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Factor Inputs and the Growth of the Manufacturing Sector among the East African Community Member States: Testing the Efficacy of the Extended Neoclassical Growth Hypothesis

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Abstract: The study aims to examine the relationship between input factors and growth rates in the output of the manufacturing sector in the five East African Community (EAC) member states. The relatively small manufacturing sector's GDP contribution to the combined GDP of the EAC member nations is the driving force behind this inquiry. We evaluate the applicability of the 1992 Mankiw, Romer, and Weil neoclassical growth framework and its subsequent developments in this study. Using a linear dynamic panel model, we utilize this methodology to obtain estimations using the first difference generalized method of moments (D-GMM. The study's findings make it clear that the gross capital formation input component is essential for forecasting changes in the rate of expansion of the manufacturing sector's output. Conversely, the East African Community's member states' manufacturing sector output growth does not seem to be much impacted by variables such as adjusted population growth and human capital. Based on our research, the East African Community (EAC) member states' output fluctuations in the manufacturing sector may be partially explained by the neoclassical growth model and its expansions. This shows that the growth framework that has been chosen might not be thorough enough to provide a thorough assessment of the variables influencing the expansion of the manufacturing sector output in the EAC member nations. The findings of our study indicate that the manufacturing sector's output growth in the EAC member states could be enhanced through the implementation of policies and programs that provide incentives for augmenting capital stocks. This can be accomplished by increasing investments from the domestic private sector as well as foreign direct investments.

Keywords: *Manufacturing sector output, extended neoclassical growth theory, D-GMM, EAC member states.*

1. Introduction

The manufacturing industry is widely recognized as a significant indicator of economic progress on a global scale. Scholarly works like those of Su and Yao (2017) and Herman (2020) demonstrate the critical role this sector plays in facilitating structural transformation, creating worthwhile employment opportunities, and fostering sustainable economic growth. Saba and Ngepah (2021) state that ongoing economic expansion is attributed to the manufacturing industry. Aiginger and Rodrik (2020) state that it is commonly known that investments in the manufacturing sector can spur economic expansion in all global economies. It is well known that a country's ability to grow and prosper is influenced by its industrial sector. Consequently, the United Nations Conference on Trade and Development UNCTAD (2020) noted that developed economies can be identified by allocating a significant portion of their budget to this sector and making it a priority. World Bank (2021) research states that the East African Community (EAC) nations' manufacturing sector's output contribution to GDP has been inadequate since the 1960s, averaging between 5.5% and 12%. This outcome is comparatively unsatisfactory when compared with the manufacturing sector's average value generation among the world's top manufacturers, which is 30%, according to the World Bank's 2021 report.

The existing literature points out that the proliferation of industrialized nations can be attributed to substantial investments in the manufacturing industry. However, new research, as reported by Xia (2019), Behuria (2019), and the East African Economic Outlook (2021), suggests that this claim is not accurate for the East African Community's member nations. The absence of value addition in the transportation of essential commodities, such as coffee, has impeded the progress of the manufacturing sector and as affirmed by UNIDO (2021), subsequently hindered the overall economic development of the East African Community (EAC) member states. Numerous scholarly works have employed the extended neoclassical growth framework to examine the underlying factors contributing to variations in economic growth across various countries. This method has been used by numerous scholars; some prominent examples are Almas (2001) and Hoeffler (2002). Mankiw, Romer, and Weil (1992) built on Solow's 1956 neoclassical growth model by emphasizing the role that human capital along with labor, physical capital, and exogenous technology plays in determining long-term growth.

The nations that comprise the East African Community (EAC) have received relatively less attention than developed countries and OECD members in the majority of previous studies that have used the extended neoclassical growth framework to examine differences in economic growth between countries. The objective of this study is to establish a reference point for the extended neo-classical growth model under the previously mentioned conditions. This would enable a more thorough investigation of the possibility that variations in factor input endowments could explain output differences in the manufacturing sector among member nations of the East African Community. It is anticipated that the process of contrasting significant growth models like the extended neoclassical growth model will yield insightful information about how well the selected growth framework works. Furthermore, this approach has the potential to propose substitute policies that could prove to be highly beneficial in harmonizing the policies that the member nations of the East African Community (EAC) undertake to enhance the overall progress and expansion of their nations.

