The Dynamics and Sources of Technical Efficiency of the Manufacturing Industries in Bangladesh

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The Dynamics and Sources of Technical Efficiency of the Manufacturing Industries in Bangladesh

Sheikh Jafar Emran^{1*} and Md. Moniruzzaman²

Abstract:

This paper aims to analyze the dynamics of technical production efficiency of the manufacturing sector in Bangladesh using the cross-sectional data collected under the Survey of Manufacturing Industries (SMI) conducted in 2006 and 2012. Based on the dynamics of mean efficiency scores among the industries derived using Stochastic Frontier Analysis(SFA) technique with Cobb-Douglas technology with half-normal distribution during the considered period three most efficiency gainer industries are ((i) Jute textile, (ii) Dying and bleaching of textiles, and (iii) Bidies respectively. On the other hand, under SFA specification with Translog production function top three efficiency gainers are (i) Jute textile, (ii) Bidies, and (iii) Fish, Crustaceans and Molluses respectively. Under constant returns to scale in Data Envelopment Analysis(DEA), based on the mean efficiency score top three efficiency gainers are (i) Fibre textile, (ii) Embroidery of textile and apparel, and (iii) Wooden furniture and fixture respectively while under variable returns to scale top three gainers are (i) Fibre textile, (ii) Embroidery of textile and apparel, and (iii) Wooden furniture and fixture respectively. Whatever technique we employ, we find that most cases garments or garments related industries remain among top performers in terms of efficiency gain. This indicates that garments industries have improved significantly in terms of efficiency to survive in world competition. Moreover, our results suggest that firm characteristics, location factors as well as ownership features are more important jointly rather than individually to enhance efficiency. Locational and ownership characteristics jointly, in most cases, are also not so influential in pulling the efficiency measures up. However, the firm characteristics are very important in raising the technical efficiency of the firms, especially in case of stochastic frontier analysis. And firm characteristics shows stronger impacts in interaction with other locational and/or ownership characteristics.

Key Words: Technical Efficiency, Stochastic Frontier, Data Envelopment Analysis, Manufacturing Industries.

GEL Classification: D22, D24, L52 & L6

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Introduction:

Bangladesh economy is characterized by lower industrial sector contribution. The share of industrial sector in GDP in 1971 was 8.7% and after 45 years of independence it has increased to 28.8% in 2016 (WDI, World Bank). Our industrial development is characterized by lack of policy consistency (first import substitution then export orientation), proper industrial planning (prioritizing agriculture and then other sectors), poor capacity expansion (backward and forward linkage), ownership crisis (nationalization then privatization) and biased concentration (focusing on single industry rather than multiple). At present industrial sector is heavily dependent on garments manufacturing and still exploiting the advantage of unskilled labor force. In recent years Bangladesh economy has adopted more liberal trade policy, therefore, it is exposed to greater internal and external competition. We all know, competition does not come alone rather it brings efficiency together. Tariff walls worldwide has become weaker and thinner, has posed local firms more unprotected than before. Therefore, one way to expand the production in both local and foreign market is to become more efficient. However, efficiency concern remains for those industries that are strategic, non-traditional and late movers.

Technical efficiency represents the efficacy of a production process by ensuring the maximum possible output given the set of inputs and technology with reference to the production function. Thus, technical efficiency can be estimated as a proportion of most effective production unit within the given sample. In this way, technical efficiency illustrates efficient resource mix to maximize output. It is calculated as ratio of actual output from the given output to the maximum possible output from given input while technology remain fixed. Similarly, technical efficiency can be identified as measures of efficiency based on quantity and often represented in technology distance functions (Chambers et al.,1996). There are many parametric and non-parametric attempts to estimate technical efficiency using multiple inputs without imposing restriction on functional form (Aigner et al., 1977; Charnes et al.,1978). But the identifying the sources of efficiency or inefficiency is not sufficient, rather understanding the symbiosis between factors those contribute to efficiency is equally important. In this ground, our paper attempt to identify the joint significance of the factors those are responsible for technical efficiency.

Basically, technical efficiency analyzes costs and scrutinizes production frontiers (Farrel, 1957). Efficiency identified on the basis of position of any production plan compare to efficient production plan or frontier. There could be many sources of efficiency or inefficiency related with different aspects or attributes of production process. Firm specific attributes, industry specific attributes or attributes related with production environment that are external to firm could affect the efficiency of firms (Page, 1980).

There has been the surge of two popular methods to analyze the sources of technical efficiency based on stochastic production functions. The first method is a two-stage estimation process that estimates stochastic production function in the first stage with efficiency score. In the second stage that efficiency scores are regressed using various explanatory variables. Second method is a one-step simultaneous equation method where efficiency effects are reflected on explicitly on firm specific variables.

The primary objective of this paper is to evaluate the technical efficiency of Bangladeshi manufacturing firms over the years along with identifying the factors that are most relevant for firm efficiency of the manufacturing sector of Bangladesh. Our aim is restricted to some specific years due to unavailability of data. In fact, we have attempted to estimate technical efficiency of various manufacturing firms in 21 selected industries, using Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA), for the years 2005-2006 and 2012. We also try to identify the sources of those efficiency measures in terms locational, ownership and firm characteristics of the manufacturing firms.

This paper has five broad sections. Introduction will be followed by relevant literature reviews. After that our methodology section outlines the data and model. Our result section presents dynamics of technical efficiency and sources of technical efficiency using our model. Our paper concludes by connecting conclusion with possible policy implications.

Literature Review:

Plethora of literatures has produced to capture the productivity measurement of various industries of various countries. The development of efficiency measurement is not new, it has started from seminal article of Farrell (1957). It leads to further flourish and development of various methods and techniques to measure efficiency and productivity. Two prototype contributions of efficiency measurements are stochastic frontier method (Aigner, 1977; Meeusen, 1977) and data envelopment analysis (DEA) (Charnes et al., 1978), where stochastic frontier is a parametric method while DEA is non-parametric method.

Frontier techniques to measure efficiency have certain strengths as well as limitations. This techniques has been discussed in detail and applied by many researchers to measure the productivity of agriculture (Battese, 1995; Førsund, 1980; Bauer, 1990; Seiford, 1990 and Bravo-Ureta, 1993). Stochastic frontier model has superiority in the sense that it handles stochastic noise. Stochastic frontier model suffers from the need of tagging an explicit functional form for the relevant technology and specifying the assumption on distribution for the inefficiency are the two most significant limitation of the stochastic frontier model. On the other hand DEA suffers from measurement error and its overly deterministic.

The objective of our paper is to estimate the technical efficiency of various manufacturing industries of Bangladesh with the help of stochastic frontier model and data envelopment analysis as well as identify the factors that are causing that efficiency. While stochastic frontier Cobb-Douglas model exhibits constant returns to scale, output oriented data envelopment analysis displays variable returns to scale. Technical efficiency results obtained from both models are comparable because both techniques readily compare observed production with regards to potential production.

The combination of a deterministic component (firm specific characteristics) and a random component (error) is considered as technical efficiency. Size of the firm, level of education of the worker etc. often affect technical efficiency or productivity (Kumbhakar, 1991).

Glut of works have been done in many countries for both cross section and panel data to estimate technical efficiency in many fields. For example, stochastic frontier model has been applied to estimate technical efficiency in US dairy firms (Kumbhakar, 1991) while both models have been employed to estimate efficiency in swine industry of US (Sharma, 1997). By using the data of French Census of Manufacturing Industries efficiency scores have been estimated and the results show that average sectoral efficiency varies between 0.70 and 0.94 in various industries (Meeusen, 1977).

In case of choosing among methodologies to estimate productivity heterogeneity in factor prices, error from measurement and dissimilar production technology plays very important role (Van Biesebroeck, 2007). Specifically, when measurement errors are non-negligible then parametric methods like stochastic frontier, instrumental variable (GMM) or semiparametric estimation provide better results.

