Assessing effects of agriculture and industry on CO_2 emissions in Bangladesh

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Abstract

The study aims to evaluate the impact of Bangladesh's agricultural and industrial sectors on CO_2 emissions using advanced modeling techniques, namely autoregressive distributed lag (ARDL) and nonlinear autoregressive distributed lag (NARDL) models. Time-series data ranging from 1990 to 2022 are analyzed to ensure data stationarity, employing the augmented Dickey-Fuller (ADF) test. Subsequently, the existence of non-linear associations is validated using the Brock-Dechert-Scheinkman (BDS) test, with further confirmation through bounds testing to establish both symmetric and asymmetric long-run cointegrating relationships. Long and short-run coefficients are assessed using linear and asymmetry ARDL models, revealing that industrialization contributes to increased carbon emissions in Bangladesh. While the ARDL model reports that the effect of agriculturalization on CO_2 emissions is insignificant in

the long-run, the asymmetry ARDL model suggests a rapid reduction in carbon emissions due to agriculturalization, observed both in the long and short-run. Additionally, imports have considerable impact on carbon emissions. Diagnostic tests have confirmed the adequacy of the model, while stability tests have validated the estimated parameters' stability. Finally, the direction of association between variables is determined by applying linear and nonlinear Granger causality tests.

1 Introduction

Environmental degradation due to CO_2 emissions has become a global challenge. Over the past few decades, we have been witnessing the effects of climate change, which is primarily due to excessive carbon dioxide emissions. According to numerous research, the majority of CO_2 emissions are attributed to non-renewable energy sources. The utilization of non-renewable energy sources is steadily rising, both in developing and developed nations. According to the [1], "Developing countries account for 63% of the annual global emissions of carbon dioxide". That is why controlling carbon dioxide emissions has become a major challenge and goal to ensure the sustainable development of low-income countries like Bangladesh. Worryingly, the country's carbon dioxide emissions are rapidly increasing day by day. The left axis (Fig 1) plotted the carbon dioxide emissions over the years ranging from 1992 to 2020, which indicates the upward trend of CO_2 emissions. Numerous prior studies have validated the relationship between socio-economic factors, such as the value added to GDP from agriculture, industry, and imports, and CO_2 emissions. The right axis (Fig 1) shows the percentage change of agriculture, industry and imports value added to GDP over 1990 to 2022, indicating that agriculture production decrease, while value added form industrial sector is increasing over the years. However, the change in import is about random.

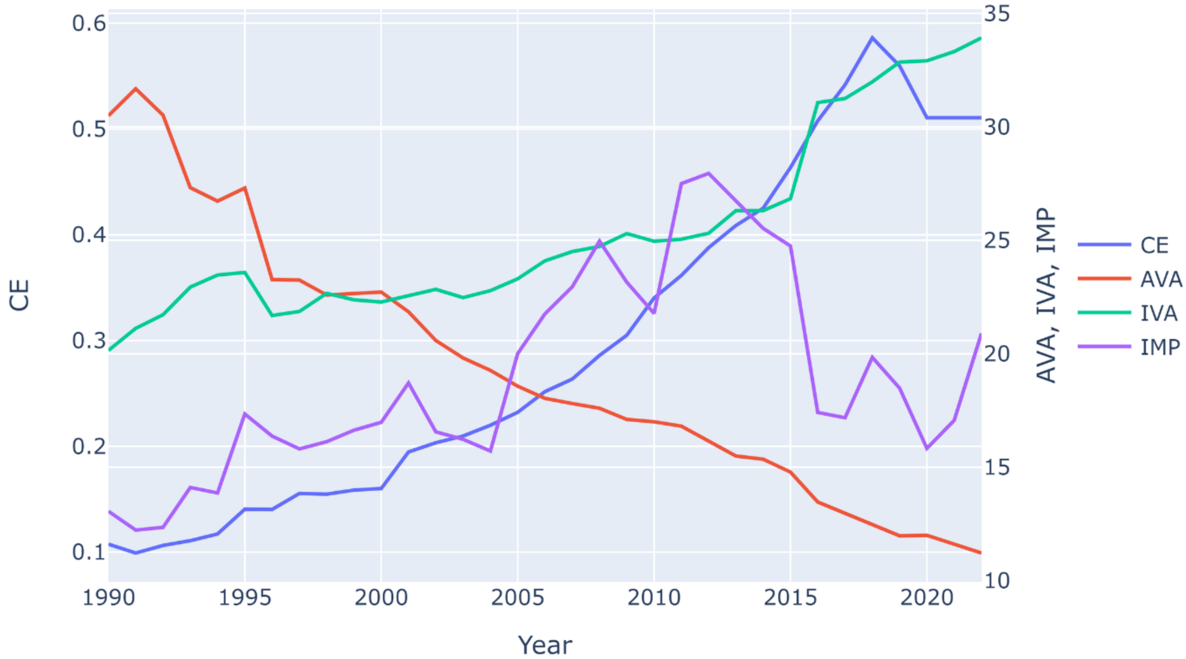


Fig 1. Trends of variables

Bangladesh is one of the countries suffering from the problems caused by this carbon dioxide emission. In the last two decades, Bangladesh has experienced various natural disasters, including floods, droughts, high tides, and cyclones. Like other countries in the world, Bangladesh's industrial sector is particularly responsible for carbon dioxide emissions. Sixteen percent of the country's total carbon emissions come from the industrial sector. Due to rice farming, field residue burning, fertilizer-induced field emissions, livestock production, including manure management, and other factors, Bangladesh's agriculture industry emits 50 metric tons of CO_2 annually [2]. However, controlling CO_2 emissions is crucial for the nation's sustainable development. There is no one study that evaluates the combined effects of the industrial and agricultural sector on carbon emission in Bangladesh with particular importance, despite the fact that few scholars have examined the agricultural and industrial sectors separately in their research. So, we decided to conduct this research in order to determine whether or not the impact of the country's industrialization and agricultural sector on carbon emissions is linear or non-linear and to what degree this impacts carbon emissions. It will also check direct impacts of imports on carbon emissions, as well as indirect impacts of imports by influencing industrialization and reducing agriculturalization of the country. “Bangladesh is currently the world's third-largest importer”, according to the FAO. Food grains including rice and wheat, edible oil, oilseeds, raw cotton, milk and milk products, spices, sugar, and coconut oil are some of the main agricultural imports into the nation. From these, cotton, sugar, and oil are in the list of top 10 import commodities of the country in 2021, according to the Bangladesh Import Statistics. Moreover, this list also includes a number of essential industrial resources, such as garbage, scrap, bituminous minerals, petroleum, medium oils, and mineral fuels. There is a chance that these import trends will have an effect on Bangladesh's CO2 emissions, both directly and indirectly. Consequently, in order to better comprehend the role of imports, our research includes an examination of them. Moreover, A new combination of variables are used in this study.

The research is comprised of five sections. We addressed the context and rationale for the subsequent investigation in the initial section. Previous research on this subject was reviewed in the second section. We elaborated on data curation and the statistical tests utilized in the analysis in the following section. Discussions and empirical findings are contained in the fourth section. In the final section, we provide recommendations for policies that reduce CO_2 emissions and draw conclusions regarding the study's limitations.

2 Literature Review

The study assesses the short- and long-run impacts of Bangladesh’s agricultural and industrial sectors on carbon emissions. A substantial amount of research has been conducted on subject of interest. Additionally, numerous investigations have been conducted in Bangladesh. Certain research investigations are carried out using time series data for a single country, whereas others utilize panel data to examine a group of countries. An element that unifies all the studies is the utilization of annual data obtained from the World Bank database. However, for this study, we considered the value added to GDP by agriculture and industry, the percentage of GDP attributed to imports of products and services, and per capita CO_2 emissions in metric tons. We will now proceed to discuss the studies that are pertinent to our variables and the objectives of our research.

It has been demonstrated on a global scale that agricultural production and CO_2 emissions are interconnected. [3] used the FMOLS approach to examine how agriculture affects CO_2 emissions in industrialized and developing nations. Their findings indicate inverted U-shaped association of CO_2 emissions and agriculture. [4] investigated the long-run association between China's agricultural output and carbon emission using the ARDL, FMOLS, CCR, and DOLS techniques. He demonstrates that as agricultural production increases, so do long-term CO_2 emissions. [5] used DOLS, FMOLS, and ARDL to investigate the relationship between CO_2 emissions and Indonesian agriculture. The analyses revealed the existence of statistically significant and positive long-run association of agricultural value added and carbon emissions. [6] propose that agriculture and CO_2 emissions have a positive relation in the short run. Carbon emissions in Brazil are hypothesized to decrease as agriculture value added rises, according to [7]. Additionally, the agricultural sector of Saudi Arabia decreases CO_2 emissions, according to [8]. A further study conducted in Saudi Arabia by [9] provides support for the hypothesis that agricultural sector expansion can result in a decrease in CO_2 emissions. By employing ARDL and NARDL, [10] determine that the contribution of agriculture value added to GDP has an adverse impact on carbon emissions in Pakistan. According to a study by [11], the agricultural sector in Pakistan is a significant contributor to CO_2 emissions. To determine the impact of Vietnam's agricultural sector on carbon emissions, [12] utilized a variety of models such as ARDL, VECM, FMOLS, DOLS, and CCR. He found that increasing agriculture value added decreases CO_2 emissions. [13] conducted a study in Bangladesh using ARDL approach to check the effects of agricultural sector on carbon emissions. They found that agricultural sector of Bangladesh positively affects CO_2 emissions. The study from [14] also support the result of [13] using ARDL and ECM that agricultural sector of Bangladesh is responsible for carbon emissions. Granger causality test results suggest that value added to GDP from agriculture (AVA) doesn't granger cause CO_2 emissions, but carbon emissions granger cause agricultural production. [15] analyzed the nexus between agricultural ecology and carbon emissions using FMOLS, DOLS and CCR. They found that agricultural sector of Bangladesh has positive significant impacts on CO_2 emissions. Granger causality test result supports the result of [14].

[16] evaluated the environmental Kuznets curve of the influence of industrialization on CO_2 emissions in Bangladesh using the ARDL approach. The researchers' findings indicate the presence of an environmental Kuznets curve that connects industrialization with CO_2 emissions. They indicate that the industrial sector of Bangladesh has a long-run impact on carbon emissions. [17] used the CCR, FMOLS, ARDL, and DOLS methodologies to analyze the association between industry value added and carbon emissions in India. The long run relationship between industrial sector and CO_2 emissions is negative but statistically negligible, according to each model. Additionally, by using the ARDL model, [18] contend that industrialization does not yield substantial consequences in the short or long-run. [19] examine the association between industrial growth and emissions of carbon in Bangladesh by employing the ARDL and Granger causality tests. Both in the short- and long-run, industrial expansion has a significant impact on CO_2 emissions, according to the study. The Granger test determined that industrial expansion is the sole cause of carbon emissions. [20] examined the impacts of industrial expansion on carbon emissions in India utilizing the NARDL model. It was discovered that industrial expansion has a short-run adverse impact on carbon emission,

but there exists a long-run positive effect on carbon emission. Increasing industry value degrades environmental quality in Europe and Central Asia by increasing carbon emissions, according to [21].

[22] utilized the VAR and Granger causality tests to examine the impact of imports on CO_2 emissions in Bangladesh. No causal relationship was identified between imports and CO_2 emissions. The outcome of restricted VAR indicates that carbon emissions and imports are related in the long term. In six regions, [23] examined the relationship between trade, imports, exports, and CO_2 emissions. Most countries' imports have a positive effect on carbon emission, whereas certain nations have a negative impact. They discovered that carbon emissions only occur when trade exceeds 40% of total GDP. [24] revealed a positive and meaningful relationship between trade openness and carbon emissions in fourteen MENA countries. Imports have long-run significant positive impacts on CO_2 emission in Algeria., according to [25]. A spatial analysis conducted by [26] in North Africa indicates that imports have a positive impact on CO_2 emissions.

Our research introduces a fresh perspective to the existing body of literature on carbon emissions in Bangladesh. We have employed both linear and nonlinear autoregressive distributed lag models to investigate the impact of both linear and nonlinear changes in the agricultural and industrial sectors, as well as the percentage of imports value added to GDP, on carbon emissions. While numerous studies have been conducted on this topic, they have used different combinations of variables and methodologies. Our study, however, is the first, to our knowledge, to specifically examine this unique combination of variables in the context of Bangladesh. This distinctive focus aims to provide a more comprehensive understanding of the factors influencing carbon emissions in the country, thereby contributing to the development of effective policy interventions for sustainable development.

3 Data and Methodology

3.1 Data

In the context of Bangladesh, the research utilizes the yearly time series dataset over 1990 to 2022 to assess the asymmetric influence that socioeconomic variables have on CO_2 emissions. Per person CO_2 emission in metric tons, the value added from industry and agriculture, and import percentages to GDP are the variables used for the study. The data were gathered from the World Development Indicators (WDI) [27]. The fill-forward technique was implemented to handle missing values. The variable's name, data sources, and units of measurement are detailed in Table 1.

