Efficiency of Listed Manufacturing Firms in Jordan: A Stochastic Frontier Analysis

Lamees Al-Durgham[1,2]*, Mohammad Adeinat[3]

[1]Department of Industrial Engineering, School of Engineering, University of Jordan, Amman, Jordan, [2]Department of Business Economics, School of Graduate Studies, University of Jordan, Amman, Jordan, [3]Department of Business Economics, School of Business, University of Jordan, Amman, Jordan. *Email: l.aldurgham@ju.edu.jo

ABSTRACT

This study examines the technical efficiency of the manufacturing firms listed in Amman Stock Exchange market (ASE) in Jordan over the period 2009-2017. The stochastic frontier approach was used to measure the efficiency. The results show that the firms have an overall efficiency of 74%, means that the firms wasted about 26% of their inputs. Among the firms, (RMCC) has the highest averageefficiency of (90%) witha standard deviation of (0.06) over the period of the study, and (IPCH) has the lowest average efficiency of (26%)with a standard deviation of (0.38) for the same period.

Keywords: Efficiency, Manufacturing Firms, Stochastic Frontier Analysis, Panel Data
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1. INTRODUCTION

Manufacturing firms in Jordan play an important role in economic development, so it is important to asset the performance of these firms. Efficiency is considered as one of the most important performance measures. This paper contributes to the literature by measuring the efficiency of the manufacturing firms listed in ASE using stochastic frontier approach.

The production function is a tool to determine the relationship between the involved resources and obtained products during the production process. This makes it possible to designate in advance the level of workforce and physical capital resources in relation to the desired production level at a given time. (Rybak and Rybak, 2016). Production function describes the transformation of a set of input into output. If a production function is estimated using the ordinary least squares (OLS), the estimated production function is the average production function. On the other hand, if we use a stochastic frontier model, the estimated production

function can be interpreted as the production possibility frontier. The stochastic frontier model is useful for empirical studies based on economic models, since the production function usually assumed in microeconomics is the production possibility frontier (Tsukamoto, 2019). The empirical use of micro data, i.e., data on individual firms, should shed light on the usefulness of the stochastic frontier production function (Lee and Tyler, 1978).

The efficiency of a production unit can be defined as the ability to obtain the maximum amount of output given the input and the technology used (Albert, 1998). There are two basic techniques which can be used for measuring efficiency which is parametric and non-parametric. One of the parametric efficiency measurement techniques is the Stochastic frontier approach (SFA) which was first proposed by Aigner et al., 1977, Meeusen and van den Broeck, 1977.

In their work (Aigner et al., 1977) proposed a model within which observed deviations from the production function could

arise from two sources: Productive inefficiency, and idiosyncratic effects.

In literature the stochastic frontier analysis was performed in different areas includes manufacturing firms (Castiglione and Davide, 2014), (Hailu and Tanaka, 2015), (Dietrich, 2010), (Le et al., 2018), metal-based durable manufacturing sector (Boyd and Lee, 2019), iron and steel firms (Filippinia et al., 2020), Furniture Manufacturing (Hamdan et al., 2019). Also the SFA was applied in agricultural economy (Saiyut et al., 2017), (Benedetti et al., 2019), and its different areas include for examples; honey production (Alropy et al., 2019), Grain production (Song and Chen, 2019), Diary farm production (Baležentis and Sun, 2020), Forestry industry (Chen et al., 2017). Other applications for SFA includes: banking system (Hasan et al., 2012) electricity distribution businesses (Anaya and Pollitt, 2017), Energy efficiency (Adom et al., 2018).

Various studies on the measurement of firms' efficiency with the utilization of stochastic frontier are briefly summarized in the following paragraphs.

