THE DYNAMIC INTERDEPENDENCE OF GLOBAL FINANCIAL MARKETS: AN ANALYSIS THROUGH DYNAMIC BAYESIAN NETWORKS

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Abstract: This study investigates the dynamic interdependence of global financial markets over time, focusing on identifying connection patterns among assets during periods of non-crisis and crisis, covering the period from 03/01/2000 to 06/23/2023. We employ Dynamic Bayesian Networks (DBN) to map the complex network of interactions between assets and reveal the topology of these connections. Our main findings indicate that over time, both in non-crisis periods and crisis periods, there is a tendency for financial assets to connect more strongly with assets located geographically nearby. This signals a process of "deglobalization" of financial markets, increasing considerations of trade-offs when analyzing risk and return asymmetries between different regionalized communities. Additionally, we observe that networks exhibit higher complexity in non-crisis periods compared to crisis moments. These conclusions substantially contribute to understanding the dynamics of global financial markets and emphasize the importance of considering factors related to regionalization and geographical interconnections when assessing risks and returns in the financial landscape. The implications of these findings are relevant for investors, portfolio managers, and policymakers, providing valuable insights for risk management and decision-making in an ever-evolving global financial environment.

Keywords: Dynamic Interdependence, Financial Markets, Dynamic Bayesian Networks, Complex Networks.
JEL classification: C11; C45; E44; G1.

1. INTRODUCTION

In recent decades, the dynamics of interdependence in global financial markets have undergone transformations, reflecting changes similar to those observed in other social systems of humanity. Various factors influence this dynamic interdependence in financial markets, with the economy and its growth prospects being key factors that significantly impact this dynamic. Indeed, positive economic growth prospects have the potential to drive corporate capital generation, positively affecting global financial markets, while unfavorable economic scenarios have the opposite effect. The analysis of connections and relationships among global financial assets is of utmost importance for investors and portfolio managers, as it enables the identification of opportunities for international diversification and the construction of hypothetical scenarios to assess the spread of stress among assets. (Youssef, Mokni, and Ajmi 2021).

In this study, we investigate the dynamics of interdependence in global financial markets, considering 23 countries whose stock indexes represented approximately 80% of the world's GDP in 2022.

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Additionally, we include five significant financial assets in the analysis: Gold, Crude Oil, 10-Year US Treasury Bonds, Volatility Index (VIX), and Copper. Regarding the methodological approach, we employ Dynamic Bayesian Networks (DBN) for the period from 01/03/2000 to 06/23/2023. This technique was chosen for its ability to capture and analyze information over time, enabling the classification and discovery of relevant patterns. (Shiguihara, Lopes, and Mauricio 2021). We observed the temporal evolution of networks and complex network measures during non-crisis and crisis periods, enabling a comprehensive analysis of interactions and patterns of financial assets over time. Additionally, DBN makes it possible to capture non-linear relationships between pairs of assets, which often escapes other conventional methods. We combined the use of DBN with a comprehensive set of complex network metrics to guide our analysis of the topology of the formed networks, as suggested by Silva and Zhao (2016), which include: i) Strictly Local Measures; ii) Mixed Measures; and iii) Global Measures.

The main findings are: 1) During non-crisis periods (5 periods) and crisis periods (4 periods), we observe a trend of reduced connections (partial autocorrelations) in both cases. Assets tend to form communities with geographically close assets, with few or no connections to assets from other communities, characterizing a process of "deglobalization" of financial markets; 2) The complex network measures used in the analysis of Dynamic Bayesian Networks (DBN) show that the USA asset has significant authority in almost all estimated networks, regardless of whether they are non-crisis or crisis periods. There are numerous hubs, which are assets, dependent on each estimated network. Their identified patterns are: i) emerging economies or not the world's top 5 largest economies; ii) commodities; iii) US10Y; and iv) VIX. In other words, these assets serve as short-term strategic allocations; 3) In econometric models that explain the return of financial assets through complex network measures, Diameter (*Diam*), Average Distance (*M_Dist*), and Modularity (*Modul*) stand out as significant variables in both non-crisis and crisis periods.

