International Journal of Accounting and Financial Reporting
ISSN 2162-3082
2025, Vol. 15, No. 3

Clustering and Characterizing Intersectoral Relationships in the US Economy Through Complex Networks

Mathias Schneid Tessmann (Corresponding author)

Brazilian Institute of Education, Development and Research – IDP, Brazil

E-mail: mathias.tessmann@idp.edu.br

Alexandre Vasconcelos Lima

Brazilian Institute of Education, Development and Research – IDP, Brazil

Marcelos de Oliveira Passos

Federal University of Pelotas – UFPel, Brazil

Omar Barroso Khodr

University of London, UK

Alex Cerqueira Pinto

Bank of Brazil and University of Bras ília, Brazil

Received: August 16, 2025 Accepted: September 19, 2025 Published: September 26, 2025

doi: 10.5296/ijafr.v15i3.23181 URL: https://doi.org/10.5296/ijafr.v15i3.23181

Abstract

This paper seeks to characterize the relevance and cluster of the intersectoral relationships of the US economy through complex networks. To this end, 21 sectoral assets are considered and their volatility transmissions and receipts are estimated to generate complex network metrics with the Force Atlas 2 algorithm. The results indicate that the most influential assets in the network are the Wilshire 5000, the S&P 500, and the DJIA Industrial. In contrast, the least influential assets are the CRB commodities, WTI crude oil, and the 2-year note. Three clusters are identified, cluster 0 focuses on commodities, especially crude oil, and includes assets that are influenced by commodity markets and that exhibit similar behavioral patterns. Cluster 1 includes fixed-income instruments, such as government bonds with varying maturities, which respond to fluctuations in interest rates and macroeconomic factors. Cluster 2 is composed of assets characterized by greater volatility across several sectors, including assets in the industrial, materials, energy, technology, healthcare, and utilities sectors, highlighting their diversified portfolio and varied market exposures.

Keywords: Intersectoral connectivity, Volatility transmission, Spillover index, Frequency decomposition

JEL Classification: E30, E44, G01, G10.

1. Introduction

The United States economy is one of the world's most diversified complex and interdependent intersectoral networks. These interdependencies can be described through intersectoral volatility transmissions, which are useful for understanding the economy's degree of dynamism and propensity to shocks. Through these linkages, the volatility of one sector can affect the stability of one or more sectors, with potentially significant implications for the economy.

The interdependencies between the technological, financial, health, and industrial sectors have been widely studied to predict market behavior and identify the probability of systemic risks arising from specific shocks in one or more sectors. Examining these interdependencies through volatility linkages provides a dynamic perspective on the resilience and vulnerabilities of the economy. Even more so when the focus is on verifying how fluctuations in one sector can have repercussions on others, generating instability throughout the intersectoral network.

Analyzing the connectivity of the US economy through the transmission dynamics of volatility in sectoral indices can provide valuable insights into the resilience of the economic system. When we study how volatility is transmitted between sectors, we can identify points of vulnerability in the economy and better understand how: (i) shocks to the economic system can have repercussions on a sector; (ii) how a shock in one sector has repercussions on another and (iii) how a shock in one sector is transmitted to all other sectors. The dynamics of volatility transmission indicate how exogenous shocks, whether economic, political, or technological, can generate waves of instability that propagate throughout the economy. A deep understanding of this connectivity not only helps investors optimize their portfolio strategies but also allows regulators to identify potential risks and implement preventative measures to mitigate adverse impacts, thus promoting a more stable and resilient economy.

Thus, this paper seeks to characterize and group, through complex networks, the intersectoral relationships of the US economy that present the greatest interdependencies based on their volatility transfers. To this end, daily data from sectoral indices from 1998 to 2021, the Diebold and Yilmaz (2012) spillover index, and the Force Atlas 2 algorithm are considered.

The results present three clusters and indicate that the most influential sectors of the connected and diversified US economy are Wilshire 5000, S&P 500, DJIA Industrial, XLI Industrial S&P, and XLB Basic Materials, while the least influential assets are CRB commodities, WTI crude oil, the 2-year note, Brent crude oil, and the 13-week bill.

Since Allen & Gale (2000), several works have been developed using complex network techniques to describe connections between sectors of the economy. In general, as presented by D'Arcangelis and Rotundo (2016), complex networks are an active and promising area of science, inspired by the empirical analysis of real-world networks. These networks allow modeling the functional structure of various fields of interest, leading to a better understanding of the dynamics and influence within systems of interconnected actors. These authors also point out the relevance of complex networks in the study of the correlation matrix, which is crucial for the ideal selection of investment portfolios.

Kenett and Havlin (2015) highlight that complex networks allow investigation of the behavior of agents within systems based on their empirical relationships, instead of assuming predefined behaviors. They emphasize the use of complex networks to uncover hidden information and relationships in financial markets, which benefits activities such as portfolio and risk management as well as quantitative trading. Kenett and Havlin (2015) also explore the analysis of the systemic structure and the effects of financial contagion, studying how the network structure influences the propagation of shocks and the rationality of financial institutions in forming connections.