Lee and Tyler, 1978 applied the stochastic frontier production function on a cross sectional data from Brazilian manufacturing fims, the Maximum likelihood technique was used in this study. Gong and Sickles, 1992 used two techniques, namely: Stochastic frontier models and data envelopment analysis to estimate firms efficiencies for a set of panel data. For the stochastic frontier approach the authors used three estimators: Maximum likelihood random effect, generalized least squares random effect, and within fixed effects. The results of the study revealed that among the three estimators of the stochastic frontier the within fixed estimator is the preferred one. The results also indicates a comparison between the results of DEA and SFA techniques (Albert, 1998) used the stochastic frontier approach to analyze the efficiency of the Spanish regions over the period (1986-1991), the authors used different distributional assumptions (half normal, truncated normal, and exponential) to estimate the efficiency (Chapelle and Plane, 2005). Applied the stochastic frontier approach on a cross sectional data in four manufacturing sectors of the Ivorian economy, the four sectors are textile and garments, metal products, food processing, wood and furniture. In this work the stochastic production function and the efficiency were estimated. The authors also studied various exogenous variables that affect firms efficiency. In the work of (Margono and Sharma, 2006) the stochastic frontier model was used to estimate the technical efficiencies and total factor productivity growths in food, textile, chemical and metal product industries in Indonesia from 1993 to 2000, they also analyzed the determinants of inefficiency. Dietrich, 2010 studied the impact of efficiency of profitability, they used a panel data for 11728 manufacturing firms in UK, the stochastic frontier method was used in the study to estimate firms efficiencies. In their work (Hailu and Tanaka, 2015) used two models the first one is the true random effects stochastic frontier model and the second is the conventional fixed and random effects model to estimate

efficiencies for aggregated and individual industry groups using a panel data from Ethiopian manufacturing sectors over the period of 2000-2009. They found a significant gap in efficiency estimates between the two methods. The result indicated that the efficiency estimates are sensitive to model specifications of firm-specific unobserved heterogeneity. Hamdan et al., 2019 used the stochastic frontier analysis to measure the efficiency level in furniture manufacturing industry in Malaysia and analyzing the technical inefficiency factor to improve firm's efficiency. Lai and Kumbhakar, 2018 used the stochastic frontier panel data model, for 40 economies over the period 1995-2006, in which the random firm-effects are separated from the persistent and transient technical inefficiency. The authors derived formulas to estimates the two types of efficiency. The simulation results indicated that as the sample size increases the biases and the mean square errors decreases. Le et al., 2018 used a stochastic meta frontier model to estimate technological gaps and identifies factors affecting variations in the technical efficiency of small and medium manufacturing firms in Vietnam using firm-level survey data in 2008. Paul and Shankar, 2020 proposed a stochastic frontier model that includes time invariant unobserved heterogeneity. They applied the model on a set of panel data from Indian farmers.

2. METHODOLOGY

In this study a stochastic frontier production function (SFPF) was used to estimate technical efficiency levels for 35 listed manufacturing firms in Jordan.

The stochastic frontier production function is defined as

$$y_{it} = A L_{it}^{\beta_1} K_{it}^{\beta_2} e^{V_{it} - U_{it}} \tag{1}$$

y_{it}: the production for firm (i) in a period (t).
L_{it}: Labor of firm (i) in a period (t)
K_{it}: Capital of firm (i) in a period (t)
β_1: Labor elasticity
β_2: Capital elasticity
$V_{it} - U_{it}$: Is the error term in the linear transformation form of the model

The linear form of this function is given by

$$\ln y_{it} = \ln A + \beta_1 \ln L_{it} + \beta_2 \ln K_{it} + V_{it} - U_{it} \tag{2}$$

Or

$$\ln y_{it} = \beta_0 + \beta_1 \ln L_{it} + \beta_2 \ln K_{it} + V_{it} - U_{it} \tag{3}$$

Where
$\beta_0 = \ln A$: Is the constant term in the linear model
β_1 and β_2 are coefficient to be estimated (which were defined above as elasticities).

The error term in equation 3 which is $V_{it} - U_{it}$ composed of two components, the first is the (V_{it}) which is the noise component that

could enter the model with either signs; this component is almost always consider as a two-sided normally variable; and the second is the (U_{it}) which is nonnegative terms, and can be used to estimate the technical efficiency or (technical inefficiency).

