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Investigating the Effects of the Covid-19 Pandemic and Climate Risks on Trade Balance in Emerging Markets

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Abstract

Background: This study examines the impact of the Covid-19 pandemic and climate threats on trade balances in 39 emerging economies, covering the period from December 2019 to April 2021.

Methods: The panel autoregressive distributed lag (ARDL) model is employed as the baseline method, with dynamic generalized method of moments (GMM) and ordinary least squares (OLS) used for robustness checks.

Results: The PMG study reveals significant impacts of key variables on the trade balance. A 1% increase in Atmospheric Carbon Dioxide Concentration (ACDC) leads to a 61.9% decrease in trade balance, while a 1% rise in the Covid-19 Index (CI) results in a 26.4% drop. The Covid-19 Uncertainty Index (CUI) causes a 39.7% fall, and a 1% decrease in Surface Temperature Change (STC) leads to a 58.7% loss in trade balance. However, a 1% rise in Sea Level Change (CSL) results in a 27.4% increase, suggesting potential benefits for countries with modern coastal infrastructure. Interaction effects show complex dynamics, with PMG showing negative coefficients, MG detecting a negative link between CUI and ExGr, and DFE revealing positive interactions between CI and ExGr. Results from the dynamic GMM and OLS models confirm the robustness of these findings.

Conclusion: The Covid-19 pandemic and climate threats exert a negative and long-term inverse impact on trade balances in emerging economies. Policy recommendations include implementing strategies to mitigate the adverse effects of Covid-19 and climate-related risks on trade while promoting economic stabilization without worsening trade imbalances

Keywords: Covid-19 risks, climate risks, trade balance and emerging markets.

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Introduction

The advent of the Covid-19 pandemic has significantly intensified external risks, resulting in abrupt fluctuations in commodity prices, trade imbalances, and changes in foreign investment patterns in emerging markets. These risks originated from disruptions in global supply chains and a decrease in export demand, which led to currency depreciation, capital outflows, and increased borrowing costs. Furthermore, socio-economic challenges, including rising unemployment, increased poverty, and health crises, became more evident during this period. Recent studies indicate a notable increase in these risks throughout the pandemic in comparison to conditions before it, emphasizing the unique challenges posed by COVID-19. [28, 61] This escalation in risks has detrimental effects on trade balances, potentially leading to reduced income, export revenues and increased costs for imports (see figure 1). For instance, [32] observed that emerging economies faced significant revenue declines, aggravating their trade deficits. Thus, understanding the dynamics of emerging markets considering the circumstances of Covid-19 is essential for recognizing their vulnerabilities. This situation emphasizes the urgent need for effective risk management strategies that address the interrelated health, economic, financial, social, and environmental challenges heightened by the pandemic [13]. Such approaches are crucial for building resilience in these economies as they navigate the complexities introduced by this global crisis.

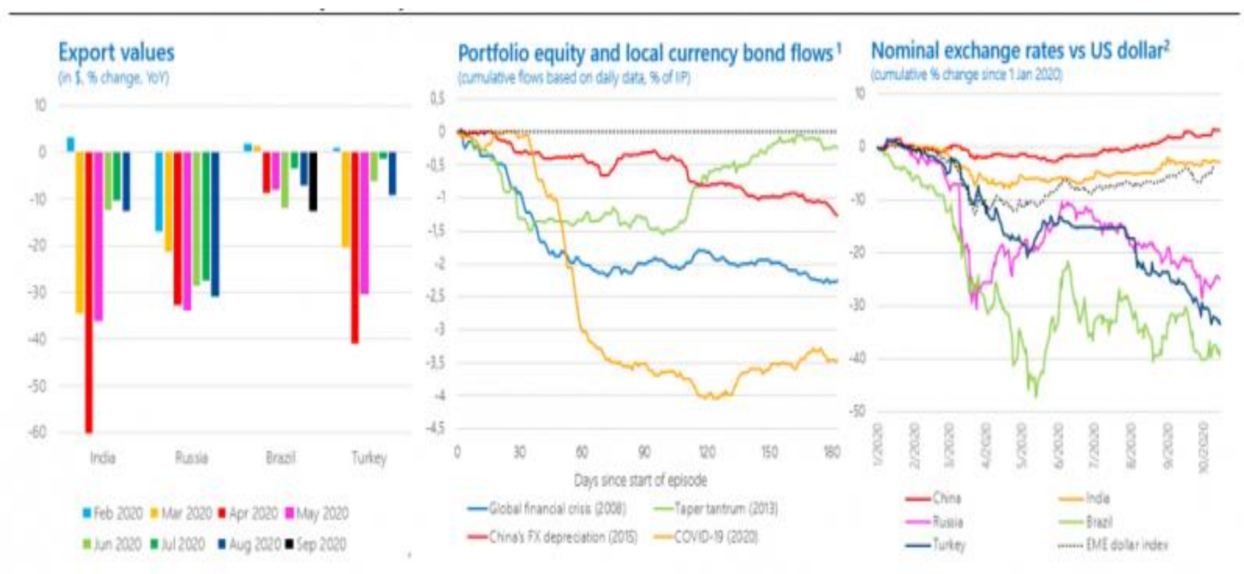

Figure 1: Multiple external risks of emerging markets before and during Covid-19

The COVID-19 epidemic has had a profound effect on economies worldwide, notably in emerging areas where it has severely disrupted trade, investment, firm operations, and movement of people. Widespread border closures, lockdowns, and supply chain disruptions brought forth by the extraordinary health crisis seriously hampered global commerce and economic expansion. [28] While nations first concentrated on resolving urgent health issues, the long-term economic repercussions quickly became apparent, especially in emerging areas that exported oil and saw significant drops in investments, exports, and revenue creation. These markets saw a sharp decline in commodity prices and income by the middle of 2020, which resulted in serious trade imbalances, currency devaluation, and financial instability. This time frame demonstrated how susceptible developing nations were to outside shocks like pandemics. [27]

The emergence of COVID-19 pandemic also disrupted social and economic activities worldwide. [61] Its economic ramifications extended far beyond health, affecting trade and business growth. COVID-19's rapid transmission led to the closure of borders and the enforcement of full or partial lockdowns, significantly impacting people's livelihoods. [9] Measures such as social distancing and mask mandates, while necessary to

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contain the spread, posed significant threats to both social well-being and economic stability. [60] Although economic activities began to recover gradually as restrictions eased, the pandemic's unprecedented effects on trade and investment persisted. This was especially true for oil-exporting emerging markets, which experienced sharp declines in oil prices—56% over seven months—and an 85% drop in oil and gas revenues during 2020. [27] These market shocks led to a depreciation in portfolio stocks, exchange rates, and local currency bond flows, destabilizing the financial systems of these markets. [28, 17] Consequently, trade imbalances worsened as domestic production plummeted, while prices for essential commodities soared, creating significant social and economic pressures, including heightened poverty, unemployment, and food insecurity. [43]

While the pandemic heightened economic uncertainty and disrupted international trade, climate change risks have long been a prominent concern in global discussions, predating the COVID-19 crisis. The World Trade Organization (WTO) has emphasized the importance of building trade capacity to enhance living standards and job creation, yet climate variability threatens the success of export-driven policies. [13] Human activities contributing to greenhouse gas (GHG) emissions have worsened the situation, leading to phenomena such as ozone layer depletion, rising atmospheric carbon dioxide levels, drought, flooding, and sea level rise [42]. These climate risks not only harm ecosystems but also disrupt supply chains, increase trade costs, and negatively impact trade balances. [16] The resultant trade deficits have exacerbated challenges in emerging markets, contributing to food insecurity, unemployment, and poverty.

Given this background, the present study investigates the dual impact of the COVID-19 pandemic and climate change risks on the trade balance in emerging markets. This research aims to fill existing knowledge gaps by: (a) conceptualizing the unprecedented uncertainties caused by COVID-19 and their effects on the trade balance, and (b) assessing the impact of climate risks, such as rising carbon dioxide concentrations, surface temperature changes, and global sea levels, on trade balance in these economies. Unlike previous studies, this research provides a comprehensive analysis by incorporating both COVID-19 and climate risks into its examination of trade dynamics. Moreover, the study employs robust econometric models, including dynamic ARDL, dynamic OLS, and GMM, to enhance the accuracy of its findings, overcoming limitations found in earlier studies that relied on gravity models and empirical trade methods [19, 31, 34]. This study contributes significantly to the existing literature by addressing the gap in research on the combined impact of COVID-19 and climate change risks on trade balance, particularly in emerging economies. While the literature on pandemic-induced trade disruptions is substantial, studies that explore the climate risks-trade nexus are scarce, especially in the context of emerging markets. Previous research has largely focused on either health crises or environmental risks in isolation. By integrating both, this study offers a more holistic understanding of the complexities facing global trade. Furthermore, the study advances the methodology by employing dynamic ARDL, dynamic OLS, and GMM models, which provide more robust estimates than the gravity models used in earlier studies, overcoming challenges related to endogeneity and unobserved heterogeneity.

This research also differs from the reviewed literature by focusing specifically on emerging markets and their vulnerability to both global health and climate risks. While existing studies have explored the impact of COVID-19 on global trade, [19, 31] they have not adequately addressed the compounded effects of climate risks. Additionally, this study's use of comprehensive climate indicators—such as global average atmospheric carbon dioxide levels, surface temperature, and sea level rise—adds depth to the analysis. This dual focus on pandemic-related and climate-induced risks, coupled with the application of advanced econometric models, offers a deeper and more detailed understanding of how trade balance works in emerging markets. This understanding goes beyond simple observations to reveal the complexities and various factors influencing trade balances in these economies. As such, the insights can help policymakers improve strategies for addressing specific health concerns and their influence on trade balances in emerging economies. The remainder of the study is organized as follows: section two reviews the pertinent literature, and section three details the methods and data source. Moreso, while section four presents the results and the discussion of the findings, section five presents the conclusion and policy recommendation.