The work contributes to the literature in various aspects. First, it complements existing literature with a temporal analysis of networks formed during non-crisis and crisis periods, through the application of a wide range of complex network measures guided to understand the behavior of financial assets over the past 24 years (01/03/2000 to 06/23/2023). This analysis stands out from traditional analysis because, in addition to estimating Dynamic Bayesian Networks (DBN) during non-crisis and crisis periods and calculating 14 complex network measures to understand how these networks behaved over the periods, we implemented static panel data estimation to verify which complex network measures are statistically significant in explaining the return of the studied financial assets. In this work, we implemented the following complex network measures: Authority Score, Hub Score, Coreness, Assortativity, Transitivity_Net_Global, and Edge_Density, from which we extracted insights into the central connections of the networks (Authority Score, Hub Score, Coreness), the probability of connections with assets with the same degree (Assortativity), the formation of triangles (Transitivity_Net_Global), and the ratio of the number of connections to the number of possible connections (Edge_Density).

Second, the work identifies communities of financial assets over the time series. We used the algorithm by Clauset, Newman, and Moore (2004), which finds the community configuration in a network that maximizes its modularity. With this tool, we were able to understand how the dynamics of financial asset communities function during non-crisis and crisis times, as well as their evolution over time. We interpret that assets within the same community are more prone to receiving financial contagion - whether positive or negative - from other members of the same community than from members of other communities. Identifying subsets of highly interconnected assets is important for public policy formulation, especially in stress scenarios, as it makes it possible to establish the degree of financial system stability in the face of adverse shocks.

Third, given the evidence of the "deglobalization" process of financial assets, it becomes increasingly important to consider factors related to regionalization and geographic interconnections when assessing risks and returns in financial markets. The implications of these findings are relevant for investors, portfolio managers, and policymakers, providing valuable insights for risk management and decision-making in a constantly evolving global financial environment.

In Section 2, we provide a brief literature review. In Section 3, we detail the theoretical framework used for the estimation of Dynamic Bayesian Networks, as well as the complex network measures employed. In Section 4, we examine the estimated networks and the calculated complex network measures, in addition to describing the econometric estimations performed. Finally, in Section 5, we present the conclusions found throughout this study.

2. LITERATURE REVIEW

Complex networks have been widely used to describe and analyze natural, artificial, and social systems, allowing us to understand the interactions between their components (Brú et al. 2014). The complexity of these systems is reflected in the intricate structure of their vertices and the diverse interactions among their complex elements (Wu, Tuo, and Xiong 2015). This approach has proven to be valuable in different areas such as sociology, biology, transportation, and economics (Huang, Zhuang, and Yao 2009; Tabak, Serra, and Cajueiro 2010). In applications within financial markets, these tools have proven to be essential in providing a comprehensive view of market risk, credit risk, and macroeconomic evaluation and systemic risk, enhancing decision-making (Gong, Tang, and Wang 2019; Kou et al. 2019).

The literature presents valuable contributions on the application of complex networks in the study of global financial markets. Since the pioneering work of Mantegna (1999), Several researchers have dedicated themselves to understanding the dynamics of interdependence and correlations in financial markets. In the stock market of the United States, we identified the authors Kim et al. (2002) who investigated the scale-free characteristics in the weighted correlation network of stocks from the Standard and Poor's 500 index. Boginski, Butenko, and Pardalos (2005) also analyzed the American stock market and found that stock price correlation follows the scale-free attribute, providing a new data mining approach for the classification of financial instruments. Tse et al. (2009) studied the structural variation of the network formed by connecting Standard & Poor’s 500 stocks, using the Power Law jointly. They obtained the result that the average error of the Power Law approximation becomes an effective indicative parameter of stock market volatility. Finally, in the field of Standard and Poor's 500 index prediction, researchers M. Kim and Sayama (2017) demonstrated that changes in network strength distributions (centrality measures) provide crucial information about future network movements. They estimated ARIMA predictive models by adding network measures that increased the accuracy of forecasts.

