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How Do Economic, Social and Institutional Factors Shape Firm-Level Energy Efficiency in Kenya's Manufacturing Sector?

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Abstract: Despite the pivotal role of manufacturing sector in industrialization and sustainable development, it continues face a high energy intensity of energy. Rising energy expenditures continues to undermine competitiveness, and long-term sustainability. The paper evaluated key drivers of firm-level energy efficiency in Kenya's manufacturing firms. Data ware obtained from World Bank Enterprise Survey (WBES) collected by IPSOS Kenya Limited and published by World Bank in 2025.The WBES is a nationally representative and publicly available firm-level survey of formal private sector enterprises. Following the inclusion and exclusion criteria, 377 firms were found to meet eligible for final analysis while the firms that didn't meet the eligibility were dropped from the analysis. The empirical findings show that there is heterogeneity in energy efficiency among manufacturing firms. According to the stochastic frontier estimates, energy efficiency indicate that capital intensity, electricity expenditure, labour costs, research and development (R&D) expenditure, export orientation, firm age, and access to production subsidies exert statistically significant positive effects on energy efficiency. Conversely, firm size exhibits a statistically significant negative relationship with energy efficiency, suggesting the presence of scale-related inefficiencies. Firm ownership and the gender of the top manager were not found to significantly influence energy efficiency.

Keywords: Efficiency, Manufacturing, Stochastic Frontier Analysis.

Introduction

Manufacturing remains central to Kenya's ambition of achieving sustainable industrialization, employment creation, and economic transformation under the country's long-term development agenda. As envisioned in Vision 2030 and reinforced through successive industrial policies, the manufacturing sector is expected to increase its contribution to gross domestic product while improving productivity and international competitiveness. However, the sector continues to face significant challenges arising from high production costs, with energy expenditure constituting one of the largest operating costs for many manufacturing firms. Despite Kenya possessing one of Africa's cleanest electricity mixes, electricity tariffs, fuel costs, and inefficient energy utilization continue to constrain firm competitiveness, export performance, and industrial growth (Macharia et al., 2022). These challenges underscore the need to improve energy efficiency as a strategic policy instrument for enhancing industrial productivity while simultaneously advancing national climate objectives.

Energy efficiency has increasingly become a cornerstone of sustainable industrial development because it enables firms to produce greater output using fewer energy inputs, thereby reducing production costs, greenhouse gas emissions, and dependence on imported fossil fuels. At the global level, improvements in industrial energy efficiency are recognized as one of the most cost-effective pathways for achieving the Sustainable Development Goals (SDG 7 and SDG 9) and the Paris Agreement commitments. In Kenya, the policy environment has similarly evolved to prioritize energy efficiency through the Climate Change Act, the Energy Act, and national climate strategies that encourage low-carbon industrial development. These policy frameworks acknowledge that improving industrial energy performance is essential not only for environmental sustainability but also for enhancing firm productivity, attracting investment, and strengthening export competitiveness.

Although previous studies have examined energy efficiency in Kenya's manufacturing sector, much of the existing literature has focused on subsector-level analyses or technical energy assessments, providing limited evidence on how firm-specific economic, institutional, and managerial

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characteristics influence energy efficiency performance (Macharia et al., 2022). Consequently, policymakers have limited empirical evidence to identify which firm-level interventions generate the greatest improvements in energy performance and industrial competitiveness. Understanding the heterogeneity of firms is particularly important because manufacturing enterprises differ substantially in technology adoption, capital investment, innovation capacity, ownership structure, export orientation, and managerial practices, all of which may influence energy efficiency outcomes.

This study addresses this gap by examining the determinants of firm-level energy efficiency among manufacturing firms in Kenya using enterprise-level data. Unlike studies that primarily estimate efficiency scores, this paper provides policy-relevant evidence on how economic, social, and institutional characteristics shape firms' energy efficiency performance. The findings contribute to Kenya's ongoing industrial transformation agenda by identifying policy interventions capable of reducing industrial energy intensity, strengthening manufacturing competitiveness, and accelerating the transition toward a low-carbon economy. The study therefore provides practical evidence to support the design of targeted industrial, energy, and climate policies that simultaneously promote productivity, sustainable manufacturing, and green economic growth.