Table 1: Variable description

Variable	Description	Measurement Unit	Source
CE	CO_2 Emissions	metric tons per capita	WDI
AVA	Agriculture, forestry, and fishing, value added	(% of GDP)	WDI
IVA	Industry (including construction), value added	(% of GDP)	WDI
IMP	Imports of goods and services	(% of GDP)	WDI

[**Note:** WDI = World Development Indicators]

3.2 Methodology

The present research examines the correlation between CO_2 emissions and several socio-economic indices to assess the specific model. A unit root test was conducted to assess stationarity and ascertain the level of integration of the variables. Additionally, the variables will be evaluated for a cointegrating connection using the ARDL Bounds test [28] and the NARDL Bounds test [29]. autoregressive distributed lag (ARDL) model [30] and nonlinear autoregressive distributed lag model [31] are used to quantify the effects of socio-economic variables on CO_2 emissions. Model performance was assessed by diagnostic tests and stability testing. In addition, we conducted a linear Granger causality test [32] and a non-linear Granger causality test [33] to evaluate the bi-directional relationships. Next figure (Fig 2) clearly illustrates all the processes.

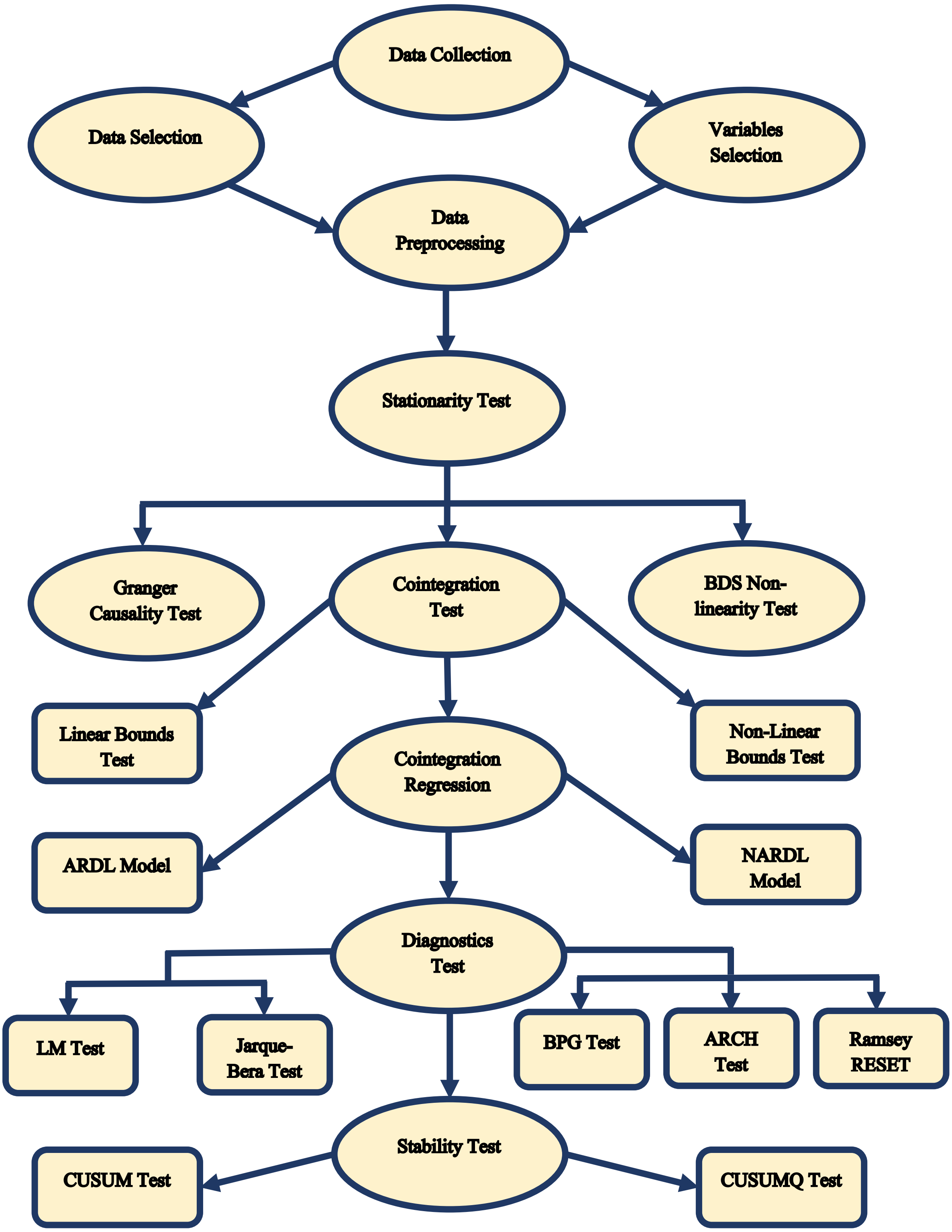


Fig 2. Analytical framework

4 Results and Discussion

4.1 Descriptive Analysis

A succinct summary of the descriptive statistics corresponding to each variable is presented in Table 2. The mean carbon dioxide (CO_2) emissions per person is 0.29 metric tons, with a slightly lower median of 0.25. The range of emissions spans from 0.099 to 0.586. The standard deviation of CO_2 emissions suggests a reduced level of variability, while other variables exhibit a moderate level of variability around the mean. The positive skewness value of all the variables indicates that the distributions have rightward tails, while kurtosis values suggesting that the distribution has heavier tails, reflecting a propensity for more extreme values. The Jarque-Bera statistics and their associated probability values suggest that the distributions closely resemble a normal distribution.

Table 2: Descriptive statistics

Variable	**CE**	**AVA**	**IVA**	**TR**
Mean	0.294893	19.40849	25.40872	18.96500
Median	0.251722	18.03402	24.09532	17.34486
Maximum	0.586158	31.67702	33.92008	27.94933
Minimum	0.099144	11.2176	20.14563	12.22721
Std. Dev.	0.159162	5.853759	4.044821	4.455375
Skewness	0.426339	0.510394	0.97824	0.516261
Kurtosis	1.743201	2.337148	2.607167	2.248467
Jarque-Bera	3.17158	2.0369	5.475434	2.242490
Probability	0.204786	0.361154	0.064718	0.325874

4.2 Unit Root Test

Before preceding ARDL and NARDL models, it is essential to check the stationarity of time series data. Every variable must be stationary at first difference or at level before applying ARDL or NARDL models. Here the order of integration is not important, it can be implemented with all variables having the same order (all I(1) or all I(0)) or a mixed order of integration (combination of I(1) and I(0)) [34]. In this study, The Augmented Dicky-Fuller test, one of the most powerful unit root tests was employed to verify stationarity. The ADF unit root test suggests that imports (IMP) and agricultural value added (AVA) are both are stationary at the level, according to the data shown in Table 3. However, after the first difference, industry value added (IVA) and CO_2 emissions (CE) exhibit stationarity.

Table 3: ADF unit root test

	None		**Constant Only**		**Constant + Trend**	
Variable	**t-Statistic**	**Conclusion**	**t-Statistic**	**Conclusion**	**t-Statistic**	**Conclusion**
CE	1.263155	Unit Root	-0.663307	Unit Root	-2.166645	Unit Root
ΔCE	-2.688374***	I(1)	-3.465515**	I(1)	-3.358182*	I(1)
AVA	-2.268312**	I(0)	-1.40909	Unit Root	-3.126411	Unit Root
ΔAVA	-2.016039**	I(1)	-3.035543**	I(1)	-2.556671	Unit Root
IVA	2.800227	Unit Root	0.56376	Unit Root	-0.990677	Unit Root
ΔIVA	-2.166134**	I(1)	-5.186671***	I(1)	-3.04438	Unit Root
IMP	0.161928	Unit Root	-1.80958	Unit Root	-5.176056***	I(0)
ΔIMP	-3.012965***	I(1)	-4.191411***	I(1)	-3.915272**	I(1)

[**Note:** *, ** and *** indicate p-value is less than 10%, 5% and 1% level of significance, respectively. Δ indicates first difference, I(0) indicates stationary at level and I(1) indicates stationary at first difference.]

4.3 Non-linearity Test

To explore non-linearity within macroeconomic variables, the study employs the Brock-Dechert-Scheinkman (BDS) testing technique [35]. Table 4 presents the results of the BDS test for non-linearity conducted on the variables AVA (Agriculture Value Added) and IVA (Industry Value Added), with CO_2 emissions serving as the response variable. The analysis reveals that the BDS statistics for both AVA and IVA are significant at the 1% level. This indicates the presence of non-linearity within these macroeconomic variables, suggesting that the relationship between these sectors and CO_2 emissions is not simply linear, but involves more complex dynamics.

Table 4: BDS Test

	AVA			IVA		
Dimension	**BDS Statistic**	**Std. Error**	**z-Statistic**	**BDS Statistic**	**Std. Error**	**z-Statistic**
2	0.181842***	0.009998	18.18793	0.153079***	0.015467	9.896942
3	0.312310***	0.016255	19.21368	0.226290***	0.025286	8.949038
4	0.405490***	0.019802	20.47676	0.249106***	0.030992	8.037847
5	0.471694***	0.021123	22.33069	0.218822***	0.033265	6.578147
6	0.520719***	0.020857	24.96591	0.120775***	0.033056	3.653678

[**Note:** *** means significant at 1% level]

4.4 Lag Length Selection

The findings from the Vector Autoregression (VAR) lag order selection criterion are shown in Table 5. The determination of the appropriate lag length is necessary for conducting the ARDL bounds test for cointegration, as the F-statistic's sensitivity is linked to this parameter. In this research, a lag length of three was selected to validate cointegration, guided by the Akaike information criterion (AIC). This decision aids in ensuring the robustness of our findings and the validity of our cointegration analysis.

Table 5: VAR lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-159.7919	NA	0.946102	11.29599	11.48459	11.35506
1	-43.59710	192.3225	0.000957	4.386007	5.328969*	4.681331
2	-30.26246	18.39260	0.001235	4.569825	6.267158	5.101408
3	-3.758500	29.24575*	0.000723*	3.845414*	6.297117	4.613257*
4	5.908596	8.000355	0.001688	4.282166	7.488239	5.286268

[**Note:** * indicates selected lag based on each criterion]

4.5 ARDL Estimates

4.5.1 Cointegration Test

It is crucial to confirm that a cointegration relationship exists before doing an ARDL analysis. In this research we utilized the Bounds test to verify cointegration over other approaches. Table 6 displays the outcomes of the Bounds test for ARDL, unveiling an F-statistic value of 7.1019, surpassing the upper limit of 4.66 at the 1% significance level. This observation signifies that there exists a long-run cointegrating relation.

Table 6: Bounds test

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	7.101971***	10%	2.37	3.2
K	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66

[**Note:** *** means significant at 1% level]

4.5.2 ARDL Model Selection

Once the long-run cointegrating relation has been established, selecting the suitable lag length for each of the underlying variables becomes crucial for employing ARDL. We prefer error terms that adhere to the standard normal distribution and are devoid of non-normality, autocorrelation, heteroscedasticity, and other such issues. Therefore, determining the right lag length is crucial [34]. The figure (Fig 3) displays the top 20 model selection findings based on Log-likelihood, AIC, BIC, HQ, and adjusted R-squared. The outcome shows that the chosen ARDL model uses up to 2, 0, 3, and 3 lags of the variable CO_2 emissions (CE), value added from agriculture (AVA), industry (IVA), and imports (IMP).

