https://doi.org/10.59865/abacj.2023.36

NETWORK ANALYSIS OF ECONOMIC SECTORS: AN EXPLORATION OF STRUCTURE USING THE HITS ALGORITHM

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Abstract

This research aimed to investigate the structure of the national economic networks in Japan, Thailand, and Vietnam, at different stages of stock exchange development. Daily return data from the Refinitiv database were used, along with excess returns calculated by subtracting short-term government bond yields from index returns in each country. Key influencers and those heavily impacted by the economic system, were identified by applying Granger causality analysis and the HITS algorithm to nine industry indices. The results showed that the industrial sector (INDUS) significantly influenced other sectors in Japan and Thailand and that the economic sectors most affected by other industries varied by country. These findings have implications for policymakers seeking to manage and mitigate potential economic impacts from influential industrial sectors and identify the industry groups most susceptible to potential crises. This study contributes to the existing literature on the topic, enhancing understanding of economic networks, while further research is still needed in different countries and at various stages of economic development to fully comprehend the intricacies of economic networks.

Keywords: Granger causality, HITS algorithm, Economic network, Economic structure, Economic impacts

INTRODUCTION

This study introduces the HITS algorithm as a measure of centrality in financial network analysis. The HITS algorithm, proposed by Kleinberg (2011), allows the identification of the most influential nodes in a network by calculating their hub and authority scores. The highest hub score indicates a node with the most outgoing connections or the most influential nodes, while the highest authority score indicates a node with the most incoming connections or the most influenced nodes (Kleinberg, 2011). This technique has previously been applied to analyze the transfer of funds in the banking industry (Xu et al., 2018), and value migration in the S&P 500 (Siudak, 2022). However, to our knowledge, few studies have adopted the HIT algorithm to analyze economic sectors linked to each other by a production (Rammrez, 2018) or cooperation network (Kullmann et al., 2002). Primarily, only the economic networks in major countries or globally have been investigated by this technique. This study investigates the potential of the Hyperlink-Induced Topic Search (HITS) algorithm to identify the most critical economic sectors and their level of influence in countries with varying levels of market development. The current literature lacks

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research in this area, which serves as the motivation for this study. The HITS algorithm is applied to economic networks to gain a deeper understanding of the underlying mechanisms of an economy. The findings have the potential to provide valuable insights for economic policymakers and researchers, filling a gap in the literature.

The interconnected nature of the financial system has been well-documented in several research studies (Inekwe et al., 2018; Papana et al., 2017). These findings demonstrate that asset returns are interdependent and that financial information flows between different assets (Yue, Cai, et al., 2020; Yue, Fan, et al., 2020). This interconnectedness highlights the importance of considering the broader financial system when analyzing individual assets and making investment decisions. Additionally, the global financial crisis has been linked to the interconnectedness of local crises with worldwide crises (Schenck et al., 2021; W. Zhang et al., 2020). Therefore, it is essential to consider the connection between financial assets when studying economic phenomena.

Evidence suggests that economic entities can influence one another through various business networks. For instance, fund managers gain valuable insights into target businesses by connecting with a manager who attended the same alums, which can aid in making a more profitable investment decision (Cohen et al., 2008). Furthermore, a crisis in the production networks of a firm can impact the market value of their member companies through the flow of income-related information within the network (Barrot & Sauvagnat, 2016). By understanding the mechanisms through which these networks shape economic entities, researchers and policymakers can give valuable insights into the functioning of the economy and devise strategies to promote economic growth and stability.

Network theory has been introduced as a valuable tool for financial analysis, assuming that funds move from one asset to another (Nagurney, 2008). The linkage of assets in return has been shown to form a financial network in various countries (Bonanno et al., 2004; Durcheva & Tsankov, 2021; Osei & Adam, 2020; Tang et al., 2019). The application of network theory in finance, which Quesnay introduced in 1758, has gained widespread acceptance in academic circles and is frequently used to explain economic phenomena within the financial system (Allen & Babus, 2011; So, Chan, et al., 2021). For example, the origin of the crisis in the Chinese financial sector was found through the analysis of the interbank network (Lin & Zhang, 2022). The volatility network also reveals the most influential market among G20 stock markets by calculating network centrality (W. Zhang et al., 2020). Additionally, the supply chain network can explain the price movement of a firm along the supply line (Rammrez, 2018). In conclusion, the application of network theory has significantly enhanced understanding of financial systems and has important implications for financial regulation and risk management strategies.

