1					
lnspr	0.07	0.22	0.12	0.20	0.02	1				
lntra	0.09	0.21	0.08	0.28	0.03	0.88	1			
lnhar	0.20	0.23	0.16	0.14	0.14	0.64	0.76	1		
lnfp	0.26	0.24	0.27	0.15	0.27	-0.08	0.01	0.19	1	
lntemp	0.05	0.07	0.09	-0.07	0.07	-0.07	-0.03	0.08	0.26	1

Table 20. Correlation coefficient between 2nd stage analysis variables.

	lndisw	*lndise*	*lnpci*	*lnbac*	*lnhigh*	*lnsec*	*lnpri*	*lnnon*	*lnrain*	*lnhumd*
lndisw	1									
lndise	-0.11	1								
lnpci	0.10	-0.07	1							
lnbac	-0.29	0.07	0.01	1						

lnhigh	0.09	0.03	-0.11	-0.21	1					
lnsec	-0.04	0.08	-0.04	0.11	0.38	1				
lnpri	0.11	-0.16	0.03	-0.38	0.29	0.16	1			
lnnon	0.01	-0.09	-0.11	-0.33	0.36	-0.06	0.71	1		
lnrain	0.15	0.16	-0.26	-0.32	0.30	0.15	0.31	0.41	1	
lnhumd	0.11	0.17	-0.23	0.05	-0.13	-0.01	-0.31	-0.27	0.11	1

Applying Stochastic Frontier Analysis (SFA) from equation 1 and adopting the half normal distribution for the inefficiency term leads to the following estimates showed in Table 21:

Table 21. Estimated coefficients when yield productivity is regressed on independent variables using MLE

Variable Type	VARIABLES	1st stage variables
Area planted	$lnarea_i$	0.474***
		(0.0000112)
DAP fertilizer	$lnDAP_i$	0.00223***
		(0.00000007)
Urea fertilizer	$lnurea_i$	-0.0569***
		(0.00000757)
Raxil fungicide	$lnRaxil_i$	0.0996***
		(.0000212)
Pallas herbicide	$lnPallas_i$	-0.467***
		(.0000252)
Sprayers	$lnspr_i$	-0.0191***
		(.0000319)
Tractors	$lntra_i$	0.0888***
		(0.00000824)
Harvesters	$lnhar_i$	0.0223***
		(.0000295)
Temperature	$lntemp_i$	0.114***
		(.000113)
Farmer to urban population	$lnFP_i$	0.156***
		(0.00000845)
	Constant	2.444***
		(.0003894)
	Observations	105

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

$LR\ chi^2(10) = 45600, \text{Prob} > chi^2 = 0.001, \text{Log Likelihood} = -75.537$

2.7.1.1. Evaluating how the model fits the data overall

In this section, the degree to which the model fits the data is examined. In evaluating fit, three approaches are used:

- Testing if individual coefficients are statistically different than zero.
- Testing the likelihood that variables jointly describe the data relationship better than the constant term alone.
- Testing to see if parameter estimates are jointly equal to zero.

Table 21's results can be evaluated on how well the variation in y_i is explained by independent variables. The null hypothesis that the impact of all explanatory variables jointly equal zero is rejected.

In terms of the model's goodness of fit, when calculating LR test, two likelihoods need to be calculated. The first one is that RHS variables produced technical efficiency scores. The other one is that the intercept is the one that used in calculating technical efficiency scores. Now the two likelihoods are used in getting LR test. So, the null hypothesis, H_0, is rejected that there is no relationship between TE and covariates in the first stage. Results of the 1st stage regression by SFA showed that LR test, which is a test of the omnibus null hypothesis that all the coefficients in the model are zero (except the constant), equals 45600 so we reject the null hypothesis that the variables are jointly zero.

The p-value of the whole model equals 0.001, which is <0.05. This test is similar to F-test checking whether all coefficients in the model are different from zero.

2.7.1.2. Estimated Parameter Interpretation in Stage 1 SFA

A positive, statistically significant relationship exists between the yield per dunam and the planted area within a district. First stage estimation indicated that the dunams planted of wheat in this sample is positively related with production per dunam. More specifically, increasing planted area by 1% is associated with an increase in productive efficiency by 0.5% ceteris paribus.

For the fertilizer, DAP fertilizer is positively related to yield per dunam at the sample means, ceteris paribus. Increasing DAP use it by 1% is associated with improvement in productive efficiency by 0.002%. The increase is consistent with a DAP rate of application near its efficient level.

Increasing the amount of Urea and Pallas applied to a wheat crop in a district appears to be negatively correlated with the yield in the district. This might be perhaps because this type of fertilizer is, on average, over-applied relative to the crop use requirements in the area, or alternatively more fertilizer is applied to soils that are inherently less productive (e.g. less water holding capacity), which we have been unable to control for in the research process because soil type is not embedded in the initial regression procedure. Increasingly use of these two inputs by 1% is associated with a decline in yield of 0.05% and 0.46% respectively keeping other variables fixed. Raxil, a seed treatment fungicide, affecting yield positively indicating a yield would increase by 0.1% with each 1% incremental increase in Raxil.

Mechanical capital varies in its effect on productivity as tractors and harvesters are positively associated with yield increases, but sprayers are negatively associated. More specifically, increasing the number of tractors and harvesters by 1% is associated with yield increase of 0.088% and 0.022% respectively. This might be due to the important role of mechanical capital in wheat production where tractors are used to prepare the soil and harvesters are efficient means for harvesting wheat compared to more labor intense alternatives. Sprayers appeared to affect yield negatively. It may be that sprayers are used only when a pest (insect or weed) is observed, and the pest already impact yields negatively, that is, the spraying prevents larger losses, but these losses have already occurred.

The ratio of farmers population to urban population is positive and statistically significant in explaining yield variation. This might be due to increasing the agricultural labor force that will increase productive efficiency. Appropriate temperature, at certain stage of growth, will increase yield since wheat can flourish in a temperature degree close to 35 Celsius or 95 Fahrenheit at the time of maturity (Thomson et al., 2002).

Now, the first stage analysis is done and TE scores are obtained using the regression output in Table 21. Summary statistic describing the district level TE scores are show in Table 22. Hotelling T-square statistic used to test the alternative hypothesis that technical efficiency scores across districts are different. Table 23 reports a t-test of means for each of the district TE for the data series.

Table 22. Summary statistics of wheat production TE obtained by SFA in each province for the year 2016.

Provinces	*Number of districts*	*Number of districts with TE > 0.9*	*Median*	*Mean*	*CV*	*Minimum*	*Maximum*
Diwniya	15	0	0.605	0.555	0.394	0.159	0.823
Diyala	18	3	0.852	0.708	0.391	0.115	0.928
Karbala	7	0	0.837	0.789	0.113	0.632	0.874
Maysan	18	1	0.313	0.370	0.782	0.020	0.909
Baghdad	5	1	0.624	0.679	0.184	0.613	0.902
Najaf	9	0	0.828	0.734	0.289	0.254	0.882
Babylon	15	0	0.840	0.749	0.231	0.245	0.879
Wasit	18	2	0.765	0.643	0.455	0.035	0.922
Total	105	7					

Based on Table 22, the province Diyala has the highest median TE score among between the eight studied provinces, while the province Maysan has the lowest median recorded. The wide range of mean TE across provinces indicates the potential for TE improvements.

For the CV, which calculated as the standard deviation divided by the mean, Karbala receives the lowest CV while Maysan has the highest. Typically, provinces and districts with high median TE have the narrowest CV. A large CV suggests great variation in wheat productivity efficiency in the province for its districts. This variability is undesirable as it is associated with less food security and widely varying household income.

depicts the dispersion of technical efficiency (TE) scores of Iraqi wheat producing districts using SFA and is organized from left to right by province name. The observed variability inspires a second stage of the analysis to know the source of differences between these districts. Interesting too is the relationship between the average TE score and the maximum TE score. If average is near the maximum, then most districts are on the efficiency frontier for the province. Amore close to the maximum suggest an outlier that is highly efficient compared to the remainder of the province. Only Karbala has an average close to the maximum TE score comparing to Wassit who got the biggest gap between minimum and average TE score.

