American Journal of Theoretical and Applied Statistics
2024, Vol. 13, No. 6, pp. 227-241
https://doi.org/10.11648/j.ajtas.20241306.15

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Research Article

Statistical Network Analysis of Macroeconomic Variables in Ghana

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Abstract

In the rapidly evolving economic landscape of Ghana, understanding the intricate interdependencies between macroeconomic variables is pivotal for informed policymaking and strategic economic planning. The study employed network analysis to enhance our comprehension of Ghana's macroeconomic dynamics. Data was sourced from the world development indicators. Initially, a statistical network was constructed to represent the interconnections between Ghana's principal macroeconomic variables using partial correlation matrix, offering a visual and analytical perspective of their relationships. Subsequently, centrality measures and other network analysis tools were utilized to identify and quantify the influence of key economic indicators within this network. Results showed that Exports, Inflation, Exchange rate, Gross Domestic Saving, Manufacturing and Gross National Expenditure played a significant role in the network. However, Agriculture and Imports were identified as most influential variables with high centrality scores across all centrality measures. Finally, Exponential Random Graph Model was employed to provide a comparative baseline, shedding light on the uniqueness or randomness of the observed interrelationships. The significant parameters in the model include the presence of edges between nodes and the presence of generalized geodesic triads (gwesp), which capture the tendency for nodes to form connections based on common neighbors. The findings also revealed that there is a probability of 16.19% for a relationship to exist between two macroeconomic variables if they are both connected to the same third variable.

Keywords

Macroeconomic Variables, Statistical Network, Partial Correlation, Exponential Random Graph Model

1. Introduction

Macroeconomic indicators are statistics that measure the overall health of an economy. They include variables like GDP growth, interest rates, inflation, unemployment, and exchange rate among others. In the last decade,

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Received: 13 November 2024; **Accepted:** 23 November 2024; **Published:** 16 December 2024

macroeconomic variables such as inflation and interest rates have played an important role in driving economic progress in both developing and industrialized countries [1].

Ghana's economy, once primarily based on agriculture, has seen a significant shift towards services and industry over the past few decades [2]. This transformation, together with the discovery of significant oil reserves in 2007 [3], has led to substantial changes in the nation's macroeconomic landscape.

While Ghana has enjoyed periods of strong economic growth, it has also faced considerable challenges such as high inflation, mounting debt, and recurrent fiscal deficits [2]. These issues have prompted a re-evaluation of the relationships among the country's macroeconomic factors and how they affect economic stability and growth.

There is a large volume of written work examining the interplay of macroeconomic variables in Ghana. The determinants of economic growth in Ghana has been explored highlighting the significance of Foreign Direct Investment (FDI), inflation, and government consumption [4]. The relationships between Ghana's macroeconomic indicators and its export performance, has been studied which underscored the importance of a stable macroeconomic environment for fostering trade [5].

However, most existing studies rely on traditional linear regression and time-series models that may fail to capture the full complexity of the economic system [6, 30, 31]. This creates a research gap in understanding the non-obvious, nonlinear interdependencies among macroeconomic variables.

The emerging field of statistical network analysis offers a potential solution to this problem. Network analysis, at its core, explores relationships [7]. When applied to macroeconomic variables, it shifts our perspective from isolated metrics to a web of interdependencies. By constructing a network where each node represents a macroeconomic variable and the edges represent the statistical relationships between them, it becomes possible to explore the complex interactions within the system [8]. However, to the best of our knowledge, such a comprehensive network analysis of Ghana's macroeconomic variables has not yet been performed. This research, therefore, aims to fill this gap.

The structure of this article is as follows: Section 2 examines the related literature; Section 3 outlines the materials, methods, and proposed model. Section 4 showcases the results and discussion; Section 5 summarizes the findings and concludes the study.

2. Review of Literature

Numerous studies have utilized network analysis to examine economic systems, predominantly focusing on developed nations and global networks. Social interactions among individuals form complex networks that influence economic outcomes [9]. The formation of networks and the interdependencies between agents' behaviors were analyzed, demonstrating the applicability of network theory in economic contexts. A study was conducted to examine the role of spatial networks in economic models, emphasizing on the impact of geographical positioning and local interconnections on regional economic outcomes [10]. Network analysis was used to study the interbank lending market, the results revealed that the layered structure of the financial system and network complexities can contribute to systemic risk during financial distress [11]. Another study mapped-out international trade network, identifying core and peripheral countries and illustrating how shocks can propagate through the global economic system [12].

A research conducted suggested that random networks could be useful for studying network formation [13]. Networks are ubiquitous in science and everyday life, with statistical models for analyzing network data becoming crucial across various fields. The Erdős–Rényi–Gilbert model laid the foundation for social science network research, leading to the field of random graph theory. Exponential Random Graph Models (ERGMs) have gained popularity in studying social networks, capable of explaining the formation and structure of these networks [14]. Another study provided guidance on usage of ERGMs, leading to their widespread applications in analyzing cumulative linkages and cross-sectional network architectures [15].

However, the application of these approaches on the economic system of individual developing economies, such as Ghana, remains limited. Most studies on the macroeconomic landscape of Ghana are based on the traditional linear models. A foundational model for understanding the interplay of macroeconomic variables, investigating the fluctuating relationships between output and unemployment using a structural vector autoregression was studied [16]. A comprehensive overview of the challenges and successes faced by African countries in managing their macroeconomies was examined, highlighting the diverse economic contexts across the continent [17]. An extensive review was carried-out on macroeconomic policies in developing countries, offering insights into the unique challenges and opportunities within African economies, including Ghana [18]. A research conducted argued that understanding the correlation between money supply and inflation is essential for effective monetary policy implementation [19]. Another study examined the effects of monetary expansion and exchange rates on consumer price inflation in sub-Saharan Africa, revealing a substantial "Granger causal" effect of exchange rates on prices in countries like Tanzania, Sierra Leone, and the Democratic Republic of the Congo [20].

3. Methodology

This section details the research methodology employed, including data sources, network construction, analysis, and the exponential random graph model (ERGM).

3.1. Data Source

The macroeconomic data used in this study were sourced from the World Bank's website, covering a substantial timeframe from 1970 to 2022. This extensive dataset captures both short-term fluctuations and long-term trends.

