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The Hurricane of Debt Hammering International Trade of Selective CARICOM Member States: Why the Region Needs Structural Reform of Official Development Assistance

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Abstract: This study sought to examine the effects of public debt and official development assistance (ODA) on the balance of trade in selected Caribbean Community (CARICOM) member states. The goal was to provide actionable policy insights that could help enhance regional economic stability. This study created a hybrid methodology that combined a panel ordinary least squares model with a deep residual network model and used it to examine data from seven Caribbean countries over the 2013–2022 period. The results indicated a significant negative dependence between public debt and trade balance, with a corresponding coefficient of −0.6153 indicating that a 1% rise in public debt was associated with a 0.62% decline in the trade balance. Additionally, ODA was found to have a positive impact, which was reflected by a 1% increase in ODA corresponding with a 1.95% improvement in the logarithmic value of the trade balance. Due to these results, this study lobbies in favor of the implementation of debt-for-climate swaps as a policy mechanism to alleviate debt burdens while facilitating the allocation of resources to climate-resilient infrastructure. This strategy seeks to facilitate long-term economic resilience in the region by addressing both fiscal sustainability and environmental challenges. A limitation of this study is that due to limitations of data, all 15 CARICOM full member states and 5 associate member states were not included. Nevertheless, the findings of this study remain valuable, as they justify the need for debt relief in the region.

Keywords: CARICOM, balance of trade, public debt, official development assistance, deep residual network

1. Introduction

Caribbean nations are among the most heavily indebted in the world. In fact, the high persistent levels of debt of the Caribbean nations are one of the region's most critical development challenges [1]. Notably, debt accumulation is typically framed through the perspective of fiscal mismanagement or narrow economic indicators. However, in the Caribbean context, debt accumulation is deeply rooted in structural vulnerabilities, such as the vulnerability to climate-related disasters and extreme weather events.

Since 2010, as a consequence of experiencing adverse weather events, the Caribbean has incurred damages to housing, agriculture, and infrastructure totaling at least US$3.2 billion [2]. In multiple instances, the damage caused by an extreme weather event has approached or even exceeded a country's annual GDP. For example, Tropical Storm Erika, which occurred in 2015, caused damages in Dominica equivalent to 90% of the country's GDP [3, 4]. In comparison, Hurricane Maria, which occurred in 2017, caused damages estimated at 226% of Dominica's 2016 GDP [5, 6]. The recent Hurricane Beryl, which made landfall on Carriacou, Grenada, as a high-end Category 4 storm in July 2024, caused approximately US$218 million in economic losses [7]. These estimates highlight the high cost associated with weather-related stressors in the Caribbean region.

Without adequate savings to replace the damaged infrastructure, the governments of the Caribbean countries must turn to borrowing as a financing mechanism. Unfortunately, borrowing to replace national infrastructure in countries that have a high risk of experiencing extreme weather events has created a precarious cycle in which climate vulnerability translates into long-term indebtedness. Even more worrisome is the fact that climate change is occurring, which would lead to an increase in the frequency and intensity of extreme weather events and would also magnify the impacts of slow-onset events such as sea level rise and salinization. As such, the Caribbean region's reliance on debt threatens to become unsustainable [8]. Moreover, the aftermath of these disasters is frequently accompanied by disruptions in key revenue-earning sectors, particularly agriculture and tourism.

This interplay between disaster-induced economic disruption and trade performance is significant. The balance of trade plays

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an important role in the region's macroeconomic stability. However, many Caribbean Community (CARICOM) member states experience a persistent balance of trade deficits driven by structural dependence on imports and limited export diversification. This dependence renders the region vulnerable to external shocks and logistical disruptions, which reinforces external imbalances [9].

The issue of public debt is inherently linked to trade performance. Rising external debt, especially when denominated in foreign currencies, results in increased requirements for debt service, which has the potential to reduce public funds available for public investment. This in turn limits the investment that could have built productive capacity to generate more revenue from exports. As such, in the absence of effective trade reforms or industrial diversification strategies, countries may find themselves in a perpetual situation of high debt and balance of trade deficits [10].

In this context, official development assistance (ODA) emerges as a relevant tool. ODA provides concessional financing that can mitigate reliance on external debt while facilitating long-term investment in infrastructure, education, and climate resilience [11]. Unfortunately, access to such funding remains constrained. Many Caribbean countries are classified as middle- or high-income based on per capita GDP, a statistic that does not account for their structural and climate vulnerabilities. This classification disqualifies them from many forms of concessional assistance, sending them toward borrowing on less congenial terms [12].

These dynamics highlight the interconnected nature of public debt, trade imbalances, and ODA. High public debt may cause a debt overhang, which may limit public investment in potential revenue-earning projects. The balance of trade deficit hinders the government's potential to generate surplus revenue to reduce its debt. Likewise, inadequate access to concessional finance further limits the government's fiscal space.

A shift in global financial architecture that considers structural vulnerability, rather than per capita income alone, could facilitate improved access to ODA for Caribbean countries. In turn, this would enable investment in productive sectors, improve export performance, and ultimately reduce the debt burden.

The objective of this study is to examine the impact of public debt and ODA on the balance of trade in selective CARICOM member states. Arising from the findings, policy recommendations will be proposed to help improve the situation in the region.

This study creates the POLS-ResNet model, which is a hybrid approach that combines the strengths of the panel ordinary least squares (POLS) model for capturing linear relationships in panel data and the residual neural network (ResNet) for modeling nonlinear patterns in data. The model was created by first estimating the linear components using the POLS model. After the residuals were generated, they were fed into the ResNet to learn complex nonlinear relationships. The final predictions are obtained by combining the linear outputs from POLS with the nonlinear outputs learned by the ResNet, resulting in a stronger and more accurate model.

The findings reveal that a 1% increase in ODA was linked to a 1.95% improvement in the balance of trade, suggesting a significant positive relationship. This indicates that foreign aid or development assistance can improve trade performance. Conversely, a 1% rise in debt corresponded to approximately a 0.62% deterioration in the balance of trade, highlighting the adverse impact of high debt on the Caribbean's ongoing trade deficit. These results reveal the importance of implementing structural reforms to enhance the region's trade balance.

Several contributions were made to this study. The first contribution is the implementation of an empirical analysis of the impact of public debt and ODA on international trade within the CARICOM region. This addresses a gap in the literature where there is limited research specifically focusing on the Caribbean. The second contribution was the employment of a nonlinear modeling approach to examine the relationships between the balance of trade, public debt, and ODA across seven CARICOM member states. This empirical research advances beyond prior studies that predominantly relied on linear regression techniques. The third contribution was the introduction and application of the POLS-ResNet model. Such a model is a hybrid approach that combines the strengths of econometric and machine learning methods, thereby capturing complex patterns in the data more effectively while improving predictive accuracy.