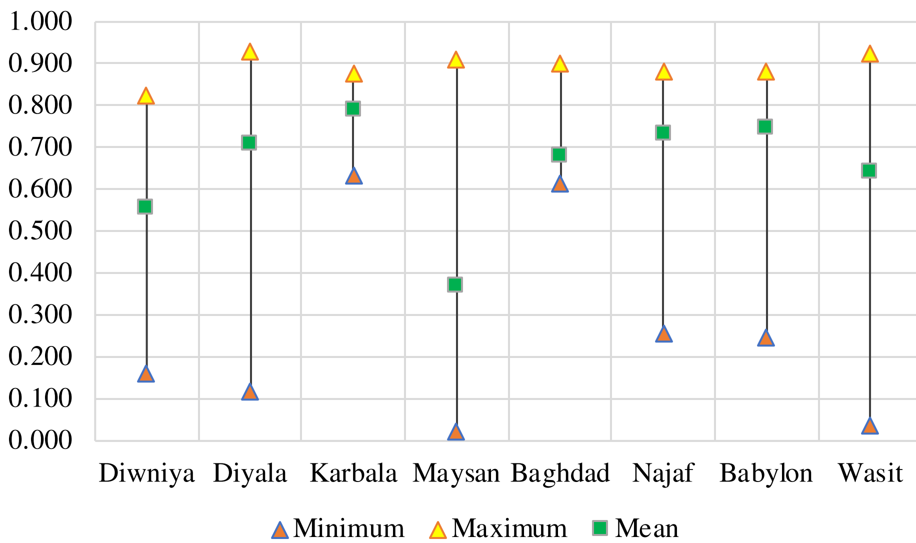


Figure 6. Distribution of TE score range by provinces using SFA.

After showing the differences in average TE graphically, the next is to implement Hotelling's T-squared statistic. The null hypothesis here is that there is no statistical difference between means of TE in the wheat producing districts in Iraq. The output of Hotelling's T-squared statistic is in Table 23.

Table 23. Results of a test determining if the mean province scores are statistically different from one another

Test that all means are the same	
Hotelling T2	312.624
Hotelling F (18,8)	22.987
Prob > F	0.001

Based on the output of Table 23, a null hypothesis of equal means is rejected, and significant difference exists among means. Now the second stage output, which is obtained by MLE is shown in Table 24.

Table 24. Coefficient estimates of TE regressed on explanatory variables in the second stage of SFA

Variable type	VARIABLE	2nd stage variables
Distance to water	$lndistowat_i$	-0.501***
		(0.124)
Distance to extension	$lndistext_i$	0.216
		(0.146)
Per capita income	$lnpci_i$	-0.289*
		(0.162)
Farmers with bachelor education	$lnbac_i$	0.0690
		(0.100)
Farmers with secondary education	$lnsec_i$	0.261*
		(0.154)
Farmers with high school education	$lnhigh_i$	-0.863***
		(0.193)
Farmers with primary education	$lnpri_i$	0.336**
		(0.141)
Farmers with no education	$lnnon_i$	0.255**
		(0.112)
Rainfall quantity	$lnrain_i$	-0.341
		(0.252)
Humidity level	$lnhumd_i$	-1.361*
		(0.752)
	Constant	10.03***
		(3.666)
	Observations	105

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Output reported in Table 24 is a district level regression in which TE is regressed on district specific variables. Table 24 provides the parameter estimates for the regression of TE on factors hypothesized to influence efficiency. Results are discussed in the next section.

2.7.1.3. Statistically significant factors negatively related to TE in Iraqi districts

Distance to water flow ($lndistowat_i$): increasing the distance to a surface water source is associated with lower level of TE, ceteris paribus. This might be related to the inefficient irrigation means that need to deliver water to districts that are far from the surface water, or the less reliable flows from as the surface sources as distance increases.

Per capita income ($lnpci_i$): increasing income in the sample is associated with lower levels of TE. This is surprising since more income is associated with more investment in wheat production in the MENA analysis. This may be because a more lucrative crop is available compared to wheat and this crop receives increasing capital, or that capital might be bid away from agriculture into more lucrative endeavors. It is unclear how incomplete capital markets might influence the provision of income to business enterprise.

High School Education Attainments ($lnhigh_i$): The increasing share of population with high school education generally is associated with lower level of TE, ceteris paribus. This might be because high school graduates have stronger skillsets compared to those without education, and those individuals are less likely to work in agriculture because of low wages. Thus, the quality of labor in agriculture falls overall with increasing educational attainment for a smaller subset of the population.

2.7.1.4. Statistically significant factors positively related to TE in Iraqi Districts

Variables that came with the largest impact explaining variation in TE are farmers with primary education (positive), farmers with secondary school (positive), farmers with no-education (positive), per capita income (negative), distance to the surface flow of water (negative), farmers with high school education (negative), and humidity level (negative). Variables mentioned previously are ordered based on the largest coefficient to the smallest impact.

Primary School Education Attainments ($lnpri_i$): As mentioned earlier, as the number of farmers with primary school education increasing, then so does TE. A strong rationale exists to increase the quality of this workforce class by providing educational opportunities. The focus of this effect may well be literacy so that farmers are better able to access and act on information from others.

Secondary School Education Attainments ($lnsec_i$): The majority of agricultural workers in the studied sample are from secondary, primary, or no education class. Estimated coefficients for more farmers with secondary school attainments is associated with higher TE level, ceteris paribus.

Non School Education Attainments ($lnnon_i$): this workforce class is the major workforce in this data sample. This class occupied 53% of the whole studied sample. As this class increased in number then so TE. This is another incentive to invest in increasing the quality of this workforce.

Humidity level in Each District ($lnhumd_i$): This is more technical variable in wheat production. This variable came statistically significant associated with TE positively. Humidity level in soils preparation and early stages of germination is very critical (MSU extension).

2.7.2. Data Envelopment Analysis (DEA)

The non-parametric approach, Data Envelop Analysis (DEA), is used with the same data set to independently examine wheat productive efficiency. The results of the previous section are compared to these results and differences are highlighted.

Just as was the case with the SFA, the DEA analysis is completed in two stages – first, the estimates for technical efficiency (TE) are calculated using a series of optimization problems for each district, and then these are regressed on explanatory variables as a means of determining differences across districts. This follows the linear equation listed in equation 3 and constraints a, b, c, and d.

Table 25 summarizes TE scores classifying each district's score into one of eight categories. The second column of Table 11 lists the number of districts in each efficiency category as estimated using DEA and VRS assumptions. Table 11 also shows mean, minimum, and maximum recorded when adopting DEA approach. Interestingly, the DEA technical efficiency mean scores are higher, and standard deviation of these scores are lower when compared to SFA.

The mean technical efficiencies obtained for data envelopment analysis when adopting variable returns to scale (VRS DEA) is 0.88. This is an indication that there might be a room for improvement, but this is limited for the best performing districts. However, 11 districts have TE less than 0.7 and they may be improved.

Table 25. Iraqi wheat producing districts: Frequency distributions of technical efficiency from DEA and SFAs models. (N=105)

Efficiency score	TE VRS[b] DEA	TE VRS[b] SFA
<0.4	1[a]	24[a]
0.4-0.5	2	9
0.5-0.6	1	3
0.6-.7	7	17
0.7-0.8	13	10
0.8-0.9	22	38
0.9-1	35	7
1	24	0
Mean	0.88	0.63
Minimum	0.29	0.02
Maximum	1	0.93
Standard deviation	0.14	0.27

a Denotes the number of districts.

b TE is technical efficiency, VRS is variable returns to scale.

Another way of showing how the technical efficiency scores distributed across the sample is through Figure 7, which indicates the number of districts falling into eight frequency distributions of TE scores.

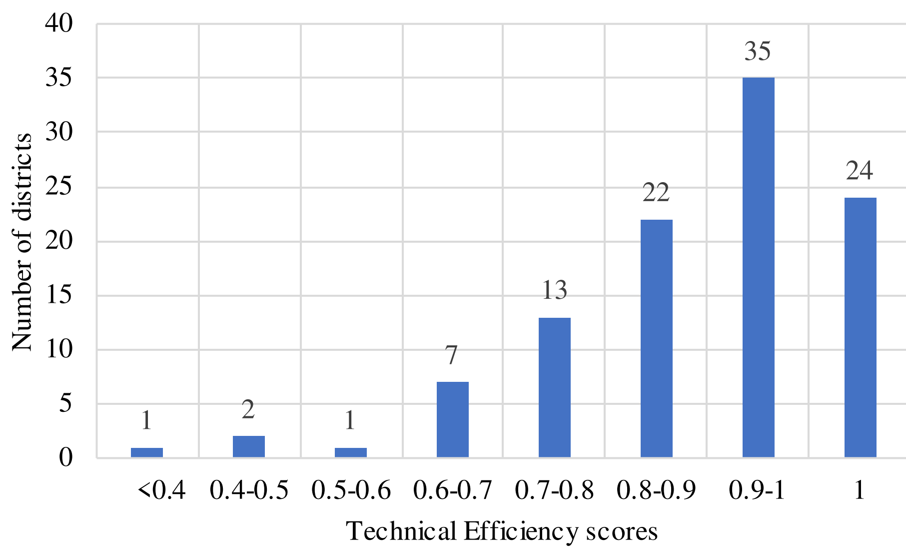


Figure 7. Distribution of technical efficiency scores as measured by DEA for the 105 Iraqi wheat producing districts

Significantly, suggests limited improvement in TE when measured by DEA. Notably, this analysis uses cross-sectional data for a single year. The previous work in MENA countries suggests TE can vary widely from year-to-year, so additional years of analysis may enhance our understanding and offer different results.

