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Factors Associated with Energy Management Adoption among Manufacturing Firms in Uganda

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Research Article

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Abstract

Energy management measures lower manufacturers' energy costs and ease pressure on constrained power systems, yet many firms in low-income countries do not adopt them. This study examines firm characteristics and operating conditions associated with adoption among manufacturing firms in Uganda. It uses the 2025 World Bank Enterprise Survey and a sample of 216 manufacturing establishments. Adoption was modelled using a binary logit model, with a probit model as a robustness check, and results interpreted using average marginal effects. About 63.0% of firms adopted energy management measures in the three years preceding the survey. Adoption was positively associated with product innovation, access to a line of credit and large firm size. Firms in Western and Eastern Uganda were more likely to adopt than those in Central Uganda. Therefore, support should prioritise smaller manufacturers, pilot financing instruments matched to energy savings, and tailor technical assistance to regional conditions, while evaluating the effectiveness of these interventions.

JEL classification: D22; L60; O13; O55; Q41

1. Introduction

Energy management is the systematic planning, monitoring, and control of energy use to continuously improve an organisation's energy performance [1]. It covers metering and monitoring consumption, setting targets, assigning responsibility for energy, maintaining equipment, changing production routines and investing in efficient technologies [2, 3]. For manufacturers, these measures lower energy bills and bring wider benefits such as higher productivity, more reliable equipment and better product quality [4], and combining management practices with technology investment yields larger savings than technology alone [5]. Better-managed plants are measurably less energy-intensive [6, 7], and wider use of formal energy management systems could deliver substantial energy and emission savings by 2030 [8].

Nevertheless, many firms do not adopt measures that appear profitable, a pattern known as the energy-efficiency gap [9–11]. Explanations include imperfect information, limited access to capital, hidden implementation costs, split incentives, weak managerial attention and competing investment priorities [12–16]. Profitable opportunities remain unexploited even at the median firm in high-income economies [17]. Adoption differs systematically across firms. Firms differ in their ability to identify, finance and implement energy-saving projects [18–20], and smaller firms face the most binding constraints [21, 22]. Organisational routines, status quo bias and short planning horizons add to these barriers, especially in smaller enterprises [23, 24]. Experience of losses from extreme weather may further shape adoption, either by raising awareness of climate risk [25, 26] or by diverting scarce resources to repairs[27].

In Sub-Saharan Africa, these decisions are taken under severe infrastructural, financial and institutional constraints. Unreliable electricity lowers firm sales and productivity [28–30] and pushes firms into costly self-generation [31–33], whose fixed costs favour larger firms [34]. Case studies from Ghana, Nigeria and Kenya show that limited capital, technical expertise and managerial commitment, together with weak innovation systems, hold back industrial energy-efficiency improvement [35, 36], whereas larger

enterprises in urban Ethiopia are more likely to use efficient technologies [37]. In Uganda, electricity consumption and industrial output are linked in the long run [38], industrial load drives peak demand [39], and most surveyed manufacturers experience power outages. Improving industrial energy efficiency would allow the existing power system to serve more users reliably [40]. Yet short-term thinking and status quo bias discourage efficiency improvements among micro and small enterprises [24], and fragmented institutional responsibilities and weak regulation hinder national-level industrial energy efficiency [41]. Uganda Vision 2040 and the Fourth National Development Plan (2025/26–2029/30), themed on sustainable industrialisation, expect manufacturing to expand rapidly. The Energy Policy for Uganda 2023 seeks greater use of energy-efficient practices, and the Energy Efficiency and Conservation Bill, 2024 proposes energy audits, energy managers and energy management systems for designated large consumers.

