Analysing the Impact of Green Finance on the Stock Market Development in BRICS Nations: A Panel ARDL Method

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ABSTRACT

The stock market is considered an essential marketplace that unites savers and borrowers, generating liquidity that enables governments, businesses, and individuals to trade shares, which is crucial for economic growth. With the provision of green finance in the financial market, there have been considerable changes in trade strategies, and risk management. Thus, the present study examines the impact of green finance (GF) on stock market (SM) along with technological factor, artificial intelligence (AI), other external factors such as trade (tr), foreign investment (FDI), exchange rate (Ex), and internal factors such as inflation (In) and domestic credit (DC) from 2000 to 2022 in BRICS nations. BRICS countries were particularly selected due to the high potential for investment. According to the results of the first- and second-generation panel unit root tests, there are no unit root issues, and the factors have a mixed order of integration. The long-term cointegration of the factors is validated by the panel cointegration test. The results show that GM, AI, FDI, and Tr have a positive effect on the stock market, whereas Ex and In have a negative effect. However, DC has a positive but insignificant impact. While in the short run, all factors except trade have a positive impact on SM in BRICS nations. These panel ARDL results were further validated by employing Augmented Mean Group (AMG) and Common Correlated Effects Mean Group (CCEMG). The findings suggested that policymakers should concentrate more on investment policies focusing on green finance and integrating AI techniques for the development of the stock market.

KEYWORDS*:* Artificial intelligence; FDI; green finance; panel ARDL; stock market; trade

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INTRODUCTION

The stock markets of the BRICS nations—Brazil, Russia, India, China, and South Africa—have grown significantly during the last 10 years. It is anticipated that the BRICS member countries' growth rates would accelerate in the near future, possibly overtaking the US and European combined growth rates by 2030 (Ganguly & Bhunia, 2022). The BRIC taxonomy was first developed by Goldman Sachs to characterise Brazil, Russia, India, and China—a collection of large emerging economies with significant potential for growth. Following the group's official formation in 2006, the first BRIC summit took place in 2009. When South Africa joined in December 2010, the group saw its first expansion, becoming known as BRICS (Toloraya, 2018). The BRICS group has become one of the most important economic blocs in the past decade, accounting for around 42% of the world's population, 26% of the global GDP, 21% of exports, 16% of global imports (Larionova, 2020). Despite being an unofficial organisation without a charter, the bloc has a more institutional character because to high levels of political engagement and the establishment of economic institutions like the New Development Bank. There is some co-movement among the BRICS markets due to the countries' increasing political and economic relations (Lehkonen & Heimonen, 2014). A uniform platform for trading stocks is provided by the stock market (Voit, 2013). While institutional investors can make significant investments, individual investors can benefit from the trading conveniences (Enisan & Olufisayo, 2009). The economy's money flow is facilitated by the stock market. It also makes the market more liquid and creates an environment that is favourable to IPOs and entrepreneurship. According to Levine and Zervos (1999), the size of the stock market plays a major part in stabilising the ways in which money may be obtained to better support investments and economic growth. Any economy that wants to transition from a traditional, rigid, and risky bank-based economy to one that is more flexible, safe, and resistant to shocks, volatility, and a lack of investor confidence must have it. Numerous studies examine the integration of global stock markets. Despite some indications that China is increasingly fragmented, Nayyar (2020) and Dsouza et al. (2024) demonstrate interconnectedness within the BRICS economies. For instance, Sharma et al. (2013) used the variance decomposition test and VAR model to identify interdependencies across the BRICS stock market based on daily data from April 1, 2005, to March 31, 2010. Using wavelet multiple correlation and daily data from January 4, 2005, to February 28, 2012, the researchers discovered that the chosen nine Asian countries were highly connected (Tiwari et al., 2013). Wu (2020) shows that estimations of stock market integration across developing economies can be significantly skewed if the influence of global market forces is ignored.

At the same time, economic theory and empirical study have long been interested in and investigating the connection between macroeconomic variables and stock prices. Research has continuously acknowledged market indices and stock prices as valid indicators for evaluating economic conditions (Abbass et al., 2022). Stock market prices are strongly impacted by a nation's economic circumstances (Riaz et al., 2022). The stock market is also significantly impacted by macro factors, including GDP, interest rates, exchange rates (ER), and inflation (Gyamfi et al., 2021).

