Impact of Supply Chain Infrastructure on Economic Welfare under External Shocks

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Abstract: As the global economies are still working diligently to recover from the COVID-19 pandemic impact, both public and private organizations are working diligently to improve resiliency of supply chains against future shocks alike. Thus, it is critical to understand the relationship between the existing vulnerabilities and current state of supply chains. This study aims to contribute building a framework to investigate the relationship between the economic welfare and supply chain structure during external shocks. Machine Learning (ML) methods are used to conduct the required analyses. The results reveal the strong relationships between the variables chosen in building the model.

Keywords: *Machine learning, multiple linear regression, supply chain resiliency, COVID, supply chain disruption.*

1. Introduction

Agile and effective logistical systems are crucial in the information age, as industrial and technical processes grow increasingly complex. The foundation of a successful supply chain (SC) is strong economic conditions and high logistic standards, such as transparency, dependability, and adaptability. Technology needs to be able to manage continuously changing processes and the increasingly complicated supply chains. The increase in diversity and data volume leads to larger information sets than ever before. It is often not viable or practical to process using typical, useful management techniques. Various methodologies and tools have been improved to analyze and assess these potentially profitable and new information sets, among them predictive analytics [1].

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Machine learning is one of such techniques that can be used effectively for forecasting. This process is successful because complex machine learning models are developed, massive data sets (also known as big data) are available, and hardware architectures like GPUs are used [2-4].

Machine learning technics are implemented to train machines how to coordinate massive amounts of information more efficient. Sometimes, traditional methodologies can't remove or analyze data and patterns from the large amount of information [5]. For machine learning technics, the need is growing owing to the available data sets' number. Machine learning technics are broadly utilized various sectors, containing the military and the medicinal area, to remove data and knowledge from information.

Programmers and mathematicians have conducted numerous researches that have led to the creation of diverse machine learning as algorithmic [6]. Christoph's survey revealed a number of widely known machine learning algorithms, including the following: Decision Tree, Random Forest, K-means, Logistic Regression, Support Vector Machine, Random Forest, Neural Networks, k-Nearest Neighbor, Naive Bayes Sorter, Extreme Learning Machine, and Ensemble Algorithms [7-12]. Benefits of applying machine learning techniques in sales and demand prediction [13–15], distribution and transportation [16–18], generation [19–21], inventory check [22], segmentation and supplier choice [23–26], and other areas have been highlighted by a few studies. Some of the most common learning algorithms and sample references together with a synopsis are illustrated in Table 1.

Table 1. Six SCM activities employ ten ML algorithms.

	Supply chain development	Storage and Inventory	Supply and Procurement	Generation	Distribution and Transportation	Sales/Demand prediction
K-means	[27]	-	-	-	-	[28]
Naive Bayes Sorter	-	[29]	[30]	[31]	[32]	–
Random Forest	[33]	-	-	[34]	[35]	–
k-Nearest Neighbor	-	-	-	[34]	[36]	[37]
Ensemble Algorithms	[33]	-	[38]	-	-	–
Logistic regression	[39]	-	[40]	[34, 41]	[35, 42]	–
Extreme Learn. Mach.	-	-	-	-	-	[43-46]
Decision Tree	-	-	-	-	[47]	[48]
Support Vect. Mach.	[49-51]	[29]	[52-58]	[34-35]	[59-60]	[61-63]
Neural Networks	[64-69]	[70-71]	[72-82]	[83]	[84-91]	[92-103]

In supply chain administration, this paper reviewed the machine learning use. While certain SCM areas are the current ML applications' focus, other areas are still underutilized. This research therefore purposes to create a relationship among recent machine learning implementations, real investigation, and the SCM work modelling. This enables the possible directions' identification for further investigation within the SCM work modelling as well as the tasks' depiction where ML approaches are already being used.