The remainder of this study is structured as follows. Section 2 furnishes a literature review. The data and methodology for the analysis are outlined in Section 3. Section 4 presents the results of the analysis. Section 5 provides a discussion. Finally, the study is concluded in Section 6.

2. Literature Review

The balance of trade, ODA, and public debt are deeply interconnected aggregates that significantly influence a country's macroeconomic stability and external sustainability. The balance of trade measures the difference between a country's exports and imports and acts as a reflection of the country's global competitiveness. In comparison, public debt is an indicator of the borrowing activities of a country's government. ODA, which often comprises concessional loans and grants from international donors, is a tool that can be used to support fiscal stability and stimulate economic development. However, the effectiveness of ODA in improving the performance of international trade depends on its absorption, allocation, and interplay with fiscal policy and debt dynamics.

2.1. Theoretical foundations: linking ODA, public debt, and trade

The absorption theory delivers one of the foremost frameworks connecting ODA to macroeconomic outcomes, stating that the effectiveness of aid is conditional on a country's absorptive capacity [13]. Ideally, ODA should finance higher consumption (C), investment (I), or government spending (G). But, by national income accounting, this should generate increased imports $(M - X)/Y$ [14]. This invites the query of whether aid enables productive investment or merely drives import consumption, with adverse implications for the balance of trade.

The Aid for Trade (AfT) framework, which is more auspicious in tone, adverts that targeted aid can trigger structural reforms, develop trade infrastructure, and liberalize economies, thus ameliorating productive and export capacity [15]. Nevertheless, the efficacy of AfT depends upon whether aid is channeled toward long-term capacity building instead of short-term donor-aligned priorities such as tied aid, which may create trade distortions.

In comparison**,** Dutch disease theory offers a prudent perspective, cautioning that excessive aid inflows can appreciate the real exchange rate, reduce export competitiveness, and encourage trade imbalances. Similarly, dependency theory asserts that aid may sustain structural weaknesses and external dependence if it debilitates domestic industry through aid-financed imports or dissuades reform.

2.2. Debt dynamics and trade: nonlinear risks and fiscal discipline

Moving the attention to public debt, the debt overhang hypothesis postulates that when countries face high external liabilities relative to their repayment capacity, it generates uncertainty and discourages both foreign and domestic investment [16, 17]. Investors expect future taxation or austerity, culminating in capital flight and suppressed economic activity. Although public borrowing can stimulate short-term demand (as per Keynesian theory), its long-run effect depends on the quality of investments made. If debt servicing prevails over fiscal spending, it crowds out investment and debilitates export-led growth.

The neoclassical perspective continues this view, highlighting the crowding-out effect where excessive public debt redirects resources from development spending and productive investment [18, 19]. Here, nonlinearities are important because while moderate debt may support growth, high debt places structural constraints on trade and macroeconomic performance.

2.3. Fiscal deficits, trade imbalances, and aid: converging hypotheses

The twin deficits hypothesis links fiscal deficits with current account (and hence trade) deficits, particularly under high capital mobility. The hypothesis presents several variants: (1) fiscal deficits drive trade deficits through higher demand and imports (Keynesian view); (2) trade deficits cause fiscal deficits; (3) bidirectional causality [20]; and (4) no causality at all (Ricardian equivalence hypothesis), which assumes forward-looking consumers neutralize the effect of government borrowing [21].

Elaborating further, the triple deficit hypothesis incorporates private savings–investment balances and posits that chronic trade deficits can result from imbalances in fiscal and private savings [22]. This framework furnishes a more thorough understanding of macroeconomic disequilibrium.

When ODA is integrated into the triple deficit framework, it becomes apparent that aid dependency, fiscal deficits, and trade imbalances can be mutually reinforcing. As Easterly [23] posits, high dependence on ODA can decrease motives for fiscal discipline and structural reform, while raising economic vulnerability. Aid inflows may replace domestic industry and the corresponding productivity by financing imports instead of projects and activities to build productive capacity. This thereby weakens trade performance and bolsters the need for more aid, creating a vicious cycle of dependency and underdevelopment.

2.4. Limitations of existing theories

The aforementioned theories, namely, absorption theory, Aid for Trade, and the debt overhang hypothesis, have conceptual limitations that restrict their explanatory power, particularly when applied to small, vulnerable economies. For instance, absorption theory assumes a linear and homogeneous relationship between aid inflows and macroeconomic variables. More broadly, modeling Small Island Developing States (SIDS) like the CARICOM economies carries meta-theoretical challenges, such as data scarcity, nonlinearity, non-stationarity, the existence of structural breaks, etc. These challenges are intermingled with short time series, insufficient data for wide cross-country analysis, and the difficulty of capturing data on economic activity in the informal sector.

2.5. Empirical gaps and Caribbean-specific challenges

Despite strong theoretical foundations, there is limited empirical research conducted on these linkages in the Caribbean. Much of the literature either generalizes from large Latin American economies or relies on linear methodologies that may overlook the complexity of the Caribbean fiscal and trade dynamics. For example, Cevik and Nanda [24] analyzed the fiscal sustainability of 16 Caribbean states and found the existence of positive debt-fiscal balance dynamics. Notwithstanding this, their methodology relied on a linear regression model, which did not consider nonlinear thresholds or asymmetric effects that are common in small island economies.

Likewise, Thompson et al. [21] examined the twin deficits hypothesis in Trinidad and Tobago (T&T) using another linear methodology, namely, the vector error correction model (VECM). While the authors address non-stationarity, the VECM method does not account for nonlinearity, which may limit the robustness of their conclusions, especially given the prevalence of structural breaks, regime shifts, and threshold effects in the data on the Caribbean small open economies.

2.6. Need for addressing the gaps and moving toward a nonlinear framework for the Caribbean

Given these gaps, this study aspires to make an empirical contribution by examining the relationship between the balance of trade, public debt, and ODA in the Caribbean, using nonlinear methods. The balance of trade will function as the dependent variable, providing an avenue to assess how fiscal conditions and aid inflows affect external competitiveness. Nonlinear modeling is more appropriate for capturing structural asymmetries, aid thresholds, and tipping points in debt sustainability, all of which are important for Caribbean SIDS steering fiscal vulnerabilities and global trade shocks.

The next section considers the data and methodology.

3. Data and Methodology

3.1. Data and variables

When assessing structural transformation in economies, especially in developing nations, it is important to consider various indicators that reflect the underlying economic health and performance. See Table 1 for a summary of the data for the study.

The balance of trade supplies insight into the competitiveness of a country's economy and its integration into the wider global market. A persistent trade deficit may indicate structural weaknesses in the economy, such as a lack of competitive industries or an overreliance on imports. Thus, the balance of trade is an appropriate variable to assess structural performance and transformation.

