Granger Causality

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Identifying causal network problems is important for effective policy and management, and recommendations on climate, epidemiology, and financial regulations. Identifying causality in complex systems can be difficult. Granger causality is an approach that uses predictability as opposed to correlation to identify causation between time series variables. Variable X is said to "Granger cause" Y if the predictability of Y declines when X is removed from the universe of all possible causative variables. The key requirement of Granger causality is separability, namely that information about a causative factor is independently unique to that variable and can be removed by eliminating that variable from the model.

Granger causality business economics environmental sciences neurosciences computer science

1. Introduction

In statistics, Granger causality analyses the information flow between time series. Granger causality was proposed and named after the developer, Clive W. J. Granger in 1969 as a linear vector autoregressive (VAR) model in econometric time series analysis [1][2][3]. In Granger causality, a cause shall precede its effect while the understanding of a cause will help to increase the accuracy to predict the effect [4][5]. In a Granger causality test, a variable may be defined in two ways, namely Granger-cause and fail to Granger-cause. If a variable is identified as a Granger-cause, the variable brings down the forecasting error in the model. On the other hand, a variable will fail to Granger-cause other variables when its historical value cannot significantly predict the future value or when there is no statistical significance in the lagged values of the equation [6]. Therefore, a time series $\{x_{m,t}\}$ is a Granger-cause of another time series $\{x_{n,t}\}$ if the history of the time series x_m enhances the prediction of x_n over the time of x_n alone. In year 2000, Schreiber [7] introduced the transfer entropy measure to quantify the statistical coherence between processes evolving over time.

With the availability of optimal estimation algorithms of VAR models, Granger causality has attracted the attention of researchers in several prominent research areas. VAR models also do not require any assumption on the physical mechanism for application. Moreover, permutation or bootstrapping are not needed to test the significance in Granger causality when the sample size is large. The result of a Granger causality test shall also remain consistent regardless of the overall signal strength [8][9][10]. Granger causality has been widely applied in several prominent areas. In neuroscience, Granger causality has been applied to functional magnetic resonance imaging (FMRI) [11][12][13], magnetoencephalography (MEG) [14][15][16], and local field potentials (LFP) [17][18][19]. Abdalbari et al. [20] used Granger causality for sleep data analysis to capture the physiological mechanisms during wakefulness and sleep. Hartmann et al. [21] studied the brain–heart interaction during sleep by using Granger causality to examine the electroencephalography (EEG) frequency bands with cortical and cardiovascular activities. Gao et al. [22] improved the classification of emotional states when Granger causality was applied with the Histogram of Oriented Gradient.

In finance, Granger causality has been used to determine the causal relationship between the financial development and economic growth in African countries [23]. The financial development and economic growth relationship has also been studied in the Middle East and North Africa (MENA) region [24]. Amano [25] studied the finance–development relationship during pre-war and post-war period in the United States, United Kingdom, and Japan. Fahimi et al. [26] investigated the globalization-driven energy consumption in Mexico, India, Nigeria, and Turkey. Candelon and Tokpavi [27] applied Granger causality in the European stock markets for spill over analysis. Coronado et al. [28] studied the cause–effect of COVID-19 news and stock market reactions in the United States and Latin America using Granger causality based on transfer entropy. Zuhud et al. [29] analysed the Malaysian stock market using Granger causality and transfer entropy. Granger causality has also been used to assess the dependency between different sectors with past time series [30]. Past studies have also used Granger causality to study Twitter sentiments' effects on stock prices [31][32]. Granger causality has also been accepted in the areas of business, management, accounting, and economics [33][34][35][36][37][38][39][40][41]. The contribution of Granger causality has also been noticed in computer science [42][43][44][45][46] and engineering [47][48][49][50][51].

Granger causality is applied in many areas such as business economics, environmental sciences, neurosciences, and computer sciences. The following sections shall review the literature on the application of Granger causality.

2. Business Economics

In business economics, Granger causality has been applied to perform a causality analysis on foreign direct investment (FDI), Islamic bank, and the capital market.

Zhang and Zhang [52] studied the impacts of gross domestic product, trade structure, exchange rates, and FDI inflow on carbon emissions in China. This research found that FDI inflow positively affected the carbon emission rate in the country. Three policy implications were made in this research. Firstly, the researchers suggested that China should improve its high value-added low carbon-intensive areas such as the advertising, maintenance, and finance sectors. Secondly, the stability of the Chinese Yuan exchange rate could be promoted to lower carbon emissions as it will affect carbon demand and trigger price fluctuation. Thirdly, the government can direct FDI into low-carbon industries or high-tech sectors.

