Journal of Sustainable Development; Vol. 15, No. 3; 2022
ISSN 1913-9063 E-ISSN 1913-9071
Published by Canadian Center of Science and Education

Effects of Energy Efficiency on Firm Productivity in Kenya's Manufacturing Sector

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Received: February 17, 2022 Accepted: March 25, 2022 Online Published: March 26, 2022

doi:10.5539/jsd.v15n3p90 URL: https://doi.org/10.5539/jsd.v15n3p90

The study was funded by AERC.

Grant ID: PT14UON2019.

Abstract

There is concern about probable energy efficiency and economic performance trade-off, particularly in developing countries which often require more energy consumption to spur their economies. This study assesses the relation between energy efficiency and total factor productivity in Kenya's manufacturing sector by applying a sample of firms in the World Bank Enterprise Survey. Energy intensity is used as a proxy for energy efficiency while total factor productivity is estimated using the Levinsohn-Petrin Algorithm. A dynamic panel data model is applied in the analysis of the energy efficiency and total factor productivity relationship which is at the sub-sector and firm size levels. The sub-sectors of concern are: chemicals, pharmaceuticals and plastics, food, textile and garments and paper and other manufacturing sub-sectors. Firm sizes of interest are: small, medium and large. The findings show heterogeneity in energy intensity across sub-sectors. Total factor productivity is also found to be heterogeneous across sub-sectors and firms of different sizes. The estimates show that in general, energy efficiency significantly promotes total factor productivity. Other factors that promote total factor productivity include capital intensity, age, size, top manager's years of experience, foreign ownership and exporting status. However, the effect of these variables varies across the sub-sectors and firm sizes. The study findings suggest that policies to improve energy efficiency should be accorded additional emphasis jointly with improvements in total factor productivity.

Keywords: energy efficiency, total factor productivity, manufacturing sector

1. Introduction

According to the International Energy Agency (IEA), energy efficiency is one of the most cost-effective approaches to deal with energy use problems (IEA, 2014). Energy efficiency is therefore important in ensuring sustainable growth. However, there is a concern in many countries, particularly developing countries where dependence on environmental resources is relatively high, regarding a possible trade-off between energy efficiency and economic performance. There is a concern because while energy efficiency is expected to bring about reductions in energy consumption, developing countries often need to increase energy production and consumption to spur their economies (Cantore et al., 2016). Moreover, resources applied in enhancing energy efficiency could be utilized in promoting economic performance. Reinforcing this opinion is an extensive view among some researchers that clean environment growth strategies pose a risk more than a prospect to growth (Dercon, 2014).

However, empirical evidence on the trade-off between a clean environment and economic performance remains limited, particularly at the micro-level. This study sheds light on the link between energy efficiency as indicated by energy intensity and economic performance using total factor productivity (TFP) as the measure of economic performance. TFP is a suitable indicator of a firm's ability to create technological change because it establishes the quantity of output that could be generated from a certain amount of inputs collectively (Cantore et al., 2016).

This study tests the hypothesis that improvements in energy efficiency bolster manufacturing firms' productivity.

The process through which energy efficiency could promote TFP is suitably captured in the Porter Hypothesis (Porter and Van der Linder, 1995). The hypothesis is a departure from the conventional view among some economists that a reduction of an externality causing input such as energy through the acquisition of new technologies stifles firm productivity by increasing the cost of production and reducing firm competitiveness. The hypothesis, however, posits that well-formulated environmental policies nurture innovations based on the employment of other inputs, support efficiency and eventually enhance productivity (Porter and Van der Linder, 1995).

Improvements in energy efficiency reduce firms' energy costs which leads to increased firm competitiveness. The improvement in competitiveness results in expanded output as well as other implicit effects. Energy efficiency improvements also encompass a rebound effect on the overall economy, as effects of such improvements spread to other sectors of the economy (Celani de Macedo et al., 2020). Energy efficiency in the manufacturing sector also brings about a fall in overall energy demand at the national level. This implies less energy-infrastructure investments. The cost savings thereof could be channelled to non-energy goods leading to the creation of jobs and value addition in the economy (Celani de Macedo et al., 2020). The cost of implementing energy efficiency programs should therefore consider the associated productivity benefits. The benefits, when captured correctly will make the energy efficiency programs appear more cost-effective, ultimately increasing their uptake.

The research concentrates on Kenya's manufacturing sector because of its significance in its bearing on the economy's performance and energy use. The sector is a strategic driver of growth as it harbours high productive economic activities. The sector has therefore taken a specifically central role in Kenya's development plan. For example, to fast-track job creation and reduce the prevailing trade deficits, Kenya intends to increase the manufacturing sector's input to GDP from 8.4 to 15% in the 2018-2022 five-year "Big Four" Agenda (Republic of Kenya, 2020). The Kenyan manufacturing sector takes the lead in electricity use and comes second in fuel use behind the transport sector. For example, in 2019, the sector consumed 50.16% of the total electricity consumed in the country. The share of fuel consumed was 12%, the second-largest behind the transport sector at 86.18%.

The energy efficiency and manufacturing firms' productivity relation, even though useful and important to policymaking, remains scarcely investigated particularly in sub-Saharan Africa (SSA). The few notable studies that have used micro-level data to study the relationship include Sahu and Narayan (2011) in India, Cantore et al. (2016) in 29 developing countries, Montalbano and Nenci (2019) in 30 Latin American Caribbean (LAC) countries and Filippini et al. (2020) in China. In Kenya, Cantore et al. (2016) investigate the relationship by applying macro-level data. This study provides a novel contribution to extant literature explaining TFP determinants by presenting the Kenyan manufacturing sector evidence at the firm level, the decision-making level. This is an important case because energy use in the sector has in the past decade increased without matching growth and contribution to GDP (Macharia et al., 2021).

The study begins by estimating TFP using the Levinson-Petrin (LP) estimation algorithm. A dynamic panel model is then analysed to establish the energy efficiency and TFP relation using panel data extracted from the World Bank Enterprise Survey (WBES) for the years 2007, 2013 and 2018. This dataset has not been previously applied in this respect. As a departure from previous studies, this study presents evidence of the relationship at the sub-sector and firm size levels. Proskuryakova and Kovalev (2015) observe that energy intensity varies by sub-sector structure and that it could be stimulated by variations in the energy input mix. Therefore, it is important to control for heterogeneity in structural energy intensity across sub-sectors and firm sizes.

The rest of this study is shaped in the following manner. Section 2 presents the literature review. The empirical model is provided in section 3. Section 4 presents empirical findings. Section 5 provides the conclusion and policy implications.

2. Literature Review

Significant effort has been applied in the investigation of industrial economic performance benefits of energy efficiency. Even though a bulk of the studies show a positive link, a few of them find a negative or no significant effect. Beginning with studies that find a positive link, Worrell et al. (2003) review the advancement in energy efficiency and productivity relation in U. S's iron and steel industry. The study finds that energy efficiency can promote the general productivity of the industry. Subrahmanya (2006) investigates the relationship between energy efficiency and economic performance in the Indian small-scale bricks and foundry clusters by employing multiple regression analysis on primary level data. High energy-efficient firms are found to be linked to higher returns to scale.