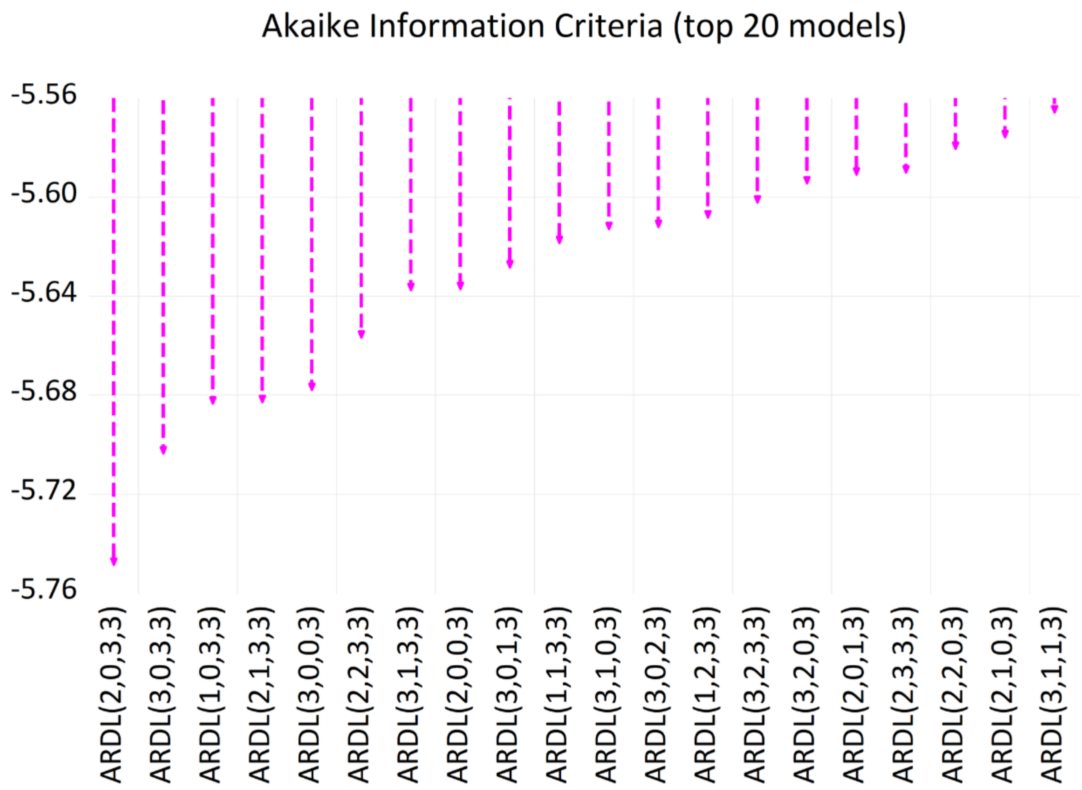


Fig 3. ARDL model selection criteria

4.5.3 Long-run and Short-run Estimates

Table 7 presents the long- and short-run outcomes of the linear ARDL model. The results demonstrate a negative long-run alliance between carbon emission and agriculture value added, suggesting a linkage between reduced CO_2 emissions and greater agricultural production. On the other hand, industrial growth and carbon emissions are positively and significantly related, as are long-run imports of goods and services and carbon emission. According to projections, CO_2 emissions will increase by 0.018 and 0.015 metric tons per capita for every 1% increase in industrial sector and imports, respectively. Additionally, imports and industrial growth have a positive short-term effect on CO_2 emissions. In the short-run, for the initial 1% GDP change in the industrial sector will result in a positive reaction in carbon emissions of 0.0093 metric tons per person. Here, ECT^{*}_{t-1} is the error correction term. The residuals from the long-run cointegration model, denoted by ECT^{*}_{t-1}, are negative and substantial, indicating a significant long-run association. The coefficient serves as an indicator of the speed of adjustment. Notably, the coefficient of the error correction term suggests that 32% of the disequilibrium in each period is corrected for the long-run trend. Furthermore, based on the R-squared value, it is observed that 77.32% of the variance in CO_2 emissions can be accounted for by the explanatory variables under consideration. The significant probability-value of the overall F test underscores the significance of the regression.

Table 7: ARDL estimates

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Long-run ARDL				
AVA_t	-0.007064	0.004514	-1.564961	0.1350
IVA_t	0.018272***	0.005926	3.083189	0.0064
IMP_t	0.015024***	0.004521	3.323107	0.0038
C	-0.313503	0.243191	-1.289124	0.2137
Short-run ARDL				
ΔCE_{t-1}	0.265723**	0.114513	2.320469	0.0323
ΔIVA_t	0.009356***	0.002319	4.034030	0.0008
ΔIVA_{t-1}	-0.000673	0.002485	-0.270776	0.7896
ΔIVA_{t-2}	0.007030***	0.002235	3.145437	0.0056
ΔIMP_t	0.001430	0.000892	1.602669	0.1264
ΔIMP_{t-1}	-0.004716***	0.001033	-4.566988	0.0002

ΔIMP_{t-2}	-0.003548***	0.001097	-3.233122	0.0046
ECT^{*}_{t-1}	-0.325733***	0.049444	-6.587938	0.0000
R-squared	0.773176		F-statistic	5.577895
Adjusted R-squared	0.634562		Prob(F-statistic)	0.000695

[**Note:** *** means significant at 1% level]

4.5.4 Model Diagnostics

The diagnostic tests result for the ARDL model are summarizes in the last part of Table 8. These tests include the Lagrange Multiplier (LM) test for Serial Correlation, the Breusch-Pagan-Godfrey test and ARCH test for heteroscedasticity, the Jarque-Bera test for normality, and the Ramsey RESET test for model specification. The results indicate that the ARDL model successfully passes all diagnostic tests, indicating the absence of serial correlation and heteroscedasticity. Furthermore, the model is deemed well-specified, and the distribution of residuals conforms to normality.

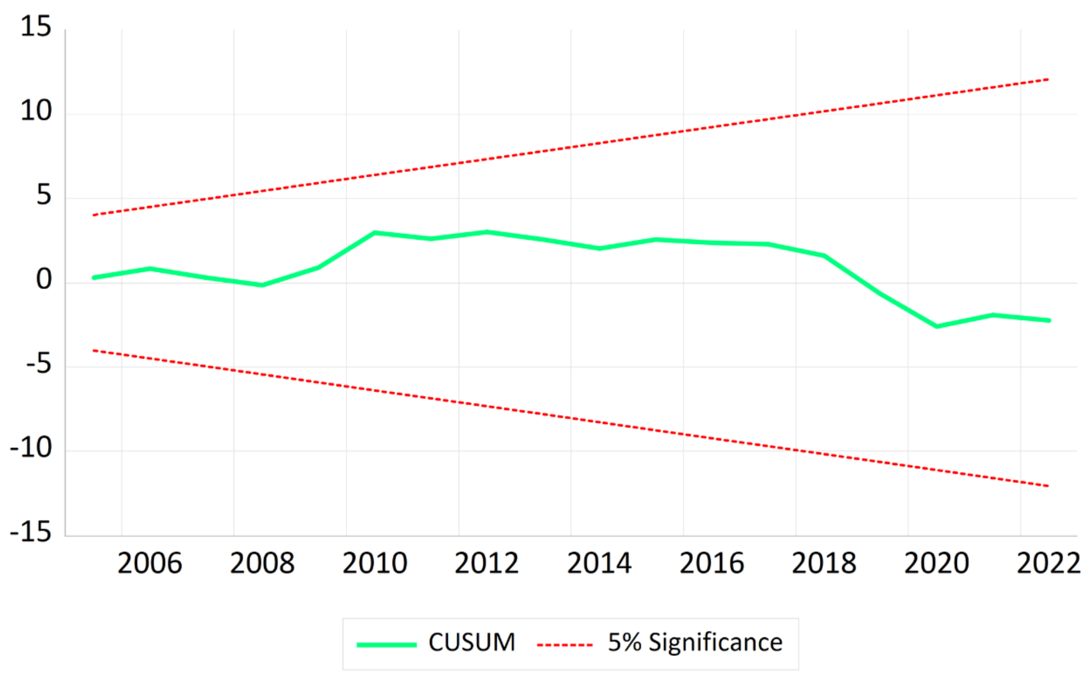
Table 8: Diagnostics tests of ARDL model

Test	**F-statistic**	**p-value**
LM test	1.827604	0.1854
Breusch-Pagan-Godfrey test	0.441557	0.9157
ARCH test	0.137611	0.9365
Jarque-Bera test	0.368515	0.8317
Ramsey RESE test	0.984207	0.4266
Chow Breakpoint test	2.880393	0.1017

4.5.5 Stability Diagnostics

The application of CUSUM and CUSUMQ tests is a crucial step in evaluating the stability of long-run parameters within the context of a linear autoregressive distributed lag (ARDL) model. Upon conducting these tests with a predetermined significance threshold of

5%, the CUSUM test graph demonstrates a reassuring outcome, suggesting that the long-run parameters exhibit stability over the observed period (see Fig 4). However, the corresponding CUSUMQ test graph unveils a nuanced picture, revealing a subtle but discernible instability around the year 2018. The discrepancy observed between the outcomes of the two tests prompts a further examination into the temporal dynamics of the model. While the CUSUM test suggests stability overall, the identified instability in CUSUMQ specifically draws attention to potential variations in the squared residuals, indicating the presence of underlying structural shifts or unaddressed factors within the specified time frame (Fig 4). To confirm the parameters stability, we also performed chow breakpoint test which results are displayed in Table 8. F-statistic and p-value of chow breakpoint test indicate that there is no structural break. As the chow breakpoint test is more powerful than the CUSUMQ test, we may conclude that the long run parameters of ARDL model are stable.



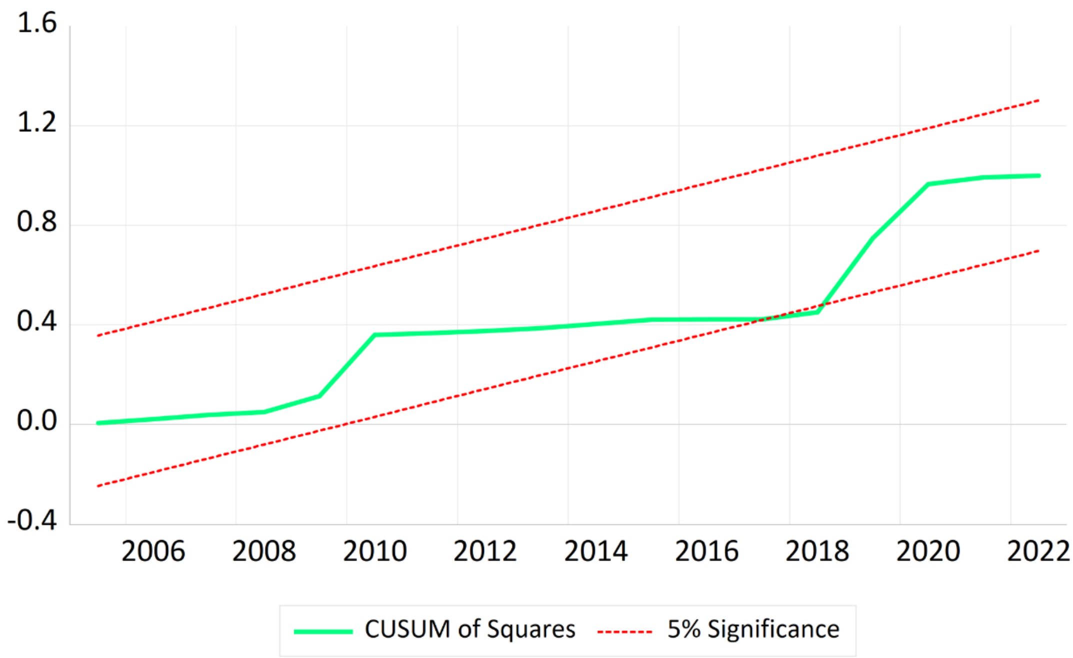


Fig 4. CUSUM & CUSUMQ test for ARDL

4.6 NARDL Estimates

4.6.1 Cointegration Test

The findings obtained from the NARDL Bounds test, as presented in Table 9, are compelling. The computed F-statistic value of 58.575 surpasses the upper limit threshold of 4.15 at the 1% significance level. This outcome strongly indicates the presence of a long-run cointegrating relationship among the variables under consideration.

Table 9: NARDL bounds test

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	58.57504***	10%	2.08	3
K	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15

[**Note:** *** means significant at 1% level]

4.6.2 NARDL Model Selection

Top 20 results of non-linear ARDL model selection criteria are shown in the next figure (Fig 5). The lag length of each variable is selected based on Log-Likelihood, AIC, BIC, HQ, adjusted R-squared. The result indicates that up to 3, 3, 3, 2, 3, 3 lags of the predefined variables CE, AVA^{+}, AVA^{-}, IVA^{+}, IVA^{-}, IMP are used in selected asymmetry ARDL model.

