Institutions and Economies
Vol. 16, No. 3, July 2024, pp. 97-116 https://doi.org/10.22452/IJIE.vol16no3.5

Economic Crisis Treatment Based on Artificial Intelligence

Mohamed F. Abd El-Aal[a]

Abstract: *There are many possible causes of an economic crisis – a financial downturn, a banking meltdown, political strife (e.g., the Russia-Ukraine war), or a health-related catastrophe (e.g., Covid-19). Some of these crises are expected, while others are "bolts from the sky." However, what is certain is that all these crises, whatever their cause, have a negative impact on global gross domestic product (GDP). If we can identify the components of output that have the most impact in an economic crisis, we might be able to mitigate its effects. Therefore, this paper uses machine learning algorithms to determine how the components of expenditure and sectoral value-added approach impact global GDP. The gradient boosting algorithm is the most accurate model for predicting and determining the impact of independent variables on a dependent variable. The results indicate that government spending has the largest effect on global GDP, accounting for 68.3% of the impact. The economic sector with the most impact on global GDP is the service sector, which affects global output by 42.3%, followed by the agricultural sector at 30.2%. Thus, stimulating government spending and the service sector may reduce the negative effects of an economic crisis.*

Keywords: Machine-learning algorithm; Economic crisis; Global gross domestic product; Gradient boosting algorithm; Neural networks
JEL Classification: C80, C81, C87

1. Introduction

From 2007 to 2009, the global financial system was hit by the most severe recession since the Great Depression. However, the question of whether the two episodes are equivalent remains unanswered. According to Aiginger (2010), who compares various indicators, the Great Depression was far worse than the Great Recession except for one factor, i.e., stock market decline. Romer (2009) argues that the Great Recession was nothing compared to what our parents and grandparents went through in the 1930s.

[a] Economics Department, Faculty of Commerce, Arish University, 45511 North Sinai, Egypt. *Email: Mohamed.fawzy@comm.aru.edu.eg*. ORCID ID: 0000-0002-6272-2805

We may be “tying or even worse than the Great Recession,” according to Eichengreen and O’Rourke (2009). However, they argue that it is not as bad when viewed internationally. “I believe that September and October of 2008 were the greatest economic collapse in global history, including the Great Depression,” testified former Federal Reserve chairman Ben Bernanke in 2011.

By now, it should be obvious that the 2008 crisis did not have the same impact as the Great Depression, during which 29% of the United States’ (US) gross domestic product (GDP) was wiped out, prices fell by 25%, unemployment climbed to 25%, and more than 9,000 banks went out of business. Some areas even returned to the barter system (King, 1933). Regardless, financial crises do negatively affect global GDP and the employment rate. As a result of the Great Recession, the global GDP growth rate declined from 2.6% in 2008 to a negative growth rate of 1.32% in 2009. As a result, the global unemployment rate rose from 5.41% in 2008 to 6.06% in 2009. However, a direct comparison is difficult because of the varying degrees of crisis involvement and regulation during and after the two periods.

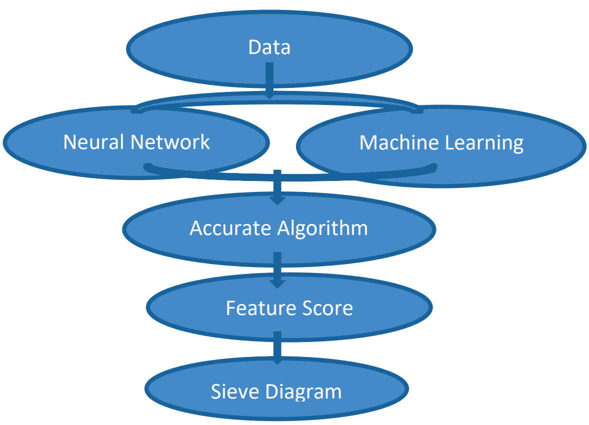
The Covid-19 pandemic, an unprecedented global phenomenon, had a wide range of impacts. By September 20, 2021, the number of deaths in the US due to Covid-19 surpassed the 675,446 deaths attributed to the 1918 Spanish flu pandemic. As a result of the devastation that it caused in every country in which it spread, the pandemic had far-reaching effects on global economic growth (Jackson, 2021). The global economic growth rate dropped from 2.6% in 2019 to -3.3% in 2020 due to Covid-19, while unemployment rose from 5.36% in 2019 to 6.57% in 2020, exceeding the effects of the 2008 Great Recession (based on a World Bank dataset). This crisis was, to borrow from Kindleberger-Minsky, a “bolt from the sky.”

The conflict in Ukraine, meanwhile, has resulted in a major humanitarian catastrophe. Over 13 million people require humanitarian aid due to displacement, and many people’s lives will be forever changed due to the trauma they have experienced. The economic situation in Ukraine is dire, and has affected global trade, refugee flows, financial movements, and market confidence. Regional supply chain and financial network disruptions and investor risk perceptions will hamper growth in the region.

