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Technical efficiency of Iraq's labour market

Haitham S. Jadaan
Faculty of Economic Sciences and Management of Sousse, University of Sousse, Tunisia
Corresponding author email: haitham.alsahi@outlook.com

Imen Ghannouchi
Faculty of Economic Sciences and Management of Sousse, University of Sousse, Tunisia
Email: imenghannouchi92@gmail.com

Anis Bouabid
Faculty of Economic Sciences and Management of Sousse, University of Sousse, Tunisia
Email: anisbouabid@gmail.com

***Abstract*---**The assessment of the Iraqi employment market is highly required since the high level of unemployment rate which achieves 13.74% in 2019 and the economic crisis from which Iraq suffers. Thus, this paper aims to investigate the technical efficiency levels of the Iraqi Labor market by referring to a set of Stochastic Frontier Analysis models (namely time-invariant models and time-variant models developed by Greene (2005)). The sample is decomposed from fifteen regions for the years extended from 2010 to 2013 and 2019 to 2020. The results provide interesting insights such as the low level of efficiency across Iraqi governorates. The results are explained by the geopolitical circumstances and socioeconomic crisis which have a tremendous impact on Iraqi market employment. After assessing the levels of technical efficiency, we turn our attention to panel data analysis of the employment market in which we proceed to Fixed Effect and Random Effect Models. The main results reveal a significant impact of work supply on the employment rate whereas unemployment does not have a significant effect.

***Keywords*--**employment market, Iraq, stochastic frontier analysis, technical efficiency.

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Technical efficiency measuring

The technical efficiency assess the DMU's capacity to fully use its inputs to produce the maximum of output or also. to provide a certain level of output while minimizing its inputs (Atkinson and Cornwell. 1994). The frontier reflects the rational behavior and the best practices of a DMU. Hence. Estimating the technical efficiency levels makes possible to know whether the DMU can increase production without using more inputs, or reduce the use of at least one input while maintaining the same production level. Thus, the efficiency measurement is based on a benchmarking process between the DMU's position and the efficient frontier.

Regarding the tools used in technical efficiency estimation, we find basically the non parametric method Data Envelopment Analysis (known as DEA) and the parametric one known as Stochastic Frontier Analysis (SFA) to compute the scores of technical efficiency. The parametric method (SFA) estimates the technical efficiency via a functional form between the output and the inputs. The non-parametric approach uses linear programming techniques to identify the best practices (Charnes et al.,1995). Indeed, the two fundamental differences between the parametric and nonparametric approaches is the taking into account of random effect in the estimation of technical efficiency and the non-specification of a functional form. In this way, Karlaftis and Tsamboulas (2012) have shown the significance difference between the methods used. and they emphasized that the measurement of efficiency should be done carefully.

Table 1. Main differences between SFA and DEA methods

SFA method	DEA method
Requirement of functional form (Cobb-Douglas. Translog. etc.).	No requirement of any functional form.
It takes into account only a single output.	It takes into account several outputs.
Ability to decompose the stochastic error into an efficiency score and a random term according to a specific distribution.	Efficiency levels are influenced by statistical noise.
Application of statistical tests to verify the robustness of the estimator	No classical assumptions because it is non-parametric method.

Our methodology begins by the application of the SFA approach since it ignores the random error from the technical efficiency scores. This approach was developed independently and simultaneously by Meeusen and Van den Broek (1977) and Aigner et al. (1977). The stochastic frontier analysis overcomes the shortcomings of the nonparametric approach by taking into account the stochastic effect. Likewise, the SFA approach makes it possible to provide quantitative analysis to the model via the study of the random effects of the input variables on the output, which is ignored for a DEA model. Despite its contributions, it should be noted that the SFA does not perform without limits; the major limit is its imposition of a defined functional form and distribution which can be not adequate with the production structure. For the estimation of technical efficiency, we use six models which are divided into two groups, the first group is qualified as panel-data time-varying inefficiency models and the second group as panel-data time-invarying inefficiency models.