The current collection of empirical research concerning the connection between input factors and growth in the manufacturing sector has predominantly centered on developed nations. There is a deficit of study on the nations that make up the East African Community, and only a small number of studies have been done on the entire African continent. Between 2008 and 2019, Olarewaju and Msomi (2021) examined the influence of physical capital on the Southern African Development Community's industrial sector. Anyanwu (2018) used the IVSLS technique to examine how human capital contributed to the growth of manufacturing value added (MVA) and the manufacturing sector in Africa between 1990 and 2011. The study conducted by Obere, Thuku and Gachanja (2013) employed annual time series data spanning 1963-2009 and used the auto-regression vector approach to investigate the correlation between urban population and growth in Kenya. Most of the extant literature has centred on investigations conducted within a single country, using time series analytical methodologies. This highlights the need for the current study to employ an alternative analytical approach. Furthermore, a significant proportion of the extant research has omitted the period following the global financial crisis, from mid-2007 to early 2009. This study makes a valuable contribution to the current body of literature by using panel data spanning the period 2000-2020 to investigate the effect of input factors on the growth of the manufacturing sector in East African nations.

2. Empirical Literature Review

This subsection provides an overview of the existing empirical literature pertaining to the topic under investigation in the present study. This study emphasizes the interconnected fields of investigation, specifies the respective contributors, outlines the extent and approach used, and presents pivotal outcomes. Anyanwu (2018) investigated the contribution of human and physical capital to the increase of manufacturing value added (MVA), measured as a percentage of GDP, in Africa's manufacturing sector. The years 1990–2011 were covered by the time series data used in the analysis. The researcher used fixed effects in the instrumental variable two-stage least squares (IV-2SLS) method for both years and sub-regions. His research findings show that the expansion of the manufacturing sector across the continent is influenced differently by several human capital indices. The research findings indicate that secondary education exhibits a significant negative correlation with MVA, while tertiary education displays a robust positive correlation with MVA. According to the study's findings, there are additional variables that may be more erratic in nature, such as how natural resources are used, domestic investments made by the government, trade openness, foreign direct investment (FDI) stock, age dependency, private sector credit, social and political globalization, civil war, and the level of energy use.

Taiwo, Adebayo, and Oluwaseun's (2021) study set out to determine how physical capital development affected the growth of the manufacturing industry in sub-Saharan Africa between 1986 and 2018. The assessment of physical capital was based on primary, secondary, and tertiary enrolment, as well as the total labor force. Meanwhile, the evaluation of industrial and manufacturing development was based on industrial value added. The findings of the study demonstrate that, although the use of physical capital has contributed to the growth of industrialization, indicators of human capital have significantly and favorably affected value added in the industrial sector. According to the research, the development of the industrial sector was affected negatively by physical capital. Research by Olarewaju and Msomi (2021) looked at how physical capital affected South Africa's manufacturing sector from 2008 to 2019. The study used a panel data set including 696 observations from 56 general manufacturing enterprises collected over a 12-year period. In addition to static (two-stage least squares, fixed effect, and random effect) and dynamic panel regression analyses.

The study employed the value-added intelligent co-efficient model and the two-step system generalized method of moments (SGMM). The research findings indicate a significant and evident correlation between the Southern African Development Community's manufacturing, physical capital, and suboptimal return on assets. The study found a significant and direct correlation between human and structural capital and return on assets. However, capital used showed an insignificant and inverse relationship. Underwriting risk, insurer size and leverage was found to have a significant inverse effect on return on assets. In the Southern African Development Community, a U-shaped association was found between physical capital and the industrial sector. The objective of Le, Duy, and Ngoc's (2019) study was to assess the relationship between physical capital and foreign direct investment (FDI) and labor productivity in Vietnam's manufacturing sector. The study looked at time series data from 1986 to 2014 to assess the degree and direction of the impact that physical capital and foreign direct investment (FDI) have had on Vietnam's manufacturing sector. The link under inquiry was examined using the cointegration regression approach in the research. The existence of cointegration among the variables has been confirmed by the limit test results.

According to Toda and Yamamoto's Granger causality research, the physical capital index and foreign direct investment have a one-way relationship with the productivity of manufacturing workers. The study's empirical findings supported the positive and long-lasting benefits of physical capital and foreign direct investment on worker productivity in Vietnam's manufacturing sector with strong statistical evidence. These findings imply that employees must enhance their skills and expertise consistently, while policymakers must implement concrete strategies to augment physical capital. Babasanya, Maku, and Amaefule (2020) conducted a study to examine the effects of national savings and the labor force on the manufacturing sector output of Nigeria for 35 years, from 1985 to 2019. This information was collected from a variety of sources, including the World Development Index (WDI), the National Bureau of Statistics (NBS), and the Central Bank of Nigeria's (CBN) 2017 statistical bulletins. The data was analyzed using the vector error correction model (VECM). The results of the VECM analysis show that the labor force and national savings have a long-term positive impact on manufacturing sector production, whereas currency rates and inflation have a long-term negative impact. The study's findings show how a number of important variables, including national savings, manufacturing labor force participation, inflation, and currency rates, affect the manufacturing sector's ability to grow and remain sustainable.