3.2. Definition of Variables

Twelve major macroeconomic variables were employed in the study. They included:

3.2.1. Gross Domestic Product (GDP)

GDP tracks the total value of everything produced in a country over a certain period. This includes all finished goods and services. It is a key indicator of a country's economic health, showing how much the country is earning, spending, and growing.

3.2.2. Gross National Expenditure (GNE)

Gross National Expenditure is made up of spending by individuals (household consumption), government spending, and investments within the country (gross domestic investment).

3.2.3. Gross Domestic Savings (GDS)

Gross domestic savings can be found by subtracting final consumption expenditure (total consumption) from GDP.

3.2.4. Manufacturing

Manufacturing is the part of the economy where raw materials are transformed into finished goods through various production methods. This includes everything from getting the materials to production, getting them to stores, and even providing customer support afterwards.

3.2.5. Gross Fixed Capital Formation (GFCF)

This term refers to all the new and existing buildings and infrastructure that get built or upgraded in an economy. This includes things like improvements to land, machinery purchases for businesses, and construction of transportation networks, schools, hospitals, and various types of buildings for housing, businesses, and industry.

3.2.6. Agriculture, Forestry and Fishing

This sector covers activities that get food and resources from the land and water. It includes raising animals (livestock production), growing crops (cultivation), forestry, fishing and hunting.

3.2.7. Official Exchange Rate

An exchange rate is basically a price tag showing how much of one currency you need to buy another currency. These prices are constantly changing based on supply and demand. Supply and demand are affected by international trade and payments, as well as money constantly moving around the world looking for the best investments.

3.2.8. Total Debt Service (TDS)

Total debt service is the total amount of money a country needs to pay back its debts each year. This includes payments on both long-term loans (with principal and interest) and short-term loans, as well as any repayments owed to the International Monetary Fund (IMF).

3.2.9. Inflation

Inflation or Consumer Price Index (CPI) tracks how much the cost of living changes over time. It does this by measuring the monthly or yearly increase or decrease in the price of a typical basket of goods and services that people buy.

3.2.10. Foreign Direct Investment (FDI)

Foreign direct investment is when a company or investor from one country puts money into a business in another country, with the goal of having a say in how that business is run. This investment can come in different forms, like buying shares in the company, putting more money back into the business from its profits, or even loans.

Imports of Goods and Service

Imports are all the things a country buys from other countries. This includes physical goods like furniture or clothes, but also services like transportation (shipping costs), insurance, travel (tourism spending), and professional services like consulting or financial advice. Basically, it is the total value of everything a country gets from abroad.

Exports of Goods and Service

Exports are all the things a country sells to other countries. This includes physical goods like furniture or clothes, but also services like transportation (shipping costs), insurance, travel (tourism revenue), and professional services like consulting or financial advice. Basically, it is the total value of everything a country sends abroad. It's important to note that exports don't include wages earned by people working abroad or income from investments made overseas.

3.3. Network Construction Based on Partial Correlation

The study employed partial correlation matrix to construct directed network of Ghana's macroeconomic variables. Each variable is seen as a node, and the strength of relationships is represented by edge weights. When building association networks based on Pearson's correlation or similar methods, it is important to remember the saying "correlation does not imply causation." This means that just because two nodes in a network have highly correlated attributes does not necessarily mean that they directly influence each other. The observed correlation between these two nodes could be driven by a shared influence from a third node. Partial correlation can help to remove the influence of other nodes when measuring the correlation between two nodes.

The partial correlation ($\rho_{ij}|s_m$) between two nodes, X_i and X_j adjusting for the attributes X_{k1},..., X_{km}(denoted by X_{Sm}), is a measure of how strongly those nodes are related to each other, after accounting for the influence of those attributes that are common to both X_i and X_j. It can be express as:

$$\rho_{ij}|s_m = \frac{\sigma_{ij}|s_m}{\sqrt{\sigma_{ii}|s_m\sigma_{jj}|s_m}} \tag{1}$$

where $\sigma_{ij}|s_m$ is the covariance between X_i and X_j after adjusting for X_{Sm}. $\sigma_{ii}|s_m$ and $\sigma_{jj}|s_m$ are variances of X_i and X_j after adjusting for X_{Sm}, respectively. S_m = $\{X_{k_1}$...,$X_{s_m}\}$, where k_1, k_2,..., k_m are specific vertices from the set *V*, and importantly, these vertices are not *i* or *j*. It contains the influence of other attributes. By adjusting for them, we can better understand the direct relationship between X_i and X_j, independent of the effects of the attributes in S_m.

There are ways to calculate partial correlation coefficients of any order using recursive formulas. For example, the partial correlation of two attributes X_i and X_j, for two nodes *i* and *j* adjusted for a third attribute, X_k of a third node *k* can be expressed as follows:

$$\rho_{ij|k} = \frac{\rho_{ij}-\rho_{ik}\rho_{jk}}{\sqrt{(1-\rho_{ik}^2)(1-\rho_{jk}^2)}} \tag{2}$$

where $\rho_{ij|k}$ denotes the partial correlation between X_i and X_j, adjusting for X_k. In other words, it measures the unique association between X_i and X_j once we have removed the influence of X_k. ρ_{ij} represents the direct correlation between X_i and X_j, without accounting for any other variables. The product $\rho_{ik}\rho_{jk}$ captures the shared correlation of X_i and X_j with X_k. Essentially, it measures how X_i and X_j are related through their individual relationships with X_k. The denominator normalizes the value to ensure the result stays within the bounds of -1 and 1 (the range of correlation values).

Instead of using the raw values of these measurements, it is more convenient to use a transformed version of the values. One such transformation is Fisher's transformation, $Z_{ij|sm}$, given as

$$Z_{ij|sm} = \frac{1}{2} log \left[\frac{(1+\rho_{ij|sm})}{(1-\rho_{ij|sm})}\right] \tag{3}$$

where $\rho_{ij|sm}$ is the partial correlation coefficient to be transformed and log is the natural logarithm. One of the primary reasons to use the Fisher's transformation is that while the distribution of $\rho_{ij|sm}$ (the correlation coefficient) is not normally distributed (especially when the true correlation is far from zero), the distribution of *z* (after the transformation) tends to be approximately normally distributed. Also, the variance of the correlation coefficient $\rho_{ij|sm}$ can change based on the true correlation. The Fisher's transformation stabilizes this variance, making it nearly constant across different true correlations. Benjamini-Hochberg Multiple Testing was employed to select the significant edges for the construction of the network.