Global geopolitical tensions cause volatility in financial markets. As a result of the conflict, the global economy’s short-term outlook has been severely damaged. The commodity markets were among the first to experience the effects of the global economic downturn. Products supplied by Russia and Ukraine have seen a steep price increase. Due to rising food and energy prices, poverty, food insecurity, and inflationary pressures are rising in many emerging markets and developing economies (EMDEs). Investment and finance costs have increased sharply in many commodities importing EMDEs. The expected tightening of monetary policy in advanced economies has also increased, making these countries more vulnerable to a financial crisis. As a result of the interactions between these dangers, the global economy is at risk of a hard landing (Guenette et al., 2022). Although it was an exceptional crisis caused by humans, it was not expected. Its negative effects on global GDP are significant.

After determining the causes of such crises and their negative effect on global GDP, we use machine learning algorithms, namely, random forest, support vector machine (SVMs), and k-nearest neighbour (KNN) algorithms, as well as neural networks and tree and gradient boosting models to determine the economic sectors that most significantly influence the global output of agriculture, industry, and services. The same applies to any spending that affects it, such as government, consumer, or investment expenditure. Figure 1 shows a description of the steps involved.

Figure 1: Steps Involved



2. Literature Review

According to Reinhart and Rogoff (2009), financial crises frequently result in a severe recession lasting around two years. Deleveraging of debts and changing risk perceptions also slow down consumption, private investment, and credit flows. As a result, the economy takes a while to recover, and unemployment rates keep rising even after the economy has resumed growth.

Gupta et al. (2007) reveal the potential variation in how financial crises affect economic growth. To determine the elements that are most likely to increase the impact of the crisis on the real economy in addition to looking for a concrete impact, they researched instances of currency crises in 91 developing nations between 1970 and 2000. According to their findings, 60% of the 195 incidents of currency crises were recessive. In comparing these crises, Gupta et al. (2007) reveals that the currency problems of the 1990s were more severe than in the 1970s and 1980s. They tried to evaluate many variables to explain the severity of crises. Economies with high capital inflows were most negatively impacted. These findings, which hold up under various assumptions, emphasise the significance of the "sudden stop" concept in slowing down the economy. Their findings also suggest that the amount of external borrowing will likely worsen the effects of crises because subsequent sharp devaluations will increase the debt load, endangering economic stability.

Ito (2004) aimed to ascertain if the various repercussions of crises differ between nations with open capital accounts and those that place limits on capital mobility. His research looks at 62 countries, including 22 industrialised nations, 40 developing nations, and 29 rising nations. The author discovered that while liberalisation decreases the likelihood of a crisis in developed nations, it raises the likelihood of a crisis in developing and emerging nations. He also discovered that financial deregulation tends to lessen the crisis' detrimental effects in industrialised nations. Additionally, a wider opening of the financial markets enables these nations to accelerate their economic trajectory and, as a result, reclaim their pre-crisis starting growth levels. The results for emerging nations seem less promising because financial liberalisation merely worsens the recessionary impact of the crisis. In this aspect, the crisis is more severe and lasts longer.

Boyd et al. (2005) discover that budgetary expenses, liquidity, and recapitalisation support are the main determinants of crisis costs when attempting to explain the severity of crises. The authors of the study found 23 incidents of banking crises between 1970 and 2000. They demonstrate that real per capita GDP is reduced between 63% and 302% during banking crises. Additionally, they acknowledge that losses have been overestimated in earlier studies.

Angkinand and Willet (2008) assess how regulation and banking supervision contribute to the severity of banking crises. Their study is limited to 35 industrialised and developing nations between 1970 and 2003. They demonstrate that loss in production, measured as the difference between the current and potential GDP levels, is relatively low in nations that offer deposit insurance coverage and adhere to stringent quality asset and capital adequacy requirements by identifying 47 banking crisis episodes. However, the extent of the crisis is not greatly explained by banking supervision.

The study by Cecchetti et al. (2009), which employs a different methodology, supports the above findings. The authors identified 40 systemic banking crisis occurrences after looking at a sample of 35 nations. They research these crises' length, scope, and manufacturing costs. According to the authors, systemic crises have caused a significant contraction in output. They then looked at the factors that affect production losses—i.e., initial circumstances, financial structure, growth rate, policy actions, and external circumstances. Their findings suggest that costs are higher when monetary crises precede banking crises, and when growth is weak before crises. They also show systemic crises are less severe when a sovereign debt default occurs concurrently.

