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The Relationship Between Bangladesh's Financial Development, Exchange Rates, and Stock Market Capitalization: An Empirical Study Using the NARDL Model and Machine Learning

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ABSTRACT

This research looks at the interplay between financial development, exchange rates, and the stock market in Bangladesh from 1995 to 2019 and employs the Nonlinear Autoregressive Distributed Lag (NARDL) model. The machine learning technique uses the iterative classifier optimizer to beat other classifiers in stock market capitalization prediction. According to our NARDL findings, changes in financial development and exchange rates positively impact stock market capitalization in Bangladesh. Negative changes in financial development and the currency rate, on the other hand, have mixed long-term and short-term consequences for the stock market. The dynamic multiplier graphs show that the response of the stock market capitalization to positive changes in financial development and exchange rates is nearly comparable to the response to negative changes. According to the Wald test, there are asymmetries among variables. We urge governments to remove barriers to development, upgrade infrastructure, expand the stock market's capacity, and restore market participants' confidence in the Bangladesh stock market.

Keywords: Dynamic multiplier, iterative classifier, NARDL, prediction, Wald test

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INTRODUCTION

The stock market's performance substantially impacts a country's economic development by bringing surplus fundholders and users together. Creating an enabling climate for investor confidence is crucial to the stock market's growth and development in a market economy. Bangladesh's economy is heavily reliant on the stock exchange. As a result, it is crucial to understand which microeconomic issues influence stock performance. Financial markets, like stock markets, are both parts of the financial system. A stronger and more stable financial system can boost overall investment and savings rates (Tuyon & Ahmad, 2016, Alquraan et al., 2016). The stock market can satisfy commercial firms' continuous financial requirements if a favorable climate for developing confidence in both stock market operations and investors. Therefore, creating an enabling climate for investor confidence in a market economy is critical to the stock market's growth and development (Kolapo & Adaramola, 2012).

Financial and economic data forecasting is crucial for academics and decision-makers to forecast their own and competitors' future status (Elliott & Timmermann (2016). Financial forecasting assists in making better business decisions without jeopardizing financial stability. Furthermore, it establishes reasonable expectations and provides a better picture of the company's future. Forecasts are important in decision-making since they help improve the efficiency of the process. As a result, businesses use capital budgeting as a tool to prepare for and manage such huge investments. However, identifying which features can be used to forecast a company's market value might be difficult. In addition to capital accumulation, long-term growth per capita fosters economic expansion. Therefore, academics and decision-makers must be able to forecast financial data to forecast their own and competitors' future performance. However, it is not always clear which features can be utilized to predict a company's market capitalization. We employed support vector machines, Bayesian networks, random forests, and iterative classifier optimizers to apply machine-learning methods to basic financial statement data. Market capitalization is a term used in the decision-making process to estimate a company's value. Various studies have been conducted to predict financial data using machine learning approaches, which backs up our findings (Chatzis et al., 2018; Uthayakumar et al., 2020). Patel et al. (2015) employed a two-stage machine learning technique for forecasting financial data. The authors used Support Vector Regression (SVR) in the first step and then fusion prediction models such as SVR–ANN, SVR–RF, and SVR–SVR in the second. They discovered that a two-stage fusion model reduced total prediction errors.

The foreign exchange rate has several effects on the stock market. For starters, domestic currency depreciation, or an increase in the foreign exchange rate, increases short-term exchange rate risk for international portfolio investors. As a result, stock market values will fall. Second, currency depreciation boosts long-term market performance by encouraging foreign portfolio investment (Drucker, 1978). Third, domestic currency depreciation may make local equities more desirable to importers, resulting in higher export revenues for the home country. Fourth, the market performance of multinational firms' international subsidiaries may be influenced by exchange rate fluctuations.

The devaluation of the domestic currency may result in higher anticipated inflation, casting doubt on the firm's future performance and triggering a short-term reduction in stock prices. Some researchers have looked at the uneven impact of the exchange rate on the stock index. In contrast, others have discovered that stock index volatility has a symmetrical effect on exchange rate changes. According to Sheikh et al. (2020), the global financial crisis disrupted nonlinear co-integrating relationships between stock market performance and currency rates.

