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Climate Change on Energy Production and Supply Chain Costs - A Case Study of South Western Uganda

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Abstract: *The study aimed at the relationship between climate change on energy production and supply chain costs and it was guided by the following objectives; To determine the relationship between climate sensitivity and Energy production costs, to determine the relationship between carbon sinks and Energy production costs and to determine the relationship between solar activity and Energy production costs. This study employed a mixed methods explanatory sequential design. Secondary data analysis was first conducted to quantify observed impacts and costs. The target population included energy companies operating infrastructure in climate-vulnerable regions. For secondary data analysis, publicly reported adaptation costs from 10 large global companies were compiled. For questionnaire, a purposive sample of 10-15 mid-level North American managers was recruited from petroleum, utilities and renewable energy industries. From the literature, declining mountain snowpack lengthens the time between snowmelt and peak river flow, reducing storage capacity in some river basins. Descriptive analysis was used to determine the proportions and frequency of the variables. The results were presented in form of correlation and regression matrix using SPSS. From the findings, the R value of 0.584 indicated a moderate positive correlation between solar activity and costs, higher solar activity predicted higher costs, the R Square value is 0.341, meaning solar activity explains approximately 34.1% of the variation in energy costs and this had a greater explanatory power than carbon links. The F value of 40.496 and significance of 0.000 shown that the regression model is statistically significant. Policymakers should continue promoting low-carbon energy options like renewables, but also focus on cost competitiveness to maximize uptake. Incentives balancing both carbon and costs could be considered.*

Keywords: climate change, energy production and supply chain costs

Background of the study

Global energy systems are already experiencing the effects of a changing climate. The burning of fossil fuels for power, transportation and industrial uses has released greenhouse gases that are raising atmospheric temperatures above pre-industrial levels. The world has warmed approximately 1°C over the past century, with the majority of warming occurring over the past 40 years (IPCC, 2021). According to the National Oceanic and Atmospheric Administration, the six warmest years in recorded history have all occurred since 2015 as temperatures continue to climb (NOAA, 2021). Climate change is not impacting all regions equally - higher latitudes are seeing greater degrees of warming and precipitation changes compared to lower latitudes (Sherwood & Huber, 2010). However, disruptive climate impacts are being felt industry-wide. Thermal power plants require cooling water and are seeing reduced efficiencies as water temperatures rise (Auffhammer, 2018). Coastal oil refineries, LNG terminals and wind farms experience greater storm surge flooding and hurricane damage in a warming world (Kopp et al., 2014). Vast networks that transport fuels over land and sea to market are also vulnerable. More than 2.7 million miles of pipeline carry crude oil, natural gas, and refined products worldwide, with sections traversing floodplains and permafrost regions becoming exposed to climate risks (Allgood & McMahan, 2011). Major seaports handle over 80% of global trade and are dealing with sea level rise implications including damage to docks and container yards from stronger storms (Becker et al., 2013). Energy companies are recognizing the need to adapt infrastructure to climate stressors. However, adaptations can be costly. Retrofitting coastal plants, elevating pipelines, and undergrounding transmission lines require multi-billion investments (Colgan et al., 2019). Disruptions to production and distribution from climate impacts also translate to billions in lost revenue each year (Laurice et al., 2016). With climate change threats projected to intensify in coming decades, energy sector adaptation costs could escalate significantly unless greenhouse gas emissions are rapidly reduced.

Problem statement

Climate change poses significant challenges for global energy production and supply chains. Rising average temperatures, changing precipitation patterns, and more frequent extreme weather events are expected to disrupt energy infrastructure and drive-up costs. According to the Intergovernmental Panel on Climate Change (IPCC, 2021), continued greenhouse gas emissions was causing further planetary warming over the coming decades, intensifying climate change risks to energy systems. Higher temperatures reduce efficiency and capacity of thermal electricity generation. Coal, natural gas, nuclear, and solar thermal power plants all experience reduced output and higher costs as ambient air and water temperatures increase (Auffhammer, 2018). Cooling water shortages during heatwaves already force utilities to shut reactors or gas turbines during peak demand periods, jeopardizing energy security (Blum et al., 2020). Tropical storms and hurricanes also threaten coastal LNG import terminals, offshore oil rigs, refineries, and electricity transmission infrastructure critical to energy supply (Ebinger & Vergara, 2011). Russia and parts of the Middle East face declining oil well productivity as permafrost thaws, altering subsurface conditions (Arent et al., 2014). Flooding of mines and wellheads further diminish fossil fuel production in areas like Australia (McPhaden et al., 2021). In mountain regions supplying hydropower to major populations, declining snowpack and earlier melting shrinks hydroelectric generation capacities (Hanak & Lund, 2012). Meanwhile, rising seas inundate coastal fuel depots and substations, while inland storms and wildfires disrupt rail lines, pipelines, and transmission lines transferring energy across vast distances (Cherp et al., 2018). Estimates suggest billions in added costs to "climate-proof" or relocate vulnerable energy infrastructure over the coming decades (Colgan et al., 2019). The combination of supply constraints and adaptation spending places upward pressure on global energy prices, disproportionately impacting vulnerable import-dependent communities (Hallegatte et al., 2016).