Centrality analysis has been widely used in several studies to analyze networks and identify key sources of information or central nodes, such as economic sectors, sources of volatility, or crises. As an illustration, a Turkish interbank study found that shocks to central institutions can have a widespread effect on the entire network (Kuzubaş et al., 2014). In addition, there are static and temporal central nodes of economic agents in the real-world financial network. Hence, risk-dependent centralities in the network can be used to predict financial and economic outcomes (Bartesaghi et al., 2020). This centrality analysis helps understand how influential nodes can transmit their effects to a more extensive system and how the failure of these critical nodes can potentially lead to significant economic crises. By examining the centrality of nodes in a network, researchers can gain valuable insights into the underlying structure and dynamics of the system.

However, a more robust method is required to reveal financial centrality. For example, some centrality measures, such as degree centrality (Lai & Hu, 2021; Wu et al.,

2020) and betweenness centrality (W. Q. Huang et al., 2016), rely on a simple count of connections without taking into account the strength or importance of these connections. As a result, these methods can lead to inaccuracies in determining the actual influence and importance of each node in a financial network. Therefore, further research is necessary to develop more centrality measures that consider the strength and importance of connections in financial networks.

LITERATURE REVIEW

The economic system consists of agents that engage in various forms of interaction, such as trading, production, and knowledge sharing. These relationships illustrate the interdependence of economic units and the potential for a crisis to spread throughout the system. To gain a deeper understanding of these relationships, economists have employed network theory, which analyzes the connections between agents within a system. Especially, Quesnay first introduced the application of network theory in finance in 1758 to explain the co-movement of asset prices, assuming that funds flow between assets within the financial network (Nagurney, 2008).

Recent financial studies have used network theory to examine financial networks in various economic systems, highlighting the different types of connections within the system. For example, research has shown that an education network can influence the outcomes of fund managers, with fund managers achieving better investment outcomes when investing in the stocks of top managers who attended the same university (Cohen et al., 2008). In recent years, there has been a growing body of research on information networks within the stock markets of the United States and China. These studies have found that the structure of these networks is dynamic and can vary over time (Yue, Cai, et al., 2020). Additionally, it has been identified that the key sources of information in the Chinese market tend to be banks, while in the U.S. market, the energy sector is the key source of information (Yue, Fan, et al., 2020). This is an important finding as it highlights the need to consider each country's specific characteristics and market structure when analyzing the flow of information within stock markets.

Moreover, the impact of a crisis on production networks can affect member market value by spreading the spillover effect throughout the supply chain (Barrot & Sauvagnat, 2016). In addition, in the U.S. stock market, there are correlation networks (Bonanno et al., 2004), and the most valuable stocks can influence the prices of small stocks through a "pulling effect" in the stock price network (Kullmann et al., 2002). Stock price networks have been recently studied in the context of the Ghana stock exchange (Osei & Adam, 2020), S&P 500 (Durcheva & Tsankov, 2021), North America (Liu et al., 2021), MENA countries (Balcilar et al., 2022), and the global market (So, Chan, et al., 2021; So, Chu, et al., 2021).

Previous studies have demonstrated the interdependence of economic units as a network and the potential for a crisis to spread throughout the system. In order to better understand these relationships, economists have employed network theory, which examines the connections between agents within a system. Several methods have been developed to estimate financial networks, but the Granger causality graph is particularly effective in analyzing time-varying and cross-lagged time series data (Liu et al., 2021). This method has been preferred over alternatives, such as correlation, covariance, Spatial Auto-regressive, or copula, for depicting directional graph networks because it can determine whether one time series can predict another (Granger, 1969). In addition, a directional financial network benefits researchers because it displays the path of influence in the economy. For example, recent studies adopted the technique to show that potential systematic risk could spread from specific sectors, such as banks, financial companies, and real estate, to the entire economic system (Cincinelli et al., 2022). It has also been shown that a few stocks can export risk to the China stock market (Gao et al., 2018). Although the granger causality graph depicts a directional financial network graph in several research articles (C. Huang et al., 2022; Papana et al., 2017; Yao et al., 2016; X. Zhang et al., 2014), a deep investigation of the directional financial graph is needed to elaborate and increase understanding of the world economy.