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Review of related literature

Covid-19 risks and the trade balance

Our review in this part focuses on highlighting the impact of Covid-19 risks on trade balance in emerging economies because the Covid-19 pandemic is the most pernicious virus worldwide and there is a fast-expanding body of research capturing the risks associated with it. We have researched relevant literature on the positions of certain nations, interstates, and economic groupings because our evaluation of prior research has not focused much on the effects of Covid-19 risks on trade balances in emerging markets. Numerous studies have addressed the impact of Covid-19 on the trade balance, including those by. [14, 19, 21, 31] For instance, [19] used a quantitative model of international trade and input-output relationships to focus on 43 nations while examining the impact of Covid-19 supply shocks on global value chains. [19] found that China experienced a 30% welfare loss with modest spillovers to other countries. From a global value chain perspective, they found that trade – the distribution of goods and services – declined by 40% in the rest of the countries surveyed. [31] found that French firms that relied heavily on imported inputs from China and the rest of the world were hit hard by the risks of COVID-19, with the lockdown policy of January 2020 causing significant disruption on a global scale delivery of goods and services. Sill on the French economy, [14] found that large French firms were disproportionately affected by the risks of Covid-19. They contended that uneven company elasticity to demand shocks by size was a factor contributing to business underperformance, export restriction, and the trade balance. [34] investigated the influence of foreign trading partners' pandemic-related blocking measures on China's export transactions, the number of Covid-19 fatalities, and the trade balance. They discovered that variability in trade responses, combined with the dampening effects of the capital goods pandemic, resulted in a drop in trade, allowing industries that can work from home to grow. Similarly, [21] found that the blockade had a dampening effect on bilateral trade flows as it affects industrial production in all sectors of the economy.

In addition, many scholars argue that global lockdowns have heightened financial risks, exacerbating the economic impact of COVID-19, which has significantly disrupted global businesses. Thus, to support this point, [62] studied the impact of supply spillovers due to the Covid-19 lockdown using a high-frequency marine world change dataset and factored in geographically accelerated risk lags to determine these supply and business challenges channels have been disrupted by the risks of Covid-19. Using the Global Value Chain (GVC) dataset, the impact of the worldwide vaccination fee on the spread of Covid-19 shocks among industrialized nations was examined by [63]. They contended that even if developed economies were to bear the whole cost of immunization, they may still incur enormous losses due to supply chain disruptions brought on by pandemics in developing nations where immunization rates are still low. Furthermore, [64] examined the effects of the Covid-19 epidemic on exports from China using gravity modeling, with a particular emphasis on commerce between Chinese provinces, alternate foreign partners, and goods. They discovered that in 2020, Chinese trade decreased its shipments by 45 per cent during the Covid-19 era considering the threats involved. The effect of dispersion in the global value chain (GVC) on GDP was investigated by. [11] By modeling what may occur if foreign locations were dependent on home inputs, they are able to discern between shocks from abroad and domestic shocks and calibrate the possible impact of restricting measures in sixty-four nations. Furthermore, [23] evaluates the supply chain results of alternative COVID-19 management strategies using an economic catastrophe model, emphasizing the indirect effects on various nations through supply chain links.

In their analysis of the relationships among the number of Covid-19 cases and deaths, the price of bilateral exports, and the purchase of machinery items for 185 nations between January and June of 2020 [26] highlight the fact that Covid-19 cases and deaths were reported in export-related locations was most likely a significant factor impeding trade between nations. They also contended that the pandemic caused a huge shock to trade balances because Covid-19 had adverse effects on final goods that were currently awaiting sale to export nations rather than semi-finished goods in importing nations. Nevertheless, this has resulted in credible consequences demonstrating that exports from a country are linked to pandemic loads in comparison to other foreign competitors. We examine the effects of Covid-19 risks on trade balances in further detail. In light of this, [37] modelled the influence of Covid-19 on GDP and trade in order to examine the effect on trade in services using a variant of global computable population

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equilibrium (CGE). They discovered that business travelers and domestic services experienced the most shocks [46] followed the macroeconomic implications of pandemic shocks on investment flows to emerging market economies using an open economic system model. Their findings indicate that the pandemic's impact on emerging markets has resulted in output losses, which have been linked to exchange rate devaluations. This has had an impact on other emerging market nations. [2] investigated the effects of pandemic-induced trade barriers on commodity exports to China, the US, the EU, the UK, and Australia within the framework of Commonwealth nations. According to their predictions, commodities exports to vacation spot markets may decline by 98% in 2020, or $123 billion, meaning that exports would lose 19–24 cents in comparison to evaluate forecasts made prior to the epidemic. [6] evaluate the impact of COVID-19 on bilateral trade flows using a state-of-the-art gravity model of trade. Utilizing monthly trade data from 68 nations that were exporting to 222 markets between January 2019 and October 2020, they ended up to their three findings. Their research indicates that countries that had already ratified regional trade agreements before the pandemic are more vulnerable to the detrimental impacts of COVID-19 on bilateral trade. They found that when indications of government activities are considered, COVID-19 has a severe and substantial affect.

[3] empirically investigated the impact of the COVID-19 pandemic on the distribution business in 2019 and 2020 using quarterly records from 146 countries. They claimed that the COVID-19 pandemic had a significant negative impact on business. Furthermore, consistent with the above assumptions, the magnitude of the effect is significant among disaggregated service sectors, reflecting the nature of services. Tourism services, supply chain utilization and manufacturing sectors were most affected. In a related observation, [1] examined the impact of Covid-19 on global trade in African LDCs. The findings highlighted the importance of African LDCs establishing bilateral trade with current economically superior trading partners to ensure that no new protectionist measures against LDCs are initiated during the crisis period. It also implies that AfCFTA can provide opportunities to sell resilience to local surrogate family members through cooperation among LDCs in Africa. In addition, ensuring food security in the least developed countries of Africa is extremely important when negotiating trade agreements. [41] assessed the impact of the Covid-19 predicament on regional countries in the East African Community (EAC) using Kenyan trade data up to May 2020. It was found that the first quarter of 2020 saw Kenyan exports develop with moderate imports, which resulted in a deficit of changes. But during the Covid-19 disaster, home exports have been fairly hit, but not all delivery chains have turned into disasters. In other words, the most important victim of the crisis was the import of investment goods, which fell for more than three months during the disaster. Additionally, Kenya's re-exports and domestic trades have been attributed to their EAC trading status, as a result of which there is an urgent need to implement the African Continental Free Trade Agreement (AfCFTA) which would usefully facilitate the exchange of resources to mitigate the negative impact of the disaster. In Nigeria, [8] examined the impact of Covid-19 shocks on economic growth in Nigeria, particularly to determine whether or not Covid-19 will reduce economic growth. They found that the pandemic has disrupted global trade and hit the Nigerian economy due to total economic lockdown measures. The occurrence of the pandemic was thought to have driven various economies to a digital alternative. In addition, there may be a need for long-term trade-related technological advances to achieve useful approaches to resource change and facilitation.

In a study on trade and GDP from 1996 to 2018[30], focusing on V4 nations. Slovakia's export finance system dropped to the bottom of the V4 in 2018. Furthermore, in 2018, Germany emerged as the main export and import countries for international V4 sites. In the light of global trade and economic expansion, the VEC model and the Granger causality test determined that there is no long-term dependency of nations.[4] provided substantial information on the COVID-19 effect in V4 foreign sites in their investigation. Of the V4 nations, Slovakia has the fewest instances and deaths, while the Czech Republic contains the most variety. When discussing EU transfers to the V4 nations, the authors point out that Poland underwent the most change, followed by Slovakia, the Czech Republic, Hungary, and Poland. €29.6 billion, €8.6 billion, €6.4 billion, and €6.3 billion were transferred. The short-term reaction of the Visegrad countries (V4) financial markets to the COVID-19 pandemic was examined by [78]. According to

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their results, market participants now expect the Czech koruna (CZK), Hungarian forint (HUF), and Polish zloty (PLN) to significantly depreciate rather than appreciate. They highlighted pandemic-induced currency depreciation by using a TGARCH model to show a positive association between reported COVID-19 cases and exchange rates. The model also revealed an adverse association between the virus's spread and Visegrad stock market indexes, indicating market volatility during the health crisis. Moreover, V4 countries are experiencing the greatest domestic downturn since the 1990s, according to the TGARCH version, which also shows a substantial negative link between V4 stock market indices and COVID-19 outbreak.[53] discovered that during the epidemic, FDI growth significantly decreased in Hungary and the Czech Republic. Covid-19 and the world's food supply are indirectly related, according to.[20] Following the epidemic,[57] discovered significant changes in the interconnection, connectivity, and density of international commerce, underscoring the necessity for more study on the pandemic's consequences on world trade.

Climate risks and the trade balance

Climate change risks are rising to the forefront of domestic and international policy priorities among policymakers as trade plays a key role in greenhouse gas emissions, exacerbating climate risks through its outcomes at the point of production and sale of manufactured products and emissions from global transport products and offers between countries.[75] Several academics have approached the subject of the connection between climate hazards and trade balance from various angles. For instance,[76] verified that the adoption of ecologically friendly machinery results in greater emission reductions. When compared with non-spousal ecological structures, this will result in a greater coalition welfare. Furthermore, [77] said that in order to forge solid agreements and advance trade in renewable energy, industrialized and developing nations must work together more. Harmonizing carbon pricing and shifting to clean energy sources require more cooperation among the US, EU, and China, the three major greenhouse gases emitters. From a different angle, liberalizing trade seems to be the only reasonable solution for controlling emissions from agriculture. International climate mitigation targets have been weakened and emissions leakage in other regions of the world has grown as a result of the European Union's mix of carbon pricing and liberalizing agriculture trade [65]. Additionally, the region around it is frequently negatively impacted by deregulation of food-related trade. Primary factors associated with the rapid growth of the agri-food cycle have been identified as tropical deforestation, loss of biodiversity, soil erosion, and excessive water consumption. Sub-Saharan Africa, Brazil, India, and Indonesia have suffered the most from lost biodiversity and deforestation. [66]

[55] and [29] investigated the connection between economic expansion and climate change. While [29] reported that prolonged variations in temperature adversely influenced actual production per capita growth in 174 nations from 1960 to 2014, with rainfall having no effect, [55] found that weather temperature considerably impacted economic growth in Lebanon. Both results emphasize the need for more investigation into the effects of climate change. The link among growth and weather in the US and the EU was studied by.[18] They discovered that rising temperatures had a detrimental effect on US and EU economic development. According to research by,[45] carbon dioxide emissions have a detrimental impact on growth over the long and short terms. Using data from 11,000 districts across 37 nations,[15] examined the non-linear connection and found that, overall, production growth in all regions responds non-linearly to temperature, peaking at lower temperatures and then abruptly decreasing. These findings emphasize how crucial it is to comprehend how weather affects economic expansion. [40] used household survey data along with mean weather and precipitation data to undertake regional-level research for South Asia. The mean level of life was investigated as a function of climate variation. According to the study's findings, in contrast to a situation where things would continue as usual, living standards have decreased in Bangladesh, India, Pakistan, Sri Lanka, Nepal, and Pakistan. The only places where there was no adverse effect were Nepal and Afghanistan because of their generally lower temperatures. For every South Asian nation, the link between temperature and consumption is U-shaped.