Similarly, Iori and Mantegna (2018) note that interest in using network concepts in modeling financial systems increased at the beginning of the 21st century, becoming widespread after the 2007 financial crisis. They verified how the structure of networks of Financial institutions influenced the spread of contagion within the banking system, exploring the relationship between the fragility of the system and the position of institutions in difficulty within the network.

Similarly, Xu et al. (2020) stated that the combination of complex network theory with various disciplines has shown efficiency in the research and processing of complex systems. They highlighted the success of this application in studies on financial systems, emphasizing its effectiveness in modeling the topological structures of financial networks. In this context, Smolyak et al. (2018) highlighted that close relationships between multiple banks contributed significantly to the scale and spread of impact during financial crises. This scenario was considered ideal for developing network methodologies that detail the origins of crises.

Tang et al. (2019) emphasized that the theory of complex networks allowed modeling and extracting topological structures of financial networks, revealing hidden information and relationships between financial markets and assets. They discussed the application of this theory to a variety of financial topics, including portfolio and risk management, quantitative trading, and visualizing market dynamics. Furthermore, the authors mentioned the use of networks in the analysis of financial risks, financial cycles, and the network of risk propagation in different countries and markets, including stock, real estate, and foreign exchange markets.

Gai and Kapadia (2010) referred to the work of Allen & Gale (2000), who used a network structure with four banks to demonstrate that the spread of contagion depended on the pattern of interconnectivity between them. Both concluded that a fully interconnected network can mitigate the impact of financial shocks. In other words, when all banks were exposed to each other - so that the amount of interbank deposits held by any one bank was distributed evenly among all other banks - the impact of a shock was easily mitigated. As noted by the authors, the model performance revealed that, on average, 12.6% of the total forecast error variance across the four markets was due to volatility spillovers. Furthermore, these repercussions were significantly greater during the 2007-2009 global financial crisis, exceeding 30%. Their findings highlighted the importance of understanding the interconnectedness of financial markets, especially during periods of economic turmoil.

In this way, our work contributes to the scientific literature that investigates the interdependencies of the economy by seeking to fill some of the existing gaps with empirical evidence for the different sectors of the North American economy. In addition to this introduction, this work has three more sections. The second explains the methodology and data, the third presents and discusses the results, and finally, the fourth presents the conclusions of the work.

2. Methodology

2.1 Data

Daily closing prices from December 22, 1998, to July 12, 2021, for US Economy sector indices and funds are considered, with 5,547 prices for each sector. Table 1 details the sector indices and funds considered and presents descriptive statistics of closing prices and returns over the period.

Table 1. Details and descriptive statistics

	Closing prices				Returns			
	Mean	Std. Dev.	Minimum	Maximum	Mean	Std. Dev.	Minimum	Maximum
S&P 500 (SPX)	1,693.2930	747.5181	676.5300	4,384.6300	0.0002	0.0124	-0.1277	0.1042
Nasdaq Composite	3,967.5080	2,736.3610	1,114.1100	14,733.2400	0.0003	0.0160	-0.1315	0.1325
Dow Jones Industrial Average (DJIA)	14,881.2600	6,303.3170	6,547.0500	34,996.1800	0.0002	0.0118	-0.1384	0.1033
Dow Jones Transportation Average (DJTA)	5,843.0840	3,051.6690	1,942.1900	15,943.3000	0.0003	0.0157	-0.1640	0.0896
Dow Jones Utility Average (DJUA)	487.3838	181.9854	167.5700	960.8900	0.0002	0.0125	-0.1175	0.1277

Wilshire 5000	70.1798	41.6704	24.5800	218.3000	0.0003	0.0125	-0.1306	0.0984
Materials Select Sector (XLB)	38.1431	14.3355	16.6300	88.6800	0.0002	0.0154	-0.1325	0.1186
Energy Select Sector (XLE)	54.7083	20.3556	19.8000	101.2900	0.0001	0.0185	-0.2249	0.1537
Financial Select Sector (XLF)	20.6623	5.9894	5.0203	38.4700	0.0001	0.0190	-0.1807	0.1524
Industrial Select Sector (XLI)	43.1685	19.6372	15.3600	105.5300	0.0003	0.0137	-0.1204	0.1013
Technology Select Sector (XLK)	39.6322	26.8948	11.5800	151.3200	0.0003	0.0164	-0.1487	0.1493
Utilities Select Sector (XLU)	38.0688	11.9984	15.2300	70.9800	0.0002	0.0234	-0.2814	0.1277
Healthcare Select Sector (XLV)	48.9630	26.4922	21.8800	128.9800	0.0003	0.0329	-0.1038	2.5759
30-Year Treasury Bond (DGS30)	4.0043	1.2482	0.9900	6.7500	-0.0001	0.0167	-0.2332	0.2569
10-Year Treasury Note (DGS10)	3.3704	1.4023	0.5200	6.7900	-0.0001	0.0234	-0.3151	0.3417
5-Year Treasury Note (DGS5)	2.7563	1.6036	0.1900	6.8300	-0.0002	0.0329	-0.3567	0.3145
2-Year Treasury Note (DGS2)	2.1419	1.8238	0.0900	6.9300	-0.0004	0.0465	-0.3514	0.3483
13-Week Treasury Bill (IRX)	1.6575	1.8286	-0.1050	6.2200	-0.0011	0.2473	-4.0073	2.5759
WTI Crude Oil	58.9245	26.7146	-36.9800	145.1600	0.0005	0.0274	-0.2814	0.4258
Brent Crude Oil	61.4961	30.3102	9.1200	143.6800	0.0005	0.0254	-0.2564	0.4120
Commodity Research Bureau Index (CRB)	240.2832	70.1056	106.2929	473.5200	0.0001	0.0109	-0.0794	0.0742

