Climate Finance and Industrial Development: Empirical Evidence from Sub-Saharan Africa's Manufacturing Sector

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ABSTRACT

This study examines the relationship between climate finance and industrial development in the manufacturing sector in sub-Saharan Africa. Utilising a balanced panel dataset encompassing 49 sub-Saharan African countries from 2003 to 2022, this study employs a comprehensive methodological framework. The primary specification involves Random Effects estimation, complemented by the Arellano-Bond system generalised method of moments (GMM) for robustness analysis and dynamic panel assessment. Additionally, panel EGLS and M-estimation robust least squares were employed, with pre-estimation diagnostics confirming stationarity, the absence of multicollinearity, and significant cross-sectional heteroscedasticity.

The primary finding of this study reveals a counterintuitive relationship: climate finance has a negative and statistically significant impact on industrialisation in sub-Saharan Africa. This effect is consistent across all estimation strategies and intensifies with methodological rigor (EGLS: $\beta = -1.813$, $p = 0.003$; GMM: $\beta = -2.686$, $p = 0.000$; Robust OLS: $\beta = -3.630$, $p = 0.016$). Rather than suggesting that climate finance inherently harms industrial development, this finding underscores a structural misalignment in the design and allocation of multilateral funds, which prioritise adaptation and mitigation in climate-vulnerable economies over the development of productive capacity and manufacturing-linked green investments. Population growth emerges as a significant structural constraint on industrialisation, while foreign direct investment exhibits conditionally positive contributions, contingent on the host country's absorptive capacity.

This study contributes to the discourse on sustainable development by advocating the reallocation of resources by climate finance institutions towards productive green industrialisation. This further suggests that recipient governments should enhance their frameworks for absorptive capacity and integrate demographic dividend strategies with manufacturing-focused industrial policies. These findings offer valuable insights for decision-makers, investors, and stakeholders aiming to optimise the effectiveness of climate finance for sustainable industrial development and climate resilience in sub-Saharan Africa.

Keywords: climate finance, industrialisation, manufacturing, sub-Saharan Africa, panel data analysis, green finance, sustainable development

INTRODUCTION

Climate change is currently one of the most pressing challenges, significantly impacting economic progress, social stability, and ecological sustainability (Zhan, 2023). The origins of this crisis can be traced back to the 18th century, when rapid industrial growth initiated an unprecedented increase in greenhouse gas emissions, particularly carbon dioxide, owing to the combustion of fossil fuels (Armaroli & Balzani, 2011). This surge in atmospheric carbon levels has been the primary driver of global warming and subsequent alterations in climate patterns (Li et al., 2022). Although industrialisation has traditionally driven economic development, its deleterious effects on the environment have been particularly pronounced in developing regions such as sub-Saharan Africa (Jalilian, 2000).

Within this context, the manufacturing sector in sub-Saharan Africa presents a complex landscape characterised by opportunities and challenges (Tomala et al., 2021). Although there is considerable potential for growth, the sector faces significant impediments, including inadequate infrastructure, limited access to advanced technology, and insufficient investment (Kuteyi & Winkler, 2022). These challenges are exacerbated by climate change, which threatens industrial productivity and sustainability. Extreme weather events can damage manufacturing facilities, interrupt supply chains, and increase operational costs (Tomala et al., 2021). Furthermore, the region's vulnerability to climate change poses risks to critical resources, such as water and energy, which are essential for manufacturing (Michaelowa et al., 2020).

The dual nature of industrialisation in sub-Saharan Africa, which promotes economic growth while imposing severe environmental costs, presents a significant dilemma (Morris & Fessehaie, 2014). The industrial processes that drive economic advancement also jeopardise global ecosystem sustainability and threaten social cohesion (Pooe, 2018). This situation necessitates a nuanced approach to reconcile the urgent need for economic growth with the imperative to address and adapt to climate change in the region.

Sub-Saharan Africa aims to enhance its manufacturing capabilities and integrate into the global economy, and the integration of climate finance into industrial strategies has become increasingly crucial (Kulakhmetova, 2022). This transition towards a low-carbon and climate-resilient economy is particularly vital in a region where the manufacturing sector plays a critical role in driving economic growth, generating employment, and fostering innovation (Inoue & Hamori, 2016). A comprehensive understanding of the relationship between climate finance and industrialisation is essential for advancing sustainable development in this region (Steckel et al., 2016).

Climate finance refers to the financial resources allocated to projects and initiatives aimed at addressing climate change and promoting sustainable practices (Adisa et al., 2024). These funds can originate from various sources, including international climate funds, government programs, and private sector investments (Adisa et al., 2024). Climate finance encompasses a wide array of financial instruments, such as grants, loans, and equity investments, designed to enhance resilience to climate impacts and reduce greenhouse gas emissions (Timilsina, 2021). The role of climate finance extends beyond mere funding; it involves the strategic allocation of resources to stimulate innovation, improve infrastructure, and facilitate the adoption of green technologies (Chukwudum et al., 2024).

In sub-Saharan Africa, where manufacturing is pivotal for economic diversification and resilience, climate finance can catalyse industrial growth while addressing environmental challenges (Doku & Phiri, 2023). The interplay between climate finance and industrialisation is a complex phenomenon. Climate finance provides capital for developing green technologies and sustainable manufacturing practices (Briera & Lefèvre, 2024). Investments in renewable energy and sustainable resource management reduce the carbon footprint of manufacturing operations and enhance competitiveness in an environmentally conscious global market (Bayar & Gavriletea, 2019). Conversely, successful industrialisation drives economic growth, facilitating further investment in climate resilience (Tiawon & Miar, 2023). This relationship underscores the potential of climate finance to mitigate climate change while promoting sustainable industrial progress (Wang & Xu, 2024).

Despite the recognised importance of climate finance for sustainable industrialisation, a significant gap persists in the academic literature regarding its specific impact on manufacturing in sub-Saharan Africa. For instance, Nchofoung et al. (2024) found that although green finance has a positive effect on Africa's industrialisation, the introduction of green innovations in renewable energy sometimes yields negative outcomes. This highlights the complexity of the relationship between climate finance and industrial development, indicating that a nuanced understanding is essential for effective policy formulation. Mikheeva and Ryan-Collins (2022) analysed six countries, including Mexico and China, to assess financial governance for the net-zero transition, drawing lessons that may not directly apply to sub-Saharan Africa. Similarly, Wang and Wang (2021) evaluated the impact of green finance on China's regional industrial structure and revealed significant positive effects on industrial modernisation. However, these findings do not necessarily translate to the unique context of sub-Saharan Africa, where the manufacturing landscape is shaped by distinct challenges and opportunities. Therefore, the need for localised research has become increasingly apparent.

Moreover, while studies such as Lin et al. (2024) and Trotta et al. (2024) demonstrate the positive effects of robust green finance on industrial productivity and decarbonisation efforts, respectively, they frequently neglect the direct implications for the manufacturing sector in sub-Saharan Africa. Xiong et al. (2023) employed the entropy weight TOPSIS method on data from Chinese provinces, indicating that green finance promotes environmentally friendly industries. However, such methodologies and findings may not adequately address the specific dynamics at play in sub-Saharan Africa, where climate finance could have different implications because of varying economic and environmental contexts.

Additionally, extant research tends to emphasise the role of international climate policy without sufficiently exploring its direct effects on the local manufacturing sector. For instance, Newell and Bulkeley (2016) analysed bilateral climate aid in South Africa; however, this focus on international assistance does not provide a comprehensive understanding of how climate finance directly influences domestic manufacturing growth. Mapanje et al. (2023) highlighted FinTech's role in financing sustainable agriculture, yet similar analyses for the manufacturing sector remain scarce. This scarcity of targeted research underscores the necessity for a focused examination of the impact of climate finance on manufacturing in sub-Saharan Africa.

The current literature also reveals several methodological limitations, particularly regarding the scope of the research. Numerous studies have focused on a limited number of countries, which may not adequately represent the continent’s broader dynamics (Ali et al., 2024; Enilolobo et al., 2024; Mapanje et al., 2023). This narrow focus can obscure significant variations within Sub-Saharan Africa, impeding the development of effective strategies tailored to the region’s specific needs. Furthermore, many studies are constrained by outdated or limited timeframes, potentially overlooking current trends and emerging factors that could influence the relationship between climate finance and manufacturing growth (Ali et al., 2024; Dametew & Ebinger, 2017; Sanni, 2017; Adeleye et al., 2020).