Jebli et al. [53] studied the causality among renewable energy usage, number of tourists, trade openness, economic growth, FDI, and carbon emissions in Central and South America. This research concluded that tourism, renewable energy, and FDI reduced carbon emissions while trade and economic growth increased carbon emissions.

Therefore, this research proposed that policies such as FDI, usage of renewable energy, and developing green tourism could benefit the environment.

Granger causality was applied to identify the direction of causality to evaluate FDI, export, and economic growth in South Africa [54]. This research confirmed that FDI and exports contributed to economic growth as there were unidirectional relationships from FDI to economic growth and FDI to exports. There was a bidirectional relationship between economic growth and export activities. The policy implications in this research included the stimulation of FDI with investor incentives, developing a fair macroeconomic environment, and wise application of loose monetary policy in South Africa.

Arogundade et al. [55] analysed the human capital, institutional quality, FDI, and poverty in sub-Saharan Africa. This research deduced that FDI had no direct relationship on the occurrence and level of poverty. FDI had negative effects on the absorptive capacity of the host country. This research proposed several policies such as to invest in human capital and perform public sector reform to reduce corruption and improve political stability.

Farooqi and O'Brien [56] studied the effects of Basel standards on Islamic and conventional banks in the Gulf region. This research concluded that the proposal of a market-based measure of bank stress led the accounting-based Tier-1 ratio and was in accordance to the Basel regulation's Pillar 3. Therefore, the use of a measure to signal bank stress can be used to identify oncoming challenges before they escalate.

Setyowati [57] investigated the factors that affected saving and financing in Islamic banks in Indonesia. This research found that there was a long-running cointegrating relationship in saving and financing to the consumer price index (CPI), manufacturing, interest rate, exchange rate, and Jakarta Islamic Index. Structural breaks occurred around January 2006 to April 2007 to signal financial crisis. There were bidirectional relationships between deposits and manufacturing, and between CPI and financing. Real activity, which was manufacturing, also affected Islamic bank financing. The policy implications in this research were to provide incentives to encourage real activity such as production and manufacturing to allow Islamic banks to fulfil their intermediary roles and to implement an effective monetary policy on inflation to stabilize the market.

Samad [58] studied the relationship between Islamic banks' return on depositors and conventional banks' deposit interest in Bahrain. This research found that there was a bidirectional relationship between Islamic banks' returns on depositors and conventional banks' interest rates.

Sharif et al. [59] assessed the time–frequency relationship between COVID-19 pandemic, oil prices, geopolitical risks, economic uncertainty, and the US stock market. This research noted that the pandemic had a larger impact on the geopolitical risks and economic uncertainty compared to the US stock market. Oil was leading the US stock market regardless of the frequency. This research suggested including a geopolitical risk index to analyse the financial impact of the pandemic. The US government should also design and implement a coherent economic strategy during and after the pandemic to foster market opening. Asset managers and investors should reassess the risk management framework to deal with the pandemic risks.

Wang et al. [60] studied the risk spill over effect from the US economic policy uncertainty (EPU) index, equity market uncertainty index, and Chicago Board Options Exchange's CBOE Volatility Index (VIX) to Bitcoin. The researchers found negligible risk spill over effects from these indices to Bitcoin. This study is beneficial to the investors when performing asset portfolio investment as Bitcoin diversifies extreme market shocks. This research suggested that future studies could check if the cryptocurrency market is immune from EPU shocks.

Robiyanto et al. [61] measured the effectiveness of ASEAN-5 initiative from the portfolio perspective. The results showed weak integration into the equity markets in ASEAN-5. However, the ASEAN-5 initiative had an effect on the capital markets. This research then suggested that investors in Malaysia, Singapore, and the Philippines should not invest excessively in Indonesia and Thailand equities when the market was unstable because Indonesia and Thailand were the net contributors to the volatility.

Athari and Bahreini [62] investigated the effects of economic policy uncertainty on travel and leisure companies' debts in western Europe. Economic policy uncertainty had adverse effects on travel and leisure companies' debt level. Countries with high economic policy uncertainty had lower debt ratios. The policy implications included the monitoring of the rise of economic policy uncertainty to stabilize cash flow for expansion and investment of travel and leisure companies, to perform portfolio diversification to reduce the adverse effects of economic policy uncertainty, and to consider firm and country-level matrices prior to setting debt ratios.

Athari [63] examined the causal relationship between financial inclusion and domestic political risk on the banking sector around the world. There were positive causal relationships from capital deregulation, credit risk inefficiency, market power, and indices in financial inclusion, political risk, and economic risk to banking stability. This research suggested that countries should increase their stability by raising financial inclusion to offer stable environments for the economy and politics.