Some research looked at the relationship between macroeconomic fundamentals and stock market response using a linear relationship between the variables. The exchange rate and stock market performance have a positive link (Habiba & Zhang, 2020; Okere et al., 2021). On the other hand, some research shows that exchange rates and the stock market have a negative relationship (Delgado, et al., 2018; Singhal et al., 2019; Adeniyi & Kumeka, 2020). Kumar and Misra (2019) and Churchill et al. (2019) provide more evidence of an inverted U-shape relationship between oil prices, exchange rates, and the stock market.

Banks have power over Bangladesh's financial system. Direct financing through the issuance of shares is rapidly becoming more common, but direct financing through corporate bonds is virtually non-existent in this country. Previous studies have found that the financial sector contributes to economic growth by lowering the cost of obtaining information, completing transactions, and encouraging savings mobilization. The financial industry in Bangladesh contributes to economic growth by cutting the cost of receiving information, executing transactions, and encouraging savings mobilization. Financial depth indicators like private credit stock and market capitalization as a percentage of GDP are widely used to assess financial development. However, there is little evidence to back up the notion that financial progress and stock market performance are linked (Alanyali et al., 2013; Musallam, 2018). It is also considered the impact of financial development on investment and productivity. We find little evidence that monetary expansion 'leads' economic growth, either directly or indirectly. Importantly, our findings are applicable to research into which metrics should be used to assess financial development. Drehmann and Juselius (2014) discovered that comparing the private credit to GDP ratio to its trend is a good indicator. All the research investigated the ability of bank credit to predict crisis occurrences and other indicators. Our research adds to the body of knowledge by demonstrating that banks are more exposed to stock market shocks with a high private credit-to-GDP ratio. To the author's knowledge, no study has been conducted globally that takes financial development and stock market performance into account.

Only a few research have been undertaken in Bangladesh to strengthen the stock market. According to Hasan and Zaman (2017), there is no significant correlation between oil prices and stock market performance. Exchange rates and the stock market, on the other hand, have a positive and considerable association. Sarwar and Hussan (2016), to confirm the significant positive link between oil prices and stock market prices in Bangladesh, used the regression estimation method. Inflation and the stock market index have a one-way short-run causal link, according to Ahmed et al. (2015). According to Khan and Yousuf (2013), exchange rates negatively link with stock prices, while the CPI does not affect stock prices. Even though the study mentioned above was conducted in Bangladesh in previous literature based on the stock market, it is insufficient to describe stock performance. To the best of the authors' knowledge, no research has been conducted in Bangladesh to examine how unequal microeconomic variables affect stock capitalization. We conducted this research to fill a gap in the literature.

Rahman et al. (2017) employ machine learning to find patterns in data to predict stock prices. Stock exchanges typically create a massive volume of organized and unstructured heterogeneous data. It is feasible to rapidly evaluate more complex, heterogeneous data and get more accurate findings using machine-learning algorithms. Most research has looked at the relationship between macroeconomic conditions and stock market performance from a linear perspective. Linear models, because of structural changes and short-term volatility, cannot state variables.

According to Raza et al. (2016), nonlinearity, such as structural fractures and asymmetric behavior resulting from bankruptcy or severe credit events, regularly influences market dynamics, especially when the sample period includes financial crises like 2007 and 2008. As a result, earlier research has shown contradictory findings. On the other hand, these variables show regular oscillations and nonlinear behavior overlooked in prior research. Previous studies have shown mixed results because of this. Furthermore, the linear model's variables will not effectively explain the stock market, resulting in a decrease in stock capitalization. The criteria utilized in this study were chosen to fill in the gaps described above and create accurate results, and they will cover both short and long-term changes in the sector and structural changes. It will be the first study to look at the asymmetric impact of microeconomic determinants on stock capitalization in Bangladesh. The nonlinear ARDL technique, proposed by Shin et al. (2014), allows us to assess asymmetries between research variables in both the short and long term.

MATERIALS AND METHOD

Data Description

This study uses annual data from 1995 through 2019 to explore the nonlinear dynamic links between Bangladesh's exchange rate, financial development, and stock market capitalization. The World Development Indicators (WDI) offered stock market capitalization (percentage of Gross Domestic Product, GDP) figures, while the Bangladesh Bank provided exchange rate (US Dollar/Bangladeshi Taka) data. There is no specific definition for the variable "financial development." Instead, researchers use various factors as proxies for financial or market development. Following Pan et al. (2019), we utilize the value of private bank credits divided by GDP as a financial development statistic as follows:

$$Financial\ development = \frac{Private\ bank\ credits}{GDP\ growth\ (annual\ \%)}$$

We used the natural logarithm to alter two variables: stock market capitalization and exchange rates. In this study, "STOCK" stands for stock market capitalization, "EXR" stands for exchange rates, and "FD" is for financial development.

