Energy efficiency in the Kenyan manufacturing sector

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ABSTRACT

As one of the highest energy-consuming sectors, Kenya's manufacturing sector share of electricity consumption in 2019 was 50.16%. That of fuel consumption was 12%, the second-highest after the transport sector. It is therefore important to analyze the sector's energy efficiency and its determinants. A stochastic frontier analysis based on the assumption of a translog production function at the sub-sector level is estimated by employing a pooled model covering the years 2007, 2013 and 2018 in the analysis of electricity efficiency and 2007 and 2013 in the analysis of fuel and total energy efficiency. The sub-sectors of interest are: chemicals, pharmaceuticals and plastics, food, textile and garments and the other manufacturing sub-sector. The results show significant potential to enhance electricity, fuel and total energy efficiency across all the sub-sectors. The findings further reveal that exporting status, research and development, top managers' experience and female ownership enhance energy efficiency. The effect of these variables is, however heterogeneous by sub-sector and energy form. Labor productivity negatively influences electricity, fuel and total energy efficiency while the effect of firm age and size is ambiguous. Finally, the study provides policy implications for the design of policies to improve energy efficiency.

1. Introduction

Energy consumption, particularly fossil fuel, has sparked a string of global resource and environmental problems, including climate change, a threat to exhaustion of energy resources, and environmental pollution. Moreover, energy consumption poses a threat to firms' competitiveness, especially during periods of high energy prices. Kenya's input to CO_2 emissions on a global level is small. However, the county's fast increasing population and expanding economic activity can result in a substantial upsurge in its future emissions (Dalla Longa and van der Zwaan, 2017). In recent years, there's been an increase in energy consumption. For instance, between 2010 and 2019, fuel consumption rose by 40.43%, while electricity consumption rose by 27.80% (Republic of Kenya, 2014, 2020a).

One of the biggest energy consumers in Kenya is the manufacturing sector. The sector is a key engine of growth as it harbors high productivity economic activities. In devising her development plan, Kenya has envisioned a specifically central role for this sector. For instance, in the 2018–2022 five-year "Big Four" Agenda, Kenya targets to raise the sector's contribution to GDP from 8.4 to 15% in a bid to accelerate job creation and cut the existing trade deficit (Republic of Kenya, 2020a).

The sector leads in electricity consumption and it's the second-biggest consumer of fuel after the transport sector. For instance, the share of electricity consumption in 2019 was 50.16%. Fuel consumption was at 12%, the second-highest after the transport sector, whose share was 86.18% (Republic of Kenya, 2020a). Given the significance of the manufacturing sector both in its impact on the economy's performance and in energy consumption, the need for energy efficiency has gained prominence. The International Energy Agency (IEA) provides that energy efficiency is the best cost-effective measure to handle energy use concerns (IEA, 2014). Energy efficiency entails the use of fewer amounts of energy in production without reducing output (Lundgren et al., 2016).

The Kenyan government has taken a leading role in promoting energy efficiency in the manufacturing sector. In partnership with the Kenya Association of Manufacturers (KAM), the Ministry of Energy and Petroleum Development established a Centre for Energy Efficiency and Conservation (CEEC) in 2006. The center aims at cutting costs and promoting the competitiveness of firms whilst fostering a clean environment. It develops energy efficiency and conservation programs tailored to help firms identify energy wastage and provides recommendations to be implemented. Such programs include energy audits intended to give recommendations that can help firms save an average of 20% of their total energy expenditure and specialized training on proper

energy management (Republic of Kenya, 2020b).

The government recently established the Kenya National Energy Efficiency and Conservation Strategy (NEECS) to coordinate energy efficiency measures in more sectors. NEECS provides a roadmap towards setting and realizing energy efficiency targets across various sectors (Republic of Kenya, 2020b). Under NEECS, CEEC is aiming at increasing energy audits in the manufacturing sector from 1800 to 4000 during 2019–2025. The sector is also expected to undertake recommended energy conservation measures to save 100 MW (MW) of electricity, 250 million liters of heavy fuel oil, and 9 million liters of industrial diesel oil from a baseline of 20 MW of electricity, 51 million liters of heavy fuel oil and 1.8 million liters of industrial diesel oil in the same period (Republic of Kenya, 2020b). In addition, NEECS sets to undertake resource mobilization in concerned government agencies to finance energy efficiency programs.

Despite efforts to intensify energy efficiency, energy consumption in Kenya's manufacturing sector has continued to expand over the years. For instance, between 2010 and 2019, the sector's fuel consumption rose from 414.6 to 635.5 thousand tonnes. Consumption of electricity rose from 3204.9 to 4441.0 GWh (Republic of Kenya, 2013, 2020a). Despite the increase in energy use, the performance of the sector remained unsatisfactory. For example, through the same period, the sector's growth rate was unstable and recorded a drop from 4.5 to 3.2%. The sector's contribution to GDP contracted from 10.7 to 7.5% (Republic of Kenya, 2013, 2018b).

The increase in energy use not backed by improved economic performance points to energy inefficiency. A rigorous examination of energy efficiency is crucial to explore the actual level of energy inefficiencies and institute feasible measures to alleviate the inefficiencies. While studies such as Lin and Long (2015), Lundgren et al. (2016), Haider et al. (2019) and Boyd and Lee (2019) have analyzed energy efficiency in the manufacturing sector in different countries, there is scant evidence in Kenya's manufacturing sector. The few related studies focus on methods of implementing energy efficiency or concentrate on economy-wide energy efficiency. For instance, Ndichu et al. (2015) explore ways of implementing energy efficiency in maize milling firms while Zhang et al. (2011) analyze the economy-wide total factor energy efficiency.

This study seeks to address the research gap by providing evidence from Kenya's manufacturing sector. The study is based on a production function framework using Stochastic Frontier Analysis (SFA). Unlike previous studies, this study provides separate evidence for electricity efficiency and fuel efficiency. Boyd and Lee (2019) observe that firm processes have varying demands for various energy forms and thus it is important to analyze electricity and fuel efficiency separately. The study also assesses total energy efficiency for robustness check. The analysis is performed at the sub-sector level. The sub-sectors of interest are: chemicals, pharmaceuticals and plastics, food, textile and garments and the other manufacturing sub-sectors.

The rest of the article is organized as follows: Section 2 provides the literature review. Section 3 illustrates the empirical model and data. Section 4 provides empirical results. Section 5 offers the conclusion and policy implications.

2. Literature review

There exist two broad measures of energy efficiency: single factor and total factor energy efficiency measures. Under the single factor, energy efficiency is conventionally indicated by energy intensity, defined as a ratio of energy input to output. Studies that have adopted this approach include Sahu and Narayanan (2011) who analyze total factor productivity and energy intensity in India's manufacturing sector and Montalbano and Nenci (2019) who perform a firm-level analysis of energy efficiency, productivity and exporting in Latin America's manufacturing sector. Even though energy intensity is easy to calculate and understand, it is not a satisfactory indicator as it takes into account a

single input that produces output thereby failing to recognize the contribution of other inputs. (Lundgren et al., 2016).