3.4. Network Analysis

In network analysis, network graphs are often the primary emphasis because they are a good way to represent interactions between different parts of a complex system. But in many instances, the characteristic linked to each component of the system is actually the most crucial factor. In the context of graph theory, a graph *(G)* is defined by two sets: an edge set and a vertex set. A graph *(G)* can be expressed as follows:

$$G = (V, E),$$

where *V* represents vertices also known as nodes. This set contains all the points in the graph. Each individual point is termed a vertex (or node). In this study, each macroeconomic variable was taken as a node or vertex. *E* represents edges. It is a set that contains all the lines connecting pairs of vertices. Each line is termed an edge. A pair *(u, v)*, where *(u)* and *(v)* are vertices in *(V)*, represents each edge. Edge *(u, v)* is equal to edge (v, u) if the graph is undirected, which means that the vertices in this pair don't matter in terms of order. However, if the graph is directed (a digraph), the order does matter, as it indicates direction from *(u)* to *(v)*.

There can be additional attributes or features associated with both vertices and edges based on how intricate the graph is. For example, edges may be weighted to show how expensive or strong a link is. Both vertices and edges can be labeled or colored to denote categories or types. In this study, edge represents the relationship or link between variables.

To understand the network's structural properties, centrality measures were computed. This helps us identify the most influential indicators and the formation of subgroups within the economy. The main measures will be degree centrality/vertex strength, betweenness, eigenvector centrality, and closeness centrality. These measures help identify economic indicators with the most connections and those that serve as important links between other variables.

A node's degree is determined by how many edges it possesses. Degree centrality tells how connected a node is, based on how many direct connections it has to other nodes. In a weighted network, however, one may want to take into consideration not just the number of connections but also the strength of those connections. The vertex strength of a given node is obtained by adding up the weights of all the edges that are incident to that node. In other words, it measures the total strength or intensity of all connections that the node possesses.

The number of times a node serves as a bridge (or broker) along the shortest path between two other nodes is quantified by betweenness centrality. A vertex's importance in a network graph is indicated by its vertex centrality. The number of shortest paths between other vertices that pass through the vertex is used to calculate it. High centrality vertices are more significant since they are essential to network connectivity and information transfer. The number of shortest pathways between two vertices that traverse a particular vertex is divided by the total number of shortest paths between those two vertices to get betweenness centrality (*cB*). It can be defined as

$$cB(v) = \sum_{s \neq t \neq v \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)} \tag{4}$$

where $\sigma(s,t|v)$ is the number of times that the vertex v is used as a bridge on the shortest paths between the nodes *s* and *t*. $\sigma(s,t)$ is the entire number of paths (links) between *s* and *t*, regardless of whether they go through v. Betweenness centrality can be normalized to the unit interval (0,1) by dividing by a factor of $(N_v - 1)(N_v - 2)/2$, where N_v is the number of vertices in the network.

Eigenvector centrality evaluates a node's impact within a network by assigning proportional scores to all nodes. This is done under the premise that connections to nodes with higher scores exert a greater influence on the score of the node in focus, compared to connections with nodes holding lower scores. The eigenvector centrality *x* of a node *v* is defined by:

$$\lambda x(v) = \sum_{t \in M(v)} x(t) \tag{5}$$

where the network's eigenvalue is represented by λ which is the constant that scales the centrality scores. $x(v)$ is the eigenvector centrality score for vertex *v*. It measures the node's centrality or significance within the network. $\sum_{t \in M(v)}$, sums over all nodes *t* that are neighbours of node *v*. In other words, it sums the centrality scores of all nodes connected to node *v*. *t* is a variable, representing the nodes in the set of neighbours of node *v*, denoted as *M*(*v*).

Closeness centrality (C_c) measures a vertex's proximity to every other vertex in a network. It is calculated by summing the distances from the vertex to all other vertices and then taking the reciprocal of that sum. It can be defined as

$$C_c(v) = \frac{1}{\sum_{u \epsilon V} dist(v,u)} \tag{6}$$

where *dist(v, u)* is the shortest path distance between nodes *v* and *u*. This measure is normalized to lie in the interval [0,1], by multiplying by a factor $N_V - 1$ where N_V is the total number of vertices in the network. Any node in the network can interact with any other node fast if it has a high proximity centrality. It measures the average farness of a node to all other nodes.

The study also considered articulation points. A cut vertex, also known as an articulation point, is a vertex in a network that disconnects the network when it is removed from the network. Identifying cut vertices can help us to understand where a network is vulnerable to attack or failure.

3.5. Exponential Random Graph Models (ERGM)

ERGMs are a kind of statistical models which explain the formation of edges in a network. ERGMs try to predict the probability of seeing a particular network structure based on certain features or configurations in the network. Here, the features (or "configurations") are different possible combinations of connections among variables. These configurations can tell us about dependencies in the network. For instance, if one connection is present, it might influence the probability of another connection being present. The ERGM can be tweaked and adjusted to study different types of networks, whether they show one-way relationships or mutual relationships. Moreover, ERGMs can also include information about the individual nodes.

Given a graph *G= (V, E)*, where *V* is the set of vertices (or nodes) and *E* is the set of edges. $y_{ij} = y_{ji}$ is a binary variable. It's either 1 if there is a connection between vertex *i* and vertex *j* or 0 if there isn't. $Y = [Y_{ij}]$ represents the adjacency matrix for the graph G. It keeps track of which vertices are connected. The ERGM is formulated as follows:

$$P_\theta(Y = y) = \frac{1}{\kappa(\theta)} exp(\textstyle\sum_H \theta_H g_H(y)) \tag{7}$$

where $P_\theta(Y = y)$ represents the probability of observing a particular graph y given parameters, θ . $\kappa(\theta)$ is a normalization constant which makes sure that the probabilities add up to 1 and H is a configuration. This configuration consists of a range of potential edges connecting a subset of vertices. θ_H is the coefficient or weight for configuration H and $g_H(y)$ is the function of the data y. It is either 1 if configuration H occurs in y or 0 otherwise. The numerator reflects a linear function in logarithmic terms given as:

$$log(\exp(\theta^T g(y))) = \theta_1 g_1(y) + \theta_2 g_2(y) + \cdots + \theta_p g_p(y) \tag{8}$$

The normalization constant:

$$\kappa(\theta) = \textstyle\sum_y exp(\sum_H \theta_H g_H(y)) \tag{9}$$

This constant ensures that the probabilities over all possible graphs y sum to 1. It involves summing over all possible configurations H.