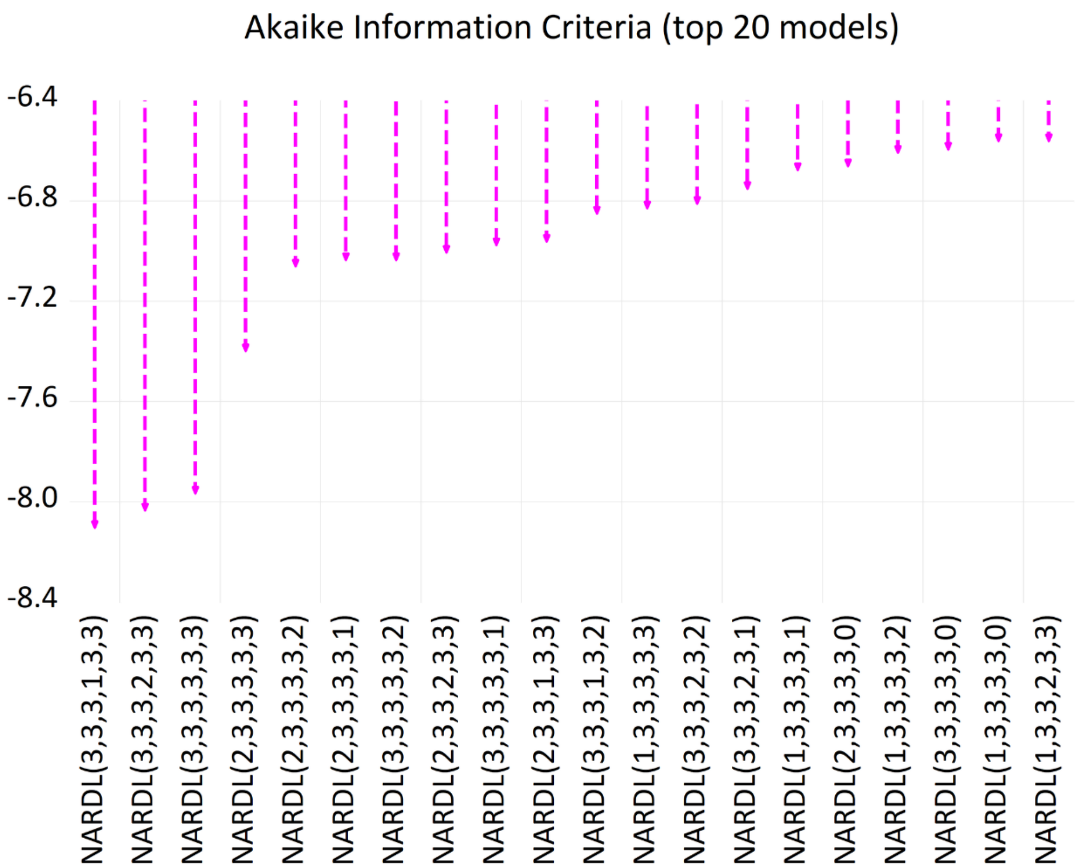


Fig 5. NARDL model selection Criteria

4.6.3 Long-run and Short-run Estimates

Table 10 demonstrates the substantial effects that non-linear ARDL has on carbon emissions, including both positive and negative changes. The result of long-run coefficients indicates that the positive components of agriculture value added (AVA_t^+) negatively affects carbon emission, while negative shocks AVA_t^- positively affect CO_2 emissions. For every 1 percent increase in positive shocks of agriculture value added to GDP, carbon emission in Bangladesh will be decreased by 0.986 metric tons per capita, while for the negative change carbon emission will be increased by 0.0145 metric tons per capita in the long-run. This shows how important the agriculture sector is to reduce CO_2 emissions in Bangladesh. However, the opposite has happened in the industrial sector. For every 1 percent increase in positive shocks of industry value added to GDP, CO_2 emissions will be increased by 0.028 metric tons per capita, while for the negative change in same amount CO_2 emissions will be decreased by 0.31 metric tons per capita in the long-run. Imports has no significant impact on CO_2 emissions in the long-run. Hence, the long-run results introduce that the agriculture and industry value added to GDP of Bangladesh has extensive significant impacts on carbon emissions. In the short-run, all the underlying variables and their lag values have significant impacts on carbon emission. Effects of own past value of carbon emission is also significant. Here the value of ECT_{t-1}^* is negative and significant, which indicates that there exists long-run relationship. The coefficient of the error correction term reveals the rate of adjustment is immediate and complete. This means that the 112% of the disequilibrium in each period has been adjusted to the long-run trend. The high R^2 along with adjusted R^2 value indicates that the model fitted well. It indicates that about 99% variance of carbon emissions can be explained by the underlying variables. The p-value from the overall F test suggest that the regression is highly significant. The coefficient of determinants from the non-linear model is larger than the linear ARDL model, which means the asymmetry ARDL model fitted well over the linear ARDL model. It additionally validates the presence of a nonlinear association between carbon emissions in Bangladesh and the agricultural and industrial sectors.

Table 10: NARDL estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Long-run NARDL				
AVA_t^+	-0.986734***	0.063662	-15.49946	0.0000
AVA_t^-	0.014499***	0.002932	4.945667	0.0017
IVA_t^+	0.028371***	0.002042	13.89661	0.0000
IVA_t^-	-0.310043***	0.019889	-15.58889	0.0000
IMP_t	0.001374	0.000831	1.654377	0.1420
C	1.294660***	0.094679	13.67417	0.0000
Short-run NARDL				
ΔCE_{t-1}	0.540734***	0.038296	14.11981	0.0000
ΔCE_{t-2}	0.310472***	0.036687	8.-62785	0.0001
ΔAVA_t^+	-0.225908***	0.013536	-16.68895	0.0000
ΔAVA_{t-1}^+	0.171863***	0.025159	6.830930	0.0002
ΔAVA_{t-2}^+	0.876391***	0.036855	23.77915	0.0000
ΔAVA_t^-	-0.037535***	0.002438	-15.39812	0.0000
ΔAVA_{t-1}^-	0.037980***	0.001730	21.95232	0.0000
ΔAVA_{t-2}^-	-0.040369***	0.002264	-17.83389	0.0000
ΔIVA_t^+	0.008280***	0.001114	7.435511	0.0001
ΔIVA_t^-	-0.170698***	0.007962	-21.43992	0.0000
ΔIVA_{t-1}^-	0.174751***	0.008570	20.39108	0.0000
ΔIVA_{t-2}^-	0.095345***	0.004831	19.73638	0.0000
ΔIMP_t	-0.002229***	0.000360	-6.195817	0.0004
ΔIMP_{t-1}	-0.002570***	0.000259	-9.928072	0.0000
ΔIMP_{t-2}	-0.002581***	0.000283	-9.136275	0.0000
ECT_{t-1}^*	-1.126626***	0.040827	-27.59485	0.0000
R-squared	0.989640		F-statistic	31.84136
Adjusted R-squared	0.958560		Prob(F-statistic)	0.000050

[**Note:** *** means significant at 1% level]

4.6.4 Model Diagnostics

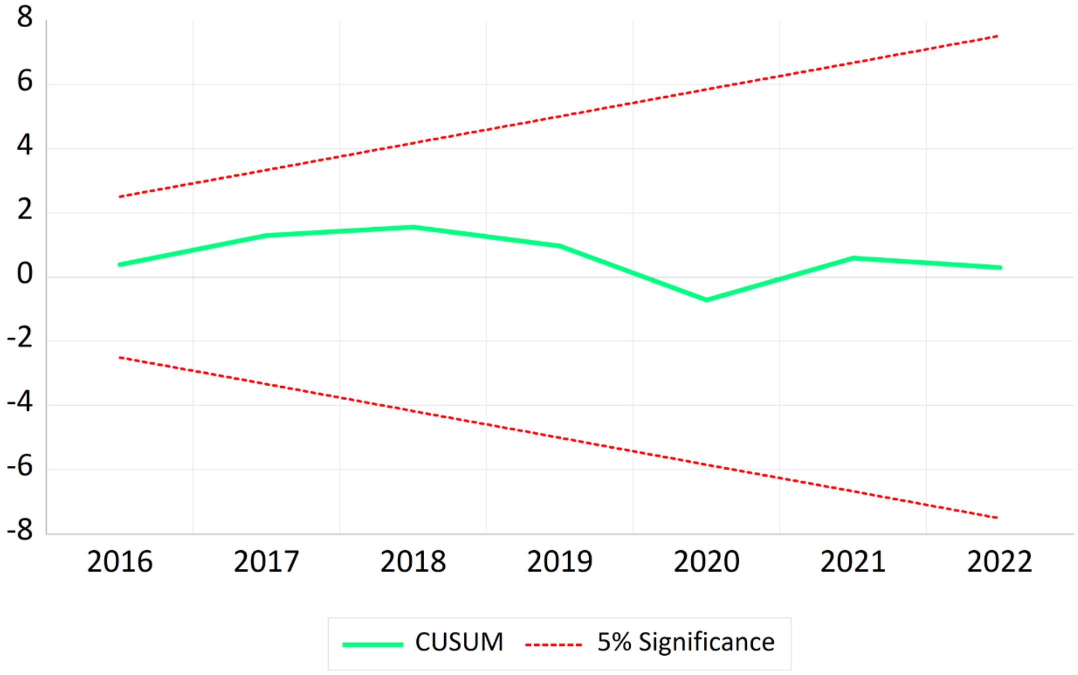
Diagnostics tests results are attached in Table 11 which are performed to investigate the autocorrelation, heteroscedasticity, normality and specification of the asymmetry ARDL model. Based on F-statistics and their respective probability values, the findings suggest that the NARDL model successfully passed all diagnostic tests.

Table 11: Diagnostics test of NARDL model

Test	F-statistic	p-value
LM Test	3.517337	0.1279
Breusch-Pagan-Godfrey Test	0.987864	0.5491
ARCH Test	0.742222	0.5383
Jarque-Bera Normality Test	0.651930	0.7218
Ramsey RESET Test	1.729547	0.2986

4.6.5 Stability Diagnostics

We again utilized the CUSUM and CUSUMQ tests to assess the stability of the asymmetry ARDL model. Both plots (Fig 6) fall within the 5 percent critical bounds, indicating the stability of the model's parameters. Additionally, the findings suggest that the long-run parameters of the asymmetry ARDL model exhibit greater stability compared to those of the linear ARDL model.



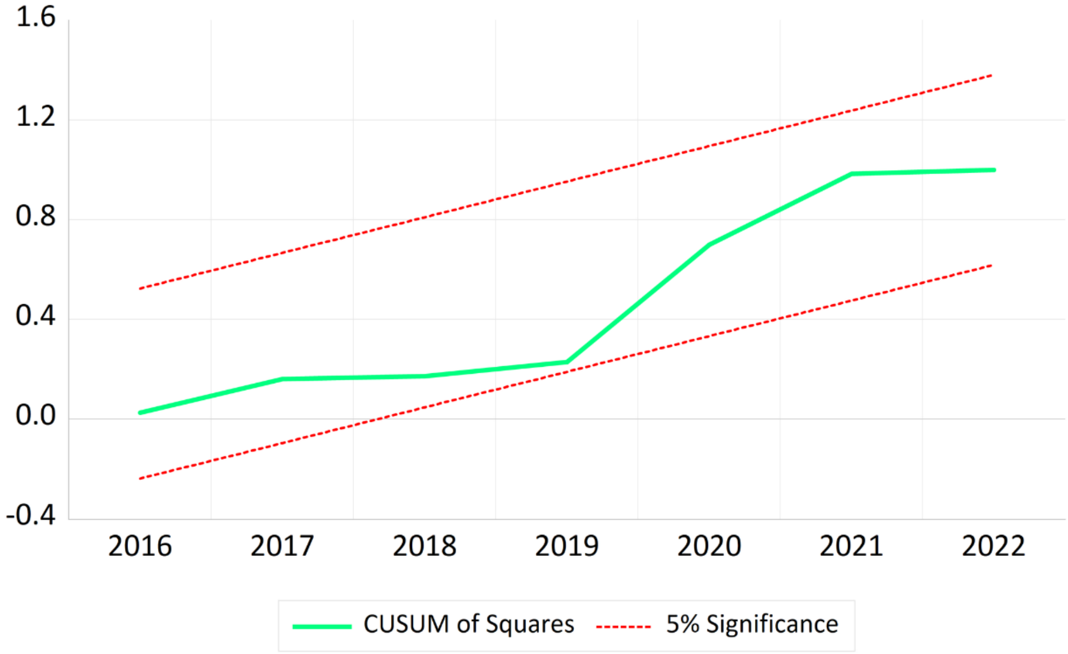
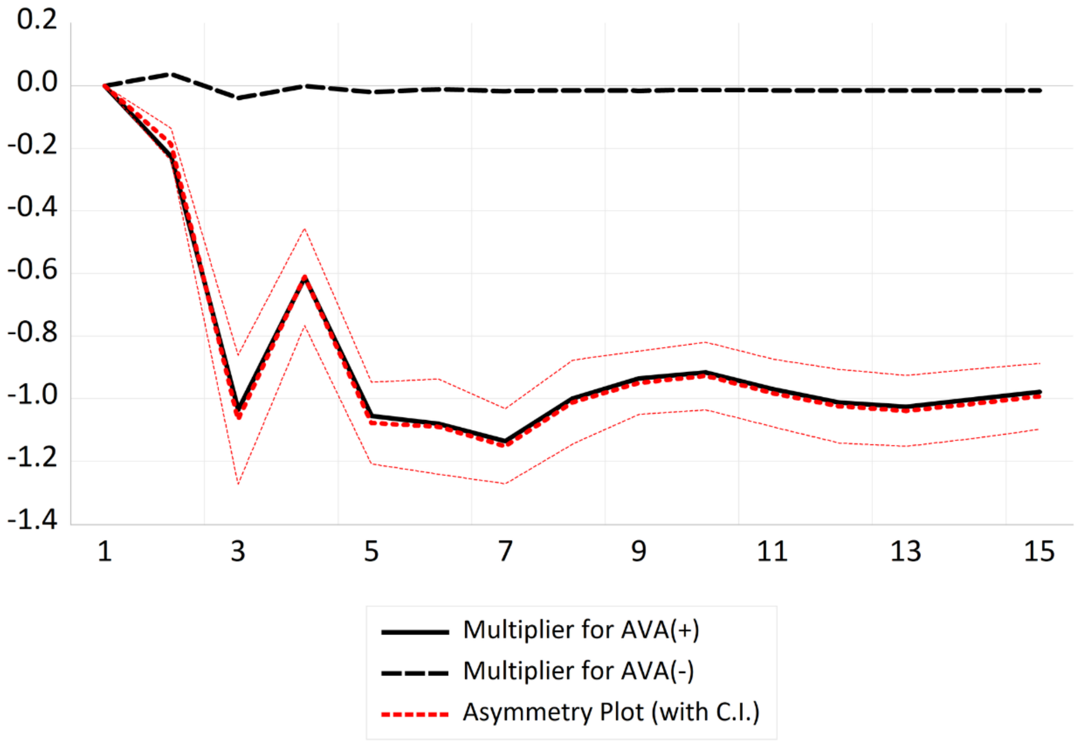


Fig 6. CUSUM & CUSUMQ test for NARDL

4.6.6 Asymmetric Dynamic Multipliers

The dynamic multiplier graph presented in two graphs (Fig 7) offers insights into the dynamic adjustments of agriculture and industry value added to GDP subsequent to a new long-run equilibrium after a positive and negative shocks. Analysis of the graph provides a notable asymmetrical association between these variables, evident from the zero line not falling within the critical bounds at the 5% level of significance. This asymmetry underscores the differential impact of changes in agriculture and industry value added on the equilibrium. Specifically, it is observed that a positive change in AVA provides a more substantial impact compared to a negative change, while conversely, a negative change in IVA has a greater effect than a positive change over the long run.