Data on exports and imports was collected from the World Trade Integrated Solution (WITS) database. This data was available in the SITC Revision 4 classification for the 2013–2022 period for Caribbean countries. The difference between imports and exports was used to calculate the balance of trade.

The balance of trade is selected as the dependent variable since it indicates the outcome of a bad structural system. A poor structural system would result in a persistent balance of trade.

Public debt refers to the amount of money that the government of a country owes to its creditors. While public debt can provide essential funding for development projects, if the public debt grows too high, the country can experience debt distress, where it may incur difficulty servicing its debt. Additionally, if the debt is too high and the debt service payments grow too large, it creates a problem where too much money will go toward servicing the debt relative to the amount of money allocated for development projects. This can lead to debt distress. Thus, debt is included as an independent variable.

Table 1
Summary of the data for the study

Name of variable	Data range	Countries
Official Development Assistance Balance of Trade Total Public Debt	2013–2022	Antigua and Barbuda, Belize, Dominica, Grenada, Guyana, Jamaica, and Suriname

Data was collected on debt from the International Monetary Fund (IMF) database. The debt variable used was the total public debt of the respective country.

ODA refers to the financial support channeled from developed nations to help fund the economic development of developing countries. ODA furnishes the necessary capital for infrastructure projects and economic reforms that are important for structural transformation. Accordingly, ODA is included as an independent variable. Data is collected on ODA from the World Bank database.

Other variables were also considered as independent variables. A variable was sought for technological intensity. Technological exports were considered, but sufficient data could not be found for Caribbean countries. Industry development was considered, but data could not be found.

The countries considered include Antigua and Barbuda, Belize, Dominica, Grenada, Guyana, Jamaica, and Suriname. These countries were considered since they had data for all the variables over the 2013–2022 period.

The 2013–2022 period was considered since it was the longest period with data available for trade (exports and imports), ODA, and debt.

Since the data covered multiple countries over time, it was panel data. There were 7 countries and 10 time series, resulting in 70 observations per variable.

3.2. Methodology

The hybrid POLS-ResNet model is proposed for the analysis over other models because traditional linear models, such as POLS, are constrained by assumptions of linearity, normality, and stationarity, which often do not hold in real-world economic datasets, especially for Caribbean SIDS where nonlinearities and structural breaks are common. While nonlinear models like artificial neural networks (ANNs) and deep learning architectures are capable of capturing complex patterns, they typically do not automatically take into consideration the panel structure of the data. As such, the POLS-ResNet model combines the strengths of both approaches by utilizing the POLS to explicitly account for the panel structure and while leveraging the ResNet's residual learning capacity to capture the nonlinear relationships that the POLS alone cannot model.

3.3. The panel ordinary least squares model

The original POLS data model is specified as follows:

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \ldots + \beta_n X_{nt} + \varepsilon_t \quad (1)$$

where Y_t is the dependent variable, $X_{1t}, \quad X_{2t}, \quad \ldots, \quad X_{nt}$ are independent variables, $\beta_0, \quad \beta_1, \quad \beta_2, \ldots, \beta_n$ are estimated parameters, and ε_t is an error term.

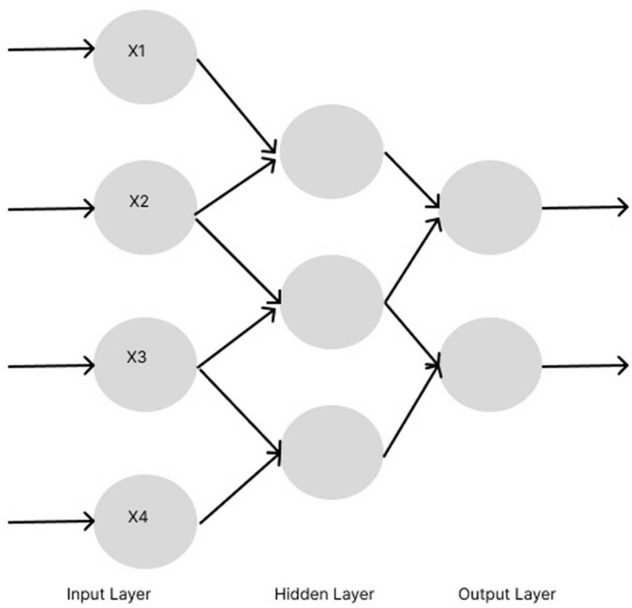
However, a traditional POLS model is constrained by the assumptions of linearity, normality, and stationarity. If these assumptions do not hold, then the corresponding estimated parameters will not be accurate.

Nonlinear relationships are often present in economic time series. For example, the balance of trade in a certain country may contain nonlinear autoregressive effects, suggesting that the current balance of trade depends nonlinearly on past balance of trade. Furthermore, particular combinations of past balances of trade may have distinct nonlinear effects on the current balance of trade, referred to as nonlinear interaction effects. Additionally, a time trend can also be nonlinear in structure, which is often neglected in linear regression analysis.

3.4. The artificial neural network model

ANNs are artificial intelligence and machine learning models that have the ability to model complex, nonlinear relationships between inputs and outputs effectively. Unlike traditional linear methods such as multiple linear regression and others, ANNs do not require strict assumptions regarding multivariate distributions, which allows these models to be applied to a wide range of problems. Moreover, this flexibility allows ANNs to prevail in situations where conventional approaches may perform inadequately, particularly when dealing with nonlinear patterns or high-volatility environments, such as financial forecasting [25–27]. Furthermore, the enhanced predictive accuracy of ANNs relative to methods such as binary logistic regression and multiple discriminant analysis has been well-documented, making them a more appropriate choice for modeling nonlinear datasets. The robustness comes from the ANN model's ability to learn from large datasets without the requirement

Figure 1
Basic structure of an ANN



of specifying predefined relationships, thus enabling the models to generalize well to new and unseen data [28].

ANNs were creatively motivated by the architecture and functioning of the human brain. They are composed of several interconnected nodes or "neurons" that imitate biological neurons. Each neuron processes input data and sends it through activation functions, analogous to how biological neurons convey signals. The connections between these neurons, also referred to as synaptic weights, play an important role in determining the strength and significance of the signals transmitted, similar to how synaptic weights in the brain influence learning and memory. This learning process occurs during network training, where the ANN adjusts its synaptic weights based on the input data and corresponding outputs to minimize prediction errors. This iterative training allows ANNs to obtain knowledge and enhance their performance over time, empowering them to recognize patterns and make predictions with good accuracy [28, 29]. Figure 1 [28] displays the basic architecture of an ANN model.

ANNs are structured in a hierarchical manner, typically comprising an input layer, one or more hidden layers, and an output layer.