METHODOLOGY

NARDL Model

We used a nonlinear autoregressive distribution lag (NARDL) model, as Shin et al. (2014) described, to study the long- and short-run nonlinear interactions between the variables. The following linear Equation 1 was proposed to investigate the influence of exchange rate and financial development on stock market capitalization in Bangladesh:

$$LNSTOCK_t = \alpha_0 + \alpha_1 LNEXR_t + \alpha_2 FD_t + u_t \quad (1)$$

STOCK, EXR, and FD represent stock market capitalization, exchange rate, and financial development.

Our model will be as follows, based on Ibrahim's (2015) and Lacheheb & Sirag's (2019) prior work and considering the asymmetric link between exchange rate, financial development, and stock capitalization (Equation 2):

$$LNSTOCK_t = \beta_0 + \beta_1 LNEXR_t^+ + \beta_2 LNEXR_t^- + \beta_3 FD_t^+ + \beta_4 FD_t^- + e_t \quad (2)$$

Where the long-run parameters relate to β_1. Positive changes EXR^+ and FD^+ and negative changes EXR^- and FD^- respectively account for the nonlinear influence of our research variables. Positive and negative changes in their partial sums in the exchange rate and financial development are represented by the following Equations 3-6:

$$EXR_t^+ = \sum_{i=1}^{t} \Delta EXR_t^+ = \sum_{i=1}^{t} max(\Delta EXR_i, 0) \quad (3)$$

$$EXR_t^- = \sum_{i=1}^{t} \Delta EXR_t^- = \sum_{i=1}^{t} min(\Delta EXR_i, 0) \quad (4)$$

$$FD_t^+ = \sum_{i=1}^{t} \Delta FD_t^+ = \sum_{i=1}^{t} max(\Delta FD_i, 0) \quad (5)$$

$$FD_t^- = \sum_{i=1}^{t} \Delta FD_t^- = \sum_{i=1}^{t} min(\Delta FD_i, 0) \quad (6)$$

Under an unrestricted error correction representation, Equation 2 can be included in the following NARDL Equation 7:

$$\Delta LNSTOCK_t = \beta + \sum_{i=1}^{q} \mu_i \, \Delta LNSTOCK_{t-i} + + \sum_{i=1}^{p} \gamma_1^+ \, \Delta LNEXR^+{}_{t-i} + \sum_{i=1}^{p} \gamma_2^- \, \Delta LNEXR^-{}_{t-i} + \sum_{i=1}^{p} \gamma_3^+ \, \Delta FD^+{}_{t-i} + \sum_{i=1}^{p} \gamma_4^- \, \Delta FD^-{}_{t-i} + \theta_1 LNSTOCK_{t-1} + + \theta_2 LNEXR_{t-1}^+ + \theta_3 LNEXR_{t-1}^- + \theta_4 FD_{t-1}^+ + \theta_5 FD_{t-1}^- + \varepsilon_t \quad (7)$$

Where q and p indicate the lag order and $\beta_1 = \theta_2/\theta_1$, $\beta_2 = \theta_3/\theta_1$,$\beta_3 = \theta_4/\theta_1$ and $\beta_4 = \theta_5/\theta_1$ are long-run asymmetric effects. Accordingly, $\sum_{i=1}^{4} \gamma_i\,' s$ are measureing the short-run asymmetric effects.

There are various steps to using the NARDL model (Lacheheb & Sirag, 2019). First, the unit root tests Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) were used. Second, we used the Brock, Dechert, and Scheinkmakn (BDS) test to see if the variables had any asymmetric relationships. Thirdly, we checked the null hypothesis of $\theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = 0$ jointly. Fourth, we establish both long-run and short-run asymmetry relationships among the variables using the Wald test. Fifth, we also employed an asymmetric cumulative dynamic multiplier (CDM).