Dietrich, 2010 mentioned that for a panel based analysis two possible stochastic frontier models can be estimated: A time-invariant efficiency model which is equivalent of fixed effects estimation, and a time varying efficiency model, the equivalent of random effects estimation. The time varying efficiency model is given by equation 3 above, while the time invariant efficiency model is given by equation 4

$$\ln y_{it} = \beta_0 + \beta_1 \ln L_{it} + \beta_2 \ln K_{it} + V_{it} - U_i \tag{4}$$

The idea of the stochastic frontier approach is that the error term consists of two components V_{it} and U_i; the first is the random error component represents the noise while the latter is a measure for the loss of efficiency or a measure for inefficiency in the production function due to technical inefficiency. These two components have different distributions, the noise term V_{it} is normally distributed with mean zero and variance σ_v^2 and is denoted as $V_{it} \sim N(0, \sigma_v^2)$. The inefficiency term U_{it} is a nonnegative random disturbance term assumed to follow either the exponential distribution, or the half normal distribution (which is a normal distribution truncated at zero) with variance of σ_v^2. When the term U_{it} equal zero means that the firm will produce its optimal output with the given input.

In stochastic frontier model with out-put oriented, inefficiency term U_i represents the log difference between the maximum attainable output and the actual output $U_{it} = ln y_{it}^* - ln y_{it}$

The inefficiency term is then $e^{-U_{it}} = \dfrac{y_{it}}{y_{it}^*}$ (Gordana et al., 2016). According to (Suyanto et al., 2014) the measure of technical efficiency (TE_{it}); calculated from equation 4; for firm i in any period , is the ratio of the observed output of the firm to its potential maximum output, in notations $TE_{it} = \dfrac{y_{it}}{y_{it}^*} = e^{-U_{it}}$. This measure of technical efficiency is equivalent to the ratio of the production for the ith firm any period the corresponding production value if the firm effect was zero (Battese and Coelli, 1988).

An important parameter to decide whether there is technical inefficiency or not in the model is θ. This parameter represents the percentage of the total variance explained by the inefficiency term, in other word it represents the ratio between the variance of the inefficiency term to the total variance of the model ($\sigma_v^2 + \sigma_u^2$) which can be written as:

$$\theta = \frac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2} = \frac{\lambda^2}{1 + \lambda^2}, \text{ Where } \lambda = \frac{\sigma_u}{\sigma_v} \tag{5}$$

If the estimated value of θ is not statistically significant, there is no technical inefficiency and the results obtained from estimation the production function by ordinary least square OLS would be efficient.

3. THE DATA AND VARIABLES

This study uses the panel data for 35 manufacturing firms listed in Amman Stock Exchange (ASE) Market over the period 2009-2017. The sample includes firms from different manufacturing sectors, namely; pharmaceutical and medical industries, chemical industries, food and beverages, paper and cardboard, printing and packaging, tobacco and cigarette, textile leather and clothing, engineering and construction. The data was collected from the annual reports of these firms.

The production function describes the relationship between output and production inputs, in this study a single output and two inputs are used in the study. The relationship between inputs and output is assumed to follow Cobb-Doughlas function.

3.1. Labor (Input Variable)
Different measures have been used in literature as a measure of labor input, examples are: The number of employees directly and indirectly engaged in production (Suyanto et al., 2014), the number of workers multiplied by working hours per capita (Tsukamoto, 2019), the total employee mans-year (Lee and Tyler, 1978), employment (Kutlu et al., 2020), the total number of workers (Hamdan et al. 2019), the number of employees (Dietrich, 2010), the Number full-time equivalent (FTE) employees (Le et al., 2018), the valued of total wage payments and man months of labor provided (Pitt and Lee, 1981), Wages which is the total wage bill, including all allowances for the firm in the year (Lundvall and Battese, 2000). In this study the total number of employees is used as a measure for the Labor.