3.5.1. ERGM Specification

Exponential Random Graph Models (ERGMs) have proven invaluable in modelling network structures. However, traditional ERGMs often fall short in capturing the intricacies of higher-order network configurations. This research introduces the utilization of alternating k-stars and k-triangles to address this limitation, offering a more comprehensive approach to ERGM model specification. To outline the steps to effectively specify ERGMs with alternating k-stars the study will begin by introducing constraints on the parameters of higher-order star structures using the equation

$$\sigma(k+1) = -\frac{\sigma_k}{\lambda} \quad (10)$$

This ensures a linear relationship between parameters for stars of consecutive orders, reducing the number of independent parameters and facilitating model estimation. The calculation of the statistic u is central to capturing the overall effect of alternating k-stars in the network. Defined as

$$u = \sum_{k=2}^{n-1}(1)^k \frac{\sigma_k}{\lambda^{k-2}} \quad (11)$$

It is a sum over all k from 2 to $n-1$ (where n is the maximum order of stars considered).

The term $(1)^k$ alternates the sign of each term in the sum. The weights $\frac{1}{\lambda^{k-2}}$ decrease as k increases, reflecting the diminishing influence of higher-order stars. This statistic represents the sum of alternating higher-order star influence. A positive alternating k-star parameter suggests networks with higher-degree nodes. A negative parameter suggests networks where high-degree nodes are improbable, resulting in less variance between node degrees.

ERGMs traditionally use transitivity parameters to capture clustering effects. However, these may not be sufficient for more complex structures. The new concept introduces k-triangles as higher-order transitivity structures. A k-triangle is a combination of k individual triangles that share a common edge. An alternating k-triangle parameter τ is introduced, where

$$\tau(k+1) = -\frac{\tau_k}{\lambda} \; for \; k \geq 2 \quad (12)$$

A statistic v is introduced, and is defined as

$$v = \sum_{k=2}^{n-1}(1)^k \frac{\tau_k}{\lambda^{k-2}} \quad (13)$$

where the summation over all k is from 2 to $n-1$ (where n is the maximum order of triangles considered).

Similar to u, the term $(1)^k$ alternates the sign of each term in the sum, and the weights $\frac{1}{\lambda^{k-2}}$ decrease as k increases. The statistic u represents the sum of alternating higher-order k-triangle effects. A positive k-triangle parameter suggests transitivity effects in the network, indicating elements of a core–periphery structure. It implies the presence of cohesive subsets of nodes forming overlapping triangles, contributing to a denser network.

The alternating k-star and k-triangle parameters provide a more nuanced way to capture higher-order network structures, addressing issues of model fitting and degeneracy in ERGMs. They offer insights into the formation of cohesive subsets and transitivity effects in complex networks.

3.5.2. Goodness-of-Fit of ERGM

In modelling, the goal is to choose the best-fitting model from a class of models. However, even the best-fit model may not accurately represent the real-world data if the class of models is not diverse or rich enough. Goodness-of-fit is crucial to ensure that the chosen model adequately captures the patterns and structures present in the observed data. It helps assess how well the model class aligns with the actual data. While goodness-of-fit is a well-established concept in traditional modelling (like linear modelling), it is still evolving in the context of network graph modelling. Network graphs have unique characteristics that make assessing goodness-of-fit challenging. In the case of Exponential Random Graph Model (ERGM), the current approach to assessing goodness-of-fit involves simulating a large number of random graphs from the fitted model. These simulated graphs are then compared to the originally observed graph. High-level characteristics or summaries of network structure like centrality measures, degree distribution, and geodesic distance, are commonly used for comparison. These metrics capture essential aspects of how nodes are connected in the network. If the characteristics of the observed network graph differ significantly from the typical values generated by the fitted random graph model, it suggests systematic differences between the assumed model class and the actual data. This misalignment indicates a lack of goodness-of-fit.

4. Results and Discussion

This section presents a comprehensive analysis of the major macroeconomic variables of Ghana using the network approach.

4.1. Partial Correlation Matrix of Major Macroeconomic Variables of Ghana

Partial correlation can help to remove the influence of other variables when measuring the correlation between two variables. From Table 1 below, the partial correlation examines the strengths and directions of the relationships between variables while controlling the effects of other variables. Exports and Imports have a very high partial correlation coefficient of approximately 0.9944. This indicates a strong positive correlation, suggesting that they move closely together. Gross Domestic Saving (GDS) and

Gross Fixed Capital Formation (GFCF) also have a relatively high positive correlation coefficient of approximately 0.9044. Gross National Expenditure (GNE) and Imports have a strong positive correlation coefficient of around 0.9200. Some variables exhibit negative correlations with others. GDP and GFCF have a negative correlation with a coefficient of approximately -0.486. Manufacturing and Exports show a moderate positive correlation with a coefficient of around 0.060. Manufacturing and GDS have a moderate positive correlation of approximately 0.4576. GNE and Manufacturing have a moderate positive correlation of about 0.2594. Some variables have weak correlations with others, indicated by coefficients close to zero. For example, Total Debt Service (TDS) shows weak correlations with most variables.

Table 1. Partial Correlation Matrix of Ghana's Major Macroeconomic Variables.

