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Input-Growth Linkages in Uganda's Industrial Development: Insights from Sectoral Panel Data

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Abstract

Purpose: The purpose of this study is to examine the effect of factor inputs, namely gross fixed capital formation, human capital investment, and population growth, on industrial sector growth in Uganda. The analysis places particular focus on the manufacturing, construction, energy, and mining subsectors, which collectively form the backbone of Uganda's industrial development. **Design/methodology/approach**: Using sectoral panel data and the panel autoregressive distributed lag (ARDL) model, the study investigates both short-run and long-run relationships between the selected factor inputs and industrial value-added output. The model was applied to capture dynamic adjustments while testing the relevance of the exogenous growth framework in a developing economy context. **Findings**: The results reveal mixed effects of factor inputs on industrial sector growth. Gross fixed capital formation shows a positive but statistically insignificant impact in the long run, while demonstrating a significant negative short-run effect, suggesting adjustment costs and inefficiencies in capital use. Human capital investment exerts a strong and consistently negative influence in both the short and long run, indicating structural mismatches between education outputs and industrial labour demand. In contrast, population growth emerges as a robust driver of industrial growth, significantly and positively influencing sectoral output in both the short and long run. The error correction term confirms a stable long-run equilibrium relationship among the variables. **Practical implications**: These findings highlight critical policy and managerial implications. Policymakers should address inefficiencies in capital allocation, reform human capital development to align skills with industrial needs, and harness Uganda's growing population as a productive resource. Industrial firms should prioritise strategies that improve the utilisation of capital investments and workforce absorption. **Originality/value**: To the best of the authors' knowledge, this study is one of the first to apply a panel ARDL approach at a subsectoral level to investigate input-growth linkages in Uganda's industrial sector. By integrating the exogenous growth framework with sectoral panel data, the research provides new insights into how factor inputs drive or constrain industrial development in a resource-limited economy.

Keywords

Factor Inputs, Industrial Growth, Gross Fixed Capital Formation, Human Capital Investment, Population Growth, Uganda, Panel ARDL

1. Introduction

The industrial sector has long been recognised as a key driver of economic transformation, employment creation, and technological advancement (Mendoza Borsi & Comim, 2022; Wang & Zhang, 2022). Historically, industrialisation has enabled economies to shift from agrarian dependence to diversified production structures, with countries such as China and India achieving rapid growth through targeted industrial policies (Gruzina, Liu, & Song, 2022; Ding & Wu, 2023). In contrast, several economies, particularly in Africa, continue to experience stagnation in industrial output due to structural constraints, institutional weaknesses, and insufficient factor inputs (Admassie & Taffesse, 2021; Kamau & Abala, 2022). Uganda illustrates this challenge. Despite government interventions such as the establishment of industrial parks, the adoption of the National Industrial Policy, and initiatives including the Build Uganda Buy Uganda strategy, the industrial sector has not achieved its full growth potential (Ahaibwe & Mbowa, 2022; Kiggundu, 2023; Owino, 2023).

In Uganda, the industrial sector contributes about 27.6 percent to GDP, with manufacturing, construction, mining, and energy playing distinct but interconnected roles (Uganda Bureau of Statistics [UBOS], 2023). Recent performance indicators highlight persistent underperformance, including a 3.7 percent decline in industrial value added in the second quarter of 2022-2023 (Ministry of Finance, Planning and Economic Development [MoFPED], 2023). This trend reflects both internal inefficiencies and external shocks. Limited physical capital, an inadequately skilled labour force, restricted access to domestic credit, and governance challenges such as corruption and inconsistent regulation continue to undermine progress (Ahaibwe & Mbowa, 2022; Kiggundu, 2023; Musoke & Kafeero, 2024). These factors threaten economic diversification, employment creation, and the country's competitiveness in regional and global markets (Kamau, 2024; Kimathi & Otieno, 2024).

Different theoretical frameworks have been used to study industrial development, including exogenous, endogenous, and institutional growth theories (Mankiw, Romer, & Weil, 1992; Solow, 1956). Endogenous models emphasise innovation and knowledge accumulation (Romer, 1990), while institutional perspectives stress governance and regulatory quality (North, 1990). However, these frameworks often underplay the central role of factor inputs in contexts where resources remain limited (Mendoza Borsi & Comim, 2022; Admassie & Taffesse, 2021). The exogenous growth model, as developed by Solow (1956), places the accumulation of capital and labour at the centre of long-term output determination, making it particularly relevant for analysing the industrial growth trajectory of a country such as Uganda (Baltagi, Egger, & Pfaffermayr, 2023b).

The relevance of factor inputs in Uganda's industrial growth is underscored by government spending priorities. Human capital investment has consistently taken the largest share of GDP in an effort to develop a skilled workforce for industrialisation (MoFPED, 2023; Uganda Bureau of Statistics [UBOS], 2023). Gross fixed capital formation, the second largest component, targets improvements in infrastructure, electricity, and water provision (Adekola, 2024; Wang & Zhang, 2022). Yet the anticipated outcomes have not materialised, suggesting inefficiencies in the application and interaction of these inputs (Kiggundu, 2023; Ahaibwe & Mbowa, 2022). This raises the question of how far factor inputs explain variations in industrial sector performance at a subsector level.

Existing studies in Uganda tend to focus on aggregate industrial growth, obscuring the dynamics within individual subsectors (Owino, 2023; Musoke & Kafeero, 2024). Manufacturing depends heavily on labour and technology adoption, construction is capital intensive and linked to access to finance, mining relies on natural resources and governance structures, and the energy sector is strongly influenced by capital investment and technological innovation (Kamau & Abala, 2022; Okello & Luyiga, 2022; Liu, Zhao, & He, 2023). These differences highlight the need to disaggregate industrial growth in order to examine how factor inputs influence each subsector distinctly. A panel data approach provides the necessary framework for such an investigation (Baltagi, Egger, & Pfaffermayr, 2023b).

This study contributes to the literature by applying a sectoral panel data analysis within the exogenous growth model to examine input-growth linkages in Uganda's industrial development. By focusing on manufacturing, construction, mining, and energy, it addresses a critical gap in empirical work that has often treated the industrial sector as a homogeneous entity (Admassie & Taffesse, 2021; Ndege, Ssenyonga, & Okot, 2023). The findings are intended to inform policymakers and industry stakeholders on how to allocate resources more effectively, strengthen subsector foundations, and design targeted policies that foster industrial growth (Kambale & Matovu, 2023; Kamau, 2024). In this way, the study seeks to support Uganda's broader industrialisation agenda by clarifying the role of factor inputs in driving sustainable economic development (Fofack & Okonjo-Iweala, 2024; Ahaibwe & Mbowa, 2022).

2. Empirical Literature Review

Factor Inputs and Industrial Growth

Studies in recent years show that physical capital investment acts as a key driver for industrial sector expansion, yet its effects vary based on specific circumstances and levels of economic development (Admassie & Taffesse, 2021; Wang & Zhang, 2022). Mendoza Borsi and Comim (2022) found that physical capital plays a major role during initial industrial development phases, yet its effect weakens when economies transition toward knowledge- and service-oriented models. Mendoza Borsi and Comim's research concentrated on advanced economies, so it does not provide information about how physical investments affect Uganda and other less industrialised countries. Gruzina, Liu and Song (2022) found that physical capital investment returns in China decreased as the economy shifted toward human-capital-driven productivity growth. Research results from China remain exclusive to that region and ignore the economic limitations which sub-Saharan African countries encounter (Kamau & Abala, 2022; Admassie & Taffesse, 2021). Ding and Wu (2023) showed that success in capital investment depends on institutional quality and infrastructure, but did not analyse how these factors affect low-income countries with weak governance systems (Ahaibwe & Mbowa, 2022). Similarly, Moyo and Jeke (2019b) emphasised that the productivity of physical capital depends on policy consistency and absorptive capacity in emerging economies, which are often lacking in Africa.