Data and Method

The effect of the COVID-19 pandemic and climate risk on trade balance was assessed using monthly data from December 2019 to April 2021 for 39 selected emerging markets economies. The study's time frame is due to

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limited data availability. Selected new measures of the COVID-19 pandemic, according to,[42] were regarded as a key indicator of the pandemic, and the impact of climate risks on trade balance was considered by examining the influence of atmospheric carbon dioxide concentration, surface temperature change, and mean sea level change. Furthermore, the study seeks to understand the impact of population dynamics and improved exports on trade balance by controlling for demography and export growth. Similarly, we accounted for trade restrictions, exchange and interest rate environments, and the interactive effect of climate change and covid-19 on trade balance. As such, the table below presents the measures of the variables as well as their sources (see table 1).

Table 1: Variable definition and Source

Variables	Acronyms	Measures	Source	Apriori
Trade Balance	TBL	The difference between exports and imports over a specific time frame	WDI (2022)	-
Covid-19 Pandemic	CVP	*Covid-19 Index (CI) *Covid-19 Uncertainty Index (CUI)	Narayan, P.K., Iyke, B.N & Sharma, S.S (2021)	- ve
Climate Change Risks	CCR	*Atmospheric Carbon Dioxide Concentration (ACDC) *Surface Temperature Change (STC) *Sea Level Change (CSL)	NOAA (2022) OECD 92022) FAOSTAT (2022)	- ve
Exchange Rates	EXR	Nominal Exchange rate	WDI (2022)	- ve
Interest Rates	INTR	Nominal interest rate	WDI (2022)	- ve
Demography	DEM	Changes in human population	WDI (2022)	+ve
Export Growth	EXGR	Export growth measures the percentage change in the value of export between two periods	WDI (2022)	+ ve
Tariff rate	TARR	Duties imposed by foreign customs on the price of imported goods, as well as taxes and other charges.	WDI (2022)	- ve

Source: Authors' Concept: The data were generated from National Oceanic and Atmospheric Administration (NOAA, 2022), Organisation for Economic Co-operation of the United Nation [44], Food and Agriculture Organization stat (FAOSTAT, 2022), 42 and World Bank Development indicators (WDI, 2022) for 39 emerging markets economies - Argentina, Bangladesh, Brazil, Bulgaria, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Iran, Israel, Kuwait, Malaysia, Mauritius, Mexico, Morocco, Nigeria, Oman, Pakistan, Peru, Philippines, Poland, Qatar, Romania, Russia, Saudi Arabia, South Africa, South Korea, Taiwan, Thailand, Turkey, Ukraine, United Arab Emirates, Venezuela, Vietnam.

Baseline Model – ARDL (p, q, p… q)

The study employed the ARDL (p, q, p… q) as the baseline model because it technically solves problems with a small data sample size. It also provides better estimation compared to other techniques.[68] The ARDL model appears to be the most effective approach because it can simultaneously estimate the long-run and as well as the short-run relationships and accept variables irrespective of their order of integration. The estimated results can be used as a policy tool to promotes trade in the emerging markets.[68] The ARDL method, unlike other estimation techniques such as the gravity model, accurately captures the dynamic structure of linear models and also effective in estimating long-run parameters [68]. Based on the above discussion, we first present basic panel model in equation (1) which was transformed into ARDL model (p, q, q… q) as shown below.

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$$y_{i,t} = \psi_1 + \sum_{j=2}^{k} \phi_j X_{i,t} + \sum_{p=1}^{s} \varpi_P Z_{p,i} + \pi_t + \xi_{i,t} \tag{1}$$

i represent the individual countries selected for the study while t is time period. $X_{i,t}$ defined the observed explanatory variables, and $y_{i,t}$ is the dependent variable. $Z_{p,i}$ is the unobserved explanatory variables. t is the trend of time, which allow for a shift of the intercept over time, measuring time effects. ϕ_j is the vector of the coefficient of variables of interest, while Z_p is the unobserved variables.

$$InZ_{i,t} = \sum_{j=1}^{p} \lambda_{i,j} InZ_{i,t-j} + \sum_{j=0}^{q} \varpi_{i,j} Y_{i,t-j} + \sum_{j=0}^{q} \omega_{i,j} Cont_{i,t-j} + \vartheta_i + \varepsilon_{it} \tag{2}$$

where $Z_{i,t}$ denotes the dependent variable, which is the trade balance, calculated as the difference between exports and imports. $Y_{i,t}$ denotes the $K \times 1$ vector of independent variables which include key measures of Covid-19 pandemic (covid-19 uncertainty index - CUI & covid-19 index - CI) and Climate risks (atmospheric carbon dioxide concentration - ACDC, surface temperature change - STC & mean sea level change - CSL). Control variables, denoted by $Cont_{i,t-j}$ include demography (DEM), tariff rate (TARR), exchange (EXR) and interest rates (INTR), as well as export growth (EXGR). Following the baseline model, all the variables are expected to be integrated of $I(0)$ or $I(1)$. $\lambda i, j$; denotes the coefficient of the lagged dependent variable while $\varpi_{i,j}$; denotes the coefficient of the independent variables. ϑ_i is the country-specific fixed effects, and $i = 1,..., N; t = 1,2,..., T; p.q$ represents the optimal lag order while ε_t denotes the error term. In addition, all variables are in the natural logarithm. Following [67] and [68], eqn. 2 is modified to account for the short run dynamic by incorporating the error correction term (ECT) as indicated in eqn. 3 below.

$$\Delta Z_{i,t} = \delta_i [Z_{i,t-1} - \rho_i Y_{i,t}] + \sum_{j=1}^{p-1} \beta_{i,j} \Delta Z_{i,t-j} + \sum_{j=0}^{q-1} \pi_{i,j} \Delta Y_{i,t-j} + \vartheta_i + \varepsilon_{it} \tag{3}$$

where $\delta_i = -(1 - \lambda_i)$ is the group-specific adjustment coefficient rate which is expected to be less than zero $(\delta_i < 0)$. ρ_i is a long-term relationship and the error correction term (ECT) is denoted $[Z_{i,t-1} - \rho_i Y_{i,t}]$. $\beta_{i,j}$ and $\pi_{i,j}$ denotes the short-term dynamic coefficients. A long-term coefficient ρ_i defined as the same in all countries. Thus, if ρ_i is significant, then there is a long-run relationship between the dependent variable and the independent variables, with all dynamics and error correction terms free to vary.[79] In order to find the most reliable and consistent estimator, we estimated pooled mean group (PMG), mean group (MG), and dynamic fixed effect (DFE). The Hausman test was used to determine whether the predictor variables are endogenous.

Robust Model – Dynamic GMM and OLS

Following the paradigms of, [12] and [10] we chose generalized method of moments (GMM) and dynamic ordinary least square (DOLS) to robustly test our findings on the impact of Covid-19 pandemic and climatic risks on trade balances in emerging countries using ARDL (p, q). [58] and [52] considered GMM to be the most effective and consistent method for this purpose due to its ability to solve the endogeneity, reverse causality, and omitted variables issues inherent in panel dynamic ARDL. Also, DOLS eliminates the endogeneity problem-related bias of OLS when estimating regression models with cointegrated variables, In In light of the preceding discussion, we specify a dynamic GMM model considering a simple dynamic panel model of the form below, while eqn. 1 above was adopted to estimate DOLS.

$$M_{i,t} = \Psi InM_{i,t-1} + \beta InX_{it} + \vartheta InC_{i,t} + \Pi_i + \Phi_{i,t}, i = 1, \ldots, N; t = 1, \ldots, T \tag{4}$$

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Eqn. (4) follow the assumptions as suggested by [10], which state that;

(i) $\Phi_{i,t}$ *are iid across time, individual and independent of* Π_i *and* $M_{i,t}$ *with* $E(\Phi_{i,t}) = 0, var(\Phi_{i,t}) = \sigma_t^2$

(ii) Π_i *are iid individual with* $E(\Pi_i) = 0, var(\Pi_i) = \sigma_\Pi^2$

Where $M_{i,t}$ is the dependent variable and $M_{i,t-1}$ is the first lag of $M_{i,t}$. Moreover, $X_{it}$is a vector of explanatory variables, while $C_{i,t}$ is the control variables which are in natural logarithm. Accounting for the interactive effect of covid-19 pandemic and climate risks, we obtained eqn. (5) below

$$M_{i,t} = \Psi InM_{i,t-1} + \beta InX_{it} + \vartheta_i InC_{i,t} + \lambda_i Interact_{i,t} + \Pi_i + \Phi_{i,t}, i = 1, \dots, N; t = 1, \dots, T \quad (5)$$

Where ϑ_i *and* λ_i are the coefficients of the control and interactive variables. From eqn. (4), we obtain

$$M_{i,t} = \Psi InM_{i,t-1} + \Pi_i. \quad (6)$$

where, $M_i = (M_{i3}, \dots, M_{IT})', M_{i,-1} = (M_{i2}, \dots, M_{i,T-1})', \Pi_i = (\Pi_{i3}, \dots, \Pi_{iT})', with\ \Pi_{i,t} = \Pi_i + \Phi_{i,t}$

In equation (4), the lagged endogenous variable ($M_{i,-1}$) and the error term ($\Phi_{i,t}$) were strongly correlated as a result of the individual effect (Π_i). [12] have utilized the first differences as a way to eliminate this effect express as;

$$\Delta M_{i,t} = \Psi \Delta M_{i,t-1} + \beta \Delta X_{it} + \vartheta \Delta C_{i,t} + \Delta \Pi_i + \Phi_{i,t} \quad (7)$$

In order to avoid using weak instruments and increase the effectiveness of the estimator, [10] suggested a system GMM estimator that uses the moment conditions of the first-difference GMM concurrently. The system GMM estimator's moment conditions can be estimated by modifying [69] specifications shown below.

$$E(H_i^{St} \Pi_i^S = 0) \quad (8)$$

where, $\Pi_i^S = (\Delta \Pi_i', \Pi_i')'$ and H_i^S is a $2(T-2) \times (T-2)(T+1)/2$ block diagonal given by

$$H_i^S = \begin{pmatrix} H_i^D & 0 \\ 0 & H_i^L \end{pmatrix} \quad (9)$$

Using equation (8), one-step and two-step system GMM is estimated as in eqns. (10) and (12) respectively:

$$\widehat{\Psi^S} = (M_{-1}^{S\prime} H^S W_G^S H^{S\prime} M_{-1}^S)^{-1} M_{-1}^{S\prime} H^S W_G^S H^{S\prime} M^S . \quad (10)$$

where, $M_{-1}^S = [(\Delta M_{1,-1}', M_{1,-1}'), \dots, (\Delta M_{N,-1}', M_{N,-1}')]', M^S = [(\Delta M_1', M_1'), \dots, (\Delta M_N', M_N')]'$, $H^S = (H_1^{S\prime}, \dots, H_N^{S\prime})'$, and;

$$W_G^S = \left(\frac{1}{N}\sum_{i=1}^N H_i^{S\prime} G H_i^S\right)^{-1}, \text{where } G = \begin{pmatrix} D & 0 \\ 0 & I_{T-2} \end{pmatrix}. \quad (11)$$

$$W_{G(2)}^S = \left(\frac{1}{N}\sum_{i=1}^N H_i^{S\prime} \widehat{\Pi}_i^S \widehat{\Pi}_i^{S\prime} H_i^S\right)^{-1} \quad (12)$$

$\widehat{\Pi_{i}}^S$ *are the fitted residuals*

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In addition, to ensure the validity of the instruments and efficient GMM estimation, other tests such as Hansen and autoregressive (AR1) were performed.