Consequently, it was recommended that the government undertake a comprehensive evaluation of the manufacturing industry and implement a restructuring plan, which should involve providing financial support to the sector and increasing its utilization of domestically sourced raw materials. The relationship between the labor force and the manufacturing sector was examined in Ogundipe and Olarewaju's (2020) study using data from the Economic Community of West African States (Ecowas). After accounting for technology, the Ecowas region's industrial sector's performance was assessed using static panel regression analysis on time series data covering the years 1990–2019. The analysis concluded that, after taking technical concerns into account, labor force composition had a significant effect on the industrial sector of the Economic Community of West African States (Ecowas). The region's manufacturing production was positively impacted by two important factors: individual internet usage and the existence of safe internet servers. Okunade (2018) used an autoregressive distributed lag (ARDL) model to examine how Nigerian manufacturing company output was impacted by labor force participation. The time series data for the study covered the years 1981–2016. The research findings indicate a positive but negligible correlation between the labor force and manufacturing business output.

However, it is noteworthy that most productive firms in Nigeria are experiencing gross underuse of their capacity. The study uncovered a significant degree of labour force underuse in Nigerian manufacturing enterprises, which reduced the favourable effect of labour force on elucidating the growth in production of Nigerian manufacturing firms. The report recommended that policymakers and the government implement measures aimed at enhancing the workforce in manufacturing firms. These measures include facilitating the acquisition of modern machinery at affordable rates, prioritizing a consistent power supply and promoting the appreciation of the workforce in Nigeria. Zhou (2019) developed a general equilibrium model that integrated Rostow's research on the function of a principal separator in the modernization process. The author presented evidence that increased population size facilitated the manufacturing sector's adoption and utilization of technology, leading to higher returns on scale. Determining the elasticity of demand for agricultural products was crucial in evaluating the advantages of population increase or technological developments in agriculture for the manufacturing sector.

An analysis of China and the United Kingdom during the early 1800s demonstrated that research and development were crucial factors for achieving consistent growth. It was also found that attaining autonomous modernisation necessitated a combination of a sufficiently large consumer market and a supply side characterised by advanced technologies. The extant literature is deficient in its coverage of the member states of the East African Community (EAC). The endogeneity of some explanatory variables in the output model has been addressed by a small number of writers using panel data analytical methods, while a significant body of empirical research has used time series analytical methods. This research addresses the problem of endogeneity of regressors in an output function by utilizing panel data analytical methods on factual data related to the member countries of the East African Community (EAC) to expand the body of existing scholarly literature on the subject.

3. Methodology

Data, Research Design and Research Approach: This study's research methodology is quantitative in nature, and data analysis is done utilizing a longitudinal research design. The variables utilized in the pan-African model are derived from the World Bank's development indicators.

Model Specification: Within the parameters of the Mankiw, Romer, and Weil (1992) neoclassical growth model and its extension, the current study employed a multiple linear regression model. The empirical model incorporates study variables that are derived from the theoretical model adopted. The present study examines a linear dynamic panel model, expressed as follows:

$yit = \alpha yi, -1 + x'i,t\beta + \mu i + \gamma t + \epsilon$_(i,t) (1)

where y_it represents the dependent variable, $\alpha yi,-1$ denotes the lagged dependent variable, $x'i,t$ is the vector of independent variables, β represents the corresponding coefficients, μi and γt are the in dividual and time fixed effects respectively, and ϵ_(i,t) represents the error term.

The cross-sectional component of this study is represented by the variable "i" and is specific to each of the different nations that are being studied. The variable "t" represents the temporal dimension, which is determined between 2000 and 2020. The variable being examined is called yit, and it has to do with the expansion of the manufacturing industry. The initial lag of the variable under investigation is represented as $yi,\ t-1$. The stimulus variables in the model are denoted by $x_{it}{}'$. The partial slope coefficient of the dynamic variable is represented by *a*, while the gradient coefficient vector of the regression variables is represented by β. The unobserved heterogeneity effect is represented by μ_i. The time dummy, denoted by γ_t, captures shocks that affect $y_{i,t}$ across the individual countries being studied. Finally, the idiosyncratic error term is represented by $\epsilon_{i,t}$. The methodology employed in constructing the empirical model for estimation adheres to the framework established by Mankiw, Romer and Weil (1992).

