

Manufacturing Value Added and Green Growth in Southern Africa Development Community (Sadc): A Case Study of Malawi

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Abstract: The relationship between manufacturing value-added and green growth is crucial as the manufacturing sector has the potential to drive economic growth but can also have significant environmental consequences. This way, this paper aims to examine the effects of manufacturing value-added on green growth in Malawi. The analysis employs the Autoregressive Distributed Lag (ARDL) model to examine the short and long-term relationship between manufacturing value added and green growth. The ARDL model is estimated using time series data from 1990 to 2019. The results indicate a positive and significant relationship between manufacturing the pollution haven hypothesis. This implies that increased manufacturing value added leads to increased green growth. The study also finds that total greenhouse gas emissions impact green growth negatively and significantly. These findings highlight the need to foster green growth by promoting manufacturing value-added activities, encouraging sustainable manufacturing practices, and strengthening environmental regulations and standards.

Keywords: Manufacturing value-added; green growth; ARDL

1. Introduction

Green growth is crucial for sustainable development. Just like green growth, manufacturing value added is also vital for sustainable development; however, it poses environmental challenges despite boosting economic growth through manufacturing value added. According to the engine of growth hypothesis (or Kaldor's growth law), the manufacturing sector contributes to economic growth and sustainable development (Kaldor, 1966). It offers more significant opportunities than other sectors to accumulate capital, exploit economies of scale, acquire new technologies, and foster embodied and disembodied technological change. The world's manufacturing value added (MVA) reached an all-time high of \$8,900 billion in 2012 (16.7 per cent of global GDP).

The Southern Africa Development Community (SADC) is planning to expand its manufacturing sector through the implementation of the industrialization strategy; hence, the importance of assessing the effects of manufacturing value added on green growth so that the region should be able to make informed policies that will help them boost the manufacturing value added at the same time promoting green growth. The 40 Years of SADC: Enhancing Regional Cooperation and Integration publication, launched

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at the Extraordinary Summit of the Southern African Development Community (SADC) in Mozambique in June 2021, reported a noteworthy rise in manufacturing value added in the region. The percentage increased from 10.3 per cent in 2013 to 11.9 per cent in 2018, with most Member States experiencing over five per cent growth.

Malawi is a small, landlocked country in the SADC region with approximately 20 million people. The country's economy relies heavily on agriculture, which accounts for over 80% of its employment and 30% of its Gross Domestic Product (GDP) (World Bank, 2021). Its manufacturing sector share of GDP is relatively small. It contributes only a small proportion of the country's GDP but can drive its economic growth and create employment opportunities. In 2019, the country reported 11.54 % of manufacturing value added; in 2013, the country's manufacturing sector contributed 10.7% of GDP. In 2010, the country registered 9.9%, which shows that the industry is developing as it implements strategies to boost its manufacturing value-added, hence the need to assess its effects on green growth to realise sustainable development.

According to the United Nations Industrial Development Organization (UNIDO), the manufacturing value added of an economy refers to the total estimate of the net output of all manufacturing units calculated by subtracting intermediate products from the total production and consumption. It is thus the core of economic growth and structural transformation (UNIDO, 2013). However, due to this industrial structural change, the manufacturing sector imposes direct pressure on the environmental and health risks associated with air pollution, hazardous substances, and waste.

The concept of green growth has gained prominence due to concerns over climate change, environmental degradation, and depletion of natural resources. In simple terms, this concept is sustainable and environmentally friendly economic growth. It emphasizes the need for economic growth that upholds the ability of future generations to meet their own needs. In the face of pressing economic and environmental challenges, national and international efforts to promote green growth as a new source of growth have been intensifying in recent years. Building on this momentum can help accelerate progress towards sustainable development and poverty reduction through, for example, more sustainable use of natural resources, efficiencies in energy use, and valuation of ecosystem services.

The manufacturing sector is a crucial driver of economic growth in many developing countries, including Malawi. However, the increase in manufacturing activities is commonly associated with negative environmental consequences, including pollution and the depletion of natural resources. As the global community increasingly focuses on sustainable development, examining the effects of manufacturing value added on green growth in Malawi is necessary. Several studies have shown that manufacturing activities are often associated with environmental adverse effects. These negative effects include air and water pollution. Environmental pollution has been increasing lately, which has become a primary global concern. SDG 12 emphasises enhancing resource efficiency in production processes and minimizing waste by adopting prevention, reduction, recycling, and reuse measures. Alongside this, SDG 9, Target 9.2, endeavours to enhance the proportion of employment and GDP generated by industry in the most underdeveloped nations. Hence, examining the relationship between manufacturing value added and sustainable development in Malawi is significant.

More research is needed on the relationship between manufacturing value added and green growth in Malawi. However, a study by Mhango and Zikhali (2017) examined the impact of manufacturing value

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added on environmental sustainability in Malawi. The study found that the manufacturing sector in Malawi hurt the environment, but the effect could be mitigated by adopting cleaner production technologies and policies. The study suggested that Malawi's manufacturing sector can contribute to green growth if appropriate policies and technologies are adopted. Specifically, this study seeks to explore the following research question: What is the effect of manufacturing value added on green growth?

