A Stochastic Frontier Analysis of Energy Efficiency in Turkish Manufacturing Industry

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Abstract:

This study investigates energy efficiency in the Turkish manufacturing industry using firm-level microdata collected by the Turkish Statistical Institute over the period 2005-2015. We use the stochastic frontier approach which allows us to measure if and how the actual performance of a firm is far from the best practice. The stochastic frontier approach is based on the simultaneous estimation of an energy-input model and an unobserved inefficiency term which is assumed to follow a truncated normal distribution. Both energy consumption and energy inefficiency are assumed to be functions of capital, labor, size, value-added, and other firm characteristics. The results from a set of balanced panel estimations show that mean energy efficiency is around 70% over the period 2005-2015, which suggests that there is still potential to improve energy efficiency in the Turkish manufacturing industry. Furthermore, the results of the inefficiency model imply that energy price level has a positive effect on energy efficiency while the impact of firm size is negative and the effect of the firm age is quadratic. Also, we find that firms with foreign capital are more energy-efficient than those without foreign capital affiliation. Exporting firms are found to be more energy-efficient than firms that do not export, as well. However, subsidized firms are less energy efficient than those that are not subsidized.

Keywords: Stochastic Frontier Analysis, Firm-Level Energy Efficiency, Turkish Manufacturing Industry

JEL Codes: C30, L60, Q40

1. Introduction

In many countries, efficient use of energy has become an important goal and effective application since it helps increasing energy savings without affecting economic growth adversely. As a net energy importer country, Turkey also has placed special emphasis on energy efficiency to meet the energy demand and to sustain economic growth by adopting regulations aiming to increase energy efficiency. In this context, the Energy Efficiency Law was adopted in 2007 and the Energy Efficiency Strategy Document came into force in 2012. This strategy document sets out the objectives of decreasing energy intensity by 20% (compared to 2011 values) until 2023 and diminishing the burden of energy costs on the economy (Energy Efficiency Law, 2007; Energy Efficiency Strategy Document, 2012).

Turkey has faced an expanding demand for energy in parallel with economic growth. According to the General Directorate of Energy Affairs (GDEA), the final energy consumption of the country has grown by about 1.8 times (from nearly 61000 thousand tons of oil equivalent (toe)[1] to about 110000 thousand toe) for the last two decades. During the same period, manufacturing energy consumption has increased approximately 1.5 times and it constitutes more than 30% of the total consumption on average. Energy Balance Sheets also show that energy consumption associated with industrial activities that the manufacturing sector dominates is the top part of the total final consumption with nearly 34% share. The residential and services sectors together have a share of about 32% in total energy consumption followed by the transportation sector (22%) and agriculture and livestock sectors (5%). Through the energy types; 68% of coal, 47% of electricity, 44% of natural gas, and 9% of petroleum products are used in industrial activities. According to detailed GDEA balance sheets in the last years and energy balances provided by the Eurostat, the manufacturing sector accounts for more than 90% of industrial activities (GDEA Energy Balance Sheets 2019; Eurostat Energy Balances, 2020). While the importance of energy efficiency is widely recognized, firm-level empirical studies analyzing energy efficiency are relatively rare. This study aims to fill this gap by examining firm-level energy use and the determinants of inefficiency in the manufacturing sector which is one of the main consumers of total energy in Turkey.

One of the commonly used measures in the analysis of energy efficiency is “energy intensity” which is defined as *the ratio of energy input to output*. In general, a drop in this ratio is linked to an increase in energy efficiency. In other words, improvement in energy efficiency is achieved as a result of a decrease in energy intensity. However, since the use of energy is affected by other factors faced by the firm during

[1] It is a unit used to aggregate different energy sources and defined as the amount of energy released by burning one tone of crude oil.

the production process, the energy intensity may not be an appropriate proxy for the energy efficiency, especially in firm-level investigations (Boyd 2008; Zhang et al., 2016). Therefore, in this study, we use stochastic frontier analysis (SFA) which regards energy inefficiency as a difference between the actual energy use of the firm and its optimal consumption and enables us to calculate this value with a parametric approach.