The next step is a better understanding of factors influencing TE variability. The second stage entails a Tobit model (McCarty and Yaisawarng 1993, Ruggiero and Vitaliano 1999, Chakraborty et al. 2001). Maximum likelihood estimation (MLE) is used to obtain the technical efficiency scores obtained by DEAP v (2.1) in an approach called two stage DEA. Estimating TE is the initial step of the DEA analysis. The second stage seeks to understand how variations in TE across districts might be explained by production and socioeconomic variables.

Table 26 contains the parameter estimates for the second stage analysis using a Tobit approach and maximum likelihood estimation.

Table 26. Output of the 2nd stage of DEA analysis for TE regressed on explanatory variables

Variable type	VARIABLES	Model 1
Distance to water	$lndistowat_i$	-0.0209*
		(0.0116)
Distance to extension	$lndistext_i$	-0.0246**
		(0.0124)
Per capita income	$lnpci_i$	0.0184
		(0.0138)
Farmers with bachelor education	$lnbac_i$	-0.0130
		(0.00837)
Farmers with high school education	$lnhigh_i$	0.0148
		(0.0172)
Farmers with secondary education	$lnsec_i$	0.00784
		(0.0118)
Farmers with primary education	$lnpri_i$	0.0270**
		(0.0107)
Farmers with no education	$lnnon_i$	-0.0203**
		(0.00951)
Rainfall quantity	$lnrain_i$	0.0478***
		(0.0173)
Humidity level	$lnhumd_i$	0.00460
		(0.0521)
	Constant	0.645**
		(0.289)
	Observations	105

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
$LR\ chi^2(10) = 30.79, \text{Prob} > chi^2 = 0.0006, \text{Log Likelihood} = 75.537$

2.7.2.1. Model Fit

The Likelihood Ratio (LR) Chi square equals 30.79 and it is larger than the critical value of chi square (9.342). In the LR test, two likelihoods are calculated- the likelihood that the explanatory variables produced the observed TE scores, and the likelihood that the constant term without covariates reproduces the observed TE scores. The ratio of these two likelihoods is used to determine the LR. The null hypothesis H_0, is no relationship between TE and the covariates in the second stage and this is rejected. The p-value of the whole model equals 0.006, which is <0.05, which is similar to an F-test in which the null hypothesis is that all coefficients are equal to zero. In other words, the LR is approved that there is a relationship between TE and the covariates in the second stage. Parameter reported as sigma is the estimated standard error of the regression; the resulting 0.118 is comparable with the estimated root mean squared error reported when using OLS, which equals 0.125.

2.7.2.2. Statistically significant factors negatively related to TE in DEA approach

The statistically significant variables in Table 12 include distance to water supply ($lndistowat_i$), distance to the extension center ($distext_{i(km)}$), number of farmers with primary school education (pri_i), number of farmers with no education level (non_i), and the amount of rain ($rain_i$) came statistically significant affecting TE scores.

One of the factors affecting TE negatively is the distance to the water flow ($lndistowat_i$). This is intuitive as the more remote the district is from surface water flows, the more inefficient it is in producing irrigated wheat. This might relate to the inefficiency of irrigation conveyance and deliver. The closer a district is to the point f diversion, the less penalty is associated with an inefficient conveyance and delivery system. ,

Distance to extension center ($distext_{i(km)}$) affects TE negatively. The more remote the extension center, the less technically efficient the district is in producing wheat. These centers are a primary source of agronomic expertise. If those centers are more remote, wheat TE scores may be lower with less opportunity for timely answers to farmer questions and diffusion of best practices. Those centers usually provide an advice on the optimal dose of fertilizers and pesticides. Workshops on the new varieties of seeds and the proper amount of seed recommended per unit of land are examples of best practice that might be taught at the extension center.

The effect of farmers with no education level ($lnnon_i$) is associated with lowering TE score. As the number of farmers without education increase, then the level of TE in wheat declines. This statistically significant relationship is not surprising so farmers with little or no education may not have access to best practices in agricultural sciences. This might be true due to their inability to read fliers or reports on the proper dose of, for example, using pesticide or fertilizer or even the optimal amount of seed recommended for each unit of land.

2.7.2.3. Statistically significant factors positively related to TE variation in the DEA analysis

Variable that affects TE scores positively is the number of farmers with primary school education level ($lnpri_i$ A small amount of education, and the experience of these farmers (generally aged greater than 55 years) suggests a positive relationship with wheat technical efficiency.

Amount of precipitation is positively associated with TE improvements ($lnrain_i$) as might be expected in arid and semi-arid regions.

2.7.3. Comparing Results of DEA and SFA in estimating TE and exploring TE variability

2.7.3.1. First Stage Comparison of DEA and SFA

Two approaches used to measure TE of wheat producing districts in Iraq relative to different production frontiers, a stochastic frontier analysis (SFA) and data envelopment analysis (DEA). As shown in , comparing TE scores obtained by using SFA and DEA revealed that there are differences in technical efficiency scores estimated from the two approaches. The mean TE scores of SFA are relatively lower than those in DEA. The mean score for TE estimated using SFA is 0.63 and mean using DEA is 0.88. Please note that both of these scores are greater than Iraqi's TE in the first essay

Table 27. Spearman correlation matrix of technical efficiency of some Iraqi wheat producing districts.

	VRS TE DEA	VRS TE SFA
VRS TE DEA	1	
VRS TE SFA P-value	0.719 (0.0001)	1

Technical efficiency scores obtained through DEA show a distribution that has a lower variability among districts comparing to the distribution of technical efficiency scores obtained by SFA. Examining the agreement between the two approaches, Spearman correlation coefficients, which is a statistical measure used to show the strength of a monotonic relationship between paired data, between the two calculated efficiency scores of the Iraqi wheat producing districts is compared and reported in Table 27. The correlation coefficient is positive and statistically significant.

In blue dots represent the TE of a district calculated via DEA and red dots represent TE calculated by SFA. The DEA plots tend to be clustered more tightly than the SFA dots. In addition, the DEA measures of TE tend to fall more often in the upper part of the graph between 0.8 and 1.0.