3. Environmental Sciences

In environmental sciences, Granger causality has been applied to assess ecological footprints, resource management, renewable energy, and carbon emissions.

Zafar et al. [64] investigated the relationship between natural resources, human capital, and FDI on the ecological footprint in the United States. Human capital and natural resources lowered the ecological footprint while economic growth and FDI elevated the ecological footprint. Several policy recommendations were given in this research. Firstly, the government should monitor and control the excessive use of natural resources by encouraging its residents to reduce their consumption and adopt efficient products. The government should also encourage sustainable consumption and sustainable infrastructure for FDI. The United States should also attract high-tech FDI that does not make a large contribution to the ecological footprint. The country should also attract investments for renewable energy sources, infrastructure, and technology to improve bio-productivity.

Philip et al. [65] to study the best policies for Malaysia to achieve the 2030 climate goal to curb carbon emissions. This research found that in the beginning of the economic growth, economic activities posed negative effects to the environment. However, the relationship was reversed at a later stage. Hence, this research recommended the deregulation of the renewable energy sector to include private and public players. The government can also offer tax reductions and credits and encourage financial institutions to support the investment in renewable energy.

Xie et al. [66] studied the effects of mineral and forestry resource volatility on the economic performances around the world from 1985 to 2021. This research found that mineral resources and forestry resources have a unidirectional causality to economic performances. However, the researchers also argued that oversupply of natural resources is detrimental to the economy of a country. Renewable energy sources should be adequate to meet output objectives. Countries also need to practice efficient use of renewable energy resources to meet sustainability goals.

Adebayo [67] investigated the environmental consequences of fossil fuels in Spain. Fossil fuels lowered the environmental quality in the short and medium term, but renewable energy improved the quality of the environment. FDI enhanced the environmental quality, but economic complexity had detrimental effects on the quality of the environment. Based on outcome, the government can carry out schemes to attract FDI and multinational players to invest in green technologies. The government can also implement and tighten the environmental regulations for multinational companies currently operating in the country. Subsidies and tax reliefs for clean technologies can be introduced. The government should also encourage the shift to an energy mix to reduce reliance on fossil fuels and increase investment in renewable energy. Economic structural change can also be accelerated to improve the knowledge intensive sectors and production input mix for efficient performances.

Huang et al. [68] measured the causality between economic policies and carbon dioxide emissions in the European Union. This study aimed to find out the relationship between macroeconomic policies, national expenditure, non-renewable energy use, renewable energy use, and carbon dioxide emissions. Monetary tools had harmful effects on carbon emissions. The tightening of monetary policy could reduce the adverse effects of carbon emissions. Policy assessment also had a unidirectional relationship with energy use.

Nketiah et al. [69] studied the impacts of tourism, renewable energy, and biocapacity in enhancing or restricting the ecological footprints in West Africa. Human capital, natural resources, tourism, and real income had positive effects on the ecological footprints in West Africa. There was unidirectional causality from ecological footprints to renewable energy usage, human capital and urbanization. A bidirectional relationship was observed between biocapacity and real income. This research suggested that countries in West Africa implement policies to deter increasing ecological footprints per capita and reduce overexploitation of natural resources.

4. Neurosciences

Granger causality has wide application in neurosciences such as cognitive, computational, and clinical neurosciences. Pesaran et al. [18] investigated large-scale brain dynamics. Granger causality was used because it was easy to apply to identify the direction of influence for temporal predictions in stochastic processes. Granger causality can also differentiate between direct and indirect influences. Wang et al. [70] studied the interacting brain networks when robot-assisted training and simulation were used. Granger causality was used to study the effective connectivity of the brain networks when while performing rehabilitation training tasks with a robotic device under various feedback conditions. Du et al. [71] aimed to find out whether a vibrotactile enhanced hand rehabilitation device could enhance sensorimotor brain activities. The training task of moving a hand and vibration simulation had strong causal influences between both sides of the cerebral hemispheres, and thus, had high training efficiency in functional cerebral hemodynamics.