At the beginning of its inception, the SFA model has not been dynamic and it has assumed that the term inefficiency is invariant over time. The model specification is expressed as follows:

$y_{it} = \alpha_0 + x_{1it} + x_{2it} + v_i - u_i$ (1)

Pitt and Lee (1981) were the first to extend the model (eq.1) by their proposition of Maximum Likelihood estimation, and the individual technical efficiency can be obtained by employing the JLMS procedure.

Regarding the time-varying models, the maximum likelihood estimation can be applied to estimate time-varying efficiency models. Kumbhakar (1990) and Batesse and Coelli (1992, 1995) were the first to introduce the specification of the time-varying inefficiency effect. In the Kumbhakar (1990) model, time-varying inefficiency is modeled as:

$u_{it} = (1 + \exp(at + bt^2))^{-1}\tau_i$, (2)

$\tau_i \sim_{iid} N^+(0, \sigma_\tau^2)$

while in Battese and Coelli (1992), time-varying inefficiency is specified as

$u_{it} = \{exp[-\eta(t - T]\}\tau_i$, (3)

$\tau_i \sim_{iid} N^+(\mu, \sigma_\tau^2)$

Recently, we find the Greene models family from which we select the true fixed effect and true random effect model. these models of True Effects (True Fixed Effect and True Random Effect) proposed by Greene (2004, 2005) follow the same principle of the Batesse and Coelli (1995) model but differ at the estimation method. In the True Fixed Effect (TFE) model, unobserved heterogeneity is modeled directly into the function using producer-specific dummy variable and estimated via a maximum likelihood method.

$lny_i = a_i + \sum_{k=1}^{K} lnx_{kit} + v_{it} - u_{it}$ (5)

We note that the True Random Effects "TRE" model is similar in motivation to that of TFE; it is stochastic with a constant term expressing a specific producer that is invariant over time. This model is estimated using the simulated maximum likelihood method.

$lny_i = (\beta_0 + w_i) + \sum_{k=1}^{K} lnx_{kit} + v_{it} - u_{it}$ (6)

The contribution of these two techniques lies in their ability to take into account the unobserved heterogeneity of the model and to integrate the impact of non-discretionary factors on the variation in efficiency levels.

$lny_i = \beta_0 + \sum_{k=1}^{K} \beta_k lnx_{ki} + e_i$; $e_i = v_i - u_i$ (4)

Where y_i is the output, x_{ki} is the vector of k input, e_i is the stochastic error term composed of two components: the random bias (v_i) and the technical inefficiency term (u_i).

To extract the inefficiency component from the composite error, distribution assumptions must be proposed for both components. As for the random error, an assumption of normal distribution is assumed. Nevertheless, several distributions are proposed for the inefficiency term, such as the exponential distribution or the half-normal distribution (both distributions were suggested in the original SFA studies), the truncated distribution (Stenvenson, 1980), and the gamma distribution (Greene, 1980). Despite the diversity of distribution hypotheses, studies by Kumbhakar and Lovell (2001) have shown that this wide range of hypotheses does not affect the change in the ranking of efficiency levels in the sense that the results are strongly correlated with each other in term of efficiency ranks and the elasticity parameters.

We apply the models discussed to a set of panel data. The data covers 15 regions for the years extended from 2010 to 2013 and 2019 to 2020, i.e.75 observations. The inputs selected are work supply and Unemployment rate, the output has been measured by the employment rate. Equation 1 is of importance as it provides the technical efficiency levels of employment market in Iraq. x_{1it} and x_{2it} represents the vector of variables transformed in logarithm which are the work supply and Unemployment rate. labor per year per region. respectively. y_{it} is the output presented as the employment rate per year per region. $(v_i - u_i)$ is the stochastic error decomposed into two terms ; $v_i$is the random error which is i.i.d. and $u_i$is the inefficiency term. Table 2 presents a descriptive statistics for these inputs and output.

Table 2. Analysis of descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Yemploy	75	3,612	0,263	3,164	4,445
X1work_supply	75	3,834	0,348	3,165	4,903
X2Un_Employ	75	5,833	0,197	5,242	6,207

The table of descriptive statistics shows a low variance level between the variables of each governorate and a small dispersion in the sample.