In the Asian continent, China stands out with various studies applied to the local financial market using the complex networks approach. You, Fiedor, and Hołda (2015) analyzed 158 stocks from the Shanghai Stock Exchange (SSE Composite Index) and discovered that the Chinese stock market is not structurally risky when compared to the stock markets of the United States and Western Europe. The authors Huang, Zhuang, and Yao (2009) used 1080 Chinese stocks (697 from the Shanghai Stock Exchange and 383 from the Shenzhen Stock Exchange) to study the structural properties and topological stability of the network, finding out that the networks follow a Power Law model. In the work of Chan, Chu, and So (2023), the authors employed Bayesian networks to predict absolute extreme returns and discovered that the network statistics of the time series from Bayesian networks and the asset distance order are variables that enhance the predictability power of absolute extreme returns for the Hang Seng and Dow Jones Industrial Average indexes.

Other Asian stock markets have also been analyzed through networks: In South Korea, Jangmin et al. (2004) used dynamic Bayesian networks to model the trend dynamics of stock prices in the stock market. In Japan, Kita et al. (2012) developed a stock price prediction algorithm for the NIKKEI 225 index using the Bayesian network. In Pakistan, Memon and Yao (2019) analyzed cross-correlations in the daily closing prices of 181 stocks listed on the Pakistan Stock Exchange (PSX), identifying substantial clustering of financial assets and a less stable global market structure, a crisis-like scenario, due to external and internal events of terrorism and political, financial, and economic crises. In Iran, Moghadam et al. (2019) studied stocks from the Tehran Stock Exchange by constructing a stock correlation network and applying centrality measures to identify stocks with higher authority in the networks. Essentially, stocks with greater market capitalization, higher risk, greater trading volume, and lower debt are considered of higher authority.

In Europe, researchers have focused on the systematic study of financial markets through complex networks. Ballester, López, and Pavía (2023) analyzed systemic credit risk in the European financial system through Dynamic Bayesian Networks, revealing that 5% to 40% of variations in European sectoral Credit

Default Swap (CDS[4]) are explained by network relationships. Caraiani (2012) investigated properties of returns in leading emerging European stock exchanges using complex networks, discovering evidence of scale-free networks and multifractality of clustering coefficients. In Turkey, Sener, Karaboga, and Demir (2019) used Bayesian networks to study the effects of the attempted coup on July 15, 2016 on the financial market.

In emerging economies, there are studies focusing on networks formed by financial assets. Bouri et al. (2018) examined implied volatility in the stock markets of BRICS[5] countries, influenced by implied volatility in commodity and stock markets of major developed countries, using a Bayesian Graphical Structural Vector Autoregressive (BGSVAR) model. On the other hand, Carvalho and Chiann (2013) applied Bayesian network concepts to identify financial contagion among stock exchanges in countries such as Brazil, Argentina, Mexico, Malaysia, and Russia, where the American stock market stood out as a point of authority in the formed networks. In Brazil, Tabak, Serra, and Cajueiro (2010) employed the minimum spanning tree method combined with complex network measures, discovering that the financial, energy, and material sectors are the most important within the network.

Other recent works have focused on the impacts of crisis events on global financial markets. Korkusuz, McMillan, and Kambouroudis (2022) analyzed the volatility transmission dynamics among key global financial indicators and G20 stock markets, applying a combination of the bivariate GARCH-BEKK model with complex network theory. Aslam et al. (2020) studied the effects of the COVID-19 pandemic using complex networks to analyze 56 global stock indices, highlighting structural changes in network connections due to the pandemic.