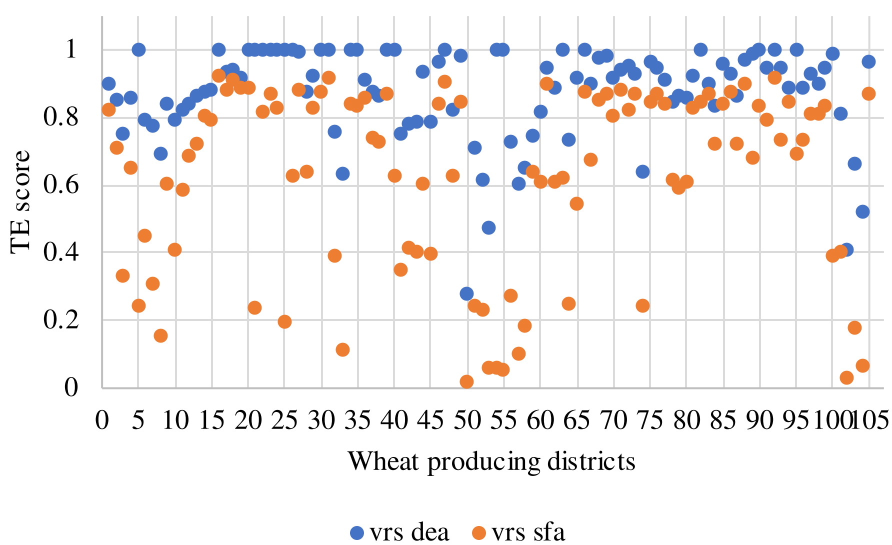
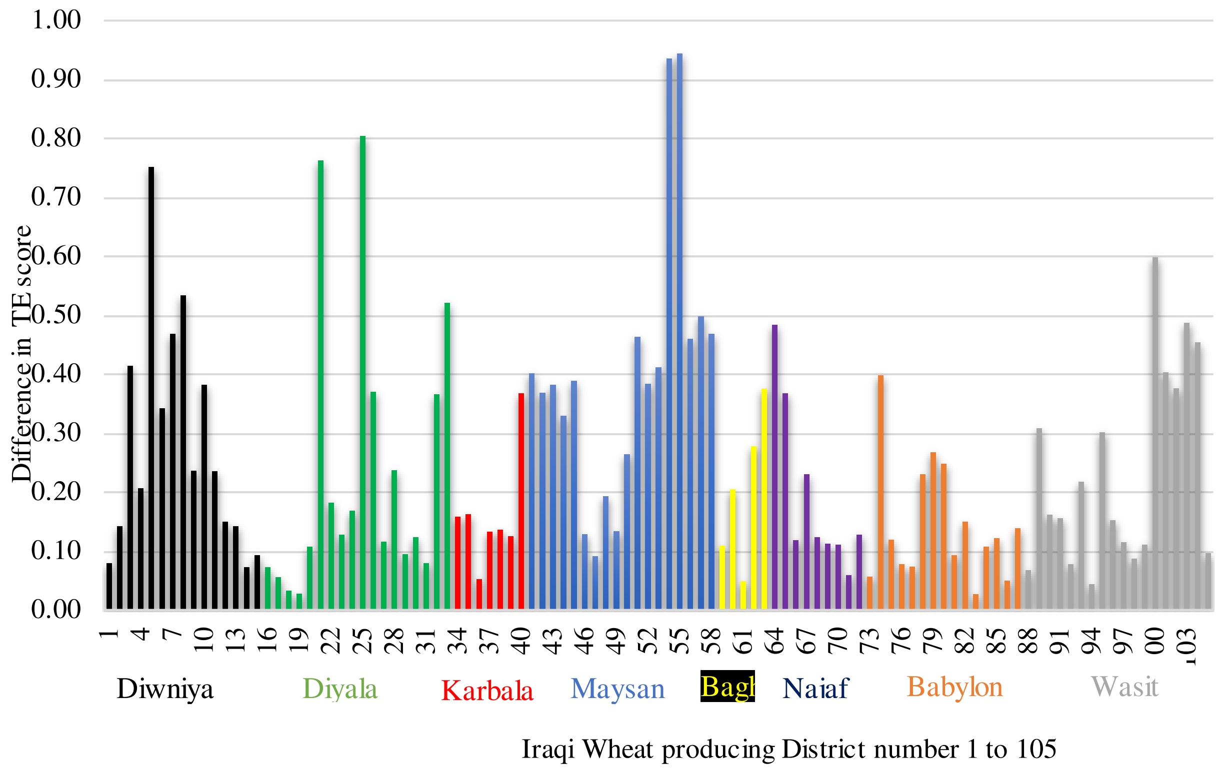


Figure 8. Comparison of DEA estimated TE and SFA estimated TE by district in Iraq in 2016

The linear distance between the TE's represented in Figure three appear to vary dramatically – the difference of the DEA TE and SFA TE are not consistent and may vary systematically due to unobserved factors. With this in mind, the mathematical difference between the scores (DEA TE minus SFATE) is plotted in.

Figure 9. Difference in TE score obtained by subtraction the SFA TE from DEA TE in all 105 Iraqi wheat producing districts (all positive differences).



The provinces with the highest bars have the greatest difference between the DEA and SFA estimates. Figure 9 indicates that the province Maysan has the highest average difference of TE across the studied sample. Maysan also receives the lowest TE score across the studied sample when SFA and DEA are adopted. The average difference is 0.40. Karbala, the highest efficient province in the wheat sample when DEA and SFA is applied, got the lowest average of the difference in TE score. One conclusion is that the low TE score represents a high stochastic error in SFA stage 1 analysis, and this is not captured in the DEA analysis. Of interest is why the difference might be larger in some provinces when compared to others.

Reasons that might explain the differences are investigated in 2.7.4 under the heading ‘Explaining Differences in TE.

Similar to the study of MENA countries, the TE measure calculated with DEA procedure are greater than these calculated by SFA procedure. This is true when district level TE scores are averaged to create a mean score for provinces in Iraq. These mean scores are shown in .

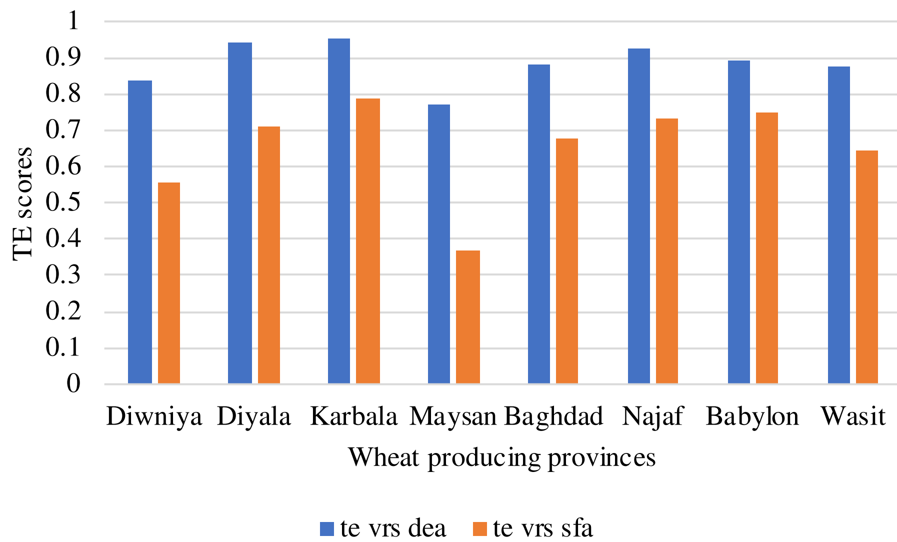


Figure 10. Average TE scores over the wheat producing provinces.

The TE of DEA scores compared to TE of SFA is consistent with Neff et al. (1993), Sharma et al. (1997), Zaibetand and Dharmapala (1999), Uri (2001), Coglan et al. (1998), Cullinane et al. (2006) and Pascoe et al. (2003). The findings of the previously mentioned literature generally indicated that SFA and DEA efficiency scores are correlated. In our case, the correlation equals (0.72) but DEA scores is higher that the SFA ones. Results here are similar to the findings of Bravo-Ureta et al. (2006), Zamanian et al. (2013), and Bayarsaihan and Coelli (2003) where they found that the DEA scores where higher. Those studies agreed that human capital, mechanical capital, and fertilizer as operational input are the most important factor explaining variation in efficiency in agriculture. However, those studies did not investigate factors that explained differences in TE between DEA and SFA.

In order to know the cause of differences in the data set, it is worth looking at Figure 1, Figure 4, and Figure 6. Examine those figures show that the lowest difference between TE obtained by DEA and SFA is found in province of Karbala. Karbala also got the highest TE in both DEA and SFA. In contrast, Maysan got the highest difference between TE scores obtained by DEA and SFA, and Maysan also has the lowest TE. The reason that Karbala got the highest TE is because of the agricultural revolution managed by Imam Hussein Agricultural City. This project is consisting of 500 acres with highly skilled and trained staff. (Imam Hussain Shrine's projects, 2019). The source of funding for this is though tourism. This area is very attractive because it is the place of the martyrdom of Hussein Ben Ali and his brother Alabbas Ben Ali, the grand sons of our prophet Mohammed. Millions of Muslims visit this place each year. So, additional capital is increased that tends to improve TE of agriculture, and the quality of the labor in this district is more skilled. Maysan does not have this comparative advantage or such initiative. This explains why TE is larger in Karbala and it may explain why the gap between TE scores obtained by DEA and SFA is smaller.

2.7.3.2. Second Stage Comparison of DEA and SFA procedure for explaining the sources of variation in TE

Second stage comparison is based on knowing if districts' specific character may influence technical efficiency score positively or negatively. Variables, which stand for the district specific characters, are regressed against TE scores obtained by SFA and DEA. These variables are distance to water (km), distance to the extension center (km), per capita income (ID), number of farmers with a bachelor degree, number of farmers with a high school education, number of farmers with secondary school education, number of farmers with primary school education, number of farmers with no education level, amount of rain falls (milliliters), and the average humidity (percentage).

Results obtained from applying DEA and SFA differ significantly. Table 28 summarizes the parameter estimates for each variable.

Table 28. Direction and statistical significance ($p<0.05$) of the second stage explanatory variables on variation in TE estimates of DEA and SFA.