In addition, in cointegrated systems, DOLS is a strategy for estimating long-run linkages while accounting for endogeneity and serial correlation. It includes leads and lags of the regressors' initial differences.[54] Its capacity to produce accurate and efficient estimates of long-run parameters accounts for its usefulness for cointegration analysis.[51] Given that DOLS produces objective and consistent parameter estimates while explicitly adjusting for endogeneity bias, it is considered more reliable than generalized Monte Carlo (GMM) estimations with small sample sizes. [59. 25] Model specification errors are less common with it than with GMM, and it is simpler to implement and understand when leads and lags of the initial differences are taken into account.[7] This model is particularly effective in predicting long-run coefficients if the coefficients are cointegrated, and DOLS provides a parametric technique that can reduce the link between explanatory factors and error terms [48]. The DOLS are defined as follows:

$$\beta DOLS = N^{-1} \sum_{i-1}^{N} \left[\sum_{t=1}^{T} (W_{i,t} - X_i)\right]^{-1} \left[\sum_{t=1}^{T} (X_{i,t} - X_i')\right] S_{i,t} \quad (13)$$

The regressor's vector is represented by Z, explanatory factors are denoted by (W = $X_{i,t} - X_i'$), $X_{i,t}$, and dependent variables are indicated by $S_{i,t}$. For unbiased estimating based on Monte Carlo simulations, the DOLS estimator surprisingly performs better in restricted samples than the ARDL, and GMM estimators. The robust adjustment for endogeinity in the explanatory variables is produced by treating endogeinity equally in a model [51, 59]

Estimation Procedure

In line with [38], a unit root test was used to determine the order of integration of a time series. When utilizing methods like cointegration analysis or ARDL, the sequence in which integration occurs determines the model's suitability for estimate and analysis of data collected over time, hence this knowledge is essential. According to [47], the unit root method provides extra details that may be used to examine the implications of the Covid-19 pandemic and climatic concerns on the trade balance in emerging markets economies by revealing if cointegration among the variables exists. [24] argued that, in light of this, unit root checks guarantee that time series studies provide strong and trustworthy results while also highlighting regions that need modification and, if ignored, might result in incorrect findings. We conducted pre- and post-estimation test using the ARDL, GMM, and DOLS hypotheses. The Arellano-Bond and Durbin-Watson test for serial correlation in the residuals, the Hansen test for instruments reliability, the Jarque-Bera test for residual normality, the Ramsey RESET test to determine whether the models are mis-specified, and the Breusch-Pagan test for residual heteroscedasticity are among the tests we conduct after performing a descriptive statistics analysis.

When estimating the GMM, we included the lagged value dependent variable ($Y_{i,t-1}$) in the model parameters to take serial correlation in the panel data into account. This is essential because, in the absence of these dynamics, estimations may become biased and unreliable. Individual-specific effects were included to account for variability that would not have been seen across cross-sectional units. To ensure that instruments used for the estimate is reliable, we utilize lag levels of $Y_{i,t}$ and $X_{i,t}$. This is necessary to manage endogeneity and confirm the accuracy, consistency, and validity of the estimations.

Unit root test

To determine if the series is stationary, panel unit root tests were carried out in accordance with [33, 35, and 36]. These tests included [70, 35, 33], and others. Therefore, heterogeneity is taken into consideration by the IPS, Fisher-ADF, and Fisher-PP tests, but the LLC test assumes that there is just one unit root process for all cross-sections. The IPS test does an independent ADF test on each cross-section, whereas the Fisher-ADF and Fisher-PP tests combine p-value computations with ADF and PP tests, respectively. However, if the estimated value is greater than the crucial value, the null hypothesis—that every series has a unit root—is rejected; if not, it is accepted.[22]

Cointegration Test

To verify the null hypothesis that nonstationary panels do not exhibit cointegration,[49] suggested seven test

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statistics. The seven test statistics fall into two categories: group-mean statistics, which average the outcomes of distinct nation test statistics, and panel statistics, which combine data along a single axis. This test does not take normalization or the true number of cointegrating links into consideration, in contrast to standard time-series analysis. Rather, the hypothesis test just considers how strong the evidence is for cointegration between two or more panel variables, or how weak it is. Both groups employ test statistics that are parametric (Augmented Dickey-Fuller, or ADF) and nonparametric (ϱ and t). Next, the test statistics are adjusted to match N(0, 1)'s null distribution. Depending on the kind of test statistic, whether trends in time were included, and the quantity of regressors, different adjustments are performed to the statistics. The results for the seven tests were estimated using the following equations, in accordance with [47]:

$$panel\ \upsilon: \quad T^2 N^{\frac{3}{2}} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11,i}^{-2}\ \hat{\in}_{i,t}^{2}\right)^{-1} \tag{14}$$

$$panel\ \rho: \quad T\sqrt{N} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11,i}^{-2}\ \hat{\in}_{i,t-1}^{2}\right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11,i}^{-2} \left(\hat{\in}_{i,t-1}\ \Delta\hat{\in}_{i,t} - \hat{\lambda}_i\right) \tag{15}$$

$$panel\ t: \quad \left(\tilde{\sigma}_{N,T}^{2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11,i}^{-2}\ \hat{\in}_{i,t-1}^{2}\right)^{-\frac{1}{2}} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \left(\hat{\in}_{i,t-1}\ \Delta\hat{\in}_{i,t} - \hat{\lambda}_i\right) \tag{16}$$

$$Panel\ ADF: \quad \left(\tilde{S}_{N,T}^{*2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2}\ \hat{\in}_{i,t-1}^{*2}\right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2}\ \hat{\in}_{i,t-1}^{*}\ \Delta\hat{\in}_{i,t}^{*} \tag{17}$$

$$group\ \rho: \quad T \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{L}_{11i}^{-2}\ \hat{\in}_{i,t-1}^{2}\right)^{-1} \sum_{t=1}^{T} \left(\hat{\in}_{i,t-1}\ \Delta\hat{\in}_{i,t} - \hat{\lambda}_i\right) \tag{18}$$

$$group\ t: \quad \frac{1}{N} \sum_{i=1}^{N} \left(\hat{\sigma}_i^2 \sum_{t=1}^{T} \hat{\in}_{i,t-1}^{2}\right)^{-\frac{1}{2}} \sum_{t=1}^{T} \left(\hat{\in}_{i,t-1}\ \Delta\hat{\in}_{i,t} - \hat{\lambda}_i\right) \tag{19}$$

$$group\ ADF: \quad \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{S}_i^{*2}\ \hat{\in}_{i,t-1}^{*2}\right)^{-\frac{1}{2}} \sum_{t=1}^{T} \left(\hat{\in}_{i,t-1}\ \Delta\hat{\in}_{i,t}\right) \tag{20}$$

To further investigate the presence of cointegration in panel data, the [71] panel cointegration test was employed. This test provides four different test statistics (two group-mean tests, two panel tests) to handle heterogeneity and cross-sectional dependency that [49] could not address. [71] method may be used to get two basic types of statistics: group statistics and panel statistics. These depend on the related relevance of the adjustment component of the ECT model in equation (3) and the least squares assessment. Mean statistics for the group based on the general form of $y_{i,t} = \theta_i + \acute{\beta}_i x_{i,t} + \pi_{i,t}$ model, where each cross-sectional unit's independent variable is $x_{i,t}$ and its dependent variable is $y_{i,t}$. Equations (21) and (22) and (23) and (24) are used for establishing G_τ and G_α, and panel tests, respectively. We employ OLS to determine the long-term connection among $y_{i,t}$ and $x_{i,t}$ for each cross-sectional unit i over time t. This allows us to establish the ECM for each cross-sectional unit, obtain the residuals from the estimated long-run connections, and calculate the four test statistics—group-mean tests and panel tests.

$$G_\tau = \frac{1}{N} \sum_{i=1}^{N} \frac{\hat{\propto} i}{SE(\hat{\propto} i)} \tag{21}$$

$$G_\alpha = \frac{1}{N} \sum_{i=1}^{N} \frac{T\hat{\propto} i}{\hat{\propto} i(1)} \tag{22}$$

The H_O of no cointegration for any one panel member is tested by G_τ, while the H_O of no cointegration for the panel members' average is tested by G_α. I. The semiparametric kernel approach of $\propto i(1)$ is $\hat{\propto}\ i(1)$ shows the standard error, SE(i).

$$P_\tau = \frac{\hat{\propto} i}{SE(\hat{\propto} i)} \tag{23}$$

$$P\alpha = T\hat{\alpha} \tag{24}$$

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Pooled data is used in P_τ to test the H_O of no cointegration for the panel as a whole, whereas average test statistics across cross-sectional units are used in $P\alpha$ to test the same hypothesis.

Results

Prior to model estimate, important pre-estimation experiments were conducted. Descriptive statistics, correlation analyses, unit root analyses, and cointegration analyses are a few of these tests. The behavior of the variables selected for the investigation is presented in Table 1. The descriptive statistics shows that the mean, median, standard deviation, skewness, and kurtosis values for each of the variables does not vary largely. The variables' minimum and maximum values are -5.809 and 6.204, respectively. These are the coefficients of the variable with the lowest and highest values. The Jarque-Bera probability values are significant, and there is no evidence of serial correlation in the series. Furthermore, except for a few variables with values greater than 0.7, the correlation matrix shown in table 2 indicates some degree of association between a few variables. The coefficients of the variables exhibit a weak correlation, raising the possibility that these variables will converge in the long run.