We can evaluate the asymmetric effect by obtaining the cumulative dynamic multiplier of a unit change in EXR_{t-1}^+, EXR_{t-1}^-, FD_{t-1}^+, and FD_{t-1}^- respectively on *LNSTOCK* (Equations 8-9);

$$m_h^+ = \sum_{j=0}^{h} \frac{\partial LNSTOCK_{t+j}}{\partial LNEXR_{t-1}^+}, m_h^- = \sum_{j=0}^{h} \frac{\partial LNSTOCK_{t+j}}{\partial LNEXR_{t-1}^-}, \text{ h=1, 2, 3,……..} \quad (8)$$

$$m_h^+ = \sum_{j=0}^{h} \frac{\partial LNSTOCK_{t+j}}{\partial FD_{t-1}^+}, m_h^- = \sum_{j=0}^{h} \frac{\partial LNSTOCK_{t+j}}{\partial FD_{t-1}^-}, \text{ h=1, 2, 3,……..} \quad (9)$$

Note that as $h \to \infty$,$m_h^+ \to \beta_1, \beta_3$ and $m_h^- \to \beta_2, \beta_4$.

Machine Learning Algorithm

In addition, we looked at the five basic machine-learning techniques for predicting stock capitalization: Support Vector Machine (SVM), Bayesian Network (BN), Adaptive boost, Iterative classifier optimizer, and Random Forest (RF).

Support Vector Machine (SVM). By expressing the instances as a set of two-type points in an N-dimensional space and producing an (N-1) dimensional hyperplane, the Support Vector Machine (SVM) splits them into two groups. SVM seeks to draw a straight line that splits those points into two categories and is as far away as possible from all of them.

Bayesian Network (BN). The Bayesian Classifier is based on Bayes' theorem and the naive assumption that each pair of attributes is independent. We employ Weka's implementation of Multilayer Perception. We compared three Weka techniques to continuous characteristics:

modeling them as a single normal, modeling them with kernel estimation, and discrediting them with supervised discretization. The Bayesian Network is an uncertainty modeling approach that employs nodes to represent variables and arcs to show direct relationships between them. When new information becomes available, the BNs model allows for dynamic updating of probabilistic assumptions about the variables.

Random Forest (RF). Random Forest (RF) generates many category trees during training and testing using many decision trees. It produces the class that is the mode of the classes as an output (classification). The decision tree learns simple decision rules based on data attributes. The more complicated the choice criteria are, the more accurate the model becomes, and the deeper the tree becomes. Overfitting of decision trees is prevented when using random decision forests. We employ Weka's Random Forest implementation.

Boosting. Freund (1997) proved that combining multiple weak models using "boosting" techniques could create a single, robust model. As a result, one of the most powerful prediction concepts in the last 20 years is an extraordinarily precise model (Hou et al., 2018). When predicting the initial weak model, boosting approaches employ the same data set to run the prediction models. Then, use prediction error rates to adjust sample and model weights to predict the next model combination, with the same weight assigned to each data set. As a result, boosting methods must be used in a specific order, which slows prediction times. However, compared to bagging methods, prediction accuracy improves.

RESULT AND DISCUSSION

Unit Root Test

When examining the order of integrating variables in time series data, the unit root test, also known as the stationary test, is the most critical criterion. In order to perform our empirical research, we used the Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) tests. The research findings are summarized in Table 1. The Schwarz information criteria (SIC) were used to determine the optimal lag structure, which included intercept and linear time trend at the level but did not include time trend in the first difference. The

Table 1
Unit root test

Variables	I(0)		I(1)	
	ADF	PP	ADF	PP
LNSTOCK	-1.020846	-1.813570	-6.883701**	-6.996329**
LNEXR	-4.719059**	-5.905791**	-3.682831**	-3.363641**
FD	-1.900001	-1.900001	-4.689254**	-4.687621**

Note. ** refer significant at 5% levels.

exchange rates are stationary at the level according to both tests, suggesting that variables I(0) are, whereas all study variables are stationary at the first difference, indicating that variables I(1). Therefore, we can use bound testing to approximate Equation 7 when there are no I(2) variables.

Brock, Dechert and Scheinkmakn (BDS) Test

It is necessary to determine whether variables are linearly or nonlinearly connected before using the ARDL or NARDL model. The Brock, Dechert, and Scheinkmakn (BDS) tests were performed to check for asymmetric associations between the variables. The hypothesis that the residual terms of the variable follow a six-dimensional independent and identical distribution is accepted, as shown in Table 2. These data suggest that the variables are nonlinear, implying that the NARDL model should be used rather than the ARDL model.