Nevertheless, despite the economic importance of the manufacturing sector in Kenya, high energy intensity still persists, consuming over 90% of the entire national energy produced. Moreover, it is regarded as one of the hardest sectors to decarbonize (IPCC, 2022; Macharia et al., 2022). Additionally, growing cost of energy consumption is estimated at 20–40% (mostly associated with outdated technologies), accounting for 50% of the total cost of production, which remains a major challenge to its competitiveness and sustainability (Graus et al., 2019; Neves et al., 2022).

Research Question

What are the key drivers of firm-level energy efficiency in Kenya's manufacturing sector?

Stochastic Frontier Approach

The stochastic energy demand frontier (SEDF) approach provides a rigorous and flexible econometric framework for estimating firm-level energy efficiency by distinguishing random shocks from technical inefficiency in energy efficiency. Unlike conventional regression models that estimate average energy demand, the stochastic frontier approach recognizes that deviations from the optimal energy demand frontier may arise from both statistical noise and inefficiency. This characteristic makes the approach particularly suitable for analysing manufacturing firms operating under heterogeneous production technologies and market conditions, where differences in managerial practices, technology adoption, and production processes influence energy utilization (Aigner et al., 1977; Meeusen & van den Broeck, 1977).The stochastic energy demand frontier can be expressed as;

$$E_i = f(X_i;\beta)exp(v_i + \mu_i) \quad 1$$

Where E_i denotes energy demand or energy consumption of firm i, X_i is a vector of production, inputs, β is a vector of parameters to be estimated $v_i \sim N(0,\delta_v^2)$ is the symmetric random error term representing the measurement errors and other exogenous shock while $\mu_i \geq 0$ is the one-sided inefficiency term representing the excess energy use above the minimum energy requirement.

Taking the natural logarithm of equation 1. give the estimable stochastic Frontier model as;

$$LnE_i = \beta_0 + \sum_{k=1}^{K} \beta_k lnX_{ki} + v_i + \mu_i \quad 2$$

$$\varepsilon_i = v_i + \mu_i \quad 3$$

is the composite error term

Following Battese and Coelli where the inefficiency term is modelled further as a function of firm-specific characteristics

$$\mu_i = \delta_0 + \sum_{m=i}^{M} \delta_m Z_{mi} + \omega_i \quad 4$$

Z_{mi} is the hypothesized variables that influence firm energy inefficiency (capital investment, firm size, research and development expenditure, labor costs, cost of electricity, firm ownership, gender of the top manager, firm age, export status of the firm and subsidy access, δ denotes the estimable parameters and $\omega_i$is the random disturbance term associated the efficiency in the model.

To allow for flexibility of substitution of production inputs and technological heterogeneity, this paper as adopted the Translog stochastic energy demand frontier, which is specified as;

$$lnE_i = \beta_0 + \sum_{k=1}^{K} \beta_k lnX_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{K} \beta_{kj} lnX_{ki} lnX_{ji} + v_i + \mu_i \quad 5$$

By permitting variable elasticities and interaction effects among inputs, the Translog specification relaxes the restrictive assumptions of the Cobb-Douglas functional form and offers a more accurate estimation of production technology (Christensen et al., 1973; Greene, 2008). The likelihood ratio test, which supported that the Trans-log model offers a noticeably better fit to the data than the Cobb-Douglas specification, provided additional support for the model's selection. The ratio of the smallest feasible energy demand to the observed energy demand is used to calculate firm-level energy efficiency, which is estimated as

Within this framework, energy demand is modelled as a function of production inputs and firm-specific characteristics, while the composite error term consists of two components. The first is a symmetric random error term that captures exogenous shocks beyond the firm's control, including measurement errors and stochastic disturbances. The second is a one-sided, non-negative inefficiency term that measures the extent to which actual energy consumption exceeds the minimum energy required to produce a given level of output under the available technology. Firms operating on the frontier are considered energy efficient, whereas deviations from the frontier indicate potential energy savings through improved resource utilization, technological upgrading, and better management practices (Kumbhakar & Lovell, 2000; Coelli et al., 2005).