A literature review of the HITS algorithm application in analyzing the economic sectors' granger causality graph reveals that this approach has been utilized in various economic studies (Cao et al., 2017; Deguchi et al., 2014; Tu, 2014; Xu et al., 2018; Yaoyun et al., 2011). The HITS algorithm, which stands for Hyperlink-Induced Topic Search, is a method for identifying the most important nodes in a network based on the number of incoming and outgoing links they possess (Kleinberg, 2011). Moreover, this method prevails over other methods as optimal for analysis-directed graphs and weak connections and provides the separated centrality referring to the origin and recipients of the network (León et al., 2018). Consequently, it has been applied to various fields, including information retrieval, social network analysis, and economics.

In economics, the HITS algorithm has been used to analyze the granger causality graph of various economic sectors such as the stock market (Tu, 2014), fund trading (Xu et al., 2018), and interbank networks (León et al., 2018). For example, one study identified the characteristics of a super-spreader bank in the interbank network in Colombia, concluding that large banks could become super-spreaders in the financial institution network (León et al., 2018). Another study found that China is the largest exporter of world economics using this method (Deguchi et al., 2014). Finally, the HITS algorithm has been used to identify the critical source of fund transfers, with the potential to detect fraudulent fund flow transactions in global transactions (Xu et al., 2018), highlighting its value as a tool for economic investigation.

The literature suggests that the HITS algorithm is effective in analyzing the granger causality graph of trading network fund transfers and can provide valuable insights into the causal relationships between different economic sectors, helping to identify the key drivers of economic movements. As Kleinberg (2011) proposed, the HITS algorithm distinguishes authorities and hubs, enabling a nuanced assessment of node importance. This distinctive characteristic sets it apart from other methods and proves its efficacy in identifying crucial nodes, as demonstrated in studies on bilateral relationships (Semanur, Hüseyin, & Halil, 2020). The HITS algorithm excels in economic network analysis by identifying key players through hub and authority scores and detecting well-connected clusters. Employing the HITS algorithm allows researchers to gain valuable insights into the structure, dynamics, and influential nodes within economic networks. While this measure has been applied in financial and economic studies, most research has focused on major countries, particularly China (Tu, 2014), and the global network (Deguchi et al.,2014). More work is needed in other countries, as a crisis can originate in any local market and spread to the rest of the world (Schenck et al., 2021).

DATA AND RESEARCH METHODOLOGY

This study investigates sector interdependence in financial markets across different levels of development. The HITS algorithm is applied to the Japanese, Thai, and Vietnam stock exchanges, representing developed, emerging, and frontier markets. Japan, Thailand, and Vietnam, offer enticing investment opportunities due to factors such as a stable economy and advanced technology in Japan, emerging market potential and favorable business environment in Thailand, and rapid economic growth and increasing foreign investment in Vietnam. The daily excess return of the Refinitiv economic sector index was used as the data source, as it reflects the aggregate price of stocks related to a particular sector and thus is a representation of economic activity in the studied countries. Using network theory in this analysis, the aim of this study is to gain a deeper understanding of economic systems and contribute to the existing literature on this topic.

This study uses excess return to mitigate the influence of the risk-free rate, a common practice in economic research. The study specifically considers the 1-year government bond rate as the short-term rate. This approach allows for a more thorough analysis of the interactions among sectors. In addition, the study period spans from July 1, 2003, to August 16, 2021, allowing for a long-term investigation, including the COVID-19 pandemic period. The excess return will be calculated using Eq (1).

$$\overline{r_t} = r_{s,t} - r_{f,t} \qquad (1)$$

Where $\overline{r}$ is the excess return at time t, and r_s and r_f are the index's daily returns and the risk-free rate at time t , respectively.