Ye et al. [72] investigated the neural features of internet gaming disorder. Granger causality test revealed that there was connectivity from the right precentral gyrus to the left precentral gyrus and dorsal anterior cingulate cortex, which affected the internet gaming disorder severity. Zhang et al. [73] proposed the cross-frequency Granger causality feature extraction and fusion in both hemispheres for EEG emotion recognition. This proposed Granger causality had higher accuracy than the same-frequency band Granger causality features. Sysoev et al. [74] used Granger causality to describe the directed network activities between the somatosensory index and rostral reticular thalamic nucleus, caudal reticular thalamic nucleus, higher order thalamic nuclei and first order ventral posteromedial thalamic nucleus during sleep and wakefulness in rats. Ursino et al. [75] interpreted cortical signals reconstructed from EEG to study brain connectivity using temporal Granger causality in individuals with autism. Fu et al. [76] used neural Granger causality to examine the changes in schizophrenia's non-linear causal couplings.

5. Computer Science

Lamsal et al. [77] used Granger causality to predict the COVID-19 daily cases in Australia from Twitter conversations. This study found that latent social media variables had extra prediction capability for forecasting models. Cai et al. [78] studied the causal effects of social bots on information diffusion in social networks for public health information in China. Granger causality found that sentiments of humans and social bots were able to predict each other. This research then suggested that emergency managers shall control the bots at the end paths and act as opinion leaders to guide internet users' sentiments. Tank et al. [79] used deep learning to propose non-linear dynamics of Granger causality with structured multilayer perceptrons or recurrent neural networks and sparsity inducing penalties on the weights.

Pirnay and Burnay [80] attempted to systemize the identification of causalities in Strategy Maps for risk management and decision-making in Belgium. A hybrid gray theory and Granger causality model was constructed for sensor correlation network structure mining on trains. After building the vehicle information network, the researchers used complex network theory to mine the vehicle information network to find the causality between the nodes. Wang et al. [81] detected a causal structure for cloud services using Granger causality. Their results noted that neural Granger causality was better on linear and non-linear time series data. For greater linear time series, linear Granger causality was more efficient. Aviles-Cruz et al. [82] studied single user activities on smartphones with data obtained from accelerometer sensors. Zhang et al. [83] used Granger causality to identify the spatiotemporal causal relationship to obtain useful features for a deep learning multitask learning model for traffic speed prediction.

Therefore, with the broad application of Granger causality and its policy implications in business, society, and public administration, this research intends to perform a bibliometric analysis of Granger causality.

References

1. Granger, C.W.J. Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. Econometrica 1969, 37, 424–438.
2. Granger, C.W.J. Testing for Causality: A Personal Viewpoint. J. Econ. Dyn. Control 1980, 2, 329–352.
3. Wijesekara, C.; Tittagalla, C.; Jayathilaka, A.; Ilukpotha, U.; Jayathilaka, R.; Jayasinghe, P. Tourism and Economic Growth: A Global Study on Granger Causality and Wavelet Coherence. PLoS ONE 2022, 17, e0274386.
4. Stokes, P.A.; Purdon, P.L. A Study of Problems Encountered in Granger Causality Analysis from a Neuroscience Perspective. Proc. Natl. Acad. Sci. USA 2017, 114, E7063–E7072.
5. Chvosteková, M.; Jakubík, J.; Krakovská, A. Granger Causality on Forward and Reversed Time Series. Entropy 2021, 23, 409.
6. Kirchgässner, G.; Wolters, J. Granger Causality. In Introduction to Modern Time Series Analysis; Kirchgässner, G., Wolters, J., Eds.; Springer: Berlin/Heidelberg, Germany, 2007; pp. 93–123. ISBN 978-3-540-73291-4.
7. Schreiber, T. Measuring Information Transfer. Phys. Rev. Lett. 2000, 85, 461–464.
8. Geweke, J. Measurement of Linear Dependence and Feedback between Multiple Time Series. J. Am. Stat. Assoc. 1982, 77, 304–313.
9. Barnett, L.; Seth, A.K. The MVGC Multivariate Granger Causality Toolbox: A New Approach to Granger-Causal Inference. J. Neurosci. Methods 2014, 223, 50–68.
10. Seth, A.K.; Barrett, A.B.; Barnett, L. Granger Causality Analysis in Neuroscience and Neuroimaging. J. Neurosci. 2015, 35, 3293–3297.
11. Wu, G.-R.; Liao, W.; Stramaglia, S.; Ding, J.-R.; Chen, H.; Marinazzo, D. A Blind Deconvolution Approach to Recover Effective Connectivity Brain Networks from Resting State FMRI Data. Med. Image Anal. 2013, 17, 365–374.
12. Roebroeck, A.; Formisano, E.; Goebel, R. Mapping Directed Influence over the Brain Using Granger Causality and FMRI. NeuroImage 2005, 25, 230–242.