Total-factor energy efficiency recognizes that modern production is multi-input-based (Lin and Long, 2015). Under this measurement are non-parametric (DEA) and parametric (SFA) approaches. The DEA requires no prior description of a production function. It determines the efficiency of decision-making units (DMUs) using linear programming where a piecewise best linear frontier is constructed from observed data. Deviations from the best linear frontier are termed as measures of inefficiency. DMUs sitting on the best linear frontier are said to be efficient. Studies using DEA are less susceptible to functional form misspecification errors, given that DEA does not demand prior specification of the functional form.

Examples of DEA applications are Mukherjee (2008a), who estimates energy efficiency in U. S's manufacturing sector during 1970–2001 and Mandal and Madheswaran (2011), who use firm-level information for the period 1989-90 to 2006-07 to explore energy efficiency in India's cement firms. Al-Refaie et al. (2016) estimate energy efficiency and productivity growth in the Jordanian industrial sector during 1999–2013. In Korea, Moon and Min (2017)assess pure energy efficiency and economic efficiency in energy-intensive firms using panel data for 63 firms during 2012–2014. Li and Shi (2014) apply DEA to analyze energy efficiency in China's industrial sector using panel data during 2001–2010. Haider et al. (2019) use a panel of 67 firms to analyze energy efficiency in India's paper industry during 2003–2014. Nevertheless, studies using DEA are likely to overestimate or underestimate energy efficiency because DEA assumes all deviations from the best linear frontier are purely outcomes of inefficiency (Chirwa, 2001).

SFA overcomes the problem by accounting for random variations in addition to inefficiency. Studies using SFA include Lundgren et al. (2016) who analyzed energy efficiency in 14 sectors of the Swedish manufacturing sector by employing an unbalanced panel of 4297 firms during 2000–2008. Lin and Long (2015) examine energy efficiency in China's chemical industry by exploiting a panel of 30 provinces during 2005–2011. Boyd and Lee (2019) measure firm-level energy efficiency and technical change in U. S's metal-based durable manufacturing sector by applying panel data during 1987–2012. Others are Filippini and Hunt (2011), who assess energy demand and energy efficiency in 29 OECD countries during 1978–2006 and Filippini and Zhang (2016), who analyze energy efficiency in 29 Chinese provinces with panel data during 2003–2012.

Researchers seem to reach a consensus that capacity exists to improve energy efficiency in the manufacturing sector that varies among firms and regions. For variations among firms, Boyd and Lee (2019) find new entrant firms to be more efficient than existing firms in U. S's metal-based durable manufacturing sector. Mukherjee (2008a) finds the largest energy-consuming sub-sectors in U. S's manufacturing sector to be relatively energy efficient. In Swedish manufacturing, Lundgren et al. (2016) establish that the food sub-sector is least fuel-efficient while the fabricated metal sub-sector is the most fuel-efficient. Further, the study finds that the rubber/plastics sub-sector is the most electricity efficient and the stone/mineral sub-sector is the least electricity efficient.

In terms of regional variation, Mukherjee (2008b) finds that Goa, Haryana and Maharashtra states perform best in energy efficiency in India's manufacturing sector while Andhra Pradesh Madhya Pradesh, Orissa and Rajasthan perform least. Lin and Long (2015) establish that energy efficiency is the largest in the Eastern region in China's chemical industry and lowest in the Western region. Lin and Wang (2014) establish that in China's iron and steel industry, firms in Northern China have relatively high energy efficiency while those in Central and Western China perform poorly.

To explain the variations in findings, various studies have assessed determinants of energy efficiency. The first is ownership structure where firms are categorized as either local or foreign-owned. Sahu and Narayanan (2011) find that foreign ownership positively influences energy efficiency. The second is firm size. Lundgren et al. (2016) study Swedish

manufacturing firms and Moon and Min (2017) Korean heavy energy-consuming firms and find energy efficiency to increase with firm size. Mandal and Madheswaran (2011) study India's cement industry and Li and Shi (2014) China's industrial sector and find energy efficiency and firm size to have a non-linear (U-shaped) relationship.

The third determinant is firm age. Boyd and Lee (2019) examine U. S's metal-based industry and Haider et al. (2019) India's paper industry and find young firms to be more energy-efficient than older firms. Mandal and Madheswaran (2011) find age to have no significant effect on energy efficiency in India's cement industry. The fourth is exporting status where Roy and Yasar (2015) and Campi et al. (2015) find exporting firms to be more energy efficient.

The fifth is Research and Development (R&D). Lin et al. (2011) study China's steel industry and Lutz et al. (2017) Germany's manufacturing firms and find R&D to positively influence energy efficiency. In contrast, Sahu and Narayanan (2011) find R&D investments to negatively influence energy efficiency. Li and Shi (2014) examine China's industrial sectors and Haider et al. (2019) India's paper industry and find R&D investments to have no significant effect on energy efficiency. The last determinant is labor productivity. Lin et al. (2011) analyze China's steel industry and Mandal and Madheswaran (2011) India's cement industry and find labor productivity to promote energy efficiency. However, Sahu and Narayanan (2011) find labor productivity to have no significant effect on energy efficiency in India's manufacturing.

Evidence on energy efficiency in the manufacturing sector in developing countries, particularly Kenya, is scarce. The few existing studies explore energy efficiency in the whole economy or analyze the implementation of energy efficiency measures. For instance, Zhang et al. (2011) analyze the total factor energy efficiency of the entire economy while Ndichu et al. (2015) assess the uptake of energy efficiency measures by maize milling firms in Kenya. This study sets to analyze energy efficiency and its determinants in Kenya's manufacturing sector. Part of the novelty of this study is to include top manager's experience and female firm ownership in assessing determinants of energy efficiency. Given that SFA accounts for both random shocks and inefficiencies, it is preferred in this study over DEA.

3. Empirical model

The pioneering works in production efficiency are by Debreu (1951) and Farrel (1957). Debreu (1951) proposed measurement of technical efficiency based on output orientation, while Farrel (1957) based measurement on input orientation. According to Kumbharkar (2000), the two measurements are jointly referred to as Debreu-Farrel efficiency and they form the basis for analysis in this study.

Consider a firm using Z inputs. The input vector $X \equiv x_1, ..., x_z$ produces output vector Q. Taking the firm's objective to be energy conservation and following Lin and Long (2015), the study adopts the stochastic input distance function form of the input-oriented model first proposed by Shepherd (1970). The function is expressed as:

$$D(Q, X) = \max\{\gamma : X/\gamma | \gamma \in W^t(Q)\}, \ W^t(Q) = \{\varepsilon R_+^Z : \text{X can produce Q}\} \quad (3.01)$$

where γ is a positive scaler "distance" by which the input vector can be

deflated and $W^t(Q)$ is the technology set which provides a set of all input vectors, $X \varepsilon R_+^Z$, with the potential to produce output vector $Q \varepsilon R_+^H$.

Equation (3.01), infers that at time t, for a specified amount of output vector Q and the present technology, the input vector X is decreased by the biggest fraction and for any viable output, $D(Q, X) \geq 1$. If $D(Q, X) = 1$, point (X, Q) sits on the production frontier, indicating full efficiency. If $D(Q, X) > 1$, point (X, Q) sits outside the frontier, implying that potentially, there is technical inefficiency in production (Lin and Long, 2015). The input distance function is assumed to be linearly homogeneous and non-decreasing in inputs, decreasing in output, concave in the input vector, and quasi concave in the output vector (Coelli, 2000).