Table 2
BDS nonlinearity test results

BDS Statistics Embedding Dimension=m					
Series	m=2	m=3	m=4	m=5	m=6
STOCK	0.138821**	0.183220**	0.251222**	0.281217**	0.291229**
EXR	0.131362**	0.198341**	0.274511**	0.291421**	0.302531**
FD	0.124421**	0.202532**	0.281245**	0.294507**	0.285850**

Note. Superscript ** indicates the acceptance of the residual alternative hypothesis at 5%

Bound Test for Co Integration

According to Bahmani-Oskooee and Bohl (2000), the long-run connection is determined by the model's optimal lag section. The Akaike information criterion (AIC), the Schwarz information criterion (SIC), the sequentially modified LR test statistic (LR), the final prediction error (FPE), and the Hannan-Quinn information criterion (HQ) are used to determine the best lag order. The best lag was "2." Table 3 shows the model estimation results for symmetric and asymmetric co-integration. The bound test verifies that there is no co-integration in a linear ARDL way because the F-statistic result of 1.529913 is less than the required lower limit of 3.79 at 5%. However, the F-statistic value of 6.549283 exceeds the upper critical constraint of 4.01 by 5%, suggesting that the nonlinear ARDL specification is co-integrated.

Table 3
Bounds test results for co-integration

Model specification	F-Statistic	95% lower bound	95% upper bound	Conclusion
Linear ARDL	1.529913	3.79	4.85	No co-integration
Nonlinear ARDL	6.665112	2.86	4.01	Co-integration

Note. The critical values are from Narayan (2005).

NARDL Short Run and Long-Run Estimates

As demonstrated in Table 4, a 1% increase in the exchange rate increases stock capitalization by 5.17% in the long run and by 3.57% in the short term. The higher profit created by greater export revenues because of the depreciation of the Bangladeshi currency will result in a rise in stock prices. Stock prices are predicted to grow as foreign portfolio investment in stocks of companies expecting higher export income rises to profit from unexpected profit opportunities. However, in the long run, a 1% decline in the exchange rate reduces stock capitalization by 6.51%—the weakening of the Bangladeshi currency wills detriment the stock market. Stock prices are likely to climb as foreign portfolio investment in companies with higher expected export income grows to profit from unexpected profit opportunities. The depreciation of the Bangladesh Taka is expected to impede stock market growth in the long run. Import costs will rise, reducing earnings and driving stock prices to fall. Furthermore, international investors may opt to sell their shares in those companies, resulting in a drop in the stock market and share prices.

Table 4
NARDL Short-run and long-run estimates

Short-run estimates			Long-run estimates		
Variable	Coefficient	Std. Error	Variable	Coefficient	Std. Error
$\Delta LNEXR^{+}$	3.56648**	6.994976	$LNEXR^{+}$	5.136664**	2.701164
$\Delta LNEXR^{-}$	0.23165**	7.264923	$LNEXR^{-}$	-6.513424***	4.057760
ΔFD^{+}	0.520730**	0.146976	FD^{+}	0.696279**	0.140615
ΔFD^{-}	0.593837**	0.263425	FD^{-}	-0.029442	0.380227

Note. ***, ** refers significant at 10% and 5% levels of significance, respectively. The terms "+" and "-" refer to the positive and negative changes, respectively. EXR_W & FD_W Indicates the Wald test result for each variable.

Furthermore, both in the short and long run, we discover a positive and significant relationship between financial development and stock market capitalization in Bangladesh. Our research shows that a 1% increase in financial development results in a 0.520% increase in short-term stock capitalization and a 0.696% increase in long-term stock capitalization. Our research also shows that a 1% decrease in financial development results in a 0.5938% increase in short-term stock capitalization. On the other hand, our findings suggest that a negative change in financial development has no long-term relevance. If the financial industry expands and capitalizes on increased volumes, it positively impacts per capita output. More banking sector development is positively associated with a stock market capitalization in global market stocks. People who have access to credit are more likely to spend more, boosting the economy's revenue. As a result, GDP (gross domestic product) rises, causing productivity to rise quicker. If the financial sector expands and capitalizes on increasing volumes, it will positively influence per capita output. Credit encourages people to spend more, resulting in an increase in revenue for the economy. Credit is used to purchase productive assets, increasing revenue and stock market value.