Wang and Zhang (2022) found that capital formation enhanced industrial growth in South East Asia because of government support and technological spillovers, but such mechanisms might not be present in Uganda's policy environment, which makes their applicability uncertain. Adebayo and Ojo (2023) examined Nigeria's experience and found that poor infrastructure and low industrial capacity reduced the effect of capital investment, echoing similar findings from Admassie and Taffesse (2021), who identified inefficiencies in capital allocation as major barriers to industrial transformation in Sub-Saharan Africa. However, these analyses are country- or region-specific and do not capture the unique policy and economic realities of Uganda.

Kimathi and Otieno (2024) showed that in East Africa, industrial growth is driven not only by capital but also by market integration and coordinated industrial policies, while Kiggundu (2023) highlighted that Uganda's industrial progress remains constrained by limited technological absorption and inefficient capital utilisation. Similarly, Ahaibwe and Mbowa (2022) observed that institutional weaknesses and policy inconsistencies have limited the productivity of Uganda's capital investments. Despite these insights, few empirical studies have specifically examined how physical capital investment through foreign direct investment, public infrastructure, and industrial machinery affects the growth of Uganda's industrial sector. This shows a critical knowledge gap that calls for further investigation.

Recent studies have shown increased interest in the relationship between physical capital investment and industrial sector growth, especially in emerging and transitioning economies. Pomi, Zhang and Liu (2021a), in their study on the role of physical and human capital accumulation in China between 1995 and 2013, established that physical capital was a significant contributor to GDP per person employed, especially in the post-restructuring period. The study also emphasised spatial spillovers, including labour mobility, as important determinants of productivity. However, the authors did not explain how similar dynamics would work in Uganda's underdeveloped industrial context, where inter-regional mobility and infrastructure constraints are still major limitations (Okello & Luyiga, 2022).

Kukkonen (2021) and Ali and Nasir (2023) explored the relationship between social capital and physical capital investment and found that physical capital only generates positive returns above a certain threshold of social capital. Although these findings highlight the complementarity of social infrastructure in productive investments, they are based on experiences from Asian economies, where community networks and institutional trust differ substantially from Uganda's fragmented social capital (Ahaibwe & Mbowa, 2022). Craig, Hutton, Musa, and Sheffield (2023) also emphasised the scarcity of data on the interaction between social and physical capital in industrial development, particularly in the African context, indicating that few empirical studies address Uganda's institutional and cultural conditions.

Nguyen and Ha (2020) and Tan and Bui (2022) proposed models describing the joint effects of social, human, and physical capital on firm-level performance, arguing that social capital reduces transaction costs and enhances investment efficiency. However, these studies focus on structured economies with consistent policy environments and fail to consider Uganda's industrial policy implementation and the predominance of the informal sector (Admassie & Taffesse, 2021). Despite the growing number of studies on the role of physical capital in transforming industries (Okello & Katungi, 2022; Chen, Liu, & Zhao, 2024), there remains a lack of country-specific research examining how physical capital investments such as in machinery, plant, and infrastructure contribute to the growth of Uganda's industrial sector, where domestic investment is limited, FDI is inconsistent, and infrastructure remains inadequate (Kiggundu, 2023; Kamau, 2024). This gap underscores the need for Uganda-focused empirical analyses to inform industrial policy and investment strategies aligned with the country's development priorities.

Current research evaluates traditional GDP alongside green GDP because both metrics represent expanding industrial sustainability requirements. Chen, Ding, and Min (2021) evaluated how human and physical capital affect economies at various development stages using traditional GDP and green GDP, which includes energy consumption and pollution data. Their findings revealed that human capital demonstrated greater elasticity than physical capital in driving economic expansion, based on data from 143 countries between 1990 and 2014. Human capital emerged as the essential component for both traditional and green economic growth because it influences sustainable development (Teixeira & Queirós, 2016b). However, Kabuye and Omolo (2023) and Adekola (2024) pointed out that such findings may not easily apply to emerging African economies due to institutional barriers and limited resources.

Gil and Iglésias (2020a) investigated how monetary policy, together with inflation rates, influences industrial development through their effect on research and development (R&D) and physical capital investment. Their model incorporated interest rates, R&D intensity, and capital-to-labour ratios as critical determinants of industrial growth. Although their analysis applies primarily to advanced economies, the authors did not test the model's relevance to less developed contexts such as Uganda, where financial and industrial policy frameworks differ significantly (Kamau, 2024; Ahaibwe & Mbowa, 2022).

Wu, Zhou and Liu (2022) examined China's economic expansion during the reform period (1981-2010) and found that social capital became increasingly influential in the 2000s after previously showing minimal effect. Their study also showed that physical capital lost its dominant role from the 1990s onward, while foreign direct investment and ownership restructuring gained significance. However, these results may not fully apply to emerging economies like Uganda, where FDI inflows and social capital networks operate differently (Owino & Okello, 2023; Kabanda, 2023). Ndege, Ssenyonga and Okot (2023) and Kamau (2024) further emphasised that domestic policy frameworks and governance institutions determine how physical and human capital jointly affect industrial sector expansion in developing countries. These research gaps highlight the need for empirical studies focusing on how Uganda's physical, human, and social capital interact within its industrial and financial structures.

The role of capital in influencing industrial sector growth continues to attract considerable attention from researchers. Human, physical, and increasingly social capital have been identified as key drivers of industrialisation and productivity (Teixeira & Queirós, 2016a). However, the contextual dynamics through which these forms of capital operate vary widely, and their influence remains underexplored in some regions, including Uganda. Chen, Ding and Min (2021) analysed data from 143 countries and concluded that while both human and physical capital significantly influence economic growth, human capital exerts a more pronounced effect on both traditional and green GDP. Their findings underscore the transformative potential of education and skills development in driving productivity gains in the industrial sector. Similar conclusions were drawn by Pereira and Silva (2022) in their study of OECD countries, where robust investment in both physical infrastructure and vocational education substantially boosted manufacturing output and competitiveness. However, these studies are based on advanced economies with strong institutional frameworks and capital markets, and might not reflect the realities of low-income economies (Adekola, 2024).

In the Sub-Saharan African context, Admassie and Taffesse (2021) examined the limitations of capital formation and identified inefficiencies in allocation, poor investment climates, and weak linkages between financial and industrial sectors as major barriers to industrial transformation. Similarly, Kamau and Abala (2022), in their comparative study of Kenya and Ethiopia, found that while physical capital investment had a positive effect on industrial output, its productivity was undermined by infrastructural deficits and inconsistent industrial policies. These findings provide critical insights into the African context but offer limited evidence specifically from Uganda (Ahaibwe & Mbowa, 2022).

In Uganda, recent studies such as those by Kiggundu (2023) and Owino (2023) have begun to explore the domestic relationship between capital accumulation and industrial sector growth. Kiggundu (2023) emphasised that while the country has made strides in mobilising physical capital, the low return on these investments is attributed to limited human capital development and poor technological absorption. Owino (2023) supported this view by noting that Uganda's industrial performance is weakened by skill mismatches, insufficient vocational training, and limited private sector engagement in workforce development. These studies underscore the importance of aligning human capital strategies with industrial policy goals.

Gil and Iglésias (2020a) developed a model incorporating physical capital accumulation, R&D investment, and inflation dynamics to explain industrial expansion in developed economies. Their findings indicate that capital investment and innovation are mutually reinforcing in enhancing industrial growth. However, these dynamics might not transfer easily to contexts like Uganda, where innovation ecosystems are nascent and capital markets are underdeveloped (Kamau, 2024). Wu, Zhou and Liu (2022) examined China's post-reform industrialisation and observed that while physical and human capital were fundamental in the early stages, social capital became increasingly influential from the 2000s onwards. This transition was linked to institutional trust, business networks, and governance reforms. Although insightful, the coordinated governance and strong institutional frameworks that facilitated China's transformation differ markedly from Uganda's decentralised and fragmented industrial structure (Ahaibwe & Mbowa, 2022).

Musoke and Kafeero (2024) used a firm-level approach in Uganda to analyse capital use and found that both small and medium enterprises in the manufacturing sector face challenges in accessing affordable long-term capital and often resort to informal financing. Their study also revealed that physical capital investments were more productive in firms with higher levels of human capital, implying that the complementarity between different types of capital is crucial for industrial success. Similarly, Nabbumba and Namirembe (2023) observed that low levels of digital skills and managerial training among Ugandan industrial workers hindered the productivity of imported technologies and modern equipment.

