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Technical Efficiency in Stochastic Frontier Production Model: an Application to the Manufacturing Industry in Bangladesh

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Abstract: This paper considers Cobb-Douglas Stochastic frontiers in which the technical inefficiency effects are defined by a model with two distributional assumptions. The model involved is the time-varying inefficiency model, proposed by Battese and Coelli (1992) applied to panel data. A truncated-normal and half-normal distributions were used in the model and the time-varying inefficiency effects was estimated. The results show that technical inefficiency has declined over the reference period and the truncated (at zero) normal distribution is preferable to the half normal distribution for the technical inefficiency effects.

Key words: Stochastic frontier production, Technical efficiency, Inefficiency effects, Panel data.
JEL Classification: C23, D24, Q12.

INTRODUCTION

In the usual stochastic frontier model it is acknowledged that the estimation of production or cost functions must respect the fact that actual production cannot exceed maximum possible production given input quantities, (Aigner, Lovell and Schmidt 1977, and Meeusen and van den Broeck 1977). Kumbhakar, Ghosh and McGuckin (1991) and Battese and Coelli (1995) were the first to suggest that determining the factors responsible for inefficiency is an essential component of efficiency analysis. The important task is to relate inefficiency to a number of factors that are likely to be determinants, and measure the extent to which they contribute to the presence of inefficiency. Kumbhakar, Ghosh and McGukin (1991) and Battese and Coelli (1995) suggested that under the assumption of truncated normal one-sided error term, the mean of the truncated normal distribution could be expressed as a function of certain covariates, a closed form likelihood function can be derived, and the method of maximum likelihood may be used to obtain parameter estimates, and provide inefficiency measures.

Stochastic frontier approach has found wide acceptance within the agricultural economics literature and industrial settings (Battese and Coelli,1992; Coelli and Battese,1996), because of their consistency with theory, versatility and relative ease of estimation. A number of studies examined the technical efficiency of manufacturing industries in developing countries (Nishimizu and Page, 1982; Abdulkhadiri and Pickles, 1990; and Chuang, 1996, Harris 1993, Sheehan 1997) and steel production Wu (1996). Some literature focused on stochastic frontier model with distributional assumptions by which efficiency effects can be separated from stochastic element in the model and for this reason a distributional assumption has to be made (Bauer 1990). Among others, an exponential distribution (Meeusen and van den Broeck 1977); a normal distribution truncated at zero (Aigner, Lovell and Schmidt 1977); a half-normal distribution truncated at zero (Jondrow *et al.* 1982) and a two-parameter Gamma or Normal distribution (Greene 1990). However, these are computationally more complex, there are no priori reasons for choosing one distributional form over the other, and all have advantages and disadvantages (Coelli, Rao and Battese 1998). Ritter and Simar (1997) found that the requirement for the estimation of two parameters in the distribution may result in identification problems and several hundreds of observations would be required before such parameters could be determined. Further a maximum of the log-likelihood function may not exist under some circumstances.

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A number of studies have also attempted to estimate time-varying inefficiency. Cornwell, Schmidt and Sickles (1990) replaced the firm effect by a squared function of time with parameters that vary over time. Kumbhakar (1990) allowed a time-varying inefficiency measure assuming that it was the product of the specific firm inefficiency effect and an exponential function of time. This allows flexibility in inefficiency changes over time, although no empirical applications have been developed using this approach (Coelli, Rao and Battese 1998). We used a time-varying inefficiency effects measure assuming truncated at zero of normal distribution by Battese and Coelli (1992) in this paper.

It is generally believed that resources in the manufacturing industries especially in under-developed countries are being utilized inefficiently. The absence of quantitative research on technical efficiency is surprising; there is a great scope for manufacturing sector to improve its technical efficiency. According to our knowledge there exists very little literature in estimating stochastic frontier production and consequently dealing with technical inefficiency in manufacturing industries production in Bangladesh have been undertaken (Samad and Patwary, 2002, 2006; Baten et. al. 2006, 2007). Thus this study is expected to provide meaningful insights into the level of industry-specific technical efficiency along with factors affecting inefficiency. The present study focuses on the manufacturing industries of Bangladesh and seeks to obtain the empirical results by specifying the Cobb-Douglas functional form and the model for the technical inefficiency effects in the stochastic frontiers. Estimation of technical efficiencies and the identification of determinants of technical efficiencies for the model are also of interest.