Results of the estimation

The main results revealed a positive and significant effect of work supply on employment market, for instance, regarding the tfe model, if the work supply increases by 1%, therefore, the work supply will increases by 0.64% . Nevertheless, the second variable used namely, the unemployment level, shows a negative impact on market employment rate in Iraqi regions .

Table 3: Estimation results via the SFA models

	Time invariant models	Time variant models

Variable	pl81	bc88	bc92	kumb90	tfe	tre
X1work_supply	0.40***	0.39***	0.79***	0.53***	0.64***	0.39***
X2Un_Employ	-0.12*	-0.11*	0.07	0.16**	0.06	-0.12*
_cons	3.16***	3.27***	0.24	0.81**		2.89***
Usigma	0.16**			0.05**	-11.55	-6.89***
Vsigma	0.01***			0.01***	-4.40***	-5.01***

Legend: * p<0.1; ** p<0.05; *** p<0.01.

Table 4: Technical efficiency estimations mean by governorate

Governorates	Mean_tfe	Mean_tre	Mean_pl81	Mean_bc88	Mean_kumb90	Mean_bc92
Baghdad	0.3233	0.0381	0.0222	0.1214	0.0130	0.0436
Basra	0.3228	0.0300	0.2467	0.3841	0.0880	0.0436
Nineveh	0.3420	0.0314	0.1755	0.3171	0.0562	0.0436
Babylon	0.3491	0.0310	0.3635	0.4934	0.1284	0.0436
Wasit	0.3175	0.0329	0.4488	0.5738	0.1900	0.0436
Dhi Qar	0.3771	0.0391	0.3687	0.4989	0.1925	0.0436
Diyala	0.3294	0.0317	0.4038	0.5316	0.1658	0.0436
Kirkuk	0.3281	0.0327	0.4500	0.5737	0.1456	0.0436
Al-Q?disiyyah	0.3143	0.0329	0.4312	0.5579	0.2112	0.0436
Muthanna	0.3279	0.0329	0.5641	0.6826	0.2676	0.0436
Salahalden	0.3173	0.0331	0.4172	0.5442	0.1740	0.0436
Najaf	0.3219	0.0315	0.4328	0.5587	0.1795	0.0436
Karbala	0.3157	0.0319	0.5004	0.6215	0.1905	0.0436
Maysan	0.3184	0.0314	0.4598	0.5851	0.2324	0.0436
Al Anbar	0.3188	0.0328	0.3590	0.4902	0.1751	0.0436
Average	0.328	0.0323	0.376	0.5023	0.161	0.0436

The main results show a low level of efficiency across Iraqian governorates, the results are explained by the economic crisis and geopolitical circumstances. Beyond the slow productivity decrease, there is instability of productivity during the analysis period. This is due to the financial and economic problems which the different market employment suffer, preventing them from improving their performance and satisfying only with the human and technical resources available without any effort to improve the economic development.