Table 1: Descriptive statistics

Var	TBL	CI	CUI	ACDC	STC	CSL	EXR	INTR	DEM	EXGR	TARR
Mean	1.341	3.815	3.958	2.427	-0.692	3.2084	2.577	1.593	1.925	1.641	2.333
Median	-2.076	3.836	3.964	5.752	-0.525	3.333	0.048	1.718	-0.426	0.939	0.446
Max	4.623	4.603	4.605	5.857	0.886	6.204	6.016	3.520	2.517	4.275	3.790
Min	-5.494	-2.120	2.073	-3.506	-5.809	-0.892	-2.996	-3.367	-3.264	-3.743	-3.613
Std. Dev.	549.9	0.399	0.265	3.511	2.105	1.232	3.371	0.882	3.585	0.533	2.377
Skewness	4.335	-7.592	-1.927	-0.114	-1.300	-0.497	-0.029	-1.045	2.282	1.558	-1.656
Kurtosis	23.43	99.42	13.07	1.084	5.769	3.371	1.049	6.345	4.506	2.443	3.619
J-Bera	136.1	262.0	320.4	101.4	303.7	77.45	105.2	350.8	31.17	80.72	133.8
Prob	0.000	0.000	0.000	0.000	0.000	0.021	0.000	0.000	0.000	0.000	0.000

Source: Authors' Concept.

According to the Spearman's correlation matrix, the majority of the variables have negative correlations (see table 2). Some of these variables include measures of the Covid-19 pandemic, such as the Covid Index (CI) and the Covid-19 uncertainty index (CUI), as well as indicators of climate change risks, such as the Atmospheric Carbon Dioxide Concentration (ACDC), Surface Temperature Change (STC), and Sea Level Change (SLC). Hence, only view variables were observed to move in the same directions, while others move in different direction indicating an inverse relationship.

Table 2: Correlation matrix results

	TBL	CI	CUI	ACDC	STC	CSL	EXR	INTR	DEM	EXGR	TARR
TBL	1										
CI	-0.811	1									
CUI	-0.543	0.885	1								
ACDC	0.796	-0.327	-0.592	1							
STC	-0.802	-0.022	0.016	0.725	1						
CSL	-0.794	-0.271	-0.022	0.023	-0.060	1					
EXR	0.819	-0.021	-0.567	-0.983	-0.271	-0.220	1				
INTR	0.530	0.021	-0.305	0.628	0.035	0.045	-0.712	1			
DEM	0.299	-0.650	0.234	0.030	-0.644	-0.284	-0.618	0.129	1		
EXGR	-0.490	0.153	-0.878	-0.134	-0.371	0.505	-0.328	0.456	0.398	1	
TARR	0.875	0.311	0.265	0.723	0.561	0.296	0.406	0.541	-0.081	0.327	1

Source: Author's Concept

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Furthermore, knowing the trend and unit root of the time-series data is essential since they are employed in the study. The ARDL (p, q), which stipulates that every variable for the study must have an integrated value of 1(0) or 1(1), was followed when performing panel unit roots tests. The ADF-Fisher Chi-square by [36], the PP-Fisher Chi-square by [72] the [33], and [35] tests are among the ones conducted. We combined the IPS, Fisher-ADF, and Fisher-PP tests as they all presume distinct unit root processes from the LLC test. The results are displayed in Table 3 below. These tests, however, are predicated on the alternative hypothesis, "no unit root," and the null hypothesis, "unit root." Therefore, if the probability value is less than 0.05, the decision rule running the tests instructs that the null hypothesis be rejected. As a result, the findings in Table 3 demonstrate that the null hypothesis has been rejected and that there is no indication of a unit root in the series for the variables. This indicates that the study's variables are integrated of 1~ (0) or 1~ (1). No variable is integrated of 1~ (2) as a result, and we draw the conclusion that the series are stationary and devoid of unit roots. Additionally, this meets one of the requirements for using ARDL for study estimation. There was also other post-estimation tests performed, such as Heteroschedascity, serial correlation, and cointegration. To reduce residual correlation in the baseline model, we estimated with the default optimal lag length (see table 6).

Table 3: Unit root test results

Variable	LLC	IPS	Fisher-ADF	Fisher-PP	Order of Integration	
					Level	**1st Diff**
TBL	-16.06*** (0.000)	-16.60** (0.030)	39.82*** (0.000)	451.82*** (0.000)	_	I~ (1)
CI	-17.40*** (0.000)	-13.77*** (0.000)	32.25*** (0.000)	42.18*** (0.010)	I~ (0)	_
CUI	-17.17* (0.071)	-14.25*** (0.000)	33.03*** (0.000)	362.4*** (0.000)	I~ (0)	_
ACDC	-49.65*** (0.000)	-44.02*** (0.000)	10.02*** (0.000)	100.2*** (0.002)	I~ (0)	_
STC	-14.06*** (0.0000)	-11.94*** (0.000)	28.54*** (0.007)	340.5*** (0.000)	I~ (0)	_
CSL	-18.12*** (0.000)	-16.25*** (0.000)	37.19*** (0.000)	394.4*** (0.000)	I~ (0)	_
DEM	-9.650*** (0.000)	-8.641*** (0.000)	221.8*** (0.000)	239.643*** (0.0000)	I~ (0)	_
EXGR	14.47** (0.041)	18.29*** (0.000)	20.68*** (0.000)	31.74*** (0.000)	I~ (0)	-
TARR	51.05*** (0.000)	74.96*** (0.000)	61.64*** (0.000)	117.0*** (0.000)	I~ (0)	
EXR	101.8*** (0.000)	96.46*** (0.000)	48.75*** (0.000)	75.22*** (0.000)	-	I~ (1)
INTR	40.78*** (0.000)	67.60*** (0.001)	54.80** (0.050)	84.39*** (0.000)	-	I~ (1)

Source: Author Concept. ***. **, & * represents the 1%, 5% and 10% significant levels.
I~ (0) represents integration order at level.
I~ (1) represents integration order at first difference.
(.) represents the probability value.

Table 3 shows the confirmed results of the unit test, which showed the variables' sequence of integration. The variables are clearly integrated at orders zero and one (I~(0)) and I~(1), respectively, which indicates that they are most likely to be cointegrated over the long term. The null hypothesis of no cointegration was investigated using three different panel cointegration techniques in order to confirm the predicted cointegration. These three cointegration tests (see Table 4 & 5)

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are the [49], [73], and [71] tests. First, we used the pedroni test, followed by a robust validation of the findings using the Kao cointegration test. The [71] test was run to confirm the preceding findings and establish a cointegration relationship because, the [50] and [73] tests were not predicated on error correction mechanism (ECM) with the premise that variables exist in their initial degree of integration. The purpose of these three tests was to accurately assess if cointegration existed in the panel.

Table 4 displays the cointegration results of [49]. Except for the panel rho statistic, evidence confirms cointegration in virtually all the seven statistics at the 1% significant level. At the 1% significance level, one of the four within dimensions is insignificant for model 1 (Panel Rho-Statistic), whereas all three between dimensions accept the alternative hypothesis of cointegration (Group PP- statistics) across the models. The Kao Panel Cointegration test was used to thoroughly verify the Pedroni test results, and the evidence generated reliable outcomes. As such, the null hypothesis of no cointegration is rejected at the 1% level of significance, supporting the evidence that the series are cointegrated.

Table 4: Panel Cointegration results

Model	Within-Dimension (Pedroni, 2003)				Between-Dimension (Pedroni, 2003)			Robust Check
	Panel v-Statistic	Panel rho-Statistic	Panel PP-Statistic	Panel ADF-Statistic	Group rho-Statistic	Group PP-Statistic	Group ADF-Statistic	Kao (1999)
1	-6.479*** (0.000)	2.459 (0.993)	-12.79*** (0.000)	-5.844*** (0.000)	3.398*** (0.002)	-15.02*** (0.000)	-3.664*** (0.000)	-9.145*** (0.000)
2	-8.357*** (0.000)	4.253*** (0.000)	-9.881*** (0.000)	-4.911*** (0.000)	5.179*** (0.000)	-21.14*** (0.000)	-7.545*** (0.000)	-11.22*** (0.000)
3	-10.71*** (0.000)	7.401*** (0.003)	-6.677*** (0.000)	-7.552*** (0.000)	8.042*** (0.000)	-10.90*** (0.000)	-5.813*** (0.000)	-14.51*** (0.000)

Source: Author Concept. ***, ** & * represents the 1%, 5% and 10% significant levels. (.) represents the probability value.

As earlier noted, [71] technique generates four major statistics, which can be classified into two major subdivisions: group statistics and panel statistics. From the group mean statistics G_τ and G_α derived from the expressions in equations 15 and 16, the results show that the null hypothesis of no cointegration should be rejected, as was also observed in padroni and Kao cointegration results. The final two panel mean estimations, whose results, illustrate the co-integration of the entire panel represented in equations (17) and (18). Considering the concerns about cross-sectional dependence, the results of the [71] cointegration results provide sufficient evidence of cointegration among the variables, as the probability values for rejecting a null or absence of a cointegration relationship are significant at 1% and 5% levels for the group statistics and relatively higher significance levels for the panel statistics.

Table 5: Panel Westerlund Cointegration results

Model	Gt	Ga	Pt	Pa
1	−3.837** (0.041)	−11.78 (0.981)	−9.921*** (0.010)	−8.284** (0.032)
2	−4.329** (0.049)	−14.73 (0.314)	−6.674*** (0.000)	−21.12** (0.021)
3	−5.198*** (0.002)	−10.33 (0.195)	−9.394*** (0.000)	−15.73** (0.017)

Source: Computed by the Author. ***, ** & * represents the 1%, 5% and 10% significant levels,
(.) represents the probability value

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Baseline Model - Dynamic ARDL

Once the cointegration has been confirmed, the long- and short-term associations between the selected variables are estimated. We have selected the MG, PMG, and DFE classes of panel estimators for this purpose. Table 6 displays the findings of the Hausman test, which was used to determine which of the MG, PMG, and DFE models was the best. Using the Hausman test, the alternative of PMG consistency is contrasted with the null hypothesis of MG's inefficiency. The results of the Hausman test, with a p-value of (0.289) > (0.05), lend credence to the null hypothesis. We can select a model that allows for heterogeneous short-run dynamics in the model with a common long-run effect since we are unable to reject the null of homogeneity. Therefore, PMG is a more reliable and efficient estimator than MG and DFE for the analysis, according to the Hausman test findings. Even though we presented the PMG, MG, and DFE findings in line with the Hausman test results, our study only paid attention to the PMG estimator results.