Variables	DEA	SFA
$distowat_{i(km)}$	-0.0209*	-0.501***

$distext_{i(km)}$	-0.0246**	0.216
pci_i	0.0184	-0.289*
bac_i	-0.0130	0.0690
$high_i$	0.0148	-0.863***
sec_i	0.00784	0.261*
pri_i	0.0270**	0.336**
non_i	-0.0203**	0.255**
$rain_i$	0.0478***	-0.320
$humd_i$	0.00460	-0.949

All told, it is inconclusive as to the preferred model, and yet policy recommendations might still be formed from the combined results.

Clear agreement occurs between the SFA procedure and the DEA procedure on the negative correlation with distance to water and the positive influence on the proportion of farmers with at least primary education.

The two estimation procedures provide differing results for some variables: a variable might be statistically significant in one estimation procedure, but not in the other. This includes:

per capita income (positive),

- proportion of farmers with high school (negative),
- proportion with secondary education (positive)
- and the amount of rainfall (positive).

Disagreement exists on the direction of the portion of farmers without any education. Humidity is found not to be significant.

2.7.4. Explaining Differences in TE

Previous discussion in first stage comparison showed that technical efficiency districts are differ in their TE scores. This was shown in , , , , Table 26. Here, a subtraction of technical efficiency obtained by DEA from technical efficiency obtained by SFA is regressed against factors in the second stage. The reason behind doing this is to investigate factors that can explain this difference more.

The question here is that what does the gap between the DEA TE estimate and SFA TE estimate represent? Perhaps the gap is a proxy for a district's ability to be resilient to stochastic shocks. With this in mind, the TE gap that is illustrated in Figure 4 is regressed on explanatory variables form Stage 2.

Table 29. Regression output testing factors investigating the difference in TE between DEA and SFA.

VARIABLES	Model 1
$lndistowat_{i(km)}$	0.0347**
	(0.0143)
$lndistext_{i(km)}$	-0.00884
	(0.0152)
$lnpci_i$	0.0106
	(0.0170)
$lnbac_i$	0.00123
	(0.0103)
$lnhigh_i$	-0.122***
	(0.0213)
$lnsec_i$	0.0178
	(0.0145)
$lnpri_i$	-0.0671***
	(0.0132)
$lnnon_i$	0.0295**
	(0.0117)
$lnrain_i$	-0.0160
	(0.0213)
$lnhumd_i$	-0.143**
	(0.0641)
Constant	1.532***
	(0.356)
Observations	105

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Based on the output of Table 29, factors that can increase the gap between technical efficiency score obtained by DEA and technical efficiency obtained by SFA are distance to water supply and the number of non-educated farmers. Factors that can narrow the difference are more farmers with high school education, more farmers with primary school education and relatively humidity variation. It may be that reducing the distance to the water supply and education and mitigate the negative wheat TE impacts of a stochastic event.

For example, increasing the distance to water supply ($lndistowat_{i(km)}$) is associated with increasing the gap between TE scores obtained by the two approaches. This might be because a surface water source can be used for irrigation when a negative stochastic event occurs, and wheat TE suffers less under these investment conditions. The same would be assumed for the number of farmers with primary school education (pri_i) but this time more primary school farmers will increase the gap. However, more non-educated farmers ($lnnon_i$) are associated with increasing the difference. This is related to the slacks obtained by DEA where those slacks were on (pri_i) and (non_i), where DEA has the ability to show the slacks of each input used and when the slack is zero, then it implies that the use of this input is efficient.

Away from the 'mutual' significance variables, more farmers with high school education is associated with narrowing the gap between the two obtained TEs. We are not sure why is that, so more work needs to be done to understand this phenomenon better. This might lead to more effective policies in enhancing wheat TE.

2.7.5. Policy Implications

The estimated efficiency measures reveal substantial productive and technical inefficiencies among Iraqi wheat producing districts. Based on the DEA second stage analysis, Iraqi wheat producing districts could, on average, increase their yield by 22% keeping the level of the inputs utilized as the same. Corresponding average obtained by SFA indicated that the output can be increased by 37% while the level of input says the same. As a result, policy opportunities for improving technical efficiency in wheat production may exist. Do the benefits of these opportunities exceed the costs? This need to be considered as a future work.

However, based on the second stage analysis, investments in extension education, education at primary and secondary levels and improved efficiency of irrigation systems are worthy of additional study.

CHAPTER 3: APPLYING LESSONS LEARNED TO IRAQI WHEAT PRODUCTION: A CASE STUDY

3.1. Introduction and objective

Food security is a critical issue for many countries, and this dissertation examines food security through the lens of the efficient production of wheat. For many countries in the MENA region, and especially in Iraq, wheat is a staple of household diets and important base industry for rural economies. The objective of this dissertation is to examine the alternatives for improving the technical efficiency of wheat production using two interrelated analyses: an efficiency study of multiple nations in the MENA region across multiple years, and inter-district, single year comparison in Iraq. Both analyses make use of the same empirical approach: Stochastic Frontier Analysis and Data Envelopment Analysis.

The objective of this final essay is to address improvements to wheat productive efficiency by synthesizing the results of the previously mentioned studies and focusing the lesson learned on Iraqi wheat production. The purpose of this essay is:

- Reviewing the key elements of improving wheat productive efficiency and appraising their utility to Iraqi wheat farming,
- Discussing the strengths and weaknesses of various policy alternatives for improving wheat production in Iraq, and
- Noting where additional research might be helpful in assessing the policy alternatives.

So, in order to do that, it worthwhile to review the objectives and key findings from the previous two essays.

3.2. Key Findings from the Cross-Country, Panel Data Analysis of Wheat Productive Efficiency in the MENA Region

One of the objectives of the first essay is to measure wheat productive efficiency in each country forming Middle East North African (MENA) countries and understanding the causes of variation in wheat TE. The objective is realized by creating a panel data of 19 MENA countries across 26 years. The panel data includes variables that measure the yield per unit land of wheat production, variables representing human capital (e.g., women's participation in the labor force, population, education of the agricultural population), financial capital (net national income, producer price index), natural capital (elevation, precipitation, harvested acres) and operating capital (harvesters, tractors, pesticides, Urea, NPK, quantity of seeds). The technical efficiency (TE) of wheat production can be determined from this data on a yearly basis for each country using two accepted methods: Stochastic Frontier Analysis (a parametric approach) and Data Envelop Analysis (a non-parametric approach). Both are implemented in this essay, and wheat TE for each country is calculated in each year. After obtaining TE scores from each approach, they are interpreted to understand the differences, if any, that may exist between countries that comprise the MENA region. The variation in TE scores is notable both when comparing across countries, and the country's own TE scores across years. The sources of variation are examined in a second stage analysis in which TE scores are regressed against important explanatory variables that include human capital, financial capital, natural capital and operating capital, as well as key policy indicators such as the presence of political instability and investment in scientific research and engagement personnel.

The contributions of this essay are in using a multiple country, time varying approach to uncovering technical efficiency for a specific crop -- wheat. A multi-country approach is particularly helpful in understanding how national policies and natural capital (e.g. precipitation) influence technical efficiency. A multi-year approach is helpful in decomposing the long-lasting impacts of input allocation decisions and policies.

A key result is that improvements are possible -- the wheat TE varies widely between countries with the highest mean wheat TE score for Egypt at 92%, and the lowest is for Yemen at 28% as illustrated in Figure 11.

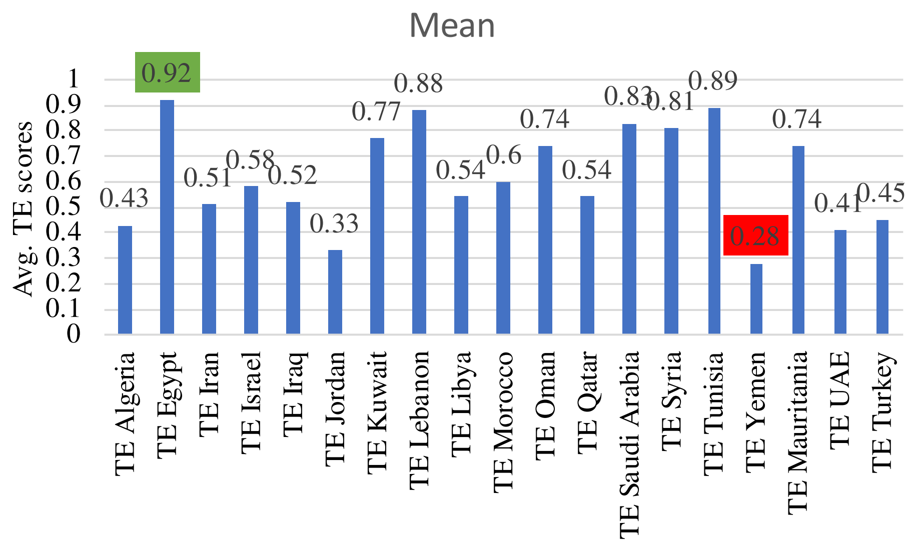


Figure 11. Comparing average TE scores across countries for the period 1991-2016

For some countries, the TE varies widely from year to year as shown in Figure 12. The wheat TE in Morocco for example (the grey line), moves dramatically between 1991 to 2016. Egypt (the blue line), maintains a consistently high level of technical efficiency across the 26. Yemen, the lowest country in terms of average TE across the 26 MENA countries, has not shown significant progress in terms of improving its TE. Iraq's wheat TE declines substantially following 2001, and then begins an upward trend, albeit at a lower level, between 2005 and 2016. Perhaps the opportunity in Iraq is to understand the next set of policy formulations that will continue, and perhaps accelerate this growth.