Table 5: Technical efficiency estimations mean per year

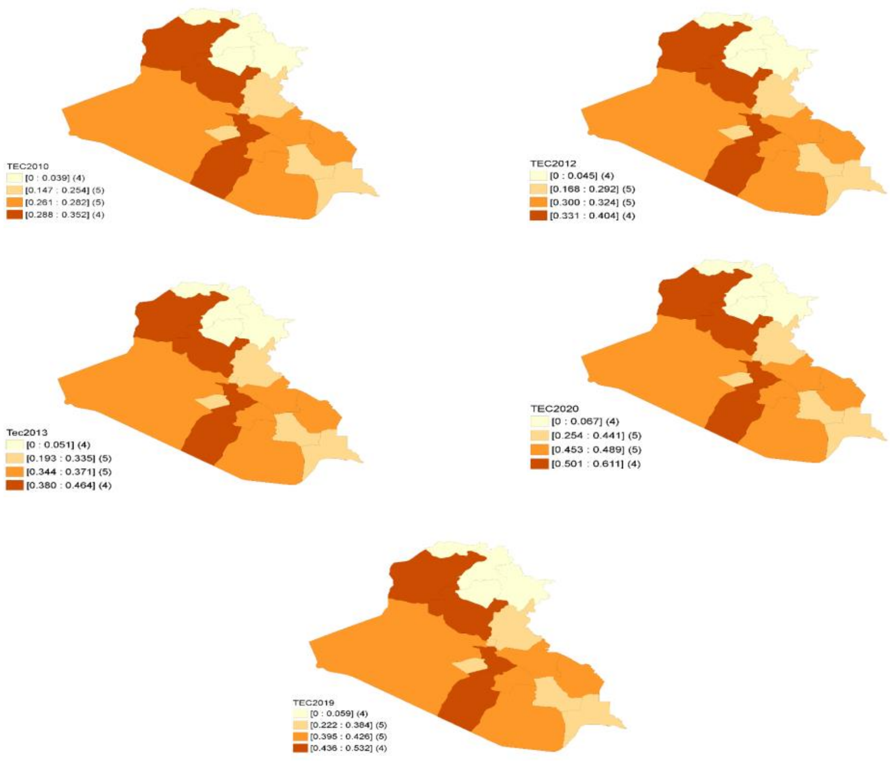
Year	Meanpl81	Meanbc88	Meankumb90	Meanbc92	Meantfe	Meantre
2010	0,3762487	0,5022844	0,0000001	6,19E-34	0,1859489	0,0221065
2012	0,3762487	0,5022844	0,1820918	8,48E-26	0,2383052	0,0361258
2013	0,3762487	0,502284	0,2067488	1,162e-17	0,521327	0,046958

		4			9	8
2019	0,3762487	0,5022844	0,2067488	1,593e-09	0,0000001	0,0274787
2020	0,3762487	0,5022844	0,2067488	0,2182137	0,6956322	0,0317901

This average score of technical efficiency has slowly increased between 2010 and 2020 (Table), we should note that regarding the models pl81 and bc88, the efficiency levels are invariant during the period of analysis. It is noteworthy that an efficiency score equal to 1 indicates that the market employment of the region is technically efficient that is to say it minimizes the exploitation of its inputs in order to produce an output level. While a score less than 1 indicates that the company is inefficient and suffers from over-use of its inputs.

The figure below shows the different evolutions levels of technical efficiency models, we reveal a difference between the six models, the model bc92 shows the lowest level of efficiency estimates, however, the bc88 model show the greatest level of technical efficiency. The tfe model shows instability during the analysis period.