Efficiency using Stochastic Frontier Model and Hypothesis Tests:

The stochastic frontier begins with Farrell's (1957) who study on efficiency measurement and lead to the development of several approaches to efficiency and productivity analysis. Among these the stochastic frontier production (Aigner et. al., 1977; Meeusen and van den Broeck, 1977) and Data Envelopment Analysis (DEA) (Charnes et. al., 1978) are the two principal methods. Stochastic estimations impose an explicit functional form and distribution assumption on the data. In the contrast, DEA does not impose any assumptions about functional form hence it is less prone to miss-specification (Wu 1996).

The stochastic frontier production function for panel data can be written as

$$Y_{it} = \exp(x_{it}\beta + V_{it} - U_{it}) \quad i = 1, 2, \ldots, N \quad t = 1, 2, \ldots, T \qquad (1)$$

where Y_{it} denotes the output for the i-th industry in the t-th time period;

x_{it} denotes the$(1\times k)$ vector whose values are functions of inputs for the i-th industry in the t-th time period; β is a $(1\times k)$ vector of unknown parameters to be estimated;

V_{it} s are the error components of random disturbances, distributed i.i.d. $N(0, \sigma_v^2)$ and independent from U_{it}.

U_{it}s are non-negative random variables associated with the technical inefficiency of production.

The model used here incorporates a simple specification of the time-varying inefficiencies following Battese and Coelli (1992) as

$$U_{it} = \{\exp[-\eta(t-T)]\} U_i, \qquad (2)$$

where η is an unknown scalar parameter to be estimated, which determines whether inefficiencies are time-varying or time invariant; and

U_{it} s are assumed to be i.i.d. and truncated at zero of the $N(0, \sigma_u^2)$ distribution.

If η is positive, then $-\eta(t-T) = \eta(T-t)$ is positive for $t < T$ and so $\exp[-\eta(t-T)] > 1$, which implies that

the technical inefficiencies of industries decline over time. If η is zero, then the technical inefficiencies of industries remain constant. However, if η is negative, then $-\eta(t-T) < 0$ and thus the technical inefficiencies of industries increase over time.

In this paper, the parameters of the stochastic frontier model (1) will be estimated using maximum likelihood estimation (MLE). The MLE method has been found to be significantly better than Corrected Ordinary Least Square (COLS) where the contribution of the inefficiency effects of the total variance is large, and is the preferred estimation technique whenever possible (Coelli, Rao and Battese 1998). Using the composed error terms of the stochastic frontier model (1), the total variation in output from the frontier level of output attributed to technical efficiency is defined by $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$. The variance parameter γ lies on the interval [0,1]. In the truncated and half-normal distribution, the ratio of industry specific variability to total variability, γ, is positive and significant, implying that industry specific technical efficiency is important in explaining the total variability of output produced. This is done with the calculation of the maximum likelihood estimates for the parameters of the stochastic frontier model by using the computer program FRONTIER Version 4.1 (Coelli, 1996a).

A series of formal hypothesis tests are conducted to determine the distribution of the random variables associated with the existence of technical inefficiency and the residual error term. These are tested through imposing restrictions on the model and using the generalized likelihood-ratio statistic (λ) to determine the significance of the restriction. The generalized likelihood ration statistic is defined by

$$\lambda = -2\{\ln[L(H_0)] - \ln[L(H_1)]\}$$

where $\ln\{L(H_0)\}$ and $\ln\{L(H_1)\}$ are the values of the log-likelihood function for the frontier model under the null and alternative hypotheses. If the null hypothesis involves γ=0, expressing that the technical inefficiency effects are not present in the model, then, λ has mixed chi-square distribution with the number of degrees of freedom given by the number of restrictions imposed (Coelli, 1995) because γ=0 is a value on the boundary of the parameter space for γ.