Despite this policy interest, the firm-level factors associated with adoption in Uganda have not been examined. International evidence links adoption to firm size, innovation, management and access to finance [19, 42, 43], but most of it comes from high-income or transition economies [15, 44] or from pooled multi-country samples [24, 25, 45, 46], which cannot show whether these relationships hold within a single low-income country where credit markets are thin, and support services are concentrated in the capital. African evidence rests mainly on qualitative case studies of selected industries [35, 36, 47]. Ugandan studies have addressed behavioural barriers among micro and small enterprises and institutional barriers at the national level [24, 41], but none has estimated how firm characteristics, regional location and direct experience of climate-related asset damage are jointly associated with adoption among formal manufacturers. Whether firms that have suffered weather damage adopt more, as pooled studies suggest [25], or less, because repairs absorb resources [27], remains untested in a low-income setting.

This study therefore examines the factors associated with the adoption of energy management measures among manufacturing firms in Uganda, using the 2025 World Bank Enterprise Survey. It estimates a binary logit model of adoption, with probit and linear probability models as robustness checks, and interprets average marginal effects. The study contributes in three ways. First, it provides the first firm-level evidence on the adoption of energy management among formal manufacturers in Uganda, complementing earlier behavioural and institutional work. Second, it tests whether direct experience of climate-related asset damage is associated with adoption in a low-income, climate-vulnerable country, a question that has so far been studied only with pooled multi-country samples. Third, it documents within-country regional differences in adoption, which firm-level energy studies rarely examine. The rest of the paper reviews the literature, describes the data and methods, presents and discusses the results, and concludes with implications for policy and research.

2. Literature review

The theoretical foundation follows the Random Utility Theory, which provides the empirical modelling foundation [48, 49]. A manufacturing firm chooses between adopting energy management measures

and continuing with existing practices, selecting the alternative with the higher expected net utility. Adoption promises lower energy costs, fewer production interruptions, and more reliable equipment, but entails expenditures on equipment, information, training, managerial time, and production disruption [18, 50]. Because only the decision is observed, the utility difference is treated as a latent variable and estimated with a binary-choice model, as in earlier studies of firms' energy-efficiency decisions [19, 42, 51].

The energy-efficiency gap framework explains why expected net benefits differ among firms facing similar prices and technologies [9, 12, 52]. Imperfect information, limited access to capital, hidden costs, risk, organisational inertia and managerial inattention raise the effective cost of adoption [13, 23, 53, 54]. Boyd and Curtis [55] describe an energy-management gap in which general management quality spills over to energy performance, and Schützenhofer [56] shows that formal energy management lowers barriers by assigning responsibility and integrating energy into routine decisions. The resource-based view posits that firms with greater financial, human, and technological resources are better positioned to identify, finance, and implement energy-saving projects [57, 58], which is why firm size, innovation, access to credit, and employee training are expected to be positively associated with adoption [59–61]. Finally, protection motivation theory suggests that direct experience of weather damage raises threat appraisal and can motivate protective action, but only when firms also have the capacity to respond [62, 63].

The reviewed Empirical literature revealed four patterns. First, firm size is the most consistent correlate of energy-efficiency investment in both high-income and developing economies [18–20, 37, 64]. Smaller firms face higher relative investment costs and weaker access to information and finance [21, 22, 65, 66]. Second, innovation and organisational capabilities raise adoption: firms that introduce new products or processes, or that have stronger absorptive capacity and management practices, are more likely to implement energy-efficiency measures [6, 7, 46, 51, 67–70]. Third, access to finance is repeatedly identified as a binding constraint on energy efficiency and green investment, particularly in emerging and transition economies [42–44, 71–73], although finance alone does not guarantee implementation when internal capacity is weak [74]. Fourth, evidence on direct exposure to extreme weather is mixed. Pooled multi-country studies find that weather losses are followed by more green energy practices and more active carbon management [25, 26], whereas firm-level studies find that losses mainly trigger replacement investment and borrowing, that their effects fade within a year or two, and that small firms are the least able to adapt [27, 75–80].