Source: Elaborated by the authors.

2.2 Diebold & Yilmaz Index

The Diebold & Yilmaz (2012) spillover index is estimated with the log-log of each sector index or fund. The method uses the Akaike lag selection criterion (AIC) to estimate the variance decompositions of a VAR model. As in Tessmann et al. (2021), to calculate the total spillover index, the error variance decomposition is estimated in H steps forward by $\theta_{ij}^{g}(H)$:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=0 \\ i\neq j}}^{N} \vartheta_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \vartheta_{ij}^{g}(H)} 100 = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \vartheta_{ij}^{g}(H)}{N} 100\#(1)$$

Where Σ is the variance matrix for the error vector ε, each i and j are a different sector of the US economy, σ_{jj} is the standard deviation of the error term for the equation jth, and e_i is the selection vector, with one as the *ith* element and zeros otherwise. Measure the directional repercussions of volatility received by the US economy sector i from all other sectors j as in Equation (2). The same applies to measuring the directional repercussions of volatility transmitted by sector index i to all other sector indexes j by inverting the relationship ij by ji in the numerator.

$$S_{i.}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \vartheta_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \vartheta_{ij}^{g}(H)} 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \vartheta_{ij}^{g}(H)}{N} 100\#(2)$$

2.3 Metrics of Network Statistics

To better understand the connections between the works cited, we used complex network metrics to better define the complementarity between our study and previous literature. Our paper conducts a statistical analysis of complex network models. It covers both the micro level, that is, the nodes (agent level), and the macro level, that is, the network as a whole.

The theoretical framework we used aligns with the research by De Oliveira Passos et al. (2022), Jackson (2010), Bonacich (1987), Fortunato (2010), Pereira (2013), and Gama et al. (2015). We employ an approach that unfolds from a broader network perspective, focusing on the interconnections of asset volatility transmissions. Later, our focus moves to the node level, where we meticulously examine indexes as distinct entities.

According to the findings of Dode and Hasani (2017), PageRank is defined as a link analysis algorithm integrated into the Google search engine. It has its theoretical basis in the concept of eigenvector centrality. Functions as a metric to measure the importance and relevance of internet pages, PageRank assesses the informative value conveyed by these pages. The hierarchical positioning of pages in Google search results depends on their perceived informative value, with those that have the highest value receiving privileged visibility.

Furthermore, the authors explain that the algorithm operates on the premise that web-based information can be systematically categorized concerning the prevalence of links. Pages that receive a higher volume of inbound links gain greater popularity. We emphasize, however, that the evaluation criteria go beyond mere quantitative considerations; the algorithm also evaluates the quality of these links, thus influencing the determination of their relevance.

PageRank consequently serves as an instrument for evaluating the relative importance of web pages. This evaluation process is supported by an emphasis on the quantity and, in particular, on the qualitative attributes of links among web pages.

The metrics of Table 3 refer to node-level attributes and encompass the following key measures: (i) the weighted degree, which entails the summation of the weighted degrees of both input and output connections; (ii) the modularity class, a metric that distinguishes the three distinct communities or clusters within the examined sample; and (iii) the PageRank. The degree, or valence, is precisely defined by the subsequent expression:

$$k_i = \sum_{j=1}^{n} a_{ij}, \quad 0 < k_i < n \tag{3}$$

and

$$k_v = |N_v| \quad 0 < k_v < n \tag{4}$$

Where a_{ij} is the entry of the *i-th* row and *j-th* column of the adjacency matrix *A*; N_v is the neighborhood of the agent (node or vertex) *V*. Further, for directed networks, we have:

k_i^+ = in-degree (number of input agents, i.e., number of edges or relations ending at agent *v*);

k_i^- = out-degree (number of output agents, i.e., number of edges or relations starting in agent *v*). The measure of the degree in directed networks is also known as prestige, an expression often used in ARS (social network analysis).