Using cross-sectional data sourced from the Center for Monitoring Indian Economy, Sahu and Narayanan (2011a) apply ordinary least squares (OLS) in assessing the energy efficiency and Indian manufacturing productivity relation. Energy efficiency is reported to have a positive effect on productivity. In 29 low-income countries, Cantore et al. (2016) assess the energy efficiency and productivity and energy efficiency and economic growth links. In the former relationship, a fixed-effects model is applied on data obtained from WBES while in the latter, a dynamic panel model is applied on data drawn from the World Bank Development Indicators (WDI). Energy efficiency is found to be a driver of higher productivity and economic growth among countries of interest.

By applying a pooled ordinary least squares regression model on a standard constant returns to scale Cobb-Douglas production function, Montalbano and Nenci (2019) examine the energy efficiency and productivity and energy efficiency and exporting links in 30 Latin American Caribbean (LAC) states using WBES firm-level data. Findings show heterogeneity in the two relationships by firm size and sub-sector. While on average there is evidence linking high energy efficiency to productivity gains, mixed results are found on the energy efficiency and trade relation. High energy efficiency is only found to be positively linked with exporting in large firms and the chemicals and mining industry. In the Republic of North Macedonia industries, Celani de Macedo et al. (2020) investigate the extent to which energy efficiency measures can concurrently create improvements in value-added, employment and energy savings using input-output models. Energy efficiency measures are found to achieve triple dividends in value-added, employment and energy saving among industries.

While applying a difference-in-difference (DID) model and firm-level data running 2003-2008, Filippini et al. (2020) investigate the productivity effects of energy efficiency programs in the Chinese iron and steel firms. Findings reveal that in general, firms participating in the energy efficiency program record faster growth in TFP. In the Italian paper and glass industries, Caragliu (2021) investigates the effects of energy efficiency-promotion strategies on firm performance by applying a pooled model on panel data running 2005-2016. Findings reveal that firms enrolled in energy efficiency support programs appear to have higher productivity. In Jiangsu, China, Jiang et al. (2021) assess whether improvements in energy efficiency pose a threat to manufacturing firms' output performance using firm-level data. Energy efficiency is found to be positively linked with high output performance in textile firms.

Moving to studies that find a negative link or no significant effect, Haider and Ganaie (2017) by employing time series data and vector error correction mechanism (VECM) find energy efficiency to negatively influence productivity in India. Pons et al. (2013) while investigating the energy efficiency technologies and manufacturing sector performance link in Spanish and Slovenian using linear regression find the application of energy-saving technologies to have no clear impact on firm economic performance, notwithstanding the former being linked to positive environmental performance. In Jiangsu, China, Jiang et al. (2021) find that energy efficiency does not significantly affect output performance in chemical manufacturing firms.

Reviewed literature on the influence of energy efficiency on manufacturing firms' performance shows that evidence is concentrated in countries in Asia, Europe and America. Evidence for Africa, particularly Kenya, is scanty yet developing countries are anticipated to consume large amounts of energy to support their growing economies. The previous relevant study by Cantore et al. (2016) on the Kenyan case applies macro-level data. However, analysis at the macro-level may not give explicit evidence to direct the behaviour of Kenyan manufacturing firms regarding energy conservation. Reviewed literature also shows that only a few studies such as Sahu and Narayanan (2011), Cantore et al. (2016) and Filippini et al. (2020) have adopted TFP as a measure of economic performance, yet this measure is a suitable indicator of a firm's ability to create technological change (Cantore et al., 2016). Finally, the majority of the studies, apart from Cantore et al. (2016) in the macro-level model, have failed to correct for potential reverse causality from economic performance to energy efficiency, even though studies such as Sahu and Sharma (2016) and Haider and Bhat (2020) have shown that economic performance can influence energy efficiency. This research seeks to investigate how energy efficiency affects TFP in Kenya's manufacturing sector by applying firm-level data, at the decision-making level. To control for potential reverse causality, a dynamic panel data model is adopted.

3. Methodology

This study seeks to assess the energy efficiency and TFP relationship at the firm level controlling for several covariates that may influence this relation. Energy intensity is adopted as an indicator of energy efficiency. According to Fan et al. (2017), energy intensity indicates energy efficiency suitably because of its simplicity and ease of application in guiding policy assessment and design. It is a measure of the amount of energy input applied in the production of a unit of output. Low energy intensity would be linked to high energy efficiency (that is lesser amounts of energy are needed to produce a unit of output). According to Subrahmanya (2006), given a measure of energy (E) and output (Q), energy intensity (EI) is stated as the ratio of energy input to output.

$$EI_{it} = \frac{E_{it}}{Q_{it}} \quad (1)$$

Analysis of TFP is founded on the theory of the firm, which describes how firms convert inputs into output using some given technology. Unlike partial productivity measures which assume that the production process involves the use of only one input, TFP is a suitable productivity measure because it considers the employment of several factor inputs in a production process (Cantore et al., 2016). Following Van Beveren (2012), the study adopts a Cobb Douglas production specification and the Solow Residual approach in measuring TFP. The Cobb Douglas function is expressed as:

$$Q_{it} = A_{it} \ K^{\alpha_k}{}_{it} L^{\alpha_l}{}_{it} M^{\alpha_m}{}_{it} \quad (2)$$

In equation (2), the output, *Q*, is stated as a function of capital, *K*, labour, *L*, materials, *M*, and Hicks neutral measure of efficiency, *A*, which denotes the productivity index. The productivity index measures the efficiency in utilization of the factor inputs (labour, capital and materials). α_k, α_l and α_m represent the output elasticities of capital, labour and materials respectively. Taking the natural log of equation (2) yields:

$$q_{it} = \beta + \alpha_k k_{it} + \alpha_l l_{it} + \alpha_m m_{it} + \varepsilon_{it} \quad (3)$$

$$\text{and } ln \ A_{it} = \beta + \varepsilon_{it} \quad (4)$$

where lower-case letters denote natural logarithms, β assesses the average efficiency within firms and time. ε_{it} denotes time-and firm-specific variation from average efficiency. It is further decomposable into discernible and indiscernible elements (Van Beveren, 2012). After decomposition, equation (3) is rewritten as:

$$q_{it} = \beta + \alpha_k k_{it} + \alpha_l l_{it} + \alpha_m m_{it} + v_{it} + u_{it}{}^q \quad (5)$$

where $\varphi_{it} = \beta + v_{it}$ denotes firm-level productivity and $u_{it}{}^q$ is an i.i.d term that represents random variations from the mean. The variations emanate from measurement error, unpredicted interruptions or other exogenous factors beyond a firm's control.

To solve for φ_{it}, equation (5) would have to be estimated. Estimating this equation using the ordinary least squares (OLS) method would provide biased and inconsistent parameter estimates because of simultaneity bias (Van Beveren, 2012). OLS estimates would be correct if only factor inputs were exogenous, that is, if factor inputs were determined separately from the firm's productivity level. However, input choices are affected by firm productivity. Thus, the amounts of inputs chosen are correlated with unobserved productivity shocks resulting in simultaneity bias (De Loecker, 2011). To overcome this challenge, Levinsohn and Petrin (2003) proposed the Levinsohn-Petrin (LP) estimation algorithm. LP is an improvement of the procedure developed by Olley and Pakes (1996) which suggested the application of investment as a proxy to unobserved productivity shocks. This procedure requires that the investment variable be non-negative and non-missing. Such a condition may however not be applicable in developing countries (Haider and Bhat, 2020).