Reviews of Swedish and European industry identify top-management commitment, in-house competence, a long-term energy strategy and cost reduction as the main drivers of energy management programmes, and lack of time and staff as the main barriers [60, 61, 81–83]. Firms with stronger energy management are more likely to approve energy-efficiency investments [84], and information instruments such as energy audits raise implementation, particularly where the recommended measures require small investments and short paybacks [50, 65, 85]. In African industry, limited capital, technical expertise and managerial commitment constrain improvement in Ghana [35]. Weak innovation systems and

dependence on foreign equipment suppliers delay adoption by food processors in Nigeria and Kenya [36], and energy audits, written energy policies and staff training on energy are associated with greater savings among Kenyan firms [86]. Among Ugandan micro and small enterprises, behavioural factors rather than energy prices explain under-investment [24], while at the national level fragmented mandates and weak coordination have slowed the institutionalisation of industrial energy efficiency [41].

Moreover, unreliable electricity raises production costs and pushes firms towards self-generation and input substitution rather than efficiency improvement [28, 31, 32, 87–89], so the direction of any association between outage experience and energy management is unclear. Regional conditions also shape green behaviour. Eco-innovation and renewable energy adoption cluster in regions with denser economic activity, stronger environmental attitudes and local spillovers [90–92], and infrastructure quality determines which firms can operate and invest [34, 93]. Within Uganda, energy access and energy poverty vary sharply across regions [94].

Three gaps follow. First, most evidence comes from high-income or transition economies or from pooled multi-country samples, while African evidence rests on qualitative case studies of selected industries [35, 36, 47]. Second, Ugandan studies have examined behavioural barriers in micro and small enterprises and institutional barriers at the national level [24, 41], but no study has estimated firm-level associations with adoption among formal manufacturers. Third, no study has tested, within a single low-income country, whether direct experience of climate-related asset damage and regional location are associated with the adoption of energy management measures once firm characteristics are held constant. This study addresses these gaps.

3. Methodology and data

The study uses secondary data from the 2025 World Bank Enterprise Survey for Uganda. The survey draws a random sample of formal establishments with five or more employees, stratified by sector, size and region. It collects information through face-to-face interviews with owners and senior managers on ownership, employment, infrastructure, finance and innovation. Moreover, its green economy module collects information on environmental and energy practices and exposure to extreme weather. The analysis is restricted to establishments whose actual economic activity falls within manufacturing divisions 10–33 of the International Standard Industrial Classification, Revision 4. The analytical sample comprises 216 manufacturing establishments, and the establishment is the unit of analysis.

Table 1
Measurement and definition of variables

Variable	Measurement and definition
Energy management adoption	Dependent binary variable: 1 if the establishment adopted energy management measures during the preceding three years, 0 otherwise.
Climate-related asset damage	1 if the establishment experienced damage to physical assets from extreme weather events, 0 otherwise.
Product innovation	1 if the establishment introduced new or significantly improved products or services during the preceding three years, 0 otherwise.
Power outage experience	1 if the establishment experienced power outages during the last fiscal year, 0 otherwise.
Access to a line of credit	1 if the establishment has a line of credit from a financial institution, 0 otherwise.
Business size	Categorical, from the survey's size classification: small (5–19 employees, reference), medium (20–99) and large (100 or more).
Region	Categorical: Central (reference), Western, Eastern and Northern.
Firm age	Years since the establishment began operations.
Employee training	1 if the establishment provided formal training programmes for permanent full-time employees during the last fiscal year, 0 otherwise.

Source: Author's construction from the 2025 World Bank Enterprise Survey questionnaire.

3.1 Empirical model and estimation

Following the random utility framework [48, 49], establishment i derives net utility from adopting rather than not adopting:

$$EM_i^* = X_i' \beta + u_i$$

1

where X_i contains the covariates in Table 2, β is a parameter vector, and u_i captures unobserved factors. Only the decision EM_i is observed, with $EM_i = 1$ if $EM_i^* > 0$ and 0 otherwise. The probability of adoption is therefore:

$$\Pr(\, EM_i = 1 | X_i) = \Pr(u_i > -X_i' \beta\,) = F(X_i' \beta\,),$$

2

where $F(\cdot)$ is the cumulative distribution function of u_i. When u_i is logistic, $F(\cdot)$ is the logistic function $\Lambda\,(\cdot)$ and Eq. (2) is the binary logit model, which is the main specification. The logistic function uses a standard model for firms' energy-efficiency decisions [19, 51] and is robust to the bounded nature

of the outcome. When u_i is standard normal, $F(\cdot)$ is $\Phi(\cdot)$ and Eq. (2) is the probit model, estimated as a robustness check. The two models differ only in the assumed error distribution [95, 96]. A linear probability model (LPM), which applies ordinary least squares to EM_i, is estimated as a transparent benchmark, although it can predict probabilities outside the unit interval and is, by construction, heteroskedastic [97].