$$k_i^+ = \sum_{j=1}^{n} a_{ij} \tag{5}$$

and

$$k_i^- = \sum_{j=1}^{n} a_{ij} \tag{6}$$

Two distinct forms of prestige are discernible in this context: (i) support and (ii) influence. Support prestige is characterized by the degree of entry, while influence prestige is associated with the degree of exit. In the context of weighted networks, strength aligns with the concept of degree, denoted as the sum of the weights assigned to the edges linked to a specific agent or to the relations associated with that agent. This equivalence is expressed precisely in Equation (7):

$$k_i^w = \sum_{j=1}^{n} a_{ij}^w \tag{7}$$

International Journal of Accounting and Financial Reporting
ISSN 2162-3082
2025, Vol. 15, No. 3

Furthermore, Equation (8) provides the centrality of the eigenvector, which is the metric that served as the basis for the development of the PageRank™:

$$x_i = \frac{1}{\lambda} \sum_{j=1}^{n} a_{ij} x_j \tag{8}$$

Where x_i/x_j represents the centrality of the agent i/j; a_{ij} denotes the adjacency matrix A ($a_{ij} = 1$ if the agents i and j are connected by an edge and $a_{ij} = 0$ if they are not); and, λ indicates the largest eigenvector of matrix A. Lastly, Bonacich (1987) introduced the eigenvector centrality, as a measure that refers about the notion that an agent's centrality is contingent upon the centrality of its relational counterparts, established through various exchanges and transactions.

This implies that the influence or economic-financial standing of an agent is intricately connected to the attributes of its alters—agents directly linked to the central agent, often denoted as the focal point or ego. In mathematical terms, the eigenvector centrality is expressed as a linear combination of the centralities of these first-order neighbors, providing a quantitative representation of the interconnected nature of centrality within the network.

3. Results

Estimating volatility's intersectoral volatility is necessary to identify sectoral relationships and clusters through complex networks. The results of the spillover index are presented in Table 2.

Table 2. Spillover index

	CRB	IRX	DGS10	DGS2	DGS30	DGS5	XLB	DCOIL BRENTEU	DCOIL WTICO	X.DJI	X.DJT	X.DJU	XLE	XLF	XLV	XLI	NASDAQ	X.SPX	XLK	XLU	WILL 5000	FROM
CRB	29.88	0.25	1.51	0.48	1.72	1.13	4.09	11.90	18.69	2.41	1.57	1.38	9.91	1.59	0.92	2.42	1.71	2.83	1.44	1.12	3.03	3.34
IRX	0.51	88.99	0.36	0.77	0.36	0.38	0.55	0.30	0.59	0.71	0.37	0.45	1.20	1.08	0.23	0.47	0.37	0.76	0.33	0.43	0.79	0.52
DGS10	1.12	0.07	22.04	9.26	19.01	18.30	2.47	0.99	0.79	3.06	2.65	0.53	2.59	2.52	1.65	3.01	1.91	2.83	1.80	0.54	2.85	3.71
DGS2	0.54	0.29	13.69	33.06	9.03	19.78	1.66	0.36	0.38	2.52	2.18	0.45	1.63	2.37	1.32	2.39	1.64	2.42	1.51	0.41	2.39	3.19
DGS30	1.44	0.10	21.48	6.88	24.92	15.38	2.58	1.11	1.17	2.94	2.44	0.42	2.87	2.53	1.54	2.88	1.76	2.74	1.60	0.45	2.78	3.58
DGS5	0.90	0.11	19.51	14.24	14.52	23.52	2.11	0.71	0.57	2.84	2.48	0.45	2.18	2.47	1.53	2.79	1.76	2.63	1.61	0.44	2.63	3.64
XLB	1.80	0.08	1.54	0.70	1.41	1.24	13.66	0.63	0.77	8.89	7.76	3.53	6.60	6.47	5.18	9.08	5.32	8.50	4.82	3.51	8.49	4.11
DCOIL BRENTEU	16.79	0.44	1.63	0.40	1.66	1.10	2.08	37.55	17.47	1.56	0.81	0.93	8.37	1.08	0.51	1.39	1.00	1.76	0.89	0.68	1.88	2.97
DCOIL WTICO	22.76	0.25	1.26	0.41	1.69	0.88	2.04	15.07	36.41	1.36	0.63	0.58	8.49	0.76	0.49	1.27	0.97	1.63	0.87	0.43	1.75	3.03
X.DJI	0.84	0.08	1.48	0.83	1.24	1.29	6.93	0.40	0.43	10.67	6.88	3.91	5.07	7.49	6.55	8.76	6.86	9.95	6.70	4.01	9.64	4.25
X.DJT	0.68	0.05	1.65	0.91	1.33	1.45	7.74	0.26	0.25	8.85	13.58	3.02	4.48	7.40	5.39	9.81	6.49	8.85	5.65	3.14	9.02	4.12
X.DJU	0.86	0.07	0.58	0.31	0.41	0.47	5.19	0.47	0.37	7.39	4.42	19.80	5.72	4.98	4.99	5.75	3.62	7.48	3.49	16.53	7.10	3.82
XLE	5.07	0.21	1.79	0.77	1.75	1.43	7.53	2.98	3.61	7.38	5.09	4.50	15.58	5.39	3.96	6.83	3.88	7.48	3.41	3.92	7.46	4.02
XLF	0.72	0.15	1.53	0.96	1.35	1.41	6.44	0.31	0.31	9.53	7.30	3.39	4.74	13.51	5.41	8.31	6.20	9.87	5.39	3.45	9.71	4.12
XLV	0.49	0.03	1.13	0.62	0.93	1.00	5.75	0.21	0.25	9.29	5.95	3.76	3.86	5.99	15.12	7.74	7.59	9.78	6.77	4.14	9.61	4.04
XLI	0.91	0.06	1.58	0.85	1.33	1.38	7.68	0.38	0.42	9.53	8.32	3.35	5.08	7.10	5.93	11.55	6.60	9.23	6.09	3.43	9.20	4.21
NASDAQ	0.71	0.05	1.14	0.67	0.92	1.00	5.12	0.29	0.35	8.49	6.24	2.35	3.33	6.05	6.65	7.52	13.09	10.48	11.93	2.63	10.97	4.14
X.SPX	0.95	0.08	1.32	0.76	1.12	1.16	6.37	0.42	0.48	9.56	6.61	3.80	4.94	7.46	6.65	8.16	8.14	10.27	7.65	3.97	10.15	4.27
XLK	0.64	0.05	1.14	0.65	0.89	0.97	4.95	0.29	0.33	8.84	5.78	2.43	3.14	5.61	6.32	7.38	12.70	10.50	13.93	2.86	10.61	4.10
XLU	0.64	0.07	0.54	0.26	0.40	0.42	5.07	0.32	0.27	7.43	4.53	16.33	4.92	4.98	5.43	5.81	3.95	7.65	4.00	19.72	7.26	3.82
WILL 5000	1.01	0.08	1.33	0.75	1.14	1.16	6.38	0.45	0.51	9.29	6.76	3.62	4.94	7.36	6.54	8.15	8.54	10.17	7.76	3.77	10.27	4.27
TO	2.83	0.12	3.63	1.97	2.96	3.40	4.42	1.80	2.29	5.80	4.23	2.82	4.48	4.32	3.68	5.23	4.33	6.07	3.99	2.85	6.06	77.28