The PMG estimator permits different short-run coefficients and error variances between groups while requiring identical long-run coefficients. This premise is more plausible given that it takes time to implement a specific policy framework while different countries use different strategies in the short term. The assumption of shared long-run coefficients resulted in a faster pace of convergence and higher standard errors, and the assumption could not be rejected at 5% significance level. The findings of the PMG (see Table 6) demonstrate the possible effects of Covid-19 and associated risks on the trade balance. The findings showed that a percentage increase in the different measures of Covid-19, proxied by Covid index (CI) produces a 26% drop in trade balance, while a percentage increase in Covid-19 uncertainty (CUI) which measures the associated risks, results in a 40% decline in trade balance in emerging economies (see column 1 & 3). This decline in the trade balance shows that COVID-19 and the associated risks have a negative impact on export rates, reducing any gains that may have accrued to the economy over a given time period. Further evidence shows that the dynamic divergence in the short run is corrected 40% of the time (see table 6, column 1). The PMG results also show that COVID-19 pandemic measures have a long-term, negative impact on trade balances (see table 6, columns 1 and 3). This result is in line with earlier empirical studies [19, 31, 14]. This study shows that Covid-19 and the associated shocks have an adverse and substantial effect on trade, the distribution of goods and services, and welfare across different economies. Additionally, it supports the assertions made by [21, 64, 37, 46, 2, 41, 8, 34], and others that Covid-19 shocks inhibit trade balance, bilateral trade and export growth.

Similarly, except for sea level change (CSL), other measures of climate change risks such as atmospheric carbon dioxide concentration (ACDC) and surface temperature change (STC) have significant and negative long-term effects on trade balance across the models. The research shows, however, that a percentage increase in ACDC and STC causes a 62% and 59% fall in the trade balance respectively (table 5, column 1). This suggests that trade balances are hampered by the hazards of climate change. Hence, the implication of this findings is that long-term changes in CO_2 concentrations and temperatures have a negative and significant impact on trade balance because extreme weather events raise trade costs by destroying or degrading transportation infrastructure and output, and as such, this affects the total amount of exported goods, and the balance of payment of the selected countries. This result is consistent with empirical evidence from earlier studies which indicates that measures of economic growth as well as the trade balance are negatively affected by climate variability. see [55, 29, 18, 45; 15, 40]

In addition, to understand the effect of population dynamics on trade balance, we control for the influence of demography. The results revealed that population dynamics have a large and positive impact on trade balance. Hence, changes in human population are directly related to trade balance. The evidence shows that a 1% increase in population dynamics or demography has significant and the potential to enhance trade balance by 36%. This result is consistent with expectation, which indicate that population dynamics is a key driver of demand and supply as well as the openness of global trade (see table 6, column 1). Given the relevance of cross-border trade, it is essential to comprehend if tariffs are a threat or a boost to trade balances. As a measure of tariff, the study examined the influence of foreign customs duties imposed on the price of goods on trade balance, and the results revealed a significant inversely relationship. This showed that the

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trade balance was negatively and significantly impacted by a percentage point rise in tariffs by 31%. This might lure customers switching their demand to other trading partners who are not taxed. A bilateral tariff imposed on a trading partner could thereby restrict overall commerce and demand. Therefore, trade balance can be promoted by the removal of tariffs in the selected emerging economies. Export growth (EXGR) is also inextricably linked to trade balance. Evidence indicates that a 70% rise in trade balance is caused by a percentage increase in EXGR. This result suggests that the trade balance of the nations under examination is influenced by the pace of increase in exports. Important factors that influence trade balance also include other variables like interest rates (INTR) and currency rates (EXR). The findings demonstrate that 1% decline in nominal exchange rate causes 69% rise in trade balance due to changes in relative prices, increasing the cost of imported items. Consumers are therefore prompted to shift their spending from imported items to domestic goods, boosting the country's external balance. According to the R-squared value, the explanatory variables used in this study explain 75% of the variation in trade balance.

The trade balance is adversely and significantly impacted by the interactions between atmospheric carbon dioxide concentration and demography (ACDC*DEM), COVID-19 uncertainty and export growth (CUI*EXGR), and COVID-19 index, and export growth (CI*EXGR) as shown in Table 6. Therefore, the ACDC*DEM and CUI*EXGR effects are in charge of a 40% and 38% decrease in the trade balance of the chosen emerging economies, respectively, while the CI*EXGR interaction influence on trade balance is demonstrated to be more severe in terms of their coefficients. This indicates that trade balance improvement may be thwarted by elevated atmospheric CO2 concentrations (ACDC), Covid-19 uncertainty (CUI), and other Covid-19 measurements represented by its index (CI). This shows that the Covid-19 epidemic has a major impact on the trade balance when paired with export growth (EXGR), Hence, a significant impact on the trade balance, either positively or negatively, is indicated by a severe coefficient. The epidemic probably caused major disruptions to export markets and worldwide supply systems, which negatively impacted emerging nations' trade balances. As also evidenced in the studies by [56] and [39], increasing ACDC and demographic (DEM) dynamics interact critically and inversely affect economic welfare and financial development. In like manner, we found that rising ACDC and demographic (DEM) in emerging economies result in a notable 40% decline in the trade balance. This implies that trade is significantly harmed by both changes in demographics and environmental deterioration. For instance, rising carbon dioxide levels may have an impact on agricultural output, which when paired with demographic changes may upset trade balances and exports. Further investigation revealed that trade balance decreases by 38% as a result of the interplay among CUI and EXGR. This demonstrates how trade balances are negatively impacted by the pandemic's uncertainty as well as obstacles to export growth. worsening the adverse consequences on trade, uncertainties during the epidemic probably resulted in less investment, interrupted trade flows, and general economic turmoil. The linkages under discussion illustrate the necessity for intricate and varied economic strategies by illuminating complicated dynamics in emerging nations' trade balances during the Covid-19 epidemic. In order to ensure sustainable growth and development, policymakers must take these interactions into account when developing initiatives that improve trade outcomes and economic resilience.

Table 6: ARDL Estimated Results

Variable	PMG			MG			DFE		
	1	2	3	1	2	3	1	2	3
Constant	5.894*** (0.000)	2.141*** (0.000)	1.829*** (0.000)	3.991*** (0.000)	2.797*** (0.000)	10.33*** (0.001)	3.687** (0.022)	0.974*** (0.011)	2.493** (0.032)
TBL (-1)	0.622*** (0.004)	0.227*** (0.074)	0.288** (0.057)	0.399*** (0.011)	0.591*** (0.001)	0.119*** (0.000)	-0.755*** (0.000)	-0.810*** (0.000)	-0.495*** (0.005)
LnCI	-0.264*** (0.010)	0.089* (0.140)		-0.212 (0.170)	-0.228*** (0.030)		-0.333*** (0.000)	0.387*** (0.002)	
LnCUI			-0.397*** (0.000)			-0.102*** (0.033)			0.266*** (0.027)

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Variable	PMG			MG			DFE		
	1	2	3	1	2	3	1	2	3
LnACDC	-0.619* (0.120)	-0.527*** (0.000)	-0.522*** (0.026)	0.462 (0.215)	-0.292*** (0.005)	-0.394*** (0.013)	0.477*** (0.000)	0.357 (0.231)	0.427*** (0.080)
LnSTC	-0.587*** (0.010)	-0.409** (0.021)	-0.089* (0.097)	0.219* (0.090)	0.535*** (0.000)	0.567*** (0.000)	-0.400*** (0.000)	0.589 (0.161)	0.744*** (0.000)
LnCSL	0.515 (0.146)	-0.344 (0.155)	0.274** (0.022)	0.582*** (0.001)	0.308*** (0.000)	0.316 (0.200)	-0.522 (0.310)	0.048* (0.098)	0.328*** (0.000)
LnDEM		0.363** (0.019)	-0.263 (0.171)		-0.801 (0.190)	0.188** (0.021)		0.762*** (0.000)	-0.239*** (0.007)
LnEXGR	0.701** (0.016)		-0.157 (0.181)	0.751*** (0.017)		0.455** (0.027)	0.160*** (0.000)		0.556 (0.182)
LnTARR	-0.312*** (0.021)	-0.432*** (0.010)	-0.622** (0.030)	0.297*** (0.000)	0.447 (0.204)	0.323*** (0.004)	-0.517*** (0.000)	0.911*** (0.040)	0.206 (0.147)
EXR	-0.687*** (0.010)	0.269 (0.182)	-0.223** (0.038)	0.406 (0.160)	-0.270*** (0.000)	0.170 (0.220)	0.433*** (0.000)	-0.544*** (0.000)	0.354*** (0.000)
INTR	0.144 (0.211)	-0.302** (0.035)	0.317 (0.301)	0.097 (0.211)	0.610*** (0.000)	0.211 (0.192)	-0.226*** (0.000)	0.617*** (0.000)	0.721*** (0.000)
Ln(ACDC*DEM)	-0.401*** (0.011)			-0.590** (0.037)			-0.257** (0.017)		
Ln(CUI*ExGr)		-0.376** (0.033)			-0.351** (0.007)			-0.503*** (0.037)	
Ln(CI*ExGr)			-0.532** (0.027)			0.466** (0.027)			0.822*** (0.014)
R^2-Square	0.750	0.610	0.711	0.569	0.775	0.811	0.661	0.650	0.707
Hausman	MG and PMG			MG	and	DFI	DFI and PMG		
$chi^2(12)$		30.87			3.012		-34.61		
$prob > chi^2$		0.289			0.015		0.001		
H_o:		Accepted			Accepted		failed		
Decision	PMG			MG			Inconclusive		
χ^2**Normal**	30.33 (0.008)	20.74 (0.031)	44.11 (0.000)	51.10 (0.001)	15.27 (0.000)	19.97 (0.002)	27.53 (0.000)	18.20 (0.014)	13.89 (0.000)
χ^2**Serial**	10.20 (2.115)	3.881 (2.033)	2.773 (0.170)	7.617 (1.071)	5.087 (0.210)	2.907 (0.152)	11.60 (0.317)	9.822 (0.200)	4.753 (0.162)
Reset	5.522 (0.014)	3.382 (0.041)	7.222 (0.102)	1.941 (0.050)	9.313 (0.221)	4.744 (0.202)	6.590 (0.111)	2.836 (0.022)	5.811 (0.057)
$\chi^2 ARCH$	1.868 (0.531)	2.336 (0.932)	5.656 (0.744)	2.336 (0.932)	1.787 (0.212)	3.465 (0.211)	1.614 (0.160)	3.599 (0.314)	1.914 (0.207)

Source: Authors' Concept. ***, ** & * represents the 1%, 5% and 10% significant levels. (.) represents the probability value.

The trade balance decreases by 38% as a result of the interplay among CUI and EXGR. This demonstrates how trade balances are negatively impacted by the pandemic's uncertainty as well as obstacles to export growth. worsening the adverse consequences on trade, uncertainties during the epidemic probably resulted in less investment, interrupted trade flows, and general economic turmoil. The linkages under discussion illustrate the necessity for intricate and varied economic strategies by illuminating complicated dynamics in emerging nations' trade balances during the Covid-19 epidemic. In order to ensure sustainable growth and development, policymakers must take these interactions into account when developing initiatives that improve trade outcomes and economic resilience. The trade balance responds to changes in the COVID-19 epidemic and climate change at a speed of about -0.697% during the first month in order to obtain full convergence to its equilibrium level.