Logit and probit coefficients are scaled by the unobserved error variance and cannot be read as probability changes or compared across models [98, 99]. The study therefore reports average marginal effects (AMEs). For a binary covariate D_k the AME is the average difference in predicted probability when the covariate switches from 0 to 1, holding the other covariates at their observed values:

$$AME_k = \left(\frac{1}{N}\right)\sum\nolimits_i [F(X_i'\beta \mid D_{ki}=1) - F\left(X_i'\beta \mid D_{ki}=0\right)],$$

3

and for firm age, it is the average derivative of the predicted probability with respect to age [100, 101]. AMEs are interpreted as percentage-point changes in the probability of adoption relative to the reference category.

All models are estimated with standard errors clustered at the firm level, which are robust to heteroskedasticity. Multicollinearity is assessed with pairwise correlations and variance inflation factors (VIFs). The fit of the logit and probit models is assessed with the Hosmer–Lemeshow test [102], the share of observations correctly classified, the area under the receiver operating characteristic curve and a link test for specification error. The LPM is checked with the Breusch–Pagan [103] and White tests for heteroskedasticity [104] and the Ramsey RESET test for functional form [105]. Consistent signs and significance across the three estimators are taken as evidence that the results do not depend on functional form.

4. Results

Table 3 summarises the analytical sample. About 63.0% of the 216 manufacturing establishments adopted at least one energy management measure in the three years before the survey, while 37.0% did not. Energy management is therefore widespread but far from universal. Only 10.6% of establishments, 23 firms, reported damage to physical assets from extreme weather, whereas 80.6% experienced power outages in the last fiscal year. Capabilities and finance are unevenly distributed. 32.4% introduced a new or improved product, 34.3% provided formal employee training, and only 11.1% had a line of credit from a financial institution. Small, medium and large firms account for 34.3%, 35.6% and 30.1% of the sample, respectively. Central Uganda hosts 35.6% of establishments, followed by Eastern Uganda with 24.5%, Western Uganda with 22.7% and Northern Uganda with 17.1%. The average establishment has operated for about 22 years.

Table 2
Descriptive statistics (N = 216)

Variable	Category	Share/mean
Energy management adoption	No	0.37
	Yes	0.63
Climate-related asset damage	No	0.894
	Yes	0.106
Product innovation	No	0.676
	Yes	0.324
Power outage experience	No	0.194
	Yes	0.806
Access to a line of credit	No	0.889
	Yes	0.111
Business size	Small	0.343
	Medium	0.356
	Large	0.301
Region	Central	0.356
	Western	0.227
	Eastern	0.245
	Northern	0.171
Firm age (years)	Mean	22.227
Employee training	No	0.657
	Yes	0.343

Source: Author's construction from the 2025 World Bank Enterprise Survey questionnaire.

Table 4 reports pairwise correlations among the covariates. All coefficients are modest. The largest in absolute value is − 0.38, between region and business size, and the mean VIF is 1.43, far below conventional thresholds of 0.8 and 10, respectively. So, multicollinearity is not a concern. Climate-related damage is weakly and negatively correlated with access to a line of credit, at − 0.12, and essentially uncorrelated with the other covariates.