Machine Learning and Artificial Intelligence is raising its popularity in the supply chain management field owing to its broad range of applications. Process optimization, forecasting, and automation are among the areas in which machine learning can add significant value to the supply chains. It can also help avoiding costly mistakes in all these spheres. Consequently, increased supply chain surplus can be shared through the supply chain partners, resulting in more profitable companies. Below is a list of many ML & AI applications currently being utilized across various industries [104]:

- Artificial Intelligent in Shipping and Logistics – Autonomous Vehicles
- Supply Chain Planning utilizing Machine Learning
- Warehouse Management – Machine Learning in Logistics
- Warehouse and Track Analysis
- Demand Prediction
- Logistics Route Optimisation
- Estimating Peak Hours utilizing Artificial Intelligent in Logistics Centers
- Supplier Relationship Management and Supplier Choice
- Foreign Language Information Cleansing and Building Information Robustness
- Workforce Design

Not only these fields have the potential to significantly enhance competitiveness of the companies, they feel the constant pressure that stems from the fierce competition to adopt ML & AI solutions to increase their operational efficiency as well as customer service levels. There is no question that AI presents many opportunities in improving customer satisfaction by means of delivering the orders with increased precision and better condition.

Since most of the studies have focused on one, two, or a small portion of the supply chain, there is a clear need in the scientific research to explore various applications of Machine Learning strategies in supply chains' diverse regions. For example, Bai et al. divided providers according to environmental characteristics using a hybrid machine learning (ML) and multiple attribute decision-making (MCDM) strategy [105]. A review of ML in SCM was done by Darvazeh et al. [106]. ML was utilized through Baryannis et al. to forecast supply chain hazards [107]. ML approaches were used by Priore et al. [108] to determine the best replenishment rules for SCM. A supervised machine learning method for robust supplier selection was presented by Cavalcante et al. [109].

Piramuthu created an automated SCM system by utilizing machine learning technics [110]. To increase the hospital drug inventory operations' effectiveness, Du et al. created one mechanism modelling based on the originally management stage employing BP neural networks and genetic algorithms [111]. The purpose of Teerasoponpong's suggested decision mechanism for resourcing and stock management is to assist medium and small-scale enterprises in gathering and utilizing data, as well as to help their decision strategy in the face of business uncertainty [112]. In order to streamline the farmers' agricultural fresh products' inventory management at several linkages, such as supermarkets, distribution centers, professional cooperatives, and other areas, Shen et al. established an integrated model [113]. The inventory control troubles' various modellings were proposed by Harifi et al. According to reference, these modellings were deterministic multi-produce, stochastic single-produce, and deterministic single-produce [114]. Dosdogru et al. suggested a novel hybrid method that consists of 2 stages and provides a general scheme for resolving the stock routing trouble [115]. In order to optimize the area, routing, and stock decision strategies for dispersion points and clients in supply chains of various levels, Wu et al. took on a multiple-period routing-inventory-location trouble with fuel usage and time windows [116]. To create the CFB function, Badakhshan and colleagues integrated cash movement modeling into the beer distribution game's SD structure [117].

A multiple-objective general algorithm optimisation scheme *k* was given by Garg et al. for simulating the whip impact using NSGA for both decentralized and centralized supply chain management. The academic community has also given potential enhancements to stock management in a stochastical environment a great deal of attention [118]. The coordinated location-stock trouble in a stochastical supply chain mechanism, where supply is randomly disturbed, was the main emphasis of Liu et al. [119]. In an equivocal environment, multiple retailer supply chain operating under vendor-controlled stock strategy for just one supplier, Karimian et al. developed a financial production quantity modelling with multiple items with a shortfall [120].

A framework for risk-based optimization was developed by Nezamoddini et al. to be used in operational choices. They put out a model that addresses uncertainty around lead times, facility disruptions, and supply, production, and distribution channel demands [121]. In order to coordinate between suppliers with limited capacity and lower supply chain risks, Liu and Li created a two level programming modelling for cooperative decision-making on product configuration and order allocation [122]. This model makes use of protective measures as well as coordination between providers.