3.2. Capital (Input Variable)
Different measures have been used as a proxy for the capital input, namely: Total fixed physical capital in money term (Lee and Tyler, 1978), value of tangible fixed assets other than land (Tsukamoto, 2019), the replacement value of Capital (Suyanto et al., 2014), the net book value of the property, plant, equipment under the non-current assets of the Balance Sheet (Majumdar and Asgari, 2017), the replacement cost of existing machinery and other equipment employed in the production process, corrected by the degree of capacity utilization (Lundvall and Battese, 2000) the net value of fixed assets at the end of the survey year (Hailu and Tanaka, 2015), total assets (Dietrich, 2010) and (Le et al., 2018). The noncurrent asset is used in this study for the capital input.

3.3. Output
For the output measure (Hamdan et al., 2019) uses total output, (Suyanto et al., 2014) and (Lundvall and Battese, 2000) use the total value of output produced by a firm, the former refers to this as the gross output. Other authors use the revenue for the output examples are (Le et al., 2018), (Castiglione and Davide, 2014) and (Dietrich, 2010), in other works the value added was used as measure of output (Tsukamoto, 2019), (Pitt and Lee, 1981), other authors used the sales as a proxy for the output (Lee and Tyler, 1978), (Kutlu et al., 2020), (Majumdar and Asgari, 2017). This study uses the sales as a measure for the output.

4. RESULTS

The true fixed effect model was used in this study for two reasons: the first one is according to applied econometrics and as a rule of thumb since the number of firms (cross sections) is greater than the number of periods of times (years) in notation (n>t) the true fixed effect is the appropriate model. The second reason is Hausman test, the test was applied on the data and it is found the fixed effect is the appropriate model. Assuming that the efficiency term (u) follows the half normal distribution, then the result of the estimated model is shown in Table 1:

$$\sigma_u = 0.6758411, \text{prob} = 0.000$$

$$\sigma_v = 5.5o10^{-9}, \text{prob} = 0.996$$

To do the diagnostic check, and according to the true fixed effect model $\theta = \dfrac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2} \approx 1$ this means that technical inefficiency accounts for approximately 100% of variation in the model, which support the use of the stochastic frontier model.

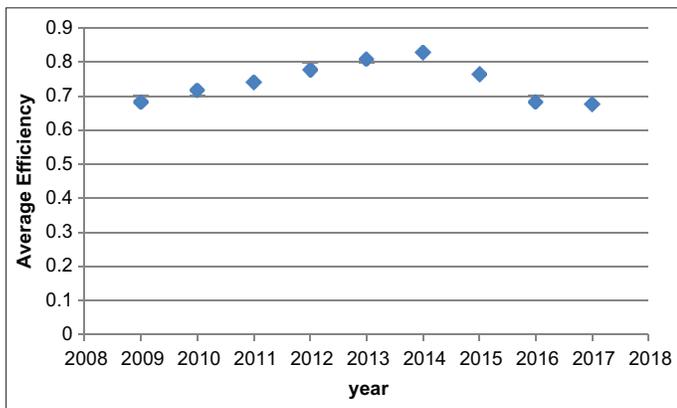**Figure 1:** Average efficiency scores over the firms

Table 1: Stochastic frontier model (true fixed effect)

Variable	Coefficient	Probability
Ln (Labor)	0.7697109	0.000
Ln (capital)	0.1766071	0.000
u	0.7835947	0.000
v	−38.0217	0.925

σ$_u$=0.6758411,prob=0.000; σ$_v$=5.5×10^{-9}, prob=0.996

Table 2: Summary of average technical efficiency via exp(−(E(u⁄e))

Year	Mean	Standard deviation	Freq
2009	0.68209532	0.27619146	35
2010	0.71552674	0.24027769	35
2011	0.73991128	0.21699955	35
2012	0.77673649	0.21627834	35
2013	0.80870628	0.14755094	35
2014	0.82655913	0.19733921	35
2015	0.76377675	0.23174145	35
2016	0.68270811	0.23477572	35
2017	0.67622538	0.25503266	35
Total	0.74136061	0.2300174	315

The model also calculate an efficiency score for each firm in each year. Table 2 and Figure 1 summarize the results for the average efficiency for each year over the 35 firms.