In the resent time, there are few literatures stating the impact of green bonds, that is green finance effects the stock market. In general, green financing plays a key role in positioning the regional economy as a high-quality, low-carbon, and environmentally friendly growth path (Wang and Zhou 2022). It has been recognised that green finance is an essential tool for raising the funds required to assist ecologically friendly initiatives and businesses (Li and Lin, 2024). Yu et al. (2023), for instance, emphasize the vital role that green financing plays in reducing environmental hazards and encouraging sustainable industrial practices, especially in emerging economies. Certification exam administration plays a crucial role in preventing "green-washing," which in turn lessens the risks connected to green expenditures for businesses. Furthermore, funding allocations to companies with high energy usage and pollutant emissions may decline as green financing develops. Redirecting financial resources to environmentally friendly and energy-efficient businesses is in line with ecological goals and creates a new strategic paradigm for financial institutions. This change reflects the ideas of sustainable economics and emphasises how important financial intermediaries are in encouraging ecologically conscious investing practices (Iram et al., 2020). This all effect the stock market of the any countries. BRICS nations being the fast growing economies, its stock market will be impacted by the green finance.

Given the preceding circumstances, the main goal of this research is to investigate how the stock market (taking the stock traded as a proxy) is affected by the financial factor, namely green finance, technological factor, namely artificial intelligence (taking the patent application as the proxy), external factors (FDI, trade openness, and exchange rate), and internal factor (inflation), specifically in the context of BRICS nations. This study adds to the body of knowledge in several ways. First, there is a lack of research using the ARDL approach to investigate the short- and long-term effects of the aforementioned factors in BRICS nations for a period from the 2000s when the impact of technology became more visible in the stock exchange. Second, the study adds green finance and artificial intelligence as a factor affecting the stock market, which has been lacking in earlier research. Additionally, the research will offer some potential recommendations on the basis of the findings.

MATERIALS AND METHODS

Data

The present research examined the dynamic short- and long-run impact of green finance (GF) along with technology factor such as artificial intelligence (AI), open economy factors such as foreign direct investment (FDI), trade (Tr), and exchange rate (Ex); and internal factor, inflation (In) and domestic credit (DC) on the stock market (SM) (taking stock traded as a proxy) in BRICS nations by employing the panel autoregressive distributive lag model method. A time series dataset spanning over 23 years, from 2000 to 2022, was used in the investigation. Data on foreign direct investment (FDI), trade (Tr), exchange rate (Ex), inflation (In), and stock market (SM) (taking stock traded in current US dollars as the proxy) were sourced from World Development Indicators (WDI) (World Bank, 2024). Additionally, data regarding artificial intelligence and green finance (GF) were sourced from the OECD statistics database. The stock market (SM) is the dependent variable in the current study. In the current study, FDI, Tr, and stock traded were measured in terms of current US$ and inflation is calculated as consumer price (annual percentage), whereas the exchange rate is measured in terms of LCU per US$, period average. The OECD's patent databases, which offer comprehensive information on patent filings categorised by technological disciplines, including AI-related advancements like machine learning, robotics, and data analytics, are the source of the AI variable, which is defined as patents for technologies related to artificial intelligence. For, green finance, we have taken data related to Environmentally related government R&D budget, percentage total government R&D. For all our data analysis and econometric modelling, we used EViews 12, an exhaustive econometric software. To ensure that the data was normally distributed, the factors were converted into logarithms. Table 1 provides a detailed overview of factors used in the study, together with information on sources, rationale, unit of measurement, and data description.

Table 1. Data description

Variable type		**Factors**	**Abbreviation**	**Units**	**Data source**
Output variable	Dependent factors	Stock traded	LnSM	Current US$	WDI
Financial variable	Independent factors	Green Finance	LnGF	Environmentally related government R&D budget, percentage total government	OECD
Technology variable		Artificial Intelligence	LnAI	Patents for technologies related to artificial intelligence	WDI

Open Economy Factors		Exchange Rate	LnEx	LCU per US$, period average	WDI
		Trade	LnTr	Net trade in goods and services (BoP,	WDI
		Foreign Direct Investment	LnFDI	Foreign direct investment, net (BoP, current US$)	WDI
Internal factor		Domestic Credit	LnDC	Private sector as a % of GDP	
		Inflation	LnIn	Consumer price annual %	WDI

Model specification

The panel ARDL model was employed for accomplishing the objectives, and similar models were used by studies such as Raihan et al. (2024), who focus on how AI affects the environment in G7 nations, and Joo and Shawl (2023), which focused mainly on the influence of FDI on economic growth along with trade, stock market capitalisation, and inflation as a few other important factors in BRICS nations. The present investigation employs the following model, which is an alternative and extended version of the model used by Raihan et al. (2024) and Joo and Shawl (2023), and this serves as the theoretical foundation. In this regard, we use the following equation.