A machine learning-based supply chain risk management model was developed by Han and Zhang [123]. In addition to promoting a collaborator dispersion optimisation framework and algorithm for a perceptive supply chain management, Cai et al. also proposed green computing energy management and built a joint optimisation modelling of VFP&VRP for logistics dispersion [124]. In a multiple area supply chain, Jolai and Gharaei used the 3-agent viewpoint of the producer, customer, and distributor to address the distribution problem and production scheduling [125].

The air transportation and manufacturing scheduling trouble with time frames for the end-date was studied by Mousavi and colleagues [126]. Deng and colleagues examined the costs associated with carbon emissions during cold storage and transportation, the temperature variations' effect on the ratio at which fresh goods degrade in the course of unloading, and the traffic patterns along the real distribution route [127].

In order to further optimise the combined estimation modelling characteristics, Khan et al. introduced a combined modelling depend on extended short- time memory, neural networks (recurrent), one genetic algorithm, and recurrent (gated) units [128]. Under the worldwide shippings supply chain, Huang and Yang created a multi-item joint purchasing framework that included integrated purchase operations, delivery, various order cycles, and inventories depend on a cruise dispersion point [129]. Shen and colleagues employed the network equilibrium approach to create a SC modelling that takes into account the effort degree of various merchants and producers, and they coupled intelligent computing and big data to examine the clever SC mechanism for agricultural products [130].

Using data from real-time supply chains, Ali and colleagues developed a new technique that shows how a SC may be created to address multiple-objective, multiple-product, and multiple-step supply chain troubles [131]. Hu and colleagues suggested an efficient Tabu research algorithm through making governments more aware of environmental issues as the creation of green supply chains has grown popular. This research finished the implementation and integration of the SCM mechanism scheme, allowing the mechanism to be portable and scalable. In the meantime, it examined the effectiveness of information grouping and CGAN balance degrees and performed them to partner choose in a dynamical supply chain [132].

In brief, machine learning (ML) has several real-world logistical applications that have surfaced in recent years, particularly in supply chain management. The investigation shows possibilities that may be impacted by the COVID-19 pandemic effect by connecting applicable machine-learning technics to the job modelling for supply-chain administration.

2. Methodology

Machine learning methods are classified based on the problem they are developed to solve [133]. Figure 1 presents such a classification based on the tasks handled by various machine learning methods.