A major advantage of the stochastic energy demand frontier is that it simultaneously estimates firm-level energy efficiency and identifies the determinants of inefficiency within a unified econometric framework. This enables the assessment of how economic factors such as capital investment, electricity expenditure, labour costs, and research and development (R&D), together with social characteristics and institutional attributes including firm size, firm age, export participation, ownership structure, and access to subsidies influence firms' energy efficiency. Consequently, the approach provides richer policy insights than conventional regression techniques by identifying the drivers of inefficient energy use while accounting for unobserved heterogeneity across firms (Battese & Coelli, 1995).

To capture technological heterogeneity and the substitution possibilities among production inputs, this study employs the Translog stochastic energy demand frontier. The Translog specification relaxes the restrictive assumptions of the Cobb–Douglas functional form by allowing variable elasticities and interaction effects among inputs. This flexibility provides a more realistic representation of production technology in manufacturing, where firms differ considerably in scale, technology, and production processes. Consequently, the Translog frontier has become the preferred specification in empirical studies of industrial energy efficiency due to its ability to improve model fit and generate more reliable efficiency estimates (Christensen et al., 1973; Greene, 2008).

Overall, the stochastic energy demand frontier approach is well suited for analysing firm-level energy efficiency because it accounts for random shocks, accommodates technological heterogeneity, and jointly estimates efficiency scores and their determinants. These features make it an appropriate framework for generating evidence to inform industrial and energy policy aimed at improving manufacturing competitiveness and promoting sustainable industrial development in Kenya.

Methodology

Using cross-sectional firm-level data from 377 manufacturing firms from the World Bank Enterprise Survey (WBES) 2025, this paper used a quantitative research design. A stochastic frontier model was employed to estimate firm-level energy efficiency and its institutional, social, and economic factors. The Translog model was chosen using the likelihood ratio (LR) test after both the Cobb-Douglas and Translog functional criteria were estimated. Descriptive statistics and Pearson correlation analysis were used prior to take a glance at the characteristics of the data and the relationships between the study variables.

Results

First, descriptive statistics of the of the study variables are presented as well as the factors that drive energy efficiency.

Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Output (Ksh)	2.263×10^{9}	1.462×10^{10}	9.00×10^{5}	2.20×10^{11}
Capital (Ksh)	8.589×10^{7}	1.364×10^{8}	5.424×10^{4}	4.996×10^{8}
Firm size (Number of employees)	148.79	547.52	51	9,983
Research and Development expenditure (Ksh)	2.169×10^{7}	1.495×10^{7}	1.50×10^{4}	5.00×10^{7}
Total labour cost (Ksh)	7.560×10^{7}	2.635×10^{8}	2.00×10^{5}	3.00×10^{9}
Firm ownership (1=foreign ownership, 0 = Local ownership)	0.30	0.11	0	1
Gender of the top manager (1 = Male)	0.75	0.61	0	1
Firm age (in years)	25.76	18.74	2	118
Firm age squared	1,013.42	1,525.60	4	13,924
Electricity cost (Ksh)	4.666×10^{6}	5.410×10^{7}	5.00×10^{4}	1.00×10^{9}
Export status (1 = Exporter;0= non-exporter)	0.44	0.12	0	1
Subsidy access (1 = access, 0 = no access)	0.37	0.06	0	1

Note: Monetary variables are reported in Kenyan Shillings (Ksh) while binary variables are coded as indicated in parentheses.