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Table 6 also shows that the F-statistic of 1.868, 2.336 and 5.656 $(\chi^2 = 0.531, 0.932 \,\&\, 0.744)$, which is not statistically significant, is the result of the ARCH test for heteroscedasticity in the model's error process. This implies that the model does not have a problem with heteroscedasticity. Higher order serial correlation is not statistically significant, according to the 10.20 $(\chi^2 > 5\%)$ F-statistic obtained from the Breusch-Godfrey serial correlation Lagrange multiplier (LM) test. As such, the null hypothesis—that is, no serial correlation in the residuals—cannot be rejected. Since the normality test resulted with a $p - value > 5\%$, supports the null hypothesis, we infer that the data display a normal distribution. R-squared gives information about the explanatory power of the model. According to the R^2 (0.75, 0.61, & 0.71), variations in the Covid-19 pandemic and climatic risks may account for 75%, 61%, and 71% of the variance in the trade balance of the emerging in emerging markets economies, respectively.

Table 7 displays the short-term component of the ARDL's findings. The error correction term characterizes the rate of disequilibrium adjustment. According to [68], it is significant and shows the expected negative sign. The results show that the ECM coefficients for the indicated models have adverse patterns at the 1% and 5% levels of statistical significance. The rate of adjustment from the short run to the long run was therefore modified by 69.7%, 81.7%, and 58.7% for models 1-3 of the pooled mean group (PMG).

Table 7: ARDL Short Run Dynamic – Baseline Model

	PMG			**MG**			**DFE**		
Variable	1	2	3	1	2	3	1	2	3
ECM	-0.697**	-0.817***	-0.587***	-0.480*	-0.791***	-0.367***	-0.852***	-0.638***	-0.663***
	(0.020)	(0.014)	(0.017)	(0.112)	(0.001)	(0.011)	(0.000)	(0.000)	(0.005)
ΔLnCI	-0.651***	-0.382***		-0.562**	-0.448**		0.373***	0.285	
	(0.000)	(0.000)		(0.020)	(0.030)		(0.000)	(0.231)	
ΔLnCUI			-0.396***			-0.412**			0.499
			(0.000)			(0.033)			(0.277)
ΔLnACDC	-0.712***	-0.660***	0.229**	-0.199**	-0.772*	0.394***	-0.714***	0.652**	-0.247**
	(0.011)	(0.000)	(0.026)	(0.015)	(0.105)	(0.013)	(0.000)	(0.012)	(0.080)
ΔLnSTC	-0.432	-0.511	-0.801*	0.419*	0.558***	0.393***	0.430***	0.445***	0.474***
	(0.161)	(0.310)	(0.097)	(0.090)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔLnCSL	-0.551***	-0.530*	-0.294***	-0.682***	0.288***	0.716***	0.252	-0.286	-0.828***
	(0.000)	(0.055)	(0.000)	(0.000)	(0.000)	(0.000)	(0.180)	(0.221)	(0.000)
ΔLnDEM		0.298***	0.613***		-0.801	-0.488***		0.262***	-0.392***
		(0.019)	(0.010)		(0.210)	(0.000)		(0.000)	(0.007)
ΔLnEXGR	0.427***		0.451***	0.305**		0.401**	0.360***		-0.656***
	(0.000)		(0.001)	(0.017)		(0.047)	(0.000)		(0.000)
ΔLnTARR	-0.332**	-0.506	0.313**	-0.290***	0.437	0.373	0.317***	0.391**	-0.620***
	(0.021)	(0.210)	(0.030)	(0.000)	(0.164)	(0.145)	(0.000)	(0.040)	(0.000)
ΔEXR	-0.268*	-0.471***	0.388	-0.436***	-0.379	0.672***	0.395***	-0.515***	0.534
	(0.053)	(0.012)	(0.183)	(0.000)	(0.210)	(0.000)	(0.000)	(0.001)	(0.190)
ΔINTR	-0.518***	-0.347**	0.597	0.339***	-0.510***	0.414	0.496	-0.347***	0.271
	(0.002)	(0.035)	(0.201)	(0.000)	(0.000)	(0.171)	(0.212)	(0.000)	(0.211)
ΔLn(ACDC*DEM)	-0.384*			-0.336***			-0.577***		
	(0.110)			(0.003)			(0.000)		
ΔLn(CUI*ExGr)		-0.221**			-0.402**			-0.275***	
		(0.014)			(0.028)			(0.001)	
ΔLn(CI*ExGr)			-0.337**			0.299**			0.378***
			(0.040)			(0.019)			(0.011)

Source: Authors' Computation. ***, ** and * represents the 1%, 5% and 10% significant levels. (.) represents the probability value.

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Robust Results - System GMM and Dynamic OLS

The dynamic system GMM and dynamic ordinary least square (DOLS) estimation techniques specified in equations (4) and (13) were used as a robust check to account for the issues of panel cointegration, endogeneity, and cross-sectional dependence that are inherent in a panel ARDL model. Consequently, Table 8 presents the summary of the results on the associations between the Covid-19 pandemic, climatic risks, and trade balance in 39 emerging markets economies. Thus, researchers like and [38] verified the effectiveness of the robust models in tackling the aforementioned issues. A significant long-term association has been found between trade balance, Covid-19 Uncertainty, climate change risks such as atmospheric carbon dioxide concentration (ACDC), surface temperature change (STC), and sea level change (CSL), according to the robust check findings from both models. The Covid-19 Index (CI), which evaluates viral spread, pandemic severity, and levels of response, had a positive association with trade balance even though it was insignificant, as seen in column 1 of the system GMM. Furthermore, the dynamic OLS results (see column 1) have been shown to be consistent with our previous findings (see Table 6). Also, we identified a significant link between CUI and trade balance. The findings demonstrate that increasing uncertainty associated with Covid-19 leads to an enormous drop in trade balance. The inverse link between uncertainty and trade balance demonstrates the pandemic's profound influence on global trade patterns. Countries with greater degrees of risk see interruptions in export demand, foreign investment, buying habits, and increasing trade expenses, including health. According to the World Health Organization (2020), the hazards of COVID-19 might exacerbate health issues such as diabetes, cardiovascular disease, chronic respiratory disorders, and cancer. These factors lead to a decline in trade balances, therefore for countries to maintain and eventually improve their trade conditions, authorities must effectively manage uncertainties through trade, health, and economic initiatives.

Table 8: Estimated System GMM and DOLS Results

Variable	System GMM			Dynamic OLS		
	1	2	3	1	2	3
Cons	0.487*** (0.011)	0.396** (0.032)	0.672*** (0.001)	0.722*** (0.000)	0.598*** (0.000)	0.383*** (0.007)
TBL (-1)	0.449*** (0.000)	-0.319*** (0.001)	0.445*** (0.020)	0.212*** (0.000)	0340*** (0.000)	0.813*** (0.000)
LnCI	0.814 (0.140)			-0.025*** (0.031)		
LnCUI		-0.327*** (0.002)	-0.662*** (0.002)		-0.562** (0.012)	-0.168*** (0.000)
LnACDC	-0.619*** (0.000)		0.198 (1.120)	-0.245*** (0.000)		-0.501*** (0.000)
LnSTC		-0.353*** (0.000)			-0.786*** (0.021)	
LnCSL	-0.213** (0.033)	-0.553*** (0.003)	-0.851*** (0.000)	0.236*** (0.008)	0.369*** (0.004)	-0.294*** (0.000)
LnDEM		-0.451*** (0.003)			0.371*** (0.004)	
LnEXGR			0.381*** (0.000)			0.472*** (0.000)
LnTARR	-0.611*** (0.000)	0.330*** (0.004)	0.423*** (0.004)	-0.285*** (0.000)	-0.025*** (0.031)	-0.511*** (0.000)
EXR	-0.064*** (0.001)	-0.227*** (0.003)	-0.075*** (0.000)	-0.156*** (0.001)	-0.461*** (0.001)	-0.472*** (0.004)
INTR	0.718*** (0.052)	0.186*** (0.052)	0.429*** (0.000)	-0.324*** (0.000)	-0.491*** (0.000)	0.562** (0.021)
Ln(ACDC*DEM)	-0.081***			-0.162**		

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	(0.001)			(0.021)		
Ln(CUI*ExGr)		-0.073***			-0.096****	
		(0.000)			(0.001)	
Ln(CI*ExGr)			-0.023***			-0.045***
			(0.000)			(0.000)
	0.520***	0.413***	0.374***			
AR (1)	(0.021)	(0.028)	(0.017)			
	0.336	0.706	0.951			
AR (2)	(0.412)	(0.211)	(0.150)			
Hansen	31.41	40.17	23.45			
	(3.196)	(1.218)	(2.191)			
Wald	(0.000)	(0.000)	(0.000)	34.10***	27.88**	19.97***
				(0.001)	(0.000)	(0.003)

Source: ***, ** and * represents the 1%, 5% and 10% significant levels, (.) represents the probability value

The results of ARDL in Table 6 have been confirmed by measurements of climate-related risks, such as ACDC, STC, and CSL, which all significantly accounted for to the decline in trade balance in emerging markets nations. This evidence concurs with [1, 3, 8], and our previous results. Hence, the negative association between disaggregated climate change indices - ACDC, STC, and CSL - and trade balance emphasizes the vital need to include climate preparedness into economic plans. To address the effects of climate variability, broad approaches are required, such as developing environment-resilient facilities implementing practices that are environmentally friendly and strengthening supply chains. Authorities must thus evaluate possible trade-offs between environmental rules and trade competition. Thus, reducing the adverse effects of variability in climate on trade balances is critical for long-term economic prosperity in emerging economies. Further analysis indicated that population increase has a substantial negative/positive association with trade balance (see GMM column 2; OLS column 2). Thus, the findings is inconsistent and in line with previous conclusions. Thus, a reversed substantial link frequently identifies difficulties including aging populations, excessive reliance ratios, labour shortages, and rising social spending, all of which can have a detrimental effect on trade balance. Conversely, a clear and significant link often indicates the possibility of better competition, increased labour availability, demographics dividend, and economic development—all of which can support the trade balance. Policymakers in emerging markets need to pay close attention to demographic indicators when formulating policies to enhance trade performance and promote general economic growth. Both the impact of export growth and the interaction effect of climate change were similar to the findings from ARDL.