13. Roelstraete, B.; Rosseel, Y. FIAR: An R Package for Analyzing Functional Integration in the Brain. J. Stat. Softw. 2011, 44, 1–32.
14. Soleimani, B.; Das, P.; Karunathilake, I.M.D.; Kuchinsky, S.E.; Simon, J.Z.; Babadi, B. NLGC: Network Localized Granger Causality with Application to MEG Directional Functional Connectivity Analysis. Neuroimage 2022, 260, 119496.
15. Gao, L.; Sommerlade, L.; Coffman, B.; Zhang, T.; Stephen, J.M.; Li, D.; Wang, J.; Grebogi, C.; Schelter, B. Granger Causal Time-Dependent Source Connectivity in the Somatosensory Network. Sci. Rep. 2015, 5, 10399.
16. Gow, D.W.; Segawa, J.A.; Ahlfors, S.P.; Lin, F.-H. Lexical Influences on Speech Perception: A Granger Causality Analysis of MEG and EEG Source Estimates. Neuroimage 2008, 43, 614–623.
17. Cadotte, A.J.; DeMarse, T.B.; Mareci, T.H.; Parekh, M.; Talathi, S.S.; Hwang, D.-U.; Ditto, W.L.; Ding, M.; Carney, P.R. Granger Causality Relationships between Local Field Potentials in an Animal Model of Temporal Lobe Epilepsy. J. Neurosci. Methods 2010, 189, 121–129.
18. Pesaran, B.; Vinck, M.; Einevoll, G.T.; Sirota, A.; Fries, P.; Siegel, M.; Truccolo, W.; Schroeder, C.E.; Srinivasan, R. Investigating Large-Scale Brain Dynamics Using Field Potential Recordings: Analysis and Interpretation. Nat. Neurosci. 2018, 21, 903–919.
19. Wang, X.; Yan, J.; Zhang, H.; Yuan, Y. Ultrasonic Thalamic Stimulation Modulates Neural Activity of Thalamus and Motor Cortex in the Mouse. J. Neural. Eng. 2021, 18, 066037.
20. Abdalbari, H.; Durrani, M.; Pancholi, S.; Patel, N.; Nasuto, S.J.; Nicolaou, N. Brain and Brain-Heart Granger Causality during Wakefulness and Sleep. Front. Neurosci. 2022, 16, 927111.
21. Hartmann, S.; Ferri, R.; Bruni, O.; Baumert, M. Causality of Cortical and Cardiovascular Activity during Cyclic Alternating Pattern in Non-Rapid Eye Movement Sleep. Philos. Trans. A Math. Phys. Eng. Sci. 2021, 379, 20200248.
22. Gao, Y.; Wang, X.; Potter, T.; Zhang, J.; Zhang, Y. Single-Trial EEG Emotion Recognition Using Granger Causality/Transfer Entropy Analysis. J. Neurosci. Methods 2020, 346, 108904.
23. Odhiambo, N.M.; Nyasha, S.; Zerihun, M.F.; Tipoy, C. 3—Financial Development in Africa: Is It Demand-Following or Supply-Leading? In Extending Financial Inclusion in Africa; Makina, D., Ed.; Academic Press: Cambridge, MA, USA, 2019; pp. 37–60. ISBN 978-0-12-814164-9.
24. Boulila, G.; Trabelsi, M. The Causality Issue in the Finance and Growth Nexus: Empirical Evidence from Middle East and North African Countries. Rev. Middle East Econ. Financ. 2004, 2, 123–138.
25. Amano, M. Finance and Development: Granger-Causality Tests for Prewar and Postwar U.S.A., U.K., and Japan. In Capital Markets, Globalization, and Economic Development; Gup, B.E., Ed.;

Innovations in Financial Markets and Institutions; Springer: Boston, MA, USA, 2005; pp. 207–217. ISBN 978-0-387-24563-8.