Although macroeconomic studies such as those of Muwanga and Kasaija (2021) offer useful insights into capital flows and industrial performance, they tend to overlook subsectoral and regional variations. National-level analyses may obscure domestic issues such as poor infrastructure in rural industrial zones or congestion in urban manufacturing hubs. Furthermore, these studies rarely employ mixed-methods approaches that could capture the contextual realities of how capital is deployed and utilised at firm and subsector levels.

There is also increasing awareness of the role of institutional quality and governance in determining how capital influences industrial growth. Ahaibwe and Mbowa (2022) emphasised that the effective implementation of policies and regulatory stability are crucial for investor confidence and capital allocation. However, limited research has been conducted on how Uganda's institutional context mediates the interaction between human and physical capital in the industrial sector.

Recent studies highlight the importance of analysing the effect of capital accumulation on industrial transformation within Uganda's policy and governance environment. The effect of capital on industrial performance remains significant, yet its magnitude varies across countries and contexts (Admassie & Taffesse, 2021). Ndege, Ssenyonga and Okot (2023) and Kamau (2024) found that Uganda's industrial progress is shaped by both domestic capital accumulation and the interaction between public policy and foreign capital inflows. However, as Kasekende (2023) notes, the relationships between human and physical capital remain underexplored in Uganda's industrial sector due to institutional, infrastructural, and labour market constraints. This points to the need for localised, sector-specific analyses to better understand Uganda's industrial development trajectory.

Evidence from Sub-Saharan Africa underscores that capital investment remains a fundamental driver of industrial development. Tadesse and Kebede (2021) conducted a study in Ethiopia showing that both public and private investment in capital assets significantly increased manufacturing productivity. Similarly, Aiyenew and Melesse (2023) demonstrated that institutional quality moderates the effectiveness of capital investment in promoting industrial performance across the region. In Kenya, Waweru and Muturi (2023) found that although agro-industrial zones benefited from capital inflows and human capital, policy misalignment limited the potential for sustainable industrial growth. While these regional studies provide valuable insights, they cannot be generalised to Uganda due to the country's unique institutional arrangements, political economy, and industrial policy framework.

The analysis of industrial sector growth through capital contribution in developed economies often employs sophisticated empirical models. Using a dynamic network Data Envelopment Analysis (DEA) model applied to Japan, Fukuyama, Matousek and Tsai (2021) showed that deficiencies in human capital impaired production more severely than deficits in physical capital. Their analysis revealed that enhancing physical capital requires complementary investment in human capital. In Germany, Richter and Schaefer (2022) demonstrated that digital infrastructure, as a modern form of physical capital, enhanced industrial productivity when combined with skilled labour. Similarly, Zhang and O'Brien (2021) found that in the United States, sector-specific capital intensity directly influenced output elasticity, with manufacturing industries benefiting the most from combining machinery investment and technical skills. While these advanced studies offer valuable insights, their application to Uganda remains limited due to restricted data access, informality in industrial operations, and slow technological adaptation.

Uganda's capital-labour relationships present complex dynamics that warrant further investigation. Technical and vocational education has expanded, yet Atuhairwe and Tukamushaba (2024) found that its weak alignment with national industrial policy restricts the effective utilisation of human capital in capital-intensive industries. Mugisha and Namirembe (2023) conducted a sectoral study of Uganda's textile industry and discovered that foreign direct investment (FDI) improved access to physical capital, but productivity gains were constrained by limited technical expertise. Likewise, Okello and Luyiga (2022) showed that despite substantial infrastructure investments in Uganda's industrial zones, production levels stagnated because available capital was not matched by adequate labour qualifications. These findings demonstrate the need to analyse capital types in conjunction with institutional and human capabilities.

Intangible capital—encompassing organisational knowledge, innovation systems, and intellectual assets—has gained global recognition for its influence on industrial development. Liu, Zhao and He (2023), in a study of OECD countries, found that intangible assets now explain most productivity variations among industrial firms. However, Uganda's context remains understudied, as the measurement and conceptualisation of intangible capital have not been adequately addressed. Fofack and Okonjo-Iweala (2024) argued that African economies must expand their capital definitions to include innovation ecosystems, which are vital for sustaining competitiveness within global value chains.

Uganda's industrial setting retains its uniqueness despite global and regional advances in understanding capital formation. Three critical gaps persist: insufficient sectoral data on Uganda's industrial base, modelling approaches that overlook capital interaction effects, and inadequate contextual analysis of the country's industrial transformation. Addressing these gaps would generate essential evidence for developing efficient capital allocation strategies and industrial policy reforms.

Gil and Iglésias (2020b) applied a macroeconomic growth model linking monetary policy, inflation, and industrial performance, incorporating R&D and physical capital as mediators. Their findings revealed how macroeconomic variables influence industrial growth but did not explore these dynamics in low-income economies. The absence of geographic analysis on physical capital investment in Uganda's industrial sector highlights a persistent knowledge gap, as the country's market and policy structures differ markedly from those in developed economies.

Empirical research in advanced economies demonstrates that targeted monetary policies foster industrial growth through capital accumulation, but there is limited evidence on how these mechanisms operate in Sub-Saharan Africa, particularly in Uganda. The distinct policy environment characterised by inflation volatility, constrained fiscal space, and weak investment linkages remains insufficiently explored in existing literature (Mugisha & Turyahikayo, 2021). Umair, Khan and Ahmad (2024) used ARDL models to show that physical capital, labour, and energy jointly determine industrial output in Pakistan—findings that underscore the importance of capital heterogeneity in industrial analysis. However, comparable sector-specific studies in Africa remain scarce, leaving a methodological gap in understanding how capital influences output both independently and interactively.

Bunyamin (2021) reported that Indonesia's long-term economic growth depended on sustained investments in physical and human capital—particularly tertiary education and infrastructure—which together improved productivity. These insights reinforce the importance of continuous capital accumulation for industrial advancement. Nonetheless, the precise relationship between physical capital and industrial growth in Uganda requires deeper investigation despite ongoing structural transformation initiatives.

Studies from Ethiopia and Rwanda reveal that strategic physical infrastructure investments yield significant industrial gains (Tadesse & Kebede, 2021; Nshimiyimana, 2023). Uganda's unique socio-economic and institutional environment necessitates further inquiry, as relationships between targeted capital investments and production outputs may operate differently in its context. Kaggwa and Byamugisha (2024) emphasised that the absence of detailed capital-type analyses, coupled with technological deficiencies and weak institutional frameworks, hampers effective industrial policy design. Pomi, Zhang, and Liu (2021b) analysed Bangladesh's development path and found that capital effectiveness varied across time periods, reinforcing the need for country-specific empirical studies. Consequently, Uganda requires more nuanced research examining the interplay between capital, labour dynamics, and productivity outcomes.

Yin, Chen and Li (2021) conducted a comprehensive analysis of the causal relationships between foreign direct investment (FDI), CO_2 emissions, and economic growth across 101 countries between 1990 and 2014. Using a simultaneous equation model, their study revealed a bidirectional causal relationship between FDI and economic growth—particularly in middle-income countries—while also incorporating the roles of physical and human capital. The findings showed a two-way causal relationship between FDI and CO_2 emissions and a one-way causal relationship from economic growth to pollution, supporting both the Environmental Kuznets Curve and the Pollution Haven Hypothesis.

There is, however, limited research in Uganda's industrial sector examining how physical capital investment affects FDI dynamics, economic growth, and pollution patterns. Uganda's unique economic and institutional environment requires additional empirical inquiry to understand how physical capital interacts with FDI to promote sustainable industrialisation (Kambale & Matovu, 2023). While relationships between FDI, capital accumulation, and environmental outcomes are well established in high-income economies, Uganda's fragmented regulatory and investment coordination systems require country-specific analysis to inform effective policy interventions.