Following Boyd (2008), it is feasible to develop a sub-vector input distance function from equation (3.01) by letting some inputs remain fixed while scaling a subset of others. Given that this study seeks to establish the maximum possible proportionate cut in energy use, energy is scaled as:

$$D_I(X_{z-1}, R, Q) = \max\left\{\gamma\left(X_{z-1}, \frac{R}{\gamma}, Q\right) \in W, \ W = \left\{(X, Q): \ (X)\text{produces} \ Q\right\}\right\} \quad (3.02)$$

where X_{z-1} is a Z-1 vector of fixed inputs and R is energy.

Empirical estimation of equation (3.02) requires a prior assumption of a functional form. This study assumes a translog production function because, unlike the Cobb-Douglas production function, it is flexible, allows for interaction among variables and does not violate the convexity condition (Lin and Long, 2015). Further, unlike other functions, it satisfies the assumption of linear homogeneity in inputs. The linear homogeneity condition is first imposed by normalizing the data. This is done by dividing the distance measure and the Z-1 inputs by the Z-th input variable (Kumbhakar et al., 2015). Given that energy is the variable of interest, it is taken to be the numeraire variable;

$$D_{Ii}X_{zi}^{-1} = g(x_i, Q_i) \ \text{where} \ x = \left(X_{1/X_z}, ..., X_{z-1/X_z}\right) \quad (3.03)$$

Taking logs on both sides yields:

$$\ln D_{Ii} - \ln X_{zi} = \ln \ g(x_i, Q_i) \quad (3.04)$$

The translog input distance function for equation (3.04) is written as:

$$\ln D_{Iit} - \ln R_{it} = \alpha_0 + \alpha_q \ln Q_{it} + \alpha_k \ln k_{it} + \alpha_l \ln l_{it} + \alpha_m \ln m_{it} + \alpha_T T_{it} + \frac{1}{2}\alpha_{qq}(\ln Q_{it})^2 + \frac{1}{2}\alpha_{kk}(\ln k_{it})^2$$
$$+ \frac{1}{2}\alpha_{ll}(\ln l_{it})^2 + \frac{1}{2}\alpha_{mm}(\ln m_{it})^2 \alpha_{kl} \ln k_{it}\ln l_{it} + \alpha_{km} \ln k_{it}\ln m_{it} + \alpha_{kq} \ln k_{it}\ln Q_{it} + \alpha_{lm} \ln l_{it}\ln m_{it} + \alpha_{lq} \ln l\ln Q_{it}$$
$$+ \alpha_{mq} \ln m_{it}LnQ_{it} + \frac{1}{2}\alpha_{TT}(\ln T_{it})^2 + \alpha_{kT} \ln k_{it}\ln T_{it} + \alpha_{mT} \ln m_{it}\ln T_{it} + \alpha_{lT} \ln l_{it}\ln T_{it} + \alpha_q \ln Q_{it}LnT_{it} \quad (3.05)$$

where $k_{it} = K_{it}/R_{it}$ is capital, $l_{it} = L_{it}/R_{it}$ is labor, $m_{it} = M_{it}/R_{it}$ is materials, R_{it} is energy, Q_{it} is output, i is firm and t is time. $\alpha_0, \alpha_z, \alpha_T, \alpha_{zj}, \alpha_{zT}$ are parameters to be estimated. T is a time trend included to capture technical change.

For $\ln D_{Iit} \geq 0$, the following symmetric conditions need to be satisfied by equation (3.05).

$$\sum_z \alpha_{zj} = \sum_z \alpha_{zy} = \sum_z \alpha_{zT} = 0, \ \alpha_{zj} = \alpha_{jz}, \ z \neq j \quad (3.06)$$

$\ln D_{it}$ in equation (3.05) is unobservable, implying estimation of the model is not feasible. Thus the equation is rearranged to obtain:

$$-\ln R_{it} = g(k_{it}, l_{it}, m_{it}, Q_{it}, T) - \ln D_{it} \quad (3.07)$$

$\ln D_{it}$ is an inefficiency term. Letting $\ln D_{it} = v_{it}, v_{it} > 0$ and introducing

the error term μ_{it} gives:

$$-\ln R_{it} = g(k_{it}, l_{it}, m_{it},\ Q_{it}, T) + \mu_{it} - v_{it} \qquad (3.08)$$

where μ_{it} is a symmetric disturbance component, which is independent and identically distributed with $N(0, \sigma_{\mu_{it}}^2)$ and $(- v_{it})$ is the technical inefficiency component, which is an identically distributed truncated random variable with $N^+(v_{it}, \sigma_{v_{it}}^2)$, $v_{it} > 0$. Equation (3.08) provides a stochastic frontier model for energy input. Transforming the equation by taking antilog yields:

$$R_{it} = g(k_{it}, l_{it}, m_{it},\ Q_{it}, T)\exp(- v_{it} + \mu_{it}) \qquad (3.09)$$

where R_{it} indicates the actual energy input, $g(k_{it}, l_{it}, m_{it},\ Q_{it}, T)$ denotes the derived energy demand function and $\exp(-v_{it} + \mu_{it})$ is a composite error component.

Based on the Debreu-Farrell efficiency framework, the derived energy demand function is taken to be the benchmark frontier. Variation of actual energy input from the energy input benchmark is the excess energy consumption resulting from technical inefficiency. Splitting the inefficient term from the composite error $(-v_{it} + \mu_{it})$ gives the energy input efficiency level:

$$EF_{it} = \frac{E(R_{it}|v_{it} \neq 0, k_{it}, l_{it}, m_{it},\ Q_{it}, T)}{E(R_{it}|v_{it} = 0, k_{it}, l_{it}, m_{it},\ Q_{it}, T)} = \exp(- v_{it}) \qquad (3.10)$$

where $E(\cdot)$ indicates conditional expectation and EF_{it} denotes energy efficiency.

To obtain determinants of energy efficiency, Battese and Coelli (1995) advocate for a first stage simultaneous estimation approach where explanatory variables are regressed on the inefficiency term v_{it} conditional on the composite error term of the model. One advantage of this approach is that it accounts for possible sources of heteroskedasticity present in the stochastic component. The model is presented as:

$$v_{it} = C_{it}\beta + \varepsilon_{it},\ \ v_{it} > 0. \qquad (3.11)$$

where C_{it} represents a vector of explanatory variables, β denotes a vector of parameters to be estimated and ε_{it} is an error term following a truncated normal distribution with mean zero and variance $\delta_{\varepsilon_{it}}^2$ truncated at $-C_{it}\beta$. A positive sign of the coefficient of an explanatory variable is interpreted to mean that the variable has a negative effect on energy efficiency and vice versa.

3.1. Econometric specification

The estimation of a stochastic frontier function using panel data can be done by various model specifications. These include the pooled model (PM), the random effects model (REM), the true fixed effects model (TFEM) and the true random effects model (TREM) (Filippini and Zhang, 2016).[1] Further, recent studies by Filippini and Hunt (2012, 2013) on the aggregate energy demand, part of the stochastic frontier models has been estimated by an adjustment proposed by Mundlak (1978). This adjustment allows for prospective unobserved heterogeneity bias and splits transient inefficiency from time-invariant unobserved heterogeneity. All these models have their relative strengths and weaknesses and the selection of a suitable model is not straightforward. It is dependent on the objective of the task, the type of data and the available variables (Filippini and Hunt, 2013).