26. Fahimi, A.; Olasehinde-Williams, G.; Akadiri, S.S. Examining the Causal Relationship between Globalization and Energy Consumption in MINT Countries: Evidence from Bootstrap Panel Granger Causality. Int. J. Financ. Econ. 2021, 26, 1886–1896.
27. Candelon, B.; Tokpavi, S. A Nonparametric Test for Granger Causality in Distribution With Application to Financial Contagion. J. Bus. Econ. Stat. 2016, 34, 240–253.
28. Coronado, S.; Martinez, J.N.; Gualajara, V.; Rojas, O. Transfer Entropy Granger Causality between News Indices and Stock Markets in U.S. and Latin America during the COVID-19 Pandemic. Entropy 2022, 24, 1420.
29. Zuhud, D.A.Z.; Musa, M.H.; Ismail, M.; Bahaludin, H.; Razak, F.A. The Causality and Uncertainty of the COVID-19 Pandemic to Bursa Malaysia Financial Services Index's Constituents. Entropy 2022, 24, 1100.
30. Bisht, K.; Kumar, A. A Portfolio Construction Model Based on Sector Analysis Using Dempster-Shafer Evidence Theory and Granger Causal Network: An Application to National Stock Exchange of India. Expert Syst. Appl. 2023, 215, 119434.
31. Ranco, G.; Aleksovski, D.; Caldarelli, G.; Grčar, M.; Mozetič, I. The Effects of Twitter Sentiment on Stock Price Returns. PLoS ONE 2015, 10, e0138441.
32. Hamraoui, I.; Boubaker, A. Impact of Twitter Sentiment on Stock Price Returns. Soc. Netw. Anal. Min. 2022, 12, 28.
33. Pao, H.-T.; Tsai, C.-M. Multivariate Granger Causality between CO2 Emissions, Energy Consumption, FDI (Foreign Direct Investment) and GDP (Gross Domestic Product): Evidence from a Panel of BRIC (Brazil, Russian Federation, India, and China) Countries. Energy 2011, 36, 685–693.
34. Hiemstra, C.; Jones, J.D. Testing for Linear and Nonlinear Granger Causality in the Stock Price-Volume Relation. J. Financ. 1994, 49, 1639–1664.
35. Soytas, U.; Sari, R. Energy Consumption, Economic Growth, and Carbon Emissions: Challenges Faced by an EU Candidate Member. Ecol. Econ. 2009, 68, 1667–1675.
36. Borozan, D. Granger Causality and Innovation Accounting Analysis of the Monetary Transmission Mechanism in Croatia. Post Communist Econ. 2011, 23, 517–537.
37. Smailović, J.; Grčar, M.; Lavrač, N.; Žnidaršič, M. Stream-Based Active Learning for Sentiment Analysis in the Financial Domain. Inf. Sci. 2014, 285, 181–203.
38. Lee, C.-C.; Chien, M.-S. Structural Breaks, Tourism Development, and Economic Growth: Evidence from Taiwan. Math. Comput. Simul. 2008, 77, 358–368.

39. Ghosh, S.; Balsalobre-Lorente, D.; Doğan, B.; Paiano, A.; Talbi, B. Modelling an Empirical Framework of the Implications of Tourism and Economic Complexity on Environmental Sustainability in G7 Economies. J. Clean. Prod. 2022, 376, 134281.

40. Wang, X.; Dong, F. The Dynamic Relationships among Growth in the Logistics Industry, Energy Consumption, and Carbon Emission: Recent Evidence from China. J. Petrol. Explor. Prod. Technol. 2023, 13, 487–502.

41. Lo, D.; Yau, Y.; McCord, M.; Haran, M. Lead-Lag Relationship between the Price-to-Rent Ratio and the Macroeconomy: An Empirical Study of the Residential Market of Hong Kong. Buildings 2022, 12, 1345.

42. Deshpande, G.; Wang, P.; Rangaprakash, D.; Wilamowski, B. Fully Connected Cascade Artificial Neural Network Architecture for Attention Deficit Hyperactivity Disorder Classification From Functional Magnetic Resonance Imaging Data. IEEE Trans. Cybern. 2015, 45, 2668–2679.

43. Li, G.; Qin, S.J.; Yuan, T. Data-Driven Root Cause Diagnosis of Faults in Process Industries. Chemom. Intell. Lab. Syst. 2016, 159, 1–11.

44. Tan, X.; Liu, Y.; Liu, D.; Zhu, D.; Zeng, W.; Wang, H. An Attention-Based Deep Convolution Network for Mining Airport Delay Propagation Causality. Appl. Sci. 2022, 12, 10433.

45. Xie, X.; Rosales, H.G. Analysis of Spatial and Temporal Differences in China's Provincial Tourism Economy Based on Parallel Data Model and IoT Applications. Wirel. Commun. Mob. Comput. 2022, 2022, 1431345.

46. Almerekhi, H.; Kwak, H.; Jansen, B.J. Investigating Toxicity Changes of Cross-Community Redditors from 2 Billion Posts and Comments. PeerJ Comput. Sci. 2022, 8, e1059.

47. Tian, Y.; He, J.; Peng, Z.; Guan, Y.; Wu, L. Lithium-Ion Battery Degradation and Capacity Prediction Model Considering Causal Feature. IEEE Trans. Transp. Electrif. 2022, 8, 3630–3647.