	GDP	Exports	Imports	TDS	Manu.	FDI	GDS	GFCF	AGRIC	GNE	Inflation	Exch. rate
GDP	1.0000	0.0319	-0.0352	-0.0001	-0.2483	-0.0791	0.293	-0.4863	-0.2726	0.1617	0.5675	-0.2457
Exports	0.0319	1.0000	0.9944	0.1773	0.0601	0.0307	0.1324	-0.084	0.123	-0.8959	-0.1103	0.1206
Imports	-0.0351	0.9944	1.0000	-0.1412	-0.1084	-0.0548	-0.1024	0.0629	-0.1463	0.9196	0.1301	-0.0918
TDS	-0.0001	0.1773	-0.1412	1.0000	0.0815	0.0278	0.1833	-0.1169	0.2497	0.1490	0.053	0.0079
Manu.	-0.2483	0.0601	-0.1084	0.0815	1.0000	-0.4624	0.4576	-0.3600	-0.2021	0.2594	0.1238	0.1125
FDI	-0.0791	0.0307	-0.0548	0.0278	-0.4624	1.0000	0.0158	-0.1036	-0.7166	0.0712	0.0947	-0.3071
GDS	0.293	0.1324	-0.1024	0.1833	0.4576	0.0158	1.0000	0.9044	-0.2182	-0.2662	-0.0578	-0.1953
GFCF	-0.4863	-0.084	0.0629	-0.1169	-0.36	-0.1036	0.9044	1.0000	0.0081	0.2972	0.1181	0.052
AGRIC	-0.2726	0.123	-0.1463	0.2497	-0.2021	-0.7166	-0.2182	0.0081	1.0000	0.0789	0.2188	-0.6916
GNE	0.1617	-0.8959	0.9196	0.149	0.2594	0.0712	-0.2662	0.2972	0.0789	1.0000	-0.1664	-0.0403
Inflation	0.5675	-0.1103	0.1301	0.053	0.1238	0.0947	-0.0578	0.1181	0.2188	-0.1664	1.0000	0.0185
Exch. rate	-0.2457	0.1206	-0.0918	0.0079	0.1125	-0.3071	-0.1953	0.052	-0.6916	-0.0403	0.0185	1.0000

4.2. Fisher's z-Transformation

One of the primary reasons to use the Fisher's transformation is that while the distribution of the correlation coefficient is not normally distributed especially when the true correlation is far from zero, the distribution after the transformation tends to be approximately normally distributed. Also, the variance of the correlation coefficient can change based on the true correlation. The Fisher's transformation stabilizes this variance, making it nearly constant across different true correlations.

Table 2. Fisher's z-Transformation Values.

	GDP	Exports	Imports	TDS	Manu.	FDI	GDS	GFCF	AGRIC	GNE	Inflation	Exch. rate
GDP	_	0.0866	-0.0954	-0.0003	-0.6878	-0.2150	0.8187	-1.4406	-0.7585	0.4424	1.6340	-0.6802
Exports	0.0866	_	7.9699	0.4860	0.1631	0.0833	0.3613	-0.2283	0.3353	-3.9355	-0.3003	0.3287
Imports	-0.0954	7.9699	_	-0.3855	-0.2951	-0.1489	-0.2787	0.1708	-0.3996	4.3027	0.3548	-0.2497
TDS	-0.0002	0.4860	-0.3855	_	0.2216	0.0755	0.5028	-0.3185	0.6918	0.4071	0.1439	0.0215
Manu.	-0.6878	0.1632	-0.2952	0.2216	_	-1.3570	1.3406	-1.0222	-0.5557	0.7200	0.3374	0.3063
FDI	-0.2150	0.0833	-0.1489	0.0755	-1.3570	_	0.0428	-0.2821	-2.4424	0.1935	0.2576	-0.8607

	GDP	Exports	Imports	TDS	Manu.	FDI	GDS	GFCF	AGRIC	GNE	Inflation	Exch. rate
GDS	0.8187	0.3613	-0.2787	0.5028	1.3406	0.0428	_	4.0575	-0.6014	-0.7397	-0.1569	-0.5366
GFCF	-1.4406	-0.2283	0.1708	-0.3185	-1.0222	-0.2821	4.0575	_	0.0220	0.8312	0.3215	0.1412
AGRIC	-0.7585	0.3353	-0.3996	0.6918	-0.5557	-2.4424	-0.6014	0.0220	_	0.2145	0.6032	-2.3080
GNE	0.4424	-3.9355	4.3027	0.4071	0.7200	0.1935	-0.7397	0.8312	0.2145	_	-0.4556	-0.1094
Inflation	1.6340	-0.3003	0.3548	0.1439	0.3374	0.2576	-0.1569	0.3217	0.6032	-0.4556	_	0.0503
Exch. rate	-0.6802	0.3287	-0.2497	0.0215	0.3063	-0.8607	-0.5366	0.1412	-2.3080	-0.1094	0.0503	_

4.3. Benjamini-Hochberg Multiple Testing

Given potential number of edges to be

$$\frac{N_V(N_V-1)}{2} \tag{14}$$

where N_V is the total number of vertices or variables, with 12 vertices or variables the potential number of edges is 66. The multiple testing is therefore used to identify significant edges for the construction of the network. From Table 3 below, nine edges out of the 66 were identified to be significant and were used for the construction of the network.

***Table 3**. P-values of the Multiple Testing.*

	GDP	Exports	Imports	TDS	Manu.	FDI	GDS	GFCF	AGRIC	GNE	Inflation	Exch. rate
GDP	_	0.9448	0.2372	0.9887	0.9268	0.2213	0.6801	0.8142	0.2031	0.8889	0.0066	0.9713
Exports	0.9448	_	0.000	0.5162	0.9937	0.4582	0.8779	0.7938	0.0002	0.1129	0.6479	0.0734
Imports	0.2372	0	_	0.9372	0.9431	0.9873	0.9686	0.076	0.0672	0.0000	0.6513	0.9500
TDS	0.9887	0.5162	0.9373	_	0.2429	0.1076	0.2852	0.9733	0.8894	0.9319	0.9966	0.9676
Manu.	0.9268	0.9937	0.9431	0.2429	_	0.7957	0.001	0.232	0.3337	0.962	0.1191	0.818
FDI	0.2213	0.4582	0.9873	0.1075	0.7957	_	0.9822	0.5853	0.0000	0.8901	0.8773	0.0915
GDS	0.6801	0.8779	0.9686	0.2852	0.001	0.9822	_	0.1106	0.5881	0.1030	0.9103	0.0025
GFCF	0.8142	0.7939	0.076	0.9733	0.232	0.5853	0.1106	_	0.5203	0.8791	0.8164	0.7902
AGRIC	0.2031	0.0002	0.0672	0.8894	0.3337	0	0.5881	0.5203	_	0.8268	0.0043	0.0000
GNE	0.8889	0.1129	0	0.9319	0.962	0.8901	0.103	0.8791	0.8268	_	0.6548	0.5766
Inflation	0.0066	0.6479	0.6513	0.9966	0.1191	0.8773	0.9103	0.8792	0.0043	0.6548	_	0.3206
Exch. rate	0.9713	0.0734	0.95	0.9676	0.818	0.0915	0.0025	0.8791	0	0.5766	0.3206	_

Figure 1 below shows the graphical display of the relationships or dependencies that exist between the major macroeconomic variables of Ghana based on partial correlation. Agriculture (Agric) being at the centre of the graph as it is connected to many other variables and Total Debt Service (TDS) as well as Gross Fixed Capital Formation (GFCF) are identified as non-reachable vertices as they are not connected to any of the variables.