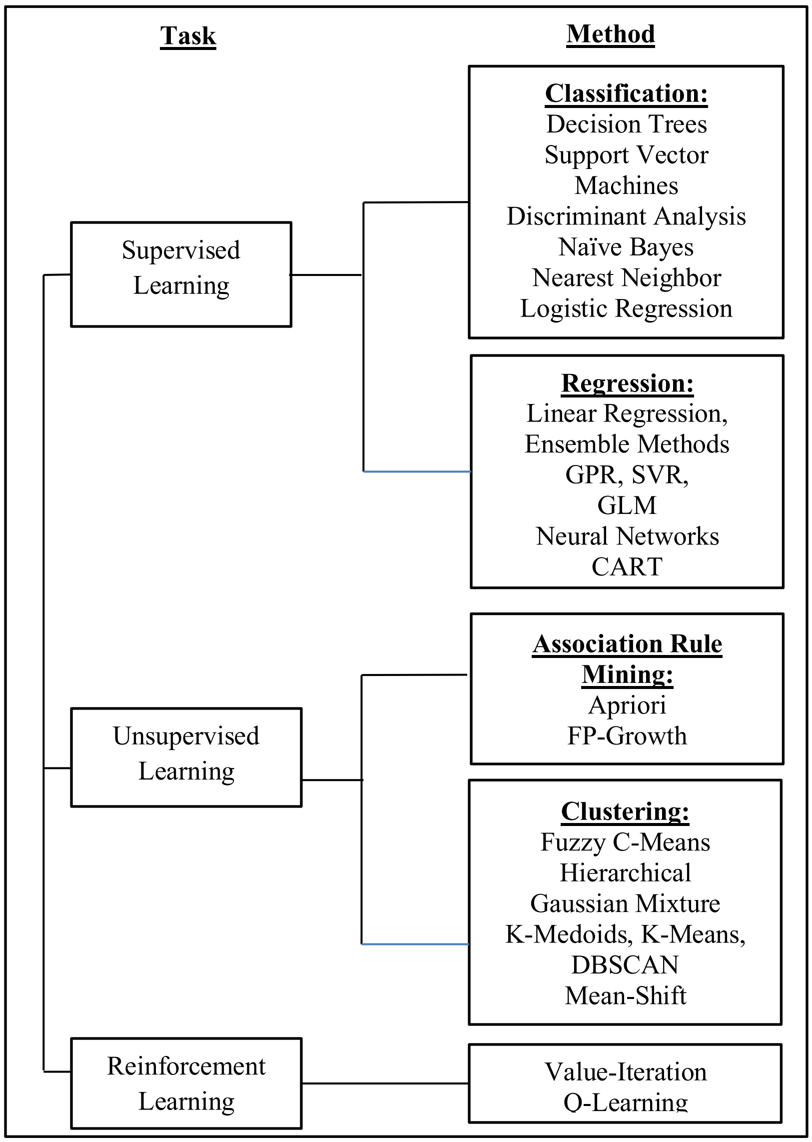

Figure 1. Machine Learning Methods

Linear Regression is one of such methods that is utilized within the scope of this study. Eight independent variables are used. Number of Covid cases/population, Number of Covid related Deaths, Death/Case ratio, Broadband penetration, Length of roads/land, Length of railroads/land, Hospital beds/population, GDP growth 2019/2020. The ratio between the GDP growth in 2020 and 2019 is treated as the dependent variable which is named as the "Slope".

2.1.Data

A dataset involving 187 countries is developed for the purpose of this study through the databases of World Bank, OECD, Global Health Observatory, and World Health Organization. The descriptions of the variables are provided in Table 2.

Table 2. Variable descriptions

Variable	Source
GDP per capita growth (annual %)	OECD and World Bank [134]
Rail transport network size	Wikipedia [135]
Road network size	World Health Organization [136]
Hospital beds	World Health Organization
COVID statistics	Global Health Observatory [136]

GDP per capita growth rate expressed as a percentage per annum in constant local currency. The gross value added by all resident manufacturers in the economy, plus any taxes on products and less any subsidies not included in the value of goods, is GDP at purchaser prices. It is calculated using World Bank and OECD national accounts data, excluding the depreciation of man-made assets and the depletion and deterioration of natural resources.

2.2.Applying machine learning algorithms

After making sure that the data is properly been cleaned and processed, the next step is dividing the data into train and test sets. The role of the train test split is crucial for knowing that models work appropriately on new data. During the determination of the train test split ratio, it is highly important to consider the data so that the variance is not too high. That is why several times the different ratios were executed in order to identify the best ratio. As a result, with the highest performance, the model was split into test and train sets with the ratio of 80 percent to 20 percent accordingly. It means that 80% of the data is dedicated to training and fitting the learning algorithms and the rest is devoted to testing the data in order to know how the model performs on new, actual, and untouched data.

Machine Learning has 2 alternatives of technics such as unsupervised and supervised learning. With unsupervised learning there is only little information known about the data and so, the main idea behind this technique is to let the computer find the hidden insights and draw the conclusions about the data by itself. Conversely, as its names suggest, the supervised learning works with the known set of data (input) and a known set of output and makes further predictions.

The supervised learning divided into Regression and Classification. To add, regression algorithms are used for the continuous variables whereas classification technique is used for the discrete data. In the case of the variable prediction, the regression model is appropriate. For making the predictions as accurate as possible, there are different regression models and methods being used by researchers around the world.