The stochastic frontier analysis may be helpful in terms of evaluating potential efficiency gaps or determinants of the inefficient use of energy, as elaborated in several studies in the literature. For example, Boyd (2008) analyzes the energy consumption of wet corn milling plants using a stochastic frontier regression and shows that there is a gap between actual and best consumption levels. Lin and Wang (2014) examine the energy efficiency in the iron and steel industry in China and find that the average energy efficiency is 0.699 with potential energy conservation of around 723.44 million tons of coal equivalent. Lutz et al. (2017) explore the drivers of energy efficiency in the German manufacturing industry using the stochastic frontier analysis. Their results suggest that there is a significant potential to advance energy efficiency in the German manufacturing industry. Also, firms exporting, innovating, and investing in environmental protection are found to be more energy efficient. Haider and Bhat (2018) examine the energy efficiency in the Indian paper industry and report a potential in energy savings. Their results also suggest that the structure of the industry and the capital intensity affect energy efficiency positively. Ouyang et al. (2019) use the stochastic frontier analysis to investigate the industrial total factor energy efficiency of nine cities in Pearl River Delta urban agglomeration in China. Their findings suggest that the effects of openness, local government spending, foreign direct investment, factor input structure, environmental regulation strength, and GDP per capita on the industrial energy efficiency are positive while enterprise-scale and energy consumption structure have a negative effect.

This study is organized as follows. Section 2 explains the econometric methodology. Section 3 describes the data set. Section 4 summarizes the econometric results. Section 5 provides conclusions and policy suggestions.

2. Methodology: Stochastic Efficiency Analysis of Energy Use

Although the stochastic frontier was originally proposed for the estimation of the production functions, it has also been used in the estimation of distance functions for multiple inputs and outputs. In the context of energy efficiency analysis, several studies have also utilized the stochastic frontier framework for a single input from a production theory perspective.

To measure energy efficiency from the production efficiency viewpoint, we define the distance function at first.

$$D_i(y, x, E) = \sup\left\{\lambda > 0: \left(\frac{x}{\lambda}, \frac{E}{\lambda}; y\right) \in T\right\}, \tag{1}$$

where T represents the possible input and output vectors, x is the non-energy inputs, E is the energy input, and y accounts for the production vector. Eq. (1) defines the input distance function as the largest amount that reduces all factor inputs, both energy, and non-energy, without harming the output level. Similarly, for the energy input, we may define the sub-vector input distance function in such a manner that only the use of energy input is minimized while keeping other inputs fixed.

$$D_{si}(y, x, E) = \sup\left\{\lambda > 0: (x, \frac{E}{\lambda}; y) \in T\right\} \tag{2}$$

Eq. (2) diminishes only the use of energy as much as possible without changing the non-energy input and output vectors. By using Eq. (2), optimal energy use is given by $E/D_{si}(y, x, E)$. Thus, the energy efficiency index may be defined as

$$EE = \frac{Energy\ consumption\ frontier}{Actual\ energy\ use\ (E)} = \frac{1}{D_{si}(y, x, E)}. \tag{3}$$

The illustration of the technical efficiency measure can be traced back to Farrell (1957). The representation of energy input efficiency in terms of distance functions using Farrell's (1957) notation may be visualized in Fig. 1 (Boyd, 2008).

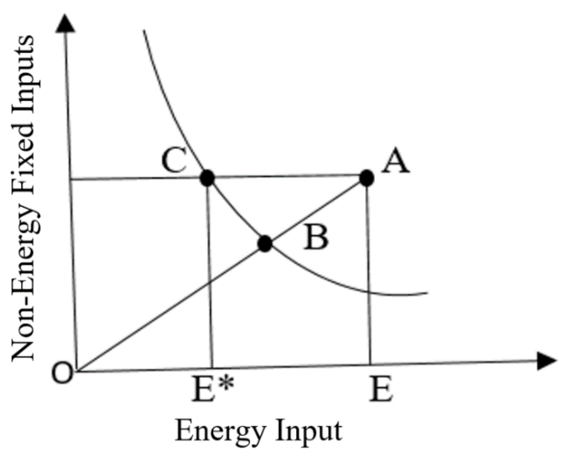

Figure 1. Illustration of Input Distance Functions

Fig. (1) shows a standard production isoquant (y) for the fixed non-energy inputs and the variable input (energy). Assume a representative firm operates at point A. In Fig. (1), the input distance function D_i is equal to the ratio OA/OB and minimizes all the fixed and variable inputs by shifting the firm from A to B. However, the sub-vector energy input distance function D_{si} is OA/OC and decreases just the energy input from E to E* and shifts the firm from A to C.