Specifically, we adopt a non-linear constant return to scale (CRS) production function, which takes this form:

$$equalmsy_{i.t} = Agcf_{i,t}{}^{\beta_2} humc_{i,t}{}^{\beta_3} (n + g + \delta)_{i,t}{}^{(1-\beta_2-\beta_3)} e^{(\mu_i+\gamma_t+\epsilon_{i,t})};\ 0 < \beta_2 +\ \beta_3 < 1 \quad (2)$$

The expression being presented is denoted as β_2 multiplied by *humc* subscripted by i and t. $(n + g + \delta)_{i,t}$The equation presented in (2) is a mathematical expression that involves the exponential function and several parameters, namely β_2,β_3,μ_i,γ_t, and $\epsilon_{i,t}$. The inequality constraint $0 < \beta_2 +\ \beta_3 < 1$ is also specified.

The variable $msy_{i,t}$ represents the value added in current US dollars of the manufacturing sector output of a given country *i* at a specific time *t*. The variable A denotes a productivity parameter that is determined exogenously. Meanwhile, $gcf_{i,t}$ refers to the gross capital formation of country *i* at time *t*, measured in current US dollars. The measure of human capital in country *i* at time *t*, is represented by the variable $humc_{i,t}$which is calculated as the total *per capita* expenditure on investment in education in current US dollars. Meanwhile, the variable $(n + g + \delta)_{i,t}$ denotes the population growth rate of country *i* at time *t*, which is adjusted for extrinsic technological advances, represented by g, and head extrinsic depreciation. The aforementioned equation (1) defines the variables μ_i, γ_t and $\epsilon_{i,t}$, while δ, as in the augmented Solow growth model (Mankiw, Romer and Weil 1992), represents a distinct parameter.

Additionally, *e* denotes Euler's constant. By defining $(1 - \beta_2 - \beta_3)$ as β_4 and applying the natural logarithm to the model variables, we can linearise equation (2) and introduce a dynamic dependent variable as a potential explanatory variable. This results in a dynamic linear econometric model that can be used for empirical estimation as:

$$Ln(msy_{i.t}) = \beta_0 + \beta_1 Ln(msy_{i.t-1}) + \beta_2 Ln(gcf_{i,t}) + \beta_3 Ln(humc_{i,t}) + \beta_4 Ln(n + g + \delta) + \mu_i + \gamma_t + \upsilon_{i,t} \quad (3);$$

Assuming that *Lne* equals 1.

Equation (3) involves several variables expressed in natural logarithmic form. Specifically, *Ln(msy)* represents the natural logarithm of output in the manufacturing sector, while β_0 corresponds to the natural logarithm of parameter A. Additionally, $Ln(msy_{t-1})$ denotes the natural logarithm of the manufacturing sector output from the previous period, $Ln(gcf)$ refers to the natural logarithm of gross capital formation, $Ln(humc)$ pertains to the natural logarithm of human capital, and $Ln(n + g + \delta)$ signifies the natural logarithm of population growth that has been adjusted for extrinsic technological advancements, as well as extrinsic depreciation, δ, and intrinsic growth, g. Finally, μ_i, γ_t and $\epsilon_{i,t}$, are defined as in equation (1).

Diagnostic Checks: Diagnostic checks refer to the process of evaluating and verifying the accuracy and reliability of data or information. The research conducts critical diagnostic evaluations on the variables included in the empirical model to assess the behavior of the data before estimation (pre-estimation diagnostic checks) and the validity and/or robustness of the estimates following estimation (post-estimation diagnostic checks). Pre-estimation tests comprise the first three diagnostic evaluations that are discussed below; post-estimation diagnostic assessments comprise the other evaluations: (i) One way to assess how much there are linear correlations between the predictor variables is to perform a multicollinearity study. This was done using pairwise correlation and the results were not greater than ±0.8, thus indicating no multicollinearity, as noted by Rendón (2012). (ii) Tests for unit roots using panel data. Because the panel data under analysis is not firmly balanced and has a time dimension that is bigger than its cross-sectional dimension (i.e., T > n), Choi (2001) proposed the Fisher-type panel unit root test, which is applied in the current study. This test is thought to be appropriate for panel data characterized by these conditions.

(iii) The panel was subjected to a cointegration test. In this study, long-term correlations between the variables in the empirical model are examined by the incorporation of a cointegration test into a panel model. The study makes use of the Johansen-Fisher cointegration test technique, which is appropriate for variables with different degrees of integration and was created for panel data. This methodology is based on the work of Maddala and Wu (1999) (iv) The Wald tests for simple and composite linear hypotheses are the main topic of this research. This study's main goal is to ascertain the entire regression's statistical significance. The null hypothesis, according to which every coefficient in the calculated regression model is equal to zero, is evaluated by this statistical test. When the Wald chi-square statistic's estimated probability value is equal to or less than the pre-established significance criterion of 0.05, the null hypothesis is rejected. (v) This study's main objective is to investigate serial correlation. The Arellano-Bond test, which Arellano and Bond originally proposed in 1991, is used in this work to determine if the first-differenced residuals have a serial correlation.