Teimouri and Brooks (2015) demonstrate that currency crises are accompanied by a considerable long-term fall in production and a sharp loss of foreign exchange reserves. According to the findings, production resumes following currency crises with a U-shaped production curve that fully restores its pre-crisis level in three years. Nier and Merrouche (2010) state that the creation of financial imbalances may have been influenced by three factors: increasing global imbalances (capital flows), lax monetary policy and insufficient supervision and control.

Kouki et al. (2017) investigate the impact of banking and monetary policy on the economic growth of 28 emerging and developed nations from 1980 to 2011 and find that the impact of banking crises on GDP growth is more severe and costly. When factors relating to the condition of the financial system, liberalisation, and the stage of institutional development, the negative impact is even greater. Lin et al. (2012), meanwhile, show that machine learning algorithms can quite accurately predict bankruptcy and credit scoring, considering that they are the main reason for global crises.

3. Methodology

Multiple machine learning techniques, including random forest, SVM, and KNN algorithms, as well as neural network and gradient boosting models, were employed in this study. Machine learning models analyse training data to develop their predictive function.

To address the current economic crisis, we evaluate six models to determine the most accurate estimate of global GDP. Data were collected for global GDP, expenditure components, and sectoral value-added from 1997 to 2020 and 1970 to 2020 from the World Development Indicators. Python was used to code the machine-learning algorithms developed using the Scikit-Learn library.

3.1 Machine learning techniques

Supervised, unsupervised, semi-supervised, and reinforcement learning are the four primary types of machine learning techniques. Their viability in addressing practical issues is elaborated on in various studies (e.g., Sen et al., 2021).

3.1.1 Supervised learning

In supervised machine learning, the inputs (e.g., a computer system receiving data) and expected results (e.g., process information sent out by a computer) are used to train an algorithm (i.e., a step-by-step method for solving an issue in a specific format) to predict future outcomes. The algorithm is considered to have mastered a task and yield a good result if it improves the accuracy of the outputs for classification or prediction. The information provided is split into two types: (1) training data, which includes training examples with one or more inputs, and (2) reference data, which includes data used in developing a supply system. Supervised learning employs mathematical modelling and uses matrices to store the data to be trained and the array vectors (feature vectors are used for extraction).

3.1.2 Unsupervised learning

When applied to a dataset, an unsupervised learning algorithm may identify recurring patterns that may then be used to classify the data into meaningful categories. Data similarity is detected using an unsupervised learning algorithm that responds to each new data point based on whether it exhibits the same pattern. Most algorithms are trained on unlabelled, uncategorised test data. In contrast, an unsupervised learning algorithm is a data-driven method that analyses a dataset that a human has not labelled. Unsupervised learning tasks include anomaly detection, dimension reduction, clustering, density estimation, feature learning, and rule discovery.

3.1.3 Semi-supervised learning

The semi-supervised learning method falls between unsupervised learning (unlabelled training data) and supervised learning (which uses labelled training data). It is a hybrid machine-learning approach that yields greater precision by utilising labelled and unlabelled data. The primary goal of unsupervised learning is to produce better prediction results than can be achieved using only labelled data. Text categorisation, fraud detection, and machine translation are all areas in which the semi-supervised learning method has been applied.

3.1.4 Reinforcement learning

In machine learning, reinforcement learning refers to the study of how software agents and computers can be used to make decisions in each setting to maximise productivity automatically. Reinforcement learning relies on a penalty system to validate the reward or reduce the danger, and its major purpose is to use derived from environmental data. Operation research, game theory, information theory, swarm intelligence theory, and genetic algorithms use reinforcement learning in some way. It is a useful tool for training artificial intelligence models to increase automation in areas such as robotics, autonomous driving, manufacturing, and supply chain logistics, as well as for applications like learning to play a game against a human opponent or navigating a complex environment without human intervention.

3.2 Neural network

Artificial neural networks try to imitate human mastery skills by simulating brain neurons using computer simulations. Feedforward and feedback (recurrent) networks are two categories that describe the design and interactions of neurons in neural networks. A feedforward network is a static network comprising a group of connected neurons that indicate a nonlinear function of its data. Information only moves forward, from inputs to outputs. The neural networks are trained to reduce the value of the loss function, which measures the total difference between the input from the model and the real label. In deep learning, recurrent neural networks (RNNs) are useful. These simulations closely reflect how people take in information and learn new things (Ayitey Junior et al., 2022).

Between 2018 and 2019, the most popular data science/machine learning techniques were decision trees, random forest, KNN, gradient boosting, SVM, and neural networks. Table 1 describes these algorithms as follows.