To estimate the energy input distance function D_{si} using SFA a functional form should be specified. Since the energy distance function is linearly homogeneous in energy, we may rearrange it as follows.

$$D_{si}(y, x, E) = E * D_{si}(y, x, 1). \tag{4}$$

If we take the natural logarithm of both sides, we have

$$\ln\big(D_{si}(y, x, E)\big) = \ln(E) + \ln(D_{si}(y, x, 1)). \tag{5}$$

Through the alternatives for the input distance function, we use the Cobb-Douglas functional form in which the logarithm of the distance function is defined in terms of the linear combination of the logarithms of the inputs and output. This relationship can be defined as follows.

$$\ln\big(D_{si}(y, x, E)\big) = \ln(E) + \beta_0 + \beta_1 \ln(y) + \textstyle\sum_{i=2}^{n} \beta_i \ln(x_i) + v, \tag{6}$$

where v is a random variable standing for the error term. If we rearrange Eq. (6), we get

$$\ln(E) = \beta_0 + \beta_1 \ln(y) + \sum_{i=2}^{n} \beta_i \ln(x_i) + v + u, \tag{7}$$

where $u = \ln\big(D_{si}(y, x, E)\big)$ is a non-negative variable and represents the sub-vector energy inefficiency. Eq. (7) is estimated as a cost frontier model.

The stochastic frontier model was proposed by Aigner et al. (1977) for the cross-sectional data set and was then adapted to the panel data context by Pitt and Lee (1981). Following these studies, several methods have been proposed to estimate the inefficiency term. As well as time-invariant models (Pitt and Lee, 1981; Battese and Coelli, 1988), models based on the assumption of time-varying inefficiency are also available in the SFA literature (Cornwell et al., 1990; Kumbhakar, 1990; Battese and Coelli, 1992; Lee and Schmidt, 1993; Battese and Coelli, 1995; Greene, 2005a, b). In addition to these, there are also studies in which the inefficiency parameter is explained by exogenous variables.

A specification was proposed by Battese and Coelli (1995) who identified u as follows.

$$u = \delta Q + w, \tag{8}$$

where Q is a set of exogenous variables, δ is an unknown vector of the parameters and w is the random component in the inefficiency term. In this study, we follow Battese and Coelli (1995) and estimate the stochastic frontier for the energy consumption and the drivers of energy inefficiency simultaneously. In particular, we estimate the following cost-minimizing energy consumption model for firm *i* in period *t*.

$$\ln(E_{it}) = \beta_0 + \beta_1 \ln(Y_{it}) + \beta_2 \ln(K_{it}) + \beta_3 \ln(L_{it}) + v_{it} + u_{it}, \tag{9}$$

where *E* represents energy use, *Y* denotes the value-added, *K*, and *L* stand for the capital stock and labor respectively. In this model, the composite error term can be defined by two parts as inefficiency term and usual error term under certain assumptions. Inefficiency term is represented by u_{it} and it is assumed to follow a nonnegative truncated normal distribution as $u_{it} \sim N^{+}(\mu_{it}, \sigma_u^2)$. The usual error term is v_{it} and it follows a normal distribution $v_{it} \sim N(0, \sigma_v^2)$.

The conditional inefficiency model to be estimated is

$$\mu_{it} = \delta_0 + \delta_1 size_{it} + \delta_2 age_{it} + \delta_3 {age^2}_{it} + \delta_4 P_t + \delta_5 t + \delta_6 k_{it} + \delta_7 l_{it} + \delta_8 exporter + \delta_9 subsidy + \delta_{10} foreign + e_{it}, \tag{10}$$

where *size* denotes the number of the employees as firm size, *age* is the age of the firm, *P* is the energy price index, *t* is the linear time trend, *k* accounts for the capital per output, *l* represents the labor per output, *exporter* is the dummy for the exporting firms, *subsidy* is the dummy for the subsidized firms, and *foreign* is the dummy for the foreign capital share in the firm.