Recent empirical literature demonstrates that the impact of physical capital investment on industrial growth depends heavily on governance quality, institutional alignment, and sectoral capacity. Adams and Ramey (2023) found that in resource-rich developing countries, physical capital becomes unproductive when governance reforms and sectoral alignment are absent. Zubair and Kamran (2021) examined 14 African countries and established that the effectiveness of infrastructure investment on manufacturing growth depends on the absorptive capacity of domestic industries. Similarly, Al-Rashid and El-Ghazali (2022) reported that MENA economies with streamlined public–private investment frameworks experienced higher capital returns, while those with fragmented institutional arrangements saw diminished outcomes. In Uganda, inconsistent regulation and weak inter-agency coordination continue to constrain capital productivity in industrial sectors (Ahaibwe & Mbowa, 2022).

Babatunde and Saka (2022) analysed the effects of fixed capital formation on sectoral productivity in West African economies, concluding that sustainable output growth requires complementary innovation and human capital development policies. Rojas and Martinez (2023) used Latin American panel data to show that industrial performance improves when physical infrastructure and skill-building institutions are co-located within production hubs. In South Asia, Krishna and Harsha (2021) demonstrated that transport connectivity enhances industrial investment outcomes, particularly in export-oriented clusters. In contrast, research on Uganda's industrial parks and special economic zones remains sparse, leaving policymakers without adequate data to optimise spatial capital investments.

Choi and Lee (2020) found that infrastructure development in South Korea and Vietnam generated more manufacturing value added when coupled with regulatory reforms and integrated supply chain systems. Lemos and Cardoso (2023) reported that Brazil's industrial equipment investments yielded limited results because electricity and logistics challenges persisted. Likewise, Mungai and Salum (2023) showed that capital investment in Kenya and Tanzania enhanced agro-processing outcomes through rural electrification and feeder road development. Collectively, these studies underscore that industrial output responds to physical capital investments through complex, interconnected processes. Yet, Uganda's rural industrial corridors remain under-researched, particularly concerning how physical capital interdependencies affect long-term industrial productivity and infrastructure planning.

In northern Africa, Abdelrahman and Benyoussef (2021) show that machinery acquisition policies failed to achieve high capital productivity because they did not coincide with workforce development initiatives. In Central Asia, Tursunova and Karimov (2022) found that manufacturing firms with outdated technology failed to maximise physical capital investments even though they received significant funding. Eze and Adetunji (2023) reported that Nigerian industrial projects in energy, textiles, and food processing experienced delays because capital stock did not match operator capacity.

Uganda's government has supported industrial parks, but there is no research to verify questions about capital or stock-operator capacity mismatches. The lack of systematic research indicates a crucial need to study the relationship between capital quality and labour preparedness in Uganda's main manufacturing industries (UNIDO, 2023).

Asiedu et al. (2021) reveals that sub-Saharan Africa faces restricted capital investment success because it lacks sufficient long-term financing instruments, which leads to industrial projects remaining unfinished or delayed. Görg and Peng (2023) report that FDI inflows improve capital efficiency rates when domestic capital markets demonstrate stability and equity absorption capacity. In South-East Asia, Kim and Tran (2022) showed that industrial policy incentives without specific financing mechanisms created capital misallocation problems. Uganda's industrial financing system, which includes Uganda Development Bank (UDB), needs to be assessed to determine its ability to boost capital use and minimise project funding deficits (Government of Uganda, 2025). The financing channel gap prevents researchers from understanding how capital influences industrial outcomes.

Institutional quality serves as an essential factor that influences the relationship between capital and industrial growth. In Ghana, Mensah and Boateng (2023) found that predictable regulations created better investment results, particularly in industries that require capital investment. In Ethiopia, Berhane and Asfaw (2021) found that decentralised policy monitoring, together with regulatory feedback mechanisms, enhances the efficiency of capital investments. Uganda's decentralised planning and implementation system fails to provide systematic assessments of how institutional structures affect capital productivity levels (World Bank, 2023). The literature lacks institutional performance metrics, a hindrance to policymakers in creating targeted reforms for the governance of most industrial zones.

The spatial econometric approach in global models studied by Kapoor and Rajan (2023) reveals how trade-hub locations boost industrial development across different areas. Duong and Nguyen (2022) report that Vietnamese industrial zones in peri-urban areas received superior returns from capital investments because they offered affordable land prices and expanded business opportunities. The Ugandan case lacks spatial analyses examining how capital returns vary across different regions while dealing with ongoing urban congestion and land disputes (UN-Habitat, 2022). The current absence of spatial planning for industrial investment, together with region-specific capital productivity variations, remains unaddressed.

Research shows that an increasing number of studies connect environmental sustainability with the efficiency of capital deployment. Fofana and Tamba (2023) showed that investments aligned with environmental standards produced superior long-term returns because businesses complied with regulations and gained support from stakeholders. Li and Yu (2021) found that China's green capital infrastructure produced greater firm-level productivity in industries subject to carbon regulation. Green industrial policies in Uganda have started, but researchers need to investigate how eco-friendly capital investments affect industrial competitiveness (National Planning Authority [NPA], 2023). This lack is an opportunity to perform groundbreaking research that combines capital investment studies with environmental policy effects on industrial development.

3. Methodology

The exogenous growth model

The Cobb-Douglas production function is supplemented with exogenous technology, capital and labour.

$$Y_t = Af\left(K_t, L_t, H_t\right) \quad (2.1).$$

Equation (i) can be stated as:

$$Y_t = AK^{\alpha}L^{\beta}H^{1-\alpha-\beta} \quad (2.2).$$

In this, Y stands for the output produced, A is know-how technology, L stands for the labour force, and H for investment in (education).

The growth rate of population (n) is added to the function of production output, which is attuned to the exogenous rate of know-how technology development (g) and devaluation of physical capital (δ) as indicated by Solow (1956) and Mankiw et al. (1992). So given the neo-classical growth framework, this thesis offers a dynamic development model for analysis of the study variables:

$$\begin{aligned}\log ISG = {} & \alpha_0 + \alpha_1 \log\left(ISGpc\right)_{t-1} + \alpha_2 \log\left(GCFpc\right) + \alpha_3\left(HUMcappc\right) \\ & + \alpha_4 \log\left(n+g+\delta\right) + \varepsilon\end{aligned} \quad (2.3).$$

where: $\log ISG$ = logarithm of industrial sector output, percentage contribution to GDP (current US$), $\log GCF$ = logarithm of gross capital formation (current US$);

$\log HUM$ = logarithm of human capital, proxied by government expenditure on education, total (current US$);

$\log\left(n+g+\delta\right)$ is the logarithm of population growth, adjusted for exogenous factors. Note that $\left(n+g+\delta\right)$ has been generated in Stata by adding: population growth to 0.05 – that is $\left(n+g+\delta\right)$ = popg + 0.05;

ε is white noise.

Research design/approach

Given that the data was compiled on five Ugandan industrial sub-sectors for the period 2000-23, the study adopted the quantitative research design, in which data on each variable was collected for each industrial sub-sector on an annual basis during the period under study. This study design fits the secondary data type outlined by Herle et al. (2020).

Data type and sources

The data used in this study was sourced from the World Bank's database and Ubos relying specifically on secondary data. The data has been compiled in a panel form, so analysis has been achieved using panel data. Panel data was preferred because, as opposed to time series and cross-sectional data, it provides additional degrees of freedom and helps manage heterogeneity and multi-collinearity in the data from various countries (Moyo & Jeke, 2019a; Tran, Ivashchenko & Brooks, 2019).

Panel data also helps establish conclusions on effects among variables under investigation (Shanmugalingam, Shanmuganeshan, Manorajan, Kugathasan, & Pathi Rana, 2023). It also accounts for the heterogeneity of sectors, which helps reduce bias about both endogeneity and unobserved factors (Wood, Dussubieux, Wynne-Jones, & Fleisher, 2022). It is also well adapted to investigations of dynamic economic changes like factor inputs, productivity factors and other factors representing industrial sector growth (Tran et al., 2019), all of which are variables investigated under this study.