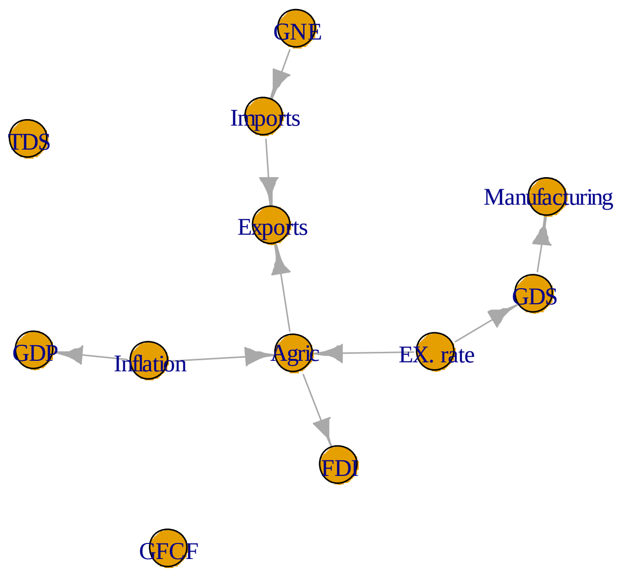

Figure 1. *Partial Correlation Network of Major Macroeconomic Variables of Ghana.*

4.4. Network Analysis/Centrality Measures

To identify the variables with most influence in the network, the various centrality measures were employed. They include degree centrality, betweenness centrality, closeness centrality and eigenvector centrality. Articulation points or cut vertices were also considered.

Degree centrality indicates the number of connections a variable has with other variables in the network. From Table 4, GDP has a degree centrality of 1, indicating that it is connected to one other variable in the network. Exports, imports, Inflation, Gross Domestic saving, exchange rate each has a degree centrality of 2, suggesting that each is connected to two other variables in the network. The high degree centrality of Imports indicates its significant interactions with other economic variables, supporting findings that imports are crucial for both consumption and production processes [21]. Also, high degree centrality for Inflation indicates its pervasive impact on other variables, corroborating findings [22], which noted a significant interplay between these factors and GDP growth. Total Debt Service and Gross Fixed Capital Formation each has a degree centrality of 0, implying that they are not connected to any other variable in the network. FDI, Manufacturing and Gross National Expenditure each have a degree centrality of 1; suggesting each one of them is connected to one other variable. Agriculture, Imports, Exports, and Inflation have relatively high degrees centrality, suggesting they are important variables in the network with multiple connections to other variables. Agriculture has a degree of four; indicating it is connected to four variables. High degree centrality of Agriculture highlights its importance in the Ghanaian economy and this supports findings [23], which noted that agriculture can trigger growth throughout the entire economy due to its interconnectedness with other sectors.

Betweenness centrality measures the extent to which a variable lies on the shortest paths between other variables in the network. From Table 4, GDP, export, Foreign Direct Investment (FDI), Total Debt Service (TDS), Manufacturing, Gross Fixed Capital Formation (GFCF), Inflation, Gross National Expenditure (GNE), and Exchange rate have centrality scores of zero, indicating that they do not lie on any shortest paths between other nodes in the network. This suggests that they do not play a significant role as a bridge or intermediary in connecting other variables. Imports and Gross Domestic Savings have betweenness centrality scores of approximately 0.0091 each, indicating a slightly higher degree of intermediary role compared to GDP and Exports. Imports and Gross Domestic Savings may play a modest role in connecting other variables within the network. This is supported by finding [24] which highlighted the role of GDS in connecting different economic sectors through savings mobilization for investment. Agriculture has a betweenness centrality score of approximately 0.0363, indicating a relatively higher degree of intermediary role compared to other variables in the network. Agriculture may play a notable role in connecting other variables within the network. This supports the literature on agriculture's integrative role in economic development, especially in agrarian economies like Ghana [25]. Variables with higher betweenness centrality scores act as important intermediaries or bridges between other variables in the network, facilitating interaction.

Closeness centrality measures how close a variable is to all other variables in the network. From Table 4, Imports, Gross Domestic Saving (GDS), and Agriculture have closeness centrality scores of 1.000 each, indicating that they are the closest variables to all other variables in the network. This suggests that they can reach other variables in the network more quickly compared to other variables. Gross National Expenditure (GNE) and Exchange Rate have closeness centrality scores of 0.6667 and 0.6250 respectively suggesting that they are relatively close to other variables in the network. However, it is not as central as Imports, GDS, or Agriculture.

Eigenvector centrality measures the influence of a variable in a network based on the concept of eigenvectors. It quantifies the importance or influence of variables within the network based on the concept of eigenvectors and eigenvalues. From Table 4, Agriculture has the highest eigen centrality score of 1.0000, indicating maximum influence within the network. This suggests that Agriculture strongly influences other variables in the network. This aligns with literature underscoring agriculture as a key sector for economic growth and poverty reduction [26]. Inflation, Exports, Gross National Expenditure and Exchange Rate have relatively high eigen centrality score of approximately 0.6667, indicating significant level of influence within the network. This is supported by literature particularly the role of exchange rates in influencing inflation and trade volumes [27]. Imports, FDI, GDP and GDS have moderate eigen centrality scores indicating a moderate level of influence within the network. This suggests that they play a significant role in influencing other variables, although their influences are not the highest. Manufacture has a smaller eigen score of 0.1533 which suggests low influence in the network. The eigen centrality scores for GFCF and TDS are approximately zero each, indicating negligible influence within the network. This suggests that GFCF and TDS have little or no influence on other variables in the network.