Granger causality testing is valuable for capturing the interdependence among sectors within markets and provides insights into their dynamics. This statistical framework, widely used in economics, analyzes causal relationships between variables in time series data, going beyond correlation by emphasizing temporal ordering. It demonstrates how one variable's past values can predict another's future, offering a deeper understanding of the intricate interconnections among sectors within markets. The Granger causality test is represented as follows:

$$\overline{r_{s_i,t}} = \alpha + \sum_{t=1}^{t} \beta_{j,t} \overline{r_{j,t-p}} + \varepsilon_t \quad (2)$$

Here, $\overline{r_{s_{i,t}}}$ denotes the dependent variable at time t, α represents the intercept term, $\beta_{j,t}$ represent coefficients measuring the lagged effect at $t-p$ of the independent variables $\overline{r_{j,t-p}}$, and ε_t captures the error term encompassing unexplained variability. The Granger causality test, indicated in Eq.(2), is a statistical test that utilizes the sum of squared residuals, $RSS_i = \sum_{t=1}^{t} \varepsilon_i^t$ and $RSS_j = \sum_{t=1}^{t} \varepsilon_j^t$, to explain the causal relationship between $\overline{r_{s_i}}$ and $\overline{r_{s_j}}$. As indicated by the Eq (3), the significance of the F-test is examined to determine the presence or absence of causal relationships between the variables, thereby enhancing our comprehension of their interrelationships.

$$F = \frac{(RSS_i - RSS_j)/k}{RSS_j/(t-2k-1)} \qquad (3)$$

In order to estimate the granger causality graph, the Granger Causality test is employed to display the directional interaction between two sectors at a significance level of 0.05 (Billio et al., 2012; Gao et al., 2018). If S_1 exhibits Granger causality toward S_2 the direction of the Graph will flow from S_1 to S_2.

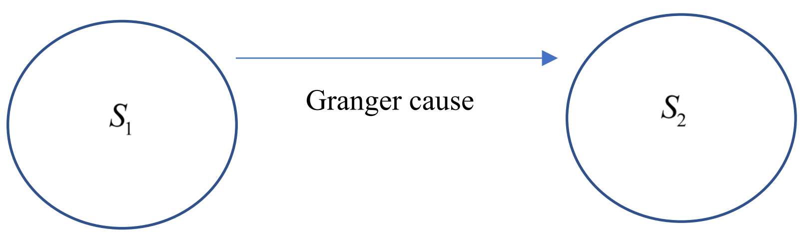

Figure 1 Granger Causality Graph

In order to identify important nodes or economic sectors in the network, the HITS algorithm is employed with two measures: hub score and authority score. These scores have been calculated for each node, as described in Eq (4). The hub score reflects the importance ofa node as a "hub" in the network based on the number of connections it has to other nodes. Similarly, the authority score reflects the importance of a node as an "authority" in the network based on the number of other nodes that connect to it. By analyzing the hub and authority scores of nodes in our network, we were able to identify the most influential and central nodes.

$$hub(\overline{r}_{S_i}) = \sum_{\overline{r}_{Sj} \in \overline{r}_{S_i,from}} auth(\overline{r}_{S_j})$$
$$auth(\overline{r}_{S_i}) = \sum_{\overline{r}_{s_j} \in \overline{r}_{S_i,to}} hub(\overline{r}_{S_j}) \tag{4}$$

The HITS algorithm was used to identify the Graph's most significant nodes. The method was achieved by assigning a "hub score", $hub(\overline{r})$, and an "authority score", $auth(\overline{r})$, to each node in the Graph. The hub score of a node was calculated by summing the authority scores of all the nodes that it was connected to, $\overline{r}_{S_j} \in \overline{r}_{S_i,from}$. Meanwhile, the authority score was calculated by summing the hub scores of all the nodes that were connected to the node in question, $\overline{r}_{S_j} \in \overline{r}_{S_i,to}$. Finally, the hub and authority scores were normalized, and the process was repeated until convergence. At this point, the scores were used to rank the importance of the nodes in the Graph. Nodes with high hub scores were considered "hubs," and those with high authority scores were considered "authorities."

EMPIRICAL RESULT

This study analyzed financial networks in various industries across the Japanese, Thai, and Vietnamese, stock exchanges using daily return data from the Refinitiv database. Excess returns were calculated by subtracting the short-term government bond yield from each respective country's index return. A total of 9 industry indices were considered in the analysis: Industrial Commodities Index (BASICMAT), Consumer Goods Index (CYCLICAL), Energy Sector Index (ENERGY), Banking and Finance Index (FIN), Healthcare Index (HEALTH), Industrial Sector Index (INDUS), Agriculture and Food Sector Index (NON-CYCLICAL), Technology Index (TECH), and Utilities Index (UTIL). The ADF (Augmented Dickey-Fuller) and KPSS (Kwiatkowski-Phillips-Schmidt-Shin) tests were employed in this study, to assess the stationarity properties of the time series data. The ADF test determines the statistical significance, with a lower p-value indicating stationarity, while a higher p-value suggests non-stationarity. Conversely, the KPSS test provides a different interpretation, where a lower value implies non-stationarity and a higher value suggests stationarity. These tests play a crucial role in evaluating the optimality of the data. Descriptive statistics for each industry in each country are presented in Table 1, providing insights into variable characteristics.