Distinguishing between a half-normal and a truncated normal distribution as the most appropriate assumption for the inefficiency distribution is undertaken the model. The half-normal distribution is a special case of the truncated normal distribution, and implicitly involves the restriction $H_0 : \mu = 0$.
Here the log-likelihood ratio of the half-normal model is that of the null hypothesis, while the log-likelihood ratio of truncated normal model is that of the alternative hypothesis. The hypothesis that efficiency is invariant over time (i.e. η=0) will be tested. The model is estimated first assuming time variant inefficiency, then restricted by modeling the frontier as time invariant.

MATERIALS AND METHODS

Empirical Stochastic Frontier Model and Variables:
This paper devotes the stochastic frontier production function technique to assess the technical efficiency of manufacturing industry, in particular, the Cobb-Douglas stochastic frontier production with the distributional assumption due to advantages over the other functional forms (Kalirajan and Flinn, 1983; Dawson and Lingard, 1989; Coelli and Battese, 1996, etc.). Since the panel data is used in this study and the sample number is not very high, the Translog specification could not be tried.

The Analysis Is Carried out as Specified in the Following Two Steps:
Step One: As a first stage in the efficiency analysis Ordinary Least Square (OLS) estimation is made on the Cob-Douglas production function. Based on the significance of the parameter estimates information will be gained in which variables should be included in the stochastic frontier analysis. In the production function, six inputs of production, Capital, Manual Labor, Non-Manual Labor, Wage rate for Manual Labor, Wage rate for Non-Manual Labor, Cost of raw materials are included. The choices of the variables are made because these inputs are conventional inputs used in manufacturing industries in Bangladesh.

Step Two: After getting necessary information about the inclusion of variables for the frontier analysis, the empirical version of stochastic frontier model (1) can be expressed with the decomposed errors:

$$\ln Y_{it} = \beta_0 + \beta_K \ln K_{it} + \beta_{ML} \ln ML_{it} + \beta_{NML} \ln NML + \beta_{WRML} \ln WRML_{it} + \beta_{WRNML} \ln WRNM_{it}$$
$$+\beta_{CRW} \ln CRW_{it} + (V_{it} - U_{it}) \ldots\ldots\ldots(3)$$

Where, the subscripts i and t represent the i-th industry and the t-th year of observation, respectively;

$i = 1, 2, ..., 31; \quad t = 1, 2, ..., 9;$

Y_{it} represents the output produced (in value);
K_{it} represents the value of capital;
ML_{it} represents the quantity of manual labor;
NML_{it} represents the quantity of non-manual labor;
$WRML_{it}$ represents quantity of the wage rate for manual labor;
$WRNML_{it}$ represents quantity of the wage rate for non-manual labor;
CRW_{it} represents Cost of Raw Materials;

"ln" refers to the natural logarithm; the β_i's are unknown parameters to be estimated; V_{it} follows $N(0, \sigma_v^2)$

and U_{it} follows a half-normal or truncated normal distribution at zero and guarantees inefficiency to be positive only.

Given the specifications of the stochastic frontier production function, defined by equation (1), the technical efficiency of the i-th industry in the t-th year is defined by (cf. Battese and Coelli, 1988)

$$TE_{it} = \frac{Y_{it}}{Y_{it}^*} = \frac{\exp(x_{it}\beta + V_{it} - U_{it})}{\exp(x_{it}\beta + V_{it})} = \exp(-U_{it}) \ldots\ldots\ldots (4),$$

where Y_{it}^* denotes the frontier output;

U_{it} denotes the specifications of the inefficiency model in equation (2).

A summary of the values of variables in the stochastic frontier model is listed in table 1.