In particular, the test performs D-GMM estimation and then looks for the existence of AR (1) and AR(2) (vi) The residuals' normality test. The normal distribution of the expected residuals is assessed in the current study using the Jarque-Bera (JB) normality test. The JB test is used to assess the null hypothesis, which states that the residuals have a normal distribution. When the estimated probability value of the chi-square statistic is less than or equal to the pre-established significance level of 0.05, the Jarque-Bera test considers the null hypothesis to be rejected. (vii) To assess a model's validity, a statistical method known as the over-identifying restrictions test establishes if the additional limits added to the model are statistically significant. Here, we investigate the over-identifying limits using the Sargan test, which assesses the general validity of the tools used for the D-GMM estimation. When considering the instruments collectively, the validity of each one is based on the null hypothesis. If the reported chi-square probability value in a statistical hypothesis test is less than or equal to the predetermined significance level of 0.05, the null hypothesis is deemed rejected.

(viii) In econometrics, the Hausman specification test is a statistical method used to assess which model fixed effects or random effects are more appropriate for a certain dataset. The Hausman specification test is used in this work to determine whether or not there is a systematic variance in the coefficients among the D-GMM, the IV estimator, and the OLS estimator. The basic premise is that the coefficients between the respective estimates produced by the two estimators do not differ systematically. Within the framework of statistical hypothesis testing, the null hypothesis is considered rejected when the reported chi-square probability value is equal to or less than the predetermined significance threshold of 0.05. If the null hypothesis is disproved, the IV estimator is a better model since it demonstrates a systematic difference in the coefficients.

4. Results

This section offers a presentation, analysis, and discussion of the results obtained from the data examination. The initial part of this study includes the fundamental descriptive statistics related to the model variables. Subsequently, a thorough evaluation of multicollinearity, unit root tests, cointegration tests, and, lastly, the regression estimates are provided. The results of the diagnostic tests conducted after estimation are summarised and co-presented in the regression estimates table.

Key Descriptive Statistics on Model Variables: The primary descriptive statistics that are looked at in this study are the arithmetic mean, the standard deviation, and the minimum and maximum values. The computation of descriptive statistics is performed based on the study variables in their initial units.

Table 1: Key Descriptive Statistics on Study Variables (all countries in the panel)

Variable	Mean	Std dev	Min	Max
Manufacturing sector output (MSY)	2.38E+09	2.36+09	8.66E+07	7.92E+09
Gross capital formation (GCF)	5.69E+09	6.43E+09	2.42E+07	2.56E+10
Human capital (HUMC)	4.58E+10	4.91E+10	1.39E+09	2.17E+11
Adjusted population growth ($n+g+\delta$)	2.932724	0.495842	1.481261	5.654993

Source: Authors' compilation.

According to Table 1's descriptive statistics, the manufacturing sector in the five EAC countries added $2.38 billion to GDP on average between 2000 and 2020. The minimum contribution recorded was roughly $86.6 million, while the maximum contribution amounted to $7.92 E+09 billion. On analyzing the raw data, it was found that the manufacturing sector's output made the smallest contribution to Burundi's overall GDP in 2003. Conversely, the manufacturing sector's output made the largest contribution to Kenya's overall GDP in 2019. In terms of gross fixed capital creation, over the period of analysis from 2000 to 2020, the five member nations of the East African Community (EAC) invested, on average, $5.69 billion. Based on the raw data analysis, Tanzania recorded the most investment, approximately $25.6 billion, in 2020, while Burundi recorded the lowest investment, roughly $24.2 million, in 2000.

The statistical summary in Table 1 indicates that, based on the total amount spent on education in the current study, the five EAC nations invested in human capital for an average of $45.8 billion between 2000 and 2020. In 2000, Burundi reported a minimum expenditure of about $1.39 billion on education, whereas in 2018, Kenya reported a maximum expenditure of roughly $217 billion on education. Table 1 presents descriptive statistics that reveal the adjusted population growth mean for the five members of the East African Community (EAC) to be about 2.9% a year during the study period (2000-2020). The minimum and maximum values were recorded respectively at roughly 1.5% and 5.7% a year. On analysing the raw data, it was determined that Rwanda experienced the lowest adjusted population growth rate in 2004, while the highest adjusted population growth rate was recorded in the same country in 2000.