Using panel data of the tea industries of Bangladesh it has been found that 49% of productive efficiency is due to technical efficiency and there exists a negative relationship existed between farm size and yield (Baten et al., 2009). By using the data of crop firms of Bangladesh it has been claimed that productivity varies widely among firms (Rahman, 2012). Large firms have highest productivity while gross return is highest in small firms as evidenced from the aforementioned studies. Additionally, age, education and family size have positive effect on efficiency as these studies claim. By analyzing production of 240 agricultural farms of Bangladesh it has been argued that there is 18-23% scope to increase production efficiency with existing input and technology (Theodoridis, 2011).

On the other hand another set of literatures focused on identifying the factors those are most relevant for firm efficiency. Technical efficiency can be related with firm specific attributes as well as industry specific attributes. Industry specific attributes, size and location of the farm together can explain approximately two-third of variation of efficiency. On the other hand, ownership structure, legal status, age of the firm, backward linkage and R&D have a lower efficiency explanatory power than presumed (Badunenko et al., 2006).

Firm size is considered one of the most crucial factor of firm efficiency and positively related with efficiency. The existence of imperfect market structure, economies of scale and market power are closely related with firm size (Page, 1984).

The three most substantial factors that potentially determine firm's efficiency are ownership, age and size (Pitt and Lee, 1981). Experience of workers, modernization and innovation affect the efficiency positively while internationalization, education of owner do not have any visible impact on efficiency as shown by using Chilean manufacturing firm data (Alvarez and Crepsi, 2003). On the other hand, external factors like market competition, utilization of productive capacity, attaining the public fund, size, organization and location of the firm are found to efficiency booster compared to prior factors (Gambau-Albert & Maudos, 2002).

In case of agriculture socio-economic factors like land owning, institutional factors like credit access, demographic factors like no of household members, environment of the vicinity like presence of manufacturing firm, environmental factors like dry region are presumed to related with efficiency (Solis et al., 2009). Firm specific variables like land size, age of the farmers and education of the farmers along with time are positively related with technical inefficiency and presumed to allow us to estimate time varying technical efficiencies (Coelli & Battese, 1996). Though educational level of farmers, household size and per capita income are found to have positive impact on technical efficiency, non-farm employment is found to have negative impact on production efficiency (Wang et al., 1996).

But most of the researchers evidences have been derived from the statistical significance of single factors while we think the scope of improvement lies. Instead of focusing on the statistical significance of single factor, our paper focuses on the significance of joint factors. Because single factor may not be sufficient to explain the efficiency alone. However, joint factor can overlay the overall relevancy of interdependence and symbiosis among factors in explaining technical efficiency.

Despite some of the works have done in Bangladesh for agricultural farms but very few works have done for industrial sector. But empirical exercises for manufacturing industries are available for other countries. Using the evidence from tea garden it has been found that technical inefficiency has weakened over the reference period. It is evident from the result that truncated (at zero) normal distribution is better than the half normal distribution for the technical inefficiency effects (Baten et al., 2009). These results suggest that technical efficiency rate has been improving gradually in Bangladesh.

Since the very few literatures related with technical efficiency manufacturing firms in Bangladesh, this paper attempts to estimate the technical efficiency with the help of both parametric and non-parametric estimation techniques. Moreover, we have identified the sources of technical efficiency and evaluated their joint significance. The contribution of this paper lies mainly in the identification of the sources of technical efficiency not only

individually but also interdependence among factors that are conducive for technical efficiency. Last but not least, our model to explain the sources of efficiency is comprehensive as we introduced firm characteristics, geographical factors as well as ownership features. Thus, this paper is more inclusive as well as innovative to explain the overall technical efficiency and its sources for manufacturing firms of Bangladesh.

Methodology

Sampling and Data

The purpose of this paper is to analyze the technical production efficiency of the manufacturing sector in Bangladesh using the cross-sectional data collected under the Survey of Manufacturing Industries conducted in 2005-2006 and 2012. Analyzing the data of two cross section surveys will help us to produce a dynamic analysis regarding the technical efficiency of the manufacturing sector in Bangladesh during the span of 6-7 years.

Under the SMI surveys 5868 industrial firms are surveyed in 2005-2006 while the number rises to 8433 in 2012. Both surveys comprise of all types of manufacturing industries namely Large, Medium, Small and Micro industries with 10 workers or more and provide the reliable data on production, sales and earnings of the firms in the manufacturing industries at national level. To ensure the coverage of all types of manufacturing industries, the surveys were conducted based on the business register (manufacturing sector) and stratification following the size class on the basis of the persons employed defined in the National Industrial Policy and number by BSIC at 4-digit level.

In order to implement this current research, we select industries and firms based on two criteria: (i) there must be at least 20 firms surveyed each year in each industry, (ii) consider only those industries/firms for whom the four-digit Bangladesh Standard Industrial Classification (BSIC) code matches across the year so that we can compare efficiency across the years. These two criteria finalize the 21 industries for both the years with 2468 firms in 2005-2006 and 3519 firms in 2012. Of the 21 industries, in 2005-2006 the largest industry (Manufacture of handloom textile) includes 624 firms and the smallest industry (Manufacture of made-up textile articles, except apparel) has 20 firms whereas in 2012 the largest industry (Manufacture of handloom textile) includes 575 firms and the smallest industry (Manufacture of structural metal products) has 21 firms.

Defining the Variables

Both the SMI surveys provide information on production, sales, earnings, capital/fixed assets, labour costs, industrial and non-industrial costs of the firms in the manufacturing industries at the national level. Based on theoretical background and following Din et. al. (2007) this paper uses the level of output, capital/fixed assets, labour costs, industrial and non-industrial costs of the firms in estimating the technical production efficiency of the manufacturing sector in Bangladesh.

Output (Y): The SMI surveys report the total production of outputs produced in the industrial firms. Produced outputs are categorized as the primary goods, the by-products, and the industrial waste. Moreover, there are some other services the firms extend to others that bring some earnings for the firms. Therefore, based on such evidences, this research defines industrial output to include the values of the following components: (a) Primary outputs, by-products, industrial waste, (b) Income earned by making others' product and other repair works, (c) Income from rental and leasing of assets, (d) Income from repairing/setting up others' machinery, (e) Income from investments and others, (f) Bonus, premium and XPL received from government for exports, and (g) Income from sales of raw materials, fuels and other supplies.

Capital (K): Capital includes the values of the fixed assets the industrial firms use on regular basis and that should have a productive life of more than one year. The SMI surveys includes the value of the following items under capital: (a) Land, (b) Land development, (c) Building/Infrastructure (for Accommodation and Factory), (d) Tools and Machinery, (e) Transport and provisions/equipments, (f) Computer, Software and related items, and (g) other fixed assets that have more than one year productive life.

Labour (L): Labour includes the payments (salary and wages, cash/non-cash benefits, social security, pension, etc related expense paid by the owner/firm) made to all kinds of employees/workers.

Industrial Cost (IC): Industrial cost consists of cost of raw materials, packing accessories, spare parts, other related supplies, fuels and electricity consumed, costs for contractual works with the factory supplies, payments for repairs and maintenance and cost of goods purchased for resale.

Non-industrial Cost (NIC): Non-industrial cost consists of cost of excise duty, sales tax, VAT, payments for transport, insurance payments, copy rights and royalties, postage, telegraph and telephone charges, printing and stationery costs, legal and professional expenses, advertising and selling expenses, traveling expenses, bank interest, rent paid for fixed assets owned by others and other such expenses incurred by the manufacturing firm. The summary of these variables is presented in table-1.