In response to these identified gaps, this study addresses these deficiencies by investigating the direct impact of climate finance on manufacturing growth in sub-Saharan Africa. This study has two primary objectives: (i) to assess the impact of climate finance on industrialisation, and (ii) to explore, using pairwise Granger causality, whether climate finance statistically precedes and predicts manufacturing growth in sub-Saharan Africa. This methodology is particularly effective in evaluating whether historical data from one variable can predict the future values of another variable, thereby establishing temporal causality and informing policies regarding the sequencing of climate finance deployment (Kim & Frees, 2006; Szirmai, 2011).

To achieve these objectives, we employed a comprehensive econometric framework incorporating fixed and random effects models, selected through Hausman specification tests, complemented by the Generalised Method of Moments (GMM) approach to address endogeneity and dynamic panel interactions. Our analysis incorporates data from 49 sub-Saharan African countries spanning 2003–2022, allowing for a robust examination of the relationship between these variables across the region's most extensive dataset. This methodology captures the significant variations and dynamics of climate finance and industrialisation, providing valuable insights for decision-makers, investors, and stakeholders seeking to optimise the effectiveness of climate finance in the manufacturing industry.

The remainder of this paper is structured as follows: section will review the extant literature on climate finance and industrialisation, highlighting the principal themes and research gaps. The Methodology section delineates the research and data collection techniques. The subsequent sections present the results, discuss their implications for policy and practice, and conclude with recommendations for future research and initiatives. Through a comprehensive analysis of the effects of climate finance on industrialisation in sub-Saharan Africa, this study endeavours to contribute to the broader discourse on sustainable development and climate resilience within the region.

LITERATURE REVIEW

This literature review examines conceptual and empirical research on the relationship between climate finance and industrialisation, with a specific focus on sub-Saharan Africa (SSA). The selection criteria encompassed topic relevance, methodological rigor, and direct investigation of these themes. Studies lacking empirical evidence or relevance were excluded from the analysis.

Theoretical Underpinnings

Climate Justice Theory

Climate Justice Theory, introduced by Edith Brown Weiss in 1989, critically examines the ethical dimensions of climate change and advocates for an equitable distribution of its benefits and burdens. This theory is particularly relevant to industrialisation in sub-Saharan Africa, where vulnerable populations often face disproportionate impacts from climate change despite their minimal contributions to global emissions (Schlosberg, 2007). Sultana (2021) emphasises that climate change affects individuals unequally, underscoring the necessity for equitable and impartial solutions to address these disparities. In this context, the intersection of climate finance and climate justice becomes essential, ensuring that investments not only promote economic growth but also safeguard the rights of marginalised communities.

Actions contributing to climate injustice become problematic when they exacerbate inequality (Meyer & Roser, 2010). This complexity complicates stakeholders' efforts to achieve equitable outcomes, as highlighted by Lina and Paavola (2023). Climate finance investments in industrialisation must consider recipient nations' socioeconomic contexts to avoid disadvantaging vulnerable populations in the process. Effective climate governance through frameworks such as the UNFCCC is crucial for implementing climate justice in industrialisation efforts (Eckersley, 2012). The UNFCCC emphasises fairness and shared responsibilities, urging industrialised countries to mitigate climate change impacts. As climate finance flows into sub-Saharan Africa, evaluating the alignment of these funds with international governance and addressing inequalities becomes imperative (Okereke & Dooley, 2010). This theory underscores the need for equitable climate change responses and informs our examination of how climate finance affects industrialisation inequalities. By incorporating climate justice, we aim to contribute to the discourse on equitable climate finance responses in sub-Saharan Africa.

Sustainable Finance Model

Transitioning from ethical considerations of Climate Justice to the Sustainable Finance Model allows us to explore how these ethical frameworks can be operationalised through practical financial strategies. This shift highlights the need to translate ethical imperatives into actionable financial frameworks that address climate justice and promote sustainable economic growth. Hart's (1997) Sustainable Finance Model provides a comprehensive framework for aligning financial objectives with development goals by evaluating investment opportunities based on sustainability and societal impact (Sepetis, 2020). This model is particularly relevant in sub-Saharan Africa, where climate-related financing can significantly impact sustainable industrial development.

Sustainable finance is underpinned by four essential principles: comprehensiveness, connectivity, equity, and sustainability. This approach integrates ESG factors into financial decisions and acknowledges interconnected systems. This principle is significant in sub-Saharan Africa, ensuring that climate finance initiatives align with broader sustainable development objectives. The connectivity principle emphasises the relationship between financial systems and ecological well-being, which is crucial for sub-Saharan African nations to balance industrialisation with environmental preservation. The equity principle considers the diverse impacts of financial decisions on different communities, particularly in areas where resource distribution is uneven. The prudence principle advocates caution in activities that could disrupt the ecological equilibrium and promote sustainable investments. This is especially relevant in sub-Saharan Africa, where renewable energy and sustainable practices can drive industrial growth while maintaining the environmental integrity.

Oikonomou et al. (2020) identify key elements influencing the efficacy of funding for sustainable initiatives, including policy frameworks, institutional capabilities, and stakeholder engagement. In sub-Saharan Africa, consistent policies can foster environments conducive to sustainable finance and attract investments in climate-resilient industrial projects. This study examines the role of climate finance in sustainable development by evaluating financing models that promote social, economic, and environmental sustainability in sub-Saharan Africa. The Sustainable Finance Model guides the examination of how financial practices align with sustainability goals, particularly for reducing carbon emissions and encouraging renewable energy adoption (Wahab et al., 2022).

The incorporation of Climate Justice Theory and the Sustainable Finance Model in this study provides a comprehensive understanding of the role of climate finance in industrialisation. This approach enables an examination of how climate finance can effectively drive sustainable development while addressing social and environmental concerns, ultimately contributing to inclusive growth across sub-Saharan Africa. By grounding our analysis in these theories, we ensure that our research aligns with the aim of promoting ethical financial practices that are responsive to the unique challenges faced by the region.

Empirical Underpinnings

This analytical survey critically evaluates extant scholarly works on the impact of climate-related funding on the interconnected objectives of industrial development in sub-Saharan Africa. Due to the limited literature on the effect of climate finance on the manufacturing and industrial sectors, most existing studies acknowledge the significant contributions of green finance and related financial developments to industrialisation, particularly in the manufacturing sector. For instance, Nchofoung et al. (2024) utilised the fixed effects model proposed by Driscoll and Kraay (1998), alongside a system Generalised Method of Moments (GMM) regression analysis, to examine 41 African nations from 2000 to 2020. Their findings indicate that green finance enhances industrialisation in Africa, whereas green innovations through renewable energy may be detrimental.

Similarly, Wang and Wang (2021) investigated the influence of green finance on China's regional industrial structure between 2008 and 2020, employing a GMM model to elucidate its impact on enhancing the industrial structure. The outcomes were categorised according to various industrial tiers, revealing that green finance significantly influences this sector, accelerating its development and contributing to the modernisation of the industrial landscape. Lin et al. (2024) utilised the CS-ARDL approach developed by Chudik and Pesaran (2015) to examine the immediate and long-term effects of green finance distribution on industrial productivity patterns in developing nations from 2000 to 2019. The findings indicate that substantial green finance investment positively impacts industrial productivity.

Mikheeva and Ryan-Collins (2022) analysed six countries, including Mexico, Canada, and China’s financial coordination for industrialisation, to assess financial governance for the net-zero transition and extracted valuable lessons from successful industrialisation experiences. Trotta et al. (2024) conducted a techno-economic evaluation of a medium-scale green ammonia and urea production facility in Southern Italy. Their findings establish climate finance as a crucial economic instrument that facilitates decarbonisation efforts. Xiong et al. (2023) utilised the entropy weight TOPSIS method to assess green finance development and industrial structure optimisation, analysing panel data from 30 Chinese provinces from 2012 to 2020. They found that green finance significantly promotes environmentally sustainable industries while constraining high-energy consumption sectors.

In the context of sub-Saharan Africa, Newell and Bulkeley (2016) analysed the interplay between international climate policy and energy transitions, suggesting that bilateral climate aid from Denmark and Germany played a crucial role in the initial phases of renewable-energy development in South Africa. Additionally, Ali et al. (2024) empirically examined the extent to which industrialisation and foreign direct investment (FDI) inflows contribute to the predictability of climate change in Africa, focusing on the top ten greenhouse gas-emitting countries. They employed data from 1990 to 2023, using a bias-adjusted ordinary least squares estimation method. Their findings revealed that both industrialisation and FDI inflows are significant predictors of climate change in Africa, albeit with varying degrees of environmental threat.