$SM_{it} = f(GF_{it}, AI_{it}, FDI_{it}, Tr_{it}, Ex_{it}, In_{it}, DC_{it})$
(1)

Where,

SM_{it} = Stock traded

GF_{it} = Green Finance

AI_{it} = Artificial Intelligence

FDI_{it} = Foreign direct investment

Tr_{it} = Trade

Ex_{it} = Exchange rate

In_{it} = Inflation

DC_{it} = Domestic credit

't' represents 'time', 'i' represent 'observation' and 'f' represent 'function'.

From the equation (1), we derive the equation (2)

$$SM_{it} = GF_{it}^{\alpha 1}, AI_{it}^{\alpha 2}. FDI_{it}^{\alpha 3}. Tr_{it}^{\alpha 4}. Ex_{it}^{\alpha 5}. In_{it}^{\alpha 6}. DC_{it}^{\alpha 7.} v_t \quad (2)$$

The following questions are the main focus of this investigation. Are BRICS nations stock markets affected by the aforementioned factors? What kind of effect does it have on the stock market? Previous research has shown contradictory results. For instance, Zhang and Ding (2023) has found that green finance has a negative impact on stock market development of China. In the research focusing on India, insignificant results are observed in the long-term impact of inflation and exchange rate on the stock market applying the ARDL model (Tejesh, 2024). Whereas Sreenu (2023) found a significant positive impact of exchange rate and inflation in the long run and a negative impact in the short run on the stock market in India. In the study, Qamruzzaman and Wei (2018) identified a long-term correlation among the variables, such as financial development (application of technology) and stock market development. In the context of Brazil, Nyasha and Odhiambo (2020) found that exchange rates and trade have a positive and significant impact on the growth of the stock market. The fluctuation of the BRICS stock indexes, both past and currently, is significantly impacted by changes in exchange rates (Caporale et al., 2015; Mroua and Trabelsi, 2020). However, there are no studies that have been undertaken to study the impact of artificial intelligence on the stock market in the BRICS nations using a high-end model like panel ARDL. By examining data from 2000 to 2022, this study attempts to fill these gaps and provide a thorough grasp of these factors determining the development of the stock market.

Unit root test

Unit root tests are often employed to test the stationarity of the factors used in the analysis. As described in the research of Joo et al. (2023), a data set is considered to be stationary if the average, variance, and covariance of the data are constant. In the current research, Im, Pesaran, and Shin (IPS), which has been introduced by Im et al. (2003), and LLC (Levin, Lin, and Chu) tests developed by Levin et al. (2002) are the first-generation unit root tests, and CIPS and CADF second-generation unit root tests, which take into consideration slope variation and cross-sectional dependency created by Pesaran (2007), were employed. Such similar tests were employed in the research undertaken by Raihan et al. (2024).

Null hypothesis: There is a unit root, or the factors of the series are not stationary.

Panel cointegration

The Pedroni panel cointegration test is used to detect if cointegration exists, assuming panel heterogeneity. Pedroni (1999) produced two distinct assessments. Panel v-statistics, panel rho-statistics, panel PP-statistics, and panel ADF-statistics are the four statistical measures used in the first test, which follows a within-dimension methodology. Three statistical measures—group statistics, group PP statistics, and group ADF statistics—as well as a between-dimension approach are used in this experiment. The null hypothesis, according to which there is no cointegration, is rejected if the p-value for each of these data points is less than the designated significance threshold.

Panel ARDL

In the present research, the development of stock market is linked to financial factor such as green finance (ii) technology factor such as artificial intelligence, (iii) open economy factor such as FDI, trade, exchange rate and (iv) internal factor such as inflation and domestic credit. The empirical model states that stock market development (taking stock traded as proxy) is a function of these technological, open economy factor as well as internal factor. In order to determine the relationship between stock market development and these explanatory factors, the study employs the following.

$$SM_t = \alpha_0 + \alpha_1 GF_t + \alpha_2 AI_t + \alpha_3 FDI_t + \alpha_4 Tr_t + \alpha_5 Ex_t + \alpha_6 In_t + \alpha_7 DC_t + u_t \quad (6)$$

Where α_0 is the intercept of the model, α_1 to α_7 are the coefficient that quantify the impact of explanatory factors in the dependent variable. Additionally, we convert our model to logarithmic form in order to prevent heteroskedasticity and autocorrelation (Hassan and Muhammed, 2024).