Kumbhakar and Lovell (2000) argue that ignoring the heteroscedasticity of v_{it} produces biased technical efficiency estimates. Also, they provide that estimates of technical efficiency and the parameters in the frontier model are biased if u_{it} is heteroscedastic. Therefore, we also introduce heteroscedasticity in inefficiency and idiosyncratic error term with the help of the following models.

$$\sigma_u^2 = \exp(z'\gamma) \tag{11}$$

and

$$\sigma_v^2 = \exp(z'\varphi), \tag{12}$$

where γ and φ is the vector of unknown parameters to be estimated and z is the set of variables including value-added, capital, and labor. Using Eq. (13), energy efficiency can be predicted as cost efficiency after the frontier estimation since Eq. (7) is a cost frontier model.

$$EE_{it} = \exp(-u_{it}) \tag{13}$$

3. Data

The data set is compiled from the Annual Industry and Service Statistics (AISS) which include detailed information on employment, expenditure, income, depreciation, and investment variables for enterprises over the period 2003-2015. TurkStat uses both full enumeration and sampling methods where enterprises having 20 or more employees and active in some special classes are subjected to full enumeration while the sampling method is used for the enterprises having less than 20 employees (TurkStat, 2015).

In this study, we employ the Annual Industry and Services Surveys (AISS) of the Turkstat for the 2005-2015 period since all variables used available only from 2005. To prepare the data set for computations, monetary variables were deflated by the appropriate price indices. Investment expenditures and depreciation are deflated by the producer price index of the capital goods group. We remove the price effects in energy expenses using the energy price index. Other variables are deflated by the producer price indices for sub-sectors which are classified according to the 2-digit numerical code of NACE[2] Rev. 2 classification. The base year is set to 2005 in all price indices used. In the frontier analysis, we use a balanced data set of firms that are available every year and employ 20 or more employees over the years.

Variable definitions are as follows:

Firm output (Y): Production value and value-added are the most common variables representing firm output in the literature. In this study, we use value-added as firm output.

Energy Use (E): The AISS data only includes the expenditure of electricity and fuels at the firm level. Therefore, energy use is defined as the real value of the expenses on energy resources.

Capital Stock (K): Capital stock is not available in the survey. We calculate a proxy for capital stock using the perpetual inventory method:

$$K_t = K_{t-1}(1-\delta) + I_t,$$

where K denotes the capital stock, δ is the deprecation rate, and I represents the investment. Following Taymaz et al. (2008), we compute the initial capital stock as $K_0 = \frac{D_0}{\delta}$ where D_0 is the real deprecation in the initial year and $\delta = 0.067$.

Labor (L): The labor variable is defined as the number of employees.

The inefficiency part of the model includes *size* and *age* as well as several firm-level characteristics. Since ownership may affect productivity, we add a *foreign* dummy variable that indicates whether a foreign shareholder has a share in the firm. In the manufacturing industry, some firms are supported by government incentives or subsidies. In order to see if these subsidies affect energy efficiency, we create a dummy variable indicating whether the firm is subsidized - or not. Exports may also affect energy efficiency through access to developed foreign markets and promote innovation and thus increase energy efficiency. Therefore, we create another dummy variable that takes the value of 1 if the firm exports. We also included non-energy inputs per output in the inefficiency model to understand how the change in the share of other factors in output affects energy efficiency. Since energy costs are one of the major cost items, the increase in energy prices may urge firms to use energy more efficiently. Thus, the energy price index which shows the general level of energy prices was also added to the model.

[2] Statistical classification of economic activities in the European Community.