RESULTS AND DISCUSSION

Ordinary Least Square Estimation:

The Ordinary least square (OLS) estimates of the parameters of Cobb-Douglas production function shows the average performance of the sample firms that are presented in table 2. The OLS estimates of the parameters are used as initial values (to estimate) for the maximum likelihood estimates of the parameters. From the analysis what we have observed that the coefficients of capital, manual-labor, non-manual labor, cost of raw materials are statistically significant in the production process. The results indicate that these input variables significantly affect the amount of production in manufacturing industries. The wage rate for both manual–labor and non-manual labor applied is found to be insignificant. So we can say that the wage of manual labor and wage of non-manual labor affected to the amount of production on the industries implying that if the wage rate is found enough for labor then production will be increased. The parameter σ is positive which indicated that the observed output differed from frontier output due to factors which are within the controls of industries. This implies that the average production function estimated using the OLS was not the right estimate of the production function in the present case. The intercept value of the ML estimate is greater than the OLS estimate further shows that, the estimate of frontier production function lies above the traditional average function.

Estimation of Stochastic Frontier Model:

The maximum-likelihood estimates for the parameters for the time-varying inefficiency Cobb-Douglas stochastic frontier production function with the assumption of half-normal and truncated normal are presented in table 3 and table 4 respectively.

In table 3 the results show that the maximum-likelihood estimate of the parameter with time-varying inefficiency effects for manual-labor input is 0.048 and 0.087 for the truncated and half–normal distribution respectively. For truncated normal distribution the coefficient of manual labor is found to be insignificant. These results also confirm the study of (Coelli et.al., 2003) where they found that labor has low output elasticity.

On the other hand, for half–normal distribution it is significant at 10% level, these estimates have been reduced for time-invaring inefficiency effects model. The parameter estimate for capital input is significantly different from zero at 1 percent level of significance for both the distributions. The coefficient of cost of raw materials is highly significant at 1% level. The wage rate for both manual labor and non-manual labor is statistically significant at 10 percent level in truncated normal distribution, but in half- normal distribution, wage rate for manual labor is insignificant while wage rate for non-manual labor is significant. So there is an overall indirect impact on wage of labors due to their technical inefficiencies to manufacturing industries production. However, the estimated values of the parameters of the Cobb-Douglas frontier production function obtained with the two distributional assumptions are roughly similar except the constant term. The log likelihood functional values for the two distributions are relatively the same to one another. The very large difference is identified in the variance parameters that arise with these two distributions.

The disturbances of two distributions are observed to be highly different in between to both the truncated normal and half-normal distributional models. Based on the truncated normal frontier model, it is found that in time-invaring inefficiency effects model var(u) accounts for 79.8% of the estimated variance of the residual error term. For the half-normal distribution, it is 95.3%. But in time-varying inefficiency effects model, for the truncated and half–normal distribution it is found 76.7% and 95.4% respectively. For the truncated and Half-normal distribution, γ is estimated at 0.768 and 0.954 respectively, this can be interpreted as follows: 77 percent and 95 percent of random variation for truncated and Half-normal distribution around in manufacturing industries production due to inefficiency. These can be interpreted that 77 percent and 95 percent of the variation in output among the industries are due to the differences in technical efficiency for the both distributions respectively. It is evident from table 3 that the estimates of λ is 1.822 and 4.563 and σ is 0.600 and 1.353 for truncated and half-normal distribution respectively are large and significantly different from Zero, indicate a good fit and correctness for the assumptions of truncated and half-normal distribution. λ is the ratio of variance of $u, (\sigma_u)$ over variance of $v, (\sigma_v)$ and is an indication that the one sided error term u dominates the symmetric error v, so variation in actual production comes from differences in industries management practice rather than random variability.

The estimates for the parameters for the time varying inefficiency model in table 3, indicate that the technical inefficiency effects tend to decline over time since the estimate for the η parameter is positive (i.e. η=.007). Also the parameter η is positive indicating that the distribution of the inefficiency effects is not more concentrated about zero than that of the half-normal distribution.

On the other hand, in table 4 the maximum-likelihood estimates of the parameter (with time-invaring inefficiency effects) for the labor input, are insignificant for both the truncated and half-normal distributions, while the coefficient of capital and cost of raw materials input coefficient are positive and 1 percent level of significant. This means that both the capital and cost of raw materials are the vital causal variables in production of manufacturing industries. In the case of both truncated and half-normal distribution the values of γ are positive and are highly significant which demonstrates that there exists technical inefficiency in the manufacturing industries of Bangladesh. The η parameter is restricted to zero in the model with time-invaring inefficiency effects.