Table 1: Description of Various Machine-Learning Algorithms

Algorithm	Description
Neural network (deep learning)	Neural networks are machine learning types that use multiple layers of nodes, such as input, hidden, and output. The nodes' varying weights and thresholds enable neural networks to function. In addition, if a node's output exceeds the threshold, the node will be activated, and the relevant data will be sent to the succeeding layer in the network; otherwise, no data will be activated. Most deep learning frameworks rely on a neural network (Sen et al., 2021).
Gradient boosting	Boosting is an ensemble classification technique that uses a continuous classification strategy predicated on the characteristics used by the subsequent model. Using weight-average boosting methods improves the performance of a poor learner model. Several weakly trained models support a much stronger trained model. A weak learner has a low correlation to the correct classification, and as the learning process continues, the correlation between the genuine classification and the resulting weak learner improves (Sen et al., 2021).
Random forest	The sampling of the dataset using the random forest model is accomplished using a tree operation. It randomly samples the dataset before building the tree to lessen the likelihood of correlated outputs. We fit the tree using bootstrapped samples to minimise error and average the results. Since each tree in a random forest model is structurally unique and randomly selects a portion of the sample to minimise the likelihood of producing identical predictions, this method is optimal for identifying missing data. We find that averaging the less accurate predictions from several trees yields the most accurate result (Sen et al., 2021).

Algorithm	Description
Decision tree	This tree-based, if-then machine learning method is named because it operates like an if-statement. The decision tree's root node is created first, followed by its child nodes. The information is sorted into categories based on the nodes' properties representing decision points. The branches connecting the nodes at various levels represent various choices, which are determined by checking the status of the node's characteristics (Sen et al., 2021).
K-nearest neighbour (KNN)	The KNN definition of label consistency requires that the label of any given instance coincides with its corresponding KNN instance. Regarding forecasting accuracy, KNN is a straightforward method that does not presuppose anything about the shape of the dataset. The benefits of cumulative learning are universally accessible, based on examples that do not require training before generating predictions. KNN is frequently used for both classification and regression learning problems (Kang, 2021).
Support vector machine (SVM)	Classification applications that employ a unique machine learning method require an independent and identically distributed dataset. After inputting x into a categorisation algorithm, SVM assigns it to a single classification out of many, in contrast to other machine learning methods that calculate probability distributions. Less effective discriminatory techniques are employed only when blueprints are necessary to save time and energy, especially in a multidimensional sector. An ideal surface equation for differentiating many classes requires a discriminating function that can forecast new occurrence labels to a high degree of certainty. An SVM's convex optimisation problems are commonly used in machine learning classification and always provide consistent optimal space values, unlike evolutionary methods or perceptions. Perceptions are very stringent for an SVM's startup and shutdown phases (Awad & Khanna, 2015).

4. Empirical Results

4.1 Model evaluation

The first step is to determine the accuracy of the algorithms. Tables 2 and 3 present the accuracy results for the employed algorithms after processing them using Python.

Tables 2 and 3 indicate that the gradient boosting algorithm is the most accurate in predicting global GDP using the expenditure or sector value-added method. In contrast, the algorithm's accuracy is greater in forecasting using the value-added by sector. In this analysis, the accuracy of the gradient boosting algorithm is a rare case in which the R-squared reaches approximately 9.99%, and the mean square error is almost negligible. Thus, it is possible to rely on the gradient-boosting algorithm to predict global

GDP and determine its most important determinants during a crisis. In the next step, we present the prediction performance of this algorithm by comparing the expected values with the actual values of GDP.

Table 2: Accuracy of Machine Learning Algorithms in Predicting Global GDP Using the Expenditure Method, 1970–2020

Model	MSE	RMSE	MAE	R^2
Gradient boosting	0.023	0.15	0.12	99
Tree	0.22	0.47	0.36	91
Random forest	0.39	0.62	0.5	84
Neural network	1.61	1.27	0.99	38
SVM	1.87	1.37	0.96	27
KNN	1.93	1.38	0.94	25

Notes: RMSE = root mean square error, MAE = mean absolute error, MAPE = mean absolute percentage error, and R^2 = coefficient of determination.

Table 3: Accuracy of Machine Learning Algorithms in Predicting Global GDP Using the Sector Value-Added Method, 1997–2020

Model	MSE	RMSE	MAE	R^2
Gradient boosting	0.001	0.028	0.023	99.9
Random forest	1.05	1.02	0.59	65
Tree	1.23	1.11	0.64	60
Neural network	1.91	1.38	1.081	37
KNN	2.15	1.46	0.94	30
SVM	2.4	1.54	0.931	22

Notes: RMSE = root mean square error, MAE = mean absolute error, MAPE = mean absolute percentage error, and R^2 = coefficient of determination.

4.2 Prediction performance

Tables 4 and 5 indicate that the expected and actual GDP values during the study period are almost identical, indicating the accuracy of the gradient-boosting algorithm. This is why it should be used to determine the most influential variables affecting global GDP.