The PM is the SFA model in its initial form introduced by Aigner et al. (1977) and modified for panel data by Pitt and Lee (1981). This model does not take the advantage provided by panel data to allow for time-invariant unobserved heterogeneity. Thus, the model can suffer from unobserved heterogeneity bias. In contrast, the REM proposed by Pitt and Lee (1981) considers the standard panel data individual random effects as inefficiency instead of unobserved heterogeneity as is the case in conventional literature on panel data econometrics (Filippini and Hunt, 2013).

To address this problem using panel data, Greene (2005a, 2005b) suggested TFEM and TREM through which the SFA model in its initial form is extended by including fixed and random individual effects respectively. In TFEM and TREM, the intercept is substituted with a series of firm-specific fixed or random effects that allow for time-invariant unobserved heterogeneity. The TFEM and the TREM can distinguish time-invariant unobserved heterogeneity from the time-varying level of efficiency component. Nonetheless, in these models, any time-invariant or persistent component of inefficiency is completely absorbed in the firm-specific constant terms (Filippini and Hunt, 2013). Thus, to the extent that there are specific sources of energy inefficiency that result in time-invariant excess energy consumption, the estimates of these models could provide relatively high and imprecise levels of energy efficiency (Filippini and Hunt, 2011).

Finally, the PM, REM and TREM could all be affected by 'unobserved heterogeneity bias'; for instance, a case where the correlation between observables and unobservables could bias some coefficients of the explanatory variables (Filippini and Hunt, 2013). To address this problem, Farsi et al. (2005a, 2005b) proposed the use of the Mundlak version of the REM. The Mundlak version is where the correlation of the firm-specific effects and the explanatory variables are considered in an auxiliary equation which is incorporated in the main equation and estimated using the REM (Filippini and Hunt, 2013). Given that correlation between the individual specific effects and the explanatory variables is at least partially captured in the model, the heterogeneity bias is expected to be relatively low.

This model would be appropriate for this study. However, despite the attractiveness of this model and other random and fixed effects models, the models failed to converge. The panel data suffers from a large number of firm entries and exits so that only a few firms are in the dataset for all the years included in the analysis. Consequently, following Filippini and Hunt (2011), the PM model fit by maximum likelihood estimation (MLE) is adopted in this study.

3.2. Data and definition of variables

The study uses data drawn from the World Bank Enterprise Surveys (WBES) for 2007, 2013 and 2018. The electricity model uses information for the three years which contains 1265[2] observations. However, 2018 does not have information on fuel spending and thus 810 observations for 2007 and 2013 are used in the estimation of the fuel and total energy models. The input distance function is estimated using output, capital, labor, materials, energy and time trend.[3] Energy is measured as the total expenditure on electricity and fuel. Output is measured as total annual sales. Capital is measured as the net book value of machinery and other equipment. Labor is measured as total wages paid to permanent,

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[1] For more detailed information on these models, see Farsi and Filippini (2009).

[2] Outliers are detected using squared Mahalabonis distance leaving 1265 observations for the electricity model and 810 observations for the fuel model.

[3] Alternatively, time dummies can be used to capture technological change as suggested in Filippini and Hunt (2012). In a preliminary analysis, time dummies were also used in the present study and the results were relatively similar.

ARTICLE IN PRESS

K.K. Macharia et al.
Energy Policy xxx (xxxx) xxx

full-time employees.[4] Materials are measured as the total cost of materials. Time trend variable is measured in years.

Following Mandal and Madheswaran (2011), Lin and Long (2014), Roy and Yasar (2015) and Haider et al. (2019) the study adopts firm size, firm age, labor productivity, foreign ownership, exporting status and R&D status in analyzing determinants of energy efficiency. Moreover, top manager's experience and female ownership status are also included. Firm size is measured as the number of employees in a firm. The effect of firm size on energy efficiency is expected to be ambiguous. Large firms could be more energy efficient than small firms. Unlike small firms, large firms have access to skilled management, enough financial resources to purchase energy-efficient technologies and a higher ability to optimize on economies of scale (Moon and Min, 2017). However, firm size could negatively influence energy efficiency. As firms grow larger, bottlenecks in management emerge, making them consume more energy (Mandal and Madheswaran, 2011).

Firm age is measured as the number of years a firm has been in existence. The effect of firm age on energy efficiency is also expected to be ambiguous. A positive effect could be observed due to gains from learning-by-doing (Mandal and Madheswaran, 2011). On the other hand, a negative effect could arise because old firms are likely to use old technologies while young firms use more recent technologies (Haider et al., 2019).

R&D is measured as a dummy variable, 1 if a firm engages in R&D and 0 if otherwise. This variable is expected to have a positive effect on energy efficiency. Engaging in R&D activities makes firms be innovative and learn about modern technologies (Lin and Shi, 2014). Top manager's level of experience is measured by the number of years a manager has worked. The effect of top manager's level of experience on energy efficiency is expected to be positive. Experienced managers are expected to have acquired the skills and techniques necessary to promote energy efficiency (Lemi and Wright, 2018).

Female firm ownership is measured as a dummy variable, 1 if a firm is female-owned and 0 if otherwise. This variable is expected to influence energy efficiency positively. According to ILO (2019), women inject teamwork, problem-solving skills, creativity and innovation and openness, which are key to promoting efficiency. Labor productivity is calculated as the ratio of output to wages.[5] The variable is expected to have a positive effect on energy efficiency. According to Mandal and Madheswaran (2011), high labor productivity is associated with the application of energy-efficient technologies.

Exporting status is measured as a dummy variable, 1 if a firm engages in exporting activities and 0 if otherwise. Exporting is expected to influence energy efficiency positively. As firms export, particularly to developed countries, they learn to enhance their technologies, and their employees get exposed to better management practices (Campi et al., 2015). Bigsten and Soderbom (2006) refer to this as learning-by-exporting. In addition, some destination countries require exporting countries to meet certain environmental standards to access their markets (Roy and Yasar, 2015).

Foreign ownership is measured as a dummy variable, 1 if a firm is foreign-owned and 0 if otherwise. The variable is expected to have a positive effect on energy efficiency. Foreign-owned firms have access to

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[4] Another measure of labour is the number of employees which should be corrected for a number of factors characterizing labour. Such factors include changes over time in employment level, degree of employment: either full or part-time, or, the average number of hours of work per employee, types of labour and quality of human capital (Heshmati, 2003). However, some of these factors are not available in the data and wage bill was considered given that it accounts for these factors to some extent.

[5] Labour productivity is also calculated as the ratio of output to number of employees. However, given that the number of employees should be adjusted for some factors that are not available in the dataset, total wage bill is used in this study.

Table 1
Descriptive statistics.