Figure(2): Technical efficiency estimations mean by governorate



Figure(2): Evolution of technical efficiency across Iraqi regions

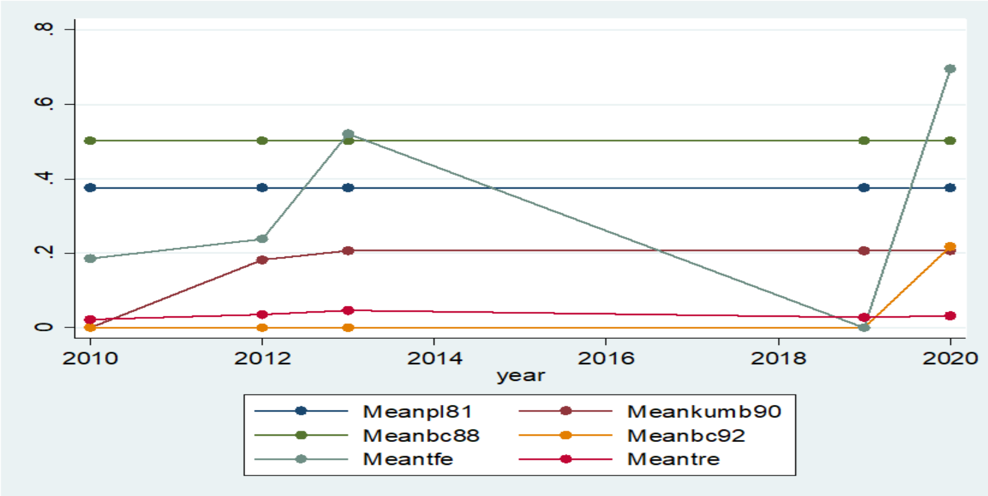


Table : Correlation matrix of technical efficiency estimates

	te_tre	te_tfe	te_pl81	te_bc88	te_kum90	te_bc92
te_tre	1.0000					
te_tfe	0.4648	1.0000				
te_pl81	-0.0697	-0.0112	1.0000			
te_bc88	-0.0766	-0.0099	0.9977	1.0000		
te_kumb90	0.3648	0.2405	0.5516	0.5481	1.0000	
te_bc92	-0.0486	0.7309	0.0000	0.0000	0.2141	1.0000

Panel data estimation

What is the fixed effect model in panel data?

According to Baltagi (2005), the fixed effect (FE) model is obtained while the U_i parameter is supposed to be fixed. That is to say that the remainder disturbances $U_{it}$are distributed identically i.i.d $(0, \sigma_u^2)$. Moreover, Hurlin (2004) explains that while referring to the fixed effect, we need to suppose that the individual effects are constants and are represented by α_i(H1). "This is mainly why it is called the fixed effect model" (Hurlin, 2004).

What is the random effect model in panel data?

To apprehend the random effect (RE) model, we should answer the heterogeneity question among individuals in a panel data. This involves the interpretation of the error component as the sum of two elements: The first component is ε_{it} similar to the one found in the fixed model and a second component which is more specific to the random effect model: This component differs from the rest of components threw the realization of a random variable U_i.

This kind of model can be expressed as follows

$$y_{it} = \alpha + x_{it}\beta + \varepsilon_{it} \quad (7)$$
$$U_i \sim IID\ (0, \sigma_u)$$

The random effect and the OLS

The random effect model is different from the OLS technique regarding the fact that is necessarily constant in the OLS become random.

$$y_{it} = \alpha + x_{it}\beta + \varepsilon_{it} \quad (8)$$

Becomes

$$y_{it} = (\alpha + U_i) + x_{it}\beta + \varepsilon_{it} \quad (9)$$

Econometrically speaking, we suppose that a several factors could affect the explained variable and are not introduced explicitly in the form of explanatory variables. These factors are approximated in the structure of the residual parameter.

Fixed Effects model VS Random effects model :
The econometric literature describes in details both the fixed and random effect model and their applications, the choice between one of them is still uneasy and several researches are always left with the question: which model to choose? a method proposed by Haussmann (1978) is to be considered. Indeed, this method is widely used to assess which model is the more adequate. This method is based on a specification test which will allow to an appropriate and convenient choice of the model. before explaining the concept of this test we need to understand better why do we need it. The ordinary least square estimator (OLS) is not efficient when there is a correlation between the error term and the explanatory variable. The Haussmann test is a specification test that determine if the coefficient of the two estimations, the fixed effects and the random effects, are statistically different. The idea of this test, postulates a hypothesis that the independence between the errors and the explanatory variables is equal to zero. Therefore, both of the two estimators are non-biased.

Let us pose the null hypothesis accordingly as the following

$$H_0 = cov\ (x, e) = 0 \quad (10)$$

Where x: an explanatory variable e: error term

If the null hypothesis is true this means that the least squares and the variables are persistent. However, in the case of panel data which covers a large sample, the difference, between the least squares estimator and the explanatory variable tend to be equal to zero:

$$q = (\hat{\beta}_{OLS} - \beta_{IV}) \rightarrow 0 \quad (11)$$

If the null hypothesis is verified, we can use directly the more efficient indicator is this case which is the least squares estimator. The second possibility is when

$$cov\ (x, e) \neq 0$$

In his case the OLS could not be used anymore, so we obtain

$$q = (\hat{\beta}_{OLS} - \beta_{IV}) \rightarrow c \neq 0 \qquad (12)$$

Several forms of this test exist. One of these forms consists of examining the difference between the least squares and the estimator of the variables. However, simpler forms can be computed easily.