Table 4: Gradient Boosting Algorithm Prediction for Global GDP Value (Expenditure Approach)

Year	Expenditure approach	
	Gradient boosting algorithm prediction	**Actual GDP growth (%)**
1970	4	3.93
1971	4.21	4.27
1972	5.37	5.62
1973	6.34	6.41
1974	1.93	1.79
1975	0.66	0.64
1976	4.93	5.30
1977	4.02	4.10
1978	4.05	4.14
1979	4.18	4.17
1980	1.97	1.88
1981	2.32	1.93
1982	0.52	0.39
1983	2.69	2.65
1984	4.43	4.68
1985	3.67	3.70
1986	3.34	3.44
1987	3.5	3.73
1988	4.42	4.64
1989	3.93	3.75
1990	3.1	2.87
1991	1.7	1.46
1992	2.25	2.07
1993	1.92	1.81
1994	3.5	3.31
1995	3.23	3.09
1996	3.67	3.62
1997	3.92	3.90
1998	2.96	2.79
1999	3.48	3.52
2000	4.37	4.49
2001	2.05	2.00
2002	2.39	2.33

Year	Expenditure approach	
	Gradient boosting algorithm prediction	**Actual GDP growth (%)**
2003	3.03	3.15
2004	4.37	4.49
2005	3.84	4.04
2006	4.31	4.48
2007	4.19	4.48
2008	2.31	2.07
2009	−1.23	−1.33
2010	4.46	4.53
2011	3.3	3.32
2012	2.67	2.71
2013	2.74	2.82
2014	2.91	3.06
2015	3.01	3.08
2016	2.85	2.80
2017	3.34	3.38
2018	3.27	3.28
2019	2.76	2.61
2020	−3.26	−3.27

Source: Author's own.

Table 5: Gradient Boosting Algorithm Prediction for Global GDP (Sector Value-Added Approach)

Year	Sectoral approach	
	Gradient boosting algorithm prediction	**Actual GDP growth (%)**
1997	3.9	3.90
1998	2.82	2.79
1999	3.47	3.52
2000	4.47	4.49
2001	2.03	2.00
2002	2.33	2.33
2003	3.13	3.15
2004	4.44	4.49
2005	4.05	4.04
2006	4.49	4.48
2007	4.48	4.48

Year	Sectoral approach	
	Gradient boosting algorithm prediction	Actual GDP growth (%)
2008	2.06	2.07
2009	−1.28	−1.33
2010	4.46	4.53
2011	3.3	3.32
2012	2.73	2.71
2013	2.82	2.82
2014	3.07	3.06
2015	3.09	3.08
2016	2.78	2.80
2017	3.33	3.38
2018	3.3	3.28
2019	2.62	2.61
2020	−3.25	−3.27

Source: Author's own.

4.3 Feature importance

One way to identify the most critical factor is to examine its impact on forecasting global GDP. Although these techniques are typically employed for prediction, learning which variables have the greatest impact on a model may be accomplished by analysing their feature importance. The outcomes of this analysis are displayed in Tables 6 and 7.

Table 6: Feature Importance Indicators (Expenditure Approach)

Expenditure component	Percentage (%)
General government final consumption expenditure	68.3
Exports and imports	14.6
Gross fixed capital formation	10.5
Households' and NPISH's final consumption expenditure	6.5

Note: NPISH = Non-profit institutions serving households.

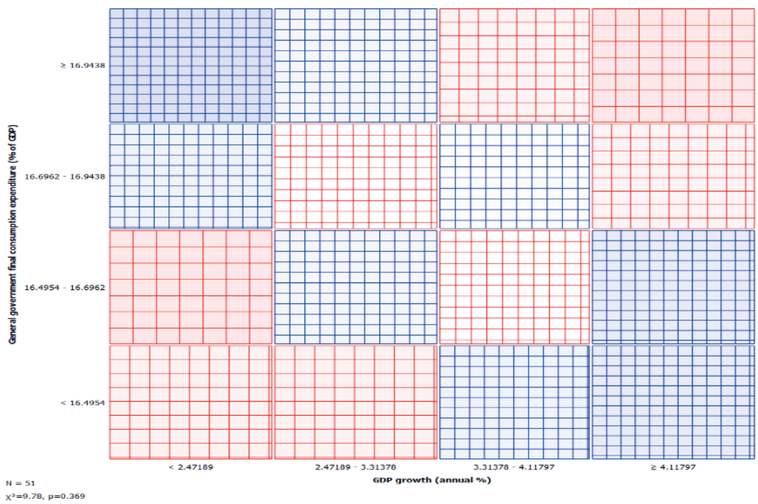
Table 7: Feature Importance Indicators (Sector Value-Added Approach)

Economic sector value-added	Percentage (%)
Services	42.3
Agriculture	30.2
Industry	27.5