The Wald Test and Diagnostic Test Results

Some diagnostic tests were also performed to support the NARDL model's dependability, as shown in Table 5. To determine error normalcy, researchers utilized the Jarque-Bera (J-B) test, the Ramsey RESET test, and the Autoregressive Conditional Heteroskedasticity (ARCH) up to order 2 for heteroskedasticity, and the serial autocorrelation LM test up to level 2 for serial autocorrelation. All diagnostic tests show that the NARDL model is accurate, meaning that it is trustworthy. The speed of adjustment (SOA) is a metric that assesses how rapidly organizations narrow the gap between their leverage last year and the leverage they want this year. According to the findings of this calculation, the rate of adjustment is around 0.88. As a result, the adjustment time is 1.135 years. After a shock, the deviance returns to normal after about a year. This rapid adjustment states that companies pursue target capital structures. When their leverage ratios vary from these targets, they make financial decisions to close the gap between the previous year's leverage and the current period's target leverage. The Wald test was performed to confirm the nonlinearities between the variables under examination. According to the Wald test results, asymmetries across variables occur at 5%.

Table 5
The Wald test and diagnostic test results

R^2	0.923248
CointEq(-1)*	-0.881251**
J-B [prob]	0.597012
R-R [prob]	0.3526
LM(1) [prob]	0.1769
LM(2) [prob]	0.1428
ARCH(1) [prob]	0.8207
ARCH(2) [prob]	0.4932
$EXR_W[X^2, prob]$	[25.20510, 0.0001]
$FD_W[X^2, prob]$	[19.30123, 0.0000]

Note. J-B and R-R refer Jarque-Bera test for error normality and the Ramsey-RESET test for model specification, respectively. LM test is for serial correlation, and the ARCH test is for autoregressive conditional Heteroskedasticity, up to the lag order given in the parenthesis. ** refers to significant at 5% levels of significance. Finally, EXR_W & FD_W Indicates the Wald test result for each variable.

The Cumulative Multipliers Dynamic Estimates

Figure 1 depicts the cumulative dynamic asymmetric multiplier findings. The solid (dashed) black lines depict how stock capitalization changes as EXR and FD move in opposite directions. On the other hand, the asymmetric line is a light-dash red line that falls between the lower and upper bands of the 95% confidence interval. As shown in Figure 1, all study variables exhibit positive and negative shocks that fall within 95% confidence lines, indicating that our NARDL model is stable. The difference between positive and negative components is depicted by an asymmetric curve, which denotes the dynamic multiplier linked to changes in EXR and FD. The dynamic multiplier graphs illustrate that