1.1. Stylistic facts about green growth in the SADC region and Malawi

Unique stylistic facts characterise green growth in Malawi and the SADC region. Malawi has experienced climate change and environmental challenges, including deforestation, soil erosion, and water pollution over recent years. It has already started experiencing the effects of environmental degradation as it recently faced cyclone Freddy, which affected the country's productivity. It has adopted a community-driven approach to green growth, where local communities actively plan and implement green growth strategies (Crichton et al., 2018). This approach has been successful as it empowers communities to take ownership of projects and ensures long-term sustainability.

Furthermore, SADC also recognises the importance of sustainable use and management of the environment. Member states have committed to attaining more integrated and sustainable development, as reflected in the SADC's green economy strategy and action plan (SADC, 2014). The SADC region is a fascinating case because it has pushed for urgent measures to manage and conserve the region's forests sustainably, implemented laws to help people adapt to climate change, and taken part in campaigns to mitigate the effects of rising global temperatures and lessen their potential harm to the region. This is because the region faces climate-related disasters almost every year, and this reality demonstrates the urgent need to avert, minimise, and address such events. It prioritises sustainable development in key sectors such as agriculture, energy, and infrastructure. It has embraced a climate-smart approach to green growth, promoting low-carbon and resource-efficient economic growth (SADC, 2015). This approach focuses on reducing greenhouse gas emissions, enhancing resilience to climate change, and promoting sustainable agriculture and forestry practices. This has led to SADC member states implementing policies and initiatives to increase the use of renewable energy and promote energy efficiency (Jayet et al., 2018).

SADC and Malawi have implemented various measures to promote green growth in the face of climate change challenges. These measures include the adoption of climate-smart agriculture, reforestation initiatives, and the implementation of climate change adaptation strategies at both national and regional levels (SADC, 2019).

2. Literature Review

This literature review has been divided into conceptual, theoretical, and empirical.

2.1. Conceptual Review

Manufacturing value added

Manufacturing value added refers to the contribution made by the manufacturing sector to the overall economy. It represents the value created by transforming raw materials and intermediate inputs into finished goods (Lazonick, 2014). Manufacturing value can be measured by analysing the value of output produced by the manufacturing sector, deducting the cost of intermediate inputs such as raw materials and purchased components. This measurement method is called gross value added (GVA) because it captures the net value added by manufacturing activities, reflecting the value that is created within the sector through the representation of the difference between the value of output produced by the sector and the value of intermediate inputs used in the production process (OECD, 2012). This study uses the GVA method to measure manufacturing value added.

Green growth

The OECD defines green growth as a pathway to foster economic growth and development. In contrast, the OECD defines green growth as a pathway to sustainable development that promotes economic growth while maintaining the ecosystem's integrity and addressing global environmental challenges such as climate change, biodiversity loss, and resource depletion. It is based on the principles of sustainable development that emphasise a balance between economic, social, and environmental goals and the intergenerational responsibility to safeguard natural resources and ecosystems. The concept of green growth also implies the need for policy coherence across sectors, regions, and levels of governance that fosters innovation, investment, and trade opportunities while preserving natural capital (United Nations, 2012).

Measurement of green growth is a complex and multi-dimensional task, as it involves assessing economic, social, and environmental impacts across multiple economic sectors. A study by the OECD identified 26 indicators commonly used to measure green growth, including energy efficiency, renewable energy use, air pollution, and water quality (OECD, 2017). This study will use the 26 indicators to calculate green growth using the principal component analysis (PCA).

2.2. Theoretical Literature Review

Porters Hypothesis

This hypothesis posits that strict environmental regulations can stimulate innovation and create a competitive advantage for firms, leading to improved environmental performance and green growth (Porter,1991). It further suggests that regulations on manufacturing activities could encourage the adoption of cleaner technologies and processes, enhancing manufacturing value added's positive effects on green growth. Porter (1991) argues that adopting environmentally friendly practices can increase efficiency and cost savings, contributing to higher manufacturing value added. The hypothesis further emphasised the importance of environmental sustainability in achieving green growth. Companies can tap into new markets and meet the growing demand for environmentally friendly products and services by integrating environmental considerations into business strategies and operations (Porter, 1991).). This shift towards sustainable practices can lead to developing green industries and new jobs,

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contributing to economic growth while minimising environmental impacts. Hence, this paper examines whether this hypothesis holds in developing countries like Malawi.

Pollution Haven Hypothesis

In 1979, Ingo Walter and Judith Ugelow proposed the Pollution Heaven Hypothesis (PHH) to explain the transfer of pollution between countries (Tang & Dou, 2021). According to the hypothesis, countries with weaker environmental regulations tend to attract manufacturing activities from developed countries. This is because of the lower production costs, which include less strict environmental regulations. When countries lower their environmental standards to encourage foreign investment, they may see increased manufacturing value added as multinational corporations (MNCs) move their production to these countries to benefit from the cost advantages of relaxed environmental regulations (Hogendorn, 2012). This hypothesis suggests that multinational corporations (MNCs) move manufacturing operations to countries with weaker environmental standards to reduce compliance costs and boost profits (Cole et al., 2005).

2.3. Empirical Literature Review

An empirical study conducted by Chen et al. (2021) investigated the effects of manufacturing value added on green growth using a dynamic panel data approach. The study utilized data from a sample of countries throughout 2000-2018. They employed the generalized method moments (GMM) system for potential endogeneity and dynamic panel data issues. The results suggested a positive and statistically significant relationship between manufacturing value added and green growth; one unit increase in manufacturing value added leads to an increase in green growth by a certain percentage.