Statistics	Output (Million Ksh)	Capital (Million Ksh)	Labor (Million Ksh)	Materials (Million Ksh)	Electricity (Million Ksh)	Fuel (Million Ksh)	Firm Size (Employees)	Firm Age (Years)	TME (Years)	LP (Million Ksh)	FO (Dummy)	FM (Dummy)	Ex (Dummy)	R&D (Dummy)
Chemicals, Pharmaceuticals and Plastics sub-sector														
Mean	1286.87	196.67	107.25	190.81	18.69	13.08	126.55	36.46	20.27	7.165	0.1741	0.5955	0.4494	0.2921
SD	7331.32	1156.15	486.19	579.73	51.16	68.52	280.44	24.29	12.97	54.64	0.3803	0.4922	0.4988	0.4560
Minimum	0.3	0.011	0.132	0.001	0.006	0.01	2	1	1	0.031	0	0	0	0
Maximum	80000	15000	5000	5000	400	600	2000	103	65	718.6	1	1	1	1
Food sub-sector														
Mean	916.74	219.56	60.75	244.06	31.95	8.431	127.23	23.93	19.17	12.26	0.1634	0.6411	0.4010	0.3020
SD	4967.97	1277.08	272.40	1348.50	253.94	52.05	473.02	13.56	11.76	150.28	0.3702	0.4803	0.4907	0.4597
Minimum	0.15	0.02	0.05	0.003	0.003	0.01	2	2	1	0.052	0	0	0	0
Maximum	84000	15000	4200	17000	3500	600	8000	65	50	2964.3	1	1	1	1
Textiles and garments sub-sector														
Mean	522.14	141.76	42.08	305.98	14.48	28.10	126.39	25.15	17.61	3.605	0.1762	0.6348	0.4565	0.2909
SD	1995.34	871.35	189.73	2121.33	124.29	219.14	346.28	16.69	10.73	13.37	0.3814	0.4820	0.4986	0.4546
Minimum	0.45	0.011	0.05	0.02	0.004	0.012	1	2	1	0.0001	0	0	0	0
Maximum	18000	12300	2500	29000	1800	1980	5500	93	50	207.31	1	1	1	1
Other manufacturing sub-sector														
Mean	2335.31	226.78	65.87	414.87	16.92	10.75	116.00	21.00	15.02	2.325	0.1509	0.6509	0.3208	0.3019
SD	21455.04	1150.73	229.93	2546.54	64.58	50.52	267.31	18.47	9.158	4.749	0.3588	0.4778	0.4679	0.4602
Minimum	0.1	0.011	0.02	0.02	0.0005	0.01	2	2	1	0.008	0	0	0	0
Maximum	425000	15000	2500	36000	900	600	2500	107	40	34.49	1	1	1	1

Note: TME, LP, FO, FM and Ex denote top manager's experience, labor productivity, foreign ownership, female ownership and exporting, respectively.
Source: Author's computation using data from WBES.

Table 2
Log likelihood test for the stochastic frontier production function.

Null Hypothesis H_0	Model	χ^2-statistics (electricity model)	χ^2-statistics (fuel model)	χ^2-statistics (Total energy model)	Critical Value
Cobb-Douglas					
	C, P and P	90.76***	97.91***	41.40***	24.384
	Food	70.32***	55.21***	81.12***	24.384
	T and G	78.20***	46.66***	104.07***	24.384
	Other manufacturing	79.17***	58.28***	117.40***	24.384
Equality of parameters					
	Overall sector model *vs*	63.43***	344.91***	305.07***	55.190
	Sub-sector based model				
No technical change					
	C, P and P	43.51***	84.35***	22.03***	11.911
	Food	18.47***	57.83***	33.07***	11.911
	T and G	19.15***	25.80***	51.44***	11.911
	Other manufacturing	30.54***	45.41***	81.80***	11.911
No efficiency effects					
	C, P and P	60.23***	66.84**	25.22**	16.274
	Food	22.63***	75.51**	106.34**	16.274
	T and G	61.86***	60.07**	100.89**	16.274
	Other manufacturing	123.02***	44.31**	92.32**	16.274

χ^2 refers to the log-likelihood test statistic, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. C, P and P is chemicals, pharmaceuticals and plastics and T and G is textiles and garments.
Source: Author's computation using data from WBES.

advanced technologies and expose their staff to special skills which help them use energy efficiently (Sahu and Narayanan, 2011).

Descriptive statistics of the dataset are presented in Table 1.

4. Empirical results

4.1. Tests

Table 2 presents log-likelihood results for tests of the production function, equality of parameters, technical change and efficiency effects. The likelihood statistics are compared with Kodde and Palm (1986) critical values at 5% level of significance. The null hypothesis for a Cobb-Douglas production function against a translog specification is rejected in all the sub-sectors, hence the translog specification is adopted. The null hypothesis for equality of parameters through the four sub-sectors is rejected in all the models. Therefore, the parameters for each of the four subsectors are different and the sub-sector models cannot be pooled. The null hypothesis for no technical change is rejected in all the sub-sectors and models. This hypothesis test decision means that the production functions in the four sub-sectors shifted over time, implying that the macroeconomic environment could have a significant effect on electricity, fuel and total energy efficiency over the considered period. In all the sub-sectors and models, the null hypothesis for no

Table 3
Multicollinearity test results.

Sub-sector	Electricity model	Fuel model	Total energy model
Translog production function			
Chemicals, pharmaceuticals and plastics	2.89	4.53	3.83
Food	3.17	3.13	3.57
Textiles and garments	3.32	3.52	3.29
Other manufacturing	2.99	3.33	3.31
Determinants of energy efficiency			
Chemicals, pharmaceuticals and plastics	3.96	5.07	5.07
Food	4.60	4.55	4.55
Textiles and garments	3.12	4.77	4.77
Other manufacturing	2.78	4.15	4.15

Source: Author's computation using data from WBES.

inefficiency effects is rejected, suggesting the existence of technical inefficiencies.

The models are also assessed for multicollinearity using variance inflation factor (VIF). When inputs used in the translog production function are highly correlated, SFA estimates become imprecise. Nevertheless, multicollinearity in these functions is minimized through centering variables around their sample means before computing their interaction terms. A VIF of 1 signals no collinearity between two regressors, while a VIF greater than 10 indicates severe multicollinearity. Table 3 provides results for the multicollinearity test.

The VIF estimates show minimal collinearity among regressors in all the sub-sectors with values ranging between 2.89 and 3.32 in the electricity model, 3.13 to 4.53 in the fuel model and 3.29 to 3.83 in the total energy model. The results also show minimal collinearity among determinants of energy efficiency. The VIF estimates range from 2.78 to 4.60 in the electricity model, 4.15 to 5.07 in the fuel and total energy models. The later models have common observations.

4.2. Elasticities

The maximum likelihood estimates of the parameters of the electricity, fuel and total energy stochastic frontier models are provided in Tables A.1, A.2 and A.3 in the appendix. The parameter estimates of output and all inputs have economically plausible signs in all the sub-sectors in the electricity model, except capital in the other manufacturing sub-sector. However, the coefficient of this variable is insignificant at 5% level of significance. In the fuel model, parameter estimates of output and all inputs have economically plausible signs, except materials in the food sub-sector. Another exception is capital in all the sub-sectors, apart from the other manufacturing sub-sector. Nevertheless, the variables with unexpected signs are statistically insignificant. In the total energy model, all parameter estimates of inputs and output have economically reasonable signs except materials in the other manufacturing sub-sector. But the coefficient on this variable is insignificant. The time trend coefficient is positive and significant in the chemicals, pharmaceuticals and plastics sub-sector in both the fuel and total energy models.