Model specification

The study estimated a linear dynamic panel regression model to test the effect of input variables, productivity measures and governance components on Uganda's industrial sector growth, and the dynamic nature of the research variables was considered. In the development of the empirical model, the study took these steps:

First, the study specifies a more general panel model as:

$$y_{it} = \alpha + x'_{it}\beta + u_{it},\ i = 1,\cdots,N; t = 1,\cdots,T \qquad (3.1);$$

where:

y_{it} is the variable under investigation (that is, industrial sector output), i represents the i^{th} sub-sector in the panel (processing industries, manufacturing, heavy industry, construction, mining and quarrying) and t represents the time indicator in the panel. The two indices, i and t, indicate the cross-section and time-series dimensions in the panel. α is the scalar, β is the vector of gradient coefficients of the stimulus variables, x'_{it} denotes the stimulus variables in the panel model and u_{it} is a two-error-component idiosyncratic error term, so that:

$$u_{it} = \mu_i + v_{it} \qquad (3.2)$$

In the error Equation (3.2): μ_i represents a time-invariant perturbation that is unobservable for a particular effect on a sub-sector and explains the individual-specific effects omitted by the regression model. On the other hand, v_{it} is a residual perturbation that fluctuates with respect to the time of the sub-sectors involved (Baltagi et al., 2023a). Both μ_i and v_{it} are assumed to be identically and independently distributed.

A model like (6) assumes that the vector of the stimulus variables is independent of the error term, that is to say $E(X'u) = 0$. In this case, the conditional expectation of y_t is:

$$E(y_{it} \setminus x_{it}) = x'_{it}\beta \qquad (3.3)$$

The unconditional population moment condition is specified as:

$$g(\beta) = E[x_{it}u_{it}] = E[x_{it}(y_{it} - x'_t\beta)] = 0 \qquad (3.4)$$

The sample moment condition is:

$$g_T\left(\hat{\beta}\right)=\frac{1}{T}\sum\nolimits_{t=1}^{T}x_{it}\left(y_{it}-x_{it}'\hat{\beta}\right)=0 \tag{3.5}$$

In the presence of one or more endogenous regressors in the x' matrix, the least squares estimator can be biased and inconsistent. The empirical model to be estimated in this study possesses some endogenous regressors, due mainly to potential simultaneity in the growth equation for the industrial sector, and so cannot be estimated by the least squares procedure, like fixed effects (FE), random effects (RE) or the pooled OLS. Such estimation procedures suffer from the endogenous consequences of variable bias (Baltagi 2008). To address the potential issues with a longitudinal approach in a "small-N, large-T" context as in this study, recent studies recommend models specifically designed for such data.

Techniques like panel auto-regressive distribution lag (ARDL) and Driscoll-Kraay standard errors, are suited for managing serial correlation and cross-sectional dependence, offering robust adjustments in large-T settings (Hoechle, 2007; Beck & Katz, 2021). Also, bias-corrected estimators like the common correlated effects (CCE) model or panel corrected standard errors (PCSE) have been used effectively in recent economic studies under similar conditions (Bai, 2021; De Silva & Khamis, 2020; Maira & Fray, 2023).

Considering the techniques mentioned, the study used the P-ARDL model since it caters for lagged values of the response variables (auto-regressive components) and lagged values of regressors (distributed lag components) to capture both past and current effects (Pesaran, Shin, & Smith, 1999; Eberhardt & Teal, 2010). It could accommodate the heterogeneity across different industrial subsectors as different cross-sectional units (Blackburne & Frank, 2007). Finally, the use of panel ARDL helps in handling variables of different orders of integration, as it allows for the estimation of both short- and long-run dynamic effects between relationships among variables under study. If the model has long-run effects, panel ARDL can be used to re-parameterise into an error correction model (ECM) to assess how quickly the dependent variable adjusts to equilibrium after a shock (Hsiao, 2003; Pesaran & Smith, 1995).

Letting z be the instrumental variable, the method of moment estimator is obtained by solving these moment conditions:

$$g\left(\beta\right)=E\left(z_{ti}u_{it}\right)=E\left[z_{it}\left(y_{it}-x_{it}'\beta\right)\right]=0 \tag{3.6}$$

The sample moment condition is given by:

$$g_T\left(\hat{\beta}\right)=\frac{1}{T}\sum\nolimits_{t=1}^{T}z_{it}\left(y_{ti}-x_{it}'\hat{\beta}\right)=0 \tag{3.7}$$

Solving (12), one obtains:

$$\hat{\beta}_{MM(IV)}=\left(\sum\nolimits_{t-1}^{T}z_{it}x_{it}'\right)^{-1}\sum\nolimits_{t=1}^{T}z_{it}y_{it} \tag{3.8}$$

If the number of instruments is greater than the number of estimated parameters, the equation is over-identified (Sabra, 2021). The ideal estimator is a panel

ARDL technique that solves an equation by minimising the vector of empirical moments: $\frac{1}{T}\sum_{t=1}^{T} z_{it}\left(y_{it} - x'_{it}\beta\right)$. It also minimises the weighted quadratic function of moments specified as:

$$J\left(\hat{\beta}\right) = \left[\frac{1}{T}\sum_{t=1}^{T} z_{it}\left(y_{it} - x'_{it}\beta\right)\right]' W \left[\frac{1}{T}\sum_{t=1}^{T} z_{it}\left(y_{it} - x'_{it}\beta\right)\right] \tag{3.9}$$

where W is the weighting matrix.

Given that the time dimension is large compared with the cross-sectional units, the study chooses to include a dynamic term of the dependent variable as an additional explanatory variable in the model and implements the Gunawan et al. (2023) and Kiviet (2020) panel ARDL (Li et al., 2021; Nguyen et al., 2024). So the study specifies a generalised linear dynamic panel model:

$$y_{it} = \alpha y_{i,t-1} + x'_{i,t}\beta + \mu_i + \gamma_t + \epsilon_{i,t} \tag{3.10}$$

where: i represents the cross-sectional dimension defined by the individual industrial sub-sectors being studied, t represents the time dimension defined by the time span 2000-20, y_{it} is the variable under investigation (that is, industrial sector growth), $y_{i,t-1}$ is the first lag of the variable under investigation, μ_i represents the unobserved heterogeneity effect, γ_t is the time dummy which captures shocks that affect $y_{i,t}$ across the individual sub-sectors being studied and $\epsilon_{i,t}$ is the idiosyncratic error term.

To address the specific objectives independently, the study specified and estimated three empirical models in the general framework of specific-to-general modelling while considering the various growth theories which the study benchmarks. On the basis of Equation (9), the three empirical models are specified:

Model 1: Specified to address the first objective of this study; benchmarks the neo-classical growth paradigm. It is specified as:

$$\begin{aligned}\ln\left(ISG_{i.t}\right) = \beta_0 + \beta_1 \ln\left(msov_{i.t-1}\right) + \beta_2 \ln\left(gcf_{i,t}\right) + \beta_3 \ln\left(humc_{i,t}\right) \\ + \beta_4 \ln\left(n + g + \delta\right) + \mu_i + \gamma_t + \upsilon_{i,t}\end{aligned} \quad (3.11);$$

where:

$\ln\left(ISG\right)$ is the natural logarithm of industrial sector growth; Therefore, industrial sector growth (ISG) in the empirical model represents the logarithm of industrial value added (% of GDP, constant US$), consistent with cross-country growth literature (e.g., Solow, 1956; Mankiw et al., 1992; Baltagi et al., 2023b). This ensures that the dependent variable accurately reflects real sectoral expansion and productivity improvements, independent of price distortions. β_0 is the natural logarithm of parameter A; $\ln\left(ISG_{t-1}\right)$ is the natural logarithm of the one-period lag of industrial sector output, $\ln\left(gcf\right)$ is the natural logarithm of gross capital formation, $\ln\left(humc\right)$ is the natural logarithm of human capital, $\ln\left(n + g + \delta\right)$ is the natural logarithm of population growth which is adjusted for extrinsic technological advances, g and head extrinsic depreciation, δ and μ_i, γ_t and $\epsilon_{i,t}$ are as defined in Equation (15).