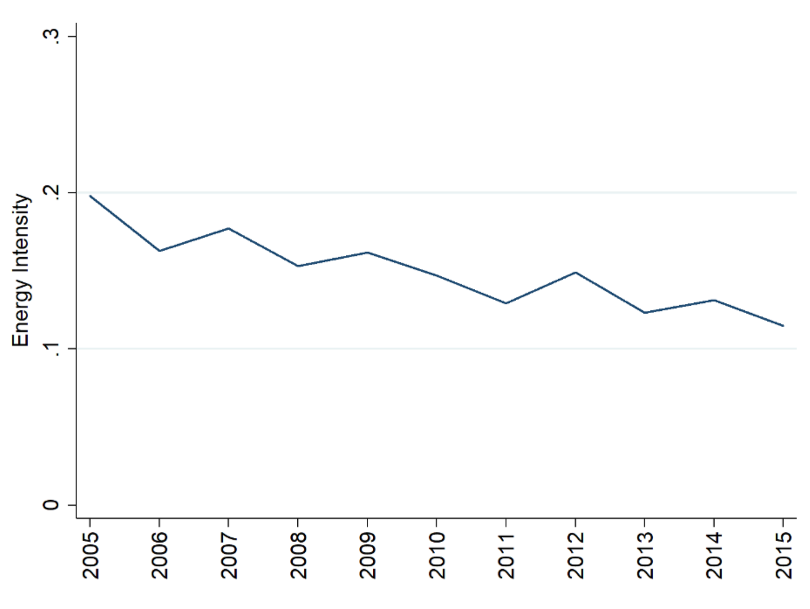

Figure 2. Average Energy Intensity in the Manufacturing Industry

Figure 2 displays the average energy intensity which may be used as a proxy for energy efficiency over the period 2005-2015. There is a total reduction of approximately 40% in the manufacturing sector during the period with an average annual decrease of 4.2% in energy intensity which is defined as the ratio of the real value of energy consumption to the real value-added in this study. When we regard the output as production value or sales, it is realized that the total drop in energy intensity is around 30%.

4. Results

The simultaneous estimation results of the energy use stochastic frontier and determinants of the inefficiency are reported in Table 1.[3]

Table 1. Estimation Results for the Energy Use Frontier

		Model 1		Model 2	
Frontier		Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
	Y	0.2093***	0.0168	0.1817***	0.0165
	K	0.4044***	0.0110	0.3788***	0.0119
	L	0.4309***	0.0329	0.3395***	0.0917
	_cons	0.3591**	0.1628	1.7949***	0.3849
Mu					
	Size	0.1153*	0.0645	0.2051**	0.0954
	Age	0.0554***	0.0102	0.0256***	0.0029
	Age^2	-0.0004***	0.0001	-0.0002***	0.0000
	P	-0.4710***	0.0896	-0.1758***	0.0248
	t	-0.0311**	0.0121	-0.0157***	0.0048
	k	0.0006***	0.0002	0.0006**	0.0003
	l	-20.3442***	5.5802	-21.4334**	9.3888
	Exporter	-0.6501***	0.1213	-0.2225***	0.0204
	Subsidy	0.0411	0.0483	0.0292*	0.0168
	Foreign	-0.2260	0.1747	-0.1133*	0.0600
	_cons	0.2328	0.2449	-0.2683	0.3653
Usigma					
	Y			-0.7532***	0.1888
	K			-0.6923***	0.1702
	L			1.3532***	0.4302
	_cons	-0.4745**	0.2072	9.1757***	2.7260
Vsigma					
	Y			0.3506***	0.0246
	K			-0.0089	0.0154
	L			-0.1088***	0.0324
	_cons	-0.2519***	0.0414	-4.4042***	0.2094
	sigma_u	0.7888***	0.0817		
	sigma_v	0.8817***	0.0183		
	lambda	0.8947***	0.0912		
	E(sigma_u)			0.0558	
	E(sigma_v)			1.0404	

Notes: Model 1 assumes homoscedasticity in the estimation while Model 2 regards heteroscedasticity. The number of the observations: 63954. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Y, K, and L denote value-added, capital stock, and labor in logarithm form respectively. Size: Logarithm of the number of the employees, age: Age of the firm, P: Energy price index, t: Linear time trend, k: Capital/output, l: Labor/output, exporter: 1 for the firms exporting, 0 otherwise; subsidy: 1 if the firm is subsidized, 0 otherwise; foreign: 1 if a share of the firm is owned by a foreign, 0 otherwise.

[3] We use the Stata routine `sfpanel` written by Belotti et al., (2013) in the estimation procedure.

As can see in Table 1, the coefficient estimates on the output and non-energy inputs are positive and statistically significant. In Model 2 where u and v are assumed to be heteroskedastic, they are statistically significant and positive as well.