Formal tests of various hypotheses are obtained using the Likelihood Ratio (L-R) statistics and are presented in table 5. The first null hypothesis, $H_0 : \gamma = 0$ which specify that there are no technical inefficiency effects in the model. Since the hypothesis is rejected so we can conclude that there are technical inefficiency effects in the model for the given level of technology and the traditional average response function was not an adequate representation for the data given the specification of the stochastic frontier model. The technical inefficiency effects having a half-normal distribution, is tested by the null hypothesis $H_0 : \mu = 0$. In our study this hypothesis is rejected which indicates that the truncated (at zero) normal distribution is preferable to the half normal distribution for the technical inefficiency effect. The hypothesis $H_0 : \eta = 0$ is rejected, indicating that the technical inefficiency effect varies significantly over time. We find that η is positive, that is inefficiencies decrease over time in manufacturing industries of Bangladesh.

Technical Efficiency: Results from Truncated Normal and Half-Normal Model:

It is revealed from table 6 that the mean technical efficiency of Bangladeshi manufacturing industries during the periods 1988-1989 to 1999-2000 for the truncated normal distribution is found to be 0.339 whereas the mean efficiency is 0.356 for the half-normal distribution. This implies that 34 percent and 36 percent of potential output is being realized by the manufacturing industries of Bangladesh according to the truncated (at zero) normal distribution and half-normal distribution respectively. This value indicates that firms can improve their output level by 66 percent and 64 percent respectively by the same set of given inputs and technology. The half-normal distribution gives higher technical efficiency estimates than the truncated normal distribution.

Industry-Specific Technical Efficiency: Results from Truncated and Half-Normal Model:

Industry specific technical efficiency to both truncated and half-normal model is given in table 7. The mean technical efficiency is found for truncated and half-normal distribution to be 34.2% and 36.7%. This result shows that average industry produced only about of 34% maximum attainable outputs for the truncated normal distribution whereas it is about 37% maximum output for half-normal distribution. For the truncated normal distribution, there is wide variation in the technical efficiencies among the different manufacturing industries: it ranges from a low of 0.072 for firms animal feeds by products, to a high of 0.924 for tobacco manufacturing, while the efficiencies among the same manufacturing industries: it ranges from a low of 0.096 for photographic and optical goods, to a high of 0.953 for tobacco manufacturing in case of half-normal distribution. The actual range in this both cases is 0.852 and 0.857 respectively. The overall mean technical efficiencies are 0.343 and 0.367 for both the truncated and half-normal distribution respectively, which implies that the manufacturing industries of Bangladesh is realizing around 34 percent and 37 percent of their potential output, on the average. These results can be compared to the findings of Baten *et al*. (2006) in which the variables like labor wage and cost of raw materials were not considered in the model and they found the mean technical efficiencies are 40 percent and 55 percent for truncated-normal and half-normal distributions respectively.

In case of both truncated normal and half-normal distributions, the value of technical efficiency is high for Tobacco Manufacturing in comparison to other industries, whereas the value of technical efficiencies for Food Manufacturing, Drugs and Pharmaceuticals products, Non-Metallic mineral products, Wearing Apparel expt. footwear are existed in between from 50 percent to 75 percent. We have observed greater technical efficiencies for different manufacturing industries in case of half-normal distribution than that of truncated normal distribution. The manufacturing industries operate 65.7 percent and 36.7 percent below the potential frontier production level with the given inputs and production technology.