Table 1 displays the sector composition of different stock exchanges. The Japanese stock exchange comprises nine sector indices, the Vietnamese stock exchange has four, and the Thailand stock exchange has six. It is important to note that the varying database records for daily returns in each market, are denoted as 'n'. The highest return was observed as NON-CYCLICAL in Vietnam, with a daily return of 0.0006 or 0.06%. In contrast, the lowest return was seen in the UTIL in Japan, with a return of -0.0001 or -0.01%. Additionally, ENERGY in Thailand had the highest volatility with an S.D. of 0.0198, while NON- CYCLICAL return in Japan had the lowest volatility with an S.D. of 0.0111. Furthermore, the ADF and KPSS tests indicate that the excess return is a suitable variable for testing in the analysis.

Table 1 Descriptive Statistics of the Daily Excess Return

Sector	Statistics	JAPAN (N=4,552)	THAILAND (N=3,658)	VIETNAM (N=2,945)
BASICMAT	Avg.	0.0002	0.0000	
	S.D.	0.0162	0.0170	**N/A**
ADF/KPSS -test (P-value)		0.0001***/0.1000	0.0000***/0.1000	
CYCLICAL	Avg.	0.002	0.0003	0.0004
	S.D.	0.0143	0.0131	0.0152
ADF/KPSS -test (P-value)		0.0001***/0.1000	0.0000***/0.1000	0.0000***/0.1000
ENERGY	Avg.	0.0000	0.0000	
	S.D.	0.0174	0.0198	**N/A**
ADF/KPSS -test (P-value)		0.0001***/0.1000	0.0001***/0.1000	
FIN	Avg.	0.0001	0.0001	0.0005
	S.D.	0.0171	0.0154	0.0146
ADF/KPSS -test (P-value)		0.0001***/0.1000	0.0001***/0.1000	0.0000***/0.1000
HEALTH	Avg.	0.0002		
	S.D.	0.0123	**N/A**	**N/A**
ADF/KPSS -test (P-value)		0.0001***/0.1000		
INDUS	Avg.	0.0003	0.0002	0.0001
	S.D.	0.0145	0.0154	0.0152
ADF/KPSS -test (P-value)		0.0001***/0.1000	0.0001***/0.1000	0.0001***/0.1000
NON-CYCLICAL	Avg.	0.0002	0.0004	0.0006
	S.D.	0.0111	0.0128	0.0142
ADF/KPSS -test (P-value)		0.0001***/0.1000	0.0001***/0.1000	0.0000***/0.1000
TECH	Avg.	0.0002		
	S.D.	0.0155	**N/A**	**N/A**
ADF/KPSS -test (P-value)		0.0001***/0.1000		
UTIL	Avg.	-0.0001		
	S.D.	0.0139	**N/A**	**N/A**
ADF/KPSS -test (P-value)	0.0001***/0.1000			

*** Significant level of 0.01

In the context of this research, Granger causality tests were employed to explore the interconnections among economic sectors in Japan, Thailand, and Vietnam. The lag selection was conducted following the methodological framework proposed by Hatemi-J and Hacker (2009), utilizing the Likelihood Ratio (LR) for lag determination and the LM-test to evaluate potential autocorrelation concerns. The outcomes unveiled the absence of autocorrelation issues within the selected lag, as evidenced by the LM-test's P-value surpassing the predetermined significance level of 0.05. Additionally, a significance level of 0.05 was adopted to assess the existence of Granger causality between sectors, thereby ensuring the robustness and dependability of our findings. Detailed statistical results can be found in Tables 2, 3, and 4.

Employing the Granger causality framework, an economic network was constructed for each country, visually depicted in Figures 2, 3, and 4, respectively. Additional details can be found in Cao et al., (2017), Deguchi et al. (2014), Tu (2014), Xu et al. (2018), and Yaoyun et al. (2011) for a more comprehensive understanding of the network construction process.