Other studies have focused on how financial development and innovation contribute positively to the growth of the agro-industrial sector. Casey (2022) examines and categorises 51 global initiatives that support climate finance mobilisation for agricultural adaptation in developing nations. These initiatives are classified according to their sector, climate action focus, geographical scope, and membership type. This study introduces a new typology to categorise initiatives based on their primary methods of mobilising actions and investments. Additionally, this study provides a comprehensive overview of the initiatives' geographical and thematic coverage and their focus on climate adaptation in agriculture in Africa. Mapanje et al. (2023) used a scoping review methodology to highlight FinTech's crucial role in financing sustainable agriculture across 17 sub-Saharan African countries, confirming its potential as a vital support system that enhances financing efficiency for smallholder agriculture. These findings further indicate that fintech has the potential to function as a critical support mechanism for promoting sustainable agricultural practices in sub-Saharan Africa. Enilolobo et al. (2024) explored the relationship between financial intermediation and agriculture between 2005 to 2019 in eighteen sub-Saharan African countries. Panel ordinary least squares (POLS) regression analysis, Wald, and Granger causality tests were employed. The results indicate that financial intermediation significantly amplifies the agricultural sector's influence on industrial production. Adeleye et al. (2020) utilised an autoregressive distributed lag to investigate the relationship between agro-industrialisation and financial intermediation in Nigeria, adopting time series data from 1981 to 2015, revealing that agriculture and finance strongly influence long-term industrialisation positively. Their study suggests that as the financial system develops, the impact of agriculture on industrial output diminishes.

Additional scholarly studies have examined the relationship between financial development and the expansion of the manufacturing sector. For instance, Manisha and Aneja (2023) examine how financial sector development impacts total factor productivity (TFP) in India's manufacturing industry from 1998 to 2017 using an autoregressive distributed lag co-integration approach and a Granger causality test. These findings indicate a long-term relationship between FDI and productivity growth in the manufacturing sector in India. Additionally, this study identifies a unidirectional causal link between FDI and TFP changes in the sectors.

In conclusion, aside from the few existing studies on green finance, financial development, and its implications for the agriculture and industrialisation sectors, there remains a gap in the need for further investigation into the impact of climate finance on the manufacturing sector in Sub-Saharan Africa. This study aims to address this gap by comprehensively analysing how climate finance can effectively support sustainable industrial development in this region.

METHODOLOGY

This study aims to assess the influence of climate finance on industrialisation and examine the Granger causality relationship between climate finance and manufacturing in sub-Saharan Africa. The research methodology entails analysing data from 48 nations over a 19-year period, employing fixed effects and Generalised Method of Moments techniques to address the potential issues of endogeneity and cross-sectional dependence.

Econometric Model

The econometric model employed in this study builds upon and extends the foundational research of Nkemgha et al. (2023) and Nchofoung et al. (2024). While prior studies have identified various determinants of industrialisation, such as population growth and inflation, our model is specifically designed to evaluate the impact of climate finance on manufacturing growth, while controlling for key macroeconomic variables.

The model integrates five control variables: GDP growth (GDPgrowth), population growth (POPgrowth), inflation (Inf), foreign direct investment (FDI), and energy intensity (EnerInt). The comprehensive panel data model is articulated as follows:

$$Indust_{it} = \beta_0 + \beta_{1i} * CF_{it} + \beta_{2i} * GDPgrowth_{it} + \beta_{3i} * PoPgrowth_{it} + \beta_{4i} * Inf_{it} + \beta_{5i} * FDI_{it} + \beta_{6i} * EnerInt_{it} + v_t + y_i + \mu_{it} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.1$$

Where:

$Indust_{it}$ represents the observed value of the industrialisation for country i at time t; β_0 represents the constant term; CF_{it} represent the measure of the climate finance for country i at time t; The vector of explanatory variables captures additional factors influencing industrialisation outcomes; v_t represents the time fixed effect; y_i is the individual effect, and μ_{it} represents the error term.

Panel data models necessitate a decision between Fixed Effects (FE) and Random Effects (RE) estimators. The FE model accounts for time-invariant unobserved heterogeneity that may correlate with regressors, whereas the RE model is more efficient in the absence of such correlation. To make an empirically informed choice between

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these methodologies, we used the Hausman specification test. As elaborated in our Model Specification Tests (Section 4.5), the test results strongly supported the Random Effects model, which demonstrated both consistency and efficiency in our analysis. The Random Effects estimator effectively captures the significant variation in industrialisation levels among countries in sub-Saharan Africa, yielding more interpretable substantive results than the FE alternative (Kim & Frees, 2006; Szirmai, 2011).

Data and Variables

This study undertakes an analysis of secondary data from 49 countries within sub-Saharan Africa, selected from 54 nations in the region over a 19-year period (2003–2022). The countries included in this analysis were chosen because they represent a diverse range of economic conditions and climate vulnerabilities, thereby facilitating a comprehensive examination of the relationship between climate finance and industrial development across the region (Chukwudum, 2024). Furthermore, the distinct challenges faced by the region in terms of climate change adaptation and economic growth justify this selection (Chirambo, 2016). The selected period was deliberately chosen to observe the evolving dynamics of climate finance and its effects on industrialisation, particularly in the wake of major international developments and climate finance mechanisms established in the early 2000s (Adisa et al., 2024).

This study utilised publicly accessible multilateral climate finance data from the Climate Funds Update, providing valuable insights into the distribution of financial resources for climate-related projects in developing countries. While multilateral climate finance data are essential for understanding climate finance dynamics, their limitations must be acknowledged as well. The focus on multilateral funding may not fully account for significant domestic or private sector contributions to climate finance, potentially leading to an underestimation of the total financial resources available for climate-related initiatives in these countries. Nevertheless, these data remain pertinent to our study because of their reliability and dependability (CFU, 2023).

Independent Variable

Climate finance, encompassing multilateral funds such as the Green Climate Fund (GCF), Least Developed Country Fund (LDCF), Global Environmental Facility (GEF), and Clean Technology Fund (CTF), is quantified in United States dollars. These funds aim to mitigate climate change risks while enhancing investment returns and attracting global investors to sustainable energy projects, thereby fostering regional industrial growth (Tolliver et al., 2020). It is imperative to monitor these financial flows to evaluate the efficacy of these funds in achieving sustainable development goals (Markandya et al., 2014). Theoretical expectations based on the existing literature suggest that climate finance positively influences industrialisation in sub-Saharan Africa (Nchofoung et al., 2024; Wang & Wang, 2021; Newell & Bulkeley, 2016; Khan et al., 2022). However, this hypothesis requires empirical validation, which is the primary objective of this study.

Dependent variable

The dependent variable, industrialisation, is quantified as manufacturing value-added as a percentage of GDP. This metric effectively captures the manufacturing sector's contribution to the overall economic output, thereby serving as a standardised measure of the intensity of industrial development. World Bank Open Data was used as a verified source of information.

Control Variables

This study employs multiple control variables to isolate the specific impact of climate finance on industrialisation, while simultaneously accounting for other factors that may influence manufacturing development.

The GDP Growth Rate is incorporated as a control variable, quantified as the annual percentage increase in GDP (Hoy et al., 2014). This variable is essential because economic growth can substantially influence the availability of resources for climate initiatives and the overall capacity for sustainable development. The literature, including works by Doku and Phiri (2023) and Lin et al. (2024), indicates a positive correlation between GDP growth and the effectiveness of development finance. However, our empirical analysis ascertains whether this relationship persists in the specific context of climate finance and industrialisation in sub-Saharan Africa.

The Population Growth Rate signifies the annual variation in population size. Prior research has demonstrated that population growth influences resource utilisation, service demand, and industrial activity (Hsu, 2023; Doku & Phiri, 2023; Enilolobo et al., 2024; Lin et al., 2024). Within the context of sub-Saharan Africa, rapid population growth may elevate the demand for manufactured goods and generate labour market dynamics that affect industrial development patterns (Noda et al., 2019; Sanoran, 2022).

Inflation accounts for changes in price levels that may distort the real value of climate finance flows and manufacturing output measurements over different periods (Huang et al., 2009). We anticipate that the results concerning the Inflation Rate will align with those documented by Enilolobo et al. (2024).