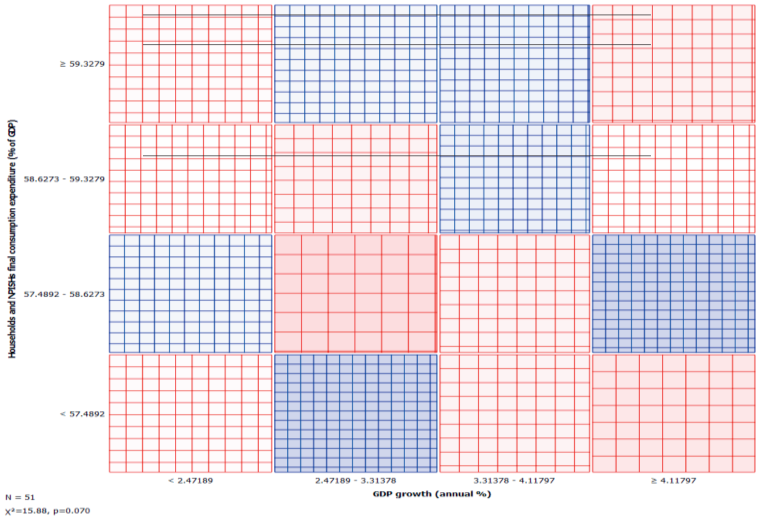
From Tables 6 and 7, we may observe the following: concerning the method of spending, government purchases have the greatest influence on global GDP at 68.3%, exports and imports at 14.6%, investment spending at 10.5%, and household sector spending at 6.5%. This is illustrated in Figure 2.

Figure 2: Sieve Diagram for Expenditure Component Feature Score

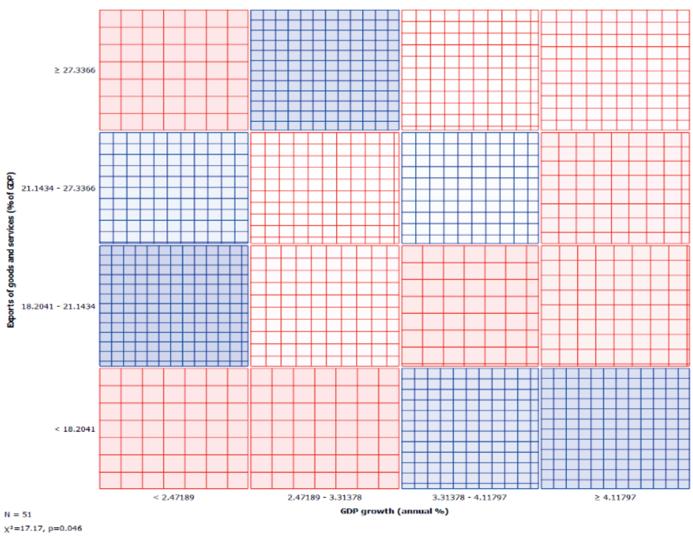
(A)



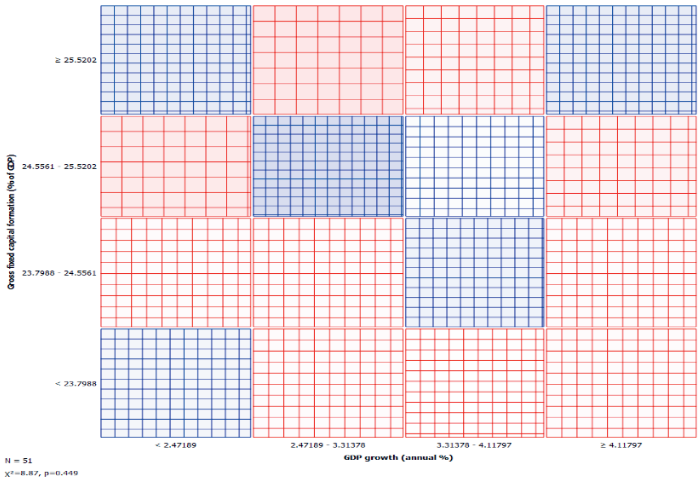
(B)


≥ 59.3279
58.6273 - 59.3279
57.4892 - 58.6273
< 57.4892
Households and NPISHs final consumption expenditure (% of GDP)
< 2.47189
2.47189 - 3.31378
3.31378 - 4.11797
≥ 4.11797
GDP growth (annual %)
N = 51
χ²=15.88, p=0.070

(C)


≥ 27.3366
21.1434 - 27.3366
18.2041 - 21.1434
< 18.2041
Exports of goods and services (% of GDP)
< 2.47189
2.47189 - 3.31378
3.31378 - 4.11797
≥ 4.11797
GDP growth (annual %)
N = 51
χ²=17.17, p=0.046

(D)