2.3.Multiple Linear Regression

Linear Regression means modeling the mathematical relationship between two or more variables. It is commonly used when one variable is used in order to explain the other variable where the independent variable is used as an explanatory variable. In addition, the Multiple Linear Regression model is used only if the target variable is continuous and not discrete.

As the name of the algorithm suggests linear regression assumes that there is a linear relationship between the target variable and the explanatory variable. However, in the real world it is very rare that one variable can be explained by only one other variable. Conversely, many factors impact on the determination of the target variable. Thus, when there is more than one explanatory variable in the dataset for the regression model, it is called Multiple Linear Regression.

The equation for the multiple linear regression model as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... \beta_p x_p + \epsilon \tag{1}$$

The sum of the linear parameters refers to $\beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... \beta_p x_p$, where the p implies to the number of independent variables and the ϵ refers to an error term. However, in the Multiple Regression equation the error term is assumed to be zero. Thus, the equation is equal to the summation of independent variables.

$$(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... \beta_p x_p \tag{2}$$

However, when the target variable is not actual but estimated, the estimated Multiple Linear Regression equation is used.

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + ... b_p x_p, \tag{3}$$

where the b_0, b_1, b_2, . . b_p are the estimates of β_0, β_1, β_2, ..., β_p and the $\hat{y}$ is the predicted value of an estimated variable. In machine learning, there are readily available libraries. Thereafter, the model is fitted with the few lines of code during the execution.

Correlation table for the independent variables are provided in Table 1.

Table 2. Correlation coefficients

	deaths	**cases/pop**	**death/case**	**broadband**	**road/land**	**rail/land**	**bed/pop**	**gdp20**	**slope**
deaths	1.000000	0.411115	0.621532	0.317851	0.243898	-0.071109	0.084367	-0.12363	-0.039024
cases/pop	0.411115	1.000000	0.330908	0.559946	0.441552	0.409735	0.216838	-0.02864	0.038608
death/case	0.621532	0.330908	1.000000	0.468342	0.425819	-0.151740	0.169080	0.08966	0.195816
broadband	0.317851	0.559946	0.468342	1.000000	0.559288	0.086937	0.628490	0.11804	0.189929
road/land	0.243898	0.441552	0.425819	0.559288	1.000000	0.366470	0.383814	0.12872	0.133543
rail/land	-0.071109	0.409735	-0.151740	0.086937	0.366470	1.000000	-0.026868	-0.06031	-0.055539
bed/pop	0.084367	0.216838	0.169080	0.628490	0.383814	-0.026868	1.000000	0.08200	0.012742
gdp20	-0.123639	-0.028646	0.089661	0.118049	0.128727	-0.060317	0.082001	1.00000	0.737945
slope	-0.039024	0.038608	0.195816	0.189929	0.133543	-0.055539	0.012742	0.73794	1.00000

3. Results and Discussion

As there are eight independent variables, the Multiple Linear Regression (MLR) model is executed. As a result of the Multiple Linear Regression model, the following coefficients were determined for each of the independent variables.

Table 3. The coefficients of the independent variables in MLR

Deaths	Cases/Pop	Death/Case	Broadband	Road/Land	Rail/Land	Bed/Pop	GDP20
0.10219365	0.05626922	0.18709134	0.12092027	0.07122655	0.05975167	0.15594519	0.79316421

Machine learning algorithm searches through the data and finds a model existing among the independent variables and the dependent variable “slope” as an indication of the direction of economic activity under stress cause by the external shocks. Below is the model reflecting the coefficients found by the algorithm:

$$y = -0.0382338 - 0.1021936(\text{deaths}) - 0.0562692(\text{cases} - \text{pop}) + 0.1870913(\text{death/case}) + 0.1209202(\text{broadband}) - 0.0712265(\text{road/land}) + 0.0597516(\text{rail/land}) - 0.1559451(\text{bed/pop}) + 0.7931642(\text{gdp20}) \quad (4)$$

In this equation, the impact of each independent variable on the changes of the dependent variable is reflected on the Multiple Linear Equation. Growth percentage of GDP per capita has a strong relationship with the dependent variable. Each one unit change on the Growth of GDP per capita is associated with an increase by 0.793 in the dependent variable.