In Equation (2), the input nodes are denoted by X_1, X_2, and X_3. The processing node is illustrated as a circle, while the output node is labeled Y. The input nodes collect incoming data, which is then sent to the processing node. Each input node's data is assigned a weight, indicated by W_1, W_2, and W_3, respectively. Additionally, the processing node is influenced by a bias (which represents past information), represented by b. Mathematically, this relationship can be expressed as follows:

$$Y = (X_1 {*} W_1) + (X_2 {*} W_2) + \ldots + (X_n {*} W_n) + b \tag{2}$$

The weights indicate the extent to which the information from each input node influences the output node. This relationship can be expressed in matrix form. For example:

$$w = (W_1\ W_2 \ldots\ W_n) \tag{3}$$

$$x = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{bmatrix} \tag{4}$$

where w denotes the matrix of weights and x represents the matrix of input data.

Equation (2) may also be represented by

$$y = WX + b \tag{5}$$

Or

$$y = \varphi(v) \tag{6}$$

where y is the output, v is the matrix representing the input data, and φ is a function referred to as the activation function. Thus, it can be expressed as:

$$y = \varphi(v) = \varphi(wx + b) \tag{7}$$

Thus, neural networks consist of multiple nodes and various connection weights.

There are different types of ANN. They can be categorized as follows: (i) feedforward neural networks; (ii) radial basis function networks; (iii) recurrent networks; and iv) multilayer perceptron (MLP) networks. Among the various categories of ANNs, the MLP is favored in technology adoption studies due to several of its advantages. MLPs have the ability to adapt autonomously without requiring changes from the researcher, allowing them (the MLP model) to effectively learn and model complex, nonlinear relationships. This flexibility is achieved through the adjustment of weight coefficients during the learning process, permitting MLPs to build accurate input-output mappings. Moreover, MLPs exhibit robustness against noisy data, making them appropriate for applications where data integrity may be compromised [28].

3.5. ResNet

He et al. [30] introduced a deep residual network (ResNet), which is a specific type of convolutional neural network (CNN), for image recognition. The ResNet is a type of CNN where the input from the previous layer is added to the output of the current layer [31]. This skip in the connection (which is known as a skip connection) makes it easier for the network to learn and allows better performance. ResNet has proven effective in various applications, such as image classification[1] and object detection.

At the core of ResNet resides the concept of residual learning, which aspires to reformulate how deep networks approximate complex functions. In traditional neural networks, layers seek to directly learn a mapping $H(x)$, where x represents the input and $H(x)$ represents the desired output. However, in ResNet, the network learns the residual function

$$F(x) = H(x) - x \tag{8}$$

which means that rather than learning the entire function $H(x)$, the network learns the difference (residual) between the input and output, that is, $F(x) + x$.

This shift in formulation provides a significant advantage. When identity mapping, that is,

$$H(x) = x \tag{9}$$

is the optimal solution, a traditional network would need to fit the identity mapping across multiple nonlinear layers. This process is difficult because the layers might struggle to approximate the identity mapping accurately, resulting in the degradation problem, where deeper networks perform worse than their shallower counterparts. In ResNet, if the identity mapping is close to optimal, the network can simply learn a residual function that is close to zero, simplifying the learning process.

The residual block is the fundamental building unit of ResNet. A residual block comprises two or more layers where the input x is sent through a series of transformations to generate an output $F(x)$. However, rather than relying solely on these transformations, ResNet adds a shortcut connection that bypasses the transformations and directly adds the input x to the output of the transformed layers. This can be formulated as:

$$y = F(x, \{W_i\}) + x \tag{10}$$

Where:
x is the input to the block.

[1] An image is a collection of pixels. Pixels are dots of color. Every pixel can be represented by a number. Thus, an image can be viewed as a matrix of numbers. Given this thought, the ResNet can be applied for pattern recognition in a matrix of numbers.

$F(x, \{W_i\})$ depicts the series of transformations applied to x (e.g., convolutions, activation functions).

Addition x guarantees that the input is transmitted to the deeper layers unaltered, allowing the network to retain the original signal if necessary.

During backpropagation, the network may effectively transmit the gradients thanks to the shortcut connection (which is the skip connection). This mitigates the vanishing gradient problem that impedes the training of deep networks.

There are two types of shortcut connections used in ResNet. They are identity mapping and projection. The application of identity mapping takes place when the input and output dimensions are identical. In this case, the input is directly added to the output without any modification. If the dimensions are different, for example, when there are changes in the number of channels or spatial resolution, a linear projection W_s is used to match the dimensions

$$y = F(x, \{W_i\}) + W_s x \tag{11}$$

This guarantees the validity of the residual addition even when the dimensions of $F(x)$ and x are not equal.

3.6. Proposed hybrid model: POLS-ResNet

This study proposes a hybrid model that combines the POLS and the ResNet models. It is implemented in the following steps:

1) Step 1: initial linear estimation (POLS)

The first step involves estimating the POLS model, which may be mathematically expressed as:

$$Y = X\beta + \varepsilon \tag{12}$$

where Y is the dependent variable, X is the matrix of independent variables, β is the vector of coefficients, and ε represents the error term. After fitting this model, the residuals are derived and are depicted as:

$$R = Y - \hat{Y} = Y - X\hat{\beta} \tag{13}$$

where $\hat{Y}$ is the predicted value from the POLS model and R represents the portion of the dependent variable that the POLS model could not explain.

2) Step 2: feed residuals to the ResNet

In the second step, these residuals are used in the ResNet framework. The ResNet learns to approximate the nonlinear relationships that the POLS model missed. This is mathematically formulated as:

$$R \approx F(X, W) = H(X, W) + X \tag{14}$$

where $F(X, W)$ denotes the residual function to be learned, $H(X, W)$ represents the nonlinear mapping learned by the ResNet, and W refers to the weights in the ResNet. The inclusion of X reveals the shortcut connection that adds the input directly to the output of the nonlinear mapping.

3) Step 3: combine POLS and ResNet predictions

In the third step, there is a combination of the predictions from both the POLS and ResNet models to produce the final output of the POLS-ResNet model. This is expressed as:

$$\hat{Y}_{final} = \hat{Y} + H(X, W) \tag{15}$$

Substituting the expressions from the previous equations can derive:

$$\hat{Y}_{final} = X\hat{\beta} + H(X, W) \tag{16}$$

This equation highlights how the POLS prediction supplies the linear component $X\hat{\beta}$, while the ResNet prediction $H(X, W)$ delivers the nonlinear component.

3.7. Summary of the proposed POLS-ResNet model

The proposed POLS-ResNet model unites the strengths of a conventional POLS model and a ResNet to capture both linear and nonlinear relationships in panel data. The process commences with an initial estimation utilizing the POLS model, which reveals the linear relationships between the dependent and independent variables. This step provides a base prediction that obtains the linear trends in the dataset. However, as linear models have limitations in capturing complex, nonlinear interactions, the residuals (the differences between the actual values and the POLS predictions) are estimated. These residuals reflect the portion of the data that the POLS model could not explain.