Table 1: Summary Statistics

Variable	2005 (A)	2012 (B)	Change (B-A)
# Firms	2468	3519	-
Privately Owned (%)	98.99[0.10]	97.13[0.17]	-1.86[0.00]
Private Limited Company (%)	72.20[0.45]	60.67[0.49]	-11.53[0.00]
Urban Firms (%)	-	54.91[0.49]	-
Micro Enterprise (%)	-	46.12[0.50]	-
SME (%)	-	36.66[0.48]	-
Firms in EPZ or Industrial parks	-	20.67[0.40]	-
Age of Firms (Years)	16.31[14.54]	-	-
# Yearly shifts	293.62[99.88]	-	-
Output	50178099[167400000]	119700000[272000000]	69473049[0.00]
Capital	33819568[150300000]	66396432[220400000]	32576863[0.00]
Labour	5738925[38130330]	22318143[63883958]	16579217[0.00]
Industrial Costs	38140123[142700000]	88007568[208600000]	49867445[0.00]
Non-industrial Costs	4965630[25761951]	3348546[17424627]	-1617084[0.00]

Standard deviation in brackets for column A & B; p-value against difference in parentheses.

The Model

This research tries to focus on the dynamics and source of that dynamic technical efficiency of the manufacturing sector in Bangladesh based on the aforementioned survey. In this connection, the first step is to determine the technical efficiency of the manufacturing sector in Bangladesh in 2005 and 2012 and consequently, second step is to find the determinants of the efficiency indicator obtained in the first step.

I) Dynamics of Technical Efficiency

There are various techniques in estimating the technical efficiency/inefficiency used by the researchers across the world, such as linear programming, stochastic frontier analysis, data envelopment analysis, Malmquist productivity indicator etc. SFA is a parametric approach based on specific functional form with constant returns to scale assumption whereas DEA is a non-parametric approach and allows for variable returns to scale. The other technique, Malmquist productivity indicator (MPI), is an application of DEA non-parametric method and this evaluates the change of efficiency overtime. Therefore, MPI requires panel data while both SFA and DEA can be applied with both cross section and panel data. That's why among these competing tools, the stochastic frontier analysis (SFA) and the data envelopment analysis (DEA) are more popular techniques.

Some studies show that the relative precision of SFA and DEA are context specific and each has some pros and cons. Unlike SFA, DEA can handle multiple outputs and multiple inputs stated in different measurement units and it requires no specific functional form. Another advantage of DEA is that this is applicable for variable returns to scale along with constant returns to scale technology. But, on the other side, the DEA is not amenable to direct application of tests of significance and statistical hypothesis testing and ignores the random noise. As to Banker, Gadh and Gorr (1993), “DEA might be the preferable technique where assumptions of typical neoclassical production theory are in question and measurement errors are unlikely. On the other hand, SFA has the advantage in handling measurement errors but functional form should closely match the properties of the underlying production technology.”

Since the utilization of SFA and DEA are context specific, there is no general rule regarding the usage of these tools. Battese and Coelli (1995), Taymaz and Saatci (1997), Njikam (2003), and Ikhsan-Modjo (2006) have used SFA for analyzing technical efficiency whereas Alvarez and Crespi (2003), Saranga and Phani (2004), Jajri and Ismail (2006), and Lee and Kim (2006) have applied DEA for the same purpose. On the other hand, some literature, i.e. Tripathy (2006), and Din et. al. (2007) etc. have used both the SFA and the DEA in estimating technical efficiency.

Therefore, for robustness, it is better to use both the competing techniques and this current research has been designed to utilize both the SFA and the DEA in estimating the technical efficiencies of various manufacturing industries in Bangladesh. Moreover, since the data used in this research are of repeated cross section, this study doesn't cover the Malmquist Productivity Indicator (MPI) analysis.

Stochastic Frontier Analysis (SFA)

The frontier model uses the theoretical idea that the ideal “frontier” can't be exceeded by any economic agent and the deviations from this “frontier” represent the inefficiencies of the agents. In implementing the idea, a regression model is specified characterized by a composite error term. The first component of the composite error term, the classical idiosyncratic disturbance, captures the measurement error and any other noise and the second component, a one-sided disturbance, represents the inefficiency. So, for the analysis of cross section data for each year, the frontier model can be expressed in the following form:

$$Y_{ij} = \alpha_j + X'_{ij}\beta_j + \varepsilon_{ij}, \quad \text{----- (I)}$$

$$\text{with } \varepsilon_{ij} = v_{ij} - u_{ij} \text{ with } v_{ij} \sim \mathcal{N}(0, \sigma_v^2); u_{ij} \sim \mathcal{F}; \text{ and } \text{cov}(v_{ij}, u_{ij}) = 0$$

Where,

Y_{ij} represents the output of the i^{th} firm in j^{th} industry

X_{ij} is a vector of inputs of the i^{th} firm in j^{th} industry

β_j is the vector of technology parameters in j^{th} industry

ε_{ij} is the sum (or the difference) of normally distributed disturbances

v_{ij} is the usual noise component to allow for random factors like the measurement and specification error assumed to be iid, and

u_{ij} is the non-negative error term that represents the technical inefficiency in production, and is assumed to be independent of v_{ij} .

SFA is conducted in two chronological steps. In the first step, since OLS estimation doesn't produce the efficiency estimates [Kumbhakar and Lovell (2000)], a production function is estimated maximizing the log-likelihood function, following Aigner, Lovell and Schmidt (1977) and Battese and Corra (1977). This gives the composite residuals $\hat{\varepsilon}_i$ for the cross-sectional data that have two components, one represents the random effects $\hat{v}_i$ and the other stands for technical inefficiency $\hat{u}_i$ based upon the parameters $\sigma_s^2 = \sigma_v^2 + \sigma_u^2$, $\lambda = \sigma_u/\sigma_v$ with $0 \leq \lambda \leq \infty$ and $\gamma = \sigma_u^2/\sigma_s^2$ with $0 \leq \gamma \leq 1$. Then the statistical significance of the inefficiencies estimated by the models will be checked. Following Battese and Coelli (1995), a one-sided likelihood ratio test with a mixed chi-square distribution $(1/2 \chi_0^2 + 1/2 \chi_1^2)$ will be applied and the null hypotheses is rejected if $LR > \chi_0^2(2\alpha)$.

The outcome of SFA can be dependent upon the properties of the production technology and the SFA can produce the best result provided that the functional form is closely matched with the properties of the underlying production technology. The existing literature is divided in using two major production frontiers; the Cobb-Douglas and the Translog stochastic frontier production functions. For example, Njikam (2003) and Tripathy (2006) have used the Cobb-Douglas stochastic production frontier while Battese and Coelli (1995), and Ikhsan-Modjo (2006) have estimated a Translog frontier production function in technical efficiency analyses, though Taymaz and Saatci (1997) have used both the Cobb-Douglas and the Translog stochastic frontier production functions for the same purpose.

In the second step, the technical efficiency $\hat{u}_i$ is disentangled from the observed compounded error $\hat{\varepsilon}_i$. In doing so, following Jondrow et. al. (1982) and Battese and Coelli (1988), the point estimate of the inefficiencies $\hat{u}_i$ is obtained given the mean or the mode of the conditional distribution of the inefficiency term u given the error term $\hat{\varepsilon}$, $E(u|\hat{\varepsilon})$ or $M(u|\hat{\varepsilon})$. Regarding the distribution of the conditional distribution of the inefficiency term Aigner et al. (1977) assumed a Half-Normal distribution, i.e. $u_i \sim N^+(0, \sigma_u^2)$, Meeusen and Broeck (1977) asked for an Exponential distribution, $u_i \sim \mathcal{E}(\sigma_u^2)$, Stevenson (1980) adopted the Truncated Normal distribution and Greene (1990) used the Gamma distributions.

Therefore, based on the existing literature, this research considers this better to measure technical production efficiency applying both the Cobb-Douglas and the Translog stochastic frontier production functions. Regarding the distribution of the conditional

distribution of the inefficiency term given the residual error term this research assumes a half-normal distribution for the Cobb-Douglas production frontier and a truncated normal distribution for the Translog production frontier.