Descriptive statistics reveal substantial heterogeneity among manufacturing firms in Kenya. Average annual output was Ksh 2.263 billion, with considerable dispersion (SD = Ksh 14.62 billion), reflecting the coexistence of relatively small firms alongside large-scale manufacturers. Capital investment also varied markedly, averaging Ksh 85.9 million, indicating significant differences in firms' production capacity and capital endowment. The average firm employed approximately 149 emloyees, although the large standard deviation (547.5 employees) and wide range suggest considerable variation in firm size. Similarly, firms invested an average of Ksh 21.7 million in research and development (R&D), while average labour costs amounted to Ksh 75.6 million, both exhibiting substantial variability across firms. Electricity expenditure averaged Ksh 4.67 million but ranged widely, reflecting differences in production intensity, technology adoption, and energy consumption patterns.

The sample comprised predominantly domestically owned firms, while approximately 75% of firms were managed by male top managers. Firms had an average operational age of 25.8 years, with ages ranging from newly established enterprises to firms operating for more than a century. The inclusion of firm age squared captures potential non-linear effects associated with organizational maturity and energy efficiency. Regarding institutional characteristics, about 44% of the firms participated in export markets, whereas only 37% reported receiving production subsidies, indicating that the majority operated without direct financial support. The observed variation across economic, social, and institutional variables provides sufficient heterogeneity for estimating the stochastic frontier model and examining the determinants of firm-level energy efficiency among manufacturing firms in Kenya.

Correlation Analysis

Pairwise correlation analysis was also done. The results indicated low to moderate correlations among the explanatory variables, suggesting that multicollinearity is unlikely to affect the SFA estimates. The highest correlation is between firm age and firm age squared (r = 0.934), which is expected since the latter is a quadratic transformation of the former. Additionally, the strongest correlation is between firm size and total labour cost (r = 0.731), while all other correlation coefficients are below 0.80. This indicates that the explanatory variables are sufficiently independent for reliable estimation of drivers of firm-level energy efficiency.

Post-Estimation Checks

Post-estimation diagnostic tests confirmed the validity and robustness of the estimated stochastic frontier model. The Translog stochastic frontier specification was validated by the likelihood ratio test, and multicollinearity diagnostics revealed no significant association between the explanatory variables. There was no indication of missing variable bias, and the Ramsey RESET and Link tests confirmed accuracy of the model specification. Additionally, the model met the underlying regression assumptions, according to the heteroscedasticity and autocorrelation tests.

Stochastic Frontier on the effects of Economic, Social and Institutional Factors on Energy Efficiency among Manufacturing Firms in Kenya

The SFA regression model estimates to what extent does these factors drive firm-level energy efficiency?. From an economic point of view, the results of the estimated regression equation reported in the equation shows plausible signs of short-run elasticities. The SFA model reports key variance components; sigma (σ^2) and sigma (σ_u), which capture the overall variability and inefficiency effects in the model. Furthermore, the results of the estimated energy demand frontier show plausible signs for the short-run elasticities from an economic point of view.

The variance in firms' energy inefficiency is captured by the parameter σ_μ, which is the standard deviation of the one-sided inefficiency term. λ is also reported and it is the relative significance of inefficiency in relation to statistical noise which is measured by the parameter λ. It is the ratio of the standard deviation of the inefficiency component to that of the random error component $(\lambda = \sigma_\mu/\sigma_v)$. The presence of energy inefficiency in the relevant industry is confirmed by a statistically significant estimate of λ, which shows that inefficiency rather than random disturbances is the main cause of deviations from the energy demand frontier. As a result, the relevance of λ confirms that the stochastic frontier model may be used to analyze drivers of energy efficiency among manufacturing firms.