Table 2 Granger Causality Test Results for the Japanese Market

	INDEPENDENT VARIABLES									
	Lag (p) = 32 LM-test (P-value) = 0.5163	BASICMAT	CYCLICAL	ENERGY	FIN	HEALTH	INDUS	NON-CYCLICAL	TECH	UTIL
DEPENDENT VARIABLES	BASICMAT	N/A	0.0932*	0.5281	0.1593	0.012**	0.0073***	0.0173**	0.2375	0.3182
	CYCLICAL	0.0266**	N/A	0.0647*	0.0000***	0.0418**	0.0125**	0.257	0.2704	0.1154
	ENERGY	0.0217**	0.055*	N/A	0.6803	0.0027***	0.7701	0.6749	0.1603	0.2514
	FIN	0.059*	0.0043***	0.0135**	N/A	0.0017***	0.0134**	0.2079	0.9708	0.3776
	HEALTH	0.8563	0.1484	0.0421**	0.0976*	N/A	0.2644	0.0969*	0.5498	0.0698**
	INDUS	0.7648	0.0447**	0.0287**	0.003***	0.7391	N/A	0.2055	0.1795	0.447
	NON-CYCLICAL	0.0001***	0.4328	0.2506	0.1569	0.9592	0.0107**	N/A	0.1913	0.0335**
	TECH	0.2414	0.0925*	0.0967*	0.4313	0.1672	0.1169	0.174	N/A	0.4456
	UTIL	0.7102	0.0302**	0.2996	0.6998	0.1734	0.0138**	0.2843	0.0018***	N/A

* Significant level of 0.10 ** Significant level of 0.05 *** Significant level of 0.01

Table 3 Granger Causality Test Results for the Thailand Market

	INDEPENDENT VARIABLES						
	Lag (p) = 16 LM-test (P-value) = 0.5677	BASICMAT	CYCLICAL	ENERGY	FIN	INDUS	NON-CYCLICAL
DEPENDENT VARIABLES	BASICMAT	N/A	0.1171	0.0796*	0.084*	0.4024	0.5151
	CYCLICAL	0.6328	N/A	0.1487	0.0001***	0.001***	0.0602*
	ENERGY	0.0190**	0.0014***	N/A	0.0000***	0.0002***	0.6108
	FIN	0.4017	0.3304	0.0807*	N/A	0.0032***	0.8679
	INDUS	0.0712*	0.4322	0.0066***	0.1252	N/A	0.1956
	NON-CYCLICAL	0.1371	0.1126	0.7111	0.4753	0.7975	N/A

* Significant level of 0.10 ** Significant level of 0.05 *** Significant level of 0.01

Table 4 Granger Causality Test Results for the Vietnamese Market

	INDEPENDENT VARIABLES				
DEPENDENT VARIABLES	Lag (*p*) = 23 LM-test (*P*-value) = 0.8628	CYCLICAL	FIN	INDUS	NON-CYCLICAL
	CYCLICAL	N/A	0.0134**	0.6184	0.9501
	FIN	0.3763	N/A	0.2253	0.4728
	INDUS	0.3441	0.0503	N/A	0.0069***
	NON-CYCLICAL	0.0394**	0.0186**	0.0262**	N/A

* Significant level of 0.10 ** Significant level of 0.05 *** Significant level of 0.01