In the following regression, we focus on determining a correlation between x and e.

$$y = \beta_1 + \beta_2 X + \ e_1 \qquad (13)$$

For this we pose a third variable, an ‘’instrumental variable ‘’ for X_i, this will allow us to make the following steps:
-First step: we estimate the model

$$X_i = a_0 + a_i Z_i + v_i \qquad (14)$$

The estimation of this model is made by the Ordinary least squares (OLS), therefore we obtain the residuals on the following form :

$$\hat{V}_i = X_i - \hat{a}_0 - \hat{a}_1 Z_i \qquad (15)$$

We repeat this step for each explanatory variable using instrumental variable in each regression.

-The second step consists of using the residuals obtained in the first step, as explanatory variables in the second regression where:

$$Y_1 = \beta_1 + \beta_2 X + \delta V_i + e_1 \qquad (16)$$

Then we estimate this ‘’artificial regression” by applying an OLS and we use a t-test to formulate the following significance hypothesis:

$$H_0: \delta = 0$$
$$H_1: \delta \neq 0$$

Where the H_0hypothesis reflects that there is no correlation between x and e and where the H_1 hypothesis rejects any correlation between X and e.

We need to highlight that the t-test is valid if there is one explanatory variable. In the case when there are many explanatory variables, the adequate test is a Fisher Test (F-test)

To conclude, we can simplify the notion of the Haussmann test by assuming that the Haussmann test could be easily apprehended under the null hypothesis that postulates an independence between errors and explanatory variables. Therefore, the Haussmann test compares the two variance-covariance matrixes of the two presupposed unbiased estimators, this could be modeled under the above equation:

$$W = \left(\beta\hat{b} - \beta\hat{a}\right)' var\ (\beta f - \beta\hat{a})^{-1}(\beta f - \beta\hat{a}) \qquad (17)$$

The result of this comparison, follows a κ^2 law with a $K-1$ degree of freedom.
Empirical results of panel data analysis:
we turn our attention with panel models estimation, therefore, we referred to OLS, fixed effect and random effect models. At this step of procedure, the same sample will be used and to check the optimal model we will apply the Hausman specification test for Endogeneity.
A panel data works with both temporal and cross section data, that is to say the variables used are submitted both to the cross section and time approaches. The model specification is explained as follows:

$$Y_{it} = \alpha + X'_{it}\beta + U_{it} \qquad (18) \qquad i = 1,..,N\ ;\ t = 1,..,T$$

i: is the individual data representing the cross section element. $i = 1,..,N$
t: representing the time element.
α : is a scalar, representing the constant parameter.
β is $K \times 1$: coefficients of exogenous variables.
X_{it} is an observation being a particular time t and concerning an individual i , on K explanatory variables.

Empirical results of Panel data models

Variable	ols	fe	re
X1work_supply	0.64***	0.35***	0.64***
X2Un_Employ	-0.03	-0.13*	-0.03
_cons	1.32***	3.01***	1.32***

Legend: * p<0.1; ** p<0.05; *** p<0.01.

The main results show a significant and positive impact of wok supply on employment rate, however, the second variable unemployment rate have a negative impact but not significant under the ols and re models. The constant parameter shows a positive and significant effect on employment rate, that is to say there is a set of implicit variables that could affect the employment market but they are not included into the model.

The Hausman test results reveal a probability equal to 0.000 that is to say we reject the null hypothesis which would mean the two models are systematically different, and therefore we will select the fe model estimation.

Table : Estimation results of panel models

Coefficient				
(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))	
	re	Fe	Difference	S.E.
X1work_sup ~y	0,6443347	0,353192	0,2911427	0,0239263
X2Un_Employ	-0,031395	-0,1283143	0,0969193	0,0495661
b = Consistent under Ho and Ha; obtained from xtreg				

B = inconsistent under Ha, efficient under Ho; obtained from xtreg
Test: Ho: difference in coefficients not systematic
chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 189.24
Prob>chi2 = 0.0000

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