Pesaran et al. (2001) developed the autoregressive distributed lag model, which is employed in this study, and it is more effective than any other cointegration technique (Panpoulou and Pittis, 2004). Both short- and long-run dynamics between the variables can be analyzed using the ARDL model when the independent variables in the model are I (0) and I (1) or jointly integrated (Fosu and Magnus, 2006). It is appropriate for time series data as it enables the inclusion of both stationary and non-stationary variables in this analysis (Fosu and Magnus, 2006). The current study employed panel ARDL. The primary justification for using panel data is that it assesses the impact collectively rather than individually, meaning that by adopting a panel perspective, relatively little information is lost (Baltagi, 2008). Furthermore, heteroscedasticity is not a problem in panel data analysis as panel data minimises the noise originating from the individual time series (Ahn et al., 2013). Additionally, panel data is most appropriate in situations when data availability is a problem, especially in developing nations where short-term variables are accessible (Khelfaoui et al., 2022). By accounting for subject-specific factors and dynamic changes brought on by repeated cross-sectional observations, panel estimate approaches account for this heterogeneity. Heterogeneous panel data modelling, or panel-ARDL, is the only focus of this work. Due to its ability to analyse both short-term and long-term dynamics between technological, open economy, and internal factors, the Panel Autoregressive Distributed Lag (ARDL) approach is well suited for this study on the BRICS countries' advancing stock market development. In order to capture the distinct economic and technical landscapes of the BRICS countries, this approach must take into account variability across cross-sections. In contrast to conventional panel data techniques, Panel ARDL addresses the possibility of various temporal dynamics within each nation by permitting varying lag lengths for every variable. Furthermore, as is typical in financial and macroeconomic datasets, Panel ARDL excels at managing variables with mixed integration orders (I(0) and I(1)). The dependent-independent variable relationship was determined via the following model.

$$InSM_t = \alpha_0 + \alpha_1 LnSM_t + \alpha_2 LnGF_t + \alpha_3 LnAI_t + \alpha_4 LnFDI_t + \alpha_5 LnTr_t + \alpha_6 LnEx_t + \alpha_7 LnIn_t + \alpha_8 LnDC_t + v_t \quad (3)$$

Equation (3) may be expressed as follows in ARDL form:

$\Delta LnSM_t = \alpha_0 + \sum_{i=1}^{n1} \alpha_{1i} LnSM_{t-i} + \sum_{i=1}^{n2} \alpha_{2i} \Delta LnGF_{t-I} + \sum_{i=1}^{n3} \alpha_{3i} \Delta LnAI_{t-i} + \sum_{i=1}^{n4} \alpha_{4i} \Delta LnFDI_{t-i} + \sum_{i=1}^{n5} \alpha_{5i} \Delta LnTr_{t-i} + \sum_{i=1}^{n6} \alpha_{6i} LnEx_{t-i} + \sum_{i=1}^{n7} \alpha_{7i} LnIn_{t-i} + \sum_{i=1}^{n8} \alpha_{8i} \Delta LnAI_{t-I} + \beta_1 LnSM_{t-1} + \beta_2 LnGF_{t-1} + \beta_3 LnAI_{t-1} + \beta_4 LnFDI_{t-1} + \beta_5 LnTr_{t-1} + \beta_6 LnEx_{t-1} + \beta_7 LnIn_{t-1} + \beta_8 LnDC_{t-1} + e_t$

(4)

When α_0 represents a drift component, Δ indicates the first difference between the variables, and et is the white noise error term. According to Gujarati (2009), the term "white noise error term" refers to an uncorrelated random error term with zero mean and constant variance σ^2. In equation (4), the coefficients from 2nd to 8th (α_{1i} to α_{8i}) suggest an association in short-term and long-term relationships, as shown by the coefficients from 9th to 16th (β_1 to β_8). Utilizing the ARDL bounds testing technique, the long-term relationship between the variables is investigated. The F statistic is used in the bounds testing method to evaluate the hypothesis. This may be stated as follows.

H_0: There is no cointegration. ($\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8$)

H_1: Cointegration exists. ($\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6 = \beta_7 = \beta_8$)

If the computed f statistic is greater than the upper bound value, the null hypothesis is rejected. The null hypothesis cannot be rejected if the computed f statistic is less than the lower bound of the critical value. We are unable to draw any conclusions if the f statistic falls between the critical values of the lower and upper bounds. On the other hand, the assumption made by Pesaran et al. (2001) allows for the introduction of an unrestricted error correction model, where the long-run elasticities are the negative coefficients of a one-lag dependent variable. The ECM version of the ARDL model is represented as follows.