Output elasticities have negative signs which is in line with the property that output decreases with input distance. The positive sign on input elasticities conforms with the non-decreasing in inputs property of

Table 4

Summary statistics for electricity efficiency point estimates.

Model	Mean	Standard Deviation	Skewness	Minimum	Maximum
Chemicals, Pharmaceuticals and plastics	0.805	0.169	−2.784	0.005	0.960
Food	0.648	0.173	−1.904	0.013	0.905
Textiles and Garments	0.786	0.191	−1.966	0.010	0.982
Other Manufacturing	0.678	0.186	−1.679	0.012	0.935

Source: Author's computation from WBES data.

input distance functions. Even though some variables have insignificant coefficients, the models are valid and can be applied in estimating efficiency for the reason that the null hypothesis $(\lambda=0)$[6] for no stochastic inefficiencies is rejected at 5% level of significance. All the sub-sectors in the three models display increasing returns to scale, implying that an increase in output would less than proportionately lead to increased energy consumption.

4.3. Electricity efficiency point estimates

Table 4 provides summary statistics of electricity efficiency point estimates by sub-sectors.

The mean efficiency scores vary across the sub-sectors, indicating varying capacities to enhance electricity efficiency. The mean electricity efficiency scores are 80.5, 64.8, 78.6 and 67.8% in the chemicals, pharmaceuticals and plastics, food, textiles and garments and the other manufacturing sub-sectors, respectively. They reveal that respective sub-sectors could produce the same level of output by reducing electricity consumption by 19.5, 35.2, 21.4 and 32.2%. Comparing results of this study with other studies, Lundgren et al. (2016) in the Swedish manufacturing sector, find average electricity efficiency in 12 sub-sectors ranges from 70% in the stone/mineral sub-sector to 98.2% in the rubber and printing sub-sector. In the Swedish pulp and paper mills industry, Blomberg et al. (2012) find electricity efficiency in four sectors to vary from 81.3% in the Kraft and wellpaper sector to 97.7% in the printing paper sector. However, the energy efficiency scores in different countries are not openly comparable to those of this study because of differences in data samples, models and estimation methods. Efficiency

Table 5

Mean electricity efficiency by size categories and sub-sector.

Sub-sector	Mean	Minimum	Maximum	Kruskal-Wallis test Statistic
Chemicals, pharmaceuticals and plastics				
Small	0.840	0.628	0.938	
Medium	0.817	0.180	0.960	7.349
Large	0.763	0.005	0.935	
Food				
Small	0.651	0.013	0.893	
Medium	0.642	0.037	0.905	6.172
Large	0.651	0.034	0.877	
Textiles and garments				
Small	0.744	0.020	0.979	
Medium	0.801	0.010	0.965	6.102
Large	0.814	0.170	0.982	
Other manufacturing				
Small	0.665	0.014	0.923	
Medium	0.688	0.012	0.922	8.022
Large	0.675	0.013	0.935	

Source: Author's computation from WBES data.

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[6] λ gives information on the proportion of the composite error term explained by the inefficiency term, v_{it}.

scores are sensitive to estimation methods, assumptions made on the distribution of error terms and data samples (Ngui and Muniu, 2012).

The maximum electricity efficiency scores are high and the minimum electricity efficiency scores are low but vary across sub-sectors. This signals the existence of very electricity-efficient and inefficient firms in each sub-sector. This corroborates the result of Lundgren et al. (2016) in the Swedish manufacturing sub-sectors. Kruskal-Wallis test of the null hypothesis that the mean electricity efficiency scores are equal in all the sub-sectors is 290.339 with 3 degrees of freedom and higher than the critical value of 7.815, resulting in rejection of the null hypothesis at 5% level of significance. Therefore, the average electricity efficiency scores are significantly different across the four sub-sectors. Nevertheless, direct comparison of the average scores across the sub-sectors in terms of whether one sub-sector is more electricity efficient than the other is less meaningful because efficiency scores are established on sub-sector specific benchmark frontier (O'Donell et al., 2008).

4.3.1. Distribution of electricity efficiency by firm size

Table 5 provides the distribution of sub-sector electricity efficiency levels by firm size. Firms are categorized into three sizes by the WBES classification. The categories are: small (5–19 employees), medium (20–99 employees) and large (over 100 employees). This analysis is important in revealing firms with the highest potential to meet electricity efficiency targets.

Table 5 shows heterogeneity in electricity efficiency across firm sizes in each sub-sector. Kruskal-Wallis test statistics are greater than the critical value of 5.991 with 2 degrees of freedom in each sub-sector. This means that the null hypothesis that the mean electricity efficiency scores are equal across all firm sizes in each sub-sector is rejected at 5% level of significance. Thus, mean electricity efficiency is significantly different across the three firm sizes in each sub-sector. There is limited evidence of common patterns in electricity efficiency across firms of different sizes. It is difficult to tell whether small or large firms are the most electricity efficient. In the chemicals, pharmaceuticals and plastics sub-sector, electricity efficiency increases monotonically with reductions in firm size. In the food sub-sector, small and large firms are equally electricity efficient and perform better than medium firms. In the textiles and garments sub-sector, electricity efficiency increases monotonically with firm size. In the other manufacturing sub-sector, medium-sized firms are more electricity efficient than small and large firms while large-sized firms are more efficient than small firms.

4.4. Fuel efficiency point estimates

Table 6 provides summary statistics of fuel efficiency point estimates by sub-sectors.

The mean fuel efficiency scores in the chemicals, pharmaceuticals and plastics, food, textile and garments and the other manufacturing sub-sectors are 73.9, 72.3, 71.5 and 68.8% respectively. These scores imply that respective sub-sectors can cut fuel consumption by 26.1, 27.7, 20.5 and 31.2% without any change in output. Comparing the findings of this study with those of other studies, Lundgren et al. (2016)

Table 6

Summary statistics for fuel efficiency point estimates.

Model	Mean	Standard Deviation	Skewness	Minimum	Maximum
Chemicals, Pharmaceuticals and plastics	0.739	0.308	−0.800	0.019	0.996
Food	0.723	0.205	−1.840	0.023	0.978
Textiles and Garments	0.715	0.200	−1.698	0.004	0.955
Other Manufacturing	0.688	0.187	−1.541	0.007	0.975

Source: Author's computation from WBES data.

Table 7
Mean fuel efficiency by size categories and sub-sector.