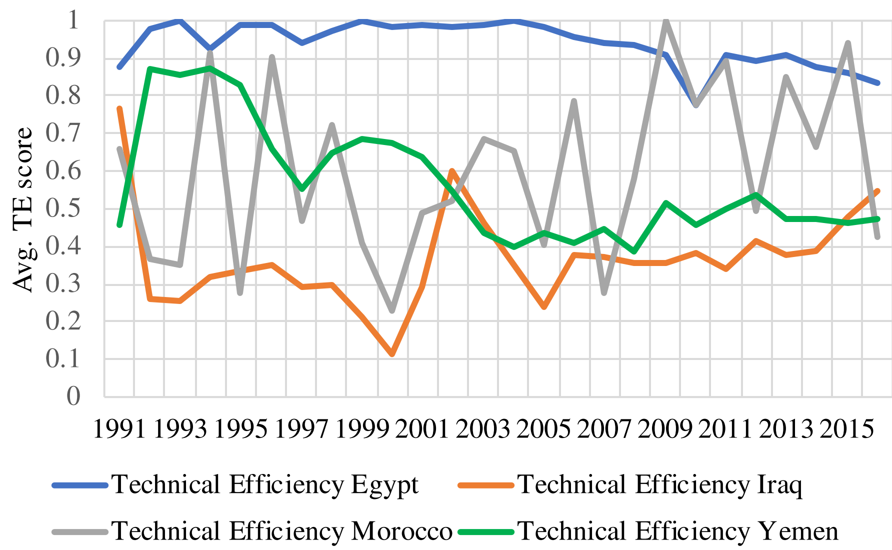


Figure 12. Comparing wheat TE for Egypt Yemen Morocco and Iraq.

A cross country comparison of the five countries with the highest wheat TE and the five countries with the lowest wheat TE is useful in describing potential sources of difference. The five countries with the highest mean TE scores are Egypt, Tunisia, Lebanon, Saudi Arabia, Syria (clearly prior to recent disruptions in this country's peace). At the opposite end of the spectrum, Turkey, Algeria, UAE, Jordan and Yemen are the countries with the lowest mean wheat TE scores.

The characteristics that distinguish the top five countries in mean TE from the lowest five countries in mean TE are increased participation of women in the labor force, the presence of scientist and extension personnel per 100 thousand farmers, access to credit for farmers, and being a political stable country. Table 30 summarizes the mean differences of the top five and lowest five countries in these areas:

Table 30. The mean differences of key factors of production for the top 5 wheat TE countries and the lowest 5 wheat TE countries (FAO, 2016).

Source of Difference	Top 5 Countries as Ranked by SFA Estimates of Wheat TE	Bottom 5 Countries as Ranked by SFA Estimate of Wheat TE
Mean Participation of Women in the Ag Labor Force	25.4%	17.6%

Mean Presence of Scientists and Extension Personnel per 100,000 farmers	40.7	35.5
Mean Level of Access to Credit (million $)	69,511.77	25,645.67
Mean Level of Political Stability	-0.50	-0.76
Mean Yield Per hectare	35,763 (hg/ha)	19,443 (hg/ha

Wheat TE scores can vary widely for a single country across multiple decades of cropping years. A wheat TE that varies widely in a country may be problematic for food security and for rural incomes, so there is some usefulness in understanding more about variation in TE. In general, countries with a mean wheat TE near the maximum TE are typically characterized by relatively high annual production of wheat with no occasional outlier year of low wheat yield and TE. Conversely, countries with a mean TE near its minimum TE are characterized by occasional bumper crops of wheat, but otherwise low wheat TE. Countries with the widest variation in TE are characterized by:

- The least access/use of energy in farming.
- The most politically unstable governments.
- The lowest availability of surface water for irrigation.

In Iraq, the mean TE is roughly at the median of the wheat TE data series.

3.3. Key Findings for the Correctional Data Analysis of Selected Wheat Producing Districts in Iraq for the year 2016

The calculation of technical efficiency is an overarching objective in the second essay, and in this essay the focus is on 105 wheat producing districts in 8 provinces of Iraq. The aim is similar – uncovering the sources and composition of wheat TE across districts so that more can be learned about policies and investments that will enhance wheat production overall. In this study, the variation in macroeconomic and national polices are removed, and there is less diversity in the natural capital available for wheat farming. The narrowed focus on Iraq is beneficial for alternative policy formulation. Similar to the study in Essay 1, a two-stage approach is used with the DEA and SFA methodologies. The cross sectional data includes variables that impact the yield per dunam, as well as factors explaining TE differences in the studied districts producing wheat, such as variables representing human capital (education of the agricultural population including the number of farmers with bachelor's degree completed, high school completion, secondary school completion, primary school, and no farmers without formal education, as well as per capita income), natural capital (humidity, precipitation, temperature, planted acres) and operating capital (harvesters, tractors, Pallas, Raxil, Urea, DAP). The wheat TE scores are calculated for districts in the middle and south of Iraq based on one year of the data for the season of 2016 using the same methodological approaches used in the empirical analysis of essay 1, i.e. DEA and SFA. The source of TE differences is examined in the second stage of analysis where TE scores are regressed in a Tobit MLE procedure against factors that include human capital (education level) financial capital (and per capita income), natural capital (rain and humidity), and the distance to the water flow and the distance to the extension center.

Factors that are positively related to yield per dunam are the total harvested area of wheat in the district, the farmer population to urban population ratio, growing season average temperature, Raxil herbicide quantity, the number of tractors and harvesters and DAP fertilizer application. Factors that negatively associated with yield per dunam are the number of sprayers, total amount of urea application, and the total Pallas application.

The wheat TE estimates for each district are derived from the first stage regression results. This wheat TE measure is then, in turn, regressed against explanatory variables representing various forms of capital. Results indicate that wheat productive efficiency is positively associated with the proportion of farmers with primary school education, the proportion of farmers with secondary school education, and the proportion of farmers with no education. Factors that are negatively related to wheat TE are per capita income, the distance to the surface agricultural water diversions, farmers with high school education, and increased levels of humidity.

The district level results can be averaged to provide a mean wheat TE score for each 8 Iraqi provinces, as has been done in Figure 3. In this illustration, Karbala records the highest mean wheat TE while Maysan records the lowest.

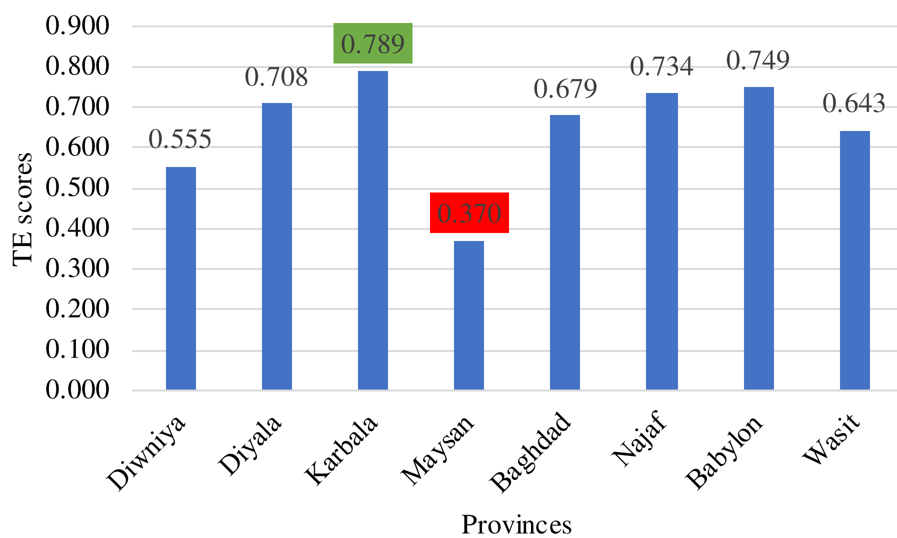


Figure 13. Means TE scores for the 105 wheat producing districts aggregated of the Iraqi province level

Similar to the first essay, wide variation exists for the wheat TE scores of the districts, and the same variation is observed when these TE scores are averaged across provinces. As an example, wheat TE scores in the province of Karbala tend to cluster at the same TE level (the blue dots) compared to the districts in Maysan (the orange dots), which shows a high level of wheat TE variation.