$\Delta LnSM_t = \alpha_0 + \sum_{i=1}^{n1} \alpha_{1i} LnSM_{t-i} + \sum_{i=1}^{n2} \alpha_{2i} \Delta LnGF_{t-I} + \sum_{i=1}^{n3} \alpha_{3i} \Delta LnAI_{t-i} + \sum_{i=1}^{n4} \alpha_{4i} \Delta LnFDI_{t-i} + \sum_{i=1}^{n5} \alpha_{5i} \Delta LnTr_{t-i} + \sum_{i=1}^{n6} \alpha_{6i} LnEx_{t-i} + \sum_{i=1}^{n7} \alpha_{7i} LnIn_{t-i} + \sum_{i=1}^{n8} \alpha_{8i} \Delta LnAI_{t-I} + \gamma EC_{t-1} + e_t$
…….(5)

Where γ represents the speed of adjustment and EC are the residual obtained from equation (5).

Robustness check

The robustness was evaluated in the paper using the DKSE, CCEMG, and AMG estimators. In addition to the residuals, Driscoll and Kraay (1998) employed the average values of the explanatory variable outcomes. Second, in the current study, we used the augmented mean group (AMG) estimator, which was proposed by Eberhardt and Teal (2010). Because the AMG estimator accounts for the CSD, mixed-order stationarity, and heterogeneity in the panel data, it produces more trustworthy results than first-generation estimators. The third estimator used in this work is the CCEMG approach, which was created by Pesaran (2006). Furthermore, both AMG and CCEMG perform better when estimating using common components that are uncertain and inconsistent. By taking into consideration temporal changes with varying factor pitches, the CCEMG resolves the identification problem.

RESULT AND DISCUSSION

Cross- Sectional Dependence Test

Table 2 displays the findings of the CDS test, which reveal there exists a strong cross-sectional dependence among the variables employed in the current research. At the 1% level of significance, CD statistics are highly significant, indicating that they are not independent among the cross-sectional units. This in turn suggests that any modifications or shocks to one unit within the panel will have an impact on the other units also. Cross-sectional dependence must be taken into consideration, as the validity and interpretation of the results are impacted by them. In order to guarantee reliable and accurate results, it is imperative to use second-generation panel data methodologies that take this dependence into consideration.

Table 2. Cross sectional dependence test

Variables	CD- Statistics	P- Value
LnSM	11.87***	0.000
LnGF	13.58***	0.000
LnAI	8.14***	0.000
LnFDI	6.33***	0.000
LnTr	17.10***	0.000
LnEx	8.99***	0.000
LnIn	13.75***	0.000

LnDC	12.47***	0.000

Source: Author's own evaluation using EViews

Slope Homogeneity Test

The results of the Pesaran and Yamagata (2008) slope homogeneity test are shown in Table 3. The delta statistics are highly significant. Hence, the null hypothesis of slope homogeneity is rejected. In other words, the slopes in the panel data model are not uniform among the cross-sectional units. This means the influence of the exogenous variable on the endogenous variable (stock traded as a dependent variable in the current study) varies, leading to a slope heterogeneity issue.

Table 3. Slope Homogeneity test result

Slope Homogeneity tests	**Δ statistic**	**P- value**
$\tilde{\Delta}$ test	12.174	0.000
$\tilde{\Delta}_{adj}$ test	16.981	0.000

Source: Author's own evaluation using EViews

Panel Unit root test

The findings of panel unit root tests, both the first generation (Levin, Lin, and Chu) as well as the second generation (CIPS and CADF), are shown in Table 4. Due to the high p-value (more than 0.05), the factors such as stock traded (LnSM), trade (LnTr), inflation (LnIn) and domestic credit (LnDC) exhibit non-stationarity at the level, which falls short of the critical value needed to reject the null hypothesis of unit root at the level in both first generation and second generation. The null hypothesis of a unit root is rejected for these factors having significant t-statistics and low p-values (less than 0.05) when first differenced. After differencing once, these factors are stationary. However, the factors such as LnGF, LnFDI, LnAI, and LnEx indicate stationarity at level in both the generation test. Therefore, for further analysis, the variables LnSM, LnTr, and LnIn are converted to first differences.