Sub-sector	Mean	Minimum	Maximum	Kruskal-Wallis test Statistic
Chemicals, pharmaceuticals and plastics				
Small	0.770	0.285	0.996	
Medium	0.763	0.086	0.995	7.072
Large	0.682	0.019	0.992	
Food				
Small	0.743	0.026	0.978	
Medium	0.712	0.038	0.973	8.330
Large	0.712	0.023	0.953	
Textiles and garments				
Small	0.680	0.011	0.939	
Medium	0.742	0.004	0.955	8.741
Large	0.725	0.252	0.936	
Other manufacturing				
Small	0.664	0.094	0.933	
Medium	0.702	0.709	0.935	8.171
Large	0.690	0.007	0.976	

Source: Author's computation from WBES data.

in 12 Swedish manufacturing sub-sectors find fuel efficiency ranges from 63.4% in the food sub-sector to 94.3% in the fabricated metals sub-sector. Very high maximum and low minimum fuel efficiency values are found across sub-sectors, revealing the presence of very fuel-efficient and inefficient firms in each sub-sector. The result is in line with Lundgren et al. (2016) in Swedish manufacturing sub-sectors. Kruskal-Wallis test for the null hypothesis that mean fuel efficiency scores are equal in all sub-sectors is 77.466 and higher than the critical value of 7.815 with 3 degrees of freedom which leads to rejection of the null hypothesis at 5% level of significance. This result implies that the average fuel efficiency levels are significantly different across the four sub-sectors.

4.4.1. Distribution of fuel efficiency by firm size

Table 7 provides the distribution of sub-sector fuel efficiency levels by firm size.

Kruskal-Wallis test statistics are greater than the critical value of 5.991 with 2 degrees of freedom in each sub-sector. This result implies that the null hypothesis that the mean fuel efficiency scores are equal in all firm sizes in each sub-sector is rejected at 5% level of significance. Consequently, mean fuel efficiency scores differ significantly across the three firm sizes in each sub-sector. There is limited evidence of common patterns in fuel efficiency across firm sizes. Thus, it is difficult to assert whether small or large firms are the most fuel-efficient. In the chemicals, pharmaceuticals and plastics sub-sector, fuel efficiency increases monotonically with reductions in firm size. In the food sub-sector, small firms are more fuel-efficient than medium and large firms. Medium and large firms in this sub-sector are equally fuel-efficient. In the textile and garments and other manufacturing sub-sectors, medium firms are more fuel-efficient than small and large firms. But large firms are more efficient than small firms in both sub-sectors.

Table 8
Summary statistics for total energy efficiency point estimates.

Model	Mean	Standard Deviation	Skewness	Minimum	Maximum
Chemicals, Pharmaceuticals and plastics	0.625	0.223	−0.542	0.063	0.967
Food	0.647	0.224	−1.453	0.054	0.943
Textiles and Garments	0.690	0.225	−1.074	0.050	0.995
Other Manufacturing	0.690	0.201	−1.571	0.056	0.962

Source: Author's computation from WBES data.

Table 9
Mean total energy efficiency by size categories and sub-sector.

Sub-sector	Mean	Minimum	Maximum	Kruskal-Wallis test Statistic
Chemicals, pharmaceuticals and plastics				
Small	0.816	0.657	0.967	
Medium	0.630	0.217	0.921	8.206
Large	0.549	0.063	0.867	
Food				
Small	0.640	0.057	0.920	
Medium	0.646	0.064	0.943	7.658
Large	0.655	0.054	0.930	
Textile and garments				
Small	0.630	0.068	0.955	
Medium	0.744	0.050	0.995	10.32
Large	0.697	0.152	0.963	
Other manufacturing				
Small	0.645	0.056	0.940	
Medium	0.707	0.089	0.962	8.898
Large	0.704	0.067	0.912	

Source: Author's computation from WBES data.

4.5. Total energy efficiency point estimates

Table 8 provides summary statistics of total energy efficiency point estimates by sub-sectors.

The average total energy efficiency scores in chemicals, pharmaceuticals and plastics is 62.5%, 64.7% in food and 69.0% in textile and garments and other manufacturing sub-sectors. The scores indicate a potential reduction in energy consumption by 37.5, 35.3, 31.0 and 31.0% in the respective sub-sectors without affecting output. Comparing this finding with those of other studies, Lin and Long (2015) find the average energy efficiency in China's chemical industry to be 68.97%. In China's iron and steel industry, Lin and Wang (2014) find average energy efficiency to be 69.90%. The study finds very high maximum and low minimum energy efficiency scores across firms indicating the coexistence of very energy-efficient and energy-inefficient firms. Kruskal-Wallis test for the null hypothesis that total energy efficiency is equal in all sub-sectors is rejected at 5% level of significance. The test statistic is 9.263 with 3 degrees of freedom and is larger than the critical value of 7.815. This result means that the mean total energy efficiency scores are significantly different across all the sub-sectors.

4.5.1. Distribution of total energy efficiency by firm size

Table 9 provides the distribution of sub-sector total energy efficiency levels by firm size.

Results in Table 9 show that Kruskal-Wallis test statistics are greater than the critical value of 5.991 with 2 degrees of freedom in each sub-sector. This result means that the null hypothesis that the mean total energy efficiency scores are equal in all firm sizes in each sub-sector is rejected at 5% level of significance. Hence, the mean total energy efficiency is significantly different across the three firm sizes in each sub-sector. There is a common pattern in total energy efficiency across firm sizes in the chemicals, pharmaceuticals and plastics and food sub-sectors but limited evidence in other sub-sectors. Total energy efficiency appears to decrease monotonically with firm size in the chemicals, pharmaceuticals and plastics sub-sector but increases monotonically with firm size in the food sub-sector. In the textiles and garments and other manufacturing sub-sectors, medium-sized firms are most energy-efficient, followed by large firms. Small firms are the least energy efficient.

4.6. Determinants of energy efficiency

The results on determinants of energy efficiency are provided in Tables A.1, A.2 and A.3. Labor productivity negatively influences electricity, fuel and total energy efficiency in all the sub-sectors, except for the food sub-sector in the electricity model. The finding is contrary to

the study's expectations. It appears that measures to improve labor productivity do not give additional emphasis to ensure a considerable level of skill advancement required to improving energy efficiency. This contradicts the outcome of Lin et al. (2011) and Mandal and Madheswaran (2011).

The effect of firm age on energy efficiency is ambiguous. Firm age negatively influences electricity efficiency in the food sub-sector, fuel efficiency in the chemicals, pharmaceuticals and plastics sub-sector and total energy efficiency in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors. The result indicates that young firms are more efficient than older firms. Probably, young firms use recent technologies while older firms use old technologies due to the huge sunk costs. This finding contrasts Jovanovic (1982) theory but, supports Haider et al. (2019). Firm age positively influences electricity efficiency in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors. The implication of this is that older firms are more electricity efficient than young firms. Older firms could be capitalizing on their long experience in production to put in place electricity efficiency measures. This finding supports Jovanovic (1982) theory and Mandal and Madheswaran (2011).

Firm age squared is included in the models to capture the non-linear relationship between firm age and energy efficiency. The variable has a negative and significant coefficient in the food and textile and garments sub-sectors in the electricity model. In the fuel model, it has a negative and significant coefficient in the other manufacturing sub-sector while in the total energy model, the negative and significant coefficient is in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors. Therefore, as firms grow older, they become more efficient. Firm age and electricity efficiency in the food sub-sector and firm age and total energy efficiency in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors have an inverted U relationship. The coefficient of firm age squared is positive in the textile and garments sub-sector, implying that advancement in age is accompanied by a decline in fuel efficiency.

The study finds a positive and significant effect of top manager's experience on electricity efficiency in the food and the other manufacturing sub-sectors. The variable also has a positive effect on total energy efficiency in the textiles and garments sub-sector. Electricity and total energy efficiency in these sub-sectors increase with top manager's level of experience. Experienced managers are likely to transform processes using skills and abilities accumulated over time. This finding supports Lemi and Wright (2018).