Source: Elaborated by the authors.

Table 2 is easy to interpret because the Diebold & Yilmaz (2012) index ranges from 0 to 100, allowing it to be interpreted as percentages. Thus, the twenty-third row shows how much volatility the sectors transmit to the market and the twenty-third column shows how much they receive from the market. As an example, the CRB index transmits 2.83% and receives 3.34% in volatility from the market as a whole. The intersection cell between the last row and the last column denotes the total connectivity of the market, serving as a signal of possible systemic risks, and was 77.28%.

It is also possible to verify the relationship between each pair of sectors. The intersection cell between the second column and the third row shows how much volatility the CRB sector sent to the IRX, which was 0.51%. Similarly, the intersection cell between the third column and second row shows when the IRX sector sent volatility to the CRB, 0.25% in this case. Table 3, with these results, presents the results of the complex network metrics measured.

Table 3. Network's metrics

Sectoral indexes	Weighted indegree	Weighted outdegree	Weighted degree	PageRanks
Willshire 5000	127.32	89.71	217.03	0.077647
S&P 500	127.54	85.58	213.12	0.077455
DJIA Industrial	121.87	89.34	211.21	0.074804
XLI Industrial S&P	109.92	88.45	198.37	0.068642
XLB Basic Materials	92.73	86.32	179.05	0.058645
XLE Energy	94.06	84.44	178.5	0.054490
Nasdaq	90.52	86.89	177.41	0.059153
XLF Financial	90.68	86.48	177.16	0.058783
DJT Transportation	88.77	86.42	175.19	0.057776
XLK Technology	80.03	86.08	166.11	0.053170
XLV Health Care	77.19	84.89	162.08	0.051781
10-Year Note	76.19	77.95	154.14	0.040434
5-Year Note	71.33	76.48	147.81	0.038031
XLU Utilities	59.86	80.28	140.14	0.039904
DJU Utilities	59.18	80.20	139.38	0.039418
30-Year Bond	62.21	75.09	137.3	0.035291
CRB Commodities	59.38	70.10	129.48	0.031152
WTI Oil	48.01	63.59	111.6	0.026028
2-Year Note	41.48	66.96	108.44	0.026429
Brent Oil	37.85	62.43	100.28	0.022669
13-Week Bill	2.57	11.01	13.58	0.008298

Source: Elaborated by authors.