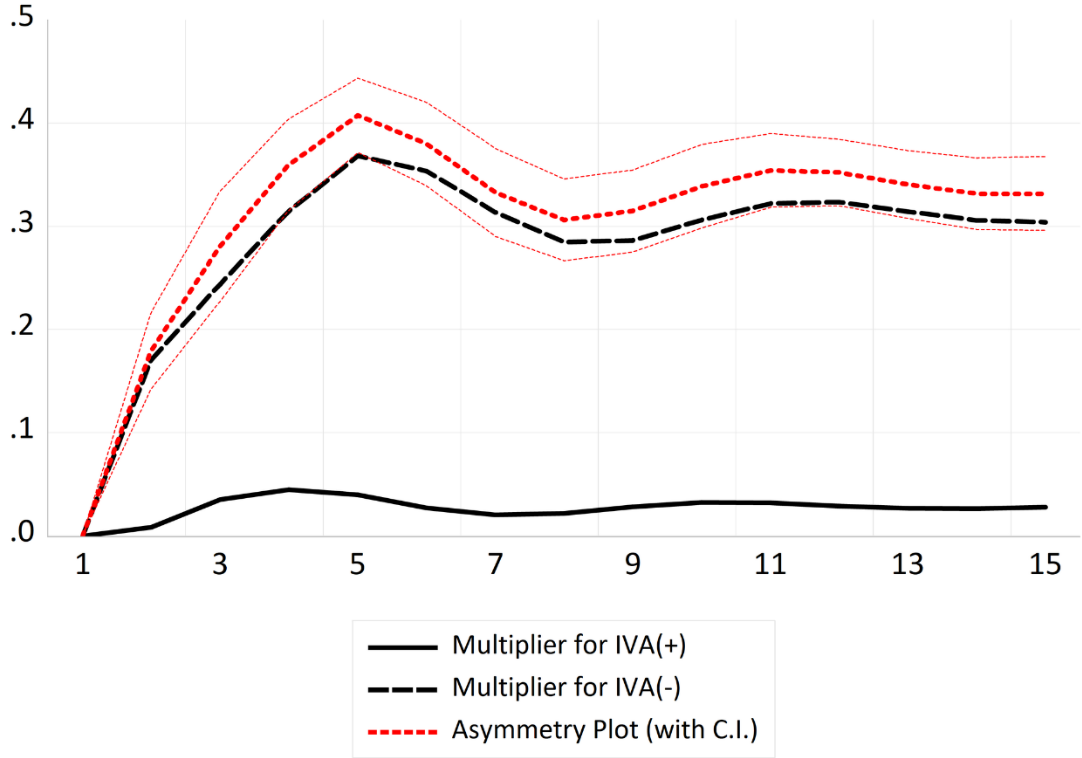


Fig 7. NARDL multiplier graph

4.7 Granger Causality Test

Finally, the investigation into causal relationships among the variables employed both linear and nonlinear Granger causality tests. Table 12 presents the results of the pairwise linear Granger causality test, revealing significant insights. Specifically, the findings indicate a unidirectional causal relationship, with CO_2 emissions Granger causing agricultural value added. Moreover, a bidirectional causality is observed between industry value added and carbon emissions, while the causality from imports to CO_2 emissions is unidirectional. Furthermore, no discernible causal relationships were found between agricultural and industrial sector, value added from agriculture and imports, or industry and imports.

Table 12: Pairwise linear granger causality test

Alternative Hypothesis:	**F-Statistic**	**Prob.**
$AVA_t \longrightarrow CE$	0.61658	0.6113
$CE_t \longrightarrow AVA_t$	4.46261**	0.0131
$IVA_t \longrightarrow CE_t$	4.30310***	0.0151
$CE_t \longrightarrow IVA_t$	3.70536**	0.0261
$IMP_t \longrightarrow CE_t$	7.00657***	0.0016
$CE_t \longrightarrow IMP_t$	0.33659	0.7990
$IVA_t \longrightarrow AVA_t$	1.38796	0.2716
$AVA_t \longrightarrow IVA_t$	0.64718	0.5927
$IMP_t \longrightarrow AVA_t$	0.76392	0.5259
$AVA_t \longrightarrow IMP_t$	0.32222	0.8092
$IMP_t \longrightarrow IVA_t$	0.71081	0.5555
$IVA_t \longrightarrow IMP_t$	0.22039	0.8812

[**Note:** "⟶" means granger causes and *** means significant at 1% level]

Table 13 presents a summary of the results obtained from the nonlinear Granger causality test, revealing significant insights. Specifically, the analysis indicates a unidirectional causality from carbon emission to negative shocks of agricultural value added, while the causality of carbon emission to positive shocks of industry value added is bidirectional. Moreover, the causality of imports to CO_2 emissions and positive shocks of agriculture added to negative shocks of industry value added is unidirectional, while the causality between negative AVA to positive AVA and negative AVA to negative IVA is bidirectional. There exists no significant causal relationship between the other pairs of variables.

399 **Table 13: Pairwise non-linear granger causality test**

Alternative Hypothesis:	F-Statistic	Prob.
$AVA_t^+ \longrightarrow CE_t$	0.42920	0.7341
$CE_t \longrightarrow AVA_t^+$	0.02920	0.9931
$AVA_t^- \longrightarrow CE_t$	0.45905	0.7137
$CE_t \longrightarrow AVA_t^-$	3.49763**	0.0326
$IVA_t^+ \longrightarrow CE_t$	3.43899**	0.0344
$CE_t \longrightarrow IVA_t^+$	4.84316***	0.0098
$IVA_t^- \longrightarrow CE_t$	0.68159	0.5727
$CE_t \longrightarrow IVA_t^-$	0.16050	0.9218
$IMP_t \longrightarrow CE_t$	7.0067***	0.0016
$CE_t \longrightarrow IMP_t$	0.33659	0.7990
$AVA_t^- \longrightarrow AVA_t^+$	6.79786***	0.0021
$AVA_t^+ \longrightarrow AVA_t^-$	21.1447***	1.E-06
$IVA_t^+ \longrightarrow AVA_t^+$	0.22560	0.8776
$AVA_t^+ \longrightarrow IVA_t^+$	0.14255	0.9333
$IVA_t^- \longrightarrow AVA_t^+$	0.13187	0.9401
$AVA_t^+ \longrightarrow IVA_t^-$	57.7520***	1.E-10
$IMP_t \longrightarrow AVA_t^+$	0.20421	0.8924
$AVA_t^+ \longrightarrow IMP_t$	0.29959	0.8253
$IVA_t^+ \longrightarrow AVA_t^-$	0.74183	0.5385
$AVA_t^- \longrightarrow IVA_t^+$	0.42863	0.7345
$IVA_t^- \longrightarrow AVA_t^-$	3.10029**	0.0476
$AVA_t^- \longrightarrow IVA_t^-$	4.96522***	0.0088
$IMP_t \longrightarrow AVA_t^-$	0.51340	0.6773
$AVA_t^- \longrightarrow IMP_t$	0.41404	0.7446
$IVA_t^- \longrightarrow IVA_t^+$	0.16025	0.9219
$IVA_t^+ \longrightarrow IVA_t^-$	0.32743	0.8055
$IMP_t \longrightarrow IVA_t^+$	0.85657	0.4782
$IVA_t^+ \longrightarrow IMP_t$	0.28593	0.8350
$IMP_t \longrightarrow IVA_t^-$	0.32110	0.8100
$IVA_t^- \longrightarrow IMP_t$	0.16433	0.9192

400 [**Note:** "⟶" means granger causes and *** means significant at 1% level]

5 Conclusion and Policy Recommendations

5.1 Conclusion

This research paper delves into the intricate nexus of CO_2 emissions within Bangladesh's agricultural and industrial sectors, as well as its import dynamics. Through the application of NARDL modeling techniques, the study uncovers compelling insights, demonstrating the adequacy of the NARDL model in comparison to its linear counterpart. The findings of the NARDL model unveil a noteworthy relationship, indicating that agricultural production exerts a negative significant long-run effect on carbon emission. Specifically, this analysis reveals a substantial reaction, whereby CO_2 emissions exhibit a negative response of 0.986 metric tons per capita for each 1% positive change in agricultural value added to GDP. Moreover, the research underscores the existence of a unidirectional causal relation, with CO_2 emissions exerting a substantial influence on agricultural production. This elucidates the intricate interplay between environmental considerations and agricultural productivity within the Bangladeshi context. Furthermore, both the symmetry and asymmetry ARDL models highlight the positive effect of industrial sector on CO_2 emission across different time horizons. In the linear model, a 1% increase in industrial value added to GDP corresponds to a carbon emission increase of 0.018 metric tons per capita. On the other hand, the nonlinear model demonstrates a more pronounced effect, indicating that for each 1% positive change of value added in industrial sector, carbon emission increase by 0.028 metric tons per person. Conversely, a negative change in industrial value added corresponds to a reduction in carbon emissions of 0.31 metric tons per person in long-run. Notably, the causal relation between the industrial sector and carbon emission is bidirectional, reflecting the intricate feedback mechanisms at play. Additionally, this research underscores the positive effect of imports on CO_2 emission within the linear model framework, further emphasizing the multifaceted nature of factors influencing CO_2 dynamics within the Bangladeshi context. In sum, these findings offer valuable insights into the complex interrelationships between socioeconomic sectors and CO_2 emission in Bangladesh, providing a nuanced understanding essential for informed policy formulation and sustainable development initiatives.

5.2 Policy Suggestions

Bangladesh's economy is largely dependent on agriculture, although this dependence has gradually decreased in recent years. The good news is that in the developed countries of the world, the tendency of environmental degradation from the agricultural sector is high, but the tendency in Bangladesh is extremely low. In contrast, the findings of this research highlight the agricultural sector's capacity to make substantial contributions to long-term carbon emission reductions. With a focus on sustainable development, it is imperative for government officials and policymakers to prioritize initiatives aimed at bolstering Bangladesh's agricultural sector. The Bangladesh Bureau of Statistics reports that within the country of Bangladesh, fallow land occupied a total of 244,000 acres in 2019. They can take several initiatives such as bringing fallow lands under agriculture, stopping deforestation, stopping illegal construction on agricultural land, increasing subsidies in the agricultural sector and creating awareness among farmers. Also bringing under strict vigilance with increased discrimination on imported agricultural products and ensuring fair prices of domestically produced agricultural products. Moreover, awareness should be created among the farmers to focus on organic farming instead of repeat farming. A major part of Bangladesh's total GDP comes from the industrial sector, although according to our research, the industrial sector is responsible for environmental pollution. So, the government and policy makers should focus on how to reduce environmental pollution from the industrial sector without reducing production. The government ought to consider raising taxes on fossil fuel usage while promoting the adoption of renewable energy sources among industrial enterprises. Focus should be on implementing stricter emission standards and promoting green technology in industries. Finally, there should be increased investment in research and public awareness campaigns to reduce carbon-dioxide emissions in various sectors.

5.3 Limitations

Despite some meaningful insights, there are some limitations also. A primary constraint pertains to the temporal scope, as the analysis exclusively encompasses data spanning the period from 1990 to 2022. This temporal constraint may restrict the comprehensive understanding of long-term trends and patterns in the variables under consideration. Another limitation is that it only deals with four variables which are CO_2 emissions, value addition to GDP of agriculture, industry and imports, although several other socioeconomic variables can be observed and proven to influence carbon emissions. Moreover, the study has only worked with the data of Bangladesh, other countries of the world are not included. To enhance the robustness and comprehensiveness of future research endeavors, it is recommended to address these limitations by extending the temporal range, incorporating a broader array of relevant variables, and encompassing data from a more diverse set of countries. By doing so, future investigations can offer a more nuanced and exhaustive comprehension of the multifaceted interplay between socioeconomic factors and carbon emission on a global level.