Table 4. *Centrality Scores.*

Economic variables	degree centrality	betweenness centrality	closeness centrality	eigenvector centrality
GDP	1	0.0000	NaN	0.2541
Exports	2	0.0000	NaN	0.6035
Imports	2	0.0091	1.0000	0.3407
TDS	0	0.0000	NaN	0.0000
Manufacturing	1	0.0000	NaN	0.1533
FDI	1	0.0000	NaN	0.4501
GDS	2	0.0091	1.0000	0.3407
GFCF	0	0.0000	NaN	0.0000
AGRIC	4	0.0363	1.0000	1.0000
GNE	1	0.0000	0.6667	0.6667
Inflation	2	0.0000	0.6667	0.6667
Exchange rate	2	0.0000	0.6250	0.6250

Articulation points, also known as cut vertices or critical nodes, are key elements in a network that, when removed leads to disconnection in the network. Six (6) out of the 12 variables serve as articulation points. These include Exports, Imports, Agriculture, Inflation, Exchange rate and Gross Domestic Saving. When any of these vertices is removed, the network would divide into two or more separate components. Agriculture being an articulation point highlights its critical role in the economic structure. This finding is confirmed by other research [28], which highlighted the vulnerability of these variables to external shocks stressing the need for robust policy frameworks to mitigate potential risks.

4.5. Modelling the Major Macroeconomic Variables with Exponential Random Graph Models (ERGMs)

4.5.1. Model Specification

Table 5. *Model Specification.*

Model	Formulation	AIC	BIC
Model 1	$log(\exp(\theta^T g(y))) = \theta_1 edges$	75.11	77.3
Model 2	$log(\exp(\theta^T g(y))) = \theta_1 edges + \theta_2 \text{degree}$	76.32	80.7
Model 3	$log(\exp(\theta^T g(y))) = \theta_1 edges + \theta_2 \text{gwesp}$	71.02	75.4
Model 4	$log(\exp(\theta^T g(y))) = \theta_1 edges + \theta_2 \text{degree} + \theta_3 \text{gwesp}$	73.09	79.66

Table 5 specifies models that attempt to describe the relationships between the major macroeconomic variables using various predictors such as edges, degree, and geometrically weighted edgewise shared partner (gwesp). These predictors capture specific ways the macroeconomic variables are connected in the network. The value of each predictor is determined by the number of these connections in the network. Edge represents the likelihood that there is a relationship between any two variables and degree represents likelihood number of edges a variable has. Geometrically weighted edgewise shared partner (gwesp) captures higher-order dependencies or network motifs beyond just pairwise connections.

From Table 5, model 3 is selected because it has the lowest AIC as well as BIC values.

4.5.2. Estimation of Selected Model

From Table 6, the estimated coefficient for the 'edges' is -2.2084 with a standard error of 0.5274. Both coefficients have p-values less than 0.05, indicating that they are statistically significant at the 5% level. This suggests that both 'edges' and 'gwesp' have a significant effect on the network structure. This indicates the effect of the presence or absence of edges between variables in the network. A negative coefficient for the 'edges' suggests that the likelihood of observing edges in the network decreases as the number of edges increases. The estimated coefficient for the geometrically weighted edgewise shared partner (gwesp) is 0.5639 with a standard error of 0.2233. This term represents the geometrically weighted edgewise shared partners, which captures higher-order dependencies in the network. A positive coefficient for the 'gwesp' term suggests that the presence of geometrically weighted edgewise shared partners increases the likelihood of observing links between variables that share common neighbors.

Table 6. *Estimated coefficients of Selected Model.*

parameter	coefficient	Std. Error	p-value
Edges	-2.2084	0.5274	0.0004
gwesp	0.5639	0.2233	0.0116

4.5.3. Goodness-of-Fit of Selected ERGM

The goodness-of-fit (GoF) provides insights into how well the estimated model fits the observed network data across various network statistics.

(i). Goodness-of-Fit Based on Degree

This examines the distribution of node degrees in the observed network compared to the simulated networks. For each degree value (degree0 to degree10), it shows the observed count, minimum, mean, maximum, and Monte Carlo (MC) p-value. The MC p-value indicates the proportion of simulated networks that have a statistic more extreme than the observed value. Higher p-values (close to 1.00) suggest good fit. From Table 7, the observed node degrees range from 0 to 10. The mean degree varies from 0.01 to 2.49. The maximum observed degree ranges from 1 to 8. Most MC p-values are relatively high, indicating good fit, except for degree4, which has a p-value of 0.40, suggesting some discrepancy in fitting nodes with degree 4.

Table 7. *Goodness-of-fit based degree.*

Observed	Minimum	Mean	Maximum	P-value
degree0	1	1.97	8	1.00
degree1	3	2.49	7	0.94
degree2	2	2.08	7	1.00
degree3	2	1.77	5	1.00
degree4	3	1.42	6	0.40
degree5	0	0.04	5	0.88
degree6	0	0.59	4	1.00
degree7	1	0.47	3	0.62
degree8	0	0.13	2	1.00
degree9	0	0.03	2	1.00
degree10	0	0.01	1	1.00

(ii). Goodness-of-Fit Based on Edgewise Shared Partner (ESP)

This assesses the presence of shared partners among edges in the network. Similar to the degree section, it presents observed counts, minimum, mean, maximum, and MC p-values for each ESP value. From Table 8, the observed ESP values range from 0 to 7. The mean ESP varies from 0.01 to 4.33. The maximum observed ESP ranges from 1 to 18. Most MC p-values are relatively high, indicating good fit, except for ESP2 and ESP3, which have p-values of 0.70 and 0.64, respectively.

Table 8. *Goodness-of-fit based edgewise shared partner (ESP).*

Observed	Minimum	Mean	Maximum	P-Value
esp0	4	3.80	11	1.00
esp1	3	4.33	14	0.92
esp2	6	3.79	16	0.70
esp3	3	2.34	18	0.64

Observed	Minimum	Mean	Maximum	P-Value
esp4	0	0.91	10	1.00
esp5	0	0.29	12	1.00
esp6	0	0.07	3	1.00
esp7	0	0.01	1	1.00

(iii). Goodness-of-fit for Minimum Geodesic Distance

Geodesic distance refers to the shortest path between two variables in a network. This section compares the distribution of minimum geodesic distances in the observed network with simulated networks. From Table 4.13, the observed minimum geodesic distances range from 0 to infinity. The mean minimum geodesic distance varies from 0.02 to 24.63. The maximum observed minimum geodesic distance ranges from 2 to 64. Most MC p-values are relatively high, indicating good fit, except for distance3, which has a p-value of 0.16.