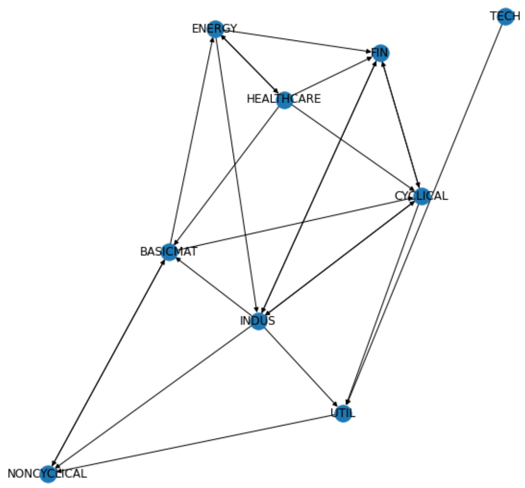

Figure 2 Network of Economic Sector in the Japanese Stock Market

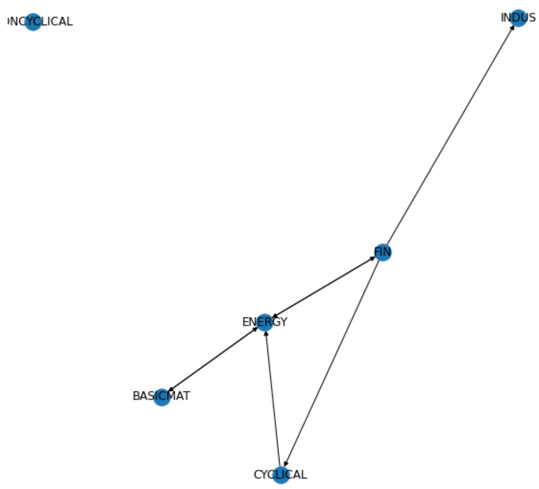

Figure 3 Network of Economic Sector in the Thailand Stock Market

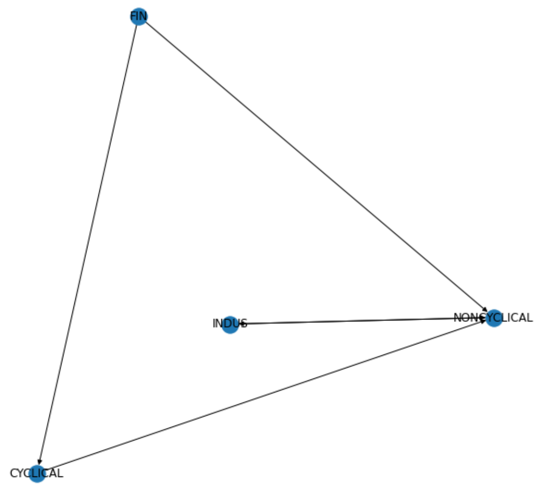

Figure 4 Network of Economic Sector in the Vietnamese Stock Market

The HITS algorithm was applied to identify each country's most important nodes in the economic sector network. Table 5 displays the hub and authority scores of these nodes. These scores can be used to understand the influence and centrality of each node in the network. The HITS algorithm is a commonly used method in network analysis and has been shown to be effective in identifying critical nodes in complex networks. By examining the hub and authority scores, we can gain insights into each country's structure and dynamics of the economic sector network.

According to the data in Table 5, INDUS was the most influential sector on the Japanese and Thai stock exchanges, as indicated by the high hub scores of 0.2405 and 0.3542, respectively. It is consistent with the value of the industrial sector in these countries' economies. In Japan, the industrial sector holds the highest value (Statista, 2021), while in Thailand, it accounts for 27.05% (Department, 2021) of the total economic value or approximately one-fifth of the economy. These findings suggest that high-value industries significantly impact economic networks in developed and developing markets. In contrast, Table 2 shows that in the Vietnam stock exchange, a frontier market, FIN appears to be particularly influential, with a hub score of 0.4142. Interestingly, the financial sector in Vietnam is ranked fourth in terms of value (Minh-Ngoc Nguyen, 2021), in contrast to the results seen in Japan and Thailand.

Furthermore, the authority scores were examined to investigate the impact of the entire network on various industries at three different levels of market development. The findings for Japan show that a developed market's financial sector was most influenced by the other sectors in the network, with an authority value of 0.1350. In Thailand, the energy sector was most affected, with an authority value of 0.5000. In Vietnam, the NON-CYCLICAL group had the biggest affect on the stock exchange, with an authority value of 0.7071. These results indicate that the economic structures of each country may differ due to variations in fundamental conditions.

DISCUSSION

The main objective of this study was to investigate the structures of Japan's, Thailand's, and Vietnam's national economic networks at different stages of stock exchange development. The employment of Granger causality analysis and the Hyperlink-Induced Topic Search (HITS) algorithm using excess return data indicate that the industrial sector (INDUS) significantly impacts other sectors within the same economy in Japan and Thailand. Furthermore, the findings reveal