The effect of firm size on energy efficiency is ambiguous. Its positive and significant effect on electricity efficiency in the other manufacturing sub-sector and fuel efficiency in the textiles and garments sub-sector implies that large firms are more electricity and fuel-efficient than small firms in respective sub-sectors. Large firms have a highly skilled workforce, enough resources to purchase efficient technologies, high specialization and a higher chance of capitalizing on economies of scale. This finding supports Jovanovic (1982) theory and Li and Shi (2014). The negative and significant effect of firm size on electricity efficiency in the food and chemicals, pharmaceuticals and plastics sub-sectors implies that small firms are more electricity efficient than large firms. This particular finding could be explained by complexities that arise in large firms that result in more electricity consumption.

Female ownership has a positive and significant effect on electricity efficiency in the food sub-sector, fuel efficiency in the chemicals, pharmaceuticals and plastics and food sub-sectors, and total energy efficiency in the chemicals, pharmaceuticals and plastics sub-sector. This finding implies that female-owned firms are likely to be more electricity, fuel and total energy efficient in respective sub-sectors. Women could be better in coordination and in skills that solve operational challenges, besides their ingenuity, novelty and openness (ILO, 2019).

The positive and significant effect of foreign ownership on fuel efficiency in the chemicals, pharmaceuticals and plastics sub-sector implies that foreign-owned firms are more fuel-efficient than domestically-owned firms. Foreign-owned firms could have access to technical assistance and technical know-how from abroad. This finding supports Sahu and Narayanan (2011).

Exporting status has a positive and significant effect on electricity efficiency in all the sub-sectors except the other manufacturing sub-sector. The effect is also felt on fuel efficiency in the chemicals, pharmaceuticals and plastics and the other manufacturing sub-sectors and total energy efficiency in the chemicals, pharmaceuticals and plastics sub-sector. This implies that in the respective sub-sectors, exporting firms are more electricity, fuel and total energy-efficient than non-exporting firms. This finding supports Campi et al. (2015). Through learning by exporting, firms enhance efficiency. Further, some buyers believe in environmentally friendly goods, which makes exporting firms adhere to environmental quality standards (Roy and Yasar, 2015).

R&D has a negative and significant coefficient in the chemicals, pharmaceuticals and plastics sub-sector in both electricity and total energy models. The same is observed in the chemicals, pharmaceuticals and plastics and the other manufacturing sub-sectors in the fuel model. This implies that firms with R&D investments are more electricity and fuel-efficient. R&D activities expose firms to innovations in modern technologies that improve energy efficiency. This finding supports Lutz et al. (2017).

5. Conclusion and policy implications

This study employs SFA under a pooled model to analyze energy efficiency and its determinants in Kenya's manufacturing sector. More precisely, the input distance function is used to model energy efficiency with the assumption of a translog production function. The results show considerable potential to improve electricity, fuel and total energy efficiency.

There is no general pattern of drivers of energy efficiency across sub-sectors. Labor productivity is found to negatively influence electricity, fuel and total energy efficiency in nearly all the sub-sectors. The effect of firm age on energy efficiency is ambiguous. It influences electricity efficiency positively in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors. But it has a negative effect on electricity efficiency in the food sub-sector and fuel efficiency in the chemicals, pharmaceuticals and plastics sub-sector. It also has a negative effect on total energy efficiency in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors.

The effect of firm size on energy efficiency is ambiguous. It influences electricity efficiency positively in the other manufacturing sub-sector and fuel efficiency in the textile and garments sub-sector. On the other hand, it influences electricity efficiency negatively in the chemicals, pharmaceuticals and plastics and food sub-sectors. The effect of top manager's experience on electricity efficiency is positive in the other manufacturing and food sub-sectors. It has the same effect on total energy efficiency in the textiles and garments sub-sector. Female firm ownership promotes electricity efficiency in the food sub-sector and fuel and total energy efficiency in the chemicals, pharmaceuticals and plastics sub-sector.

Foreign ownership positively influences fuel efficiency in the chemicals, pharmaceuticals and plastics sub-sector. Exporting influences electricity efficiency positively in all the sub-sectors except the other manufacturing sub-sector. It also influences fuel efficiency positively in the chemicals, pharmaceuticals and plastics and the other manufacturing sub-sectors. The same influence is observed on total energy efficiency in the chemicals, pharmaceuticals and plastics sub-sector. R&D positively influences electricity and total energy efficiency in the chemicals, pharmaceuticals and plastics sub-sector. It has the same effect on fuel efficiency in the chemicals, pharmaceuticals and plastics and the other manufacturing sub-sectors.

Kenya requires policies to stimulate energy efficiency in the manufacturing sector. Given the heterogeneity in drivers of efficiency across sub-sectors and energy forms, the policies should be sub-sector

and energy-specific. The policy proposals can be summarized as follows:

1. Strengthen technological innovation. The adoption of new technologies is the basis of energy efficiency. The government needs to increase R&D funds to enable the discovery of modern technologies and the development of new equipment. Available data shows that in 2018, R&D funding stood at only 0.48% of GDP. The funding was below the 2% recommended in the National Research Fund (NRF) Science, Technology and Innovation Act 2013. Further, the government may foster R&D subsidies. It could provide low-interest loans or tax incentives to firms that invest in R&D.

In the context of industrial structure, there is need to substitute old technologies with new technologies. Given that the high sunk costs could be the main barrier to technological change, there is need to provide financial incentives such as low-interest loans, tax exemptions and subsidies.

2. Promote exports. Exporting promotes electricity efficiency in all sub-sectors apart from the other manufacturing sub-sector, fuel efficiency in the chemicals, pharmaceuticals and plastics and the other manufacturing sub-sectors and total energy efficiency in the chemicals, pharmaceuticals and plastics sub-sector. There is need for the government to promote exports beyond the creation of export processing zones. Sourcing foreign markets is particularly important in this regard.

3. Promote the growth of firms in the manufacturing sector. Firm size positively influences electricity efficiency in the chemicals, pharmaceuticals and plastics sub-sector and fuel efficiency in the textiles and garments sub-sector. There is need for the government to provide a favorable business environment to enable firm growth.

4. Promote female ownership in firms. Female ownership positively influences electricity efficiency in the food sub-sector, fuel efficiency in the chemicals, pharmaceuticals and plastics and food sub-sectors, and total energy in the chemicals, pharmaceuticals and plastics sub-sector. The government needs to devise policies that increase the visibility of female entrepreneurs in these sub-sectors.

5. Other policies. Promotion of foreign ownership, particularly in the chemicals, pharmaceuticals and plastics sub-sector where this variable influences fuel efficiency. Through foreign ownership, there will be spillover effects to local firms. The government also needs to increase awareness of energy efficiency in firms. For instance, if producers learn the benefits of energy efficiency measures, such measures may be scaled up.

CRediT authorship contribution statement

Kenneth Kigundu Macharia: Conceptualization, Visualization, Methodology, Software, Data curation, Investigation, Writing – original draft, and final report. **John Kamau Gathiaka:** Supervision, Writing – review & editing. **Dianah Ngui:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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