Table 3 presents the analyses of complex networks, but for reasons of space, only the weighted degree, which is the sum of the other two degrees - in-degree and out-degree, is discussed. The weighted degree serves as a metric for the support and prestige of influence of an industry in the network. It is an essential measure for assessing the influence of industries within the economy, particularly in terms of volatility transmission. According to column 4 of Table 3, the assets that exert the most substantial influence on volatility variations, listed in descending order, are the Willshire 500 (217.03), S&P 500 (213.12), DJIA Industrial (211.21), XLI S&P Industrial (198.37) and XLB Basic Materials (179.05). On the other hand, assets that demonstrate less influence include CRB Commodities (129.48), WTI Oil (111.6), 2 Year Note (108.44), Brent Oil (100.28), and 13 Week Bill (13.58).

Column 5 of Table 3 displays the PageRanks of the indexes in descending order. The high correlation between this network metric and the weighted degrees is evident. As postulated by Kim et al. (2016), the manifestation of a substantial correlation between PageRanks and weighted ranks in directed and weighted networks is not uncommon.

Indeed, such a correlation is considered desirable, as defined by the authors, as it signifies a synergy between the quantitative (weighted ranks) and qualitative (PageRanks) aspects. This increases the consistency and robustness of the obtained results. The identification of modularity classes allows the clustering of the network. Table 4 presents the results of the network clusters. Furthermore, the Force Atlas layout algorithm is employed to visually depict the structural features of the complex network. The results are shown in Figure 1.

Table 4. Cluster analysis

Sectoral Indexes	Modularity class	Similarities/Sectors
CRB Commodities, 13-Week Bill, Brent Oil, WTI Oil	Cluster 0	Commodities (Oil, above all)
10-Year Note, 2-Year Note, 30-Year Bond, 5-Year Note	Cluster 1	Fixed income
Willshire 5000, S&P 500, DJIA Industrial, XLI Industrial S&P, XLB Basic Materials, XLE Energy, Nasdaq, XLF Financial, DJT Transportation, XLK Technology, XLV Health Care, XLU Utilities, DJU Utilities	Cluster 2	Higher volatilities (diversified sectors)

Source: Elaborated by authors.

International Journal of Accounting and Financial Reporting
ISSN 2162-3082
2025, Vol. 15, No. 3

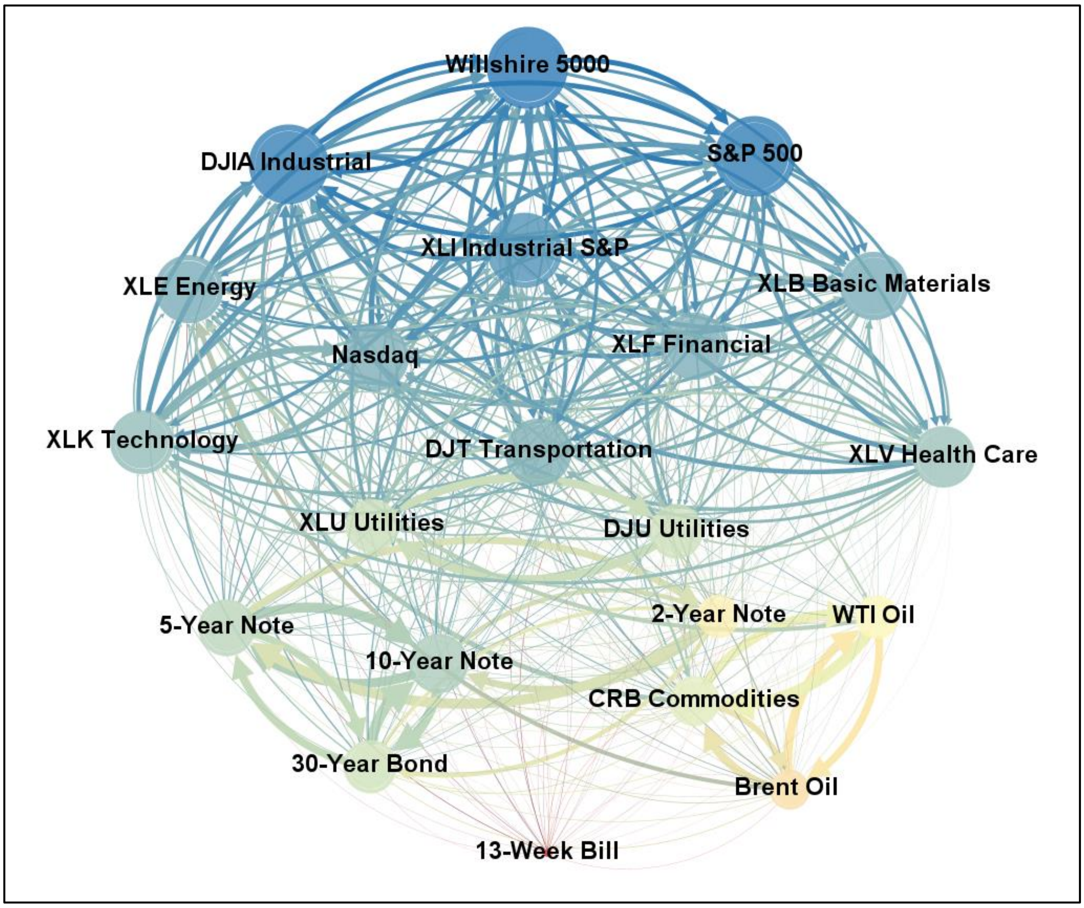

Figure 1. Network visualization

Source: Elaborated by authors.