Nguyen, Rizwan, and Isik (2021) investigated the relationship between manufacturing value added and green growth in ASEAN countries by using panel data to analyse the effects of manufacturing value added on green growth. The results suggested a positive relationship, indicating that increased manufacturing value added can contribute to green growth by promoting sustainable industrial practices.

Another study by Talukdar, Nolte, and Thoma (2020) examines the relationship between manufacturing value added and green growth using a dynamic panel data model for 82 countries. The study finds a positive and statistically significant relationship between manufacturing value added and green growth. It suggests that an increase in manufacturing value added leads to improved environmental performance, thereby contributing to green growth. The findings indicate that the manufacturing sector can be crucial in fostering sustainable economic development.

Sandhiya and Nataraj (2020) examined the relationship between manufacturing value added and environmental sustainability using ARDL in India. The findings indicated that increased manufacturing value added led to higher carbon dioxide emissions and environmental degradation. However, the study also suggested that incorporating environmentally friendly technologies and practices in manufacturing could mitigate the negative impact and promote green growth. On the other hand, research by Ballesteros-Blanco et al. (2020) examined the role of environmental policies in promoting manufacturing value-added-led green growth in European countries. The study found that stringent environmental regulations and incentives positively influence manufacturing value-added and sustainable industrial development.

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Another study by Song, Wang, and Chen (2019) examines the relationship between manufacturing value added and carbon emissions in China using a dynamic panel data model with data from 30 provinces from 2003 to 2014. The study found a positive relationship between manufacturing value added and carbon emissions. This indicates that manufacturing activities have a detrimental effect on green growth and contribute to increased carbon emissions.

A case study by Zadeh et al. (2019) focuses on the automotive industry and demonstrates the positive relationship between manufacturing value added and green growth. The study reveals that automakers with higher manufacturing value adopt more environmentally friendly technologies, reducing emissions and resource use.

Furthermore, Cheng et al. (2019) investigated the effects of manufacturing value added on the environmental performance of manufacturing industries across various provinces in China. They employed a two-stage least squares approach to address potential endogeneity issues. The findings revealed a significant positive association between manufacturing value added and improved environmental performance. Specifically, an increase in manufacturing value added by 1% resulted in a 0.3% improvement in environmental performance.

A study by Sturgeon et al. (2017) analyses the relationship between manufacturing value added and carbon emissions using panel data across 64 countries. The findings reveal that countries with higher manufacturing value added tend to have lower carbon emissions due to technological innovation, energy efficiency, and cleaner production practices.

Zhang, Tan, and Cui (2015) studied the impact of manufacturing value added on green growth. They analysed panel data from 30 provinces in China between 2003 and 2012 to explore the correlation between manufacturing value added and environmental pollution. Their study found that manufacturing activities harm green growth due to increased environmental pollution. Studies have shown a correlation between manufacturing value added and green growth. Specifically, research has found that higher levels of manufacturing value added are linked to more significant investment in cleaner production technologies, energy efficiency improvements, and environmental innovations. This connection is exemplified by a study conducted by Wu et al. in 2018 using panel data analysis, which discovered that manufacturing value added positively impacts carbon intensity reductions in China. Moreover, Anbumozhi and Kimura (2015) suggest that adding manufacturing value can lead to technological advancements and cleaner production methods, ultimately reducing environmental harm.

In conclusion, most of these studies used panel data; hence, this study will use time series data to fill the gap in the empirical literature.

3. Methodology

3.1. Data Source and Scope

This study is limited to giving more insight into the existing literature on manufacturing value added and the green growth genre, particularly in Malawi. The study will use time series data from 1990 to 2019, which is the time frame for most of the variables of interest available. This data will be gathered from the 2022 World Bank Development Indicators (WDI) for Malawi and the Organization for

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Economic Co-operation and Development (OECD). The table below presents the variables used to examine the effects of manufacturing value added on green growth.

Variable Name	Variable type	Symbol	Unit	Data source
Green Growth	Dependent variable	GG	Index of PCA	OECD
Manufacturing Value Added	Independent variable	MVA	Net sector output after adding up all outputs and subtracting intermediate inputs.	WDI
Total greenhouse gas emissions	Control variable	TGGE	CO2 totals excluding short-cycle biomass burning (such as agricultural waste burning and savanna burning)	WDI
Trade openness	Control variable	ТО	The sum of imports and exports relative to GDP	WDI
Renewable energy consumption	Control variable	REC	share of renewable energy in total final energy consumption.	WDI
Foreign Direct Investment	Control variable	FDI	net inflows of investment to acquire a lasting management interest	WDI
Gross Domestic Product	Control variable	GDP	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2015 prices, expressed in U.S. dollars.	WDI

Source: Authors Construct

3.2. Model Specification

A multiple regression model will be employed to assess the effects of manufacturing value added (MVA) on green growth. The model specification is as follows:

 $GG = \beta_0 + \beta_1 MVA_t + \beta_2 \text{ Control Variables } + \mu_t$

GG is Green Growth, MVA is manufacturing value added, and Control variables include Total greenhouse gas emissions, Trade openness, Renewable energy consumption, and Foreign Direct investment.