Furthermore, some studies have explored the interaction between financial assets and macroeconomic indicators to verify potential influences between the real economy and the financial market. In research conducted in China, the results did not show a consistent relationship between macroeconomic indicators and the financial market across different analyzed time periods (Liu et al. 2019; Liu, Feng, and Guo 2021). Similarly, in the economies of the United States and Turkey, consistent evidence of the dynamics of macroeconomic indicators concerning the financial market was not found (Lu, Guo, and Tian 2016; Hatipoglu and Uyar 2019). Lastly, there are studies that explored connections between stock markets, commodities, and currencies (Reboredo, Ugolini, and Hernandez 2021; Tessmann et al. 2023).

These studies demonstrate the relevance of complex networks as a powerful tool for understanding relationships between financial assets, the hierarchy of connections, and the dynamics of interactions. The analysis carried out in these studies contribute to the advancement of knowledge about financial markets, enabling a better understanding of their patterns and behaviors. The complex network approach has proven

[4] A credit default swap (CDS) is a contract between two parties in which one party purchases protection from the other one against losses from the default of a borrower for a defined period of time.
[5] It is an acronym that started as BRIC in 2001, coined by Jim O'Neill (a Goldman Sachs economist) for Brazil, China, India, and Russia. Later in 2010, South Africa was added to become BRICS.

to be crucial in providing valuable insights that can be applied in investment strategies, economic policies, and decision-making.

3. METHODOLOGY

3.1. Primary Concept of Bayesian Network (BN)

A Bayesian Network (BN) is a graphical structure that allows us to represent an uncertain domain and reason about it. A BN consists of nodes and edges (arcs or links). The nodes represent a set of random variables within the domain. The set of edges (arcs or links) connects pairs of nodes, representing direct dependencies between the variables. Assuming the variables are discrete, the strength of the relationship between variables is quantified by conditional probability distributions associated with each node. The only restriction on allowed edges in a BN is that there should be no directed cycle, meaning you cannot return to a node simply by following directed edges. Therefore, these networks are called Directed Acyclic Graphs (DAGs) (Korb and Nicholson 2004).

Let $G = (V, E)$ be a directed acyclic graph (DAG), where V is a finite set of nodes, and E is a finite set of directed edges between the nodes. Each node $v \in V$ in this graph represents a random variable X_v and comprises the set of variables in G. Given any pair of nodes X and $Y \in V$, if there is a directed edge from X to Y, X is called the parent node of Y. For each parent node of v, the notation $pa(v)$ is adopted. Additionally, a conditional probability function between v and $pa(v)$ is defined as $p\left(x_v \middle| x_{pa(v)}\right)$. The set of relational probability functions in the network is denoted as P. A BN for a given set of random variables is the pair (G, P).

It is important to highlight that the theory of Bayesian Networks (BN) includes the concept of *d-separation*, which guarantees the conditional and directional independence of a set of random variables (Carvalho and Chiann 2013). The Markov condition implies that all *d-separations* are conditional independences, and all conditional independences implied by the Markov condition are identified by *d-separation*. In other words, if $(\mathbb{G}, P)$ satisfies the Markov condition, every *d-separation* in $\mathbb{G}$ is a conditional independence in P. Furthermore, every conditional independence that is common to all probability distributions satisfying the Markov condition with DAG $\mathbb{G}$, is identified by *d-separation* (Korb and Nicholson 2004; Neapolitan 2004).

3.2. Bayesian Network Learning

Analyzing from a statistical perspective, learning a network represents the estimation of model parameters based on a certain criterion and having knowledge of a specific dataset (Carvalho and Chiann 2013).

The Bayesian approach is used to estimate parameters within the network, aiming to encode uncertainty about the parameters θ into a $prior$ distribution $p(\theta)$ and applying the data $\bar{d}$ (through the likelihood function). By applying Bayes' theorem, the uncertainty is updated with the $posterior$ distribution $p(\theta|\bar{d})$, as per Equation 1:

$$p(\theta|\bar{d}) = \frac{f(\bar{d}|\theta)h(\theta)}{\int_{\theta\in\Theta} f(\bar{d}|\theta)h(\theta)d\theta}, \theta \in \Theta, \tag{1}$$

given Θ as the parameter space, $\bar{d}$ as the random sample from the probability distribution $p(x|\theta)$, and $p(\bar{d}|\theta)$ as the likelihood function.