48. Shahandashti, S.; Ashuri, B. Forecasting Engineering News-Record Construction Cost Index Using Multivariate Time Series Models. J. Constr. Eng. Manag. 2013, 139, 1237–1243.

49. Liu, D.; Niu, D.; Wang, H.; Fan, L. Short-Term Wind Speed Forecasting Using Wavelet Transform and Support Vector Machines Optimized by Genetic Algorithm. Renew. Energy 2014, 62, 592–597.

50. Su, C.-W.; Yuan, X.; Tao, R.; Umar, M. Can New Energy Vehicles Help to Achieve Carbon Neutrality Targets? J. Environ. Manag. 2021, 297, 113348.

51. Shahandashti, S.; Ashuri, B. Highway Construction Cost Forecasting Using Vector Error Correction Models. J. Manag. Eng. 2015, 32, 04015040.

52. Zhang, Y.; Zhang, S. The Impacts of GDP, Trade Structure, Exchange Rate and FDI Inflows on China's Carbon Emissions. Energy Policy 2018, 120, 347–353.

53. Ben Jebli, M.; Ben Youssef, S.; Apergis, N. The Dynamic Linkage between Renewable Energy, Tourism, CO2 Emissions, Economic Growth, Foreign Direct Investment, and Trade. Lat. Amer. Econ. Rev. 2019, 28, 2.
54. Sunde, T. Foreign Direct Investment, Exports and Economic Growth: ADRL and Causality Analysis for South Africa. Res. Int. Bus. Financ. 2017, 41, 434–444.
55. Arogundade, S.; Mduduzi, B.; Eita, H. Foreign Direct Investment and Poverty in Sub-Saharan African Countries: The Role of Host Absorptive Capacity. Cogent Econ. Financ. 2022, 10, 2078459.
56. Farooqi, M.F.; O’Brien, J. A Comparison of the Impact of the Basel Standards upon Islamic and Conventional Bank Risks in the Gulf State Region. J. Islam. Account. Bus. Res. 2019, 10, 216–235.
57. Setyowati, N. Macroeconomic Determinants of Islamic Banking Products in Indonesia. Economies 2019, 7, 53.
58. Samad, A. Is There Any Causality between Islamic Banks’ Return on Depositors and Conventional Banks’ Deposit Interest: Evidence of Causality from Bahrain’s Financial Market. Bus. Econ. Horiz. 2018, 14, 894–912.
59. Sharif, A.; Aloui, C.; Yarovaya, L. COVID-19 Pandemic, Oil Prices, Stock Market, Geopolitical Risk and Policy Uncertainty Nexus in the US Economy: Fresh Evidence from the Wavelet-Based Approach. Int. Rev. Financ. Anal. 2020, 70, 101496.
60. Wang, G.-J.; Xie, C.; Wen, D.; Zhao, L. When Bitcoin Meets Economic Policy Uncertainty (EPU): Measuring Risk Spillover Effect from EPU to Bitcoin. In Finance Research Letters; Elsevier: Amsterdam, The Netherlands, 2019; Volume 31.
61. Robiyanto, R.; Nugroho, B.A.; Handriani, E.; Frensidy, B. Measuring the Effectiveness of ASEAN-5 Initiatives from Emerging Market Portfolio’s Perspective. Cogent Bus. Manag. 2023, 10, 2167292.
62. Athari, S.A.; Bahreini, M. Does Economic Policy Uncertainty Impact Firms’ Capital Structure Policy? Evidence from Western European Economies. Environ. Sci. Pollut. Res. 2022, 30, 37157–37173.
63. Athari, S.A. Financial Inclusion, Political Risk, and Banking Sector Stability: Evidence from Different Geographical Regions. Econ. Bull. 2022, 42, 99–108.
64. Zafar, M.W.; Zaidi, S.A.H.; Khan, N.R.; Mirza, F.M.; Hou, F.; Kirmani, S.A.A. The Impact of Natural Resources, Human Capital, and Foreign Direct Investment on the Ecological Footprint: The Case of the United States. Resour. Policy 2019, 63, 101428.