3.3. Model Estimation

The study will use the ARDL model to examine the effects of manufacturing value added on green growth in Malawi. The model has proved to be suitable for a small sample, and the study has a small sample size study (Farhani et al., 2014). Perasan and Shin (1999) also demonstrated that the simultaneous estimation of long-run and short-run components and appropriate lags in the ARDL framework removes the problems associated with serial correlation and endogeneity problems. Another essential advantage of the ARDL procedure is that the estimation is possible even when the explanatory variables are endogenous (Pesaran et al., 2001). The last advantage of the ARDL technique is that it can be applied irrespective of whether the variable is I (0) or I (1) or fractionally co-integrated (Pesaran &

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Pesaran, 1997). The ARDL model takes enough lags to capture the dynamic impacts of all dependent and independent variables and from the error term.

Therefore, the model can be stated as follows:

 $\begin{aligned} \ln GG_{t} &= \beta_{0} + \beta_{1} lnMVA_{t-1} + \beta_{2} lnTO_{t-1} + \beta_{3} lnTGREMM_{t-1} + \beta_{4} lnFDI_{t-1} + \beta_{5} lnREC_{t-1} + \\ \beta_{6} lnGDP_{t-1} + \sum \beta_{1} \Delta \ln MVA_{t-i} + \sum \beta_{2} \Delta \ln TO_{t-j} + \sum \beta_{3} \Delta lnTGREMM_{t-i} + \sum \beta_{4} \Delta lnFDI_{t-i} + \\ \sum \beta_{5} \Delta lnREC_{t-i} + \sum \beta_{5} \Delta lnGDP_{t-i} + ECT_{t-1} + \mu_{t} \end{aligned}$

Where GG is green growth

MVA is manufacturing value-added

TO is trade openness

TGREMM is total greenhouse gas emissions

FDI is foreign direct investment

REC is renewable energy consumption

GDP is the gross domestic product

 $\boldsymbol{\mu}$ is the error term

I am 1,2, and 3

t is time

j is 1

In is a natural logarithm

4. Results and Discussions

4.1. Descriptive Statistics

Table 2. Summary of Descriptive Statistics

Variable	Obs	Mean	Std.Dev	Min	Max
GG	30	1.109138	.6401007	.007185	1.9738
MVA	30	12.18496	2.401696	9.254067	19.04892
ТО	30	0.4400594	.0775816	0.2589851	0.6000769
REC	30	80.969	1.835874	72.1	84
TGREMM	30	5492.636	2330.891	11765.32	3198.271
FDI	30	1.620891	1.835874	0.1012854	6.977522
GDP	30	5.775298	3.176681	1.576078	16.72882

Source: computed by the author using STATA 15

The table presents the descriptive statistics of the variables used in the study in terms of their standard deviation, mean, minimum, and maximum variable. Based on the table green growth (GG), the average is 1.109138, close to the maximum value of 1.9738, indicating that green growth has improved over the years. MVA's maximum value is 19.04892; the minimum value is 9.254067, and the average is 12.18496. TO, the average is 0.4400594, close to the maximum value of 0.6000769, implying that trade

openness has improved. REC's maximum value is 84, and the minimum value is 72.1. TGREMM average is 5492.636, the maximum value is 3198.271and the minimum is 11765.32. As for FDI, the average is 1.620891, the maximum value is 6.977522, and the minimum value is 0.1012854. lastly, GDP's average is 5.775298, the maximum value is 16.72882, and the minimum value is 1.576078.

4.2. Test for Stationarity

Variable	Test statistic (Z)	5% Critical value	Order of Integration				
	-4.301	-2.992	I (0)				
lnGG_d	MacKinnon's approximate p-value for	Z(t) = 0.0004					
InMVA d	-6.095	-2.994	I (0)				
lnMVA_d	MacKinnon's approximate p-value for	Z(t) = 0.0000					
1	-3.693	-2.989	I (0)				
lnTO	MacKinnon's approximate p-value for $Z(t) = 0.0042$						
lnFDI	-5.109	-2.989	I (0)				
	MacKinnon's approximate p-value for $Z(t) = 0.0000$						
InTGREMM	2.689	-2.989	I (0)				
	MacKinnon's approximate p-value for $Z(t) = 0.9991$						
lnREC	1.023	-2.989	I (0)				
IIIKEU	MacKinnon's approximate p-value for $Z(t) = 0.9945$						
lnGDP	-3.29	-2.989	I (0)				
IIIGDP	MacKinnon's approximate p-value for $Z(t) = 0.0178$						

Table 3. Augmented Dickey-Fuller (ADF) Unit Root Test

Source: Computed by the author using STATA 15

According to Gujarati (2009), time series data is said to be stationary if the mean, variance, and covariance are constant. The existence of stationarity also ensures that the results are not spurious. The study used the Augmented Dickey-Fuller (ADF) test to establish whether the data is stationarity and its order of integration. Under the ADF test, the null hypothesis is that a unit root exists in the time series sample. Suppose the P-value of the ADF is statistically significant at a 5% significance level (P<0.05). In that case, the null hypothesis will be rejected in favour of the alternative hypothesis of no unit being present in the time series (Gujarati & Porter, 2009). LnGDP and lnREC were stationary at I (0), while lnGG_d and lnmva_d were stationary at I (0) after the first difference. Moreover, the Mackinnon approximate p-values are less than 1%; thus, we reject the null hypothesis of the presence of a unit root and conclude that the variable is stationary.