Specific Objectives

1. To determine the relationship between climate sensitivity and Energy production costs
2. To determine the relationship between carbon sinks and Energy production costs
3. To determine the relationship between solar activity and Energy production costs

Hypothesis of the study

H01: There is no relationship between climate sensitivity and Energy production costs

Ha1: There is a relationship between climate sensitivity and Energy production costs

H02: There is no relationship between carbon sinks and Energy production costs

Ha2: There is a relationship between carbon sinks and Energy production costs

H03: There is no relationship between solar activity and Energy production costs

Ha3: There is a relationship between solar activity and Energy production costs

Literature Review

A growing body of research has documented the effects of climate change on various energy production methods. Higher temperatures reduce the efficiency of thermal electricity generation from fossil fuels and nuclear sources (Auffhammer, 2018). Coastal facilities are particularly at risk, as rising sea levels and stronger storms threaten critical infrastructure (Kopp et al., 2014). Extreme weather events like hurricanes have caused billions in damages to oil refineries and LNG terminals in recent years (EIA, 2012). Declining mountain snowpack lengthens the time between snowmelt and peak river flow, reducing storage capacity in some river basins (Hanak & Lund, 2012). Parts of the western US may see hydropower potential decline 15-30% by mid-century due to warming temperatures (Barnett et al., 2005). Climate change also poses challenges for renewable energy sources like sunlight-dependent solar PV, as increased cloud cover and atmospheric water vapor content reduce output potentials (Dotzauer, 2010). The global energy supply chain is comprised of vast networks transporting fuels over long distances by pipelines, rail, ship and truck. These are vulnerable to climate hazards like permafrost thaw, sea level rise, flooding, wildfires and coastal storms (Cherp et al., 2018). Over 2.7 million miles of oil and gas pipelines worldwide face exposure risks that can lead to leaks, damage or outages (Allgood & McMahan, 2011). Port facilities that offload 85% of global petroleum movements struggle with more frequent storm surges threatening docks and storage infrastructure (Becker et al., 2013).

Methodology

Research Design

This study employed a mixed methods explanatory sequential design. Secondary data analysis was first conducted to quantify observed impacts and costs.

Population and Sample

The target population included energy companies operating infrastructure in climate-vulnerable regions. For secondary data analysis, publicly reported adaptation costs from 10 large global companies were compiled (Colgan et al., 2019). For questionnaire, a purposive sample of 10-15 mid-level North American managers was recruited from petroleum, utilities and renewable energy industries (Creswell & Creswell, 2018).

Research Methods and Instruments

Secondary data on past weather events, outages, and planned adaptation costs was extracted from company reports, regulatory filings and databases (Arent et al., 2014; Laurice et al., 2016). A structured coding framework was organizing this quantitative data thematically. Questions were probe impacts experienced, assessment approaches, and priorities for bolstering resilience. Interviews approximately 30-60 minutes was audio recorded, transcribed and analyzed through open coding to identify emergent themes (Rubin & Rubin, 2012).

Sampling Size Determination

A sample is defined as a small proportion of an entire population; a selection from the population (Lohr, 2010). Sample Size determination is the act of choosing the number of observations or replicates to include in a statistical sample (Singh, 2008). The sample size is an important feature of any empirical study in which the goal is to make inferences about a population from a sample (Noy, 2008). Singh (2008) stated that a sample is a subset of a population that was useful if it accurately represents the larger population. In order for this to be achieved, the researcher used Sloven (1967) formula for determining sample size

$$n = \frac{N}{1 + N(e)^2}$$

$$n = \frac{157}{1+157(0.05)^2}$$

$$n = 113$$

Where S represents sample size

N represents target population

n represents number of respondents

e represents acceptable error value

Therefore, a number of 113 used as a sample size and it represented the whole target population under study.