(i) Cobb-Douglas Stochastic Production Frontier assuming a half-normal distribution:

The Cobb-Douglas Stochastic Production Frontier is assumed to be of the following form with a half-normal distribution:

$$\ln Y_{ij} = \beta_{0j} + \beta_{1j} \ln K_{ij} + \beta_{2j} \ln L_{ij} + \beta_{3j} \ln IC_{ij} + \beta_{4j} \ln NIC_{ij} + v_{ij} - u_{ij} \text{----- (II)}$$

where, Y_{ij} is output of the i^{th} firm in j^{th} industry,

K_{ij} is the amount of capital used in the i^{th} firm in j^{th} industry,

L_{ij} is the average number of persons engaged in the i^{th} firm in j^{th} industry,

IC_{ij} is the industrial cost in the i^{th} firm in j^{th} industry,

NIC_{ij} is the non-industrial cost in the i^{th} firm in j^{th} industry,

v_{ij} represents the measurement and specification error with normal distribution i.e.

$$v_{ij} \sim \mathcal{N}(0, \sigma_v^2)$$

u_{ij} represents the technical inefficiency in production with half-normal distribution i.e.

$$u_{ij} \sim N^+(0, \sigma_u^2)$$

(ii) Translog Stochastic Production Frontier assuming a truncated normal distribution:

The Translog Stochastic Production Frontier is assumed to be of the following form with a truncated normal distribution:

$$\ln Y_{ij} = \alpha_j + \beta_{1j} \ln K_{ij} + \beta_{2j} \ln L_{ij} + \beta_{3j} \ln IC_{ij} + \beta_{4j} \ln NIC_{ij} + \gamma_{1j} (\ln K_{ij})^2 + \gamma_{2j} (\ln L_{ij})^2 + \gamma_{3j} (\ln IC_{ij})^2 + \gamma_{4j} (\ln NIC_{ij})^2 + \delta_{1j} (\ln K_{ij})(\ln L_{ij}) + \delta_{2j} (\ln K_{ij})(\ln IC_{ij}) + \delta_{3j} (\ln K_{ij})(\ln NIC_{ij}) + \gamma_{4j} (\ln L_{ij})(\ln IC_{ij}) + \delta_{5j} (\ln L_{ij})(\ln NIC_{ij}) + \delta_{6j} (\ln IC_{ij})(\ln NIC_{ij}) + v_{ij} - u_{ij} \text{---- (III)}$$

where, Y_{ij} , K_{ij} , L_{ij} , IC_{ij} , NIC_{ij} , u_{ij} and v_{ji} are as defined earlier, and u_{ij} has truncated normal distribution.

Therefore, application of the above two steps will result in the point estimates of the technical inefficiency term. Once such point estimates are obtained for each year, the estimates of the technical efficiency can be derived as $\text{Efficiency} = \exp(-\hat{u}_i)$ where $\hat{u}_i$ is $E(u|\hat{\epsilon})$ and later the magnitude and significance of the change in technical efficiency in each industry can be analyzed rigorously.

Data Envelopment Analysis

The other popular alternative technique in estimation of technical efficiency is the Data Envelopment Analysis (DEA). The DEA is a non-parametric mathematical linear programming technique for the construction of a production frontier based on the notion of input oriented technical efficiency. The extent of technical inefficiency is treated as the difference between observed data and frontier.

There are two forms of DEA; the input-oriented and the output-oriented DEA. In case of input-oriented DEA the inputs are minimized and the outputs are kept at their current

levels whereas the output-oriented DEA aims to capture the maximum increase in production, maintaining input levels constant. Coelli and Rao (2003) indicate that both measures provide the same scores relative to technical efficiency under constant returns of scale (CRS) technology and the scores vary for variable returns of scale (VRS) technology. The variable returns to scale (VRS) frontier fits the data more closely and, henceforth, the efficiency scores under VRS are expected to be higher than those from CRS technology.

This research aims to capture the maximum proportional increase in production, maintaining input levels constant and, therefore, uses the output-oriented DEA approach. Moreover, this study uses DEA under two alternative assumptions; constant returns to scale and variable returns to scale.

II) Sources of Technical Efficiency

From the previous step, four estimates of technical efficiency: two estimates under stochastic frontier analysis (SFA)-one with Cobb-Douglas production with half-normal distribution and the other with Translog production with a truncated normal distribution and another two estimates under data envelopment analysis (DEA)-one with constant returns of scale (CRS) technology and the other with variable returns of scale (VRS) technology. Once the estimates of technical efficiency are obtained, this research estimates the following linear regression to identify the locational, ownership and firm characteristics as the potential sources of efficiency of the manufacturing sector in Bangladesh in 2005 and 2012.

$$\xi_{ijkst} = \alpha + G_i' \beta + O_i' \delta + F_i' \gamma + \theta_k + \psi_s + \eta_{ijkst} \text{---- (IV)}$$

where, ξ_{ijkst} is the efficiency estimate of the i^{th} firm generated under k^{th} estimation process. G is a vector of geographical factors (distance from capital, distance from Chittagong seaport, whether the firm is in urban area, and whether it is in export processing zone or in industrial park), O is a vector of two firm owner characteristics (whether the firm is privately owned, and whether this is a private limited company), F is also some vector of firm characteristics (whether the firm is a micro enterprise, whether it is a small & medium enterprise, age of the firm based on establishment year, and number of operational shifts in last 12 months), and η_{ijkst} is for the specification error. For distance calculation, we identify the firms' location at upazilla (sub-district) level and find the geo-coordinates (latitude and longitude) at that location using data from Bangladesh Bureau of Statistics (BBS). We also take the geo-coordinates of capital Dhaka and the top seaport Chittagong. Then we calculate the straight-line Euclidean distance of the two coordinates. Since some regional as well as industry-wise shocks might have some role, we use region fixed effects θ_k for region (sub-districts) k . Moreover, we also control for industry fixed effects ψ_s . In order to address the Moulton problem, we use robust standard error clustered at upazilla (sub-district) level. As we have more than 160 clusters at each year, the asymptotic properties are assumed to satisfy.

In addition to checking the statistical significance of each of the geographical, ownership and firm characteristics, following Battese and Coelli (1995), we also check the joint significance of the concerned factors, to identify the factors contributing toward technical efficiency.

Discussion and Results

Dynamics of Technical Efficiency of the Industries

In estimating the technical efficiencies of various manufacturing industries in Bangladesh and to ensure consistency this research has utilized two competing techniques of efficiency estimation, i.e. stochastic frontier analysis (SFA) and data envelopment analysis (DEA). Moreover, in case of SFA both the Cobb-Douglas and the Translog production functions have been estimated with separate set of assumptions regarding the technical inefficiency term in the composite error and based on these the efficiency score for each of the firms has been estimated and the estimated coefficients are tabulated in Annex 1. In case of DEA such efficiency score has been estimated given both constant returns to scale (CRS) and variable returns to scale (VRS) technology. So, in total, this research uses four techniques to generate the technical efficiency of the manufacturing sectors in Bangladesh in 2005 and 2012.

Table 2 presents the mean efficiency scores of the 21 industries under all these four techniques for the years 2005-2006 and 2012. Among the 21 industries, based on the mean efficiency scores derived under different criteria, we can find the top-most efficient industries. Moreover, we also can check the dynamics by calculating the change of the mean efficiency scores.

It is found that, with respect to the stochastic frontier analysis with Cobb-Douglas production under half normal distribution, the top three most efficient industries during 2005-2006 are (i) Tanning and dressing of leather and fur, (ii) Fish, Crustaceans and Molluses, and (iii) Grain mill products except rice respectively while in 2012 the top three are (i) Fish, Crustaceans and Molluses, (ii) Tanning and dressing of leather and fur, and (iii) Embroidery of textile and apparel respectively. In terms of efficiency gain over the years we observe that the top three industries are ((i) Jute textile, (ii) Dying and bleaching of textiles, and (iii) Bides respectively.