In the LP estimation process, unobserved productivity shocks are proxied by intermediate inputs. The reasoning behind this is that firms record positive values for intermediate inputs (materials and energy) used every year and keep records of these observations. Following Levinsohn and Petrin (2003), an optimal material demand function is outlined to address simultaneity bias as follows:

$$m_{it} = m(k_{it}, \ \varphi_{it}) \quad (6)$$

The function is presumed to be monotonically increasing in φ_{it} implying that if firms experience higher productivity shocks in the present period, demand for materials will be higher in the subsequent period. Given that the monotonicity condition binds and that materials are strictly increasing in φ_{it}, equation (6) could be inverted to allow unobserved productivity shock to be stated as a function of observable inputs as follows:

$$\varphi_{it} = \varphi(k_{it}, \ m_{it}), \text{ where } \varphi(.) = m^{-1}(.) \quad (7)$$

Using equation (7) in equation (5) yields:

$$q_{it} = \beta + \alpha_k k_{it} + \alpha_l l_{it} + \alpha_m m_{it} + \varphi(k_{it}, m_{it}) + u_{it}{}^q \quad (8)$$

Another function $\emptyset(k_{it}, m_{it})$ is defined as:

$$\emptyset_{it}(k_{it}, m_{it}) = \beta + \alpha_m m_{it} + \alpha_k k_{it} + \varphi_t(k_{it}, m_{it}) \quad (9)$$

In this case, $\emptyset_{it}(k_{it}, m_{it})$ is analysed as second-degree polynomial in k_{it} and m_{it}. Substituting equation (9) in (8) yields:

$$q_{it} = \alpha_l l_{it} + \emptyset(k_{it}, m_{it}) + u_{it}{}^{q} \tag{10}$$

Estimation of equation (10) using OLS yields the coefficient α_l together with $\emptyset$ and this constitutes the first step estimation. The subsequent step begins with the postulation that the future projected productivity follows a Markov process (Haider and Bhat, 2020). In other words, future expected productivity is a function of the present value and unexpected innovations in productivity denoted by ξ_{it}. This could be written as:

$$\varphi_{it} = E[\varphi_{it} | \varphi_{it-1}] + \xi_{it} \tag{11}$$

Two-moment conditions need to be applied in the identification of the coefficients α_m and α_k. The first-moment condition is:

$$E[(\xi_{it} + u_{it}{}^{q})k_{it}] = 0 \tag{12}$$

It assumes that capital remains unchanged within the same period after innovations in productivity. The second-moment condition assumes that productivity growth in the present period and material demand in the preceding period are uncorrelated. This yields:

$$E[(\xi_{it} + u_{it}{}^{q})m_{it-1}] = 0 \tag{13}$$

Given the assumptions in equations (11-13), Levinsohn and Petrin (2003) propose the following expectation in the estimation of the coefficients on capital and material:

$$E[q_{it+1} - \alpha_l l_{it+1}] = \beta + \alpha_m m_{it+1} + \alpha_k k_{it+1} + E[\varphi_{it+1} | \varphi_{it}] \tag{14}$$

Denoting $(\varphi_{it}) = \beta + E[\varphi_{it+1} | \varphi_{it}]$, equation (14) is rewritten as:

$$q_{it+1} - \alpha_l l_{it+1} = \alpha_m m_{it+1} + \alpha_k k_{it+1} + f(\emptyset_{it} - \alpha_m m_{it} - \alpha_k k_{it}) + \xi_{it} + u_{it}{}^{q} \tag{15}$$

With the employment of extracted estimates of α_l and $\emptyset$ and presuming a third-order polynomial expansion of $(\emptyset_{it} - \alpha_m m_{it} - \alpha_k k_{it})$ for the functional form f, equation (15) can be estimated to obtain consistent estimates for material and capital (α_m, α_k). After all the coefficients have been derived, TFP for each firm is computed as the deviation of a firm's predicted level of output from the actual output level as follows:

$$TFP_{it} = q_{it} - \widehat{\alpha_k} k_{it} - \widehat{\alpha_l} l_{it} - \widehat{\alpha_m} m_{it} \tag{16}$$

Equations (2) to (16) cover TFP estimation. The next stage involves the estimation of the effect of energy efficiency on TFP transformed into levels. Following Cantore et al. (2016) and Montalbano and Nenci (2019) TFP is modelled as a function of energy efficiency as follows:

$$TFP_{it} = g(EF_{it}) \tag{17}$$

Several explanatory variables that could affect the relation are also included in the model, which yields:

$$\ln TFP_{it} = \gamma + \theta_{EF} \ln EF_{it} + \theta_c C_{it} + \theta_w W_i + \mu_{it} \tag{18}$$

where ln is the natural log, γ is the intercept, μ_{it} is an error term, C_{it} and W_i are vectors of firm-specific variables which could be time-variant and time-invariant, respectively. θ_{EF} is the coefficient of energy efficiency. θ_c and θ_w are vectors of coefficients for time-variant and time-invariant controls, respectively.

Estimating equation (19) using the OLS method could lead to biased estimates of energy efficiency since the variable is potentially endogenous (Cantore et al., 2016). The sources of endogeneity include omitted unobservable firm characteristics and reverse causality (Cantore et al., 2016). For instance, for omitted firm characteristics, the managerial ability could potentially influence the uptake of energy efficiency technologies by firms and at the same time affect firm TFP. For reverse causality, if high energy-efficient firms are observed to have higher TFP, it could be because high energy efficiency results in greater TFP or that firms with high TFP are those capable of using energy efficiently. To address the problem of omitted variable bias, the constant coefficient is allowed to vary across firms. Reverse causality is taken care of following Haider and Bhat (2020) who adopt a dynamic panel data model that incorporates past period explained variable as an independent variable in the current period. The resulting equation is:

$$\ln TFP_{it} = \theta_P \ln TFP_{it-1} + \theta_{EF} \ln EF_{it} + \theta_c C_{it} + \theta_w W_i + \gamma_i + \mu_{it} \tag{19}$$

where TFP_{it-1} is the previous period TFP, γ_i is the firm-specific intercept and θ_P is the coefficient of TFP_{it-1}. The lagged explained term reduces the feedback effect from TFP to energy efficiency. The logic behind this is that the decision to improve technology to enhance energy efficiency is made in preceding periods persuaded by a firm's performance.

Even though the fixed effects and random effects panel data models are suitable in addressing unobserved firm heterogeneity, they are not able to address reverse causality. To solve for reverse causality, Arellano and Bond

(1991) recommend a generalized method of moments (GMM) estimator for dynamic panel models that employ lagged values of the explained covariates as instruments of the endogenous variables. To ascertain the validity of the instruments, the Sargan-Hansen test of overidentifying restrictions is applied. Alternatively, a two-stage least squares (2SLS) estimator could be adopted instead of GMM. To ascertain the appropriate estimator for the current data, the Pagan and Hall (1983) test of heteroscedasticity in the error term is performed. The GMM estimator is relatively more efficient than 2SLS in the presence of heteroscedasticity. Nevertheless, in the absence of heteroscedasticity, the 2SLS estimator is relatively more efficient.

3.1 Data and Definition of Variables

The research employs a panel dataset obtained from the WBES for 2007, 2013 and 2018. The World Bank collects information on enterprises to have an understanding of the business environment firms face in the private sector. This information is intended to help the World Bank understand the business environment firms face in the private sector so that the bank can develop policies to promote businesses.

Energy intensity is estimated using energy and output. TFP is estimated using capital, labour and materials. Energy is quantified as the total outlay on electricity and fuel. Output is quantified as overall revenue by firms. Capital is quantified as the net book value of machinery and other equipment. Labour is quantified as aggregate salaries given to permanent, full-time workers. Materials are quantified as the overall spending on materials.