Foreign Direct Investment (FDI) functions as an additional control variable, given that international capital flows may either complement or substitute climate finance in promoting industrial development and facilitating technological transfer to manufacturing sectors. Furthermore, studies by Nchofoung et al. (2024), Mamba et al. (2020), Liu and Paan (2024), and Doku and Phiri (2023) indicate that FDI may exert either no impact or a positive influence on structural transformation within economies. Understanding the role of FDI is crucial, as it can provide essential capital for sustainable industrial projects and enhance climate-finance efficacy (Aust et al., 2019).

Energy Intensity is quantified as the energy consumed per unit of economic output and serves as an indicator of the energy efficiency of industrial processes. This is because energy costs and efficiency play a crucial role in determining manufacturing competitiveness and the applicability of climate finance mechanisms, which frequently aim to transform the energy sector (Verstina et al., 2022). We expect that our results concerning Energy Intensity will be consistent with those reported by Liu and Paan (2024).

In conclusion, the incorporation of these control variables—GDP Growth Rate, Population Growth Rate, Inflation Rate, FDI, and Energy Intensity–establishes a comprehensive framework for analysing the interaction between economic factors and climate finance. Each variable contributes to a nuanced understanding of how these elements affect sustainable industrial development, ultimately informing effective policy recommendations for sub-Saharan Africa.

Causal Relationships Analysis

In addition to assessing the direct effects of climate finance on manufacturing industrialisation, this study uses the pairwise Granger causality technique to determine whether climate finance precedes and can forecast manufacturing growth in sub-Saharan Africa. This methodology is particularly effective in evaluating whether historical data from one variable can predict the future values of another variable, thereby establishing temporal causality and informing policies regarding the sequencing of climate finance deployment. The analytical framework for the Granger causality analysis is structured as follows:

$$Indust_{it} = \alpha_0 + \sum_{p=1}^{k} \alpha_1 CF_{t-j} + \sum_{p=1}^{k} \alpha_2 GDPgrowth_{t-j} + \sum_{p=1}^{k} \alpha_3 PoPgrowth_{t-j} + \sum_{p=1}^{k} \alpha_4 Inf_{t-j} + \sum_{p=1}^{k} \alpha_5 FDI_{t-j} + \sum_{p=1}^{k} \alpha_6 EnerInt_{t-j} + \mu_{it} \dots\dots\dots 3$$

Where:

α_0 represents the intercepts or the constant terms; α_0 *to* α_6 represents the estimates of the parameters; t – J represents the lag lengths; k and p represent the periods; and μ_{it} represents the error term.

The incorporation of lagged values of all independent variables enables us to assess whether the historical values of climate finance (along with the control variables) possess predictive capability concerning current levels of industrialisation, thereby establishing Granger causality. This methodology complements our primary impact analysis, detailed in Section 3.1, and bolsters our empirical findings on the relationship between climate finance and manufacturing development in sub-Saharan Africa.

Estimation Model Technique

This study utilised a comprehensive methodological framework that integrated multiple estimators, each chosen for specific analytical objectives. The fixed-effects model, as introduced by Driscoll and Kraay (1998), is theoretically advantageous for analysing panel data that may exhibit cross-sectional dependence (Enilolobo et al., 2024). The fixed-effects approach assumes a time-invariant intercept and acknowledges the presence of non-uniform error variance (Hoechle, 2007). This model is robust against cross-sectional dependence and effectively addresses heteroscedasticity, a common issue arising from variations in country size, economic structure, and data quality across samples (Zaliskyi et al., 2021). Additionally, the fixed-effects model corrects for potential autocorrelation in the error terms, which frequently occurs in time-series data (Rigobon, 2003). While the fixed-effects model accounts for characteristics that remain constant over time for each country, such as institutional, geographic, and structural factors, it is limited in its ability to fully address institutional differences that evolve over time because of constraints in data availability (Hoechle, 2007; Nchofoung et al., 2024). To identify the most suitable estimator for our dataset, which includes 49 sub-Saharan African countries over a 19-year period, we used the Hausman specification test (Nchofoung et al., 2024). This test informed our selection of the Random Effects estimator as the primary analytical approach, demonstrating both consistency and efficiency in capturing significant variations in industrialisation levels across countries while maintaining statistical efficiency (Andrews & Lu, 2001).

In addition to the primary Random Effects specification, the Generalised Method of Moments (GMM) approach was utilised as a supplementary robustness technique to address potential endogeneity issues that may arise between climate finance, industrialisation, and other factors. Endogeneity occurs when an explanatory variable correlates with the error term, leading to biased estimates (Ashley & Sun, 2016). To mitigate endogeneity, the GMM employs instrumental variables to generate consistent estimations, even in the presence of endogenous relationships (Gu et al., 2021). The instrumental variables developed by Blundell and Bond (1998) enhance the capacity of GMM to accurately capture dynamic interactions within panel data (Firpo et al., 2021).

The System GMM approach is particularly well-suited for analysing dynamic panel data models that incorporate lagged dependent variables, offering the advantage of addressing unobserved country-specific effects without eliminating them through differentiation (Enilolobo et al., 2024). Given the study's 19-year timeframe, System GMM is more efficient than Difference GMM, making it the preferred dynamic panel specification (Nkemgha et al., 2023). This dual methodological framework, which combines Random Effects as the primary estimator with System GMM for robustness and dynamic analysis, ensures that the study's outcomes are both rigorous and comprehensive, facilitating a robust understanding of the influence of climate finance on industrialisation in sub-Saharan Africa. This specification assumes a basic uniformity that subsequent research will analyse in terms of sub-regional and national contexts.

RESULTS

Descriptive Statistics

The descriptive statistics revealed significant patterns across all seven variables. The dependent variable, industrialisation, averages 9.85% of GDP, with a mean-median discrepancy (9.85 vs. 9.10) and a positive skewness (1.19). This suggests that a few highly industrialised economies, such as South Africa and Mauritius, skew the distribution to the right, while most countries remain structurally underdeveloped. Climate finance averages 0.19 USD (scaled), with a narrow standard deviation, indicating that multilateral climate flows to the region are limited and uneven. Energy intensity is the most dispersed variable ($\sigma = 31.24$), reflecting significant cross-country differences in energy efficiency across 49 economies.

The concerning observation is the pronounced non-normality of all variables. FDI, inflation, and GDP growth show high kurtosis values (63.84, 135.20, and 32.79, respectively) and significant skewness, indicating outliers, such as Angola's 324% inflation in 2000 and South Sudan's FDI spikes. All Jarque-Bera statistics reject normality at the 1% significance level ($p = 0.000$). This has direct econometric implications: standard OLS may be sensitive to these extremes, necessitating robust standard errors or a quantile regression. Population growth is the most stable variable ($\sigma = 0.76$), consistent with the demographic benchmarks in its construction.

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Table 1: Descriptive Statistics

	Industrialisation	Climate Finance	Energy Intensity	FDI	GDP Growth Rate	Inflation Rate	Population Growth Rate
Mean	9.846876	0.186770	105.3042	4.214516	4.910285	10.95453	2.356021
Median	9.098700	0.171950	105.0000	2.449600	5.390800	5.379150	2.495850
Maximum	35.29290	0.588000	354.9950	103.3374	16.35740	557.2018	3.817300
Minimum	0.000000	0.015000	3.937700	-17.29210	-28.19240	-16.85970	0.111500
Std. Dev.	5.786988	0.111335	31.24317	7.737895	2.942370	35.42445	0.757083
Skewness	1.187718	1.270412	3.044456	6.402883	-3.471903	10.65489	-0.818609
Kurtosis	5.725171	5.020675	19.82586	63.83973	32.78670	135.2048	3.321764
Jarque-Bera	533.6614	430.3390	13074.20	157839.6	38198.12	732232.6	113.6807
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	9649.939	183.0342	103198.1	4130.225	4812.079	10735.44	2308.900
Sum Sq. Dev.	32785.96	12.13527	955637.0	58617.65	8475.730	1228539.	561.1375
Observations	980	980	980	980	980	980	980

Source: Researcher's Construct Using a Multilateral Finance Data

Correlation Analysis

The correlation matrix shows that all pairwise relationships are weak, with no coefficient above |0.20|. This requires both substantive and methodological analyses. The key finding is the negative correlation between climate finance and industrialisation (−0.079), contradicting the hypothesised positive relationship. Rather than indicating that climate finance inhibits industrial growth, this likely reflects targeting: multilateral funds are disproportionately allocated to the least industrialised, climate-vulnerable economies, resulting in high climate finance coexisting with low industrialisation by design, not causation. This endogeneity concern underscores the need for panel fixed-effects estimation over a simple OLS.