Table 2: Industry-wise Mean Efficiency Scores

Industry (BSIC)	# Firms		Stochastic Frontier Analysis (SFA)						Data Envelopment Analysis (DEA)					
			Cobb-Douglas production with half-normal distribution			Translog production with truncated normal distribution			Constant Returns to Scale (CRS)			Variable Returns to Scale (VRS)		
	2005	2012	2005	2012	Change	2005	2012	Change	2005	2012	Change	2005	2012	Change
Fish, Crustaceans and Molluses (1020)	50	45	0.56 [0.15]	0.82 [0.07]	0.26 (0.00)	0.70 [0.16]	0.90 [0.04]	0.20 (0.00)	0.95 [0.05]	0.96 [0.02]	0.01 (0.33)	0.97 [0.05]	0.98 [0.02]	0.01 (0.08)
Grain mill products except rice (1061)	76	217	0.55 [0.15]	0.76 [0.09]	0.22 (0.00)	0.69 [0.15]	0.86 [0.09]	0.17 (0.00)	0.92 [0.05]	0.95 [0.02]	0.03 (0.00)	0.93 [0.05]	0.96 [0.02]	0.02 (0.00)
Rice/rice milling (1063)	462	460	0.52 [0.15]	0.76 [0.08]	0.24 (0.00)	0.68 [0.17]	0.87 [0.08]	0.18 (0.00)	0.90 [0.06]	0.97 [0.02]	0.07 (0.00)	0.92 [0.06]	0.98 [0.02]	0.06 (0.00)
Bakery products (1071)	236	569	0.50 [0.08]	0.71 [0.09]	0.20 (0.00)	0.73 [0.07]	0.84 [0.11]	0.12 (0.00)	0.91 [0.04]	0.97 [0.03]	0.06 (0.00)	0.93 [0.04]	0.98 [0.02]	0.05 (0.00)
Other food products (1079)	28	176	0.50 [0.12]	0.74 [0.12]	0.24 (0.00)	0.72 [0.08]	0.85 [0.13]	0.13 (0.00)	0.93 [0.04]	0.98 [0.02]	0.05 (0.00)	0.95 [0.04]	0.98 [0.02]	0.03 (0.00)
Bidies (1201)	59	153	0.45 [0.21]	0.73 [0.10]	0.28 (0.00)	0.61 [0.29]	0.83 [0.10]	0.22 (0.00)	0.91 [0.18]	0.96 [0.02]	0.05 (0.00)	0.92 [0.18]	0.97 [0.02]	0.05 (0.00)
Fibre textile (1311)	157	170	0.49 [0.13]	0.74 [0.13]	0.25 (0.00)	0.69 [0.15]	0.84 [0.15]	0.16 (0.00)	0.71 [0.07]	0.94 [0.04]	0.23 (0.00)	0.82 [0.10]	0.96 [0.04]	0.14 (0.00)
Dying and bleaching of textiles (1313)	114	60	0.49 [0.10]	0.77 [0.15]	0.28 (0.00)	0.71 [0.09]	0.86 [0.16]	0.15 (0.00)	0.93 [0.04]	0.97 [0.03]	0.05 (0.00)	0.94 [0.04]	0.98 [0.03]	0.04 (0.00)
Jute textile (1314)	35	86	0.43 [0.15]	0.75 [0.14]	0.32 (0.00)	0.63 [0.19]	0.85 [0.16]	0.22 (0.00)	0.94 [0.08]	0.98 [0.04]	0.03 (0.00)	0.97 [0.07]	0.98 [0.04]	0.02 (0.09)
Handloom textile (1315)	624	575	0.50 [0.09]	0.75 [0.06]	0.25 (0.00)	0.72 [0.11]	0.87 [0.05]	0.16 (0.00)	0.91 [0.06]	0.97 [0.04]	0.05 (0.00)	0.93 [0.06]	0.97 [0.04]	0.04 (0.00)
	20	24	0.50	0.72	0.23	0.70	0.83	0.13	0.98	0.99	0.01	0.99	0.99	0.00

Made-up textile articles,			[0.11]	[0.14]	(0.00)	[0.11]	[0.17]	(0.00)	[0.03]	[0.03]	(0.48)	[0.01]	[0.03]	(0.89)
Cordage, rope, twine and netting (1394)	24	38	0.50	0.72	0.21	0.70	0.83	0.12	0.97	0.98	0.02	0.98	0.99	0.01
			[0.12]	[0.11]	(0.00)	[0.13]	[0.13]	(0.00)	[0.02]	[0.02]	(0.00)	[0.02]	[0.01]	(0.02)
Embroidery of textile and apparel (1411)	59	71	0.49	0.77	0.27	0.67	0.85	0.19	0.91	0.99	0.08	0.93	0.99	0.06
			[0.11]	[0.15]	(0.00)	[0.11]	[0.17]	(0.00)	[0.03]	[0.03]	(0.00)	[0.04]	[0.02]	(0.00)
Knitted and crocheted fabrics (1430)	172	529	0.53	0.74	0.21	0.72	0.84	0.13	0.91	0.97	0.06	0.94	0.98	0.04
			[0.13]	[0.12]	(0.00)	[0.13]	[0.15]	(0.00)	[0.05]	[0.03]	(0.00)	[0.04]	[0.03]	(0.00)
Tanning and dressing of leather and fur (1511)	58	54	0.59	0.79	0.20	0.72	0.88	0.15	0.94	0.99	0.05	0.95	0.99	0.04
			[0.12]	[0.08]	(0.00)	[0.09]	[0.06]	(0.00)	[0.04]	[0.01]	(0.00)	[0.04]	[0.01]	(0.00)
Sawmilling and planning of wood (1610)	92	61	0.53	0.73	0.20	0.69	0.84	0.16	0.92	0.98	0.06	0.93	0.99	0.05
			[0.11]	[0.07]	(0.00)	[0.11]	[0.07]	(0.00)	[0.05]	[0.01]	(0.00)	[0.05]	[0.01]	(0.00)
Corrugated paper and paperboard (1702)	36	60	0.52	0.76	0.24	0.73	0.88	0.14	0.95	0.99	0.04	0.97	0.99	0.03
			[0.09]	[0.05]	(0.00)	[0.08]	[0.03]	(0.00)	[0.03]	[0.01]	(0.00)	[0.02]	[0.01]	(0.00)
Pharmaceuticals, medicinal chemical products (2100)	51	58	0.51	0.68	0.16	0.71	0.75	0.04	0.88	0.96	0.08	0.93	0.98	0.05
			[0.13]	[0.18]	(0.00)	[0.13]	[0.19]	(0.19)	[0.07]	[0.03]	(0.00)	[0.06]	[0.02]	(0.00)
Polythene products (2221)	25	23	0.51	0.68	0.17	0.72	0.80	0.08	0.97	0.99	0.02	0.97	0.99	0.02
			[0.11]	[0.14]	(0.00)	[0.10]	[0.17]	(0.05)	[0.03]	[0.02]	(0.00)	[0.03]	[0.02]	(0.01)
Structural metal products (2511)	34	21	0.54	0.72	0.17	0.71	0.83	0.11	0.91	0.98	0.07	0.94	0.99	0.04
			[0.13]	[0.11]	(0.00)	[0.08]	[0.12]	(0.00)	[0.05]	[0.02]	(0.00)	[0.04]	[0.02]	(0.00)
Wooden furniture and fixture (3101)	56	69	0.51	0.73	0.22	0.72	0.86	0.14	0.91	0.99	0.08	0.93	0.99	0.06
			[0.10]	[0.06]	(0.00)	[0.08]	[0.06]	(0.00)	[0.05]	[0.01]	(0.00)	[0.05]	[0.01]	(0.00)
All Industries	2468	3519	0.51	0.74	0.23	0.70	0.85	0.15	0.90	0.97	0.07	0.93	0.98	0.05
			[0.12]	[0.10]	(0.00)	[0.13]	[0.11]	(0.00)	[0.08]	[0.03]	(0.00)	[0.07]	[0.03]	(0.00)

Standard deviation in brackets and p-value against no difference in parentheses.