In the investigation of the effect of energy efficiency on TFP, several explanatory variables are included as control variables. Following Kreuser and Newman (2018), Harris and Moffat (2015), Satpathy et al. (2017), Fernandes (2008), Rath (2018) and Seker and Saliola (2018), the control variables include firm age, firm size, foreign ownership, exporting status, capital intensity, R&D and top manager's experience. Firm age is defined as a firm's total years of existence. It is anticipated to have an unclear effect on TFP. A positive effect could be realized because of learning-by-doing effects (Kreuser and Newman, 2018). Alternatively, firm age could have a negative influence given that old firms could be employing outdated equipment as young firms employ the latest equipment (Harris and Moffat, 2015).

Firm size is expressed as the number of employees. The effect of this covariate is also anticipated to be unclear. Large firms could be having higher TFP compared to small firms because they have better access to the market and enough financial resources to acquire the latest technologies (Satpathy et al., 2017). On the other hand, small firms could have higher productivity because they are more flexible and have less complex management structures (Seker and Saliola, 2018).

R&D is defined as a dummy covariate, 1 if a firm participates in R&D, else 0. The covariate is anticipated to positively influence TFP. R&D activities promote TFP through two channels (Harris and Moffat, 2015). In the first channel, R&D promotes TFP by stimulating process and product innovations. Through process innovation, production is made at a greater efficiency, which is mainly realized through reduced costs. In product innovation, new products are developed more efficiently compared to existing products. In the second channel, R&D enhances TFP by developing firms' absorptive capacity. This promotes a firm's capability to detect, absorb and utilize external knowledge from other establishments and R&D players, for instance, universities and research institutions (Harris and Moffat, 2015).

Foreign ownership is expressed as a dummy covariate, 1 if a firm has foreign ownership, else 0. Foreign ownership is anticipated to positively influence TFP. Firms with foreign ownership have superior technologies and their workforce is exposed to advanced skills in production, management and marketing which make them have higher TFP (Harris and Moffat, 2015). Exporting status is expressed as a dummy covariate, 1 if a firm is an exporter, else 0. The covariate is anticipated to have a positive influence on TFP. Literature shows that exporting firms learn from foreign buyers about new production technologies which helps them to enhance their TFP. It is also possible that exporting firms improve their production technology to take advantage of the stringent but more profitable foreign markets (Fernandes, 2008).

Top manager's level of experience is expressed as the time in years a top manager has been working. The variable is expected to positively influence TFP. Managers with a long experience are anticipated to possess skills and techniques to guide production towards improved productivity (Fernandes, 2008). Capital intensity is expressed as the ratio of capital to labour. The variable is projected to positively affect TFP. High capital intensity firms have modern and advanced production techniques that improve productivity (Rath, 2018).

Descriptive statistics of the data are presented in Tables 1 and 2.

Table 1. Descriptive statistics of inputs and output

Statistics	Output (Million Ksh)	Capital (Million Ksh)	Labor (Million Ksh)	Materials (Million Ksh)	Energy (Million Ksh)	Capital Intensity (Million Ksh)
Chemicals, Pharmaceuticals and Plastics sub-sector						
Mean	1286.87	196.67	107.25	190.81	29.03	13.08
SD	7331.32	1156.15	486.19	579.73	62.29	34.27
Minimum	0.3	0.011	0.132	0.001	0.015	0.0035
Maximum	80000	15000	5000	5000	360	355.56
Food sub-sector						
Mean	916.74	219.56	60.75	244.06	101.20	22.81
SD	4967.97	1277.08	272.40	1348.50	1065.51	201.61
Minimum	0.15	0.02	0.05	0.003	0.01	0.001
Maximum	84000	15000	4200	17000	20029.79	3891.67
Textiles and garments sub-sector						
Mean	522.14	141.76	42.08	305.98	26.22	22.01
SD	1995.34	871.35	189.73	2121.33	118.62	223.92
Minimum	0.45	0.011	0.05	0.02	0.003	0. 0004
Maximum	18000	12300	2500	29000	1080	4730.77
Other manufacturing sub-sector						
Mean	2335.31	226.78	65.87	414.87	67.39	19.10
SD	21455.04	1150.73	229.93	2546.54	930.90	83.69
Minimum	0.1	0.011	0.02	0.02	0.0025	0.002
Maximum	425000	15000	2500	36000	20100	1009.12

Table 2. Descriptive statistics of determinants of TFP

Statistics	Firm Size (Employees)	Firm Age (Years)	TME (Years)	FO (Dummy)	Exporting (Dummy)	R&D (Dummy)
Chemicals, Pharmaceuticals and Plastics sub-sector						
Mean	126.55	36.46	20.27	0.1741	0.4494	0.2921
SD	280.44	24.29	12.97	0.3803	0.4988	0.4560
Minimum	2	1	1	0	0	0
Maximum	2000	103	65	1	1	1
Food sub-sector						
Mean	127.23	23.93	19.17	0.1634	0.4010	0.3020
SD	473.02	13.56	11.76	0.3702	0.4907	0.4597
Minimum	2	2	1	0	0	0
Maximum	8000	65	50	1	1	1
Textiles and garments sub-sector						
Mean	126.39	25.15	17.61	0.1762	0.4565	0.2909
SD	346.28	16.69	10.73	0.3814	0.4986	0.4546
Minimum	1	2	1	0	0	0
Maximum	5500	93	50	1	1	1
Paper and other manufacturing sub-sector						
Mean	116.00	21.00	15.02	0.1509	0.3208	0.3019
SD	267.31	18.47	9.158	0.3588	0.4679	0.4602
Minimum	2	2	1	0	0	0
Maximum	2500	107	40	1	1	1

Note: TME, FO and Ex denote top manager's experience and foreign ownership, respectively.

4. Empirical Findings

4.1 Average Energy Intensity

Table 3 provides findings of average energy intensity.

Table 3. Average energy intensity

Sub-sector	Energy intensity
Chemicals, pharmaceuticals and plastics	0.120
Food	0.413
Textile and Garments	0.064
Paper and other manufacturing	0.225

The food sub-sector has the highest energy intensity score of 0.413. It signals the least energy efficiency among the four sub-sectors. Theoretically, this implies that firms in this sub-sector apply the highest amount of energy in the production of a unit of output. The paper and other manufacturing sub-sector follow with a score of 0.225 and the chemicals, pharmaceuticals and plastics sub-sector with 0.120. The textiles and garments sub-sector has the least energy intensity score of 0.064, implying that this sub-sector is the most energy-efficient.

4.2 Elasticities

A linearized Cobb-Douglas production function is analysed using the LP estimation algorithm for each sub-sector based on the assumption that firms in a particular sub-sector use common technology (Kreuser and Newman, 2018). Table 4 provides LP and OLS estimates of the production function. OLS estimates are provided for robustness check.