Table 1: Summary Statistics of Output and Input Variables

Variable	Description	Mean	Std. deviation	Min.	Max.
Y	Gross Output	14.619	2.544	5.332	19.482
K	Capital	13.633	2.562	4.779	18.864
ML	Manual Labor	4.753	.611	1.000	7.086
NML	Non-Manual Labor	4.807	.614	2.647	7.381
WML	Wage Rate for Manual Labor	3.913	.583	.500	5.381
WNML	Wage Rate for Non-Manual Labor	3.239	.565	1.465	19.216
CRW	Cost of Raw Materials	14.106	.564	.020	19.216

N=279

Table 2: OLS Estimates of Cobb-Douglas Production Function

Variable	Parameters	Coefficients	S.E.	T-Ratio
Constant	β_0	1.043*	.279	3.74
K	β_1	.257*	.023	10.969
ML	β_2	.087**	.055	1.589
NML	β_3	-.085**	.054	-1.587
WRML	β_4	.091@	.072	1.265
WRNML	β_5	-.0834@	.072	-1.152
CRW	β_6	.708*	.021	33.774
SIGMA	σ^2	.200		
Ln Likelihood		-168.147		

N=279

*, **, ***, Significance level at 1%, 5%, 10% consecutively
@ means insignificant, S.E = Standard Error

Table 3: Maximum-Likelihood Estimates of the Cobb-Douglas Stochastic Frontier Model with Time-varying Inefficiency Effects

Variable	Parameter	Truncated - Normal			Half-Normal		
		Coefficient	S.E	T-Ratio	Coefficient	S.E	T-Ratio
Constant	β_0	3.704*	.449	8.239	4.229*	.458	9.223
K	β_k	.231*	.029	8.059	.193*	.030	6.407
ML	β_k	.048$^{@}$	.054	.883	.087***	.049	1.752
NML	β_k	.059$^{@}$	.056	1.062	.090***	.057	1.574
WRML	β_k	.063$^{@}$	.063	1.006	.054$^{@}$	.061	.889
WRNML	β_k	.081$^{@}$	.063	1.279	.112***	.066	1.690
CRW	β_k	.564*	.0266	21.239	.535*	.028	19.410
Sigma	σ	.600*	.051	7.052	1.353*	.634	2.886
Gamma	γ	.768*	.049	15.530	.954*	.017	54.971
Mu	μ	1.052*	.161	6.545	0	0	0
Eta	η	.007	.007	.946	.011***	.006	1.843
Log-likelihood function		-105.627	-110.439				
			Estimated variances of the underlying variables				
u	σ_u^2			.276			1.291
v	σ_v^2			.084			.062
Lamda (σ_u / σ_v)	λ			1.822			4.563
ε(Residual error)				.360			1.353
$var(u)/var(\varepsilon)$				.767			.954
Mean Efficiency				.339			.356

*, **, ***, Significance level at 1%, 5%, 10% consecutively
@ Means insignificant, S.E. = Standard Error

Table 4: Maximum-Likelihood Estimates of the Cobb-Douglas Stochastic Frontier Model with Time-Invariant Inefficiency Effects

Variable	Parameter	Truncated - Normal			Half-Normal		
		Coefficient	S.E	T-Ratio	Coefficient	S.E	T-Ratio
Constant	β_0	3.535*	.376	9.406	3.842*	.435	8.827
K	β_k	.236*	.028	8.426	.210*	.029	7.071
ML	β_{ML}	.020$^{@}$	.049	.408	.059$^{@}$	.048	1.239
NML	β_{NML}	.085**	.055	1.555	.095*	.058	1.642
WRML	β_{WRML}	.100**	.059	1.687	.084**	.062	1.349
WRNML	β_{WRNML}	.107**	.062	1.720	.127**	.066	1.912
CRW	β_{CRW}	.558*	.026	21.293	.539*	.028	19.056
Sigma	σ	.649*	.057	7.385	1.352*	.650	2.811
Gamma	γ	.799*	.419	19.084	.954*	.018	53.199
Mu	μ	.116*	.196	5.923	0	0	0
Eta	η	0	0	0	0	0	0
Log-likelihood function			-107.856			-112.124	
			Estimated variance of the underlying variables				
u	σ_u^2		.337			1.289	
	σ_v^2		.085			.063	
Lamda (σ_u / σ_v)	λ		1.991			4.523	
ε(Residual error)			.422			1.352	
$var(u)/var(\varepsilon)$	.798		.953				
Mean Efficiency			.326			.364	

*, **, ***, Significance level at 1%, 5%, 10% consecutively
@ Means insignificant, S.E. = Standard Error