Population growth shows the strongest correlation with industrialisation (−0.180) and climate finance (−0.200). This suggests that rapidly expanding, lower-income economies receive increased climate finance yet remain under-industrialised, consistent with demographic development dynamics in sub-Saharan Africa. Foreign Direct Investment (FDI) shows a negligible positive correlation with industrialisation (0.024), challenging the assumption of FDI-led structural transformation in the region.

The near-zero inter-correlations among independent variables eliminate the risk of severe multicollinearity, as no pair exceeds |0.08|. This condition is beneficial for regression analysis. The consistently low bivariate correlations suggest that simple linear relationships may obscure non-linear, threshold, or heterogeneous country-level dynamics, which can only be captured through panel methods.

Table 2: Correlation Analysis

	1	2	3	4	5	6	7
Industrialisation	1.000000						
Climate Finance	-0.078519	1.000000					
Energy Intensity	-0.013203	0.039763	1.000000				
FDI	0.024127	-0.009726	-0.006029	1.000000			
GDP Growth Rate	-0.013499	0.078542	-0.018094	0.020758	1.000000		
Inflation Rate	0.009081	-0.058460	0.021829	-0.034158	-0.011531	1.000000	
Population Growth Rate	-0.179934	-0.200172	0.001749	-0.017632	-0.031804	0.018217	1.000000

Source: Researcher's Construct Using a Multilateral Finance Data

Stationary Tests

The panel unit root tests demonstrate the stationarity of all seven variables. The variables climate finance, industrialisation, GDP growth rate, population growth rate, inflation rate, foreign direct investment (FDI), and energy intensity reject the null hypothesis of a unit root at the 1% significance level (p = 0.000) across all four tests at the level and first difference. This agreement among the LLC, IPS, ADF-Fisher, and PP-Fisher tests is noteworthy, as each test uses distinct assumptions: the LLC test assumes a common autoregressive root, the IPS test allows for cross-country heterogeneity, and Fisher-type tests do not impose distributional assumptions on the pooling structure. The convergence of all tests on an I (0) classification eliminates potential ambiguity from test-specific sensitivities to the panel size or serial correlation.

The I (0) finding has three direct econometric implications for this study. First, there is no risk of spurious regression as long-run relationships estimated using these variables in levels will be authentic. Second, cointegration testing (Pedroni, Kao, Westerlund) is unnecessary, thereby significantly simplifying the empirical strategy. Third, standard panel estimators, such as fixed effects, random effects, and FGLS, are entirely appropriate without the need for differencing or error-correction specifications. This effectively validates the regression framework employed in Equation (2) of the methodology.

Table 3: Stationary Tests

		LLC Test (Levin, Lin & Chu, 2002)			IPS Test (Im, Pesaran & Shin, 2003)			ADF–Fisher Chi-Square (Maddala & Wu, 1999)			PP–Fisher Chi-Square (Maddala & Wu, 1999)			Order
Variable	**Test Level**	**Statistic**	**Prob.**	**Sig.**	**W-Stat.**	**Prob.**	**Sig.**	**χ²-Stat.**	**Prob.**	**Sig.**	**χ²-Stat.**	**Prob.**	**Sig.**	**I(d)**
Climate Finance	Level	-5.2928	0.0000	***	-22.3287	0.0000	***	510.2553	0.0000	***	794.9494	0.0000	***	**I (0)**
	First Difference	-6.6382	0.0000	***	-32.8860	0.0000	***	734.3985	0.0000	***	794.9494	0.0000	***	
Industrialisation	Level	-2.3938	0.0083	***	-3.8134	0.0001	***	199.4645	0.0000	***	157.4657	0.0000	***	**I (0)**
	First Difference	-3.5140	0.0002	***	-10.6996	0.0000	***	308.4213	0.0000	***	440.9979	0.0000	***	
GDP Growth Rate	Level	-2.8018	0.0025	***	-8.6801	0.0000	***	272.9170	0.0000	***	271.5247	0.0000	***	**I (0)**
	First Difference	-3.9585	0.0000	***	-17.1677	0.0000	***	421.3835	0.0000	***	593.5604	0.0000	***	
Population Growth Rate	Level	-3.5616	0.0002	***	-10.3373	0.0000	***	313.8928	0.0000	***	520.1218	0.0000	***	**I (0)**
	First Difference	-5.2811	0.0000	***	-24.9080	0.0000	***	573.6846	0.0000	***	762.9671	0.0000	***	
Inflation Rate	Level	-3.3445	0.0004	***	-8.8790	0.0000	***	293.2057	0.0000	***	464.6102	0.0000	***	**I (0)**
	First Difference	-5.0283	0.0000	***	-22.7035	0.0000	***	533.6128	0.0000	***	754.4613	0.0000	***	
FDI	Level	-3.2518	0.0006	***	-7.8245	0.0000	***	283.1239	0.0000	***	567.5490	0.0000	***	**I (0)**
	First Difference	-4.9292	0.0000	***	-23.0567	0.0000	***	515.8163	0.0000	***	778.5935	0.0000	***	
Energy Intensity	Level	-3.0435	0.0012	***	-7.4838	0.0000	***	274.1010	0.0000	***	204.8823	0.0000	***	**I (0)**
	First Difference	-3.9299	0.0000	***	-11.5134	0.0000	***	334.5273	0.0000	***	427.5211	0.0000	***	

Source: Researcher's Construct Using a Multilateral Finance Data

Model Specification Tests

The Hausman test results were unequivocal. With a chi-square statistic of 1.5765 across six degrees of freedom and a probability of 0.9543, the null hypothesis of random effects consistency is upheld. This outcome is clear; a p-value of 0.9543 falls within the non-rejection region, indicating no significant evidence of a systematic correlation between country-level unobserved heterogeneity and regressors. Thus, the random effects estimator is both consistent and efficient, making it preferred over fixed effects.

Independent variable-level comparisons support this conclusion. The coefficients for both the fixed and random effects are nearly identical across all six regressors. The most significant absolute difference was observed in the population growth rate (−1.944 vs. −1.648), yet this still yielded a probability of 0.7662, which far exceeded any conventional threshold for concern. Climate finance exhibits the smallest divergence (−0.200 vs. −0.204, p = 0.9956), indicating that the random effects estimator captures its effect with virtually no endogeneity bias compared to fixed effects estimator.

The fixed-effects equation has a co-integration structural limitation. Despite a strong model fit ($R^2 = 0.795$, F = 66.co-integrationn), each regressor is statistically insignificant, including the constant's counterpart, climate finance ($\beta = -0.200$, $p = 0.890$). This indicates within-country variance exhaustion: once 49 country dummies absorb cross-sectional structural differences, the residual year-to-year variation within each country over 20 periods is insufficient to identify the precise marginal effects. The fixed effects estimator identifies coefficients from short-run fluctuations stripped of the between-country economic context, which carries the most meaningful variation in industrialisation levels across sub-Saharan Africa.

This finding has significant methodological implications. The Hausman test justifies the application of the Random Effects (RE) model on statistical grounds and enhances substantive interpretability: the RE estimator effectively captures the variation between countries, which is where the narrative of climate finance and structural transformation is situated within this dataset. The almost negligible individual probabilities in the Fixed Effects (FE) equation do not indicate misspecification but are rather a consequence of the estimator's inherent design.

Table 4: Model Specification Tests

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	Decision
Cross-section random	1.576506	6	**0.9543**	**Fail to reject H_0 → Random Effects preferred**

Variable	Fixed Effects Coef.	Random Effects Coef.	Prob.	Interpretation
Climate Finance	-0.200093	-0.203503	0.9956	**No systematic difference**
Energy Intensity	-0.003466	-0.003488	0.9618	**No systematic difference**
FDI	0.007726	0.007807	0.8387	**No systematic difference**
GDP Growth Rate	-0.037616	-0.038294	0.8399	**No systematic difference**
Inflation Rate	0.000340	0.000335	0.9606	**No systematic difference**
Population Growth Rate	-1.944556	-1.648464	0.7662	**No systematic difference**

Variable	Coefficient	Std. Error	Prob.	Sig.
C	14.979020	3.184050	0.0000	***
Climate Finance	-0.200093	1.443726	0.8898	
Energy Intensity	-0.003466	0.003950	0.3805	
FDI	0.007726	0.011525	0.5028	
GDP Growth Rate	-0.037616	0.036904	0.3083	
Inflation Rate	0.000340	0.002518	0.8927	
Population Growth Rate	-1.944556	1.278799	0.1287	

Source: Researcher’s Construct Using a Multilateral Finance Data

Multicollinearity Check

The variance inflation factor (VIF) analysis yielded a definitive conclusion: multicollinearity was not a concern in this model. All six centred VIFs, which were diagnostically significant, ranged from 1.002 to 1.053. This close clustering around one exemplifies the orthogonality among the regressors. No variable increased its standard error by more than 3% owing to linear relationships with others. This finding is consistent with the correlation matrix presented in Table 2, where no pairwise coefficient exceeds |0.20|.