Multicollinearity Checks: A correlation matrix was created by analyzing the pairwise correlation coefficients between the explanatory variables in the empirical model. A transformation process was applied to the variables before the correlation analysis. Compiling the estimated correlation coefficients in Table 2.

Table 2: Correlation Coefficients among the Explanatory Factors (probability values are shown by figures in parentheses)

Explanatory variable in the model	1	2	3
Gross capital formation's natural logarithm (*Lngcf*)	1		
Human capital's natural logarithm (*Lnhum*)	0.1004 (0.4082)	1	
Natural logarithm of adjusted population growth [Ln (n+g+δ)]	0.0515 (0.6018)	-0.0230 (0.8499)	1

Source: Authors' compilation. 1= Gross capital formation's natural logarithm, 2= Human capital's natural logarithm, 3=Natural logarithm of adjusted population growth.

Table 2 displays the estimated pairwise correlation coefficients between the explanatory variables in the analyzed model. These values fall within a range that keeps the regression model free from major multicollinearity issues. Stated otherwise, the empirical model's predictors exhibit pairwise correlation coefficients with absolute values not exceeding ±0.8. Therefore, the selected explanatory variables in the model for empirical analysis are considered suitable for inclusion without concerns about multicollinearity in the model under study.

Stationarity Tests on All Model Variables: The panel data under examination lacks robust balance and shows a larger time dimension than the cross-sectional dimension. Consequently, we employ the Fisher-type panel unit root test approach, recommended by Choi (2001) and deemed suitable in these circumstances, on the model's variables. The third table contains a summary of the panel unit root tests that were run on each of the model's variables.

Table 3: Unit Root Test Results on All Variables in the Empirical Model

Variable name	Variable in levels	Variable in first difference	Order of integration of the variable
	Estimated statistic (p-value in brackets)	**Estimated statistic** (p-value in brackets)	
Manufacturing sector output's natural logarithm (*Lnmsy)*	**P: 5.3221** (0.8687) Z: **0.9945** (0.8400) L: **0.9207** (0.8176) Pm: **-1.0460** (0.8522)	**P: 29.4462***** (0.0011) Z: **-3.4254***** (0.0003) L: **-3.5647***** (0.0006) Pm: **4.3483***** (0.0000)	I(1)
Gross capital formation's Natural logarithm (*Lngcf)*	**P: 9.0002** (0.5321) Z: **-0.3086** (0.3788) L: **-0.2918** (0.3863) Pm: **-0.2236** (0.5885)	**P: 29.9281***** (0.0009) Z: **-3.4719***** (0.0003) L: **-3.6250***** (0.0005) Pm: **4.4561***** (0.0000)	I(1)
Human capital's Natural logarithm (*Lnhumc)*	**P: 6.6023** (0.7624) Z: **0.9546**	**P: 91.0266***** (0.0000) Z: **-5.7725*****	

	(0.8301)	(0.0000)	
	L: 0.9655	L: -11.2314***	
	(0.8289)	(0.0000)	
	Pm: -0.7597	Pm:18.1181***	I(1)
	(0.7763)	(0.0000)	
Natural logarithm of adjusted population growth [*Ln(n+g+δ)]*	P: 84.9695***	-	
	(0.0000)		
	Z: -6.1369***	-	
	(0.0000)		
	L: -10.3155***	-	
	(0.8289)		I(0)
	Pm: 16.7637	-	
	(0.0000)		

Source: Authors' compilation: P=Inverse chi-square statistic; Z=Inverse normal statistic; L=Inverse Logit t-statistic; Pm=Modified inverse chi-square statistic. *** indicates significance at 1% level.

Table 3 presents the results of the unit root test and indicates that the variables in the empirical model display different levels of integration ordering. The results of the unit test demonstrate that the original form of the four computed statistics for the variables *Lnmsy, Lngcf,* and *Lnhunc* rejecting the non-stationarity null hypothesis is not advised. However, at their respective initial differences, the same four statistics actually reject the null hypothesis of non-stationarity for these variables. However, the results of the unit root test show that every one of the four computed statistics refutes the null hypothesis. According to this the variable is non-stationar at the level of *Ln(n+g+δ).* The findings from the unit test indicate that the variables *Lnmsy, Lngcf*, and *Lnhunc* exhibit an integration of order one, I(1), while the variable *Ln(n+g+δ)* demonstrates an integration of order zero, I(0).

Cointegration Test Results: The Johansen-Fisher cointegration test is used in cases where the model's variables exhibit varying orders of integration. The integration orders of our model variables were found to be distinct. The results of the cointegration test are summarised in Table 4.