It can be noted that Energy supply and finance variables were excluded due to data and methodological limitations. Disaggregated time-series data on energy supply for individual industrial subsectors were unavailable for the entire study period, and using aggregate national data would introduce measurement bias. Financial indicators such as domestic credit and interest rates were omitted because of high correlation with gross fixed capital formation, which already captures the investment-finance dimension of industrial growth. Therefore, only gross fixed capital formation, human capital investment, and population growth were retained as consistent and reliable inputs within the exogenous growth framework.

4. Results

Descriptive statistics for variables in Model one

The study undertook a descriptive analysis of the variables applied in Model 1. The role of a descriptive analysis is to view the nature of the occurrence of the variables and the trends across time. The results are presented in Table 1.

The results in Table 1 show that industrial sector growth has an average value of 4538.239, with a broad standard deviation of 7922.768, indicating a lot of variation in growth rates across different industrial sub-sectors. The lowest growth rate recorded is 26, while the highest reaches a remarkable 39270.67, pointing to some sectors experiencing exceptionally high growth. For gross fixed capital formation, the average is 157.7413, but the standard deviation of 216.6401 suggests significant variability in capital investments across the different areas. The minimum value of −38.2951 indicates that some subsectors may have experienced disinvestment, while the maximum value of 975.6124 shows considerable capital investment in others. Population growth averages 3.0654 and has a standard deviation of 0.1954, indicating that population increases are relatively stable across the subsectors.

Table 1. Descriptive statistics of variables across the subsectors over time.

Variable	Std dev	Mean	Min	Max
Industrial sector growth	7922.768	4538.239	26	39270.67
Gross fixed capital formation	216.6401	157.7413	−38.2951	975.6124
Population growth	0.195433	3.0654	2.7816	3.4964
Human capital investment	10.43214	19.3388	−1.1187	39.4307

Source: Author's own computations.

The growth rates range from a low of 2.7816 to a high of 3.4964, suggesting that while there are some differences, they are relatively minor. Human capital investment averages 19.33887 with a standard deviation of 10.4321, indicating a range of investment levels in education and skills across the different sub-sectors. The lowest recorded investment is −1.1187, which might point to a possible lack of investment, while the highest is 39.4307, showing that there is a significant investment in human capital for some sub-sectors.

These descriptive statistics show significant variability among the variables when observing the high standard deviations. This high variability is evidence of a need to investigate these variables. So as to proceed with the investigation, variables were log-transformed to be fit for statistical analysis.

Unit root tests on Model variables

The study examined the unit root test among the study variables to understand their nature of stationarity. Unit root tests on lagged variables were examined with one lag and with a trend. This approach is justified as it ensures the robustness of the stationarity analysis, which is essential for reliable econometric modelling. Using one lag and including a trend, the unit root test accounts for potential autocorrelation and deterministic trends typical in macro-economic variables. The results are presented in Table 2.

Table 2. Im-Pesaran-Shin unit-root test results.

	levels		**First Difference**		**Integration**
Variable	**Statistic**	***p*-value**	**Statistic**	***p*-value**	
Industrial growth	−1.1518	0.1247	−4.0622	0.0000	I (1)
Gross fixed capital formation	−17.479	0.0000	-	-	I (0)
Human capital investment	−1.2657	0.1028	−2.2171	0.0133	I (1)
Population growth	−2.7028	0.0034	-	-	I (0)

Source: Author's own computations.

For industrial growth, the level test statistic is −1.1518 with a *p*-value of 0.1247. This indicates that one cannot reject the null hypothesis of a unit root, suggesting that the series is non-stationary at this level. However, when looking at the first difference, the statistic drops to −4.0622 with a *p*-value of 0, meaning it is highly significant. This result suggests that the first difference in industrial growth is stationary, classifying it as integrated of order I (1), which means it becomes stationary after differencing once. In the case of gross fixed capital formation, the level statistic is −17.479 with a *p*-value of 0, which is highly significant. This allows one to reject the null hypothesis of a unit root, indicating that this series is stationary at levels and classified as I (0), meaning it does not require differencing.

For human capital investment, the level statistic is −1.2657 with a *p*-value of 0.1028, suggesting that it is non-stationary at the 5% significance level. However, the first difference statistic is −2.2171 with a *p*-value of 0.0133, which is significant. This means that human capital investment is also integrated of order I (1), as it becomes stationary after first differencing. Population growth shows a levels statistic of −2.7028 with a *p*-value of 0.0034, which is significant enough to reject the null hypothesis of a unit root, indicating that this variable is stationary at levels and classified as I (0).

The results indicate that gross fixed capital formation and population growth are stationary at levels I (0). At the same time, industrial growth and human capital investment are non-stationary at levels but become stationary after the first differencing I (1). So the variables to be included in the model exhibit mixed orders of integration. This prompted the study to consider efficient estimation methods when there are mixed integration orders.

Multicollinearity check

The study checked for multi-collinearity by examining the correlation coefficients among the study variables. The results of the analysis are presented in Table 3.

Table 3. Pairwise correlation coefficients for study variables.

	Industrial growth	Gross fixed capital formation	Human capital investment	Population growth
Industrial growth	1			
Gross fixed capital formation	0.4037 (0.000)	1		
Human capital investment	0.156 (0.089)	0.4079 (0.000)	1	
Population growth	−0.5114 (0.000)	−0.4548 (0.000)	−0.3894 (0.000)	1

Source: Author's own computations.

The results in Table 3 indicate that industrial growth is correlated positively with gross fixed capital formation (0.4037), meaning that industrial growth also tends to rise as capital formation increases. However, its correlation with human capital investment is weaker (0.156), suggesting a less clear relationship. Notably, there is a strong negative correlation between industrial growth and population growth (−0.5114), indicating that higher population growth may be linked to lower industrial growth. Gross fixed capital formation has a strong positive correlation with human capital investment (0.4079), showing that areas with higher capital investment also tend to invest more in human capital. On the other hand, it correlates negatively with population growth (−0.4548), suggesting that regions experiencing higher population growth may have lower levels of capital formation. Human capital investment is correlated negatively with population growth (−0.3894), indicating that investment in human capital tends to decrease as population growth increases.

Optimal lag selection for the model

The study determined the optimal lag structure for the model using the Akaike information criterion (AIC), ensuring the most efficient balance between model fit and complexity. The findings are presented here (Table 4):

Table 4. Optimal lag selection among variables.

Variable	Most common lag
Industrial growth	2
Gross fixed capital formation	0
Human capital investment	2
Population growth	1
Optimal lag structure	(2, 0, 2, 1)

Source: Author's own computations.

The results indicate that industrial growth and human capital investment are best represented with a lag of 2, signifying that their respective past values could influence their current states significantly. This suggests that the effects of these variables manifest over a two-period horizon, necessitating the inclusion of two lags to capture their dynamics accurately. Conversely, gross fixed capital formation is determined to have an optimal lag of 0, indicating that its current value explains its effect sufficiently without the need for historical lags. Also, population growth exhibits a requirement for one lag, suggesting that its preceding value contributes meaningfully to its current level. The final model lag structure is represented collectively as (2, 0, 2, 1).

Cross Sectional Dependence Test

The study tested for cross-sectional dependence among the study variables given that the data consist of multiple industrial sectors operating within the same national economic environment. Since these sectors are likely influenced by common macroeconomic shocks, policy interventions, and market conditions, their error terms may be correlated across panels. To account for this possibility, the Pesaran (2004) Cross-Sectional Dependence (CD) test was employed. This test is appropriate for panel datasets with small cross-sectional dimensions (N) and moderate time periods (T), and it assesses whether residuals are correlated across units. Detecting cross-sectional dependence is crucial, as its presence can bias standard error estimates and lead to inefficient or invalid inferences if not addressed (**Table 5**).

Table 5. Group variable: ID, Number of groups: 5, Average no. of observations: 27.50, Panel is: unbalanced.

Variable Tested	CD Statistic	*p*-value	Average Correlation (corr)	Absolute Correlation (|corr|)
Residuals (resid)	14.76	0.000	0.995	0.995

The results of the Pesaran (2004b) Cross-Sectional Dependence (CD) test, presented in **Table 4**. X, reveal a CD statistic of 14.76 with a *p*-value of 0.000. Given that the *p*-value is well below the 1 percent significance level, the null hypothesis of cross-sectional independence is strongly rejected. This indicates the presence of strong cross-sectional dependence among the industrial sectors included in the study. The high average correlation coefficient (0.995) further confirms that the residuals are highly correlated across sectors.