Table 5 Hub and Authority Scores

Rank	**Japan**				**Thailand**				**Vietnam**			
	Hub		Authority		Hub		Authority		Hub		Authority	
1	INDUS	0.2405	FIN	0.1982	INDUS	0.3542	ENERGY	0.5000	FIN	0.4142	NON-CYCLICAL	0.7071
2	HEALTH	0.1956	CYCLICAL	0.1950	FIN	0.2915	CYCLICAL	0.3229	CYCLICAL	0.2929	CYCLICAL	0.2929
3	BASICMAT	0.1274	BASICMAT	0.1435	BASICMAT	0.1771	FIN	0.1771	INDUS	0.2929	INDUS	0.0000
4	CYCLICAL	0.1274	UTIL	0.1212	CYCLICAL	0.1771	BASICMAT	0.000	NON-CYCLICAL	0.0000	FIN	0.0000
5	ENERGY	0.0997	NON-CYCLICAL	0.1211	ENERGY	0.000	INDUS	0.000	N/A			
6	FIN	0.0894	ENERGY	0.0964	NON-CYCLICAL	0.000	NON-CYCLICAL	0.000	N/A			
7	NON-CYCLICAL	0.0443	INDUS	0.0947	N/A		N/A		N/A			
8	TECH	0.0375	HEALTH	0.0298	N/A		N/A		N/A			
9	UTIL	0.0375	TECH	0.0000	N/A		N/A		N/A			

that the banking and finance sector (FIN) is the most critical sector in Vietnam, which aligns with previous studies that have emphasized the financial sector's influence in frontier markets (Ahmed & Ansari, 1998). These results emphasize the significance of the industrial, banking, and finance sectors, in shaping the economic landscape in these countries. The high value of the industrial sector in Japan and Thailand suggests that it plays a vital role in driving economic growth in these countries. driving economic growth in these countries. On the other hand, the results from Vietnam revealed the importance of the financial sector in shaping the economic landscape.

Notably, Vietnam's network exhibited sparsity with a limited number of nodes, which may impact the HITS algorithm's efficacy. The existence of influential nodes, or "hubs," can introduce bias into the ranking of other nodes and influence the accuracy of the algorithm's outcomes. However, in the context of a small network, it has been observed in Benzi, Estrada and Klymko (2013) that the highest hub and authority scores can be the same, consistent with advanced methods. Given the limitations of the data, the results obtained can be considered acceptable but should be interpreted cautiously.

Additionally, the analysis indicates that the economic sectors most affected by other industries exhibit variation across the countries studied. Specifically, it was found that the banking and finance sector (FIN) in Japan, the energy sector (ENERGY) in Thailand, and the agriculture and food sector (NON-CYCLICAL) in Vietnam were particularly susceptible to the influence of other sectors. These findings have important implications for policymakers, as they suggest that practical efforts to manage and mitigate potential economic impacts should be tailored to the sectors and industries most influential and susceptible within a given country. Furthermore, this information can aid in identifying industry groups that may be particularly vulnerable to potential crises, thus allowing for proactive measures to mitigate such risks.In conclusion, the findings suggest that various levels of market development have distinct economic structures, including sectors that shape the economy and those that are significantly impacted by other sectors. Understanding these economic structures is crucial for examining economic conditions in any country or at any stage of economic development. This research provides insight for policymakers and investors seeking to navigate the economic landscape of these countries and for future studies investigating the structure of economic networks in different countries and stages of market development.

CONCLUSION AND RECOMMENDATION

This study analyzed the economic networks of the stock exchanges in Japan, Thailand, and Vietnam, using daily return data from the Refinitiv database and excess return calculated by subtracting the short-term government bond yield from the index return of each respective country. The HITS algorithm was applied to nine industry indices to identify key influencers and those heavily impacted by the economic system. The findings revealed differences in the economic structure of each country and emphasized the importance of considering the unique structure of an economic system in economic research. The HITS algorithm proved to be effective in understanding complex relationships within economic systems.

In summary, the HITS algorithm offers substantial benefits to policymakers, investors, and academics analyzing economic networks. It aids policymakers in identifying critical sectors and taking precise actions to prevent crises. Investors can leverage the algorithm to identify influential nodes and anticipate their future actions, enhancing investment strategies. In academia, the HITS algorithm advances economic theory by revealing network structures and dynamics. Overall, it improves decision-making, deepens understanding of economic phenomena, and has practical implications for policymaking, investment strategies, and academic research in economics.

However, further research is necessary in different countries and at various stages of economic development in order to fully comprehend the intricacies of economic networks. This study contributes to the existing literature on this topic and enhances understanding of economic networks.

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