Table 4: The Johansen-Fisher Co-Integration Test Results (the test assumes a linear deterministic trend)

Hypothesized No of CE(s)	Fisher Stat[a] (from trace test)	Prob	Fisher Stat[a] (from Max-Eigen test)	Prob
None	117.0***	0.0000	104.8***	0.0000
At most 1	29.98***	0.0000	22.75***	0.0009
At most 2	12.98**	0.0434	11.16*	0.0835
At most 3	10.57	0.1026	10.57	0.1026

Source: Authors' compilation. [a] Probabilities are computed using asymptotic chi-square distribution.*, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Table 4 displays the results of the Johansen-Fisher cointegration test. It illustrates how, at a 5% significance level, the Max-Eigen statistic and the trace statistic both reject the null hypothesis of an "at most 1" cointegrating equation. These cointegration test findings indicate that there is cointegration between the variables under study, indicating that the empirical model has at least one cointegrating equation. The panel model that was taken into account for the investigation shows relationships of long-term equilibrium. Although cointegration links are indicated by the panel model, we have chosen not to employ cointegration regression estimate approaches such as completely modified OLS, dynamic OLS, or panel vector error correction. Alternatively, the first-differenced generalized method of moments (D-GMM) estimator proposed by Arellano and Bond (1991) could be employed in the investigation. The estimation takes into consideration measurement error, endogeneity of the regressors, and unobserved country-specific effects. It also incorporates instrumental variables. Because of the gross capital creation variable's potential endogeneity, the D-GMM estimator was chosen. As demonstrated by studies like Nkoa and Wujung (2014), Nweke, Odo, and Anoke (2017), and

Onwiodiokit and Otolorin (2021), this variable has been shown in the past to be an endogenous regressor in growth functions.

Regression Estimates: The D-GMM estimator was used in the study to mitigate the influence of unobserved effects specific to each country and the endogeneity of the variable *"Lngcf"*. Table 5 provides a summary of the regression estimates along with the outcomes of the diagnostic tests conducted after estimation.

Table 5: D-GMM Estimation Regression Estimates

Dependent Variable: Natural Logarithm of Manufacturing Sector Output (*Lnmsy*)			
Independent Variable	**Coef**	**Std Err**	**Prob**
Natural logarithm of manufacturing sector production lagged by one period $(Lnmsy)_{t-1}$	0.7427***	0.073937	0.000
Gross capital formation's natural logarithm (*Lngcf)*	0.2780***	0.083541	0.001
Natural logarithm of human capital (*Lnhumc)*	0.0043	0.004405	0.326
Natural logarithm of the adjusted population growth $[Ln(n+g+\delta)]$	-0.2366	0.254907	0.353
Const.	-0.9089	1.731771	0.600

Instrumentisation

Instrumented variable: *Lngcf*

GMM-type Instruments for first difference equation: $Lnmsy_{t-2}$, $Lnhumc_{t-1}$, $Lngcf_{t-2}$, $Ln(n+g+\delta)$

Standard instruments for first difference equation: $\Delta Lnhumc$, $\Delta Ln(n+g+\delta)$

Instruments for the level equation: Constant

Diagnostic tests

1. Wald chi-sq. test for Ho: All slope coefficients are simultaneously zero: p>chi-sq. = 0.000
2. Arellano-Bond test for Ho: No AR(1) in first difference errors: p>Z = 0.1537
3. Arellano-Bond test for Ho: No AR(2) in first difference errors: p>Z = 0.1321
4. Jarque-Bera normality of residuals test for Ho: Normally distributed residuals: p>chi-sq. = 0.087
5. Sargan test of over-identifying restrictions for Ho: instruments are jointly valid: p>chi-sq. = 0.242
6. The Hausman specification test for Ho: The difference in coefficients between the D-GMM estimator and the OLS is not systematic: p>chi-sq. = 0.002

Source: Authors' compilation after D-GMM estimation. *** indicates significance at a 1% level.

The following are the results of the post-estimation diagnostic tests: The null hypothesis is rejected because the Wald chi-square statistic is significant at a level that is lower than the chosen significance threshold. This suggests that the model as a whole has statistical significance. Based on the computed Z-statistics, the Arellano-Bond test results show that the null hypothesis that there is no first-order and second-order serial correlation cannot be rejected. This is supported by the corresponding p-values which exceed the significance level. These results imply that serial correlation is not inhibited by the residuals derived from the estimations. The chi-square statistic from the Jarque-Bera test produces insufficient information to reject the null hypothesis at a 5% significance level. This implies that the residuals of the computed regression have a normal distribution (iv) The Sargan test of over-identifying limitations demonstrates the general validity of the instruments used in the D-GMM estimate because the chi-square statistical test is unable to reject the null hypothesis at the 5% level. (vii) The Hausman specification test rejects the null hypothesis since the chi-square statistic's p-value is less than the significance level. The observation implies that there is a consistent variation in the coefficients of the D-GMM estimator and the OLS estimate, thereby signifying that D-GMM is a more desirable estimator.