Note: The edge colors are clear yellow (weak connectivity/volatility), light green (intermediate), light blue (strongest), and dark blue (strong).

The cluster analysis results are shown in Table 4, where the modularity classes of the different assets were calculated based on the similarities between the sectors. Cluster 0 brings together commodities, with a notable emphasis on oil. This cluster contains assets intrinsically linked to primary materials markets, particularly influenced by factors in this economic field. The sectors in Cluster 0 tend to exhibit similar patterns or behaviors, highlighting their similar characteristics.

Moving on to Cluster 1, this category encompasses assets associated with fixed-income securities, including several government bonds with varying maturities. The assets grouped in this cluster respond strongly to fluctuations in interest rates and broader macroeconomic variables that impact the bond market.

Finally, Cluster 2 separates assets from different sectors characterized by high volatility. This cluster lists assets from different sectors, which characterizes a diversified portfolio. The nomenclature of "higher volatility" attributed to this cluster suggests that the assets contained in it present relatively high levels of price volatility. The sectors covered by Cluster 2 include industrials, materials, energy, technology, healthcare, and utilities. This combination of sectors highlighted the diverse composition of positions within Cluster 2, contributing to its characterization as a repository of assets with varying degrees of exposure to market risks.

About the results of Figure 1, the Force Atlas 2 algorithm was chosen because it is easy to generate a layout distribution that corresponds to the segmentation of the sample into three clusters. In the complex network in Figure 1, the first cluster is composed of six assets: DJIA Industrial, Willshire 5000, S&P 500, XLE Energy, XLI Industrial S&P, and XLB Basic Materials.

The last part of the portfolio is composed of several assets divided into different subgroups. The first subgroup includes XLK Technology, Nasdaq, DJT Transportation, XLF Financial, and XLV Health Care. The second subgroup includes 5-year Notes, XLU Utilities, 10-Year Note, 30-Year Bond, DJU Utilities, 2-Year Note, WTI Oil, CRB Commodities, and Brent Oil. We highlight that the 13-week note has the lowest degree of connectivity compared to the portfolio assets.

4. Conclusion

This paper sought to characterize the intensity of intersectoral relationships and cluster the sectors of the US economy through complex networks. To this end, volatility transmissions between sectoral indices or funds were estimated using the Diebold & Yilmaz spillover index, which allowed us to measure the weighted entry degree, the weighted exit degree, the average weighted degree, PageRanks, modularity classes, and eigenvector centrality.

The analysis comprises daily closing prices from December 1998 to July 2021 for 21 different US sector indexes or funds, specifically the Wilshire 5000, S&P 500, DJIA Industrial, XLI S&P Industrial, XLB Basic Materials, XLE Energy, Nasdaq, XLF Financial, DJT Transportation, XLK Technology, XLV Health Care, 10-Year Note, 5-Year Note, XLU Utilities, DJU Utilities, 30-Year Bond, CRB Commodities, WTI Oil, 2-Year Note, Brent Oil, and 13-Week Note.

The results indicate that weighted degree, combining weighted indegree and outdegree, is crucial to assess the influence of assets within a network, particularly concerning volatility transmission. The most influential sectors, classified by weighted classes, are the Wilshire 5000, S&P 500, DJIA Industrial, XLI Industrial S&P, and XLB Basic Materials. In contrast, the least influential assets are CRB Commodities, WTI Oil, 2-Year Note, Brent Oil, and 13-Week Bill. In addition, the PageRanks of these sectors show a strong correlation with the weighted classes, highlighting the relationship between these metrics and increasing the robustness of the results. Overall, the Wilshire 5000 index has the greatest influence, while CRB Commodities, WTI Oil, and 13-Week Bill have the least influence within the network.

The indices were clustered based on similarities, where cluster 0 focuses on commodities - especially oil - and includes sectors influenced by commodity markets, exhibiting similar behavior patterns reflected by their connectivity. Cluster 1 includes fixed-income instruments, such as government bonds with varying maturities, that respond to interest rate fluctuations and macroeconomic factors. Cluster 2 consists of assets from diversified sectors, characterized by higher volatility. This cluster includes assets in industrials, materials, energy, technology, healthcare, and utilities, highlighting their diversified portfolio and varied market exposures.