Through the inefficiency drivers, foreign capital affiliation, exporting, energy price level, labor per output are found to be negative meaning that they have a positive impact on energy efficiency. Besides, the linear time trend is also estimated negatively for inefficiency implying that technical progress over time positively affects energy efficiency. Also, a quadratic relationship between the age of the firm and efficiency is found. On the other hand, the size, capital stock per output, and subsidized variables are positive indicating that their effects on energy efficiency are negative.

In addition to these estimates, the efficiency levels of the manufacturing industry can also be predicted by using Eq. (13). The mean energy efficiency index based on Model 2 is displayed in Fig. (3).

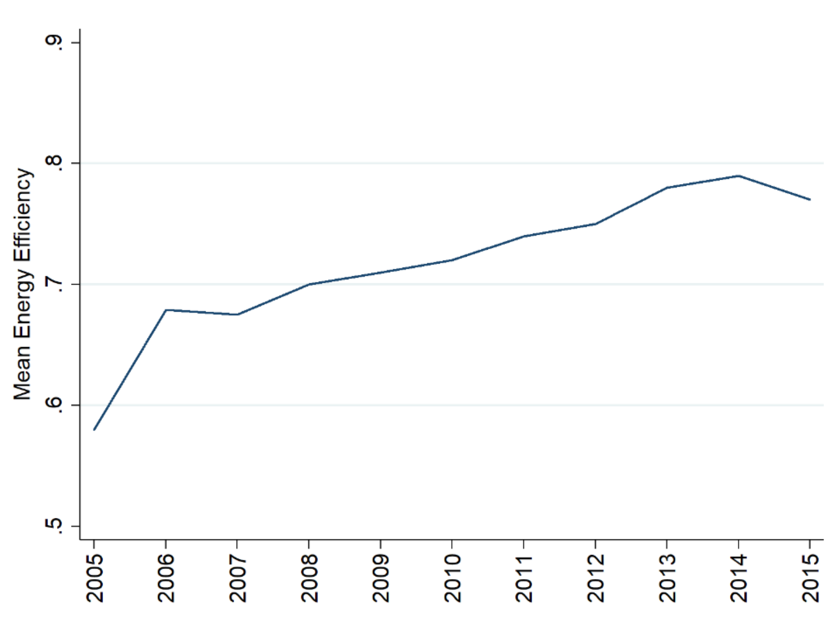

Figure 3. Mean Energy Efficiency in Manufacturing Industry

As seen in Fig. (3), there is an increasing trend in energy efficiency over the period. Technical progress boosting energy efficiency may have been experienced over time. Precautions and incentives included in the energy efficiency law which was adopted in 2007, may also have contributed to this improvement. Although an overall increase is observed during the period, there is still significant space for energy saving in the manufacturing industry.

5. Conclusion

In this analysis, we deploy firm-level data from the manufacturing industry to estimate a stochastic frontier model for energy use and the determinants of energy efficiency simultaneously. According to the results, non-energy inputs and firm output have a significant and positive effect on energy consumption. These results are plausible as the increase in other production factors requires energy usage. In the inefficiency model; foreign capital affiliation, exporting, energy price level, and labor share in output are found to increase energy efficiency and statistically significant at conventional levels while size, capital intensity, and subsidized variables reduce energy efficiency. Also, empirical results imply that there is a significant saving potential even in the years when the efficiency level is the highest. Thus, it should be aimed to continue and develop policies that increase energy efficiency. Especially in energy-intensive sub-sectors, improving and installing energy-efficient technologies should be considered. At first glance, it can be said that raising awareness at the firm level has positive effects on energy efficiency since an increase in labor share per output is found to improve efficiency. Also, it is seen that promoting export has a positive effect on energy efficiency. Similarly, firm level subsidy programs also should be re-evaluated in the light of improving energy efficiency. While our preliminary results provide new insights into the energy consumption and energy efficiency, further investigation needs to be performed. In particular, in order to see the robustness of results due to potential sectoral heterogeneity, the empirical analysis may also be carried out at the two-digit sectors in the manufacturing industry.

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References

Aigner, D., Lovell, C.K., and Schmidt, P. (1977). Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics*, 6(1), 21-37.