The second step involves inserting these residuals into the ResNet. ResNet, known for its ability to handle deep architectures and prevent issues like vanishing gradients, is charged with the responsibility of learning and approximating the nonlinear relationships that the POLS model missed. Using the independent variables as inputs, the ResNet learns to map them to the residuals through multiple hidden layers. The key feature of the ResNet, the shortcut (or skip) connections, enables it to focus on learning the residual (which is the nonlinear component) while proficiently propagating information across layers.

In the last step, the final output of the proposed POLS-ResNet model is generated by combining the predictions from both the POLS and ResNet models. The POLS prediction furnishes the linear component, while the ResNet prediction shows the nonlinear component. By consolidating these two predictions, the proposed POLS-ResNet model can embody both linear and complex nonlinear patterns in the data.

In summary, the proposed POLS-ResNet model can be mathematically represented as:

$$\hat{Y}_{final} = X\hat{\beta} + (F(X, W) + X) = X\hat{\beta} + H(X, W) + X \tag{17}$$

See Figure 2, which is a simplification of the POLS-ResNet model.

The proposed POLS-ResNet model can be mathematically represented as a consolidation of linear and nonlinear mappings, where the linear aspect comes from POLS and the nonlinear aspect is captured through a ResNet. This dual-stage modeling framework has the advantages of both interpretability and predictive power, mak-

Figure 2
Simplified POLS-ResNet model

The proposed POLS-ResNet model can be mathematically represented as a consolidation of linear and nonlinear mappings, where the linear aspect comes from POLS and the nonlinear aspect are captured through a ResNet. This dual-stage modeling framework has the advantages of both interpretability and predictive power, making it appropriate for high-dimensional panel data with nonlinear characteristics.

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The next section considers the results.

4. Results

The results of the POLS-ResNet model are contained in the Figure A1. However, the diagnostic outcomes are displayed in Section 4.1. Section 4.2 furnishes an interpretation of the POLS-ResNet model results.

4.1. Diagnostics results

The coefficient of determination (R^2) was 0.7342, meaning that approximately 73.42% of the variance in the dependent variable (log of the balance of trade (log_BoT) can be explained by the independent variables in the model. This indicates a relatively strong fit, though there remains a portion of variance (about 26.58%) that is unaccounted for. This model is accepted as other models generate an R^2 below 50%.

The coefficient of determination in between (R^2 Between) was 0.9874. This suggests that 98.74% of the variance between the different entities (countries) can be explained by the model, indicating that the differences between the groups are substantial and effectively represented by the model.

The coefficient of determination in within (R^2 Within) was 0.4605. This establishes that 46.05% of the variance within entities (over time) is captured by the model. This may reflect that while the model explains the differences between countries well, it is less effective in accounting for changes over time within those countries.

The F-statistic of 11.049, with a probability value of 0.0050, reveals that the model as a whole is statistically significant. The low probability of 0.005 can be interpreted as the existence of evidence to simultaneously reject the null hypothesis that all the coefficients are simultaneously equal to 0. This suggests that the coefficients are statistically significant from 0.

The probability values of the computed parameters are all below the 10% and 5% significance levels. This indicates that for each parameter, the null hypothesis that the parameter is equal to 0 can be rejected at the 10% and 5% significance levels.

Additional diagnostic tests are displayed in Figure 3. These are applied to the ResNet.

From Figure 3, it can be seen that the Ljung-Box test is applied. The Ljung-Box test is a statistical test used to determine whether there are significant autocorrelations in a time series. The null hypothesis (H0) is that there is no serial correlation at any lag up to a certain number of lags. The alternative hypothesis (H1) suggests that there is significant serial correlation present.

Ljung-Box test produced a probability of 0.5579 in hidden state 1. Since the null hypothesis of the Ljung-Box test has no serial correlation or white noise, the probability value of 0.5579 suggests that the null hypothesis should not be rejected at the 1%, 5%, and 10% levels of significance. This means that there is no serial correlation in hidden state 1 (Note the hidden state is a hidden layer from the ResNet).

The Ljung-Box test produced a probability of 0.6797 in hidden state 2. This suggests that there is no serial correlation in hidden state 2, indicating that the residuals from this hidden state do not exhibit patterns over time and behave like white noise. Thus, when the ResNet was applied to the residuals, it removed the serial correlation and properly modeled the dependencies.

4.2. Model results interpretation

The constant had a value of −23.093. This indicates that when all independent variables are zero, the log_BoT would be −23.093. Notwithstanding, such a result is not directly interpretable in a practical sense, given that not all independent variables will be at zero. This is included for modeling purposes.

The ODA variable generated a coefficient of 1.9543. This indicates that a 1% increase in ODA corresponds with approximately a 1.95% rise in the log_BoT, suggesting a positive relationship. This strong positive effect may imply that increases in foreign aid or development assistance positively impact the balance of trade, corroborating the idea that such assistance can enhance trade performance.

The debt variable estimate of −0.6153 conveys a negative relationship, meaning that a 1% increase in debt corresponds with about a 0.62% worsening in the balance of trade. Although the effect is less prominent than that of ODA, it reflects the consequences of high debt on the Caribbean's persistent balance of trade deficit. As such, the evidence reveals the need for structural reform to improve the balance of trade in the Caribbean.

The next section facilitates a discussion and policy recommendations.

5. Discussion and Policy Recommendations

5.1. Debt discussion

The estimated debt coefficient of −0.6153 substantiates that a 1% increase in debt is associated with approximately a 0.62% worsening in the balance of trade. This negative relationship shows the burden of external debt on Caribbean economies, supporting the debt overhang hypothesis. This posits that excessive debt obligations may ultimately have an adverse effect of debt on trade performance.

High levels of debt are a significant barrier to sustainable development in CARICOM member states [32]. Many countries in the region have debt-to-GDP ratios that exceed sustainable thresholds, which hinder their ability to channel development funding toward critical sectors such as healthcare, education, and infrastructure.

Definitely, debt relief is needed to free up fiscal space for CARICOM nations to invest in their development priorities.

Figure 3
Additional diagnostics performed on the ResNet

```
Ljung-Box test statistic for hidden state 1: 8.7301, p-value: 0.5579
Ljung-Box test statistic for hidden state 2: 7.4773, p-value: 0.6797
Fail to reject null hypothesis: No significant autocorrelation in hidden state 1.
Fail to reject null hypothesis: No significant autocorrelation in hidden state 2.
```

Acknowledging the debt problem, in 2017, the Economic Commission for Latin America and the Caribbean (ECLAC) lobbied for a debt-for-climate swap in the Caribbean region and established a task force to facilitate its implementation [33].