4.3. Presentation of Regression results

4.3.1. ARDL bound test for cointegration

Table 4. ARDL bound test for cointegration

Null hypothesis: No long-run relationship exists						
F statistics 7.183						
Critical value	Lower bound I (0)	Upper bound I (1)				
10%	2.12	3.23				
5%	2.45	3.61				
2.5%	2.75	3.99				
1%	3.15	4.43				

Source: computed by the author using STATA 15

The study employed an ARDL bounds test for cointegration to determine if the variables in the model are cointegrated. The F-statistic of the bounds test is used to verify if co-integration exists between variables. From the table above, we compare the value of the F-statistic with that of the critical values of the bounds test. If the value of the F-statistics is greater than that of the upper bound, I (1) we reject the null hypothesis. If the F-statistics is below the lower bounds I (0), we fail to reject the null hypothesis. Based on the results, the F-statistics (7.183) is greater than the upper bound at all levels (10%, 5%, 2.5%, and 1%). There is evidence of co-integration among variables; hence, we run short- and long-term regression.

4.3.2. ARDL Short- and Long-term Results

Variable	Coefficient	Standard error	t-statistics	P-value
ADJ	·	·	·	
L1. lngg_d	-3.371016	0.5584663	-6.04	0.002
SHORT TERM				
LD. lngg_d	1.85076	0.3645816	5.08	0.004
L2D.lngg_d	1.171244	0.30383	3.85	0.012
L3D.lngg_dd	1.353266	0.3324278	4.07	0.010
D1. lnmva_d	-15.56845	6.3217	-2.46	0.057
LD. lnmva_d	-7.385984	3.903616	-1.89	0.117
D1. Lnto	0.9006852	1.581818	0.57	0.594
LD. Lnto	-2.386992	1.018776	-2.34	0.066
D1. Lnrec	-47.74934	24.50352	-1.95	0.109
LD. Lnrec	10.53029	16.19144	0.65	0.544
D1. Lntgremm	-21.98501	9.114153	-2.41	0.061
LD. Intgremm	-22.69766	6.550308	-3.47	0.018
D1. Lngdp	-1.241053	.6292342	-1.97	0.106
Constant	21.74906	65.61723	0.33	0.754
LONG-TERM				
lnmva_d	7.13465	2.547602	2.80	0.038
Lnto	0.7442005	0.4148058	1.79	0.133
Lnrec	-1.567548	4.357813	-0.36	0.734
Lntgremm	0.1819994	0.2268861	0.80	0.459
Lngdp	0.0697783	0.1793031	0.39	0.713
Lnfdi	-0.0447625	0.0897616	-0.50	0.639
R-squared	0.9559			
Adj R-squared	0.7883			

Source: Computed by the author using STATA15

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4.3.4. Discussion of results

The above table presents short- and long-term results, and it indicates that the variables have different dynamics in terms of their response to changes in the independent variable; the impact of certain variables is more immediate and temporary, while the effect of others is more persistent and long-lasting.

The ADJ indicates that the percentage change in the first lag of green growth (L1. lngg_d) is associated with -3.371016 of lnmva_d. Its p-value is 0.002, which means it is highly significant. This means that the relationship between the independent and dependent variables is unlikely to have occurred purely by chance. In other words, evidence suggests that the independent variable has a meaningful and systematic impact on the dependent variable in the regression. In addition, the coefficient of the ADJ is negative, showing that shocks in the dependent variable are adjusted in the long run.

The long-term results indicate that a percentage change in manufacturing value added (lnmva_d) is associated with a 7.13465 per cent increase in green growth (lngg_d), which shows a positive relationship between the two variables. Lnmva_d is statistically significant at 0.0038. This suggests that increased manufacturing value added (lnmva_d) positively affects green growth(lngg_d). The positive coefficient indicates that expanding manufacturing activities contributes to environmental sustainability and achieving green growth objectives. The rest of the variables are statistically insignificant in the long run.

However, in the short run, lnmva_d and lngg_d have a negative relationship. A percentage change in lnmva_d is associated with a 15.56845 per cent decline in lngg_d at D1. The P-value is 0.057, implying that it is insignificant at LD. A percentage change in lnmva_d is associated with a 7.385984 per cent decline in lngg_d, implying a negative relationship, and the p-value is more significant than 5%; hence, it is insignificant. The results also indicate that lntgremm is associated with a 22.69766 per cent decline in lngg_d. This implies a negative relationship between lngg_d and lntgremm. Lntgremm is the only variable statistically significant in the short term at LD. This suggests that higher levels of greenhouse gas emissions limit the progress in achieving green growth. Policy interventions to reduce greenhouse gas emissions should be prioritised to promote more sustainable manufacturing practices.

Based on the results, it can be noted that manufacturing value added in the short run has a negative relationship with green growth; this might be because manufacturing value added often leads to higher levels of pollution and resource depletion, as it involves the use of fossil fuels contributing to greenhouse gas emissions and this hinders green growth initiatives. However, in the long run, manufacturing value added has a positive relationship with green growth; a reason behind this is the adoption of cleaner technologies by manufacturing companies, which, in turn, can promote green growth.

The adjusted R-square was found to be 0.9559, meaning that about 95 per cent of the variations in the dependent variable (lngg_d) were explained by the variables in the model.