Table 3
Pairwise correlations among covariates

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
(1) Climate asset damage	*1.00*							
(2) Product innovation	*0.02 (0.79)*	*1.00*						
(3) Outage experience	*0.10 (0.16)*	*0.10 (0.16)*	*1.00*					
(4) Access to credit	*−0.12 (0.07)*	*0.20 (0.00)*	*0.14 (0.04)*	*1.00*				
(5) Business size	*−0.02 (0.80)*	*0.19 (0.01)*	*−0.01 (0.84)*	*0.22 (0.00)*	*1.00*			
(6) Region	*0.01 (0.89)*	*−0.26 (0.00)*	*0.10 (0.13)*	*−0.15 (0.02)*	*−0.38 (0.00)*	*1.00*		
(7) Firm age	*0.03 (0.67)*	*0.06 (0.37)*	*0.02 (0.73)*	*0.15 (0.02)*	*0.34 (0.00)*	*−0.31 (0.00)*	*1.00*	
(8) Employee training	*0.07 (0.32)*	*0.17 (0.01)*	*0.21 (0.00)*	*0.24 (0.00)*	*0.26 (0.00)*	*−0.14 (0.04)*	*0.25 (0.00)*	*1.00*
Mean VIF	**1.43**							

P-values in parentheses. Source: Author's construction from the 2025 World Bank Enterprise Survey for Uganda.

The regression results shown in Table 5 include the LPM, logit, and probit estimates, along with their AMEs. The main associations are generally similar across the three estimators, although the estimate for the Northern region differs in both size and significance. The logit and probit AMEs differ by about one percentage point or less. The Hosmer–Lemeshow statistic is 9.43, with an associated p-value of 0.307, so the model fit is not rejected. Furthermore, the logit model correctly classifies 77.8% of establishments and has an area under the ROC curve of 0.80. The p-value for the squared-prediction term in the link test is 0.441, providing no statistically significant evidence of specification error. The LPM accounts for 27.8% of the variation in adoption, while the Breusch–Pagan, White and RESET tests do not reject their respective null hypotheses. The interpretation given below is based on the logit AMEs in column 3. With regard to access to credit, the LPM coefficient of 0.190 is less than the logit AME of 0.228.

Three clear features are positively linked to adoption. Firms that had introduced a new or improved product were 15.4 percentage points more likely to have adopted energy management measures than firms that had not, a result significant at the 5% level. Moreover, firms with a line of credit were 22.8 percentage points more likely to have adopted than those without a line of credit, and the association

was also significant at the 5% level. Large firms were 17.8 percentage points more likely to have adopted than small firms, a difference that is significant at the 5% level. On the other hand, medium-sized firms had an estimated adoption probability 1.0 percentage point lower than that of small firms, but this difference was not statistically significant.

Compared with those in Central Uganda, firms in Western and Eastern Uganda were, respectively, 31.8 and 34.8 percentage points more likely to adopt, and both associations were significant at the 1% level. Yet firms in Northern Uganda were estimated to be 12.6 percentage points less likely to adopt than firms in Central Uganda, although this difference was not statistically significant in either the logit or probit models. It was only significant at the 10% level in the LPM.

The other covariates are not found to be statistically linked with adoption at the conventional level. Climate-related asset damage has an average marginal effect of − 6.0 percentage points and a standard error of 9.5 percentage points. Furthermore, both outage experience and employee training have positive AMEs of 3.1 and 4.4 percentage points, respectively, while the effect of firm age is about zero per year.

Table 4
Adoption of energy management measures among manufacturing firms in Uganda