LnIn	**LnEx**	**LnTr**	**LnFDI**	**LnAI**	**LnGF**	**LnSM**	**Variables**	
-1.394 (0.336)	-1.697***	-1.265 (0.089)	-3.657***	-2.774***	-1.624 (0.002)	-1.985 (0.085)	I (0)	Levin-Chu
-3.911***	-3.694***	-3.617***	-7.698***	-3.148***	-3.363***	-4.185*** (0.003)	I (1)	
-4.333 (0.518)	-1.745***	-3.611 (0.742)	-3.867***	-2.972***	-5.001***	-5.691 (0.619)	I (0)	CIPS
-8.691***	-3.981***	-8.462***	-5.029***	-5.142***	-6.144***	-10.418***	I (1)	
-2.364 (0.075)	-4.267**	-6.948 (0.258)	-4.187**	-4.256*	-0.262**	0.695 (0.417)	I (0)	CADF
-6.311**	-7.239**	-10.697	-8.917**	-8.522*	-5.147**	-6.112*** (0.000)	I (1)	
I(1)	I(0)		I(0)	I(0)	I(0)	I(1)		Decision

LnDC	-1.216 (0.418)	-3.742***	-4.842 (0.635)	-9.365***	-2.481 (0.086)	-5.452*	I(1)

Table 4. Panel Unit Root

Source: Author's own evaluation using E-Views software

Note: *** indicates the significance

Panel Cointegration

The findings of Pedroni's cointegration test, which was used to determine whether there was a long-term connection between the variables, are displayed in Table 5. Two sets of substitute theories are assessed: Common autoregressive coefficients within the dimension (ii) and individual autoregressive coefficients between dimensions (iii). Despite being statistically insignificant, the panel v-statistic and rho-statistic are both negative, suggesting conflicting evidence for a long-term relationship. Nonetheless, the highly significant panel PP-statistic and panel ADF-statistic results show that the no cointegration hypothesis is strongly refuted. Furthermore, the significantly negative Group PP and Group ADF statistics clearly contradict the null hypothesis that there is no cointegration between panels. The group rho-statistic is positive but not significant if individual autoregressive coefficients between dimensions are assumed. Although there may be some variance in the autoregressive coefficients within and between dimensions, these results typically demonstrate that there is evidence of cointegration across the variables in the panel dataset.

Table 5. Panel Cointegration result

Alternative hypothesis: common AR coefs. (within- dimension)				
	Statistic	**Prob.**	**Weighted Statistics**	**Prob.**
Panel v-statistic	-0.75215	0.84239	-0.75104	0.86100
Panel rho-statistic	-1.52014	0.92014	-1.49852	0.95014

Panel PP-Statistic	-8.14512	0.00001	-5.10074	0.00013
Panel ADF-Statistic	-3.23021	0.00015	-3.77484	0.00000
Alternative hypothesis: individual AR coefs. (between dimension)				
	Statistic		Prob.	
Group rho-statistic	-4.17414		0.5201	
Group PP-Statistic	-7.74521		0.0000	
Group ADF-Statistic	-8.01041		0.0003	

Source: Author's own evaluation using E-Views software

Panel ARDL

Employing the panel ARDL technique, the study identified the long-term and short-term impacts of explanatory variables such as LnGF, LnAI, LnFDI, LnTr, LnEx, LnIn and LnDC on the dependent variable LnSM. Table 6 presents the long-term results of the panel ARDL approach. Green finance (LnGF) has a positive impact on the stock market (LnSM) in the long term, with a coefficient value of 0.42 indicating that 1 percent rise in the LnGF, woulf increase the growth of stock market by 0.42 percent. This was supported by the existing studies such as Li and Lin (2024) and Zhang and Ding (2023). This may be due to the fact that By promoting sustainable investments and increasing investor trust in ecologically conscious businesses, green financing has a beneficial effect on the stock market. Green practices draw ESG-conscious investors, which raises demand and stock values as more companies implement them. Green bonds and government incentives encourage investment in sustainable industries, which fosters long-term growth and innovation. This change strengthens the resilience of financial markets, lowers environmental risks, and supports global climate objectives. Overall, by balancing financial gains with environmental responsibility, green finance not only promotes ecological sustainability but also enhances stock market performance and stability.

Artificial intelligence (AI) developments are a contributing factor to the rise in stock market activity, as seen by the positive and significant long-term coefficient of LnAI.