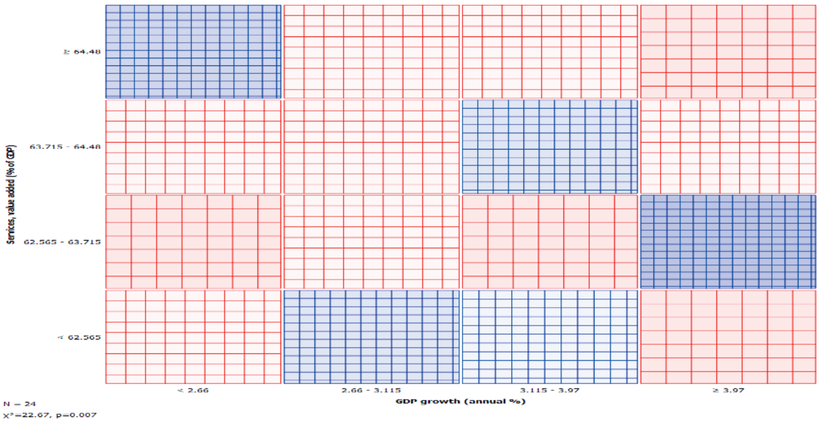


The area of each rectangle in this graph corresponds to the predicted frequency, while the number of squares in each rectangle represents the observed frequency. The density of shading represents the difference between observed and predicted frequency (proportional to the standard Pearson residual), with colour used to denote whether the standard deviation from independence is positive (blue) or negative (red). The shading of the blue rectangle and the number of squares is clearest in (A).

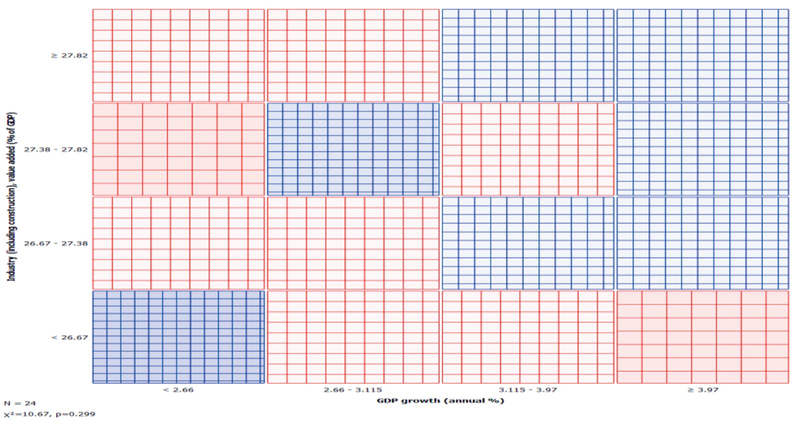
Regarding the value-added method for each sector, the most influential sector is the ser-vices sector (42.3%), followed by the agricultural sector (30.2%), and the industrial sector (27.5%). This is illustrated in Figure 3 below, in which shading of the blue rectangle and the number of squares is clearest in (A).

Figure 3: Sieve Diagram for Economic Sector Value-Added Feature Score

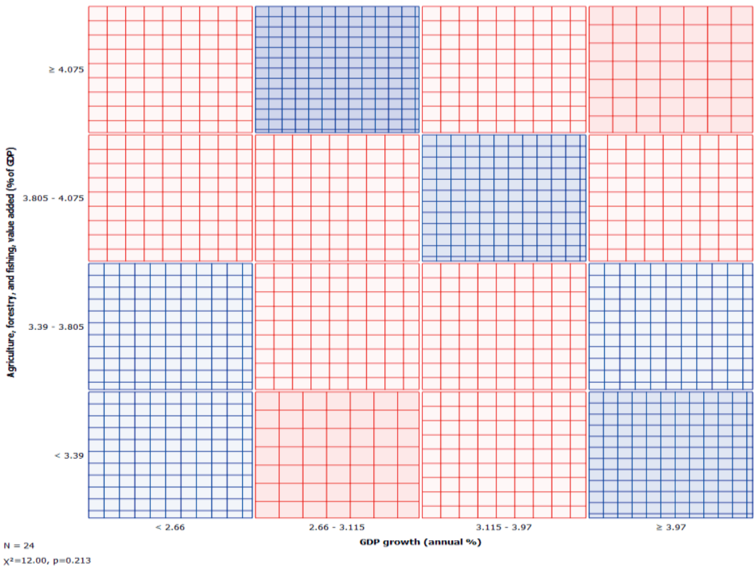
(A)



(B)



(C)



5. Conclusion

An economic crisis of any kind has a negative effect on global GDP. Their economic, social, and political consequences have been disastrous. The contraction of global output exacerbates unemployment, not only in the country where the crisis originates but also in many countries worldwide. Therefore, limiting the negative effects of an economic crisis is imperative for all countries.