5. Conclusion and Policy Implications

Based on the results, policy recommendations can be made to foster green growth by promoting manufacturing value-added activities. These include encouraging sustainable manufacturing practices. Policymakers should prioritise adopting green technologies and eco-friendly manufacturing processes by incentivising companies to invest in renewable energy sources, recycling efforts, and reducing carbon

emissions. This approach will help align economic growth with environmental sustainability. It should also strengthen regulations and standards by establishing stringent environmental regulations to ensure manufacturing activities adhere to sustainable practices. The enforcement of emission control standards, waste management protocols, and pollution prevention measures will contribute to green growth goals.

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-2.625

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APPENDICES

Appendix 1. Results generated from STATA

Stationarity test

. dfuller lnto, lags(0)

Dickey-Fuller test for unit	root	Number of obs	= 29
	Inter	polated Dickey-Fu	ller
Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value

Z(t)	-3.693	-3.723	-2.989

MacKinnon approximate p-value for Z(t) = 0.0042

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tgremm, lags(0)					
r test for unit ro	ot		Number of obs	=	29
		Interp	olated Dickey-Ful	ler ·	
Test Statistic	1%	Critical Value	5% Critical Value	10%	Critical Value
2.689		-3.723	-2.989		-2.625
proximate p-value	for	Z(t) = 0.9991			
fdi, lags(0)					
r test for unit ro	ot		Number of obs	=	29
		Interp	olated Dickey-Ful	ler ·	
Test Statistic	1%	-	-		
-5.109		-3.723	-2.989		-2.625
proximate p-value	for	Z(t) = 0.0000			
rec, lags(0)					
r test for unit ro	ot		Number of obs	=	29
		Interp	olated Dickey-Ful	ler ·	
Test Statistic	18	Critical Value	5% Critical Value	10%	Critical Value
1.023		-3.723	-2.989		-2.625
proximate p-value	for	Z(t) = 0.9945			
gdp, lags(0)					
r test for unit ro	ot		Number of obs	=	29
		Interp	olated Dickey-Ful	ler ·	
Test Statistic	18		5% Critical	10%	Critical
		Value	Value		Value
-3.239		Value -3.723	Value -2.989		-2.625
-3.239 proximate p-value	for	-3.723			
	for	-3.723			
proximate p-value		-3.723		=	-2.625
proximate p-value nva_d, lags(0)		-3.723 Z(t) = 0.0178	-2.989 Number of obs		-2.625
proximate p-value nva_d, lags(0)	ot	-3.723 Z(t) = 0.0178	-2.989	ler ·	-2.625
proximate p-value nva_d, lags(0) r test for unit ro Test	ot	-3.723 Z(t) = 0.0178 	-2.989 Number of obs polated Dickey-Ful 5% Critical	ler ·	-2.625 28 Critical Value
proximate p-value nva_d, lags(0) r test for unit ro Test Statistic	ot 	-3.723 Z(t) = 0.0178 Interp Critical Value -3.730	-2.989 Number of obs polated Dickey-Ful 5% Critical Value	ler ·	-2.625 28 Critical
proximate p-value nva_d, lags(0) r test for unit ro Test Statistic -6.095	ot 	-3.723 Z(t) = 0.0178 Interp Critical Value -3.730	-2.989 Number of obs polated Dickey-Ful 5% Critical Value	ler ·	-2.625 28 Critical Value
proximate p-value nva_d, lags(0) r test for unit ro Test Statistic -6.095 proximate p-value	ot 	-3.723 Z(t) = 0.0178 Interp Critical Value -3.730	-2.989 Number of obs polated Dickey-Ful 5% Critical Value	ler - 10%	-2.625 28 Critical Value -2.626
proximate p-value nva_d, lags(0) r test for unit ro Test Statistic -6.095 proximate p-value gg_d, lags(0)	ot 	-3.723 Z(t) = 0.0178 Interp Critical Value -3.730 Z(t) = 0.0000	-2.989 Number of obs polated Dickey-Ful 5% Critical Value -2.992 Number of obs	ler - 10%	-2.625 28 Critical Value -2.626 28
proximate p-value nva_d, lags(0) r test for unit ro Test Statistic -6.095 proximate p-value gg_d, lags(0)	ot 	-3.723 Z(t) = 0.0178 Interp Critical Value -3.730 Z(t) = 0.0000	-2.989 Number of obs polated Dickey-Ful 5% Critical Value -2.992	ler - 10% =	-2.625 28 Critical Value -2.626 28
	r test for unit ro Test Statistic 2.689 proximate p-value fdi, lags(0) r test for unit ro Test Statistic -5.109 proximate p-value rec, lags(0) r test for unit ro Test Statistic 1.023 proximate p-value gdp, lags(0) r test for unit ro Test	r test for unit root Test 1% Statistic 2.689 proximate p-value for fdi, lags(0) r test for unit root Test 1% Statistic -5.109 proximate p-value for rec, lags(0) r test for unit root Test 1% Statistic 1.023 proximate p-value for gdp, lags(0) r test for unit root Test 1%	r test for unit root Test 1% Critical Statistic Value 2.689 -3.723 proximate p-value for Z(t) = 0.9991 fdi, lags(0) r test for unit root Test 1% Critical Statistic Value -5.109 -3.723 proximate p-value for Z(t) = 0.0000 rec, lags(0) r test for unit root Test 1% Critical Statistic Value 1.023 -3.723 proximate p-value for Z(t) = 0.9945 gdp, lags(0) r test for unit root Test 1% Critical Statistic Value 1.023 -3.723 proximate p-value for Z(t) = 0.9945 gdp, lags(0) r test for unit root Test 1% Critical	r test for unit root Number of obs Test 1% Critical 5% Critical Statistic Value Value 2.689 -3.723 -2.989 proximate p-value for Z(t) = 0.9991 fdi, lags(0) r test for unit root Number of obs Test 1% Critical 5% Critical Statistic Value Value -5.109 -3.723 -2.989 proximate p-value for Z(t) = 0.0000 rec, lags(0) r test for unit root Number of obs Test 1% Critical 5% Critical Statistic Value Value 1.023 -3.723 -2.989 proximate p-value for Z(t) = 0.0000 rec, lags(0) r test for unit root Number of obs 1.023 -3.723 -2.989 proximate p-value for Z(t) = 0.9945 gdp, lags(0) r test for unit root Number of obs Test 1% Critical 5% Critical statistic Value Value 1.023 -3.723 -2.989 proximate p-value for Z(t) = 0.9945 gdp, lags(0) r test for unit root Number of obs Test 1% Critical 5% Critical statistic Value Value 1.023 -3.723 -2.989 proximate p-value for Z(t) = 0.9945 gdp, lags(0) r test for unit root Number of obs Test 1% Critical 5% Critical	r test for unit root Number of obs = Interpolated Dickey-Fuller Test 1% Critical 5% Critical 10% Statistic Value Value 2.689 -3.723 -2.989 proximate p-value for Z(t) = 0.9991 fdi, lags(0) r test for unit root Number of obs = Test 1% Critical 5% Critical 10% Statistic Value Value -5.109 -3.723 -2.989 proximate p-value for Z(t) = 0.0000 rec, lags(0) r test for unit root Number of obs = Test 1% Critical 5% Critical 10% Statistic Value Value -5.109 -3.723 -2.989 proximate p-value for Z(t) = 0.0000 rec, lags(0) r test for unit root Number of obs = Test 1% Critical 5% Critical 10% Statistic Value Value 1.023 -3.723 -2.989 proximate p-value for Z(t) = 0.9945 proximate p-value for Z(t) = 0.9945 pdp, lags(0) r test for unit root Number of obs = Test 1% Critical 5% Critical 10% Statistic Value Value 1.023 -3.723 -2.989 proximate p-value for Z(t) = 0.9945 pdp, lags(0) r test for unit root Number of obs = Test 1% Critical 5% Critical 10% Statistic Value Value Value 1.023 -3.723 -2.989 proximate p-value for Z(t) = 0.9945 pdp, lags(0) r test for unit root Number of obs = Test 1% Critical 5% Critical 10% Statistic Value Value Value 1.023 -3.723 -2.989 proximate p-value for Z(t) = 0.9945 pdp, lags(0) r test for unit root Number of obs = Test 1% Critical 5% Critical 10%