65. Philip, L.D.; Emir, F.; Udemba, E.N. Investigating Possibility of Achieving Sustainable Development Goals through Renewable Energy, Technological Innovation, and Entrepreneur: A Study of Global Best Practice Policies. Environ. Sci. Pollut. Res. 2022, 29, 60302–60313.
66. Xie, M.; Irfan, M.; Razzaq, A.; Dagar, V. Forest and Mineral Volatility and Economic Performance: Evidence from Frequency Domain Causality Approach for Global Data. Resour. Policy 2022, 76, 102685.
67. Adebayo, T.S. Environmental Consequences of Fossil Fuel in Spain amidst Renewable Energy Consumption: A New Insights from the Wavelet-Based Granger Causality Approach. Int. J. Sustain. Dev. World Ecol. 2022, 29, 579–592.
68. Huang, W.; Saydaliev, H.B.; Iqbal, W.; Irfan, M. Measuring the Impact of Economic Policies on Co2 Emissions: Ways to Achieve Green Economic Recovery in the Post-Covid-19 Era. Clim. Change Econ. 2022, 13, 2240010.
69. Nketiah, E.; Song, H.; Obuobi, B.; Adu-Gyamfi, G.; Adjei, M.; Cudjoe, D. The Impact of Ecological Footprint in West Africa: The Role of Biocapacity and Renewable Energy. Int. J. Sustain. Dev. World Ecol. 2022, 29, 514–529.
70. Wang, D.; Huang, Y.; Liang, S.; Meng, Q.; Yu, H. The Identification of Interacting Brain Networks during Robot-Assisted Training with Multimodal Stimulation. J. Neural. Eng. 2023, 20, 016009.
71. Du, Q.; Luo, J.; Cheng, Q.; Wang, Y.; Guo, S. Vibrotactile Enhancement in Hand Rehabilitation Has a Reinforcing Effect on Sensorimotor Brain Activities. Front. Neurosci. 2022, 16, 935827.
72. Ye, S.; Wang, M.; Yang, Q.; Dong, H.; Dong, G.-H. Predicting the Severity of Internet Gaming Disorder with Resting-State Brain Features: A Multi-Voxel Pattern Analysis. J. Affect. Disord. 2022, 318, 113–122.
73. Zhang, J.; Zhang, X.; Chen, G.; Huang, L.; Sun, Y. EEG Emotion Recognition Based on Cross-Frequency Granger Causality Feature Extraction and Fusion in the Left and Right Hemispheres. Front. Neurosci. 2022, 16, 1512.
74. Sysoev, I.V.; van Luijtelaar, G.; Lüttjohann, A. Thalamo-Cortical and Thalamo-Thalamic Coupling During Sleep and Wakefulness in Rats. Brain Connect. 2022, 12, 650–659.
75. Ursino, M.; Serra, M.; Tarasi, L.; Ricci, G.; Magosso, E.; Romei, V. Bottom-up vs. Top-down Connectivity Imbalance in Individuals with High-Autistic Traits: An Electroencephalographic Study. Front. Syst. Neurosci. 2022, 16, 932128.
76. Fu, Y.; Niu, M.; Gao, Y.; Dong, S.; Huang, Y.; Zhang, Z.; Zhuo, C. Altered Nonlinear Granger Causality Interactions in the Large-Scale Brain Networks of Patients with Schizophrenia. J. Neural. Eng. 2022, 19, 066044.

77. Lamsal, R.; Harwood, A.; Read, M.R. Twitter Conversations Predict the Daily Confirmed COVID-19 Cases. Appl. Soft Comput. 2022, 129, 109603.

78. Cai, M.; Luo, H.; Meng, X.; Cui, Y.; Wang, W. Network Distribution and Sentiment Interaction: Information Diffusion Mechanisms between Social Bots and Human Users on Social Media. Inf. Process. Manag. 2023, 60, 103197.

79. Tank, A.; Covert, I.; Foti, N.; Shojaie, A.; Fox, E.B. Neural Granger Causality. IEEE Trans. Pattern Anal. Mach. Intell. 2022, 44, 4267–4279.

80. Pirnay, L.; Burnay, C. How to Build Data-Driven Strategy Maps? A Methodological Framework Proposition. Data Knowl. Eng. 2022, 139, 102019.

81. Wang, Q.; Shwartz, L.; Grabarnik, G.Y.; Arya, V.; Shanmugam, K. Detecting Causal Structure on Cloud Application Microservices Using Granger Causality Models. In Proceedings of the 2021 IEEE 14th International Conference on Cloud Computing (CLOUD), Chicago, IL, USA, 5–10 September 2021; pp. 558–565.

82. Aviles-Cruz, C.; Rodriguez-Martinez, E.; Villegas-Cortez, J.; Ferreyra-Ramirez, A. Granger-Causality: An Efficient Single User Movement Recognition Using a Smartphone Accelerometer Sensor. Pattern Recognit. Lett. 2019, 125, 576–583.

83. Zhang, K.; Zheng, L.; Liu, Z.; Jia, N. A Deep Learning Based Multitask Model for Network-Wide Traffic Speed Prediction. Neurocomputing 2020, 396, 438–450.