The mean efficiency scores among the industries derived using the stochastic frontier with Translog production with truncated normal distribution indicate that the 2005-2006 top three efficient industries are (i) Corrugated paper and paperboard, (ii) Bakery products, and (iii) Handloom textile respectively while in 2012 the industries in the same lists are (i) Fish, Crustaceans and Molluses, (ii) Corrugated paper and paperboard, and (iii) Tanning and dressing of leather and fur respectively. Again, in terms of efficiency gain over the years we observe that the top three industries are (i) Jute textile, (ii) Bidies, and (iii) Fish, Crustaceans and Molluses respectively.

In terms of the DEA, the technical efficiency scores have been estimated under both the constant returns to scale and variable returns to scale assumptions. Under both the assumptions the mean efficiency scores are much higher for all the industries for both years in DEA compare to SFA.

Under constant returns to scale in DEA, based on the mean efficiency score, the most three efficient industries in 2005 are (i) Made-up textile articles, except apparel, (ii) Cordage, rope, twine and netting, and (iii) Polythene products respectively, while in 2012 the three most efficient industries are (i) Made-up textile articles, except apparel, (ii) Polythene products, and (iii) Corrugated paper and paperboard respectively. In terms of efficiency gain over the period 2005-2012 the top three industries included (i) Fibre textile, (ii) Embroidery of textile and apparel, and (iii) Wooden furniture and fixture respectively.

Under variable returns to scale in DEA, the mean efficiency score indicates that the most three efficient industries in 2005 were (i) Made-up textile articles, except apparel, (ii) Cordage, rope, twine and netting, and (iii) Corrugated paper and paperboard respectively and in 2012 the three most efficient industries were (i) Made-up textile articles, except apparel, (ii) Cordage, rope, twine and netting, and (iii) Corrugated paper and paperboard respectively. With regard to the improvement in technical efficiency the top three industries included (i) Fibre textile, (ii) Embroidery of textile and apparel, and (iii) Wooden furniture and fixture respectively.

A comparison of efficiency scores across techniques shows that on average, and in most of the cases efficiency scores using the data envelopment analysis are higher than those obtained by using the stochastic frontier. Within the data envelopment analysis, the efficiency scores are higher in case of variable returns to scale than those under the assumption of constant returns to scale. This result is contrasting with the evidence suggested in the literature of Lin and Tesang (2005) & Ghani and Mahmood (2007). Overall there is a consistency of efficiency rankings which confirms that results are not so sensitive to the technique used.

For all the industries together, the mean efficiency score derived using SFA increased significantly from 0.51 in 2005-06 to 0.74 in 2012 under Cobb-Douglas technology and from 0.70 in 2005-06 to 0.85 in 2012 under Translog technology, indicating an improvement in efficiency of the large-scale manufacturing sector, though the DEA

analyses don't show any significant improvement in technical efficiency over the years and the score under all techniques indicate that there is still some scope of improvement. For industry-wise analysis, based on the significance (at least 10% level) and sign of the progression of the technical efficiency scores, this research categorizes the available 21 manufacturing industries of Bangladesh as backward (significant negative progression), forward (significant positive progression) and level (no significant progression) under each of the four techniques. Whether an industry goes forward or backward is decided by the decision under majority of the four tools used and if there is a tie for an industry, we term this industry as level (neither forward nor backward). Since change in efficiency score is always statistically positive or zero, under all the four scenario above, this implies that the industries listed above are remaining at the same stage (only three industries: Fish, Crustaceans and Molluses under DEA constant returns to scale, Made-up textile articles under DEA method, and Pharmaceuticals, medicinal chemical products under SFA Translog production with truncated normal distribution) or moving forward (the other industries) in terms of efficiency gain, although their respective rate of efficiency gain varies, may be due to some certain reasons. Now, let's have a look on the sources of efficiency gain.

Sources of Dynamics of Technical Efficiency

Once it is decided whether an industry is becoming more technically efficient, it becomes relevant to find the source of such progress. To get the sources of the dynamics, this research estimates the linear regression equation (IV) and tabulated the regression coefficients in the two panels of Table 3. In table 3A, the binary variables titled urban firm and firm in EPZ/industrial park are included to capture the effect of locational factors on efficiency. In the same table, we have included privately owned firms and the private limited companies to gather the evidences of ownership on efficiency. On the other hand, firm characteristics have been included to gather the impact of such features on efficiency. Our model incorporates four features of firm characteristics namely micro enterprises, SME firms, age of the firms and number of operational shifts in the last 12 months. Besides, firm's distance from two strategic points i.e. Dhaka (the capital city) and Chittagong (the biggest port city) have been introduced in the SFA and DEA regressions under various specifications to capture the efficiency impact of geographical location. We have kept blank in those points where specific information is not available. In SFA technique for 2012 data under Cobb-Douglas specification only the Urban firm, Micro enterprise and SME firm variables are statistically significant. Estimates are obtained by controlling industry fixed effects and upazilla (sub-district) fixed effects. In 2005 the coefficient of number of yearly operational shifts is statistically significant but the impact is almost negligible. On the other hand, in SFA technique under Translog specification in 2012 only SME firms and Microenterprise variables are statistically significant.

On the contrary, in DEA technique under constant returns to scale in 2005 only the variable named private limited company is statistically significant while in 2012 privately owned, micro enterprise and SME firm variables are statistically significant under same specification. On the other hand, under variable returns to scale with same specification in 2005 only the coefficient of privately owned variable is statistically significant. Though all other variables are not statistically significant, the values of R-squared are quite high for all regressions. With most of the statistically insignificant controls with high R-squared is an indication of multicollinearity and a joint significance test makes more sense.

In this process, we have presented the result of joint significance of these controls in table 3B in with various interactions. In table 3B, the binary variables urban firm and firm in EPZ/industrial park are included in our locational vector represented by β , the ownership vector includes the privately-owned firms and the private limited companies represented by δ , the firm characteristics vector include the bottom four covariates, namely, micro enterprises, SME firms, age of the firms and number of operational shifts in the last 12 months denoted by γ . Then we have introduced the interactions of these three vectors and tested their joint significance namely (β, δ) , (β, γ) , (γ, δ) and (β, δ, γ) . Precisely, we conduct the above significance tests under seven different scenarios. We find that locational characteristics matter only for SFA efficiency score under Cobb-Douglas production with half-normal distribution, and ownership characteristics alone are not jointly significant. Moreover, locational and ownership characteristics jointly, in most cases, are also not so influential in pulling the efficiency measures up. However, the firm characteristics are very important in raising the technical efficiency of the firms, especially in case of stochastic frontier analysis. And firm characteristics shows stronger impacts in interaction with other locational and/or ownership characteristics.

Table 3A: Sources of Technical Efficiency

Independent Variables	Efficiency under Stochastic Frontier Analysis (SFA)						Efficiency under Data Envelopment Analysis (DEA)					
	Cobb-Douglas production with half-normal distribution			Translog production with truncated normal distribution			Constant Returns to Scale (CRS)			Variable Returns to Scale (VRS)		
	2005	2012	FE	2005	2012	FE	2005	2012	FE	2005	2012	FE
Urban Firm	-	0.020** (0.008)	-	-	0.014 (0.009)	-	-	0.002 (0.002)	-	-	0.001 (0.002)	-
Located in EPZ/industrial park	-	-0.008 (0.006)	-	-	-0.010 (0.007)	-	-	0.000 (0.002)	-	-	0.000 (0.002)	-
Privately Owned	0.015 (0.030)	0.023 (0.015)	0.019 (0.014)	0.006 (0.044)	0.023 (0.017)	0.023 (0.016)	-0.015 (0.012)	0.007* (0.004)	0.008 (0.005)	-0.037*** (0.011)	0.006 (0.004)	0.00 (0.00)
Private Limited Company	-0.016 (0.013)	0.006 (0.010)	-0.000 (0.008)	-0.008 (0.016)	0.004 (0.011)	-0.001 (0.007)	-0.021*** (0.006)	-0.001 (0.002)	-0.005 (0.003)	-0.002 (0.006)	-0.001 (0.002)	0.00 (0.00)
Micro Enterprise	-	0.026** (0.012)	-	-	0.032*** (0.012)	-	-	0.015*** (0.003)	-	-	0.004 (0.003)	-
SME Firm	-	0.025*** (0.009)	-	-	0.024** (0.010)	-	-	0.011*** (0.003)	-	-	0.004 (0.002)	-
Firm Age	-0.000 (0.000)	-	-	-0.000 (0.000)	-	-	-0.000 (0.000)	-	-	-0.000 (0.000)	-	-
# yearly operational shifts	0.000** (0.000)	-	-	0.000* (0.000)	-	-	0.000 (0.000)	-	-	0.000 (0.000)	-	-
Constant	0.463** (0.032)	0.686*** (0.018)	0.638*** (0.014)	0.677*** (0.044)	0.800*** (0.021)	0.776*** (0.016)	0.916*** (0.013)	0.950*** (0.005)	0.937*** (0.005)	0.952*** (0.014)	0.967*** (0.005)	0.955* (0.00)
Observations	1,548	3,407	5,361	1,548	3,407	5,361	1,548	3,407	5,361	1,548	3,407	5,36
R-squared	0.267	0.166	0.559	0.215	0.130	0.335	0.501	0.211	0.496	0.352	0.163	0.38