There are several different approaches for analyzing the performance of a given algorithm in machine learning. Within this paper several metrics such as MSE, RMSE, MAE, and R Squared were used. In statistics, the correlation is indicated by R and it is given in a range of from -1 to 1. It implies that if the correlation is closer to 1, that increase in *x* leads to an increase in *y*. Whereas if the correlation is closer to -1 then the increase in x implies the decrease in *y*. And 0 means there is no correlation between two or more variables. However, in machine learning it is popular and more useful to use R Squared. Consequently, the most popular and the most effective performance metrics for regression type algorithms were selected. There are R squared, Mean Absolute Error, Mean Squared Error and Root Mean Squared error.

Table 4. The performance metrics for each algorithm

R^2	MAE	MSE	RMSE
0.55288233135	0.079863980214	0.0089600428482	0.094657502863

After using and applying those algorithms, first we look at the most important metric which is R Squared. R squared explains how strongly the changes in independent variables can cause the changes in independent variables. It also indicates the relationship of two or more variables, however, it ranges from 0 to 1 in order to avoid the misleading caused by the negative variance. In other words, R squared shows in percentage how the changes in independent variables can affect the target-dependent variable. For Multiple Linear Regression, the R squared shows 55% if rounded. It means that the dependent variables can be explained by independent variables only in a ratio of 55 to 100. The chart below shows the ratio of predicted values in comparison to the actual values.

The comparison of the actual and predicted values of the dependent variable is provided in Figure 3. The results clearly indicate that the ML algorithm does a significant job in approximating the actual values.

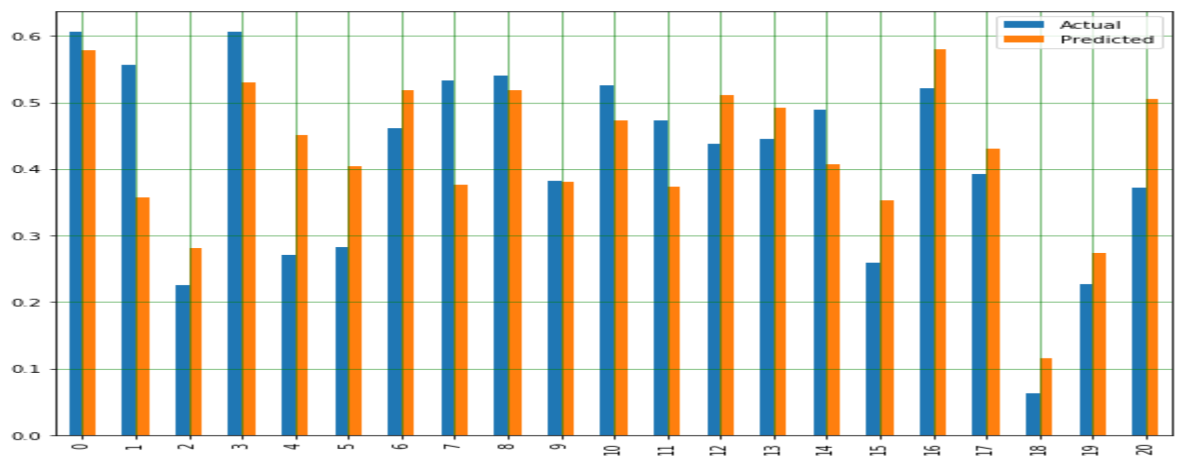

Figure 3. Actual vs. Predicted values

Except the R squared for analyzing the performances of algorithms three more metrics were chosen. These are Mean Absolute Error, Mean Squared Error, and Root Mean Squared Error. Mean absolute error is a measure of the average magnitude of error generated by the regression model. It calculates the absolute difference between the model prediction and the actual values. The formula of the mean absolute error is as follows:

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \tag{5}$$

$MAE = mean\ absolute\ error$

$y_i = prediction$

$x_i = true\ value$

$n = total\ number\ of\ data\ points$

As the formula calculates the average magnitude of errors, if MAE shows 0, it means that the model works perfectly well on the new dataset. Thus, closer values of MAE to zero indicate a better model in terms of estimating the dependent variable. Multiple Linear Regression resulted in a MAE showing approximately 0.07. Overall, it is assumed that all the models have a low probability of making errors.

In regression problems Mean Squared Error is one of the most popular metrics to measure. It is also called a cost function. It is highly similar to the mean absolute error, however instead of taking the absolute value of residuals, it squares them up. In addition, it is highly important to use MSE, because if there are outliers in the dataset, they become much larger. In the case of predicting the model, it is essential to get MSE in order to find the deviation between the actual and predicted values. The formula that determines the mean squared error is as follows:

$$MSE = \frac{1}{n}\sum_{i=!}^{n}\left(Y_i - \widehat{Y_\iota}\right)^2 \quad (6)$$

$MSE = mean\ squared\ error$

$Y_i = observed\ values$

$\widehat{Y_\iota} = predicted\ values$

$n = number\ of\ data\ points$

Table 5. Error Terms

R^2	MAE	MSE	RMSE
0.5528823313	0.07986398021	0.008960042848	0.09465750286

Root Mean squared error is also one of the most popular evaluation metrics in regression problems. Its origin comes from the Mean squared error. The Root Mean Squared Error is basically the square root from the mean squared error. In comparison to MSE it represents the standard deviation of the residuals and it explains how large the residuals are being dispersed in the data. RMSE is more easily explainable, because it takes a square root of the squared values. The formula of RMSE is as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \widehat{x_\iota})^2}{N}} \quad (7)$$

where;

$RMSE = root - mean\ square\ error$

$\widehat{x_\iota} = estimated\ values$

$x_i = actual\ values$

$N = number\ of\ non - missing\ data\ points$

Various statistical tests are conducted to further analyze the reliability and validity of the model. Having strong correlations between the independent variables result in high multicollinearity which means one variable can be used to predict another. However, this is an undesired situation as it leads to redundant information, causing skewness of the results in the model [137].

The methods below are widely used to detect multicollinearity:

- Excessive variance among the coefficient estimates of different models.
- Non-significant t-tests for each of the individual slopes ($p > 0.05$) while significant F-test for testing all of the slopes ($p < 0.05$).
- High correlations between pairs of predictor variables.

Also it should be noted that evaluation of correlations between pairs of predictors can be misleading. A linear dependence may still exist among three or more variables while pairwise correlations are small. Another measure called variance inflation factors (VIF) is employed by many to detect multicollinearity in such cases. As the name suggests, variance inflation factor is used to calculate how much the variance is inflated. If there is multicollinearity, estimated coefficients' standard errors are inflated. In a multiple regression model, a VIF exists for each predictor. For instance, VIF factor for the estimated regression coefficient b_j (VIF_j) is a factor by which b_j coefficient's variance is inflated by the correlation between the predictor variables of the model.

VIF for the j^{th} predictor is calculated as follows:

$$VIF_j = \frac{1}{1-R_j^2} \tag{8}$$

where R_j^2 calculated by regressing the jth predictor over the rest of the predictors.

A VIF value of 1 indicates that there is no correlation among the j^{th} predictor and the remaining predictor variables, which means the variance of b_j is not inflated. VIF values that are higher than 4 indicate a need for further investigation, while the values over 10 point out significant multicollinearity that needs to be corrected.