Table 5: Generalized Likelihood-Ratio Test of Hypothesis of the Stochastic Frontier Production Function

Null hypothesis	Log-likelihood function	Test Statistic	Critical value*	Decision
$H_0 : \gamma = 0$	-120.582	125.042	7.05	Reject H_0
$H_0 : \eta = \mu = 0$	-112.124	12.994	5.99	Reject H_0
$H_0 : \mu = 0$	-110.439	9.624	3.84	Reject H_0
$H_0 : \eta = 0$	-107.856	4.458	3.84	Reject H_0

Notes: All critical values are at 5% level of significance.
The critical value for this test involving γ=0 is obtained from table of Kodde and Palm (1986).

Table 6: Year wise Mean Efficiencies of Manufacturing Industries in Bangladesh by Two Distribution

Year	Mean Efficiency For Truncated Normal	Mean Efficiency For Half-Normal
1988-1989	0.330	0.342
1989-1990	0.332	0.345
1990-1991	0.334	0.349
1991-1992	0.337	0.352
1992-1993	0.339	0.356
1993-1994	0.342	0.359
1995-1996	0.344	0.363
1997-1998	0.346	0.366
1999-2000	0.348	0.370
Average	0.339	0.356

Table 7: Technical Efficiencies of Different Manufacturing Industries of Bangladesh

Industry	Efficiency ForTruncated-Normal	Efficiency For Half-Normal
Food Manufacturing (311-312)	0.513	0.653
Beverage industry (313)	0.282	0.259
Tobacco Manufacturing (314)	0.924	0.953
Animal feeds & By-Products (315)	0.072	0.180
Manufacturing of Textiles (321-322)	0.485	0.624
Wearing Apparel Expt. Footwear(323)	0.631	0.740
Leather And Its Products (324)	0.354	0.395
Foot Wear Expt. Vulcanize/Mold(325)	0.301	0.297
Ginning Press & Baling of FIB. (326)	0.315	0.300
Wood &Wood cork Products (331)	0.279	0.279
Furniture & Fixtures Mfg. (332)	0.296	0.263
Mfg. Paper & Its Products (341)	0.330	0.366
Printing & Publishing (342)	0.365	0.380
Drugs & Pharmaceutical Products (351)	0.559	0.619
Industrial Chemicals (352)	0.344	0.404
Other chemical Products (353)	0.498	0.542
MISC. Petroleum Prods. &Coal (355)	0.178	0.138
Mfg. Rubber Products (356)	0.243	0.224
Mfg. Plastic Products (357)	0.218	0.233
Pottery China & Earthenware (361)	0.261	0.260
Mfg Glass & Its Products (362)	0.259	0.235
Non-Metallic Mineral Prods. (369)	0.532	0.555
Iron &Steel Basic Inds. (371)	0.363	0.417
Fabricated Metal Products (381-382)	0.324	0.353
Non-Electrical Machinery (383)	0.344	0.192
Electrical Machinery (384)	0.409	0.442
Mfg. Transport Machinery (385)	0.313	0.347
Scientific Precision Etc. (386)	0.131	0.097
Photographic & Optical Goods (387)	0.134	0.096
Decorative Handicrafts (391)	0.149	0.288
Other Mfg. Industry (393-394)	0.224	0.211
Mean	0.343	0.367

Note: Numbers in parentheses are industrial codes according to the Bangladesh Standard Industrial Classification (BSIC).

Conclusions:

In this study we have estimated the stochastic frontier production and industry-specific technical efficiency for the manufacturing industries of Bangladesh. The result shows that the time-varying inefficiencies parameter, η, are positive for the truncated normal and half-normal distribution. These indicate that technical inefficiency has declined over the reference period. Through the several tests, it is observed that the technical inefficiency effects are significant but the technical efficiency rate is found gradually increasing over time in Bangladesh. The potential output values (34 percent and 36 percent) are realized by the manufacturing industries of Bangladesh according to truncated normal and half-normal distributions respectively. It indicates that industries can increase their output level with the same level of inputs and technology by simply improving industry's level of efficiency.

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