Table 9. Goodness-of-fit for minimum geodesic distance.

Observed	Minimum	Mean	Maximum	P-value
1	16	15.54	38	0.88
2	21	16.85	36	0.80
3	15	6.63	20	0.16
4	3	1.75	10	0.50
5	0	0.45	6	1.00
6	0	0.13	3	1.00
7	0	0.02	2	1.00
Inf	11	24.63	64	0.88

(iv). Goodness-of-Fit Based Model Statistics

This evaluates how well the model fits overall network statistics, such as the total number of edges and the GWESP statistic. From Table 10 the observed values for edges and gwesp are compared with simulated values. The mean values for edges and gwesp are close to the observed values. The MC p-values are relatively high for both statistics, indicating good fit.

Table 10. Goodness-of-fit for model statistics.

Statistic	Observed	Minimum	Mean	Maximum	P-Value
edges	16.0000	2	15.5400	38.0000	0.88
gwesp	18.8880	0	18.2616	83.8910	0.80

(v). Goodness-of-Fit Plot Based on Minimum Geodesic Distance

In network analysis, the geodesic distance between two nodes refers to the shortest path connecting them along the network edges. The minimum geodesic distance diagnostic in ERGM compares the distribution of these shortest path lengths in the observed network with the distribution of the simulated network under the fitted model. The observed distribution curve represents the frequency (or probability) of different geodesic distances observed in the real network data. The simulated or expected distribution curve represents the frequency of geodesic distances predicted by the ERGM model. In a well-fitting model, the observed and expected distributions should align or be closed together. This indicates that the model captures the patterns of connection distances well. There should not be significant deviations or large discrepancies between them. If there are significant deviations between the observed and expected distributions, this might suggest the model underestimates the number of directly connected nodes or overestimates the clustering of nodes in the network. From Figure 2, the simulated network distribution curve is shown with bold solid lines and the light curve represents the distribution of the observed network. From the Figure it is clear that both distributions align and there are no significant deviations or large discrepancies between them indicating a good fit of the model. The rightmost box-plot represents the proportion of non-reachable pairs.

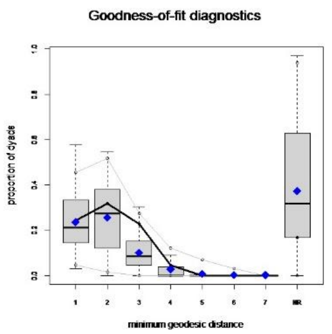

Figure 2. Goodness-of-fit based on minimum geodesic distance.

4.6. Model Inference

The coefficients of the edges term and geometrically weighted edgewise shared partner (gwesp) term in the specified model (Table 6) provide a single homogeneous conditional probability for all connections in the network. The coefficients of edges and gwesp represent their log-odds. To compute the total conditional log-odd for edges term and gwesp we sum their log-odds. The log-odds for edges and gwesp are -2.2084 and 0.5639 respectively therefore the total conditional log-odd is given by -1.6445.

To convert the conditional log-odd to probability the logistic function is applied. It is given as

$$probability = \frac{1}{1+\exp(-\log(odds))} \tag{15}$$

Substituting the conditional log-odds into equation (15),

$$probability = \frac{1}{1+\exp(1.6445)} \approx 0.1619 \tag{16}$$

The probability of 0.1619 or 16.19% indicates the likelihood that two macroeconomic variables will be directly connected by an edge if they share a common neighbor (another macroeconomic variable). This probability reflects the tendency for interconnectedness among macroeconomic variables. If two variables are neighbors in the network (i.e., they are both connected to a common third variable), there is a 16.19% chance that they will also be directly connected to each other. If, for example, Inflation and Exports share a common neighbor such as Agriculture, there is a 16.19% probability that Inflation and Exports will also be directly connected by an edge in the network. This implies that the presence of certain macroeconomic relationships (edges) between variables can facilitate the formation of additional links between other variables that share common neighbors. It suggests that the presence of certain economic relationships can influence the formation of new connections between other variables, leading to a network structure characterized by interconnectedness and interdependence. This supports findings by Adam and Siaw (2010) that emphasized the interconnectedness of macroeconomic variables by highlighting that exchange rate fluctuations impact trade volumes, investments, inflation, import and export prices. This also confirms similar findings that underscored the importance of sectorial interdependencies [29]. Their study showed that growth in agriculture can positively affect GDP, Manufacturing and other areas of the economy.

5. Conclusion and Recommendations

Key findings from the study include the identification of pivotal variables and these variables include Agriculture, Exports, Imports, Manufacturing, Gross Domestic Saving (GDS), Exchange Rate and Inflation, which exhibit significant influence across multiple centrality measures. Agriculture and Imports had been the most influential variables in the network structure as they exhibited significant influence across all the centrality measures. These variables play critical roles in driving economic activity, facilitating trade and investment flows, and shaping overall economic performance.

Based on the model, the triadic closure (the tendency for variables in a network to form new connections based on existing relationships) highlights the interdependence and interconnectedness of the macroeconomic variables. Changes in one variable can have ripple effects on others through indirect relationships in the network.

It is recommended that the government should implement comprehensive agricultural policies that provide better access to credit, modern farming techniques, and infrastructure development (irrigation systems, storage facilities) to enhance the sector's contribution to GDP and exports, given its significant centrality. Policymakers should implement policies to reduce dependency on imports by promoting local production and import substitution strategies. This will help stabilize the trade balance, preserve foreign exchange reserves, and promote the growth of local industries, thereby enhancing overall economic resilience. Policy interventions targeted at specific macroeconomic variables may lead to unintended consequences or spillover effects on other variables in the economy, there is therefore the need for policymakers to implement robust monitoring and evaluation mechanisms to track the outcomes of policy interventions and identify any emerging spillover effects or risks.

Abbreviations

EPRGMs	Exponential Random Graph Models
ERPT	Exchange Rate Pass-Through
GDP	Gross Domestic Product
GFCF	Gross Fixed Capital Formation
GDS	Gross Domestic Savings
GNE	Gross National Expenditure
TDS	Total Debt Service
FDI	Foreign Direct Investment
gwesp	Geometrically Weight Edgewise Shared Partner

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Conflicts of Interest

The authors declare no conflicts of interest.

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