Table 2B: Sources of Technical Efficiency: Implication of Distances

Distance from Capital (Dhaka)	-0.047 (0.067)	0.016 (0.033)	0.006 (0.026)	-0.023 (0.060)	-0.017 (0.030)	-0.004 (0.027)	-0.024 (0.034)	0.003 (0.008)	-0.032** (0.013)	-0.050 (0.039)	0.003 (0.007)	-0.040 (0.01)
Distance from Seaport (Chittagong)	0.094 (0.065)	0.002 (0.036)	0.013 (0.029)	0.090 (0.059)	-0.014 (0.037)	0.005 (0.032)	0.016 (0.037)	0.019** (0.008)	0.032** (0.012)	0.027 (0.042)	0.013* (0.007)	0.027 (0.01)

Notes: Estimates are obtained by controlling industry fixed effects and upazilla (sub-district) fixed effects in Panel A. Panel B use exactly the same other covariates as in Panel A while controlling dist fixed effects instead of upazilla fixed effects. Robust standard errors clustered at upazilla (sub-district) level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3B: Joint Significance Test (P-value of Rejecting H_0)

Insignificant Factors	Null Hypothesis (H_0)	Efficiency under Stochastic Frontier Analysis (SFA)						Efficiency under Data Envelopment Analysis (DEA)					
		Cobb-Douglas production with			Translog production with			Cobb-Douglas production with			Translog production with		
		half-normal distribution			truncated normal distribution			half-normal distribution			truncated normal distribution		
		2005	2012	FE	2005	2012	FE	2005	2012	FE	2005	2012	FE
Location characteristics only	$\beta = 0$	-	0.026	-	-	0.123	-	-	0.590	-	-	0.929	-
Ownership characteristics only	$\delta = 0$	0.404	0.284	0.422	0.863	0.383	0.347	0.004	0.121	0.085	0.005	0.178	0.524
Firm characteristics only	$\gamma = 0$	0.040	0.019	-	0.053	0.028	-	0.728	0.000	-	0.505	0.296	-
Location and ownership	$\beta = \delta = 0$	0.404	0.022	0.422	0.863	0.084	0.347	0.004	0.208	0.085	0.005	0.454	0.524
Location and firm characteristics	$\beta = \gamma = 0$	0.040	0.008	-	0.053	0.020	-	0.728	0.000	-	0.505	0.531	-
Ownership and firm characteristics	$\delta = \gamma = 0$	0.059	0.060	-	0.166	0.082	-	0.021	0.000	-	0.015	0.161	-
Location, ownership and firm	$\beta = \delta = \gamma = 0$	0.059	0.014	-	0.166	0.036	-	0.021	0.000	-	0.015	0.317	-

Notes: Joint significance tests are conducted based on the regression results in Table 2A. Here, the binary variables urban firm and firm in EPZ/industrial park are included to count for locational factors, the ownership factors include the privately-owned firms and the private limited companies, while the firm characteristics include the bottom four covariates, namely, micro enterprises, SME firms, age of the firms and number of operational shifts in the last 12 months.

Conclusion and Policy Implications:

Bangladesh has become one of the largest exporter of garments in recent years. This can be resulted from efficiency gain of firms operating in this sector. This paper finds that whatever methods is being employed garments related industries outperform other industries in terms of efficiency accrual over time. For the all industries together mean efficiency has increased significantly that helps Bangladesh to exploit its comparative advantage and reinforce its share in world trade. Both textile and apparel has become more efficient and relevant contributing factor is the labors employed in those sectors. This indicates efficiency gain is generated from the millions of cheap workers working in textile and garment industries of Bangladesh. In aggregate, whatever the technology we employ under SFA, during 2005 to 2012 there is a significant improvement in technical efficiency specifically in large manufactories industries. However, DEA analyses do not indicate any improvement in technical efficiency and the scope of improvement still remains for all type of manufacturing industries.

The most significant implication of our paper is not only reporting the industries where efficiency gain has been accrued but also identifying the factors that are responsible for that efficiency gain. We find that firm characteristics, location factors as well as ownership features are more important jointly rather than individually to enhance efficiency. Our results suggest that that locational characteristics vector matter only for SFA efficiency score under Cobb-Douglas production with half-normal distribution while ownership characteristics vector alone is not jointly significant. Furthermore, locational and ownership characteristics jointly, in most cases, are not so important to boost efficiency. However, the firm characteristics vector is very important in raising the technical efficiency of the firms. Thus, firm characteristics shows stronger impacts in interaction with other locational and/or ownership characteristics.

References:

- Aigner DJ, Lovell CAK, & Schmidt P (1977) Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6:21-37.
- Alvarez R, & Gustavo C (2003) Determinants of technical efficiency in small firms. *Small Business Economics* 20:233-244.
- Baten MA, Kamil AA, & Fatama K (2009) Technical efficiency in stochastic frontier production model: an application to the manufacturing industry in Bangladesh. *Australian Journal of Basic and Applied Sciences* 3(2): 1160-1169.
- Baten MA, Kamil AA, & Haque MA (2009) Modeling technical inefficiencies effects in a stochastic frontier production function for panel data. *African Journal of Agricultural Research* 4(12): 1374-1382.

- Bauer PW (1990) Recent developments in the econometric estimation of frontiers. *Journal of econometrics* 46(1-2):39-56.
- Banker RD, Gadh VM, & Gorr WL (1993) A Monte Carlo comparison of two production frontier estimation methods: Corrected ordinary least squares and data envelopment analysis. *European Journal of Operational Research* 67(3):332-343.
- Battese GE, & Corra GS (1977) Estimation of a production frontier model: with application to the pastoral zone of eastern australia. *Australian Journal of Agricultural Economics* 21(3):169-179.
- Battese, GE, & Coelli, TJ (1988) Prediction of firm-level technical efficiencies with a generalised frontier production function and panel data. *Journal of Econometrics* 38:387-399.
- Battese, GE, & Coelli TJ (1995) A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics* 20(2):325-332.
- Coelli, T. J., & Battese, G. E. (1996). Identification of factors which influence the technical inefficiency of Indian farmers. *Australian journal of agricultural economics*, 40(2), 103-128.
- Badunenko, O., Fritsch, M., & Stephan, A. (2006). *What determines the technical efficiency of a firm? The importance of industry, location, and size* (No. 33/2006). Friedrich-Schiller-Universität Jena, Wirtschaftswissenschaftliche Fakultät.
- Bravo-Ureta BE, & Pinheiro AE (1993) Efficiency analysis of developing country agriculture: a review of the frontier function literature. *Agricultural and Resource Economics Review* 22(1):88-101.
- Chambers, R. G., Chung, Y., & Färe, R. (1996). Benefit and distance functions. *Journal of economic theory*, 70(2), 407-419.
- Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. *European journal of operational research* 2(6):429-444.
- Coelli, TJ, Rao DS (2003) *Total factor productivity growth in agriculture: a Malmquist index analysis of 93 countries, 1980-2000*. Centre for Efficiency and Productivity Analysis Working Paper Series 02/2003.
- Din M, Ghani E, Mahmood T (2007) Technical efficiency of pakistan's manufacturing sector: a stochastic frontier and data envelopment analysis. *The Pakistan Development Review* 46(1):1-18.
- Farrell MJ (1957) The measurement of productive efficiency. *Journal of the Royal Statistical Society Series A (General)* 120(3):253-29.
- Førsund FR, Lovell CK, Schmidt P (1980) A survey of frontier production functions and of their relationship to efficiency measurement. *Journal of econometrics* 13(1):5-25.
- Gumbau-Albert, M., & Maudos, J. (2002). The determinants of efficiency: the case of the Spanish industry. *Applied Economics*, 34(15), 1941-1948.