3.3. Concept of Dynamic Bayesian Network (DBN)

Dynamic Bayesian Network (DBN) is a temporal extension extensively used to model temporal relationships among variables over different time periods (Murphy 2002). The unfolding of an interaction graph over time is highly beneficial for accommodating potential loops and feedbacks in the network's topology, as required by definition for a Bayesian Network (Nagarajan, Scutari, and Lèbre 2013).

In a DBN, it is assumed that the dependency relationships are represented by a Vector Autoregressive Process (VAR), where it is important that the time series are stationary. In a VAR(p) process of order p, the observed variables at any time $t \geq p$ satisfy Equation 2:

$$X(t) = A_1 X(t-1) + \cdots + A_i X(t-i) + \cdots + A_p X(t-p) + B + \varepsilon(t). \tag{2}$$

Where:

$X(t) = (X_i(t)), i = 1, \dots, k,$ is the vector of k observed variables at time t;

$A_i, i = 1, \dots, p$ are coefficient matrices of size $k\ x\ k$;

B is a vector of size k that represents the baseline measurement for each variable;

$\varepsilon(t)$ is a vector of white noise of size k, with zero mean $E(\varepsilon(t)) = 0$ and time-invariant positive definite covariance matrix $Cov(\varepsilon(t)) = \Sigma$.

Thus, if we assume a VAR(p) of order 1, as in Equation 3:

$$X(t) = AX(t-1) + B + \varepsilon(t), \quad com \quad \varepsilon(t) \sim N(0, \Sigma), \tag{3}$$

the edges are defined between two successive time periods, and this set of edges is determined by all nonzero coefficients in matrix A. If an element $a_{ij}, i \neq j$, is non-zero, then the network includes an edge from $X_i(t-1)$ to $X_j(t)$. Additionally, we assume that the error term for each variable X_i is independent of the other variables and their respective error terms, meaning the elements off the diagonal in Σ can be set to 0.

3.3.1. *Significance Measures: local false discovery rate (fdr) and q-value*

An efficient estimator of the covariance matrix can be obtained by setting the empirical correlation coefficients to zero and the empirical variances to their medians (Nagarajan, Scutari, and Lèbre 2013).

In this context, the work conducted by Schäfer and Strimmer (2005) and Opgen-Rhein and Strimmer (2007) present an algorithm that enables robust estimation of VAR(1) coefficients for Dynamic Bayesian Networks. Gaussian Graphical Models (GGM) are estimated for each Directed Acyclic Graph (DAG) based on applying shrinkage estimators to estimated covariances and partial correlation matrices, which represent the interactions between variables. The network structure is determined by including edges in descending order of coefficients and employing multiple tests of the local false discovery rate (local fdr), which tests the existence of false positives (edges with null probability) and eliminates them. Thus, only significant edges remain.

In Equation 4, we define the observed partial correlations $\tilde{r}$ in the edges:

$$f(\tilde{r}) = \eta_0 f_0(\tilde{r}; k) + (1 - \eta_0) f_A(\tilde{r}), \tag{4}$$

where f_0 is the null distribution, η_0 is the (unknown) proportion of "null edges", and f_A is the distribution of observed partial correlations assigned to actually existing edges. The null density f_0 is given by:

$$f_0(\tilde{r}; k) = (1 - \tilde{r}^2)^{(k-3)/2} \frac{\Gamma\left(\frac{k}{2}\right)}{\pi^{1/2}\Gamma\left(\frac{(k-1)}{2}\right)} = |\tilde{r}| \mathrm{Be}\left(\tilde{r}^2; \frac{1}{2}, \frac{k-1}{2}\right), \tag{5}$$

where $\mathrm{Be}(x; a, b)$ is the Beta distribution and k is the degrees of freedom, equal to the reciprocal variance of the null $\tilde{r}$. Fitting this mixture density allows k, η_0, and f_A to be determined. Subsequently, we can calculate the specific edge's false discovery rate (fdr) using Equation 6:

$$\mathrm{Prob}(\text{aresta nula}|\tilde{r}) = \mathrm{fdr}(\tilde{r}) = \frac{\hat{\eta}_0 f_0(\tilde{r}; \hat{k})}{\hat{f}(\tilde{r})}. \tag{6}$$