Table 4. Parameter estimates of production functions in Kenya's manufacturing sector

	LP				OLS			
	C,P and P	Food	T and G	P and OM	C, P and P	Food	T and G	P and OM
Dependent variable: lnQ								
ln$L$	0.497***	0.429***	0.571***	0.408***	0.535***	0.432***	0.558***	0.435***
	(0.115)	(0.0560)	(0.0890)	(0.0728)	(0.0643)	(0.0442)	(0.0637)	(0.0429)
ln$K$	0.0396	0.135	0.133	0.332**	-0.00894	0.0538	0.117***	0.0214
	(0.228)	(0.137)	(0.0836)	(0.139)	(0.0539)	(0.0331)	(0.0383)	(0.0285)
ln$M$	0.831***	0.443***	0.121	0.0907	0.398***	0.451***	0.310***	0.497***
	(0.277)	(0.144)	(0.129)	(0.196)	(0.0544)	(0.0364)	(0.0473)	(0.0348)
RTS	1.368	1.007	0.825	0.831	0.924	0.937	0.985	0.953

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C, P and P is chemicals, pharmaceuticals and plastics sub-sector, T and G is textiles and garments sub-sector and P and O M is paper and other manufacturing sub-sector.

In LP, the model of interest, the elasticity of output with respect to labour is statistically significant at 5% level of significance across the four sub-sectors. The elasticity of output with respect to materials is only statistically significant in the chemicals, pharmaceuticals and plastics and food sub-sectors. The elasticity of output with respect to capital is only statistically significant in the paper and other manufacturing sub-sector. The coefficient of labour is higher in OLS than in LP estimation across the four sub-sectors aside from the textiles and garments sub-sector. According to Kreuser and Newman (2018), this indicates that labour is positively correlated with productivity shocks. Therefore, the labour coefficient in OLS estimation is biased upwards. OLS underestimates the coefficient of labour in the textile and garments sub-sector. This suggests that labour employed in this sub-sector has a negative correlation with productivity shocks. Therefore, the labour coefficient in OLS estimation is biased downwards.

All the coefficient estimates of capital in LP are higher than those in OLS. This suggests that capital is negatively correlated with productivity shocks. Consequently, the coefficient estimates of capital in OLS estimation are biased downwards. The coefficient estimates of materials in OLS are larger than those of LP in all the sub-sectors except in the chemicals, pharmaceuticals and plastics sub-sector. This suggests that materials are positively correlated with productivity shocks. Thus, the coefficient of materials in OLS estimation is biased upwards.

All the factor elasticities have economically plausible signs. Holding all other factors constant, an increase in any one input results in increased output. All the sub-sectors report a higher elasticity of labour compared to capital. The elasticities of capital and labour are higher than those of materials in the textile and garments and paper and other manufacturing sub-sectors. However, the elasticity of materials is higher than those of capital and labour in the chemicals, pharmaceuticals and plastics and food sub-sectors. The sum factor elasticities give an insight into returns to scale in each sub-sector. The chemicals, pharmaceuticals and plastics and food sub-sectors report increasing returns to scale, implying that a proportional rise in inputs would result in a more than proportionate rise in output. The textiles and garments and paper and other manufacturing sub-sectors report decreasing returns to scale, implying that a proportionate rise in inputs would bring about a less than proportionate rise in output.

4.3 Estimated Average TFP by sub-sector

The average productivity in each sub-sector is presented in Table 5.

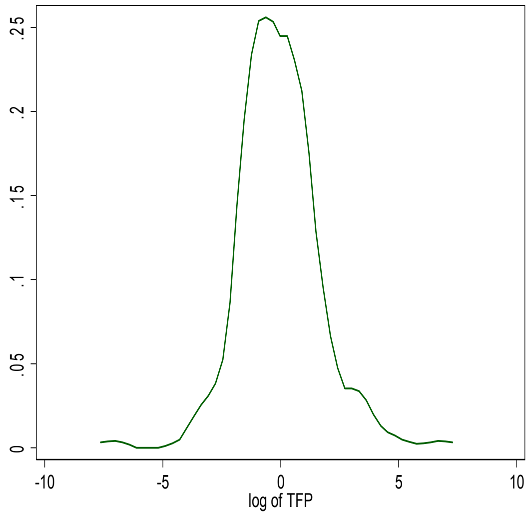
Table 5. Average TFP

Sub-sector	Average TFP
Chemicals, pharmaceuticals and plastics	3.071
Food	2.925
Textile and Garments	2.079
Paper and other manufacturing	2.722

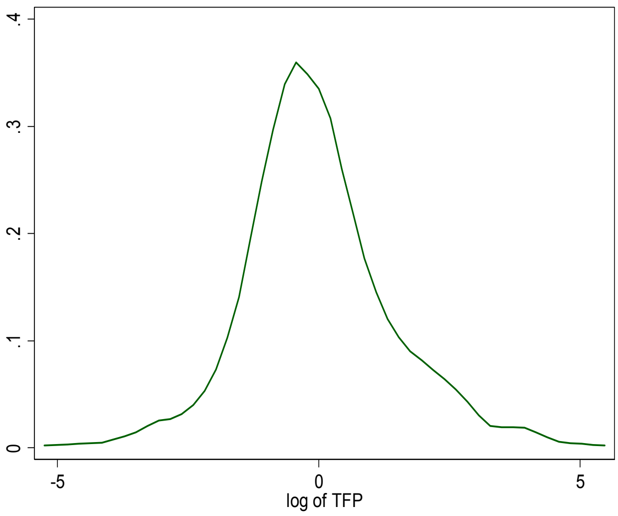
The average TFP in the chemicals, pharmaceuticals and plastics, food, paper and other manufacturing and textile and garments sub-sectors are 3.071, 2.925, 2.722 and 2.079 respectively. The average TFPs are not directly comparable across the sub-sectors given that production functions are different across sub-sectors (Kreuser and Newman, 2018). Technology is assumed to be common within the sub-sectors but different across them. Nevertheless, TFP distribution across sub-sectors could be compared (Kreuser and Newman, 2018). TFP distribution is more useful in explaining the extent of heterogeneity in productivity levels within and across the sub-sectors. According to Tybout (2000), heterogeneity in productivity across firms occurs significantly, even when the manufacturing sector is narrowly defined.

TFP distribution plots of each sub-sector are presented in Figure 1. The y-axis contains densities of the distributions while the x-axis contains logarithms of TFP. A widely dispersed plot denotes greater heterogeneity across firms within a sub-sector (Kreuser and Newman, 2018). Of concern also is whether firms are highly concentrated in the higher segment or lower segment of the TFP distribution. A tight dispersion in TFP distribution is witnessed in the paper and other manufacturing and chemicals, pharmaceuticals and plastics sub-sectors. This indicates less heterogeneity in productivity in these sub-sectors. The distribution of TFP in the food sub-sector shows tight dispersion but not as in the paper and other manufacturing and chemicals, pharmaceuticals and plastics sub-sectors. This also signals minimal heterogeneity in productivity.

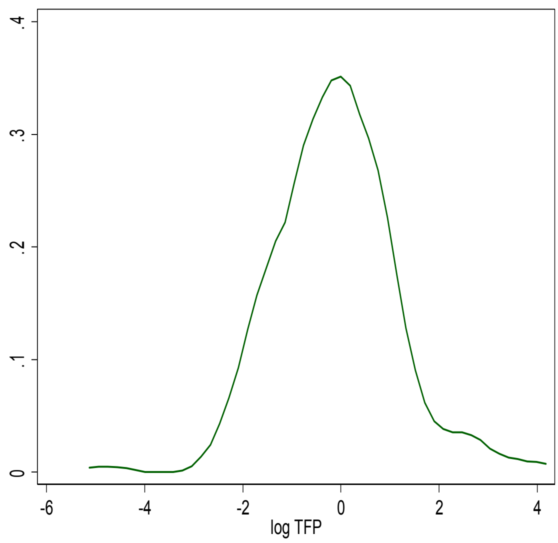
The textiles and garments sub-sector TFP distribution shows that this sub-sector has the widest dispersion, especially on the lower parts of the plot, and a relatively sizable density below the mean. This points to relatively sizable heterogeneity in TFP, implying the coexistence of firms with large productivity and firms with low productivity in the sub-sector. Such a distribution signals the existence of rigidities or other distortions that hinder the efficient allocation of resources within the sub-sector (Kreuser and Newman, 2018).