- Greene WH (1990) A gamma-distributed stochastic frontier model. *Journal of Econometrics* 46:141–164.
- Ikhsan-Modjo M (2006) *Total factor productivity in Indonesian manufacturing: a stochastic frontier approach*. Monash University (ABERU Discussion Paper 28).
- Jajri I, Ismail R (2006) *Technical efficiency, technological change and total factor productivity growth in Malaysian manufacturing sector*. MPRA (Munich Personal RePEc Archive) (Paper No. 1966.) downloaded from: http://mpra.ub.uni-muenchen.de/1966/01/MPRA_paper_1966.pdf
- Jondrow J, Lovell CAK, Materov IS, Schmidt P (1982) On estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics* 19:233-238.
- Kumbhakar SC, Ghosh S, McGuckin JT (1991) A generalized production frontier approach for estimating determinants of inefficiency in US dairy farms. *Journal of Business & Economic Statistics* 9(3): 279-286.
- Kumbhakar SC, Lovell CAK (2000) *Stochastic frontier analysis*. Cambridge: Cambridge University Press.
- Lee JY, Kim JW (2006) *Total factor productivity and R & D capital in manufacturing industries*. East West Center Working Paper 89.
- Lin LC, & Tseng LA (2005) *Application of DEA and SFA on the measurement of operating efficiencies for 27 international container ports*. In Proceedings of the Eastern Asia Society for Transportation Studies, Bangkok, Thailand, 5(September): 592-607.
- Meeusen W, Broeck JD (1977) Efficiency estimation from Cobb-Douglas production function with composed error. *International Economic Review* 18(2): 435–444.
- Njikam O (2003) *Trade reform and efficiency in Cameroon's manufacturing industries*. African Economic Research Consortium, Nairobi, AERC Research Paper 133.
- Page, J. M. (1980). Technical efficiency and economic performance: Some evidence from Ghana. *Oxford economic papers*, 32(2), 319-339.
- Page Jr, J. M. (1984). Firm size and technical efficiency: applications of production frontiers to Indian survey data. *Journal of Development Economics*, 16(1-2), 129-152.
- Pitt, M. M., & Lee, L. F. (1981). The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of development economics*, 9(1), 43-64.
- Rahman KMM, Mia MIA, & Bhuiyan, MKJ (2012) A stochastic frontier approach to model technical efficiency of rice farmers in Bangladesh: an empirical analysis. *The Agriculturists* 10(2):9-19.
- Saranga H, & Phani BV (2004) The Indian pharmaceutical industry—an overview of internal efficiencies using data envelopment analysis. *Indian Institute of Management, Calcutta*, WPS-495.

- Seiford LM, & Thrall RM (1990) Recent developments in DEA: the mathematical programming approach to frontier analysis. *Journal of Econometrics* 46(1-2):7-38.
- Sharma KR, Leung P, & Zaleski HM (1997) Productive efficiency of the swine industry in Hawaii: stochastic frontier vs. data envelopment analysis. *Journal of Productivity Analysis*, 8(4):447-459.
- Solís, D., Bravo-Ureta, B. E., & Quiroga, R. E. (2009). Technical efficiency among peasant farmers participating in natural resource management programmes in Central America. *Journal of Agricultural Economics*, 60(1), 202-219.
- Stevenson RE (1980) Likelihood functions for generalised stochastic frontier estimation. *Journal of Econometrics* 13:57- 66.
- Taymaz E, & Gulin S (1997) Technical change and efficiency in Turkish manufacturing industries. *Journal of Productivity Analysis* 8:461–475.
- Theodoridis AM, & Anwar MM (2011) A comparison of DEA and SFA methods: a case study of farm households in Bangladesh. *The Journal of Developing Areas* 95-110.
- Tripathy S (2006) *Are foreign firms allocatively inefficient?: a study of selected manufacturing industries in India*. Paper presented at the Fifth Annual GEP Postgraduate Conference, Leverhulme Centre for Research on Globalisation and Economic Policy (GEP), Nottingham. http://www.nottingham.ac.uk/economics/leverhulme/conferences/postgrad_conf_2006/Tripathy1.pdf
- World Bank Group (2014). *World development indicators 2014*, World Bank Publications.
- Wang, J., Wailes, E. J., & Cramer, G. L. (1996). A shadow-price frontier measurement of profit efficiency in Chinese agriculture. *American Journal of Agricultural Economics*, 78(1), 146-156.

Annex

Annex 1: Stochastic Frontier Regression Results

Independent Variables	Cobb-Douglas production with half-normal distribution		Translog production with truncated normal distribution	
	2005	2012	2005	2012
ln(Capital)	0.076*** (0.011)	0.018*** (0.004)	0.328*** (0.075)	-0.050* (0.029)
ln(Labour)	0.212*** (0.017)	0.135*** (0.007)	0.269* (0.139)	0.518*** (0.064)
ln(industrialcosts)	0.618*** (0.011)	0.789*** (0.005)	0.203** (0.083)	0.497*** (0.050)
ln(non – industrial costs)	0.067*** (0.009)	0.035*** (0.004)	0.162** (0.078)	0.112*** (0.035)
ln ² (Capital)	-	-	0.014*** (0.003)	-0.003** (0.001)
ln ² (Labour)	-	-	0.051*** (0.010)	0.046*** (0.005)
ln ² (Industrial costs)	-	-	0.078*** (0.004)	0.075*** (0.003)
ln ² (Non – industrial costs)	-	-	0.006** (0.003)	0.014*** (0.002)
ln(Capital) * ln(Labour)	-	-	-0.022** (0.009)	0.011*** (0.004)
ln(Capital) * ln(Industrial costs)	-	-	-0.030*** (0.006)	-0.004 (0.003)
ln(Capital) * ln(Non – industrial costs)	-	-	0.005 (0.005)	0.004 (0.002)
ln(Labour) * ln(Industrial costs)	-	-	-0.082*** (0.010)	-0.116*** (0.006)
ln(Labour) * ln(Non – industrial costs)	-	-	0.010 (0.008)	0.000 (0.004)
ln(Industrial costs) * ln(Non – industrial costs)	-	-	-0.029*** (0.006)	-0.029*** (0.003)
Constant	2.210*** (0.156)	1.463*** (0.058)	1.932** (0.835)	0.588 (0.444)
Observations	2468	3519	2468	3519
Sigma (u)	1.054	0.465	16.192	6.821
Sigma (v)	0.524	0.213	0.414	0.158

Standard errors in parentheses.

Legend: *** p<0.01, ** p<0.05, *

Declarations:**Consent for publication:**

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Availability of data and materials:

Bangladesh Bureau of Statistics(BBS) of Bangladesh conducted Survey of Manufacturing Industries in 2005-2006 and 2012. Data can be purchased from BBS by \$2000.

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SJE and MM together planned, discussed together to answer some pertaining research questions related with efficiency of manufacturing industries. MM analyzed the data while SJE have written the paper in terms of literature review and results and discussion. We have analyzed the data together.

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