Interpretation and Discussion of the Regression Estimates: The effect of the physical capital input on the manufacturing sector growth in the EAC member countries. In the model under discussion, the physical capital input was approximated using gross capital formation. The partial slope coefficient for the natural logarithm of gross fixed capital creation is positive and statistically significant at the 5% significance level, according to regression estimates shown in Table 5 (Coef = 0.2780, $p < 0.05$). These findings suggest that gross capital formation has a major beneficial role in assisting the member states of the East African Community in their efforts to increase their industrial output. Mankiw, Romer & Weil (1992) highlighted the favourable effect of physical capital on output growth, a notion that has been reiterated by numerous related empirical studies, like those by Adejumo, Olomola and Adejumo (2013), Olarewaju & Msomi (2021), and Taiwo, Adebayo and Oluwaseun (2021). The aforementioned findings provide a rationale for the East African constituents to execute measures, like augmenting assistance towards both domestic and foreign investments, to amplify gross capital formation as a catalyst towards accomplishing the EAC industrialization blueprint of 2012-2032.

The Effect of the Human Capital Input on Manufacturing Sector Growth in the EAC Member Countries: The study assessed the human capital input by quantifying the overall expenditure on education. According to the data presented in Table 5, the estimates suggest that the partial slope co-efficient on the natural logarithm of human capital is positive. At the 5% level, though, it is not statistically significant (Coef = 0.0043; $p > 0.05$). According to this estimate, the expansion of the industrial sector in the nations that make up the East African Community is not significantly predicted by human capital. This result is not quite in line with what we had anticipated. However, low levels of investment in human capital may be the reason why the human capital component has not been able to influence the growth of manufacturing sector output in the East African Community (EAC) member countries. This, in turn, could be clarified by the relatively trivial proportions of budgetary allotments to the education and health sectors by the EAC member countries in their overall annual budgets. As a result, individuals experiencing poor health could exhibit reduced productivity, which could potentially hinder the growth of the manufacturing sector. The study's findings are not entirely consistent with a specific body of relevant research that, when considered in the context of the empirical literature, has demonstrated a substantial and positive association between output growth and human capital (such as those by Mamuneas et al., 2006; Anyanwu, 2018; and Rumanzi et al., 2021). Our study's conclusion regarding the relationship between human capital and output growth aligns with the results of previous similar studies, including Johansson's (2015) investigation.

The Effect of Population Growth on Manufacturing Sector Growth in the EAC Member Countries: Table 5 displays the regression estimates, which reveal that the partial slope co-efficient on the adjusted natural logarithm of population growth for extrinsic technological advances (g) and head extrinsic depreciation (δ) is negative. At the 5% level, this coefficient (Coef. = -0.9089, $p > 0.05$) is not statistically significant, though. The negative sign is consistent with the predictions of the neoclassical growth theory, which was developed by Mankiw, Romer, and Weil (1992) after Solow (1956) initially presented it. This theory posits that long-term economic growth is restricted by a surge in population. The findings of this study, which evaluates the relationship between population expansion and industrial output growth, contradict those of Zhou (2019) and Strielkowski (2019), who found a favorable association between the two.

5. Conclusion

This research aimed to estimate the increase of manufacturing sector output in each of the five East African Community (EAC) member nations by evaluating the predictive ability of input factors, as outlined, in Mankiw, Romer, and Weil's (1992) extended neoclassical growth model. The impact of variations in three main input parameters was investigated in this study, specifically: physical capital stock, quantified by gross capital formation; human capital stock, quantified by the overall investment in education; and labor stock, quantified by population growth, adjusted for extrinsic technological advancements and head extrinsic depreciation. Based on the estimates, the gross capital formation input variable proves to be a substantial predictor of changes in the growth of manufacturing sector output. On the other hand, population growth and human capital input variables do not show a significant ability to influence changes in the growth of manufacturing sector output in the East African Community nations. The findings of our research indicate that the neoclassical growth model and its expansions may be partially responsible for the variations in manufacturing sector output among the East African Community's (EAC) member nations. This shows that the existing growth framework may not be thorough enough to assess the factors influencing the expansion of the manufacturing sector output in the EAC member states.

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