These findings are useful for the scientific literature investigating intersectoral relationships in the economy by bringing empirical evidence for the United States, for policymakers concerned with systemic risk, and investors. This is because, when these methodologies are applied, sectors are categorized based on their similarities and patterns of market response, demonstrating the practical application of network analysis metrics in quantitative finance studies.

Finally, this work is limited by not identifying the shocks experienced by each sector, nor their causes. Future research could incorporate external economic factors, such as geopolitical events and changes in monetary policy, contributing to a better understanding of how these influences affect sectoral indices and their spillover effects within the network. The analysis could be expanded to include sectoral indices from global markets, providing insights into the degree of interconnectedness between international markets and how shocks are transmitted from a given country's economic sector to the sectors of others. We intend to use dynamic network analysis techniques to observe the evolution of relationships between sectoral indices over time, which could identify intersectoral changes in response to major economic events, offering valuable insights into market stability and resilience.

Interest Statement

We declare no conflict of interest in carrying out this research.

References

Allen, F., & Gale, D. (2000). Financial contagion. *Journal of Political Economy*, *108*(1), 1-33. https://doi.org/10.1086/262109

Bonacich, P. (1987). Power and centrality: A family of measures. *American Journal of Sociology*, *92*(5), 1170-1182. https://doi.org/10.1086/228631

D'Arcangelis, A. M., & Rotundo, G. (2016). Complex networks in finance. *Complex Networks and Dynamics: Social and Economic Interactions*, 209-235. https://doi.org/10.1007/978-3-319-40803-3_9

De Oliveira Passos, M., Gonzalez, P. L., Tessmann, M. S., & de Abreu Pereira Uhr, D. (2022). The greatest co-authorships of finance theory literature (1896-2006): scientometrics based on complex networks. *Scientometrics*, *127*(10), 5841-5862. https://doi.org/10.1007/s11192-022-04482-8

Diebold, F. X., & Yilmaz, K. (2009). Better to Give than to Receive: Forecast-Based Measurement of Volatility Spillovers. In *International Institute of Forecasting Workshop on Predictability in Financial Markets, Lisbon, Portugal, January*.

Dode, A., & Hasani, S. (2017). PageRank algorithm. *IOSR Journal of Computer Engineering (IOSR-JCE)*, *19*(1), 01-07. https://doi.org/10.9790/0661-1901030107

Fortunato, S. (2010). Community detection in graphs. *Physics Reports*, *486*(3-5), 75-174. https://doi.org/10.1016/j.physrep.2009.11.002

Gai, P., & Kapadia, S. (2010). Contagion in financial networks. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *466*(2120), 2401-2423. https://doi.org/10.1098/rspa.2009.0410

Gama, J., Carvalho, A. C. P. D. L. F. D., Faceli, K., Lorena, A. C., & Oliveira, M. (2012). Extração de conhecimento de dados: data mining.

Iori, G., & Mantegna, R. N. (2018). Empirical analyses of networks in finance. In *Handbook of Computational Economics* (Vol. 4, pp. 637-685). Elsevier. https://doi.org/10.1016/bs.hescom.2018.02.005

Jackson, M. O. (2008). *Social and economic networks* (Vol. 3, p. 519). Princeton: Princeton University Press. https://doi.org/10.1515/9781400833993

Kenett, D. Y., & Havlin, S. (2015). Network science: a useful tool in economics and finance. *Mind & Society*, *14*, 155-167. https://doi.org/10.1007/s11299-015-0167-y

Kim, J. H., Candan, K. S., & Sapino, M. L. (2016). Locality-sensitive and re-use promoting personalized PageRank computations. *Knowledge and Information Systems*, *47*, 261-299. https://doi.org/10.1007/s10115-015-0843-6

Pereira, L. M., de Oliveira Ribeiro, C., & Securato, J. R. (2012). Agricultural commodities pricing model applied to the Brazilian sugar market. *Australian Journal of Agricultural and Resource Economics*, *56*(4), 542-557. https://doi.org/10.1111/j.1467-8489.2012.00594.x

Smolyak, A., Levy, O., Shekhtman, L., & Havlin, S. (2018). Interdependent networks in Economics and Finance-A Physics approach. *Physica A: Statistical Mechanics and its Applications*, *512*, 612-619. https://doi.org/10.1016/j.physa.2018.08.089

Tang, Y., Xiong, J. J., Luo, Y., & Zhang, Y. C. (2019). How do the global stock markets Influence one another? Evidence from finance big data and granger causality directed network. *International Journal of Electronic Commerce*, *23*(1), 85-109. https://doi.org/10.1080/10864415.2018.1512283

Xu, R., Mi, C., Mierzwiak, R., & Meng, R. (2020). Complex network construction of Internet finance risk. *Physica A: Statistical Mechanics and its Applications*, *540*, 122930. https://doi.org/10.1016/j.physa.2019.122930