Distinguishing between centred and uncentered Variance Inflation Factors (VIFs) is crucial, as their conflation represents a frequent interpretative error. The uncentered VIFs, reaching values of 12.41 for energy intensity, 11.15 for population growth rate, and 30.21 for the constant, may appear concerning but provide no meaningful insight into multicollinearity among substantive regressors. Uncentered VIFs are inflated by variable mean values and intercept inclusion in auxiliary regressions, measuring the distance from the origin rather than the collinearity structure. The uncentered VIF of 30.21 for the constant lacked diagnostic significance. Only centred VIFs, which exclude the intercept, accurately identify linear dependence among predictors, and all six centred VIFs remain below the conservative threshold of 5, let alone the standard threshold of 10.

The coefficient variances support this observation: the range across variables (from 2.63×10^{-5} for inflation to 2.787 for climate finance) indicates real differences in variable scaling rather than variance inflation from the collinearity. This result, which shows no multicollinearity, confirms that all six control variables can be included concurrently without caco-integration estimation instability. The individual insignificance in the fixed effects equation is attributed to limited within-country variation rather than inflated standard errors from the collinear regressors.

Table 5: Multicollinearity Check

Variance Inflation Factors			
Sample: 2003 2022			
Included observations: 980			
	Coefficient	Uncentered	Centered
Variable	Variance	VIF	VIF
Climate Finance	2.787301	4.019116	1.052947
Energy Intensity	3.37E-05	12.40539	1.002726
FDI	0.000549	1.299757	1.002159
GDP Growth Rate	0.003818	3.815883	1.007413
Inflation Rate	2.63E-05	1.101522	1.005291
Population Growth Rate	0.059684	11.14934	1.042553
C	0.990241	30.20930	NA

Source: Researcher’s Construct Using a Multilateral Finance Data

Heteroskedasticity Tests

The heteroskedasticity test results are decisive and significant in this study. The likelihood ratio statistic of 923.35 with 49 degrees of freedom ($p = 0.000$) strongly rejects the null hypothesis of homoskedasticity, confirming that error variances differ across the 48 countries examined. The log-likelihood increase of 461.68 units, from −3087.15 under the restricted heteroskedastic assumption to −2625.47 under EGLS, signifies a fundamental restructuring of the variance architecture. This validates the cross-section weighted estimator as necessary and appropriate for this study.

The EGLS analysis, after correcting for heteroskedasticity, presents a significantly different perspective compared to the insignificant fixed effects equation in Table 4. Four variables were statistically significant. Climate finance has a negative impact on industrialisation ($\beta = -1.813$, $p = 0.003$) because multilateral funds are allocated to the least industrialised and climate-vulnerable economies, resulting in a targeting-driven negative association. Energy intensity is positively significant ($\beta = 0.008$, $p = 0.000$), indicating that countries with higher energy consumption per output maintain greater manufacturing capacity. Foreign direct investment (FDI) shows a small positive effect ($\beta = 0.017$, $p = 0.024$), confirming that foreign capital inflows support industrial development, aligning with Nchofoung et al. (2024) and Mamba et al. (2020). Population growth emerges as the strongest predictor ($\beta = -1.229$, $t = -10.99$, $p = 0.000$), suggesting that demographic expansion exerts downward pressure on the manufacturing share of GDP, a structural constraint in sub-Saharan Africa (SSA).

GDP growth and inflation rates remain statistically insignificant, indicating that macroeconomic fluctuations do not substantially alter industrialisation trajectories over the study period. The Durbin-Watson statistic of 2.005 confirms absence of serial correlation, while the F-statistic of 27.94 ($p = 0.000$) shows joint significance of the model. The discrepancy between the weighted R^2 (0.147) and unweighted R^2 (0.015) reflects the scale transformation in the EGLS weighting, where the weighted statistic assesses the fit in the re-scaled variance space, while the unweighted statistic evaluates the fit on the original industrialisation series.

Table 6: Heteroskedasticity Tests

	Value	Df	Probability	Decision	
Likelihood Ratio	**923.3541**	49	**0.0000**		
LR Test Summary	**Restricted LogL**	**Unrestricted LogL**	**LogL Gain**	**Interpretation**	
Log-likelihood	-3087.149	-2625.472	**461.677**		
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**Sig.**
C (Intercept)	11.390100	0.409113	27.8410	0.0000	***
Climate Finance	-1.813034	0.608484	-2.9796	0.0030	***
Energy Intensity	0.007639	0.001248	6.1217	0.0000	***
FDI	0.016765	0.007430	2.2563	0.0243	**
GDP Growth Rate	-0.002691	0.020226	-0.1330	0.8942	—
Inflation Rate	-0.000593	0.000863	-0.6868	0.4924	—
Population Growth Rate	-1.229493	0.111905	-10.9870	0.0000	***
Statistic	**Value**	**Statistic**	**Value**	**Statistic**	**Value**
R-squared	0.146979	**Adjusted R-squared**	0.141719	**F-statistic**	27.942020
Log likelihood	-2625.472000	**AIC**	5.372392	**Schwarz criterion**	5.407303
Mean dep. Var	20.639310	**S.D. dep. var**	24.354880	**S.E. of regression**	5.760090
R-squared	0.015341	**Sum sq. resid.**	32282.990000	**Mean dep. var**	9.846876

Source: Researcher's Construct Using a Multilateral Finance Data

Regression Analysis

The Generalised Method of Moments (GMM) results provide the most robust and credible estimates. Three factors establish GMM's superiority over estimated generalised least squares (EGLS) and Fixed Effects (FE) specifications. First, including the lagged dependent variable (Industrialisation (−1)) models the dynamic nature of industrial development, as the current manufacturing share is influenced by the previous period's share. Second, the first-difference transformation eliminates time-invariant country fixed effects without dummy variables that would consume degrees of freedom. Third, the Arellano-Bond instrument specification (@DYN (Industrialisation, −2)) addresses endogeneity in dynamic panels by instrumenting the lagged dependent variable with deeper lags, eliminating the simultaneity bias affecting FE and EGLS estimates. The J-statistic of 43.08, with a probability of 0.425, fails to reject the null hypothesis of valid over-identifying restrictions, confirming the instrument set's exogeneity and correct GMM specification. With an instrument rank of 49 matching cross-sections, the instrument count is controlled for proliferation issues common in GMM panel studies.

The lagged industrialisation coefficient of 0.515 ($t = 42.45$, $p = 0.000$) is the most significant finding. This coefficient indicates that industrialisation in sub-Saharan Africa is highly persistent and path-dependent, with approximately half of each country's current manufacturing share attributable to its previous level. This aligns with the findings of Nchofoung et al. (2024), who document structural inertia in African industrial development, and with the broader literature on industrial convergence in developing economies reviewed by Lin et al. (2024). The coefficient value of 0.515, between 0 and 1, confirms conditional convergence: countries are neither locked into permanent industrial trajectories (requiring a coefficient of 1) nor experience explosive divergence (requiring a coefficient exceeding 1). This has direct policy implications: interventions that shift industrialisation in one period can be compounded in subsequent periods through this persistence mechanism.

Climate finance shows a significant negative effect, with a coefficient of −2.686 ($t = -5.11$, $p = 0.000$), which is larger than the EGLS estimate of −1.813 and estimated with greater precision after accounting for dynamic endogeneity. The consistent negative sign across specifications enhances robustness, exceeding the single-equation reliability. This finding does not suggest that climate finance is intrinsically harmful to industrial development in developing countries. Rather, it highlights a structural misalignment in the design and allocation of multilateral funds, which predominantly concentrate on adaptation and mitigation efforts in climate-vulnerable and least industrialised countries while insufficiently prioritising the enhancement of productive capacity, technology transfer, and green investments associated with manufacturing. The prevailing climate finance framework prioritises environmental resilience over facilitating the economic transformation essential for structural change in sub-Saharan Africa. This finding contradicts the hypothesised positive relationship and optimistic view of Tolliver et al. (2020), who claim that green finance fosters sustainable industrial growth. However, this aligns with Newell and Bulkeley (2016), who note that multilateral climate finance primarily targets adaptation and mitigation in vulnerable, least industrialised economies rather than productive structural transformation. Similarly, Khan et al. (2022) observe that climate finance allocation in developing economies is influenced by vulnerability indices rather than absorptive capacity, resulting in targeted endogeneity that leads to a negative cross-sectional association. Wang and Wang (2021) report mixed effects of climate finance on economic outcomes in African contexts, noting that delays in disbursement, implementation inefficiencies, and predominance of grant-based adaptation funding over productive investment may hinder industrial returns.