Since they affect both internal and foreign trade in emerging economies, we also looked at other macroeconomic factors including interest rates and exchange rates. The business community suffered significantly when the country went into complete economic shutdown in an effort to stop the rapid spread of the Covid-19 virus. While some countries import a lot and export less, others produce more. In a similar vein, some governments find it extremely difficult to promote profitable trade both within and between their borders [74]. The exchange rate and interest rate were the main forces behind trade during the epidemic; therefore the model had to take these into account. We find that the interest rate has a positive significant long-run association with the trade balance in emerging economies, whereas the EXR has a negative negligible long-term association with the trade balance. We draw the conclusion that the Covid-19 epidemic and the concerns posed by climate change have a significant influence on the trade balance in emerging nations based on the results of the baseline and robust models. These results are in line with previous empirical results from [20, 75, and 4]. By implementing concerted measures, emerging economies may mitigate the adverse effects of the Covid-19 pandemic and the climate crisis on their international trade balance. By taking these actions, we can increase our resistance to shocks in the future and promote equitable, long-term economic growth. Even in the face of global issues, policymakers must take a proactive stance to guarantee that trade fosters economic progress.

First- and second-order autocorrelations were consistently supported by the available data. While AR2 has a p-value greater than 0.05, AR1 has a p-value less than 0.05. Thus, the significant AR1 finding is expected and does not imply that there is a problem with the model. Additionally, the absence of second-order autocorrelation is shown by the non-significant AR2, which shows that the model description and instrumentation are appropriate. We endorse the H_O that there is no second-order autocorrelation in the error terms based on the results displayed above. To make sure the instruments used in the model are sufficient and do not overidentify the equation, we also examine the p-value of the Hansen-Sargan test or the J-test up to a 5% threshold. Since there is not enough evidence to refute the H_O of instrument validity, the p-value is greater than 0.05, suggesting that the instruments are valid.

Discussions

The findings of the ARDL, System GMM, and dynamic OLS models provide insight on how global crises, notably the Covid-19 epidemic and climate threats, influence trade balance dynamics. The ARDL model demonstrates that both Covid-19 and climate change have a significant long-term negative impact on emerging market trade balances, owing to increasing uncertainty and environmental dangers that restrict trade flows. Furthermore, the PMG estimator effectively distinguishes between short-run dynamics and long-term equilibrium, demonstrating that, while short-term adjustments are more gradual, the long-term negative impacts on trade balances are significant, particularly in context with escalating uncertainty surrounding the pandemic and rising levels of atmospheric carbon dioxide. The System GMM and dynamic OLS approaches, utilised as supplementary checks, provide further support for these results while addressing possible issues like as endogeneity and cross-sectional dependency. Both models support the assumption that increasing pandemic uncertainty, along with growing climatic risks (such as greater carbon emissions and temperature changes), exacerbates trade imbalances. The dynamic OLS findings are consistent with the ARDL results, emphasising that trade balances are very susceptible to both economic and environmental shocks, with a significant reduction seen in countries experiencing increased uncertainty during the Covid-19 crisis.

The ARDL findings show the intricate linkages between the COVID-19 epidemic, climate threats, and developing countries trade balances. The findings of the PMG estimator indicate that the COVID-19 pandemic and related risks have a significant impact on trade balances. A 1% increase in the COVID-19 index (CI) results in a 26% loss in trade balance, whilst a 1% increase in COVID-19 uncertainty (CUI) leads to a 40% decline. These results underscore the detrimental consequences of the pandemic and its uncertainties on trade, supporting previous research by [19] and [14], which also found negative effects on exports and trade flows. Climate change factors, namely atmospheric CO2 concentration (ACDC) and surface temperature change (STC), have a significant long-term impact on trade balances. A 1% rise in ACDC or STC leads to a 62% and 59% drop in the trade balance, respectively. This demonstrates how severe weather events caused by climate change raise trade costs by interrupting transport and infrastructure, impacting trade flows. These findings are consistent with research such as [15] and 29], which suggest that climatic variability impacts economic outcomes, particularly trade balances. The addition of population dynamics emphasises the complexity of trade balance factors. The findings show that a 1% increase in population results in a 36% improvement in trade balance, supporting the idea that demographic shifts drive demand and impact trade patterns. To confirm the ARDL results, we used dynamic system GMM and dynamic OLS as rigorous tests. These models indicate the large negative effect of COVID-19 uncertainty on trade balance and support the ARDL findings, notably the strong long-term links between trade balance and pandemic risks. The dynamic OLS and GMM models back up the ARDL's findings, indicating that the negative impacts of pandemic and climate risks on commerce are constant across several estimating methodologies.

Implications of the Finding

The implications of these results show the critical need for policymakers to consider the cumulative and often long-lasting impacts of global crises on trade patterns. These crises destabilise emerging market trade balances, having a long-term detrimental impact on economic stability and development. Governments must thus establish comprehensive policies to alleviate present threats while also planning for future disruptions. This study emphasises the need for strong frameworks that

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handle both short- and long-term dangers posed by global crises. Policymakers should prioritise investments in climate resilience, economic diversification, and infrastructure to lessen susceptibility to future climatic shocks. This might include encouraging sustainable practices and assisting industries that are less vulnerable to global upheaval. Furthermore, efforts targeted at lowering trade uncertainty, such as improving policy coordination at the national and international levels, may assist to stabilise trade flows. Improving policy coordination, notably in trade agreements, border control, and crisis response measures, is critical for mitigating the harmful consequences of global shocks. Finally, establishing cooperation among governments, the corporate sector, and international organisations is critical to increasing adaptive capability. Policymakers may better equip emerging nations to handle future global issues and lessen the negative effect on trade balances by strengthening the global trade system and increasing their resilience.

Conclusion

The study examined how trade balances in 39 emerging market nations were affected by COVID-19 and climate-related concerns between December 2019 and April 2021. Whereas robust models such system generalized methods (GMM) and dynamic OLS were employed, ARDL was part of the baseline methodology. The results showed a significant inverse link between trade balances, climate change risks, and COVID-19 pandemic measures. Additionally, the study found a negative association between the Covid-19 Uncertainty Index (CUI) and the Covid-19 Index (CI), indicating the pandemic's significant effects on global trade. The analysis discovered that higher levels of Covid-19 infections and more uncertainty caused a worsening in the trade balance, showing that the pandemic disrupted supply networks, lowered global demand, and increased economic volatility. These disruptions have resulted in significant trade imbalances, emphasizing the necessity for proactive governmental actions to offset the negative effects and promote economic stability. Subsequent analysis showed that there was a positive and significant relationship between Surface Temperature Change (STC) and trade balance in developing economies, as well as a negative significant long-run connection between Atmospheric Carbon Dioxide Concentration (ACDC), STC, and trade balance. This demonstrates the strong connection between the risks of climate change and a deteriorating trade balance in emerging economies. While the STC measures variations in the earth's surface temperature, the ACDC analyzes the amount of greenhouse gases in the atmosphere. Increases in temperature and atmospheric carbon dioxide have an adverse impact on trade balance, disrupting industrial activity, upsetting agricultural productivity, and raising the frequency and severity of natural disasters. Large trade imbalances are the outcome, which underscores the urgent need for comprehensive policy actions to reduce the effects of climate change and promote sustained economic growth in emerging markets.

The trade balance of emerging nations is positively and significantly impacted by Surface Temperature Change (STC) owing to variables such as higher agricultural production and energy exports from renewable energy sources. Increased trade competitiveness may result from lower heating costs brought on by climate change. Risks also exist, though, from the wider negative consequences of climate change, such as severe weather and long-term damage to the environment. Policies that tackle these problems are essential to ensuring sustained economic growth. The trade balance is also influenced by other control factors such as interest rates, tariffs, export growth, exchange rates, and demographic shifts. Population growth policies combined with measures to limit these factors can increase domestic output and consumption, foster competitiveness, safeguard regional industries, increase trade surplus, and draw in foreign investment.

Additionally, the interaction term (ExGr*CUI) demonstrated how the Covid-19 outbreak's unpredictability affects the association between trade balance and ExGr. The information indicates that increased uncertainty brought on by Covid-19 lessens the positive effects of export growth on the trade balance, as seen by the data and the significant and negative coefficient of interaction term. This implies that, for emerging countries, improvements in trade balance are offset by pandemic-related uncertainties (such as supply chain disruptions, market volatility, and erratic governmental responses), even when exports are rising. In order to contribute to the trade balance's long-term sustainability despite current challenges, policymakers should work to reduce uncertainty through clear communication, stable policies, and aid for enterprises to navigate ambiguity. Moreover,

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DEM*ACDC postulates that the demographic makeup of a nation affects how environmental degradation affects its trade balance. Greater atmospheric CO2 levels combined with specific demographic characteristics have a negative effect on the trade balance, as indicated by the interaction term coefficient, which is negative and significant. This may suggest that, in developing nations, environmental degradation makes trade balances worse, particularly when population increases. This may suggest that the detrimental effects of climate change on trade balances are amplified in emerging economies, particularly as the population increases. The interaction between export growth and trade balance was directly impacted by the Covid-19 pandemic, as the ExGr*CI statistics show. The findings demonstrate that even in situations when export growth is positive, the immediate effects of the Covid-19 pandemic—lockdowns, decreased economic activity, and health problems—have a detrimental effect on the trade balance. This shows that the pandemic's negative effects on emerging countries outweigh the advantages of increased exports, most likely because of higher production costs, logistical challenges, and a decline in global demand.

Based on these results, it was recommended that the infrastructure supporting the healthcare system be strengthened in order to better manage and control health emergencies and enable quicker reactions to pandemics in the future. Appropriate vaccination measures should be promoted by emerging-market governments in order to help stop the spread of Covid-19, lessen its consequences on the economy, and rebuild confidence in global trade. Raising spending on digital trade infrastructures and broadening export products and markets to lessen dependence on a few, pandemic-prone industries might improve trade resiliency and enable commerce to continue even in the face of physical shutdowns and limitations. Furthermore, it is advisable to incorporate all-encompassing approaches for disaster risk reduction in order to alleviate the impact of severe weather events. Promote carbon absorption practices, such as afforestation and replanting, to reduce emissions and lessen the effects of warming temperatures. The authorities should Spend more in renewable energy sources such as hydro power, wind, and solar. By utilizing favorable weather, these sources can reduce reliance on fossil fuels. bring part in international climate agreements to ensure that efforts to address climate change are synchronized. International cooperation is necessary to share resource and best practices.

Availability of data and material

Data for each of the variables such as Trade Balance, Covid-19 Pandemic, Climate Change Risks, exchange rates, Interest Rates, Demography, Export Growth, and Tariff rate for the period December 2019 to April 2021 sourced from the Narayan, P.K., Iyke, B.N and Sharma, S.S (2021), NOAA (2022), OECD (2022), FAOSTAT (2022), and World Bank (2022).
Data are available under the terms of the Creative Commons Attribution 4.0 International license (CC-BY 4.0).

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Authors' contributions

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