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Methodology: Md. Mushaddiqul Islam Amin, Md. Mahafuzur Rahman.

Writing – original draft: Md. Mushaddiqul Islam Amin, Md. Mahafuzur Rahman.

Writing – review & editing: Md. Mushaddiqul Islam Amin, Md. Mahafuzur Rahman.

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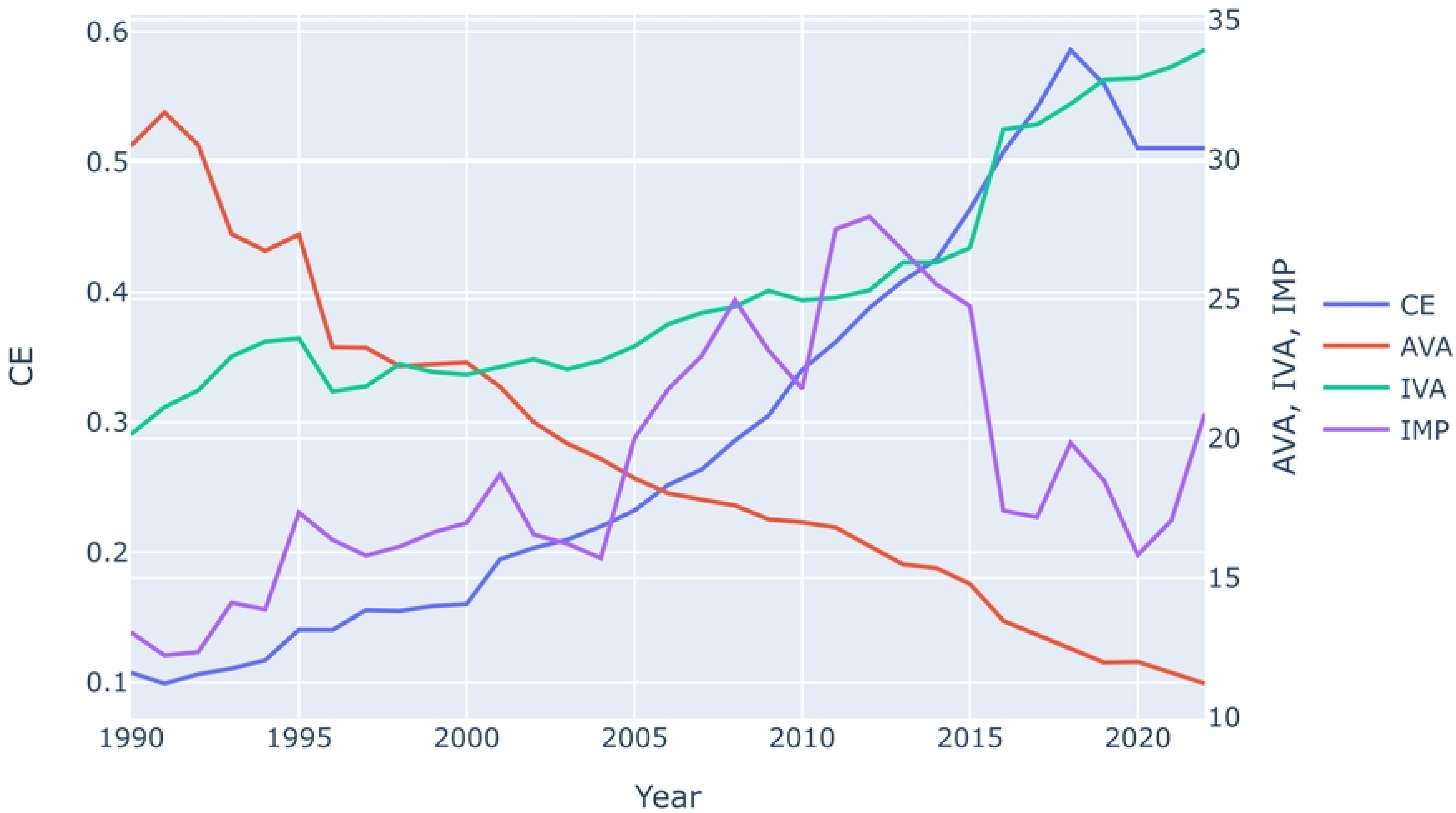
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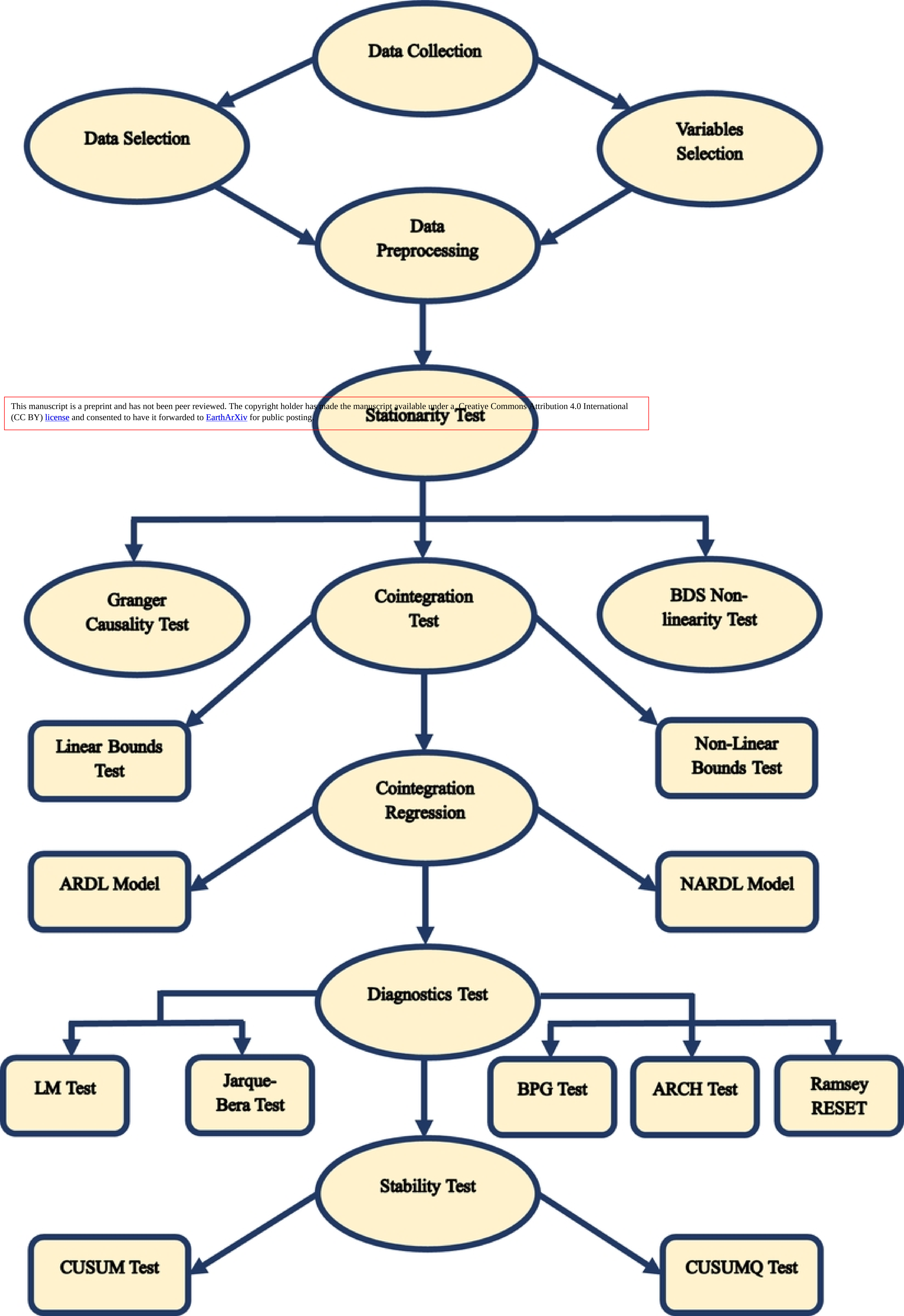
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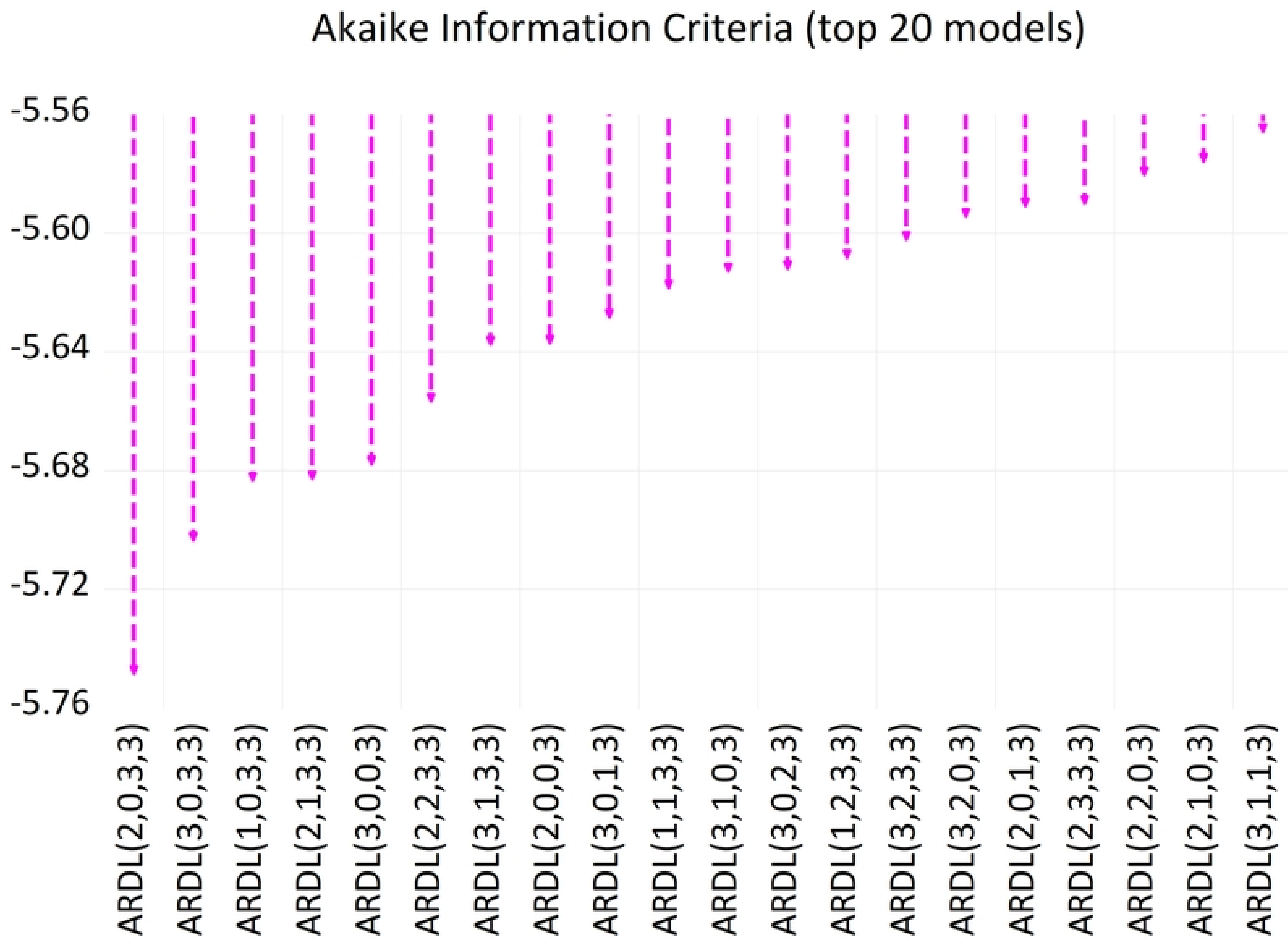