The ECLAC proposed debt-for-climate swap is a mechanism and a framework to address the Caribbean's unsustainable debt burden while simultaneously mobilizing financing for climate change resilience-building projects. Under this arrangement, a climate finance donor, such as a multilateral development bank, a consortium of donor countries, or a specialized climate fund, would purchase the region's external debt from its creditors. Given that debt swaps often involve a haircut, which is a reduction in the nominal value of the debt, it is reasonable to expect a discount in the purchase process, reducing the total repayment obligations of Caribbean nations. This approach provides an opportunity for Caribbean governments to shift their debt repayments away from external creditors and toward a dedicated mechanism that prioritizes climate resilience.

One of the major advantages of this mechanism is that it offers a dual benefit: it alleviates the region's debt distress while ensuring that much-needed financial resources are available for climate action. Historically, the high debt levels in Caribbean nations have limited their fiscal space, hindering the ability of the corresponding governments to invest in climate adaptation, infrastructure development, and sustainable economic initiatives. Through restructuring debt repayments into a mechanism that directly funds green projects, the Caribbean Resilience Fund (CRF) can help bridge the financing gap for climate resilience and sustainable development in the region.

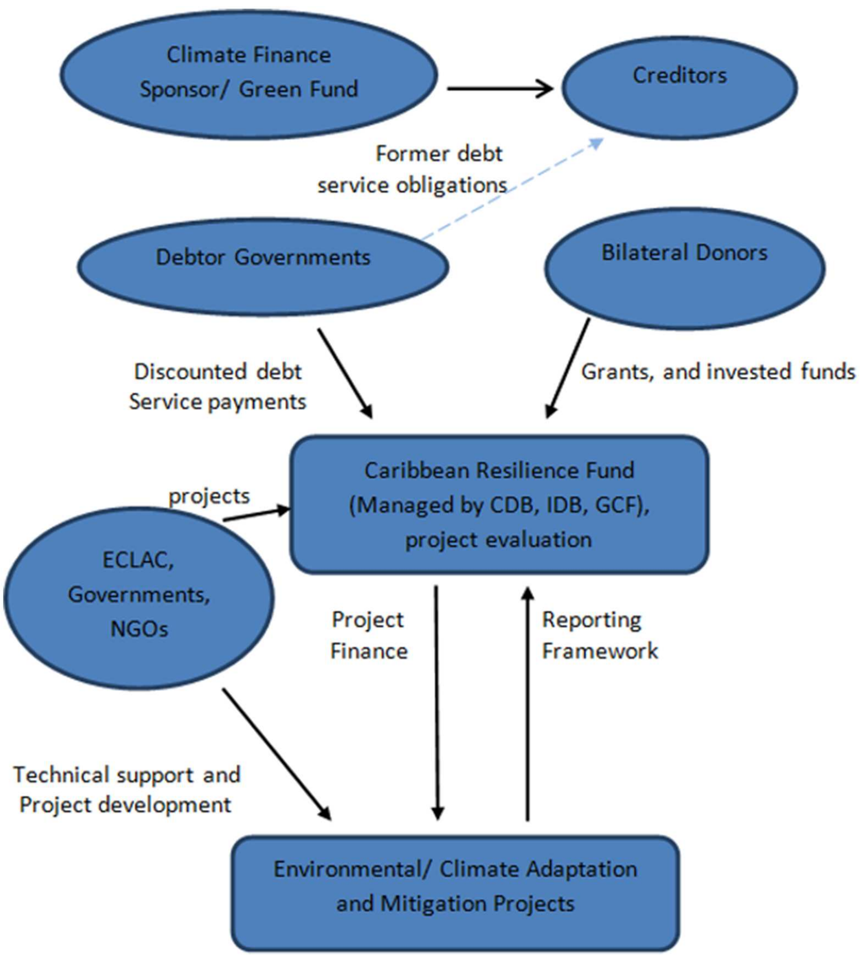
Nevertheless, the efficacy of the debt-for-climate swap is contingent upon various elements, encompassing the creditor's inclination to participate, the extent of the debt relief provided, and the governance framework of the CRF. To ensure that funds are allocated efficiently to climate projects, a clear and transparent governance framework must be established. Furthermore, mechanisms for monitoring and evaluation should be put in place to track progress, ensuring accountability and optimal resource utilization. See Figure 4 [34].

As such, this study recommends that a debt-for-climate swap should be pursued for the CARICOM member states. The recommended debt-for-climate swap can be implemented through the following steps:

1) Step 1 – identifying a climate finance donor

The debtor government must first secure a climate finance donor. This is an important step, as the donor should be an institution that has dedicated funds for climate action and regularly provides grants to governments. The donor must have the financial capacity to offer substantial funding, given that public debt in Caribbean nations typically amounts to millions of dollars. Potential donors include climate finance mechanisms under the United Nations Framework Convention on Climate Change (UNFCCC). If the Green Climate Fund (GCF) is considered, the country must undergo

Figure 4
Overview of the logistics of the ECLAC debt relief and resilience-building initiative



the accreditation process. Alternatively, the government may collaborate with an accredited regional entity, such as the Caribbean Community Climate Change Centre (CCCCC), to facilitate the debt-for-climate swap as a GCF project.

2) Step 2 – securing the climate finance donor's commitment

The success of the debt-for-climate swap depends on the climate finance donor's willingness to purchase the government's debt from its creditors. Without the donor's commitment to acquiring the debt, the initiative could not proceed.

3) Step 3 – negotiating the terms of the debt-for-climate swap

All key stakeholders, including the climate finance donor, debtor government, and creditors, must negotiate the terms of the swap. Discussions should cover the portion of debt to be purchased, the haircut granted, and the quantity of funds allocated to a dedicated trust fund. Furthermore, they must agree on the types of climate projects to be financed, the governance structure of the trust fund, and its operational framework.

4) Step 4 – establishing a trust fund

A trust fund should be created to manage the financial resources generated through the debt-for-climate swap. The fund should be capitalized with the proceeds from debt service payments and should have the capacity to accept contributions from additional donors to expand its impact.

5) Step 5 – executing the debt-for-climate swap

Once the terms are finalized, the climate finance donor proceeds with purchasing the government's debt from its creditors, thereby formalizing the debt-for-climate swap arrangement.

6) Step 6 – monitoring and accountability

A strong monitoring framework must be established to track the implementation and efficacy of the debt-for-climate swap. This includes oversight of expenditures, assessment of project deliverables, and mechanisms to ensure responsible fiscal management. Moreover, safeguards such as fiscal rules should be introduced to prevent the government from accumulating unsustainable levels of new debt in the future.