The Equation 6 highlights the local fdr as the posterior probability of an edge being null given $\tilde{r}$. In the estimation process, the q-values associated with each edge and the probabilities of an edge being non-null $(1 - \mathrm{fdr})$ are calculated, and these quantities can be used to define the significance level of the edges.

The q-value is a measure of statistical significance adjusted by the FDR (False Discovery Rate) and is used to address multiple testing statistical problems, where q-values represent the expected percentage of false positives among significance tests. On the other hand, p-values only indicate the significance level considering the overall number of performed tests (Storey 2002).

Storey (2002) defines the FDR as the expected proportion of false positives among all rejected hypotheses multiplied by the probability of at least one rejection occurring. Storey (2003) establishes the pFDR (positive false discovery rate) to demonstrate that we are conditioned on at least one positive finding occurring:

$$\text{pFDR} = \mathbb{E}\left(\frac{V}{R}|R > 0\right), \tag{7}$$

where V is the number of type I errors (or false positive results), and R is the number of rejected hypotheses. For a set of rejection regions $\{\Gamma\}$, these could be all sets of the form $[c, \infty)$ for $-\infty \leq c \leq \infty$), where the p-value of an observed statistic $T = t$ is defined as:

$$p - \text{value}(t) = \min_{\{\Gamma: t \in \Gamma\}} \{\Pr(T \in \Gamma | H = 0)\}. \tag{8}$$

According to Storey (2002), the p-value provides a measure of the strength of the observed statistic in terms of committing a type I error, i.e., it is the minimum rate of type I error that can occur when rejecting a statistic with value t for the set of rejection regions. On the other hand, the q-value is a measure of the strength of an observed statistic in relation to pFDR, being the minimum pFDR that can occur when rejecting a statistic with value t for the set of significance regions (Storey 2003). Thus, for an observed statistic $T = t$, the q-value of t is defined as:

$$q(t) = \inf_{\{\Gamma: r \in \Gamma\}} \{\text{pFDR}(\Gamma)\}. \tag{9}$$

When statistics are independent p-values, the definition is simplified, and the set of rejection regions takes the form $[0; \gamma]$ and pFDR can be written more simply. Therefore, for a set of hypothesis tests conducted with independent p-values, the q-value of the observed p-value p is:

$$q(p) = \inf_{\gamma \geq p} \{\text{pFDR}(\gamma)\} = \inf_{\gamma \geq P} \left\{\frac{\pi_0 \gamma}{\Pr(P \leq \gamma)}\right\}. \tag{10}$$

According to Schäfer and Strimmer (2005) , the q-value is intrinsically related to local Bayesian Fdr statistics. Efron (2005) asserts that using local Fdr is more appropriate because it naturally fits the mixture model setup and considers dependencies among estimated correlation coefficients. Therefore, we choose to use it as our measure of significance.

Efron (2007) asserts that the Bayesian posterior probability that a case is null given z, by definition, is the local false discovery rate:

$$\text{Fdr}(z) \equiv \Pr\{\text{null}|z\} = \frac{p_0 f_0(z)}{f(z)} = \frac{f_0^+(z)}{f(z)}, \tag{11}$$

where $p_0 = \Pr\{\text{null}\}, f_0(z) = \text{density if null},$

$p_1 = \Pr\{\text{non} - \text{null}\}, f_1(z) = \text{density if non} - \text{null}.$