Battese, G. E., and Coelli, T. J. (1988). Prediction of Firm-Level Technical Efficiencies with a Generalized Frontier Production Function and Panel Data. *Journal of Econometrics*, 38, 387–399.

Battese, G. E., and Coelli, T. J. (1992). Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India. *Journal of Productivity Analysis*, 3, 153–169.

Battese, G.E., and Coelli, T.J. (1995). A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics*, 20, 325-332.

Belotti, F., Daidone, S., Ilardi, G., and Atella, V. (2013). Stochastic Frontier Analysis Using Stata. *The Stata Journal*, 13(4), 719-758.

Boyd, G. A. (2008). Estimating Plant Level Energy Efficiency with a Stochastic Frontier. *The Energy Journal*, 29(2), 23-43.

Cornwell, C., Schmidt, P., and Sickles, R. C. (1990). Production Frontiers with Crosssectional and Time-Series Variation in Efficiency Levels. *Journal of Econometrics*, 46, 185–200.

Energy Efficiency Law. (2007, May 2), *Official Gazette* (No: 26510). Access: http://www.resmigazete.gov.tr/eskiler/2007/05/20070502-2.htm

Energy Efficiency Strategy Document 2012-2023, (2012, February 25), *Official Gazette* (No: 28215). Access: http://www.resmigazete.gov.tr/eskiler/2012/02/20120225-7.htm

Eurostat. (2020). *Energy Balances* [Data File]. Retrieved from https://ec.europa.eu/eurostat/web/energy/data/energy-balances

Farrell, M. J. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society Series A, General*, 120(3), 253-281.

General Directorate of Energy Affairs. (2019). *Energy Balance Sheets* [Data File]. Retrieved from https://www.eigm.gov.tr/tr-TR/Denge-Tablolari/Denge-Tablolari

Greene, W. (2005a). Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model. *Journal of Econometrics*, 126, 269–303.

Greene, W. (2005b). Fixed and Random Effects in Stochastic Frontier Models. *Journal of Productivity Analysis*, 23, 7–32.

Haider, S., and Ahmad Bhat, J. (2018). Inter-State Analysis of Energy Efficiency- A Stochastic Frontier Approach to the Indian Paper Industry. *International Journal of Energy Sector Management*. 12(4), 547-565.

Kumbhakar, S. C. (1990). Production Frontiers, Panel Data, and Time-Varying Technical Inefficiency. *Journal of Econometrics*, 46, 201–211.

Kumbhakar, S. L., and Lovell, K. (2000). *Stochastic Frontier Analysis*. Cambridge: Cambridge University Press.

Lee, Y. H., and Schmidt, P. (1993). A Production Frontier Model with Flexible Temporal Variation in Technical Efficiency. *The Measurement of Productive Efficiency: Techniques and Applications*, 237-

255.

Lin, B., and Wang, X. (2014). Exploring Energy Efficiency in China's Iron and Steel Industry: A Stochastic Frontier Approach. *Energy Policy*, 72, 87–96.

Lutz, B.J., Massier, P., Sommerfeld, K., and Löschel, A. (2017). Drivers of Energy Efficiency in German Manufacturing: A Firm-level Stochastic Frontier Analysis. *Centre for European Economic Research (ZEW). Discussion Paper*, (17-068).

Ouyang, X., Mao, X., Sun, C., and Du, K. (2019). Industrial Energy Efficiency and Driving Forces Behind Efficiency Improvement: Evidence from the Pearl River Delta Urban Agglomeration in China. *Journal of Cleaner Production*. 220, 899-909.

Pitt, M.M., and Lee, L.F. (1981). The Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry. *Journal of Development Economics*, 9(1), 43-64.

Taymaz, E., Voyvoda, E., and Yılmaz, K. (2008). Türkiye İmalat Sanayiinde Yapısal Dönüşüm, Verimlilik ve Teknolojik Değişme Dinamikleri. *ERC Working Papers in Economics*, 8(04).

TurkStat. (2015). Annual Industry and Service Statistics Survey. http://www.turkstat.gov.tr/

Zhang, S., Lundgren, T., and Zhou, W. (2016). Energy Efficiency in Swedish industry: A Firm-Level Data Envelopment Analysis. *Energy Economics*, 55, 42-51.