A 1% increase in AI leads to 0.36% increase in stock traded (SM) illustrates how AI may improve trading efficiency, decision-making, and market analysis. Faster transactions, greater risk assessment, and enhanced investing strategies are made possible by AI-driven algorithms, which also increase market liquidity and draw in more players. This increase in the use of AI encourages trading volume and increases investor confidence. AI's revolutionary influence on financial markets and long-term economic growth is therefore highlighted by the close connection between it and stock market activity. These results were in line with the studies by Mohanram (2005) and Pagliaro (2023), who reported that AI has a positive role in the development of the stock market. Similarly, FDI has a positive and significant effect on LnSM; a 1 percent increase in LnFDI increases LnSM by 0.34 percent. Adediran (2023) found a similar results. The stock market (LnSM) benefits greatly from foreign direct investment (FDI); for instance, a 1% increase in LnFDI causes a 0.34% increase in LnSM. This relatiosnhip illustrates how foreign direct investment (FDI) boosts investor confidence, attracts money, and promotes economic growth—all of which in turn boost stock market activity. Improved infrastructure, knowledge transfer, and job creation are frequently the results of FDI, which improves business performance and draws in further capital. Foreign investors' involvement in local markets boosts trade volume and liquidity, which supports long-term financial and economic growth and strengthens the stock market.

A higher level of trade activity improves stock market performance, according to the positive and substantial long-term coefficient of trade (LnTr). The stock market (LnSM) rises by 0.21% for every 1% increase in LnTr, indicating that more trading improves market liquidity and participation. Stronger economic activity is reflected in higher trade volumes, which boost investor confidence and company performance. As a result, trading volumes and market capitalisation increase as more local and foreign investors participate in the stock market. All things considered, more trade promotes economic integration, draws in investment, and fortifies the depth and effectiveness of the financial system. This was consistent with the findings of Dino (2023), which showed that a rise in trading volume had a beneficial impact on the stock prices of businesses that are part of the S&P 500 index. With a coefficient of -0.11, the exchange rate (LnEx) and stock traded (LnSM) have a negative long-term connection, indicating that currency depreciation deters stock market activity. Lesser trade volumes and capital outflows result from foreign investors receiving lesser profits as the local currency declines.

Additionally, it increases the cost of imports, which impacts investor sentiment and business profitability, ultimately decreasing market participation. However, studies that focus on the stock market and exchange rate generally produced contradictory findings, stating of negative and positive impact, with studies by Moussa and Delhoumi (2021) and Jawaid and Ui Haq (2012) showing positive and significant impact, whereas the negative impact has been identified in the research undertaken by Khan (2019).

With a 0.07% drop in stock traded for every 1% increase in inflation, the long-term and substantial impact of inflation (LnIn) on the stock market (LnSM) suggests a decline in investor confidence. Excessive inflation reduces buying power, raises expenses, and breeds economic ambiguity, all of which deter investment. Over time, this results in decreased stock market activity and fewer company earnings. These findings were supported by the earlier findings of Uwubanmwen (2015). This was in contradiction to the findings of Kwofie and Ansah (2018).

Table 6. Long term estimations of parameter in Panel ARDL method

Variables	**Coefficient**	**Std. error**	**t-statistic**	**Prob.**
LnGF	0.4215	0.1141	2.1001	0.003
LnAI	0.3674	0.1195	3.0111	0.038
LnFDI	0.3411	0.0811	2.0012	0.001
LnTr	0.2152	0.4515	0.8963	0.002
LnEx	-0.118	0.2541	-0.1485	0.022
LnIn	-0.071	0.9017	-1.0369	0.005
LnDC	0.231	0.5101	-2.3651	0.054

Source: Author's own evaluation using E-Views software

The findings of the ARDL approach in the short run are given in Table 7. The coefficient of the error correction term indicates the pace of adjustment from the short to the long term for any disequilibrium and long-term causality correlations. Error correction is important. According to the coefficient of the ECM, which is -4.698, the current year's correction for errors and shocks from the previous year will be made at a rate of 46.98%. The results of the short-term impact analysis show that LnGF has the highest positive effects on the stock market (LnSM), with coefficient values of 0.49. Following green finance, LnAI. LnFDI, LnEx, LnIn and LnDC also affect the stock market (LnSM) positively with coefficient values of 0.58, 0.35, 0.38, 0.26, and 0.15 respectively. However, trade negatively affected the stock market in the short run with a 1% increase in trade (LnTr), which decreased the stock traded by 0.24. The short-term negative impact of trade (LnTr) on stock traded (LnSM) is caused by the potential changes or disruptions that arise with an increase in trade. In the short term, increased trade volumes may lead to market volatility as businesses adjust to changes in supply, demand, or external factors like trade agreements or tariffs. Stock trading activity may decrease as investors become more cautious due to this uncertainty.