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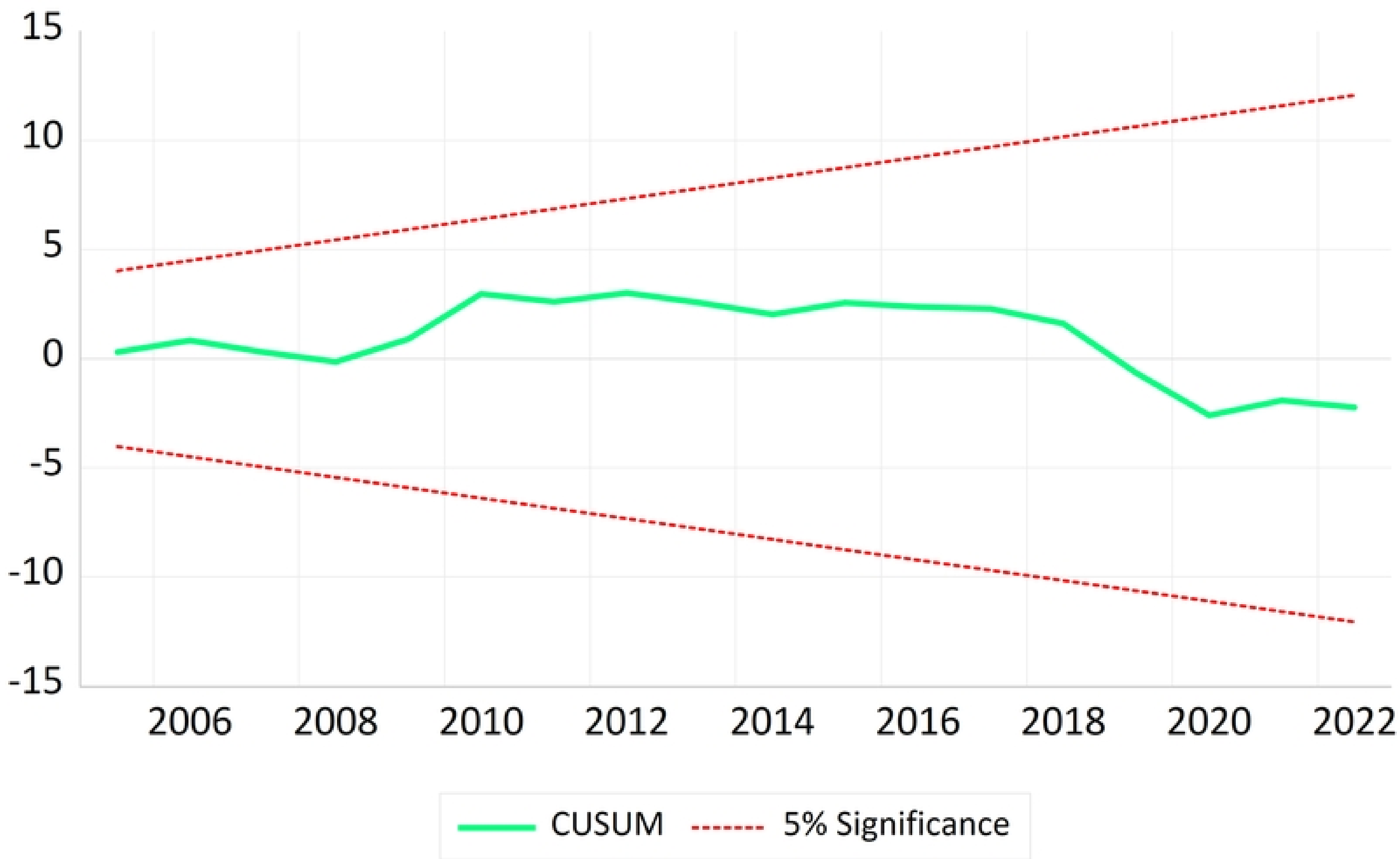
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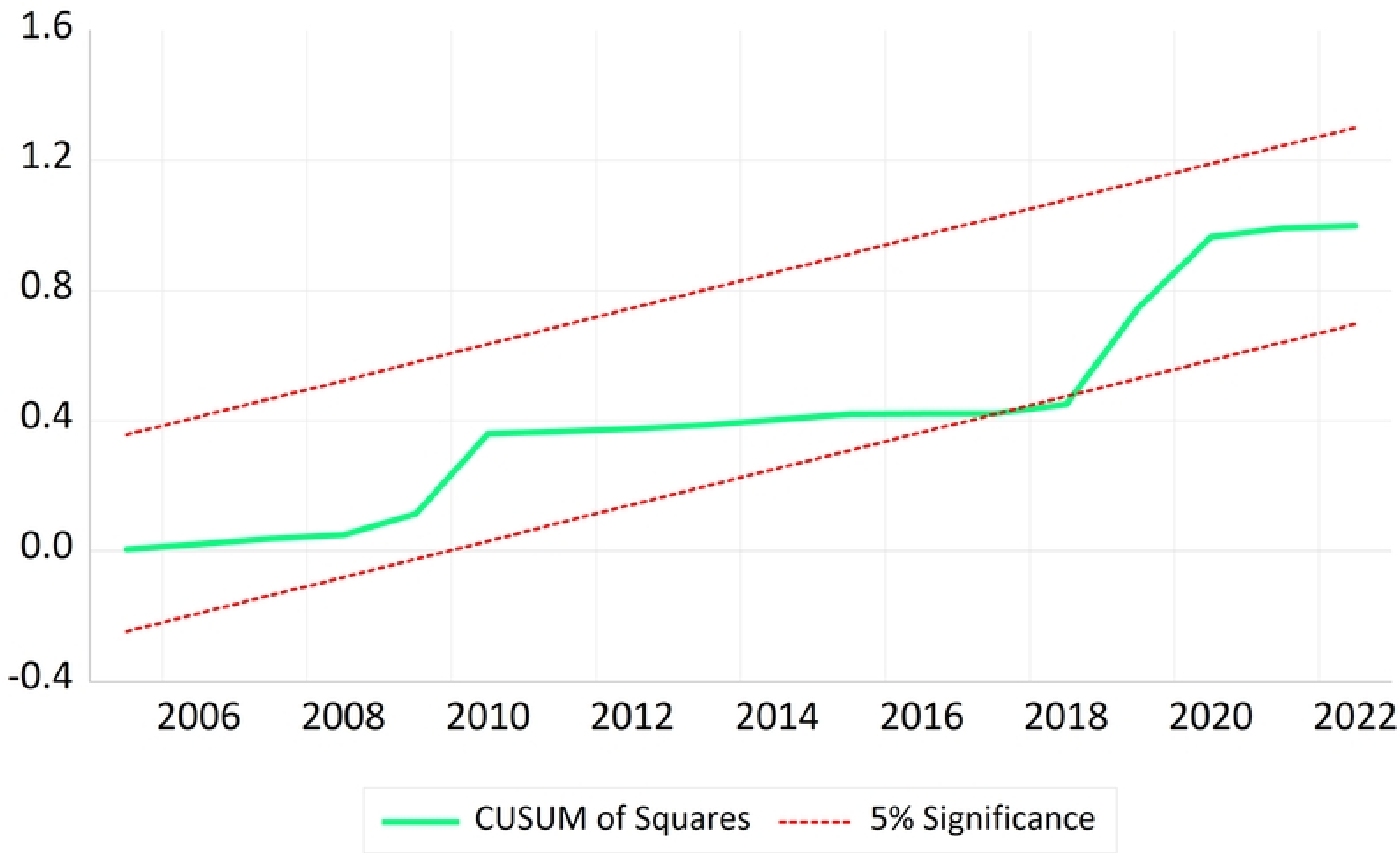
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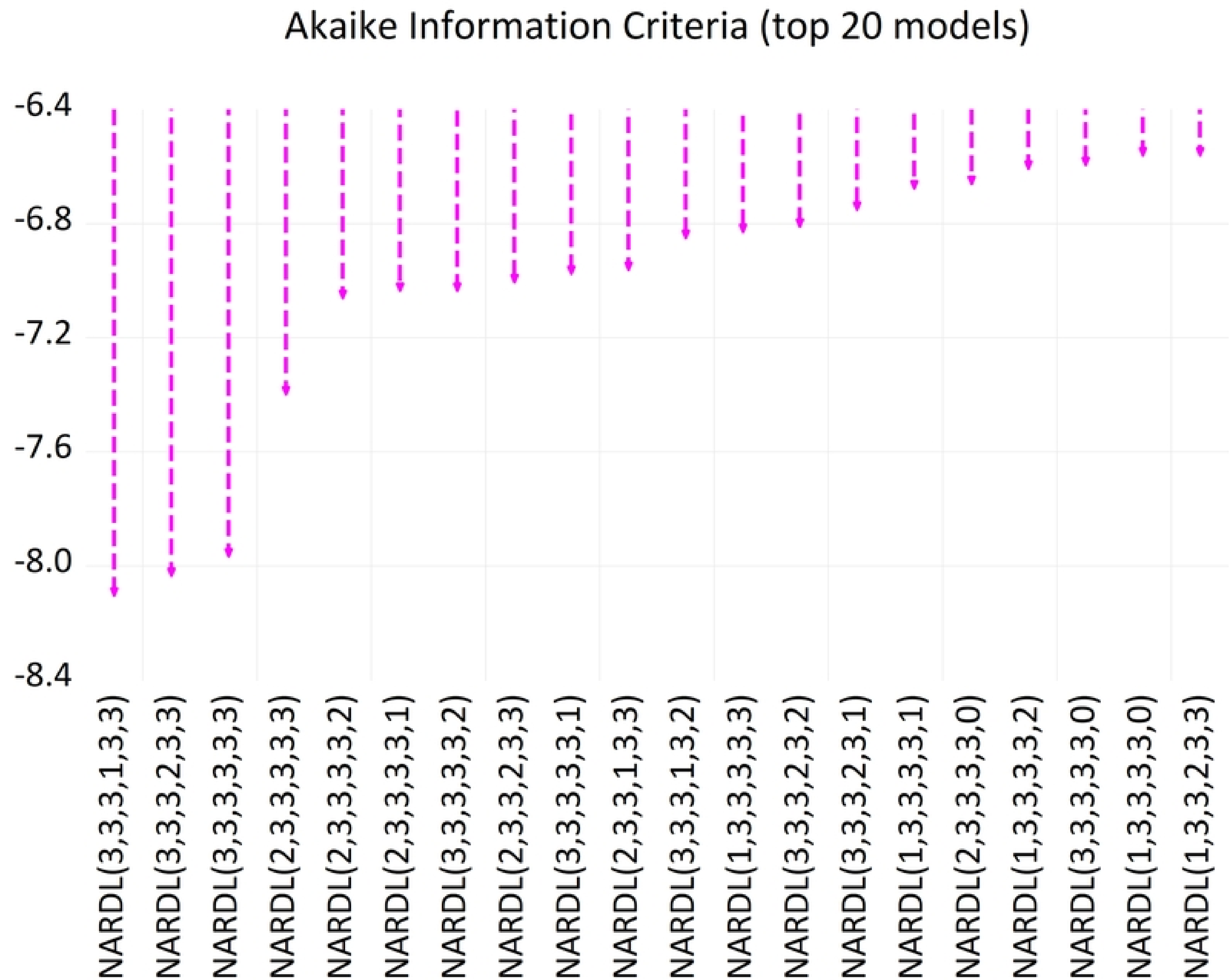
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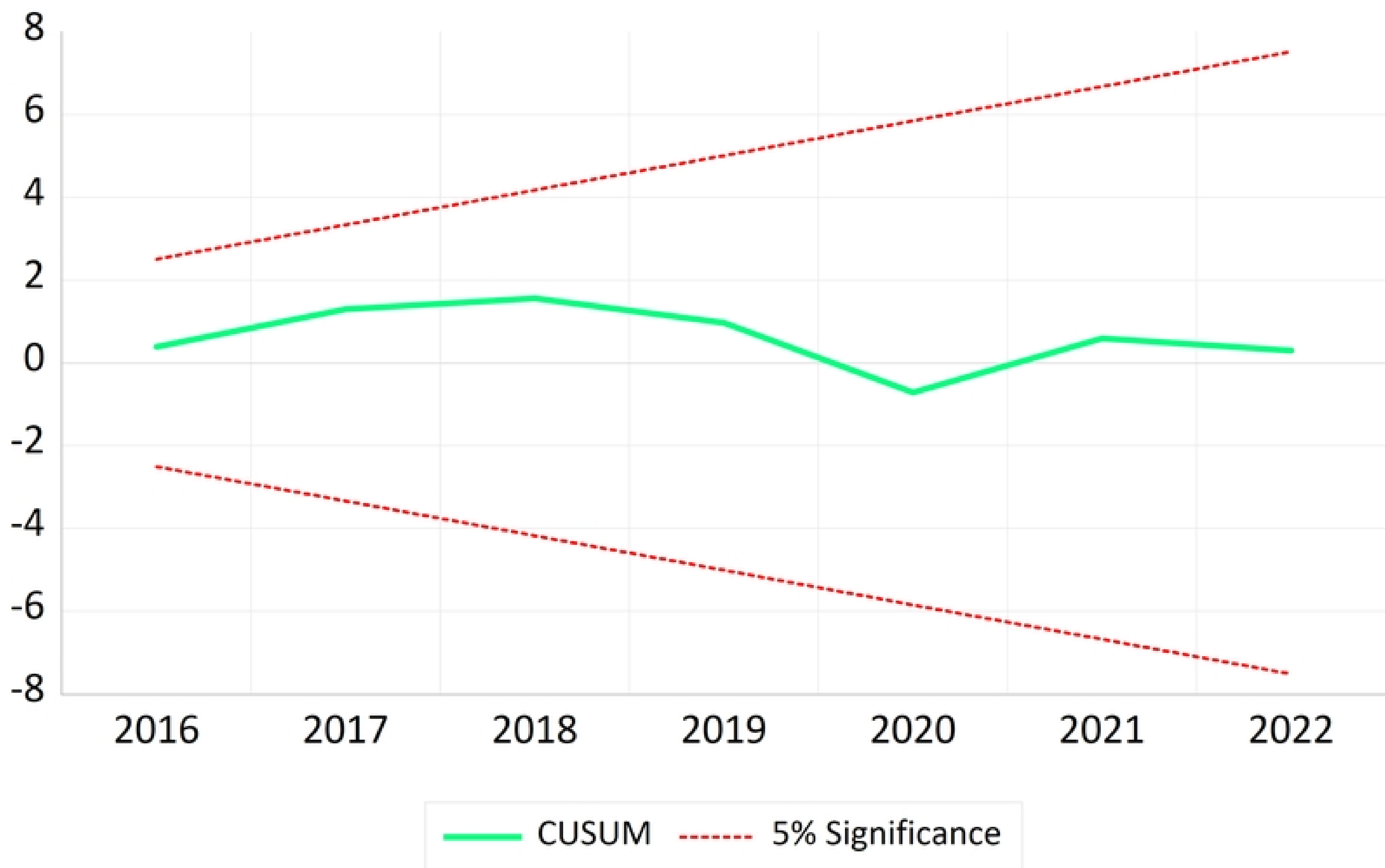