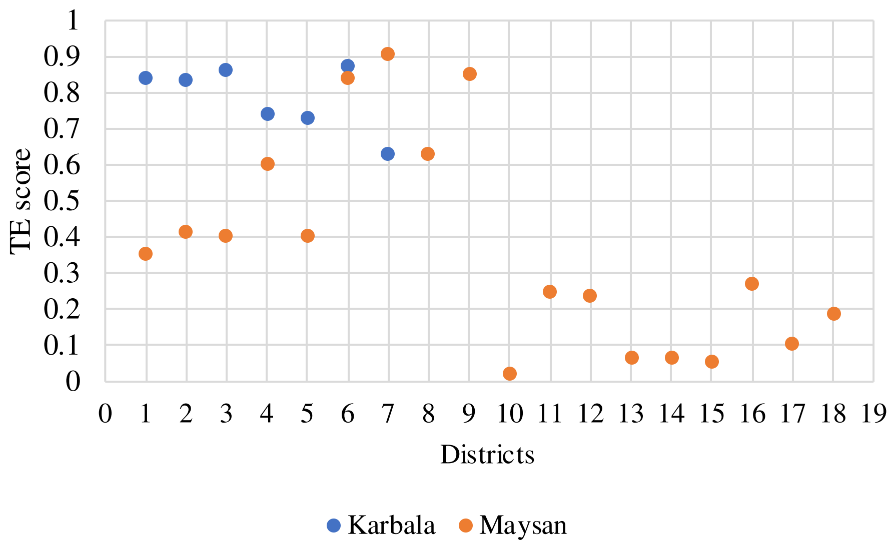


Figure 14. Comparing TE scores for Karbala's districts blue dots, n=7) and TE scores for Maysan (orange dots, n=18).

Factors that distinguish the top two provinces in mean TE from the lowest two in mean TE are distance to the agricultural surface water diversion, proportion of farmers with a primary school education, number of farmers with high school education, per capita income, proportion of farmers with a secondary school education, and farmers who do not have formal education in their background (i.e. making them more educated).

Table 31. The mean differences of key factors of production for the top 2 wheat TE provinces and the lowest 2 wheat TE provinces (MOA, 2016).

Source of Difference	Top 2 Provinces as Ranked by SFA Estimates of Wheat TE	Bottom 2 Provinces as Ranked by SFA Estimate of Wheat TE
distance to the agricultural surface water diversion	32.5	33.9
proportion of farmers with a primary school education	205	31
number of farmers with high school education	222	444
proportion of farmers with a secondary school education	23	16
and farmers who do not have formal education in their background	330	260
Mean Yield Per dunam	270 (kg/dunam)	158 (kg/dunam)

In terms of the variation of TE in wheat producing districts, it is important to understand factors that explain the variation in TE. Districts with the widest variation in TE are characterized by:

- Low per capita income (so investment capital for wheat productivity improvements may be scarce).
- Long distances to surface water irrigation diversions.
- The greatest share of farmers without education.

3.4. Policy Analysis: Understanding Iraqi Wheat Production

In order to formulate potential policy alternatives, it is helpful to understand the context of Iraqi wheat production. Wheat production in Iraq is divided into a crop that is mainly rain fed, y in the northern parts of the country and those acres that are irrigated, which is primarily concentrated in Mesopotamian Plain centered around the two great rivers, Tigris and Euphrates. The provinces studied in essay two are almost entirely irrigated and lie within the Mesopotamian Plain.

In the Mesopotamian Plain, irrigated spring wheat is planted in March-April (the majority of wheat falls in this category in the Mesopotamian Plain) and winter wheat is planted in October-November to allow for a period of dormancy over the cooler winter months. Bishay (2003) separates the planted area of wheat in Iraq into irrigated areas and rain fed area. Ninewa, Dahuk, and Erbil are provinces located in the north of Iraq. Wheat produced in these provinces is rainfed and accounts for 49% of the wheat planted area. The other 51% is irrigated and mainly grown on the Mesopotamian plain. (ICARDA, 2012).

In terms of land holdings for farming, wheat production is generally characterized by small land areas farmed by nearby households. Rain fed farms in the Northern of Iraq tend to be larger (10-30 hectares) comparing to the irrigated farms in the Center South of Iraq (1-2.5 hectares (ha)). Average yield in Iraq is 1.1 ton/ha compared to the world average which is about 2.8 ton/ha (Bayer, 2019). Wheat farms in the Northern Iraq belong to Kurdistan, a federal distinct entity has their own government and ministries that distinct from the government and ministries of the federal government.

In terms of wheat species, Iraq uses hard red winter wheat (HRW) varieties. As long as ago as 10,000 years, wheat was first grown in Iraq, and now it is planted in the same area where it was originated in the land between Tigris and Euphrates that is known as Fertile Crescent. Currently, Iraqi supply covers only one third of the wheat demand that estimated to reach 235 million bushels (6.4 MMT) (USW, 2015). This local production is mixed with imported wheat to make the flour that is used to make the Iraqi flatbread.

Iraqi consumers seek a high protein flat bread which they can obtain only by HRW. This HRW is needed because of the way that they bake the bread. They use a round tandoor oven and the gluten content must be strong enough to adhere to the inner walls of the tandoor (Kansas Wheat, 2015).

Government policies for agriculture focus on subsidizing inputs such as pesticides, herbicides, seeds, fertilizers, and machines and other farming equipment. The wheat pricing scheme is also controlled and determined by the government (Miller Magazine, 2018).

In terms of the surface water flow used for irrigation, Turkey and Iran have built dams upstream reducing the amount of water to the Tigris and Euphrates to 50% of its historical flows (citation needed here). The reduced flows have significant negative impacts on agriculture resulting in the government banning most agricultural activities in the summer. This impact is less significant on heat, which reaches its maturity in mid-summer.

Importantly, ISIS in 2014 took Salahuddin, Nineveh, Kirkuk and Anbar, areas that considered to be the Iraqi cereal belt. To sum up, lack of water means nearly one million tons of wheat production has been lost Significant interest exists in improving total wheat production in Iraq.

3.5. Egypt as an example of a high performing, technically efficient wheat sector

Egypt is an example of an elite wheat producer in the MENA region. Based on the analysis reported in chapter 1, Egypt records the highest wheat TE score among the MENA countries, and has a consistent, if slightly downward trending wheat TE. It is worth investigating the agricultural system in Egypt and tracing the reasons behind obtaining this higher TE score.

In terms of irrigation scheme, Egypt has four river basins. one basin is called the Northern Interior Basin. This basin is 520,881 km^2 in size which reaches 52% of the total area of Egypt's east and southeast. A second basin is called the Nile Basin. The estimated area of this basin is 326,751 km^2 accounts for 33% of the area located in the central part of the country. The Mediterranean Coast Basin covers 65,568 km^2 or 6% of the total area of the country. The last basin is the Northeast Coast Basin covering 88,250 km^2 along with the cost of the Red Sea covering 8% of the country.

With the availability of the Nile river is a natural capital advantage for Egypt. This river supplies virtually agricultural water in Egypt, and the river's flows are controlled by the High Aswan Dam (MWRI, 2005). In 1959, a Nile Water Agreement took place between Egypt and Sudan. By this agreement, 55,500 million m^2/year flows yearly from the Nile into Egypt and 500 million m^2/year is estimated to be the renewable surface water available per year (FAO, 2016). The water sharing agreement represents an advantage of infrastructure capital as it guarantees a minimal level of flows for planning purposes.

In terms of ground water, Egyptian agriculture is estimated use 1 billion m^2/year from Nubian Sandstone aquifer. This aquifer is located in the Western Desert and is considered an important source of ground water. Based on all of that, Egypt is considered to have the world's largest supplied renewable water flowing from neighbor countries.

This availability of water along with the efficient use allows Egypt to be a leader in wheat TE across the 26 years analyzed in this study.