Table 7. Short term estimations of parameter in ARDL method

Variables	Coefficient	Std. error	t-statistics	Prob.
COINTEQ01	-0.4698	0.0854	-5.178	0.003
DLnGF	0.4912	0.2333	2.623	0.001
DLnAI	0.4218	0.1484	1.745	0.003
DLnAI(-1)	0.5863	0.1429	1.851	0.004
DLnFDI	0.3524	0.0325	5.174	0.030
DLnTr	-0.1433	0.1125	-5.215	0.000
DLnTr(-1)	-0.2421	0.7512	-2.215	0.048
DLnEx	0.3636	0.1339	3.669	0.003
DLnEx(-1)	0.3887	0.1691	3.188	0.004
DLnIn	0.1912	0.3205	2.913	0.038
DLnIn(-1)	0.2625	0.4215	2.178	0.033
DLnDC	0.1533	0.5621	1.652	0.024
C	-20.362	0.1253	-12.634	0.001

Source: Author's own evaluation using E-Views software

Robustness Check

The findings of the long-run panel ARDL estimation were validated by employing Driscoll Kraay Standard Error (DKSE), Augmented Mean Group (AMG), and Common Correlated Effects Mean Group (CCEMG) estimation. As shown in Table 8, the results are consistent with the panel ARDL estimation. The estimation of DKSE, AMG, and CCEMG confirmed that LnGF, LnAI, LnFDI, and LnTr have a significant positive impact on LnSM in the long run. For instance, a one percent increase in LnGF increases LnSM by 0.54, 0.71, and 0.62 according to DKSE, AMG, and CCEMG, respectively. Additionally, as indicated by the panel ARDL findings, LnEx and LnIn have a negative impact, though LnEx has a negative impact; it is an insignificant impact on LnSM. Therefore, it can be concluded that the findings of DKSE, AMG and CCEMG are consistent with the output of the panel ARDL model.

Table 8. DKSE, AMG and CCEMG estimation

Variables	DKSE	AMG	CCEMG
LnGF	0.54**(0.027)	0.71**(0.033)	0.62***(0.001)
LnAI	0.46** (0.036)	0.61*** (0.001)	0.48**(0.036)
LnFDI	0.36** (0.025)	0.43*** (0.018)	0.46** (0.054)
LnTr	0.45** (0.0)	0.39*** (0.009)	0.42*** (0.005)
LnEx	-0.12** (0.024)	-0.04 (0.458)	-0.28 (0.674)
LnIn	-0.06** (0.032)	-0.12*** (0.01)	-0.14** (0.02)
LnDC	-0.45** (0.044)	-0.06 (0.523)	-0.23 (0.589)
Constant	5.751** (0.036)	13.265*** (0.007)	8.362*** (0.003)
Observations	115	115	115
Number of groups	5	5	5

Source: Authors' own evaluation using EViews.

Note: Standard error in parentheses; *** p< 0.01, **p<0.05

CONCLUSION

The panel ARDL technique was used in this study to investigate the short- and long-term impacts on stock market development (LnSM) of important macroeconomic and financial variables, including green finance (LnGF), artificial intelligence (LnAI), foreign direct investment (LnFDI), trade (LnTr), exchange rate (LnEx), inflation (LnIn), and domestic credit (LnDC). The long-term results showed that while inflation and exchange rate volatility have a negative effect on the volume of stocks traded, green finance, artificial intelligence, foreign direct investment, trade, and domestic credit had a positive and substantial impact on the stock market. The majority of factors continued to have a positive impact on the stock market in the short term, with green financing having the highest impact, followed by AI and FDI. However, trade has a short-term negative impact, most likely because of volatility, adjustment frictions, or transient uncertainty that come with increasing trading activity. A stable long-term equilibrium is confirmed by the considerable and negative error correction term, which also shows a robust adjustment speed towards equilibrium following short-term shocks. The study's conclusions have numerous significant policy ramifications. First, governments and financial institutions can encourage sustainable finance by increasing green financial instruments, providing tax breaks, and enforcing open environmental reporting requirements, as evidenced by the positive impact of green financing on the stock market. In addition to advancing environmental goals, this will boost investor confidence and stock market stability. Second, given AI's significant impact on stock market performance, more funding should be allocated to digital infrastructure, fintech innovation should be encouraged, and regulatory frameworks that permit the safe and moral integration of AI technology into financial markets should be established. Third, legislators should improve political stability, regulatory effectiveness, and investor protection measures to guarantee a favourable investment climate as FDI continues to have a favourable impact on the market. Fourth, even if trade has long-term advantages, its short-term volatility highlights the significance of creating policies that support trade while shielding home markets from sudden shocks, maybe through risk mitigation and adaptive trade techniques.

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