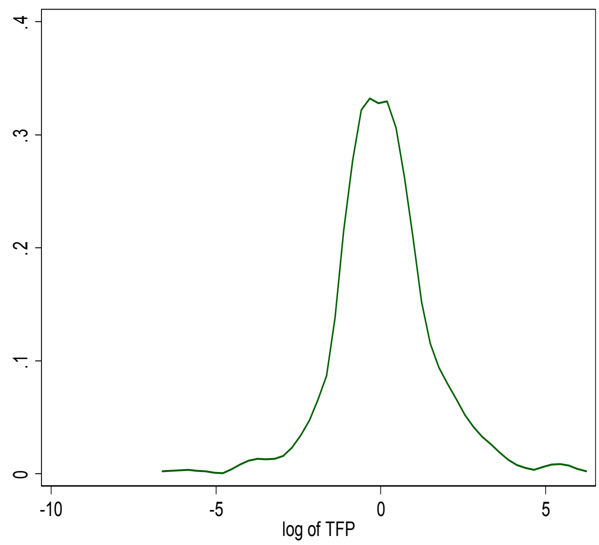
Chemicals, pharmaceutical and plastics sub-sector



Food sub-sector



Textile and garments sub-sector



Paper and other manufacturing sub-sector

Figure 1. TFP distribution in the Kenyan manufacturing sector

4.4 Estimated Average TFP by Sub-Sector and Firm Size

The heterogeneity of TFP in Kenya's manufacturing sector is further analysed on the firm size attribute. The empirical literature provides that firm size is one of the major sources of heterogeneity in productivity (Van Biesebroeck, 2005; Fernandes, 2008). The analysis is crucial in singling out firm sizes with the highest potential to improve productivity and receive the most resources. The WBES categorization of small (5-19 workers), medium (20-99 workers) and large (over 100 workers) firms is followed. Findings are provided in Table 6.

Table 6. Average TFP by sub-sector and firm size

Sub-sector	Size category		
	small	medium	large
Chemicals, pharmaceuticals and plastics	2.923	2.658	3.865
Food	2.784	2.669	3.395
Textile and garments	2.303	1.969	1.938
Paper and other manufacturing	3.200	2.432	2.650

In the chemicals, pharmaceuticals and plastics and food sub-sectors, TFP is highest in large firms. In these sub-sectors, TFP is higher in small firms compared to medium firms. That large firms possess the highest TFP could probably be because they have better access to financial resources that allow them to upgrade their production technology and achieve better performance. It could also be that large firms can hire workers with better skills. This finding supports Van Biesebroeck (2005), and Seleem and Zhaki (2018).

In the textile and garments and paper and other manufacturing sub-sectors, small firms have the highest TFP. This could be because small firms are more flexible with less complex management structures. The results for the textiles and garments sub-sector show that productivity decreases monotonically with an increase in firm size. This corroborates Fernandes (2008) and Seleem and Zhaki (2018). TFP is higher in large firms compared to medium firms in paper and other manufacturing sub-sector.

4.5 Effects of Energy Efficiency on TFP

The findings of the energy efficiency and TFP relation are provided in Table 7. We perform dynamic panel data estimation using the clustered robust technique to deal with potential heteroscedasticity.

Table 7. Regression results of the effect of energy efficiency on TFP

TFP	Food Sub-sector	T and G Sub-sector	P and O M Sub-sector	Overall Sector
TFP_{t-1}	-0.180	0.048	0.253	0.0821
	(0.227)	(0.045)	(0.250)	(0.0674)
Energy efficiency	3.246^{***}	0.001^{***}	0.227^{*}	0.220^{***}
	(0.819)	(0.0003)	(0.129)	(0.0432)
Capital Intensity	1.738^{**}	0.0121^{***}	-0.342^{***}	0.00136^{*}
	(0.818)	(0.00265)	(0.0768)	(0.000744)
Firm age	0.500^{*}	-0.247	1.367^{***}	0.0299^{***}
	(0.292)	(0.449)	(0.320)	(0.0107)
Firm size	-0.152	-0.068	0.00145^{**}	0.0546^{**}
	(0.591)	(0.069)	(0.000698)	(0.0268)
Top Manager's experience	0.0734	0.015	0.00916	0.210^{*}
	(0.135)	(0.010)	(0.0142)	(0.116)
Foreign owned	-1.672	0.616^{*}	-1.333	0.222
	(3.740)	(0.315)	(1.008)	(0.209)
Export	0.894	0.739^{**}	-0.593	-0.162
	(3.286)	(0.367)	(0.536)	(0.157)
R&D	1.390	0.831^{***}	-0.443	0.114
	(3.327)	(0.170)	(0.395)	(0.162)
Year dummy (base year: 2007)				
2013	-22.50^{*}	0.171^{**}	2.337	-3.152^{***}
	(12.66)	(0.343)	(3.827)	(0.718)
2018	-23.36	0.294	-0.640	-3.381^{***}
	(15.60)	(0.032)	(3.425)	(0.787)

Region dummy (base region: Nyanza)				
Central	0.643	1.564	-0.718	0.565
	(6.839)	(2.747)	(1.574)	(0.436)
Coast	4.312	-2.828	-1.752	0.368
	(6.350)	(3.102)	(1.681)	(0.406)
Nairobi	4.058	0.215	-1.297	0.481
	(6.351)	(2.413)	(1.590)	(0.389)
RV	5.485	-0.258	-2.074	0.354
	(6.588)	(2.773)	(1.823)	(0.415)
Sub-sector dummy (base C P and P)				
Food				0.194
				(0.261)
T and G				-0.0819
				(0.244)
P and O M				-0.0299
				(0.289)
Endogeneity Test				
H0: Exogenous				
Chi-sq	3.936	3.215	6.280	4.349
Prob> chi-sq	0.037	0.047	0.067	0.012
Heteroskedasticity test				
H0: Homoskedasticity				
Chi-sq	30.19	32.35	52.21	38.44
Prob> chi-sq	0.088	0.028	0.000	0.042
Sargan-Hansen test				
Chi-sq	8.051	9.252	4.684	6.410
Prob> chi-sq	0.781	0.160	0.585	0.698

Dependent variable: TFP

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

T and G is textiles and garments and P and O M is paper and other manufacturing. RV is Rift Valley region and D denotes a dummy variable. TFP_{t-1} is the first lag of TFP.

Table 7 presents results by sub-sector. The sub-sectors of concern are: food, textile and garments and paper and other manufacturing sub-sectors. The chemicals, pharmaceuticals and plastics sub-sector has a low sample size and the estimation failed convergence tests. Consequently, this sub-sector has been dropped. Results of the overall sector are also provided for robustness check. The null hypothesis for exogeneity of energy efficiency is rejected at 5% level of significance in all sub-sectors except the textile and garments sub-sector where it is rejected at 10% level of significance. In the overall sector, the null hypothesis is rejected at 5% level of significance. The findings indicate the existence of endogeneity which could be addressed by adopting a 2SLS estimator or GMM estimator. At 5% level of significance, the Pagan and Hall (1983) test confirms the presence of heteroscedasticity across all the sub-sectors apart from the food sub-sector where this is confirmed at 10% level of significance. In the overall sector model, the presence of heteroscedasticity is confirmed at 5% level of significance. Given the presence of heteroscedasticity, GMM becomes the preferred estimator. The Sargan-Hansen test of the null hypothesis of overidentifying restrictions is accepted at 5% level of significance in all sub-sectors and the overall sector. Thus, all the instruments adopted in the models are valid.