Regression Output on the effects of Social, Economic and Institutional factors on Energy Efficiency

Stoc. frontier normal/half-normal model Number of obs = 377

Wald chi2(11) = 288.37

Log likelihood = -9274.5734 Prob > chi2 = 0.0000

Efficiency (EE)	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Lncapital	0.3198	0.0375	8.54	0.0000	0.2464	0.3932	***
LnFirm size	-0.0005	0.0002	-2.39	0.0169	-0.001	-0.0001	**
LnResearch and Development	0.4348	0.1999	2.17	0.0296	0.043	0.8266	**
Lntotallabourcost	0.0005	0.0000767	6.52	0.0000	0.00035	0.00065	***
Firmownership	0.2894	0.3196	0.91	0.3652	-0.337	.9157	
Gender of the top manager	0.2668	0.212	1.26	0.2082	-.01487	.6823	
Firmage	0.0492	0.0116	4.24	0.0000	0.0265	0.072	***
Firmagesq	-0.0005	0.00015	-3.25	0.0012	-0.0007	-0.0002	***
Lncostofelectricity	0.3026	0.0382	7.92	0.0000	0.2277	0.3775	***
Export_status	0.0147	0.0045	3.25	0.0012	0.0058	0.0235	***
Subsidyaccess	0.4348	0.1999	2.17	0.0296	0.043	0.8266	**
Constant	9.693	0.8116	11.94	0.0000	8.1022	11.2837	***
/insig2_v	0.4862	0.2096	2.32	0.020	0.0753	0.8971	
/insig2_u	0.5016	0.5639	0.89	0.374	-0.6037	1.6069	
sigma_v	1.2752	0.1336			1.0384	1.5660	
sigma_u	1.2851	0.3623			0.7394	2.2332	
sigma2	3.2775	0.6504			2.0026	4.5524	
Lambda (λ)	1.0077	0.4844			0.0582	1.9571	

**** p<.01, ** p<.05, * p<.1*

Source: Authors' Compilation, 2026

Wald Chi-square (11) = 288.37 tests whether all coefficients of the frontier model slope are simultaneously zero. The large value of the Wald test (288.37) shows that the regressors (social, economic and institutional factors) are jointly and statistically significant in explaining firms' energy efficiency. The value of p from the probability of Chi-square test is 0.000 < 0.05, hence the null hypothesis that the regressors are not jointly determined is rejected. This shows that the regressors are statistically and are significantly determined meaning that the capital, firm size, research and development, total labour cost, firm's ownership, gender of the top manager, firm's age, cost of electricity, exports, and subsidies access jointly explain firm energy efficiency.

Log likelihood = −9274.5734 measures how well the model fits the observed data under maximum likelihood estimation. Therefore, the model is appropriate to show the how social, economic and institutional factors affects firm efficiency. In Isolation, the log-likelihood value is neither appropriate nor inappropriate; but it is mostly helpful when comparing various models.

The log likelihood for the model estimated is −9274.5734. Since the model was estimated using maximum likelihood, it shows that the estimation process was successful in generating valid parameters. Additionally, this serves as an indicator that the estimation procedure successfully converged and yielded reliable parameter estimates. This, therefore, supports the suitability of the SFA model in analysing the effects of social, economic and institutional factors on energy efficiency. It is also important to note that the stochastic frontier analysis model does not provide the usual measure of coefficient of determination (R^2). This is due to the fact that the stochastic frontier analysis model is slightly different from the ordinary least squares regression model, both in its construction as well as in the estimation technique used.

While the ordinary least squares regression technique involves the decomposition of the error term into one single

symmetric term and then measures the degree of fit through the proportion of variation in the dependent variable explained by the model, in stochastic frontier analysis, the error term is decomposed into two separate terms (Adler, Kivel & Zucker, 2026). These terms include the symmetric random error term (v_i) representing the statistical noise and the one-sided inefficiency term (u_i).