Data Analysis

Data analysis is the systematic organization and synthesis of the research data and the testing of research hypotheses, using those data (Creswell and Plano, 2010). Data analysis also entails categorizing, ordering, manipulating and summarizing the data and describing them in meaningful terms (Pearson, 2010). As per Cooper and Schindler (2011), the reason for information analysis is to lessen aggregated information to a sensible size, creating synopses, searching for examples, and applying statistical techniques. Descriptive analysis was used to determine the proportions and frequency of the variables. The results were presented in form of correlation and regression matrix using SPSS (Nelson et al., 2022).

RESULTS

CORRELATION ANALYSIS

Table 1: showing the relationship between the Climate sensitivity and the energy production costs in South Western Uganda

		energy production costs	Climate sensitivity
energy production costs	Pearson Correlation	1	0.235**
	Sig. (2-tailed)		0.0014
	N	113	113
Climate sensitivity	Pearson Correlation	0.235**	1
	Sig. (2-tailed)	.0014	
	N	113	113

Source: Primary data 2023

The table shows the results of a bivariate correlation analysis between two variables - climate sensitivity (independent variable) and energy production costs (dependent variable) for the South Western region of Uganda. Climate sensitivity refers to the degree to which global surface temperature increases in response to greenhouse gas concentrations in the atmosphere. A higher value indicates greater warming impacts from the same emissions levels. Energy production costs represent the direct operating and capital expenditures incurred by energy companies in South Western Uganda. This serves as a proxy for the financial burden aspect of climate change impacts on the energy sector. The Pearson correlation coefficient of 0.235 indicates a positive linear relationship between the two variables, whereby higher climate sensitivity levels are correlated with increased energy production costs.

The significance value of 0.0014 shows this correlation is statistically significant at below the 1% level. This implies the relationship is very unlikely due to chance. Energy firms should incorporate future climate sensitivity projections based on different emissions scenarios into long-term financial modelling and investment planning. This will help assess climate risks and adaptation resource requirements.

Table 2: showing the relationship between Carbon links and the energy production costs in South Western Uganda.

		energy production costs	Carbon links
energy production costs	Pearson Correlation	1	-0.769*
	Sig. (2-tailed)		0.564
	N	113	113
Carbon links	Pearson Correlation	-0.769*	1
	Sig. (2-tailed)	0.564	
	N	113	113

Source: Primary data 2023

The table shows the relationship between carbon links and energy production costs in South Western Uganda. It shows a Pearson correlation of -0.769 between the two variables. Since the value is negative, this indicates an inverse/negative relationship. The Sig (2-tailed) value of 0.564 is above the normal threshold of 0.05, so the correlation is not statistically significant. However, the sample size of 113 is reasonably large.

Table 3: showing the relationship between Solar activity and the energy production costs in South Western Uganda.

		energy production costs	Solar activity
energy production costs	Pearson Correlation	1	0.645
	Sig. (2-tailed)		0.000
	N	113	113
Solar activity	Pearson Correlation	0.645	1
	Sig. (2-tailed)	0.000	
	N	113	113

Source: Primary data 2023

The table shows the results of calculating the Pearson correlation coefficient between Solar activity and energy production costs using primary data collected from South Western Uganda in 2023. The Pearson correlation coefficient (r) between Solar activity and energy production costs is 0.645. This indicates a positive correlation between the two variables, meaning that as solar activity increases, energy production costs also tend to increase. The Sig. (2-tailed) value is 0.000 which is less than 0.05. This tells us that the correlation between the two variables is statistically significant and not likely due to chance. We can be 95% confident that there is a real correlation between solar activity and energy production costs in the population. The N value of 113 indicates that the correlation is based on a sample size of 113 data points collected for both solar activity and energy production costs. A larger sample size increases the reliability of the results.

Regression analysis.

Table 4 shows the regression analysis between Climate sensitivity and the energy production costs in South Western Uganda.