Energy efficiency is found to positively affect TFP across all the sub-sectors and the overall sector. This means that bolstering energy efficiency yields double dividends. Higher TFP is realized in the process of ensuring clean production. The finding is in line with the Porter Hypothesis. According to the hypothesis, the cost of acquiring clean production technologies is offset by cost savings arising from the use of such technologies, a phenomenon known as innovation offset (Porter and Van der Linder, 1995). This finding is useful in dispelling fear, particularly in developing countries, where there is disquiet on the implications of reductions in energy use on growth.

Therefore, for firms to increase TFP and become more competitive, they need to change their high energy-dependent production activities. The result supports Cantore et al. (2016) in 29 low-income countries of interest and Montalbano and Nenci (2019) in the manufacturing sector in Latin America.

Capital intensity is found to positively influence TFP in the food and textile and garments sub-sectors. A similar finding is reported in the overall sector. This could mean that high capital intensive firms have recent technologies and advanced production processes which play a big role in enhancing TFP. This supports Montalbano and Nenci (2019) in the food, textiles and apparel and chemicals and minerals sub-sectors in Latin America and Rath (2018) in India's textile sub-sector. However, capital intensity is found to negatively influence TFP in the paper and other manufacturing sub-sector. This suggests that firms with high levels of capital have lower TFP. The finding corroborates Van Biesebroeck (2005).

Firm age is observed to positively influence TFP in the food and paper and other manufacturing sub-sectors. This too is observed in the overall sector. This outcome is in line with Sahu and Narayanan, (2011) and Kreuser and Newman (2018). It is also in line with the Jovanovic (1982) theory which postulates that firms discover their productivity capabilities with time, and in the process, low productivity firms leave the industry as the high productivity firms thrive. According to Coad et al. (2013), this process makes the average productivity of firms that survive attrition increase with time. The result can also be expounded by the learning-by-doing effect. Firms learn of new production techniques with time and assimilated them into their production processes, ultimately boosting their TFP.

Firm size positively affects TFP in the paper and other manufacturing sub-sector and the overall sector. The finding contradicts Montalbano and Nenci (2019) who find firm size to positively influence TFP in all the Latin America manufacturing sub-sectors aside from the other manufacturing sub-sector. However, this outcome supports the Jovanovic (1982) theory which explains that firms start small. Many of them exit and the remaining ones grow in size and quickly converge into the industry average size and productivity. Before exiting, firms decline in size and productivity (Van Biesebroeck, 2005). The outcome could also be explained by the ease in access to credit by large firms compared to small firms which they use to update their technologies and boost TFP.

Foreign ownership has a positive influence on TFP in the textiles and garments sub-sector. It could be argued that for foreign investors to find it justifiable to establish or acquire local ownership, they must have characteristics that give them an upper hand in cost over local firms. Such characteristics include better technologies, management and access to delivery and advertising means (Fernandes, 2008; Harris and Moffat, 2015). The result supports Sahu and Narayanan (2011) and Harrris and Moffat (2015).

Exporting status positively influences TFP in the textiles and garments sub-sector. This indicates that there were TFP premiums for exporting firms. Literature provides two main reasons for this finding: learning-by-exporting effects and self-selection into foreign markets. In the former, exporting firms are exposed to knowledge flows, spillovers, technological transfers and technical support and to more severe competition in foreign markets which bolsters TFP (Montalbano and Nenci, 2019). Exporting firms could also be producing using advanced technologies to meet strict but profitable requirements of foreign clients. This supports Montalbano and Nenci (2019). By self-selection, high TFP firms may be the ones that can participate in exporting activities. Fernandes (2008), however, observes that self-selection and learning-by-exporting are not mutually exclusive given that high TFP firms with the advantage of accessing export markets could persistently have better TFP due to acquaintance with exporting

R&D positively influences TFP in the textiles and garments sub-sector. Probably, engaging in R&D activities leads to process and product innovation which boosts TFP. Moreover, R&D activities could have enhanced the firm's absorptive capacity thereby boosting TFP. This corroborates Harris and Moffat (2015), Satpathy et al. (2017) and Kreuser and Newman (2018). Top manager's experience has an insignificant effect on TFP across sub-sectors. However, this variable has a positive effect on TFP in the overall sector. Applying skills and expertise acquired over time, experienced top managers are likely to transform the production process to achieve high TFP. This corroborates Fernandes (2008).

TFP is found to decrease in 2013 relative to 2007 in the food and textile and garments sub-sectors. Probably, the business environment for these sub-sectors was less conducive in 2013. TFP is also found to decrease in 2013 and 2018 relative to 2007 in the overall sector.

4.6 Effect of Energy Efficiency on TFP by Firm Size

We extended the research to the investigation of whether the effect of energy efficiency on TFP varies with firm size. Estimation is also performed using the clustered robust model to correct for potential heteroscedasticity. The results are provided in Table 8.

Table 8. Regression results of the effect of energy efficiency on TFP by firm size

TFP	small firms	medium firms	large firms
TFP_{t-1}	-6.343	0.167	0.205
	(4.069)	(0.167)	(0.196)
Energy efficiency	5.346^{***}	0.572^{***}	0.0000536
	(1.507)	(0.134)	(0.000720)
Capital intensity	0.455^{***}	0.011^{*}	0.247^{*}
	(0.0831)	(0.006)	(0.141)
Firm age	0.973^{**}	-0.461^{*}	1.388^{**}
	(0.421)	(0.263)	(0.685)
Top Manager's experience	0.103	-0.001	0.000705
	(0.562)	(0.021)	(0.0388)
Foreign owned	-8.182	1.198^{*}	-0.464
	(11.60)	(0.627)	(1.222)
Export	12.63^{**}	-0.601	1.013
	(6.121)	(0.400)	(0.864)
R&D	-11.80	0.403	0.145
	(17.06)	(0.394)	(0.846)
Year dummy (base year: 2007)			
2013	-37.99	-1.306	-6.085
	(58.47)	(1.375)	(4.901)
2018	-58.44	-1.273	-6.070
	(55.63)	(1.540)	(5.597)
Region dummy (base region: Nyanza			
Central	-26.17	-1.602^{*}	1.655
	(24.05)	(0.965)	(1.209)
Coast	-12.75	-1.607^{***}	0.712
	(31.01)	(0.791)	(1.053)
Nairobi	3.737	-1.625^{***}	0.933
	(31.72)	(0.746)	(1.132)
Rift Valley	-32.54	-1.039	1.069
	(32.41)	(0.768)	(2.568)
Sub-sector dummy (base C P and P)			
Food	73.52^{***}	-0.401	0.551
	(25.86)	(0.579)	(0.781)
P and OM	25.03	-0.351	-0.197
	(23.07)	(0.546)	(0.882)
T and G	31.72	-0.651	-0.388
	(22.35)	(0.576)	(0.851)
Endogeneity Test			
H0: Exogenous			
Chi-sq	6.923	5.285	3.134
Prob> Chi-sq	0.009	0.022	0.077
Heteroskedasticity Test			
H0: Homoskedasticity			
Chi-sq	36.83	34.65	34.62
Prob> Chi-sq	0.025	0.042	0.043
Sargan-Hansen test			
Chi-sq	2.792	10.45	9.022
Prob> chi-sq	0.732	0.729	0.425

Dependent variable: TFP

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C, P and P is chemicals, pharmaceuticals and plastics, T and G is textiles and garments and P and O M is Paper and other manufacturing. TFP_{t-1} is the first lag of TFP.