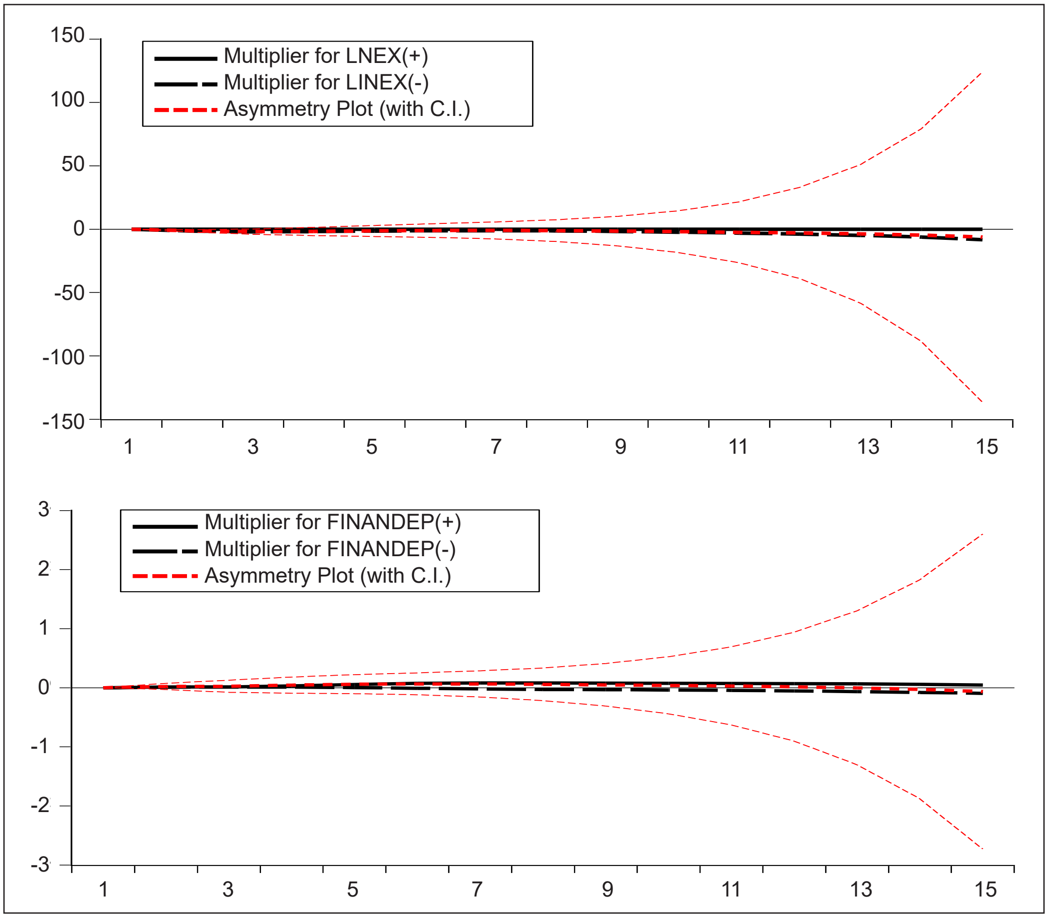

Figure 1. Cumulative dynamic multipliers (CDM)

the stock market capitalization responds nearly identically to positive changes in financial development and exchange rates as it does to negative changes.

NARDL Model Stability Check

Every statistical study's robustness must be tested for parameter stability. Brown et al. (1975) suggested applying the stability test for the CUSUM and CUSUMSQ parameters after determining the short- and long-term coefficients. Figure 2 shows the results of the CUSUM and CUSUM Square tests, suggesting that the model is quite stable.

Prediction of Stock Market Capitalization in Machine Learning Approaches

Policymakers must forecast and estimate macroeconomic parameters such as stock market capitalization. Table 6 shows the results of machine learning classifiers. The Root Mean Squared Error (RMSE) is a form of error that is rather common. The most widely used