The estimated constant term is positive and statistically significant which indicates the baseline level of energy efficiency across manufacturing firms is much higher than zero, as indicated by the positive and statistically significant estimated coefficient. This means that when all explanatory variables are held constant, the intercept represents the expected energy efficiency. However, because some variables were transformed in natural logarithmic form, this is not practically useful. The constant is therefore best interpreted as giving the baseline from which the effects of the explanatory variables on energy efficiency are measured and capturing the average influence of missing factors. Its significance, therefore, suggests that factors not explicitly included in the model also contribute to variations in energy efficiency among manufacturing firms in Kenya.

The parameter $/lnsig2v$ is statistically significant and represents the log of the variance of the random error component. Its suggests that random shocks outside the firm's control such as market conditions, measurement errors, or external disturbances contribute significantly to deviations from the production frontier. The estimated standard deviation of random noise is sigma σ_v = 1.275, indicating that part of the variation in output is due to uncontrollable factors rather than inefficiency.

Variance of Inefficiency (σu^2)

The parameter $lnsig2u$ represents the log variance of the inefficiency term μ_i. Although the coefficient is positive, it is statistically insignificant, implying weak evidence that inefficiency variation is strongly distinguishable statistically from zero based on this parameter alone. The estimated standard deviation of inefficiency is $\sigma_u = 1.285$, suggesting that firm-specific inefficiency contributes meaningfully to deviations from the frontier.

Total Variance

The estimated $\sigma^2 = 3.278$ represents the total variance in the composite error term, $\sigma^2 = \sigma v^2 + \sigma \mu^2$. The σ^2 represent the variance attributed with technical inefficiency while $\sigma \mu^2$ represents the variance attributed to random errors, measurement errors and other factors beyond the firm's control while Lambda ($\lambda = \sigma u / \sigma v$) is a measure of variance importance that captures the relative importance of technical importance to random noise. It measures how much differences in inefficiency come from technical inefficiency instead of random factors.

Lambda (λ) is calculated as; $\lambda = \sigma u / \sigma v = 1.008$. This suggests inefficiency and random noise contribute almost equally to deviations from the frontier. The variance decomposition suggests that differences in firm output are not driven solely by random shocks, but also by technical inefficiency. The fact that σ_μ slightly exceeds σ_v and λ exceeds one, it indicates that inefficiency plays a meaningful role. For Gamma, (γ), $\gamma = \sigma u^2 / (\sigma u^2 + \sigma v^2) \approx 0.504$. This implies approximately 50% of total variation in output is due to technical inefficiency.

Capital has a positive and statistically significant effect on energy efficiency. It suggests that a 1% change in capital translates to a 0.3198% increase in energy efficiency of firms. This implies that higher levels of capital contribute positively to increase in the capability of firms to produce near the frontier production process and therefore be more technically efficient.

The relationship between firm size and energy efficiency is statistically significant and negative This implies that, *ceteris paribus*, a 1% increase in firm size leads to 0.0005% decrease in firms' energy efficiency. It can therefore be interpreted that large firms face inefficiencies as a result of bureaucratic rigidity, poor coordination, or high operating costs, making them fall away from the production frontier.

Research and development expenditure showed a positive and statistically significant relationship. This shows that, *ceteris paribus*, a one percent increase in research and development increases energy efficiency by 0.43%. Firms that allocate more resources for research and development perform better in terms of efficiency. Expenditure on research and development allows manufacturing firms to innovate their production processes. It enables firms to optimize their production processes hence they become less energy intensive. Through innovation of production processes, firms make the whole process structure less energy consuming, this way helps achieve structural reduction in energy consumption, not just marginal, explaining why such high coefficients were found in this meta-stochastic frontier.

Total Labour cost has a positive and statistically significant relationship with energy efficiency. This means that a one percent increase in labour cost, leads to 0.0005% increase in energy efficiency holding other factors constant. Even though the numerical magnitude of the coefficient appears small it indicates that labour cost plays a critical role in determining energy efficiency in manufacturing firms. Higher labour costs often suggest a more skilled and experienced workforce. This workforce is crucial in determining how efficiently production processes are managed. Skilled workers tend to operate complex machinery better, spot inefficiencies in real-time, and adjust production methods to cut down on energy use. In energy-intensive manufacturing firms, even small boosts in operator skills can lead to significant reductions in energy waste for

each unit of output produced. This explains why firms with higher labour costs often show better energy efficiency in the stochastic frontier results.