From the endogeneity test as shown in Table 8, the null hypothesis for exogeneity of energy efficiency is rejected in small and medium firms at 5% level of significance and in large firms at 10% level of significance. This is indicative of endogeneity in the models, which calls for the adoption of the 2SLS or GMM estimator. The null hypothesis of homoscedasticity is rejected at 5% level of significance in all firm sizes. Thus, the GMM estimator is preferred in this study. From the Sargan-Hansen test, the null hypothesis of validity of overidentifying restrictions is accepted at 5% level in each of the size cohort models. Thus, the instruments adopted in each of the cohort models are valid.

All firm sizes have positive and significant energy efficiency coefficients except large firms. These findings confirm that there exists a positive link between high energy efficiency and high TFP in firms even across firm sizes. The outcome is consistent with the Porter Hypothesis and Montalbano and Nenci (2019). However, for Montalbano and Nenci (2019), energy efficiency positively influences TFP in micro, medium and large firms but has an insignificant effect in small firms. Capital intensity positively influences TFP across all the firm sizes. This implies that firms that produce with a large capital stock per employee, which could be characterized by modern technologies, are linked to higher TFP. This supports Montalbano and Nenci (2019).

Firm age affects TFP ambiguously. Firm age positively influences TFP in small and large firms. This confirms the Jovanovic (1982) theory. In the medium firms, firm size negatively affects TFP, implying that younger firms have higher TFP than old firms. The finding is consistent with sections of literature that postulate that young firms employ new technologies while old firms use old technologies. Young firms are flexible to technological changes but old firms suffer from inertia effects, which manifest in two forms: liability of obsolescence and liability of senescence (Coad et al., 2013). In the former, old firms fail to be flexible enough to accommodate changing business environments. In the latter, old firms become inflexible due to accrued rules, norms and organizational settings. The outcome of this study contradicts Seleem and Zhaki, (2018) who find firm size to negatively affect TFP in large firms and have no significant effect in small and medium firms.

Foreign ownership is found to positively influence TFP in medium firms. Probably, foreign firms in this size cohort have features that provide them an edge in cost reduction over local firms which boosts TFP. Such characteristics could include better technology and management or access to delivery and advertising means (Fernandes, 2008; Harris and Moffat, 2015). The finding contrasts Seleem and Zhaki (2018) who find foreign ownership to significantly affect TFP in the small firms but have no significant effect in the medium and large firms.

Exporting status is found to positively affect TFP in small firms. The TFP premiums could be a result of learning-by-exporting effects and self-selection to export markets. This could also be because small firms produce using advanced technologies in the process of meeting stringent but profitable requirements of foreign markets. This finding contradicts Montalbano and Nenci (2019) who find exporting status to promote TFP in medium firms but have no significant effect on TFP in small and large firms.

With regards to regional dummies, TFP is found to decrease in Nairobi, Central and Coast regions relative to the Nyanza region in the medium-sized firms. Probably, these regions have a less favourable environment compared to Nyanza region. On sub-sector dummies, TFP is found to increase in the food sub-sector relative to the chemicals, pharmaceuticals and plastics sub-sector in small firms.

5. Conclusion and Policy Implications

Energy efficiency is considered to be the best approach for dealing with energy use-related issues. However, there is concern among economists on the firm productivity outcome of energy efficiency. This study applies a dynamic panel model to assess the effect of energy efficiency on TFP in the Kenyan manufacturing sector. Energy intensity is applied as an indicator of energy efficiency while the LP estimation algorithm is applied in estimating TFP.

Average energy intensities in the chemicals, pharmaceuticals and plastics, food, textiles and garments and paper and other manufacturing sub-sectors are 0.120, 0.413, 0.225 and 0.064 respectively. Average TFPs in respective sub-sectors are 3.071, 2.925, 2.722 and 2.079. In the analysis of the effect of energy efficiency on TFP, the chemicals, pharmaceuticals and plastics sub-sector is dropped as estimation fails convergence test due to low sample size. The overall sector model is included for robustness check. Energy efficiency is found to positively influence TFP in all the sub-sectors of interest and the overall sector. The finding confirms the Porter Hypothesis.

There is no general pattern of control variables across sub-sectors. Capital intensity is found to positively affect TFP in the food and textiles and garments sub-sectors. However, in the paper and other manufacturing sub-sector, capital intensity is found to negatively influence TFP. Firm age positively influences TFP in the food and paper and other manufacturing sub-sectors. Firm size promotes TFP in the paper and other manufacturing sub-sector. Exporting and R&D are found to positively influence TFP in the textile and garments sub-sector.

The empirical assessment is also done at the firm size level to control for firm heterogeneity. Firm sizes of interest are: small, medium and large. Energy efficiency is found to promote TFP in small and medium firms. Capital intensity promotes TFP in all firm sizes. Firm age has an unclear effect on TFP. It positively affects TFP in small and large firms but has a negative effect in medium firms. Foreign ownership promotes TFP in medium firms. Exporting positively influences TFP in small firms.

From the empirical findings of this study, several policy implications can be made. In general, the study finds higher energy efficiency to be related to stronger TFP. This dispels the fear that there could be a trade-off between improvements in energy efficiency and economic performance in developing economies, which has led to stagnation of international discussions on climate change treaties. This study proposes that in the development of policies to enhance energy efficiency, non-energy benefits in terms of productivity improvements ought to be taken into account. Incorporating such benefits makes the energy efficiency measures to be more cost-effective.

More policies to enhance TFP can be drawn from findings of the control variables. The study establishes strong heterogeneity by sub-sector and firm sizes revealing that there can be no common solution across the sub-sectors and firm size categories. Policies to improve productivity should therefore be sub-sector and firm size specific. Capital intensity is in general found to positively affect TFP, signalling that capital deepening and widening provides a viable channel to promote productivity. This study recommends that policies that increase the uptake of capital, especially technological superior investments associated with modern and advanced technologies and innovations, be designed.

Firm size positively promotes TFP in the paper and other manufacturing sub-sector and the overall sector. The government needs to develop policies that stimulate the growth of firms. Providing an enabling business environment would particularly be beneficial in this regard. Exporting positively promotes TFP in the textiles and garments sub-sector and small firms. The government needs to boost exports beyond the establishment of export processing zones. Locating foreign markets is specifically imperative in this respect. Other policy proposals include the promotion of foreign ownership, especially in medium firms where this variable positively influences TFP. This is important for technological inflows and spillover effects. It is also important for the government to boost the uptake of R&D in manufacturing firms, especially in the textiles and garments sub-sector where this has a positive effect on TFP. Inducements such as low-interest loans and tax incentives could also be extended to firms that have R&D programs.

Acknowledgments

We appreciate the invaluable comments and concepts provided by researchers in two Biannual conferences held by African Economic Research Consortium (AERC) in 2019.

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