As a result of the negative impact of the global financial crises on the global GDP growth rate, it is necessary to determine the components of this output according to the spending approach and value-added sectors to determine the relative importance of each component and its impact on global output growth. The study concludes that global government spending is the most influential on global output growth according to the expenditure approach. Nevertheless, the service sector has more influence on the growth of global output compared to agriculture and industry. Thus, in the event of financial crises and, consequently, a contraction of global GDP, its effects can be mitigated by increasing government spending and strengthening the role of the service sector.

References

Aiginger, K. (2010). The Great Recession vs. the Great Depression: Stylized facts on siblings that were given different foster parents. *Economics*, *4*(1), 2010–2018. http://doi.org/10.5018/economics-ejournal.ja.2010-18

Angkinand, A. P., & Willett, T. D. (2008). Political influences on the costs of banking crises in emerging market economies: Testing the U-shaped veto player hypothesis. *Macroeconomics and Finance in Emerging Market Economies*, *1*(2), 279–297. https://doi.org/10.1080/17520840802252878

Awad, M., & Khanna, R. (2015). *Efficient learning machines: Theories, concepts, and applications for engineers and system designers*. New York: Springer Nature.

Ayitey Junior, M., Appiahene, P., & Appiah, O. (2022). Forex market forecasting with two-layer stacked Long Short-Term Memory neural network (LSTM) and correlation analysis. *Journal of Electrical Systems and Information Technology*, *9*(1), 1–24. https://doi.org/10.1186/s43067-022-00054-1

Boyd, J. H., Kwak, S., & Smith, B. (2005). The real output losses associated with modern banking crises. *Journal of Money, Credit, and Banking*, *37*(6), 977–999. http://doi.org/10.1353/mcb.2006.0002

Cecchetti, S. G., Kohler, M., & Upper, C. (2009). Financial crises and economic activity. *NBER Working Paper*, *w15379*. https://ssrn.com/abstract=1478797

Eichengreen, B., & O'Rourke, K. H. (2009). A tale of two depressions. *CEPR*. https://cepr.org/voxeu/columns/what-do-new-data-tell-us

Guenette, J. D., Kenworthy, P. G., & Wheeler, C. M. (2022). Implications of the war in Ukraine for the global economy. *EFI Policy Note*, *3*. https://bit.ly/45A4Jxn

Gupta, P., Mishra, D., & Sahay, R. (2007). Behavior of output during currency crises. *Journal of International Economics*, *72*(2), 428–450. https://doi.org/10.1016/j.jinteco.2006.10.003

Ito, H. (2004). Is financial openness a bad thing? An analysis on the correlation between financial liberalization and the output performance of crisis-hit economies. *UC Santa Cruz International Economics Working Paper*, *04-23*. http://doi.org/10.2139/ssrn.621801

Jackson, J. K. (2021). Global economic effects of Covid-19. *Congressional Research Service*, *R46270*. https://crsreports.congress.gov

Kang, S. (2021). K-nearest neighbor learning with graph neural networks. *Mathematics*, *9*(8), 830. https://doi.org/10.3390/math9080830

King, M. (1933). Back to barter. *Annals of Public and Cooperative Economics*, *9*(2), 257. https://econpapers.repec.org/article/blaannpce/v_3a9_3ay_3a1933_3ai_3a2_3ap_3a257-261.htm

Kouki, M., Belhadj, R., & Chikhaoui, M. (2017). Impact of financial crisis on GDP growth: The case of developed and emerging countries. *International Journal of Economics and Financial Issues*, *7*(6), 212-221. https://www.econjournals.com/index.php/ijefi/article/view/4359

Lin, W. Y., Hu, Y. H., & Tsai, C. F. (2011). Machine learning in financial crisis prediction: A survey. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, *42*(4), 421–436. https://doi.org/10.1109/TSMCC.2011.2170420

Nier, E., & Merrouche, O. (2010). What caused the global financial crisis: Evidence on the drivers of financial imbalances 1999–2007. *IMF Working Paper*, *2010/265*. https://bit.ly/3PLjqYl

Romer, C. D. (2009). From recession to recovery: The economic crisis, the policy response, and the challenges we face going forward. *The White House: President Barack Obama*. https://obamawhitehouse.archives.gov/administration/eop/cea/FromRecessionToRecovery

Rosser, J. B., Rosser, M. V., & Gallegati, M. (2012). A Minsky-Kindleberger perspective on the financial crisis. *Journal of Economic Issues*, *46*(2), 449–458. https://doi.org/10.2753/JEI0021-3624460220

Sen, J., Mehtab, S., & Engelbrecht, A. (2021). Machine learning: Algorithms, models and applications. *IntechOpen*. https://doi.org/10.5772/intechopen.94615

Teimouri, S., & Brooks, T. J. (2015). Output recovery after currency crises. *Comparative Economic Studies*, *57*(1), 75-102. https://www.jstor.org/stable/26752475