Energy intensity exhibits a sign reversal, with significant implications. Energy intensity shifts from positive and significant in the EGLS model (+0.008, $p = 0.000$) to negative and significant in the GMM model (−0.018, $p = 0.000$). This reversal is theoretically meaningful and not mere statistical noise. The EGLS between-country analysis shows that more industrialised economies consume more energy per unit of output owing to heavier manufacturing sectors. The GMM within-country first-difference analysis reveals a different dynamic: increased energy intensity within a country reduces industrialisation. This aligns with Liu and Paan (2024), who show that energy efficiency improvements in developing economies facilitate manufacturing growth through cost reductions and productivity gains. Similarly, Verstina et al. (2022) argued that reducing energy intensity is essential for sustainable industrial expansion. These two results operate on different dimensions of variation. They suggest that while high-energy economies are more industrialised in cross-sectional analyses, deteriorating energy efficiency within a country suppresses its industrial development over time.

Foreign Direct Investment (FDI) exerts a positive and significant influence, as shown by its effect size ($\beta = 0.011$, $t = 6.50$, $p = 0.000$), estimated using the generalised method of moments (GMM). The robustness across the EGLS and GMM specifications reinforces their validity. Nchofoung et al. (2024) document a positive relationship between FDI and industrialization in Sub-Saharan Africa (SSA), attributing this to technology transfer, capital deepening, and supply chain integration. Mamba et al. (2020) observe that FDI inflows facilitate structural transformation when directed towards manufacturing sectors rather than extractive industries. Doku and Phiri (2023) report a positive, albeit heterogeneous, effect of FDI, noting that its industrial impact depends on the host country's absorptive capacity. The GMM coefficient of 0.011 indicates that a one-percentage-point increase in FDI as GDP share results in a 0.011 percentage point rise in manufacturing value added. This effect, while modest, is statistically robust and aligns with FDI serving as a facilitating rather than a transformative force in SSA industrialisation.

GDP growth shifts from statistically insignificant in the EGLS model (p = 0.894) to negative and significant in the GMM model (β = −0.043, t = −2.83, p = 0.005). Both the sign and significance changes are meaningful. Within the first-differenced GMM framework, periods of high GDP growth in sub-Saharan Africa (SSA) are often driven by commodity booms, service expansion, or consumption-led growth, which may not contribute to manufacturing value added. Resource booms can displace manufacturing through Dutch Disease dynamics, as appreciating exchange rates reduce the competitiveness of industrial exports. This aligns with Hoy et al. (2014), who observed that GDP growth in resource-dependent African economies frequently bypasses manufacturing, and with the premature de-industrialisation literature (Rodrik, 2016), which documents declining manufacturing shares during growth in developing economies.

The transition from EGLS, where inflation is statistically insignificant (p = 0.492), to GMM, where it becomes positive and significant (β = 0.005, t = 3.68, p = 0.000), requires careful consideration. In a first-differenced dynamic framework, short-term inflation increases may align with expansions in nominal industrial output, particularly when manufacturing output is priced in domestic currency, and GDP deflators lag price adjustments. This should not be seen as endorsing inflation for industrial growth; rather, it reflects the nominal component of the manufacturing value-added measurement in high-inflation contexts within sub-Saharan Africa. Huang et al. (2009) document non-linear effects of inflation on economic activity, noting moderate inflation can coexist with output growth in developing economies. Similarly, Enilolobo et al. (2024) find an ambiguous relationship between inflation and industrialisation in West African panels, emphasising that the effect depends on whether real or nominal measures are used.

Population growth shows a notable reversal, transitioning from strongly negative in the EGLS (β = −1.229, p = 0.000) to strongly positive in the GMM (β = 2.165, t = 11.48, p = 0.000). This contradiction is resolved by acknowledging that these estimates capture different phenomena. The EGLS cross-country results reflect that rapidly growing populations in Sub-Saharan Africa (SSA) are predominantly in less industrialised economies, indicating a demographic-development correlation. The GMM within-country first-difference result shows the short-term dynamic: as population growth accelerates, domestic demand increases, stimulating the manufacturing output. This demand-side population dividend is documented by Noda et al. (2019), who find that population growth in early-stage economies can generate industrial demand to expand the manufacturing share of the economy. Doku and Phiri (2023) and Lin et al. (2024) report positive population-industrialisation dynamics in sub-samples of African economies where domestic market effects prevail. The long-term structural constraint captured by EGLS and the short-term demand stimulus captured by GMM operate on different temporal horizons and should be reported.

Table 7: Regression Analysis

Dependent Variable: Industrialisation				
Method: Panel Generalized Method of Moments				
Transformation: First Differences				
Sample (adjusted): 2005 2022				
Periods included: 18				
Cross-sections included: 49				
Total panel (balanced) observations: 882				
White period instrument weighting matrix				
White period standard errors & covariance (d.f. corrected)				
Instrument specification: @DYN (Industrialisation, -2)				
Constant added to instrument list				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Industrialisation (-1)	0.514750	0.012127	42.44714	0.0000
Climate Finance	-2.686339	0.525647	-5.110536	0.0000
Energy Intensity	-0.017622	0.001973	-8.930354	0.0000
FDI	0.010849	0.001668	6.503270	0.0000
GDP Growth Rate	-0.043297	0.015289	-2.831854	0.0047
Inflation Rate	0.004866	0.001323	3.677609	0.0002

Population Growth Rate	2.165126	0.188529	11.48432	0.0000
	Effects Specification			
Cross-section fixed (first differences)				
Mean dependent var	0.040207	S.D. dependent var		1.612569
S.E. of regression	1.931295	Sum squared resid		3263.662
J-statistic	43.07955	Instrument rank		49
Prob(J-statistic)	0.424866			

Source: Researcher's Construct Using a Multilateral Finance Data

Robustness Checks

To evaluate the reliability and consistency of the baseline EGLS estimates, this study utilised two supplementary estimation methodologies: the Arellano-Bond system GMM, which addresses dynamic endogeneity and unobserved heterogeneity, and M-estimation robust least squares employing bisquare weighting to mitigate the impact of outliers and extreme observations identified in the descriptive statistics. The findings across all three specifications are largely consistent and mutually reinforcing, thereby providing substantial confidence in the study's core empirical conclusions.

The consistent finding across the robustness checks pertains to climate finance. The negative and statistically significant association between climate finance and industrialisation is confirmed under EGLS ($\beta = -1.813$, $p = 0.003$), GMM ($\beta = -2.686$, $p = 0.000$), and robust OLS ($\beta = -3.630$, $p = 0.016$). The magnitude of this coefficient increases as the estimation methods become more rigorous, thereby excluding heteroskedasticity, dynamic endogeneity, and outlier contamination as potential explanations. This represents the study's most robust finding and indicates that multilateral climate finance flows do not result in industrial development gains for sub-Saharan African economies over the study period.

The adverse structural impact of the population growth rate on industrialisation is consistently corroborated across two static specifications: EGLS ($\beta = -1.229$, $p = 0.000$) and robust OLS ($\beta = -0.800$, $p = 0.000$). The positive sign observed under GMM reflects a distinct short-run within-country demand dynamic rather than contradicting the long-run structural relationship. The reduction of the coefficient from −1.229 to −0.800 following outlier correction indicates that while extreme observations may amplify the magnitude, the fundamental finding that demographic pressure constrains industrialisation remains valid and robust.

The positive impact of Foreign Direct Investment (FDI) on industrialisation is consistently observed across all three analytical models, achieving statistical significance in both the EGLS ($p = 0.024$) and GMM ($p = 0.000$) frameworks, while losing significance under M-estimation ($p = 0.245$). This pattern suggests that the relationship between FDI and industrialisation is genuine but varies across specific national contexts rather than functioning as a uniform structural mechanism across the entire panel. Consequently, this finding is considered conditionally robust, with policy implications dependent on the absorptive capacity of the host country.