Firm ownership has a positive but statistically insignificant effect on efficiency. Although the coefficient suggests that foreign owned firms may be more efficient than their counterparts, the lack of statistical significance indicates insufficient evidence to conclude that firm ownership has a meaningful influence on technical efficiency.

Gender of the top manager has a positive and statistically insignificant relationship with energy efficiency. While firms managed by female top managers appear to exhibit higher efficiency, the effect is not statistically significant, suggesting no strong evidence that gender of top manager systematically influences firms' technical efficien

Firm age has a positive and statistically significant effect on efficiency. Holding other factors constant, 1 unit increase in firms' efficiency by approximately 0.492 units. This points out to the fact that older firms tend to be more efficient due to accumulated experience, learning-by-doing, and established operational routines. However, the negative and significant coefficient for firm age squared suggests an inverted U-shaped relationship, where efficiency increases with age up to a certain point and then declines, implying that older firms may eventually face structural rigidity or technological obsolescence that reduces efficiency.

Total cost of electricity has a positive and statistically significant effect on efficiency. This suggests that greater electricity cost, often associated with improved operational capacity and production intensity, contributes to firms operating closer to the efficiency frontier.

On Export status of the firm, it has a positive and statistically significant effect on efficiency Exporting firms appear more technically efficient than non-exporters, possibly due to exposure to international competition, better technologies, and learning-by-exporting effects that improve resource utilization. Firms that spend more electricity are typically more mechanized, more automated, and operate with higher capacity utilization. In such cases, cost of electricity reflects production intensity and technological sophistication, which enhances efficiency by reducing unit costs and improving output per input combination. Therefore, cost of electricity becomes an indicator of how effectively firms are utilizing modern production systems.

For Subsidy access, it has a positive and statistically significant effect on efficiency. This indicates that firms with subsidy access, *ceteris paribus*, are more likely to operate efficiently, as subsidies access may ease financial constraints, support technology adoption, and facilitate efficient allocation of productive resources.

Conclusion

This study analyzed the economic, social, and institutional drivers of energy efficiency among Kenya's manufacturing firms from a stochastic frontier analysis perspective. The findings indicated that energy efficiency depends on both economic, social as well as institutional factors. The findings underscore enhancing energy efficiency does not only depend on technology but needs innovation, human capital, and institutions factors as well.

Policy Recommendations

The results of the research have several significant implications for policymakers, development partners and other stakeholders within the manufacturing firm-level context. The recommendations outlined below include specific actors and ways of implementing the actions to improve energy efficiency in manufacturing sector.

i. To increase efficiency, the government needs to introduce appropriate policies. First, the government need to create conditions for technological upgrading and innovation among manufacturing firms. It is possible to achieve this by using tax incentives for firms investing in new machinery, creation of innovative funds, fostering linkages between manufacturing firms and research institutions, as well as provision of affordable finance to firms via credit guarantee schemes and reductions in borrowing costs.

ii. Moreover, to tackle the energy inefficiency, the government/firms can consider investing in energy efficiency improvement projects. Considering the benefits brought by subsidies, the emphasis must be made on effective use of subsidies, which means that it is necessary to provide incentives related to investment and R & D, but not expenditure.

iii. Investment by the relevant stakeholders should be encouraged in areas such as technology, R & D, and skills training to increase operational efficiency. Energy-efficient manufacturing procedures must be employed, along with continuous improvement in their manufacturing systems.

iv. The development partners can support manufacturing firms through technical capacity building, and financing incentives to encourage energy efficiency. These development partners can even help the local firms share their knowledge with international firms through various partnership initiatives, along with financing and researching in energy efficiency initiatives.

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