Table 6. VIF Values

1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
2.4	3.2	5.9	6.2	3.4	1.8	3.9	3.4

Residuals homoscedasticity is one of the assumptions of multiple regression and it consists of investigating whether regression residuals or forecasting errors have a constant variance. Breusch-Pagan heteroscedasticity test is used for this purpose [138] using squared original regression residuals as dependent variable along with original regression independent variables and evaluating if independent variables are statistically significant together.

Breusch-Pagan test formula notation is as follows:

$$\epsilon_t^2 = \alpha + \beta_1 x_{1,t} + \beta_2 x_{2,t} + e_t \qquad (9)$$

where;

ϵ_t^2 : squared forecasting errors or original regression estimated residuals,

α : regression constant,

β_1 *and* β_2 : regression coefficients,

$x_{1,t}$ *and* $x_{2,t}$: original regression independent or explanatory variables data,

e_t : forecasting errors or regression residuals.

Heteroscedasticity is determined based on the following condition involving Breusch-Pagan Lagrange multiplier (BPLM) statistic *p-value*:

If $p - value\ <\ \alpha$ level of statistical significance then

Residuals were heteroscedastic with $(1-\ \alpha)$ level of statistical confidence.

Otherwise, residuals were homoscedastic with $(1-\ \alpha)$ level of statistical confidence.

Residuals Homoscedasticity Breusch-Pagan Test results below are used to test the heteroscedasticity in the model. The results indicate that we cannot reject the null hypothesis of constant variance. Thus, there is no evidence of heteroscedasticity.

BPLM Test Statistic: 35.1661

BPLM Test P − Value: 0.6897

Next, normality tests are used to check if the data is obtained from a sample exhibiting normal distribution. Various graphs can be used to test the normality of a variable. We can visually test the normality using graphs. A Quantile-Quantile Plot is utilized to plot the theoretical quantiles against the actual variable quantiles. If our data comes from a normal distribution, we should see all the points placed on a straight line which is the case illustrated in Figure 4.

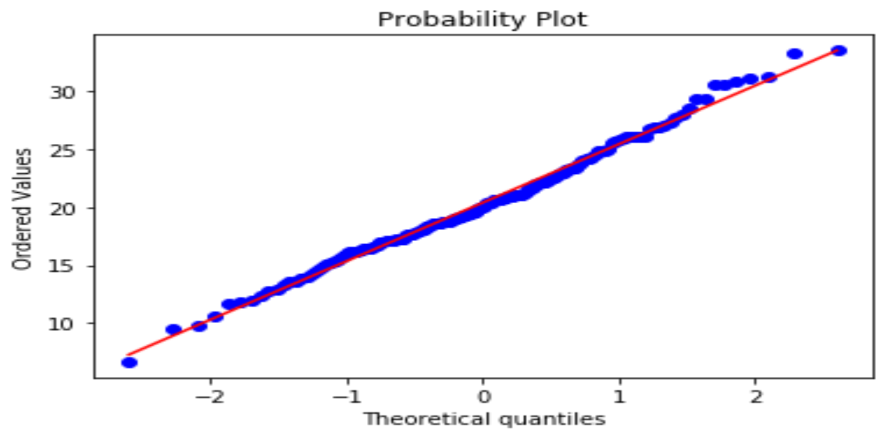

Figure 4. Normality graph

4. Conclusions

This study aims to contribute building a framework to investigate the relationship between the economic welfare and supply chain structure during external shocks. Machine Learning (ML) methods are used to conduct the required analyses. ML algorithm used in this study searches through the data and finds a model existing among the independent variables and the performance of an economy under stress caused by the external shocks. The results reveal the strong relationships between the variables chosen in building the model. However, this research is designed to build a machine learning framework which can be further expanded in a future research by incorporating new variables given the availability of data for a representative set of countries. Another venue for a future research is the investigation of relationship on a regional basis as opposed to the global scale utilized here.

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