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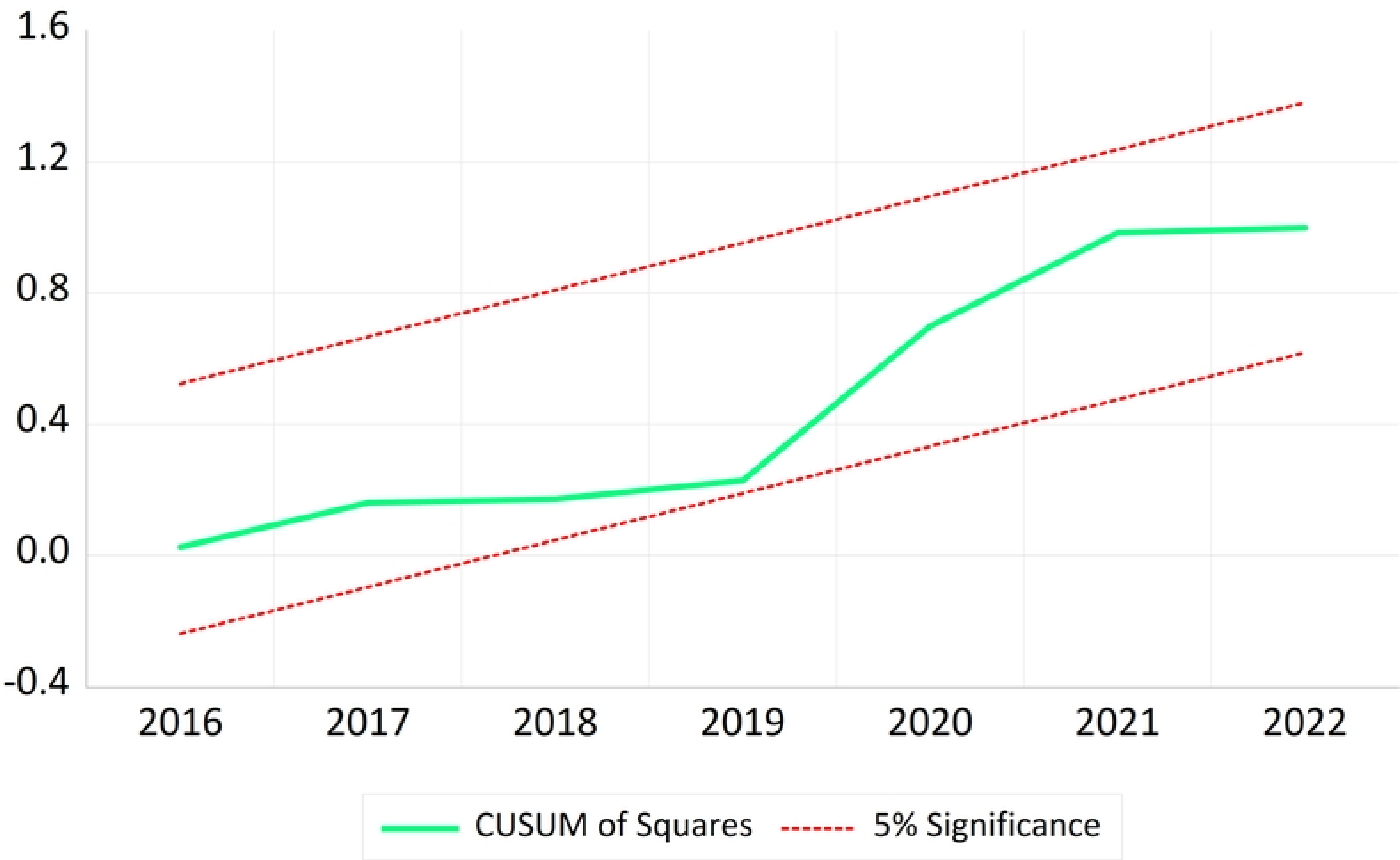
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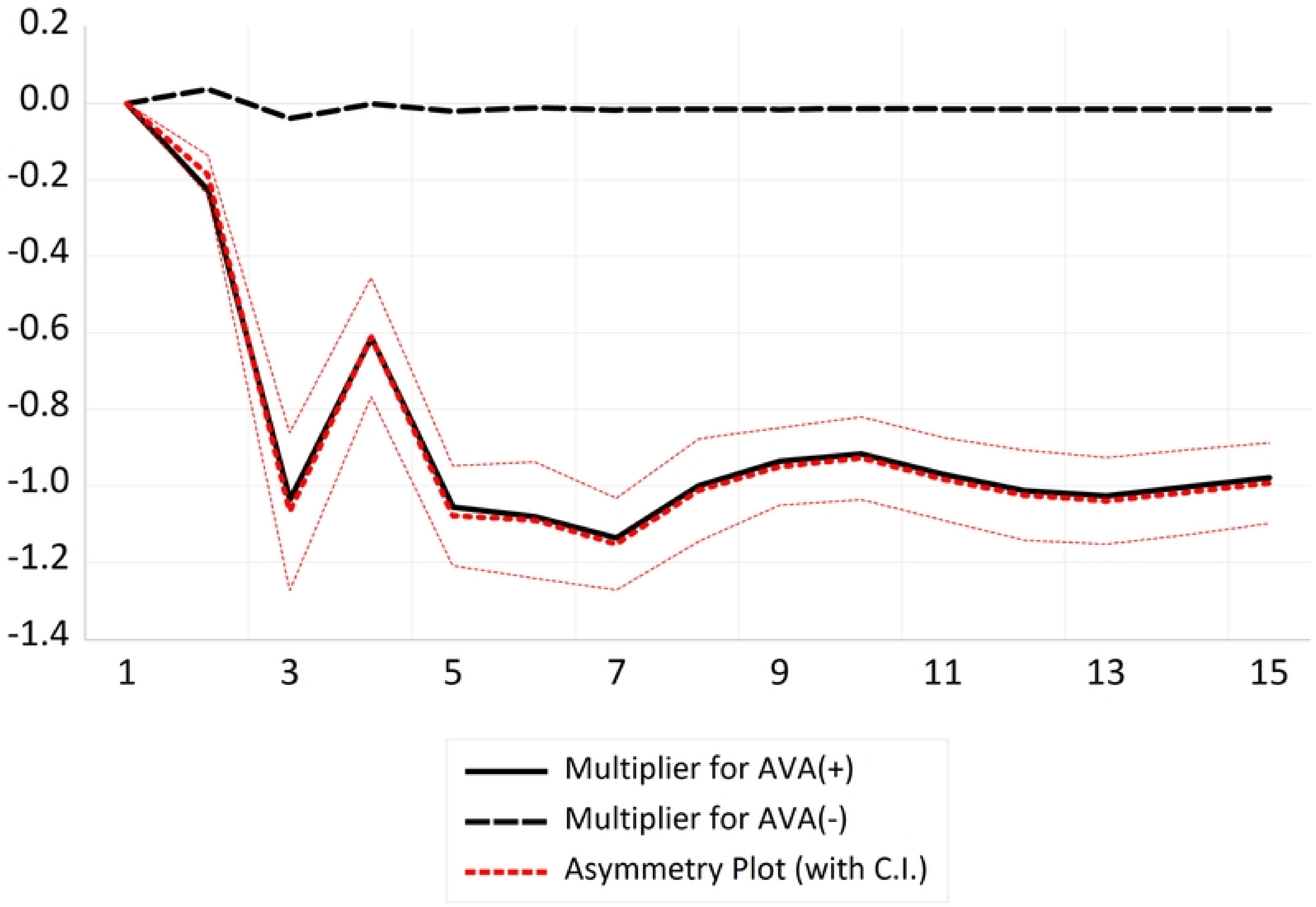
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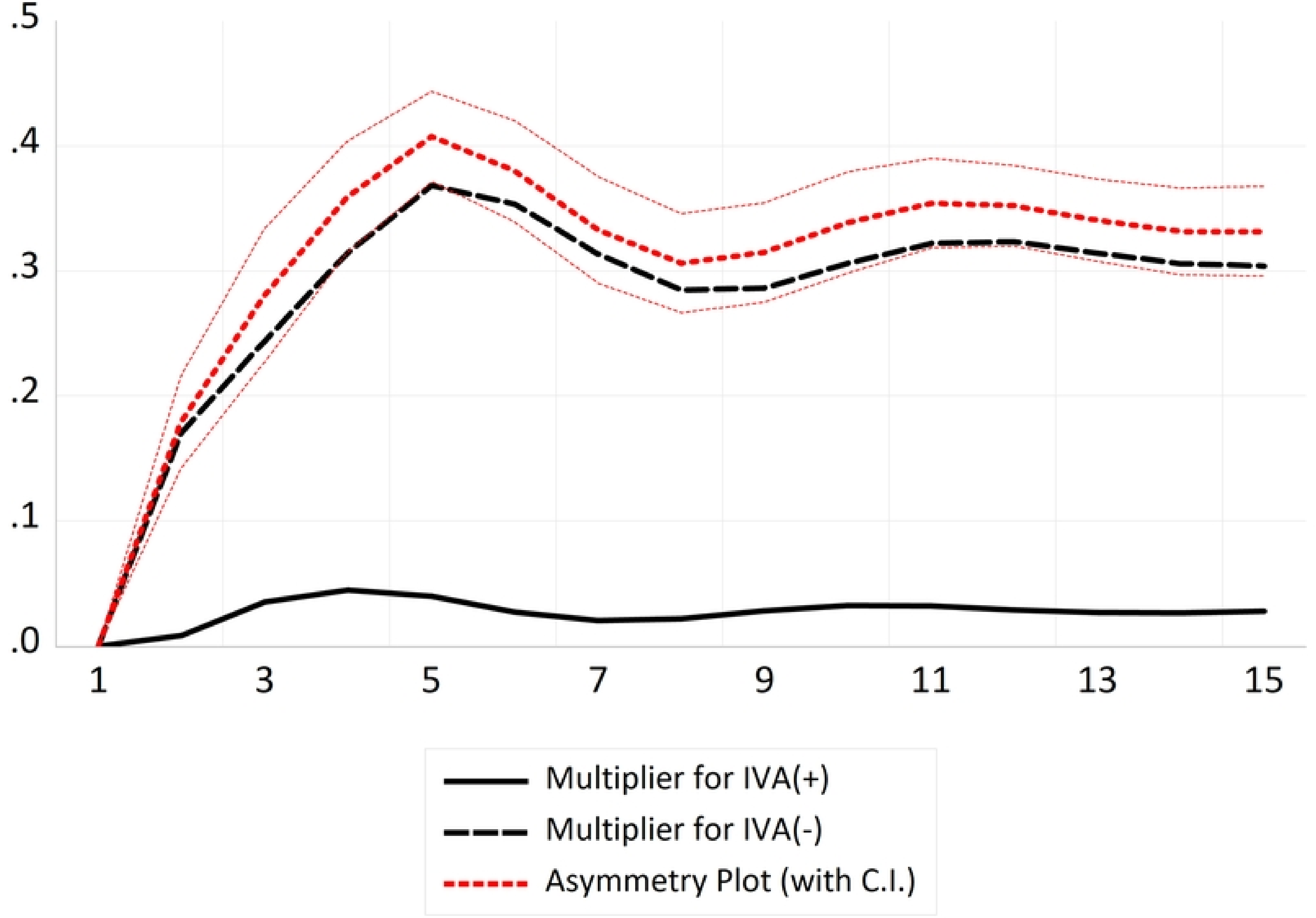
Multiplier for AVA(+)
Multiplier for AVA(-)
Asymmetry Plot (with C.I.)



.5
.4
.3
.2
.1
.0
1
3
5
7
9
11
13
15
Multiplier for IVA(+)
Multiplier for IVA(-)
Asymmetry Plot (with C.I.)