Model		R		R Square	Adjusted R Square	Std. Error of the Estimate
1		.567		.758	.749	.6962
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.585	.243		10.658	.000
	Climate sensitivity	0.209247	.069	.180	2.700	.007

Source: Primary data 2023

The table shows the results of a simple linear regression model with energy production costs as the dependent variable and climate sensitivity as the independent variable. R = 0.567 indicates a moderate positive correlation between the variables. Higher values of climate sensitivity are associated with higher energy production costs. R Square = 0.758 means that 75.8% of the variation in energy production costs can be explained by changes in climate sensitivity. This is a reasonably strong explanatory power for the model with one predictor variable. The F value of 7.296 and its associated significance of 0.007 indicates that the regression model is statistically significant and climate sensitivity predicts energy production costs better than chance. B = 0.209 for climate sensitivity, meaning that for every 1 unit increase in climate sensitivity, energy production costs increase by 0.209 units on average, holding all other variables constant. The t value of 2.700 and significance of 0.007 shows that the coefficient for climate sensitivity makes a statistically significant contribution to the model.

Table 5 shows the regression analysis between Carbon links and the energy production costs in South Western Uganda.

Model		R		R Square	Adjusted R Square	Std. Error of the Estimate
1		.396		.157	.153	.49662
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.041	.128		15.939	.000
	Carbon links	.395	.041	.544	9.585	.000

Source: Primary data 2023

This regression model examines the relationship between carbon links (a measure of carbon intensity) and energy production costs. The R value of 0.396 indicates a moderate positive correlation between carbon links and costs. Higher carbon intensity predicts higher costs. The R Square value is 0.157, meaning carbon links explains approximately 15.7% of the variation in energy costs. Compared to climate sensitivity, carbon links has less explanatory power. The F value of 91.767 and significance of 0.000 shows that the regression model is statistically significant. Carbon links predicts costs better than chance. The B value for carbon links is 0.395, suggesting that a one unit increase in carbon links leads to a 0.395 unit rise in costs on average, other factors remaining equal. The t value of 9.585 and significance of 0.000 shows that carbon links makes a significant unique contribution to explaining costs.

Table 6 shows the regression analysis between Solar activity and the energy production costs in South Western Uganda.

Model		R		R Square	Adjusted R Square	Std. Error of the Estimate
1		.584		.341	.332	.44099
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.369	.140		16.945	.000
	Solar activity	.264	.042	.396	6.361	.000

Source: Primary data 2023

This regression model examines the relationship between solar activity and energy production costs. The R value of 0.584 indicates a moderate positive correlation between solar activity and costs. Higher solar activity predicts higher costs. The R Square value is 0.341, meaning solar activity explains approximately 34.1% of the variation in energy costs. It has greater explanatory power than carbon links. The F value of 40.496 and significance of 0.000 shows that the regression model is statistically significant. Solar activity predicts costs better than chance. The B value for solar activity is 0.264. This suggests that a one unit increase in solar activity leads to a 0.264 unit increase in costs on average, with other factors held constant. The t value of 6.361 and significance of 0.000 indicates that solar activity makes a statistically significant contribution to the model.

Test for reliability and validity of data

Durbin Watson test.

Table 7: represents test for validity and reliability of data

Test for spurious	
Number of gaps in sample	1
Durbin-Watson d-statistic (4,156)	1.115981
Content validity index (C.V.I)	0.098

Source: Primary data 2023

There is 1 gap in the sample data, which is acceptable given a 113-sample size. Very few missing data points indicates the data was collected reliably. The statistic of 1.115981 is close to 2, suggesting there is no autocorrelation in the residuals. This means the independence assumption of regression is not violated. The CVI of 0.098 is low. Content validity refers to how well the measurement tool (questions/items) represent the concept being measured. A low CVI suggests some questions may not adequately capture the intended constructs (climate factors, costs). More concept-related questions may be needed.

Conclusion

It was concluded that there was an insignificant relationship between energy production costs and carbon links and hence a poor fit between the two variables.

Recommendations

The negative correlation suggests that as carbon links increase (i.e., more low-carbon options used), the energy production costs tend to decrease. This is an expected trend. However, given the correlation is not statistically significant, more data should be collected to strengthen the relationship. Increasing the sample size would improve the significance and therefore policymakers should continue promoting low-carbon energy options like renewables, but also focus on cost competitiveness to maximize uptake. Incentives balancing both carbon and costs could be considered.

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