5.2. ODA discussion

The regression results reveal a strong positive relationship between ODA and the balance of trade in the Caribbean, as evidenced by the ODA coefficient of 1.9543. This indicates that a 1% increase in ODA corresponds to approximately a 1.95% improvement in the log of the balance of trade. The substantial positive effect implies that foreign aid plays a considerable role in enhancing trade performance. This can be achieved through infrastructure development, capacity building, and financial support for key export sectors. This result aligns with the reasoning that development assistance can be indispensable to promoting economic growth and trade expansion in developing economies, particularly SIDS like those in the Caribbean.

Foreign aid may improve the balance of trade by channeling investments to productive sectors, improving infrastructure, and supporting institutional reforms that enhance export competitiveness. Furthermore, ODA can relieve foreign exchange constraints, helping countries to finance imports of capital goods required for industrialization and economic diversification. However, the efficacy of ODA in shepherding trade improvements relies on how aid is allocated and whether it is directed toward productive investments rather than consumption. The effective application of ODA has the potential to assist countries in mitigating trade imbalances through the fortification of domestic industries and the cultivation of more export-oriented economies.

The CARICOM member states face unique economic and developmental challenges that necessitate a reevaluation of the international frameworks governing access to ODA and concessional finance.

The categorization of CARICOM member states as middle-income countries predicated on per capita GDP is a misleading approach that does not accurately represent their economic circumstances. Although the value of their per capita GDP may seem comparatively high, this is primarily attributable to their small populations rather than economic strength. For instance, countries like Antigua and Barbuda, Dominica, and Grenada have small populations, which inflates their per capita GDP figures. However, these nations face pronounced economic constraints, including limited natural resources, small domestic markets, and high dependence on imports. Furthermore, their economies are often reliant on a narrow range of sectors, such as tourism and financial services, which are highly vulnerable to external shocks, as demonstrated by the COVID-19 pandemic and the 2008 global financial crisis.

As a result of their middle-income classification, CARICOM member states are ineligible for accessing concessional finance and ODA, which are typically reserved for low-income countries. This exclusion is particularly detrimental given the region's susceptibility to climate change, which exacerbates its economic vulnerabilities. The impact of hurricanes, rising sea levels, and other climate-related disasters is disproportionately severe on CARICOM member states, causing significant economic losses and impeding their long-term development. To exemplify this, Hurricane Maria in 2017 inflicted damages equivalent to 226% of Dominica's GDP, highlighting the region's susceptibility to external shocks. The current international framework fails to consider these vulnerabilities, rendering CARICOM nations exposed to risks without the financial support required to build resilience and achieve sustainable development.

Addressing structural vulnerabilities and achieving sustainable development in CARICOM member states hinges upon access to concessional finance and ODA. Concessional finance, which offers lower interest rates and longer repayment periods, is necessary for funding infrastructure projects, climate adaptation measures, and social programs. However, the current eligibility criteria for such financing are based on outdated metrics that do not reflect the unique challenges faced by SIDS like those in CARICOM.

Structural reforms at the international level are required to amend these criteria and ensure that CARICOM nations can access concessional finance. One potential solution is the incorporation of vulnerability indices into the eligibility framework. These indices would consider factors such as economic exposure to external shocks, climate vulnerability, and debt sustainability, providing a more accurate assessment of a country's need for concessional financing.

Moreover, international financial institutions such as the World Bank and the IMF should adopt more flexible lending criteria for CARICOM member states.

5.3. Relevance to other studies

The results from this study are comparable to other studies. For example, Rajah and Dayant [35] provide important insights into the debt sustainability challenges facing Pacific SIDS, offering parallels to the Caribbean context. The study focuses on Fiji, Papua New Guinea (PNG), Samoa, and Tonga – countries that, like Caribbean SIDS, deal with small economic bases, geographic isolation, and a high degree of exposure to external shocks. The authors note that even in "normal" times, Pacific SIDS face uniquely difficult financing conditions due to their extreme geography and vulnerability to climate and economic shocks. The COVID-19 pandemic intensified these challenges, collapsing key sectors like tourism, especially in Fiji, where domestic debt levels were already high before the crisis. The decline in international travel led to significant revenue shortfalls, resulting in elevated pressures on government budgets and threatening debt sustainability. In Samoa, PNG, and Tonga, the issue was contextualized more as a short-term liquidity constraint as opposed to being insolvency, but in all cases, the inability to launch large-scale stimulus responses, due to the contracted fiscal space and access to concessional finance, emerged as a common constraint.

The findings from Rajah and Dayant [35] study are highly analogous to the Caribbean experience. Just as Pacific SIDS suffered from the collapse in tourism, Caribbean economies experienced major external shocks during the pandemic, particularly in trade and tourism, worsening existing fiscal vulnerabilities and forcing greater reliance on debt. Both regions face long-standing structural constraints that hinder economic diversification and amplify the economic fallout of global shocks. Notably, Rajah and Dayant [35] advocate for increased upfront financing, particularly through external grants and carefully structured debt relief programs that prioritize economic recovery over simple debt forgiveness. Such a recommendation is comparable to the recommendation for debt relief through a debt-for-climate swap made in this study.

The next section concludes this study.

6. Conclusion

Caribbean nations are among the most heavily indebted in the world, with persistently high debt levels surfacing as a major barrier to economic development. One of the primary contributors to this debt crisis is the region's high vulnerability to climate-related disasters, which necessitate frequent borrowing for recovery and resilience-building efforts. These financial constraints hinder the ability of governments to invest and build their economies.

A novel hybrid model combining POLS and a deep residual network (ResNet) was used to investigate the relationship between the balance of trade, public debt, and ODA across seven CARICOM countries across the 2013–2022 period. The estimated debt coefficient of −0.6153 suggests that a 1% increase in debt leads to approximately a 0.62% deterioration in the balance of trade. This corroborates the debt overhang hypothesis, which posits that excessive debt burdens negatively impact economic performance by constraining trade and investment. The findings reinforce the need for debt relief strategies to create fiscal space for sustainable development in the region.

This study recommends the use of a debt-for-climate swap to provide CARICOM member states with a structured pathway toward debt reduction while financing climate resilience projects. The first step in implementing this initiative is securing a climate finance donor with the financial capacity to purchase the region's debt. Potential donors include international climate finance mechanisms under the UNFCCC. The success of this initiative depends on the donor's willingness to acquire the government's debt from its creditors.

Once a donor is secured, negotiations must occur between the debtor government, the creditors, and the donor. These discussions will determine the amount of debt to be purchased, the size of the haircut (reduction in the face value of the debt), and the portion of funds channeled to a dedicated trust fund. The trust fund, established as part of the swap, will manage financial resources and support climate adaptation projects.

After the debt-for-climate swap is executed, effective monitoring and accountability mechanisms must be implemented. This includes oversight of expenditures, evaluation of climate projects, and fiscal safeguards to prevent future public debt accumulation. If successfully deployed, this initiative can reduce debt burdens while enhancing climate resilience, allowing CARICOM nations to focus on long-term sustainable development.