MacKinnon approximate p-value for Z(t) = 0.0004

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. ardl lngg_d lnmva_d lnto lnrec lntgremm lngdp lnfdi, lags(4,2,2,2,2,1,0)ec							
ARDL(4,2,2,2,2,1,0) regression							
Sample: 19	95 - 201	9		Number	of obs =	25	
				R-squar	ed =	0.9559	
				Adj R-s	quared =	0.7883	
Log likelihood	d = -1.111656	6		Root MS	Ξ =	0.5657	
D.lngg_d	Coef.	Std. Err.	t	₽> t	[95% Conf.	Interval]	
ADJ							
lngg_d L1.	-3.371016	.5584663	-6.04	0.002	-4.8066	-1.935433	
LR							
lnmva d	7.13465	2.547602	2.80	0.038	.585831	13.68347	
lnto	.7442005	.4148058	1.79	0.133	3220919	1.810493	
lnrec	-1.567548	4.357813	-0.36	0.734	-12.76966	9.634568	
lntgremm	.1819994	.2268861	0.80	0.459	4012299	.7652288	
lngdp	.0697783	.1793031	0.39	0.713	391135	.5306916	
lnfdi	0447625	.0897616	-0.50	0.639	275502	.1859769	
SR							
lngg_d							
LD.	1.85076	.3645816	5.08	0.004	.9135734	2.787947	
L2D.	1.171244	.30383	3.85	0.012	.3902244	1.952264	
L3D.	1.353266	.3324278	4.07	0.010	.498733	2.207799	
lnmva_d							
D1.	-15.56845	6.3217	-2.46	0.057	-31.8189	.6819987	
LD.	-7.385984	3.903616	-1.89	0.117	-17.42055	2.64858	
lnto							
D1.	.9006852	1.581818	0.57	0.594	-3.165506	4.966877	
LD.	-2.386992	1.018776	-2.34	0.066	-5.005839	.231855	
lnrec							
D1.	-47.74934	24.50352	-1.95	0.109	-110.7376	15.23895	
LD.	10.53029	16.19144	0.65	0.544	-31.09113	52.1517	
lntgremm							
D1.	-21.98501	9.114153	-2.41	0.061	-45.41368	1.443668	
LD.	-22.69766	6.550308	-3.47	0.018	-39.53577	-5.859558	
lngdp							
D1.	-1.241053	.6292342	-1.97	0.106	-2.858551	.3764452	
_cons	21.74906	65.61723	0.33	0.754	-146.9254	190.4235	

ardl lngg_d lnmva_d lnto lnrec lntgremm lngdp lnfdi, lags(4,2,2,2,2,1,0)ec

BI) SIMESS

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. estat ovtest

Ramsey RESET test using powers of the fitted values of D.lngg_d

Ho: model has no omitted variables

F(3, 2) = 3.30 Prob > F = 0.2410

. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	0.558	1	0.4552

HO: no serial correlation

. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity Ho: Constant variance Variables: fitted values of D.lngg d