Variables	(1) LPM	(2) Logit	(3) AME	(4) Probit	(5) AME
Climate asset damage (Yes)	−0.060	−0.357	−0.060	−0.176	−0.051
	(0.107)	(0.558)	(0.095)	(0.324)	(0.095)
Product innovation (Yes)	0.156**	0.916**	0.154**	0.527**	0.151**
	(0.063)	(0.396)	(0.064)	(0.222)	(0.062)
Outage experience (Yes)	0.049	0.184	0.031	0.126	0.037
	(0.078)	(0.418)	(0.072)	(0.247)	(0.073)
Access to credit (Yes)	0.190**	1.564*	0.228**	0.855**	0.218**
	(0.081)	(0.834)	(0.096)	(0.423)	(0.089)
Business size (Medium)	0.006	−0.059	−0.010	−0.020	−0.006
	(0.076)	(0.441)	(0.078)	(0.249)	(0.076)
Business size (Large)	0.189**	1.095**	0.178**	0.666**	0.186**
	(0.089)	(0.505)	(0.082)	(0.293)	(0.080)
Region (Western)	0.304***	1.682***	0.318***	0.992***	0.314***
	(0.098)	(0.573)	(0.093)	(0.328)	(0.092)
Region (Eastern)	0.323***	1.897***	0.348***	1.144***	0.351***
	(0.080)	(0.498)	(0.079)	(0.291)	(0.079)
Region (Northern)	−0.184*	−0.652	−0.126	−0.414	−0.136
	(0.096)	(0.541)	(0.106)	(0.317)	(0.105)
Firm age (years)	0.001	0.003	0.000	0.001	0.000
	(0.002)	(0.011)	(0.002)	(0.007)	(0.002)
Employee training (Yes)	0.048	0.264	0.044	0.132	0.038
	(0.069)	(0.405)	(0.068)	(0.231)	(0.066)
Constant	0.314***	−1.063*		−0.622*	
	(0.106)	(0.561)		(0.330)	
Observations	216	216	216	216	216
R-squared	0.278				
Breusch–Pagan χ^2 [p]	0.98 [0.323]				

Variables	(1) LPM	(2) Logit	(3) AME	(4) Probit	(5) AME
Ramsey RESET F [p]	1.71 [0.166]				
White χ^2 [p]	74.49 [0.133]				
Hosmer–Lemeshow χ^2 [p]		9.43 [0.307]		5.37 [0.717]	
Correctly classified (%)		77.78		77.31	
Area under ROC curve		0.799		0.796	
Link test: _hat [p]		1.047 [0.001]		1.043 [0.001]	
Link test: _hatsq [p]		−0.067 [0.441]		−0.103 [0.451]	

*Standard errors clustered at the firm level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. Columns (3) and (5) report average marginal effects (percentage-point changes expressed as proportions). Reference categories: small firms; Central region. Source: Author's construction from the 2025 World Bank Enterprise Survey for Uganda.*

5. Discussion

The positive association between large size and adoption is consistent with the energy-efficiency gap framework and with evidence from Spain, Slovenia, Ethiopia and the United States that larger firms are more likely to invest in energy efficiency [18–20, 37]. A plausible mechanism is that energy management involves fixed costs for audits, metering, specialist staff and management time, which large firms can spread over greater output and finance internally, while a given percentage saving yields a larger absolute return. The absence of a difference between medium and small firms suggests that this advantage emerges only at a threshold. Firms with 20–99 employees may still lack dedicated technical staff and borrowing capacity. This agrees with evidence that SMEs are heterogeneous and that barriers vary systematically with size [21, 22, 106].

Product innovation is associated with a 15.4-point increase in the probability of adoption. Thus, introducing new products typically requires reviewing production lines, inputs and equipment, which creates occasions to identify energy savings and signals a general capacity to change routines. The finding is in line with European evidence that innovating firms adopt more energy-efficiency technologies [67, 68], that cost savings drive energy-efficiency eco-innovation [107, 108], that organisational capabilities raise eco-innovation intensity [69] and that green practices and innovation move together across developing countries [70]. In Uganda, evidence consistently indicates that intellectual capital supports environmental innovation among manufacturers [109].

Access to a line of credit shows the largest firm-level association, 22.8 points. This is consistent with the energy-efficiency gap framework, which identifies access to capital as a central barrier, and with evidence that financing raises SMEs' energy-saving measures in Europe [42], that credit constraints

lower green investment in emerging markets [43, 73], that relaxing credit constraints raises manufacturers' energy efficiency [71], and that formal credit access raises energy management adoption among Indian food firms [72]. Credit may finance the upfront cost of equipment, audits and process changes, or firms that obtain credit may simply be better organised and more creditworthy [74].