It is clear from the results that the firms have an average efficiency of (74.13%) and the values of the average efficiency increases for the period (2009-2014) then the values decrease for the period (2014-2017). the standard deviation values show ranges between (0.14 and 0.27) which depicts large variability in efficiency values between the years.

In order to compare between firms efficiencies, we calculated the average efficiency for each firm over the period of the study (2009-2017). The results are in Table 3.

The results show that (RMCC) firm has the highest average firm efficiency of 90.3%, with a standard 0.06. over the period of the study. On the other hand IPCH firm has the lowest average value of efficiency over the same period. The table also shows the rank of the firms according to efficiency average values.

Table 3: Summary of technical efficiency via exp(−(E(u⁄e))

Firm ID	mean	Standard deviation	Freq	Rank:1:highest; 35: lowest
AALU	0.85998219	0.14342407	9	5
AEIN	0.67683856	0.27593563	9	29
AIFF	0.64022638	0.31143809	9	30
ARWU	0.84516318	0.17369138	9	9
ASAS	0.8662701	0.07681949	9	4
ASPMM	0.76628378	0.12387552	9	18
DADI	0.76359864	0.1151	9	20
EICO	0.67881628	0.22046061	9	28
EKPC	0.83476361	0.17476105	9	10
ELZA	0.71187177	0.16108083	9	25
GENI	0.84795407	0.10548618	9	7
HPIC	0.75605785	0.17129484	9	21
ICAG	0.5275168	0.28271713	9	33
IPCH	0.26136759	0.38007336	9	35
JODA	0.78566232	0.11136531	9	14
JOIC	0.7641923	0.18169178	9	19
JOIR	0.53834638	0.343576244	9	32
JOIP	0.78041687	0.20224355	9	16
JOWM	0.87604049	0.06430024	9	3
JPHM	0.73691859	0.1674612	9	23
JPPC	0.7435023	0.22221875	9	22
JVOI	0.68093692	0.13240233	9	27
MDED	0.84556024	0.1225757	9	8
NATA	0.76836005	0.13626273	9	17
NATC	0.71630919	0.17003428	9	24
NATP	0.82738841	0.11516923	9	11
NCCO	0.85649797	0.13447888	9	6
NDAR	0.69660593	0.17785773	9	26
PHIL	0.49133409	0.29855283	9	34
RMCC	0.90334266	0.0680444	9	1
UCIC	0.79081451	0.27749102	9	13
UMIC	0.884855	0.12422283	9	2
UTOP	0.61134447	0.26633363	9	31
WIRE	0.82330294	0.9333678	9	12
WOOD	0.78477885	0.10061236	9	15
Total	0.74136061	0.23001714	315	

5. CONCLUSION

This study estimates the efficiency of Jordanian Listed manufacturing firms in Amman Stock Exchange during the period 2009-2017, the parametric stochastic frontier approach was used on the panel data of 35 firms. The technical inefficiency term is assumed to follow the half normal distribution. Is it found that the firms have an average technical efficiency of 74%, which means that the firms wasted about 26% of the inputs. The average efficiency score was calculated for each firm over the period of the study, and then the firms were ranked according the efficiency scores. Among the 35 firms, the firms: (RMCC, UMIC, and JOWM) have the highest efficiencies with values of 90.3%, 88.5%, 87.6% respectively. On the other hand the firms: (IPCH, PHIL, ICAG) have the lowest efficiencies with values of 26.1%, 49.1%, 52.8% respectively. The study also calculated the average efficiency for each year and revealed that the values of the average efficiency increases for the period (2009-2014) from 68.2% to 82.7% then the values decrease for the period (2014-2017) from 82.7% to 67.6%.

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