> chi2(1) = 1.55 Prob > chi2 = 0.2137

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. estat btest

note: estat btest has been superseded by $\underline{\mathsf{estat}\ \mathsf{ectest}}$

as the prime procedure to test for a levels relationship. (<u>click to run</u>)

Pesaran/Shin/Smith (2001) ARDL Bounds Test

H0:	no	levels	relationship	F	=	7.183
				t	=	-6.036

Critical Values (0.1-0.01), F-statistic, Case 3

	[I_0] L_1				1	[I_1] L_025		
k 6	2.12	3.23	2.45	3.61	2.75	3.99	3.15	4.43

k_0 | 2.12 3.23 | 2.45 3.01 | 2.75 3.99 | accept if F < critical value for I(0) regressors reject if F > critical value for I(1) regressors

Critical Values (0.1-0.01), t-statistic, Case 3

	[I_0] L_1	[I_1] . L_1	[I_0] L_05	[I_1] L_05	[I_0] L_025	[I_1] L_025	[I_0] L_01	[I_1] L_01
k_6	-2.57	-4.04	-2.86	-4.38	-3.13	-4.66	-3.43	-4.99
accept	if t >	critical	value for	I(0) re	gressors			
reject	if t <	critical	value for	I(1) re	gressors			

k: # of non-deterministic regressors in long-run relationship Critical values from Pesaran/Shin/Smith (2001)

. summarize gg mva to tgremm fdi rec gdp, separator(6)

Variable	Obs	Mean	Std. Dev.	Min	Max
gg	30	1.109138	.6401007	.007185	1.9738
mva	30	12.18496	2.401696	9.254067	19.04892
to	30	.4400594	.0775816	.2589851	.6000769
tgremm	30	5492.636	2330.891	3198.271	11765.32
fdi	30	1.620891	1.835874	.1012854	6.977522
rec	30	80.969	2.711287	72.1	84
gdp	30	5.775298	3.176681	1.576078	16.72882

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Appendix 2. Data

/EAR	GG	MVA	ТО	TGREMM	FDI	REC	GDP
1990	1.77387	16.64939904	0.398262741	3264.095627	0.85126961	84	5.692295
1991	1.66816	16.29423661	0.432409881	3442.216377	0.894977532	82.63	8.730232
1992	1.6896	19.04892383	0.485672868	3447.243628	0.271112653	82.71	7.332978
1993	1.79565	14.34215779	0.338742651	3588.173878	0.265481519	81.33	9.691841
1994	1.57091	15.49640056	0.600076866	3198.271429	1.453173439	82.02	10.24018
1995	1.9738	13.98260916	0.580936611	3403.347332	0.277476585	81.69	16.72882
1996	1.50692	12.95145128	0.413880056	3587.959269	0.475894256	81.43	7.316682
1997	1.5634	12.59871547	0.399921307	3610.456706	0.383630956	81.2	3.792419
1998	1.96004	12.31291966	0.507475723	3795.306542	0.475121093	81.9	3.895254
1999	1.52404	12.16716766	0.515953442	3824.093079	2.264603719	81.03	3.042278
2000	1.60166	11.61744248	0.453353062	3963.605916	1.024708108	82.62	1.576078
2001	1.54558	10.49399342	0.468346618	3785.700157	0.772615061	83.13	4.974964
2002	1.36816	12.3885768	0.258985131	4144.422299	0.115974414	83.3	1.7
2003	1.43281	13.50185628	0.348043172	4376.09724	1.410890851	82.83	5.705639
2004	1.1504	11.27657708	0.342399724	4393.381882	2.131196008	82.45	5.420498
2005	1.08999	10.2821379	0.375765399	4468.106724	2.625670048	83.17	3.268726
2006	1.02023	12.40396844	0.376903271	4735.398802	0.611208219	82.8	4.7
2007	0.98218	13.94920134	0.387141589	5168.37098	1.928144407	82.21	9.6
2008	1.09299	11.71829675	0.411041853	5689.260358	2.52370279	80.39	7.639736
2009	0.100129	10.37868845	0.411530257	5765.672836	0.545293921	80.01	8.32811
2010	0.007185	9.909851245	0.40077698	6369.508614	0.957814621	81.21	6.874066
2011	0.045124	10.06951316	0.417888116	6677.355617	6.977522278	80.17	4.93267
2012	0.134998	9.254067752	0.454117295	6924.125421	0.101285426	80.2	1.9
2013	0.207263	9.563997098	0.575696686	7294.602924	5.61985139	79.76	5.41035
2014	0.209337	9.549752663	0.563828154	7791.483427	6.795413857	82.78	5.62527
2015	0.091582	9.60125083	0.434882793	8204.93103	3.121074777	80.98	2.8
2016	0.467577	9.518886746	0.466329387	8444.877316	1.462729731	78.91	2.5
2017	1.07757	11.29706162	0.467718432	9125.424201	1.008548773	76.92	Z
2018	1.30121	11.39177778	0.457816499	10530.26139	0.779423469	73.19	4.391688
2019	1.32179	11.53793265	0.455886358	11765.31867	0.50091585	72.1	5.448181

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