This outcome suggests that Uganda's industrial sectors are jointly influenced by common macroeconomic factors such as national industrial policy, infrastructure conditions, fiscal interventions, and market-wide shocks. In other words, developments in one sector are likely to affect others, reflecting the integrated nature of the country's industrial system. The detection of cross-sectional dependence implies that standard estimation techniques assuming independent residuals may yield biased results. Consequently, the study employed the Driscoll–Kraay estimator as a robustness check to ensure valid inference under conditions of cross-sectional dependence.

Hausman test for an appropriate estimator

Table 6. Hausman test results.

	(b) mg	(B) pmg	(b − B) Difference	sqrt(diag(V_b − V_B)) S.E.
Gross fixed capital formation	0.95643	−0.4953	1.45167	1.33748
Human capital investment	0.45494	−0.4272	0.88213	1.48205
Population growth	11.0097	−7.1989	18.2086	26.4595
chi2(3)			= (b − B)'[(V_b − V_B)^(−1)](b − B)	
			= 0.85	
Prob>chi2			= 0.8374	
			(V_b-V_B is not positive definite)	

b = consistent under Ho and Ha; obtained from xtpmg; B = inconsistent under Ha, efficient under Ho; obtained from xtpmg; Test: Ho: difference in coefficients not systematic; Source: Author's own computations.

The results in **Table 6** compare the estimates obtained from the mean group (mg) estimator and the pooled mean group (PMG) estimator for the three variables. The differences in coefficients between these two estimators are substantial, with values of 1.45167, 0.88213, and 18.2086 for the respective variables. However, the chi-squared statistic is 0.85, accompanied by a high p-value of 0.8374. This high p-value suggests that one cannot reject the null hypothesis, indicating that the coefficient differences observed are not statistically significant. In practical terms; this outcome implies that the pmg estimator is more efficient in this context. The lack of significant differences between the two estimators means that the pmg approach, which pools the data across groups and assumes a typical long-run relationship, is an appropriate choice for analysis. It leverages the efficiency of pooled estimation, allowing for more precise parameter estimates while reflecting the underlying relationships among the variables.

Before estimating the PMG-ARDL model, a panel cointegration test was conducted to confirm the existence of a long-run relationship among the study variables. The Westerlund (2007) error-correction-based panel cointegration test was preferred because it performs well in small-N, large-T samples and allows for cross-sectional dependence across subsectors (Persyn & Westerlund, 2008; Eberhardt & Teal, 2010). The results confirmed the presence of cointegration, as the group and panel test statistics were significant at the 5 percent level, indicating that industrial sector growth, gross fixed capital formation, human capital investment, and population growth move together in the long run. This finding validates the use of the PMG-ARDL approach for analysing both short-run dynamics and long-run equilibrium relationships (Pesaran, Shin, & Smith, 1999).

Given that the study examines the influence of key input factors on industrial growth across five sectors in Uganda, the presence of cross-sectional dependence is contextually expected. The sectors operate within the same macroeconomic environment and under common industrial and fiscal policies, leading to correlated shocks and intersectoral spillovers. Accordingly, while the Pesaran CD test confirmed cross-sectional dependence, this dependence reflects shared national influences rather than model misspecification. Therefore, the study proceeded with the PMG-ARDL estimation to extract the long-run equilibrium effects and short-run adjustment dynamics among industrial growth, capital formation, human capital investment and population. A robust test using the Driscoll-Kraay estimator was employed.

The PMG estimator was retained as the baseline model because it effectively captures both short-run and long-run relationships in dynamic heterogeneous panels and remains valid under moderate cross-sectional dependence. Moreover, with a small cross-section (N = 5) and moderate time dimension (T = 23), the Common Correlated Effects (CCE) estimator was unsuitable, as it requires large N for reliable estimation of cross-sectional averages. Instead, the Driscoll-Kraay estimator was employed as a robustness check to correct for potential bias from cross-sectional dependence (Table 7).

PMG – ARDL Results

Table 7. Panel ARDL results.

D. Industrial growth	Coefficient	Std err	z	$p > z$	[95% conf	Interval]
Gross fixed capital formation	0.075943	0.063276	1.2	0.230	−0.04808	0.199961
Human capital investment $_{\text{L2.}}$	−0.94987	0.122096	−7.78	0.000	−1.18917	−0.71057
Population growth $_{\text{L1.}}$	3.028076	0.919533	3.29	0.001	1.225826	4.830327
Short run						
Error correction term	−0.37913	0.07361	−5.15	0.000	−0.5234	−0.23485
D. (Gross fixed capital formation).	−0.06831	0.031211	−2.19	0.029	−0.12948	−0.00714
D. (Human capital investment)	−2.98583	0.720522	−4.14	0.000	−4.39803	−1.57363
D. (Population growth)	2.689654	0.594328	4.53	0.000	1.524792	3.854516
Constant	2.473465	0.455799	5.43	0.000	1.580116	3.366815

Source: Author's own computations.

The panel ARDL results for Model 1 provide insights into the determinants of industrial sector growth in Uganda as interpreted here:

Gross fixed capital formation and industrial sector growth in Model 1

The results show that, in the long run, gross fixed capital formation (GFCF) exhibits a positive relationship with industrial growth, which however is not statistically significant (coefficient = 0.0759, *p*-value = 0.23). This contradicts the study's hypothesis (H1), which anticipated a significant positive contribution of

GFCF to industrial growth. While investments in fixed capital are expected theoretically to boost industrial productivity, the findings may reflect inefficiencies in capital allocation, poor infrastructure quality, or under-used investments in Uganda's industrial sub-sectors. For instance, research by Boamah et al. (2018) found that while GFCF affects economic growth positively in 18 Asian economies, inefficiencies and weak institutional frameworks could limit its effect in underdeveloped economies. Similarly, Stupnikova and Sukhadolets (2019) found that the effectiveness of GFCF in promoting growth is influenced heavily by macro-economic stability and efficient infrastructure management.

In the short run, GFCF demonstrates a statistically significant negative relationship with industrial growth (co-efficient = −0.0683, p-value = 0.029). This suggests that increases in GFCF disrupt industrial sector performance in the short term, possibly due to adjustment costs, delayed returns on capital investments or misaligned investment priorities. For example, Nigo and Gibogwe (2023) emphasised that while GFCF promotes industrial value added in the long run, its short-term effect can be negligible or disruptive due to capital mismanagement and poor planning in sub-Saharan Africa.

Human capital investment and industrial sector growth in Model 1

The results for human capital investment reveal a consistently negative effect on industrial sector growth in both the short and long run, aligning with the H2 of the study. In the long run; the co-efficient is strongly negative (−0.9499, p-value < 0.01), indicating that human capital development is not translating effectively into industrial growth. This outcome suggests possible inefficiencies in Uganda's education system, a mismatch between workforce skills and the needs of industrial sub-sectors, or a structural underemployment of skilled labour. Supporting these findings, Adejumo et al. (2013) indicate that while human capital has influenced industrial value-added in Nigeria, its contribution to industrial output remains weak due to systemic challenges in translating educational attainment into productive outputs.

In the short run, the negative effect is even more pronounced, with a coefficient of −2.9858 (p-value < 0.01). This sharp decline may reflect immediate adjustment costs, delays in workforce readiness or the inability of industrial sectors to absorb newly skilled labour effectively. Similar findings are observed in studies from sub-Saharan Africa, where Teixeira and Queirós (2016a) show that the lack of appropriate industrial structures to integrate educated individuals often results in negative returns from human capital investments.

These outcomes contrast with global expectations that human capital drives productivity and growth positively. Cinnirella and Streb (2017), examining historical data from Prussia, emphasise that the ability of human capital to enhance innovation and productivity depends on well-aligned industrial systems and efficient labour use strategies.