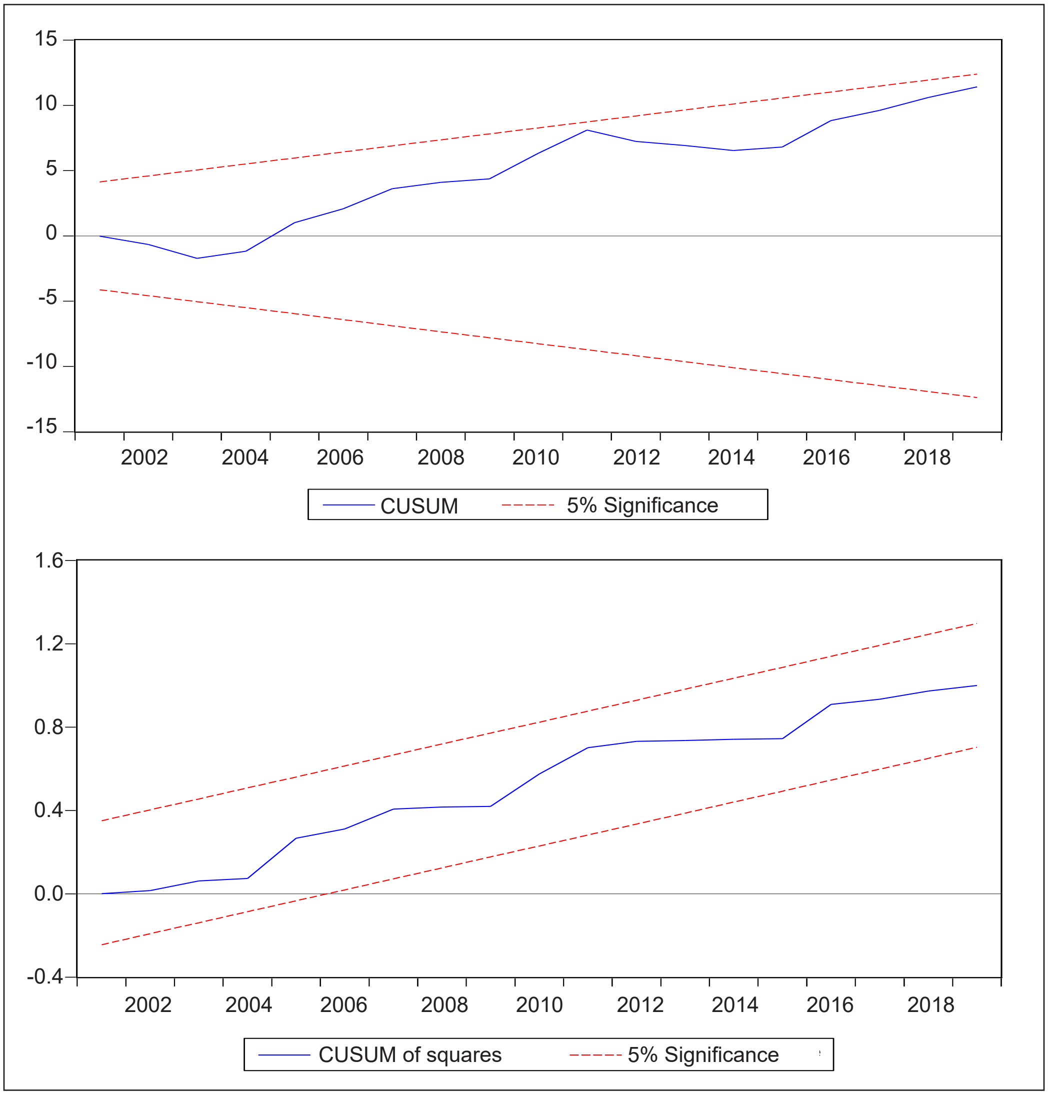

Figure 2. CUSUM and CUSUM of Square test for model stability

criteria are Mean Absolute Error and Mean Absolute Percentage Error, abbreviated as MAE and MAPE, respectively. The value of the criteria mentioned above is also compared in this study. The model with the lowest criteria value mentioned above would be the most suited. Ten-fold cross-validation is used to test the accuracy of all classifiers. The precision of BN and SVM is the same (80.11%).BN and SVM both have the same level of accuracy (80.11%). Adaptive boost has a greater accuracy rate (81.31%) than RF (75.56%). Overall, the iterative optimizer classifier beats other classifiers in stock capitalization prediction, with the lowest RMSE (0.2032), MAE (0.2112), and MAPE (10.112) values and the best accuracy (82.52%).

Table 6
Machine learning techniques for stock market capitalization prediction

Classifiers	Accuracy	RMSE	MAE	MAPE
SVM	80.11%	0.2321	0.2672	10.254
BN	80.11%	0.2412	0.2216	10.123
RF	75.56%	0.2541	0.2632	11.592
Adaptive boost	81.31%	0.2434	0.2442	11.586
Iterative classifier optimizer	82.52%	0.2032	0.2112	10.112

CONCLUSION

In Bangladesh, we used the NARDL model to examine the relationship between financial development, exchange rates, and stock market capitalization. From 1995 to 2019, the stock market has had strong, asymmetric effects on exchange rates and financial development. In the short run, both positive and negative changes in exchange rates and financial development have a large and favorable impact on stock capitalization. Beneficial changes in both variables, on the other hand, have a considerable and positive impact on stock capitalization. In contrast, negative changes in exchange rates have a long-term negative impact on stock capitalization. The dynamic multiplier graphs show that when a positive change occurs, the stock capitalization response is nearly identical to when a negative change occurs. Therefore, the iterative classifier optimizer is the most effective strategy for predicting stock capitalization with the lowest RMSE, MAE, and MAPE values and the highest accuracy.

Bangladesh's government may pass important financial market legislation. Furthermore, the government may monitor state-owned firms' credit performance, and researchers are studying the flow of financial resources from input to output to improve financial efficiency and, as a result, stock market performance. Finance for the private sector is a significant aspect in encouraging private investment due to a shortage of foreign capital inflows. As a result, the Bangladesh Bank should maintain the current monetary policy. The private sector credit ceiling might be raised to encourage private investment in Bangladesh while keeping a careful eye on credit utilization. The empirical findings suggest that policymakers should focus on long-term strategies. Therefore, the Bangladesh Bank should stick to its monetary policy, and the loan cap for the private sector might be raised to boost private investment in Bangladesh while keeping a careful eye on credit utilization.

A future study on the entire South Asian region should be completed using panel data based on the NARDL model to investigate nonlinear links between financial development-oil-gold-exchange rates and regional stock indexes.

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