Benjamini and Hochberg (1995) theorized about the discovery rate that relies on tail areas rather than densities. Assuming $F_0(z)$ and $F_1(z)$ as the cumulative distribution functions corresponding to $f_0(z)$ and $f_1(z)$, they define $F_0^+(z) = p_0 F_0(z)$ and $F_0(z) = p_0 F_0(z) + p_1 F_1(z)$. Consequently, we can infer that the posterior probability of a case being null given its z-value, $\mathcal{Z}$, is less than some value z is:

$$\mathrm{Fdr}(z) \equiv \Pr\{\mathrm{null}|\mathcal{Z} \leq z\} = \frac{F_0^+(z)}{F(z)}. \tag{12}$$

Therefore, $\mathrm{Fdr}(z)$ corresponds to the q-value defined by Storey (2002) and to the false discovery rate value of the tail area achieved at a specific observed value $\mathcal{Z} = z$. Analytically, Fdr is a conditional expectation of fdr:

$$\mathrm{Fdr}(z) = \frac{\int_{-\infty}^{z} \mathrm{fdr}(\mathcal{Z}) f(\mathcal{Z})\, d\mathcal{Z}}{\int_{-\infty}^{z} f(\mathcal{Z})\, d\mathcal{Z}} = E_f\{\mathrm{fdr}(\mathcal{Z})|\mathcal{Z} \leq z\}, \tag{13}$$

E_f indicates the expectation concerning $f(z)$. In other words, $\mathrm{Fdr}(z)$ is the average of $\mathrm{fdr}(\mathcal{Z})$ for $\mathcal{Z} \leq z$. $\mathrm{Fdr}(z)$ will be lower than $\mathrm{fdr}(z)$ in the usual situation where $\mathrm{fdr}(z)$ decreases as $|z|$ increases. In the works of Schäfer and Strimmer (2005) and Opgen-Rhein and Strimmer (2007), the authors detail the construction of the algorithm.

Finally, we can express that each new DAG ($posterior$ distribution) is composed of the previous DAG's data ($prior$ distribution) plus the data from that period (likelihood). Therefore, the parameters are sequentially updated over time, so that the past parameters of dependency influence the estimation of future dependency. It is important to mention that the initial distribution ($prior$) is uniform. By analyzing the networks formed over the periods, we will observe changes in interactions between assets through the direction of edges.

3.4. Application of Complex Network Measures

Once the estimations of Dynamic Bayesian Networks are performed, we apply the toolbox of complex network measures to investigate how large sets of dynamic systems, interacting through complex wiring topology, can behave collectively (Silva and Zhao 2016).

In this work, we will categorize our complex network measures following the classification proposed by Silva and Zhao (2016) , which categorizes these measures into three categories:

1st- Strictly Local Measures: they use only information from the vertex itself to be computed, meaning they are always vertex-level measures;

2nd- Mixed Measures: they utilize strictly local information and topological information from their direct and indirect neighborhoods. The additional information can range from a topology that is simply quasi-local, such as the number of triangles in the neighborhood, to long-range information like the shortest path between the two farthest pairs of vertices. These mixed measures are always vertex-level measures;

3rd- Global Measures: they utilize the entire structure of the network to be computed. Global measures are always network-level measures.

The measures considered in this work are explained subsequently.

3.4.1. Strictly Local Measures

i. *Degree*: the degree of a vertex v is the total number of vertices adjacent to v in an undirected graph. The degree of a vertex v is denoted by k_v. Equivalently, we can define the degree of a vertex as the cardinality of its neighborhood set and state that for any vertex v, $k_v = |\mathcal{N}(v)|$, that is,

$$k_v = |\mathcal{N}(v)| = |\{u: (v,u) \in \mathcal{E}\}| = \sum_{u\in\mathcal{V}} \mathbb{1}_{[(v,u) \in \mathcal{E}]}, \tag{14}$$

$\mathbb{1}_{[K]}$ represents the Kronecker[6] delta or indicator function that returns 1 if the logical expression K is true; otherwise, it returns 0.