For the regional pattern, Central Uganda, which contains the capital city, Kampala, and most support institutions, would lead in adoption. Establishments in the Western and Eastern regions were about a third more likely to adopt than those in the Central region, conditional on size, innovation, credit and the other covariates. Several mechanisms are possible. Manufacturing outside the Central region includes many agro-processing firms that use substantial amounts of process heat and electricity, thereby raising the payoff from energy management. Electricity supply and tariffs may be less reliable or more costly outside the capital, increasing attention to energy costs, and regional programmes or peer effects may generate local spillovers of the kind documented in Germany and Italy [90–92]. The lower but statistically insignificant adoption in Northern Uganda is consistent with weaker infrastructure and higher energy poverty in that region [93, 94].

The climate-related asset damage coefficient was negative but not statistically significant. Implying that experiencing asset damage from any climate shock did not prompt firms in Uganda to adopt energy management measures. These results are unlike studies that pooled multi-country data, which show that weather losses are followed by more green energy practices [25, 26]. Those effects were stronger where governance was good, and protection motivation theory predicts protective action only where firms have the capacity to respond [62, 63]. In a low-income setting, damage may raise awareness while simultaneously diverting funds to repairs, consistent with evidence that firms absorb weather shocks mainly through replacement investment and borrowing [27, 75], that the effects of such shocks fade quickly [76, 77], and that firms adapt only when managers actively attend to climate impacts [110, 111]. The weak negative correlation between damage and credit access also suggests that damaged firms may be more credit-constrained. Outage experience, employee training and firm age were likewise not associated with adoption. Firms in African countries typically respond to unreliable supply by installing generators or substituting inputs rather than by managing energy use [31, 32, 88].

6. Conclusion and implications

This study examines energy management adoption among 216 manufacturing establishments in Uganda using the 2025 World Bank Enterprise Survey and binary logit, probit and linear probability models. The logit average marginal effects show that product innovation, access to a line of credit and large firm size are positively associated with adoption. Product innovators and establishments with credit lines have adoption probabilities 15.4 and 22.8 percentage points higher than their respective comparison groups. Moreover, large establishments are 17.8 percentage points more likely to adopt than small establishments. These associations are statistically significant at the 5% level. Furthermore, establishments in Western and Eastern Uganda have adoption probabilities 31.8 and 34.8 percentage points higher than those in Central Uganda, respectively, with both differences significant at the 1% level.

Nevertheless, the Northern–Central difference is not statistically significant in the logit or probit models, although it is significant at the 10% level in the linear probability model. Climate-related asset damage, power outages, employee training, firm age and medium size have no statistically significant associations in the logit model. The principal positive associations remain evident across the three specifications. Three implications follow. First, the large–small adoption difference supports evaluating assistance for smaller manufacturers through shared energy audits, metering tools and technical guidance. Second, the innovation and credit associations support integrating energy management into industrial upgrading programmes and investigating whether financing instruments can facilitate adoption. Third, the regional differences warrant an examination of local operating conditions and the tailoring of support accordingly, without assuming that Northern Uganda has significantly lower adoption than Central Uganda. Finally, the cross-sectional design identifies conditional associations but cannot establish causality, the sequence of adoption decisions or changes over time, highlighting the need for future studies to use successive survey rounds to examine adoption patterns and, where establishments can be followed, the timing of adoption decisions.

Declarations

Ethics approval and consent to participate:

Not applicable. The study used anonymised secondary data collected by the World Bank; no human participants were recruited, and no identifiable personal data were used.

Consent for publication:

Not applicable.

Competing interests:

The author declares no competing interests.

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Author Contribution

D.T. conceptualised the study, developed the methodology, analysed and interpreted the data, and wrote and revised the manuscript. D.T. approved the final version.

Data Availability

Yes. I used research data in this study.The data are from the 2025 World Bank Enterprise Survey for Uganda and are available through the World Bank Enterprise Surveys portal upon registration: https://www.enterprisesurveys.org. Replication files are available upon reasonable request.

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