Energy intensity presents a theoretically coherent but empirically divergent outcome. The positive correlation between energy consumption and industrialisation is corroborated by both the EGLS and robust OLS methodologies. Conversely, the negative dynamic effect observed under the GMM reflects the intra-country cost associated with declining energy efficiency over time. These findings are not contradictory; rather, they operate on distinct analytical dimensions: cross-sectional structural capacity and intra-country temporal efficiency, both of which are valid.

The GDP growth and inflation rates are insignificant across the EGLS and robust OLS methods, with their significance in GMM due to short-run nominal dynamics rather than stable relationships. These variables were retained as controls but yielded no substantive policy insights. The robustness checks confirm that the study's central findings, particularly climate finance's negative impact and the demographic constraint on industrialisation, are not artefacts of the estimation assumptions, outlier sensitivity, or dynamic misspecification. The empirical narrative remains stable and consistent across multiple methodological perspectives, enhancing the credibility of policy conclusions.

Table 8: Robustness Checks

Dependent Variable: Industrialisation				
Method: Robust Least Squares				
Sample: 2003 2022				
Included observations: 980				
Method: M-estimation				
M settings: weight=Bisquare, tuning=4.685, scale=MAD (median centered)				
Huber Type I Standard Errors & Covariance				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
Climate Finance	-3.629734	1.508993	-2.405403	0.0162
Energy Intensity	0.008678	0.005248	1.653703	0.0982
FDI	0.024625	0.021182	1.162572	0.2450
GDP Growth Rate	-0.045787	0.055850	-0.819819	0.4123
Inflation Rate	-0.003967	0.004634	-0.856030	0.3920
Population Growth Rate	-0.800000	0.220812	-3.622989	0.0003
C	11.08172	0.899427	12.32087	0.0000
	Robust Statistics			
R-squared	0.017390	Adjusted R-squared		0.011330
Rw-squared	0.027692	Adjust Rw-squared		0.027692
Akaike info criterion	952.5531	Schwarz criterion		989.9345
Deviance	23563.25	Scale		5.002146
Rn-squared statistic	21.46272	Prob(Rn-squared stat.)		0.001514
	Non-robust Statistics			
Mean dependent var	9.846876	S.D. dependent var		5.786988
S.E. of regression	5.740644	Sum squared resid		32065.21

Source: Researcher's Construct Using a Multilateral Finance Data

CONCLUSION AND RECOMMENDATION

This study investigates the relationship between climate finance and industrialisation across 48 sub-Saharan African countries from 2003 to 2022. Utilising a balanced panel comprising 980 observations, the analysis employs a range of econometric methods, including panel EGLS, Arellano-Bond system GMM, and M-estimation robust least squares. Pre-estimation diagnostics confirm that all variables are stationary at level I (0), multicollinearity is absent, and cross-section heteroscedasticity is both present and significant, thereby validating the EGLS specification as the primary estimator. The Hausman test, when correctly interpreted, supports the consistency of random effects, while the GMM J-statistic confirms the validity of the instruments throughout the analysis.

Climate finance has a negative and statistically significant impact on industrialisation in sub-Saharan Africa. This effect is consistent across all estimation strategies and intensifies the methodological rigor. Structural misalignment, rather than fund ineffectiveness, adversely impacts climate finance in sub-Saharan Africa's industrialisation. This highlights a design and allocation misalignment, prioritising adaptation and mitigation in vulnerable, least industrialised economies while neglecting investments in productive capacity, technology transfer and green manufacturing. Four institutional dynamics influence this negative correlation: funds primarily support adaptation in non-manufacturing sectors, such as water security and agriculture, based on vulnerability rather than manufacturing advantage. Funds go to the least industrialised, climate-vulnerable economies with minimal industrial investment capacity and limited governance, while emerging manufacturing countries with stronger institutions receive less support. Climate-financed projects require extended implementation for industrial spill-overs, but the study captures only short-to-medium-term effects, overlooking infrastructure investments and technology transfer impacts.

Based on these findings, three policy recommendations are proposed. First, multilateral climate finance institutions, including the Green Climate Fund, Global Environment Facility, and Clean Technology Fund, should reallocate SSA funds towards productive green industrialisation. This should support renewable energy-linked manufacturing, climate-resilient agro-processing, and low-carbon infrastructure with industrial spill-over effects. Second, recipient governments must enhance absorptive capacity frameworks to transform climate finance inflows into sustainable industrial investments rather than short-term projects. Third, demographic dividend strategies should be integrated with industrial policy, ensuring that expanding working-age populations enter productive manufacturing through coordinated skills development and industrial zone investment rather than the informal sector.

Limitations and Suggestion for Further Studies

This study has several limitations that must be considered when interpreting its findings. The fixed-effects model uses country-specific dummy variables to account for the invariant characteristics of the countries. Assuming a uniform relationship between climate finance and industrialisation across economies may overlook such disparities. Sub-Saharan Africa has countries at various stages of development, from least developed to middle income, each with unique institutional frameworks and industrial foundations. Multilateral funds for adaptation and mitigation in less industrialised economies imply that climate finance effectiveness depends on institutional and economic context. Future research should explore whether this negative relationship persists or whether environments with robust manufacturing, advanced absorptive capacities, and effective governance yield different outcomes. National case studies and sub-regional analyses can reveal the diverse impacts of climate finance on industrial development in sub-Saharan Africa. Future research should focus on (i) assessing climate finance outcomes across sub-regions, such as West, East, Southern, and Central Africa; (ii) contrasting countries with high absorptive capacity and effective industrial policies with those with weak governance; (iii) examining the interaction between existing manufacturing bases and climate finance distribution; and (iv) using multilevel analysis to decompose variance from regional, national, and sectoral factors.

Quantitative investigations often lack mechanistic explanations, as econometric analyses may link climate finance and industrialisation without clarifying their adverse relationship. To determine whether this results from fund misallocation, institutional constraints, governance challenges, or structural factors, deeper investigation beyond statistical analysis is needed. Quantitative methods fail to explain why adaptation-focused funds dominate, how institutions use climate finance, and the implementation barriers that exist. This requires qualitative research that integrates policy analysis, institutional evaluation, and stakeholder insights. A mixed-methods exploration of causal mechanisms is crucial, as the climate finance framework prioritises environmental resilience over economic transformation, inadequately promoting structural change in sub-Saharan Africa. To understand this misalignment and identify intervention points, future research should use mixed methods: (i) Policy Document Analysis: Examine climate fund design documents to understand adaptation prioritisation; (ii) Stakeholder Interviews: Conduct interviews with climate fund administrators, officials, policymakers, and manufacturing representatives to explore decision-making and constraints; (iii) Sectoral Case Studies: Analyse manufacturing subsectors (renewable energy equipment, climate-resilient agro-processing, low-carbon steel) to identify successes and challenges; and (iv) Institutional Capacity Assessment: Evaluate how absorptive capacity frameworks influence climate finance use in countries with varying governance and expertise.

This study uses Climate Funds Update data to examine climate finance allocation for initiatives, treating finance as a single measure and ignoring fund-type differences that affect industrialisation. The negative coefficient may suggest adaptation-focused finance predominance rather than finance ineffectiveness for industrial development. The analysis does not distinguish between (a) adaptation versus mitigation/green industrialisation funds, (b) public/concessional finance versus private instruments, (c) capacity-building versus infrastructure projects, or

(d) disbursement methods (direct project support, sector-wide, or budget support) that impact absorptive capacity and industrial outcomes. Future research should disaggregate climate finance by type, instrument, and sectoral focus to identify the mechanisms that yield significant industrial development returns. This involves (i) analysing adaptation-dominant funds versus green industrialisation finance to determine whether negative relationships reverse for mitigation/green growth instruments; (ii) comparing concessional public finance, market-rate instruments, blended finance, and private sector mobilisation to identify manufacturing development mechanisms; (iii) quantifying climate finance for manufacturing-linked activities (renewable energy equipment, climate-smart agriculture, green construction) versus non-manufacturing sectors (water management, ecosystem restoration) with sectoral-level regression analysis; (iv) examining how direct project finance, budget support, and capacity-building impact industrial adoption and technological upgrading; and (v) conducting threshold and saturation analysis using quantile regression or threshold models to determine whether finance thresholds must be surpassed for positive industrial effects.

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Statement of Contributions

Shamwil Abdul-Karim

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Declaration of Competing Interests

The author declares that there are no competing interests. No financial support or personal relationship influenced the design, execution, analysis, or interpretation of this study.

Data Availability Statement

The data used in this study are available upon request.

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