The regression results reveal a strong positive dependence between ODA and the balance of trade in the Caribbean, with an ODA coefficient of 1.9543. This corroborates that a 1% increase in ODA corresponds to a 1.95% improvement in the log of the balance of trade. The considerable positive effect reflects the important role of foreign aid in ameliorating trade performance by supporting infrastructure development, capacity building, and financial assistance for key export sectors. These findings correspond with the broader argument that development assistance can stimulate economic growth and trade expansion in developing economies, particularly SIDS like those in the Caribbean.

While ODA is beneficial, CARICOM member states' classification as middle-income countries, determined by per capita GDP, prevents them from easily accessing concessional finance. The relatively high per capita GDP figures stem from their small populations rather than true economic strength. Consequently, these countries are excluded from concessional financing options, which are typically reserved for low-income nations.

The exclusion from concessional finance is particularly problematic given the Caribbean's vulnerability to climate change and external shocks. Frequent threats from extreme weather events, rising sea levels, and environmental degradation endanger economic stability, creating an urgent need for financial assistance to build climate resilience. Without access to concessional finance, these nations struggle to implement necessary adaptation and mitigation strategies, further exacerbating their economic vulnerabilities.

Structural reforms at the international level are necessary to revise the eligibility criteria for concessional finance and ensure that CARICOM nations can access the financial support needed for sustainable development. Expanding access to ODA and concessional finance would supply the necessary fiscal space for Caribbean countries to fortify their economies, enhance trade performance, and develop long-term resilience.

A limitation of this study is that, although CARICOM comprises 15 full member states and 5 associate members, due to insufficient data, not all countries could be included in the analysis. Nevertheless, the findings remain relevant as they can bolster advocacy for debt relief initiatives, such as debt-for-climate swaps, within the region.

6.1. Contributions of this study

This study makes several contributions to the existing literature. First, there is limited empirical research examining the impact of public debt and ODA on international trade in the CARICOM region. Despite the significant role of debt and foreign aid in shaping economic outcomes, few studies have explored their effects on trade performance. This research is particularly relevant given that many CARICOM member states took on additional debt during the COVID-19 pandemic while simultaneously experiencing a decline in international trade due to global lockdown measures. Certainly, by addressing this gap, the study provides insights into how debt and ODA influence trade balances in CARICOM. The lessons learned and policy recommendations can be extended to other small, open economies.

Second, this study applies a nonlinear modeling approach to analyze the relationship between the balance of trade, public debt, and ODA across seven CARICOM member states. This methodological choice builds upon previous research, which primarily relies on linear regression techniques. Since economic relationships often exhibit nonlinearity, traditional linear models may fail to capture the true dynamics of the data. By utilizing a nonlinear approach, this study ensures a more accurate estimation of the effects of debt and ODA on trade performance, thereby improving the reliability of its findings.

Third, a key methodological contribution of this study is the introduction and application of the POLS-ResNet model. This new hybrid model integrates POLS regression with a deep residual network (ResNet), a type of ANN. Through combining the strengths of both econometric and machine learning techniques, the POLS-ResNet model enhances predictive accuracy and better captures complex patterns in the data. Unlike traditional linear models, which may produce biased estimates in the presence of nonlinearities, the POLS-ResNet model can learn intricate relationships and generate more reliable results.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available at https://github.com/doncharles005/POLS-ResNet.

Author Contribution Statement

Don Charles: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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Appendix

Figure A1
Results of the POLS-ResNet model

```
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:                log_BoT   R-squared:                        0.7342
Estimator:                   PanelOLS   R-squared (Between):              0.9874
No. Observations:                  11   R-squared (Within):               0.4605
Date:                Mon, Sep 30 2024   R-squared (Overall):              0.7342
Time:                        22:20:08   Log-likelihood                   -15.300
Cov. Estimator:            Unadjusted
                                        F-statistic:                      11.049
Entities:                           2   P-value                           0.0050
Avg Obs:                       5.5000   Distribution:                     F(2,8)
Min Obs:                       3.0000
Max Obs:                       8.0000   F-statistic (robust):             11.049
                                        P-value                           0.0050
Time periods:                       8   Distribution:                     F(2,8)
Avg Obs:                       1.3750
Min Obs:                       1.0000
Max Obs:                       2.0000

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
const         -23.093     8.4745    -2.7250     0.0260     -42.635     -3.5508
log_ODA        1.9543     0.4176     4.6797     0.0016      0.9913      2.9173
log_debt       0.6153     0.6560     0.9380     0.3757     -0.8973      2.1279
==============================================================================


Size of residuals: (11,)
Reduced residuals: [ 0.8232968  -0.5996308   0.45498041 -1.03330513 -1.74482844  1.2142027
  1.63002381  0.06983495 -0.1294769   0.2306192  -0.91571662]
Epoch [100/1000], Loss: 0.9875
Epoch [200/1000], Loss: 0.9661
Epoch [300/1000], Loss: 0.9605
Epoch [400/1000], Loss: 0.9554
Epoch [500/1000], Loss: 0.9510
Epoch [600/1000], Loss: 0.9471
Epoch [700/1000], Loss: 0.9436
Epoch [800/1000], Loss: 0.9404
Epoch [900/1000], Loss: 0.9376
Epoch [1000/1000], Loss: 0.9350
Final MSE: 0.9350
Layer: layer1.fc1.weight, Weights: [[ 0.21953912  0.33567885  0.22652149]
 [ 0.35204437  0.3848525   0.56616086]
 [-0.43883824  0.4776692  -0.49104825]
 [ 0.04775283  0.18068843  0.38224742]
 [ 0.06807376  0.5118565  -0.49493876]
 [-0.10662679  0.27527127 -0.40101567]
 [ 0.35890037 -0.3660429   0.5024688 ]
 [ 0.56747615  0.10570705 -0.56764835]
 [ 0.5596974  -0.32601717  0.5633589 ]
 [-0.25964087 -0.22125325  0.46041107]]
Layer: layer1.fc1.bias, Weights: [-0.14580683 -0.35372186 -0.44374716 -0.45768374  0.5579319   0.20500404
  0.569396   -0.14425352 -0.27691594 -0.01702964]
Layer: layer1.fc2.weight, Weights: [[-0.06252869  0.17653546 -0.22354558 -0.31445464 -0.06914054  0.21645124
  -0.1426057  -0.27330664  0.26502624 -0.04598626]
 [ 0.05630801  0.17129874  0.09038568  0.10222566  0.20818423  0.17103985
   0.17986834 -0.1277192  -0.20575164  0.13019094]
 [ 0.0965201   0.19537689  0.0385567  -0.04118935  0.35110041 -0.15341596
  -0.15440978 -0.26086143 -0.21601582 -0.15329753]]
```