Population growth and industrial sector growth in Model 1

Population growth emerges as a strong and consistent driver of industrial growth in both the short and the long run, aligning with H3 of the study. In the long run; the co-efficient is positive and highly significant (3.0281, p-value = 0.001), indicating that a growing population contributes to industrial sector growth by expanding the labour force and increasing market demand for industrial goods. This finding aligns with evidence from Kahyarara (2020), who showed that population growth in Tanzania influences labour productivity and economic output positively, particularly in labour-intensive sectors.

This positive effect persists in the short run, with a significant co-efficient of 2.6897 (p-value < 0.01). The results suggest that population growth sustains industrial sector activity in the short term by providing a steady workforce and driving consumer demand. Similarly, Khan et al. (2021) found that the working-age population in South Asia supports industrial expansion and urbanisation, further enhancing industrial sector growth. However, such benefits depend on having sufficient industrial capacity to absorb the growing labour force.

The negative and highly significant co-efficient of the error correction term (−0.3791, p-value < 0.01) confirms the stability of the model and indicates the presence of a long-run equilibrium relationship among the variables. Roughly 37.91% of deviations from the long-run equilibrium are corrected in each period, ensuring that the system gradually returns to balance over time. This aligns with Wonyra (2018), who indicated that industrial sector performance is influenced by demographic dynamics, with long-term adjustments ensuring sustained growth despite initial disequilibria.

Comparison of PMG-ARDL and Driscoll-Kraay Estimation Results for Industrial Growth Determinants

Table 8. PMG-ARDL and Driscoll-Kraay estimation results.

Variable	PMG-ARDL Long-run Coefficient	p-value	Driscoll-Kraay (FE) Coefficient	p-value
Gross Fixed Capital Formation)	0.076	0.230	0.404	0.002
Human capital investment	−0.950	0.000	−0.098	0.707
Population growth	3.028	0.001	8.725	0.02
$ECT(-1)$	−0.379	0.000	—	—
Observations	115		115	
Within R²	—		0.546	
F-statistic	—		41.74	

The results for gross fixed capital formation show contrasting outcomes between the PMG-ARDL and Driscoll-Kraay estimations. Under the PMG model, the coefficient for GFCF is positive (0.076) but statistically insignificant (p = 0.230), implying that, in the long run, investment in physical capital does not exert a strong or consistent impact on industrial output across Uganda's sectors. This weak result could reflect inefficiencies in investment allocation, delays in capital utilization, or the dominance of non-productive capital spending. However, when cross-sectional dependence is accounted for using Driscoll-Kraay standard errors, the coefficient becomes both positive and significant (0.404, $p = 0.002$). This shift suggests that ignoring inter-sectoral linkages in the PMG model likely masked the true contribution of capital accumulation to industrial growth. The robust DK result therefore confirms that investment is indeed a key determinant of industrial performance once shared policy and macroeconomic effects are controlled for (**Table 8**).

For education expenditure, the PMG results indicate a strong negative and statistically significant coefficient (−0.950, $p = 0.000$), implying that increases in government spending on education are associated with lower industrial output in the long run. This counterintuitive finding may stem from a structural mismatch between education priorities and industrial skill demands, where resources are directed toward general education rather than technical or vocational training relevant to industry. The Driscoll-Kraay results, however, show that this relationship becomes statistically insignificant (−0.098, $p = 0.707$) when cross-sectional dependence is considered. This suggests that the observed negative relationship in the PMG model is not robust and may be capturing transient or correlated sectoral effects rather than a genuine causal link. The insignificance under DK reinforces the idea that education spending's impact on industrial productivity is delayed or indirect, requiring better targeting toward industrially relevant human capital.

The findings for population, are consistent and positive across both models, confirming it as the most reliable driver of industrial growth in Uganda. Under the PMG model, the coefficient is large and highly significant (3.028, $p = 0.001$), showing that population growth promotes industrial expansion by enlarging the labour force and domestic market base. The Driscoll–Kraay results amplify this relationship, with an even higher coefficient (8.725, $p = 0.020$), indicating that once cross-sectoral interdependencies are accounted for, the contribution of population growth to industrial output becomes even stronger. This consistency across models highlights that population dynamics through labour availability, market demand, and urbanization, play a central and robust role in driving Uganda's sectoral industrial performance.

In comparing the two estimation approaches, the PMG-ARDL model serves as the structural framework, capturing both short-run dynamics and long-run equilibrium relationships, while the Driscoll-Kraay model functions as the robustness check against cross-sectional dependence. The PMG model's significant error correction term (−0.379, $p = 0.000$) confirms the existence of long-run cointegration among the variables, validating its use for dynamic analysis. However, the presence of strong cross-sectional dependence across sectors warranted the use of Driscoll-Kraay standard errors to ensure reliable inference. The consistency in the positive effect of population and the strengthened significance of capital formation under DK estimation confirm the robustness of these determinants. In contrast, the loss of significance for education expenditure underscores the need for better-aligned human capital proxy variables. Together, both models provide a coherent and reliable picture: PMG identifies the underlying long-run structure of industrial growth, and Driscoll-Kraay confirms that these relationships remain valid when accounting for shared sectoral shocks.

5. Conclusions

The findings reveal that capital formation remains central to Uganda's industrial growth trajectory, though its effectiveness depends greatly on the efficiency of investment utilization. While long-run results suggest a weak direct contribution, the robustness analysis indicates that when intersectoral linkages and shared policy effects are considered, investment becomes a strong driver of industrial output. This points to structural inefficiencies rather than a lack of investment impact, issues such as delayed project execution, poor infrastructure quality, and misaligned investment priorities likely constrain capital productivity. Strengthening institutional capacity, improving project management, and channelling investments toward industrially strategic areas are therefore critical for enhancing the growth effects of capital formation.

In contrast, human capital investment, represented by education expenditure, shows a weak and inconsistent relationship with industrial growth. The negative long-run coefficient suggests that current education spending has not translated into productivity gains, reflecting both a mismatch between educational output and industrial skill needs, and the limited scale of Uganda's investment in human capital. Moreover, education expenditure may be a weak proxy for industrially relevant skills, as it captures general education spending rather than targeted investments in technical or vocational training. This underscores the need for Uganda to expand and reorient its education policy toward skills development aligned with industrial requirements to foster a more effective link between human capital and industrial performance.

Finally, population growth emerges as a robust and consistent engine of industrial expansion. The positive and significant relationship across all estimations highlights Uganda's demographic advantage through an expanding labour force and growing domestic market that stimulate both production and consumption. However, the long-term benefit of this demographic momentum will depend on the country's ability to create sufficient employment opportunities, upgrade industrial capacity, and integrate young workers into productive sectors. These findings emphasize that Uganda's path to sustainable industrial development lies in improving the efficiency of capital use, reforming education policy to produce industry-ready skills, and harnessing population growth through job-rich industrialisation strategies.

6. Recommendations

This study therefore makes the following recommendations:

To maximize the growth impact of gross fixed capital formation, Uganda must focus on improving the efficiency and quality of its investment processes. This entails strengthening project appraisal and monitoring systems, ensuring transparent procurement, and aligning infrastructure and industrial investments with long-term productivity goals. The government and private sector should jointly prioritize capital projects with high industrial spillover potential, while enhancing institutional capacity for project execution and maintenance. Improving capital efficiency will help translate investment spending into tangible industrial output and long-run growth.

Uganda should reorient its education and training systems toward developing technical and vocational skills that directly support industrial growth. Policy efforts should focus on strengthening industry-education linkages, expanding vocational programs, and aligning curricula with industrial technology and labour demands. However, the weak relationship between education expenditure and industrial output also suggests that the proxy used may not fully capture sector-specific skill development. Future research should incorporate more precise indicators, such as vocational enrolment or industrial training data, which could not be applied in this study due to limited data availability across sectors.

With population growth consistently supporting industrial output, Uganda should leverage its demographic advantage by creating more productive employment opportunities in manufacturing and related sectors. This can be achieved by expanding industrial parks, supporting small and medium-sized enterprises (SMEs), and promoting labour-intensive industries that absorb large segments of the workforce. Complementary investments in urban infrastructure, energy, and transport will enhance industrial clustering and market access. Proactive planning is essential to transform demographic growth into a sustainable source of industrial development, income generation, and social stability.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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