The Egyptian government has invested significant funds in irrigation districts to ensure adequate water supplies even in terms of relative scarcity. As an example, the Egyptian government implemented the horizontal expansion plan in an area of 3.4 million feddans, where part of this expansion is served by

Nile river and the other part is served by ground water. The other project is The South Valley Development Project (SVDP). The idea behind SVDP is to double cultivated area by increasing it from 2.5 million feddans (1 million ha) to 4.5 million (about 1.8 million ha). A third project is Al Salam Canal Development Project (SCDP). This is a large exclamation project in the Eastern Delta and Sinai Peninsula. Other projects are West Delta Irrigation Improvement Project (WDIIP) and the 4 Million Feddans Development Project (Quosy, 2019).

To sum up, Egypt is able to attain and sustain a high wheat TE rank between through a combination of infrastructure investments and institutional reforms. While Iraq does not have the same natural capital as Egypt, the lessons learned from the Egyptian experience can help form policy alternatives for Iraq.

3.6. A synthesis of policy alternatives to be explored with more in-depth research

This dissertation has examined wheat technical efficiency in a cross-country, time varying quantitative analysis, a cross-sectional inter-district analysis and a brief case study of Iraqi and Egyptian agricultural policy. A synthesis of these three analyses can help guide the further exploration of policy instruments designed to improve wheat productive efficiency in Iraq.

3.6.1. Policy alternatives to be examined more closely

This section proposes policy alternatives that, based on the previous analysis, are useful to consider as a means for improving wheat productive efficiency in Iraq. The recommendations are not complete; rather, policymakers are encouraged to commission more intensive analysis with emphasis in the social benefit-cost outcomes of these proposed alternatives, and more quantitative analysis will assist in understanding the feasibility of the alternatives. Potential policy initiatives include:

- A national initiative to ensure literacy of existing farmers in rural areas and to promote primary school education for rural children;

- Microfinance cooperatives to be implemented by women in wheat producing districts. These cooperatives might be used to facilitate the purchase and maintenance of shared mechanical capital.
- Infrastructure investment improving the conveyance, application and quality of water resources from surface water diversion points;
- International compacts for water distribution in the Tigris-Euphrates river system;
- Embedding agronomic and irrigation water extension expertise at extension centers located in closer proximity to key wheat producing regions. The emphasis of these centers is best placed on learning that is multiplied via farmer demonstration.

Each policy is founded on empirical results from the dissertation or the qualitative assessment of the Iraq-Egyptian case study. As an example, the international compacts policy alternative is a result of the example of the Nile River allocation scheme, and the difficulties currently being experienced because of upstream diversions of the Tigris-Euphrates system. Likewise, the investment in extension expertise in agronomic production and agricultural water irrigation draws directly from the relatively high impact coefficients on the science and extension experts per 100,00 people in the quantitative studies, and the Egyptian experience.

Choosing among these alternatives depends importantly on social benefit-cost analysis, as well as an understanding of the existing political capital and political power dynamics. In addition, the feasibility of any policy initiative rests on the existence of policy "levers" that when pulled, can achieve the desired outcome.

A necessary condition for political and economic success of policy initiatives depends importantly on an understanding of relative ease with which policy variables can be influenced. If a policy variable cannot be influenced, then the policy is not feasible. Influence can rest on the ability to control a policy variable with strategic investments. Figure 5 summarizes the ease with which variables considered in this study might be controlled.

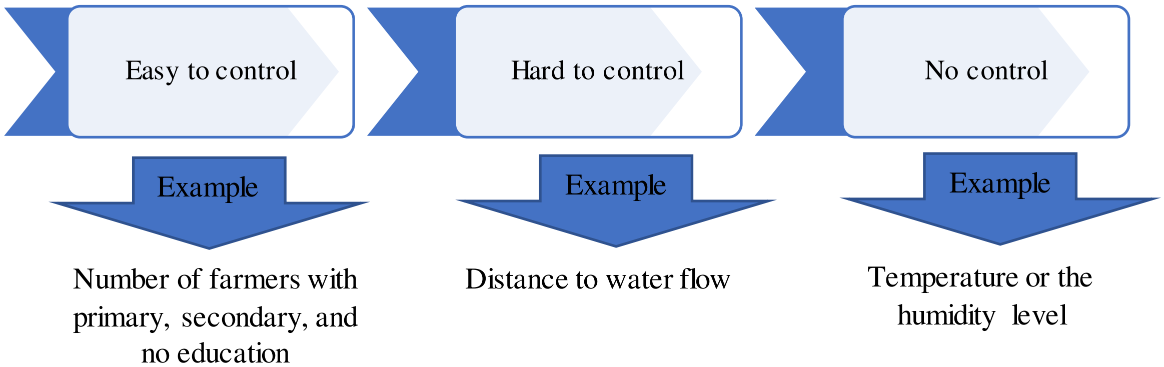


Figure 15. levels of control for sources that explain the difference in TE

Education is an important element of the first policy initiative that focuses on literacy for adults and school aged children. Investments in schools, teachers and associated infrastructure provide a platform or additional educational attainment, and while it is not easy done, the investment needed to control this initiative is relatively minor. It is more difficult to develop, construct and use wisely infrastructure to enhance irrigated wheat production. However, if the distance to surface irrigation can be "shortened" by reducing conveyance and application losses, then social benefits may result. While effects of high temperatures and precipitation shortages can be mitigated by the timing of wheat planting and the use of irrigation, variables that are very difficult to control are increasing the humidity of the growing region and altering the elevation of the same.

Producers can often be the innovators that provide technology transfer to their peers. Peer to peer extension education and local knowledge is the basis behind S. This program had been established with an aim targeting the grants of USDA and outreach programs for farmers (SARE, 2012). A similar program, if it is applied either in MENA countries or in Iraq, elevate human capital by sharing ideas of benefit to wheat farmers, researchers, and educators who want to establish innovation in the wheat industry in terms of farm profitability, water and land protection. SARE Iraq, as SARE US, can form four regional councils where each council has some expert practitioners. The job of those experts is to set priorities targeting each problem in wheat production. SARE Iraq can also conduct a learning center contain a library of publications, information and other educational materials. This approach can adopt the similar techniques to those developed by SARE US where Iraq can give the farmer the money to demonstrate an agricultural activity with a condition that the farmer need to show what he is going to do to another farmer. In some sense, this policy will enable the Iraqi government to treat the farmer as a short-term extension specialist for a little part of what he is doing. This encourages investments in human capital, and it increases the adoption of new technology.

3.7. Limitations

The limitations of this study include the availability of data directly representing the factors wheat productivity such as the soil water holding capacity, growing degree days for the crop, watter application efficiency. Instead, proxies are used for effects, or these effects have been omitted. In this sense, the results should be taken as preliminary, and more sophisticated data collection can assist in improving results so that effective policy analysis may be performed.

As an example, the MENA study is examined using a panel data set. The data is both time varying and spread across many locations. In this instance, certain fixed effects in time or space may not be controlled due to a lack of data. The consequences of the omitted variables are bias estimates. Technical efficiency is derived from the error term in the SFA econometric investigation, so it may be the case that not accounting for fixed effects increases the econometric error, and thus impacts the estimate of (in)efficiency. A cascade effect results, as when TE is regressed on variables, it results in potentially biased estimates from the second stage process.

My committee members have encouraged me to examine the robustness of results in this dissertation using a fixed effect model (FE). This is something that I plan to do in subsequent research that will result in a policy brief and journal article submissions. Generally, in fixed effect model, the following can be observed:

- Group means is fixed comparing to the random effect model where group means are a random sample from the population.
- In fixed effect model, data is according to some observed actors, in our case time and country.

This approach can be applied in the first essay of this dissertation. A future work needs to be implemented comparing the current results already obtained in essay 1 with the results incorporating FE. This will give an insight about the robustness of the results when controlling for certain observable factors. Results will not only be compared on how to interpret signs but also based on the statistically significant factors.

Soil type is an important factor of production in wheat farming, and the soil type can influence yield because it is fundamental in determining nutrient cycling, water infiltration and water holding capacity. Soil data is unavailable for this study, and this is a limitation of the analysis. Future work would be improved through the use of soil maps and soil sampling. One of the limitations of the current study, in the first essay, is the enrollment of the women workforce in the education process came statistically insignificant. As we know that increasing the quality of human capital has its own effect on increasing productive efficiency. In our case, this worth more investigation, probably a study needs to be proposed studying factors affecting enrolment of women workforce in education. It might be related to the cultural pattern in some rural areas where women are only allowed to do certain activities not other ones and the one that they allowed to do is related to work in agriculture not going to school.

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