ii. *In-Degree and Out-Degree*: the notion of vertex degree can be further extended to the in-degree, $k_v^{(in)}$, and the out-degree, $k_v^{(out)}$, when a graph is directed:

$$k_v^{(in)} = \sum_{u\in\mathcal{V}} \mathbb{1}_{[v \in \mathcal{N}(u)]} = \sum_{u\in\mathcal{V}} \mathbb{1}_{[(u,v) \in \mathcal{E}]}, \tag{15}$$

$$k_v^{(out)} = \sum_{u\in\mathcal{V}} \mathbb{1}_{[u \in \mathcal{N}(v)]} = \sum_{u\in\mathcal{V}} \mathbb{1}_{[(v,u) \in \mathcal{E}]}, \tag{16}$$

$$k_v = k_v^{(in)} + k_v^{(out)}. \tag{17}$$

3.4.2. Mixed Measures

i. *Authority Score*: It is the main eigenvector of $\mathbf{A}^{\mathrm{T}}\mathbf{A}$, where $\mathbf{A}$ is the adjacency matrix of the graph. The measure is known to be the first approach to centrality proposed by Jon Kleinberg. An authority is a vertex pointed to by many important hubs - such as a significant research article or authoritative figure on a particular subject.

ii. *Hub Score*: It is the main eigenvector of $\mathbf{A}\mathbf{A}^{\mathrm{T}}$, where $\mathbf{A}$ is the adjacency matrix of the graph. The measure is known to be the second approach to centrality proposed by Jon Kleinberg. A hub is a vertex that points to many important authorities - such as a review article in a network of scientific citations.

iii. *Coreness (K-core)*: It is the maximum subgraph in which each vertex has at least a degree of k. The coreness of a vertex is k if it belongs to the k-core but not to the (k + 1)-core.

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[6] In mathematics, the Kronecker delta (named after Leopold Kronecker) is a function of two variables, typically only non-negative integers. The function equals 1 if the variables are equal and 0 otherwise.

iv. *Transitivity (Clustering Coefficient)*: It measures the probability that adjacent vertices of a vertex are connected. We apply the Global Transitivity, which is the ratio of the count of triangles to the count of connected triples in the graph. We use the definition by A. Barrat:

$$C_i^w = \frac{1}{s_i(k_i - 1)} \sum_{j,h} \frac{w_{ij} + w_{ih}}{2} a_{ij} a_{ih} a_{jh}, \tag{18}$$

where s_i is the strength of vertex i, a_{ij} are elements of the adjacency matrix, k_i is the degree of vertex i, and w_{ij} are the weights.

3.4.3. Global Measures

i. *Diameter*: The diameter of $\mathcal{G}$, T, is the length of the largest pairwise distance in $\mathcal{G}$. Formally, it is given by:

$$T = \max_{u,v \in \mathcal{V}} d_{uv}. \tag{19}$$

The diameter can be interpreted as the longest chain of intermediation in the network.

ii. *Mean Distance*: It calculates the average path length in a graph by computing the shortest paths between all pairs of vertices (in both directions for directed graphs, as in our case).

iii. *Modularity*: measures how good the division is, or how separated different types of vertices are from each other. In other words, the main idea of modularity is to calculate the fraction of edges that fall within given groups minus the expected value if the edges were randomly distributed. For a given division of the network's vertices into some modules, modularity reflects the concentration of vertices within the modules compared to a random distribution of links among all vertices, regardless of the modules. In Equation 20, we present the formula for calculating modularity for directed graphs as presented in this work:

$$Q = \frac{1}{m} \sum_{i,j} \left(\mathbf{A}_{ij} - \gamma \frac{k_i^{out}\, k_j^{in}}{m} \right) \delta(c_i, c_j), \tag{20}$$

where m is the number of edges, $\mathbf{A}_{ij}$ is the element of the adjacency matrix in row i and column j, $k_i^{out}$is the out-degree of i, k_j^{in} is the in-degree of j, c_i is the type (or component) of i, c_j is the type of j, the sum covers all pairs i and j of vertices, and $\delta(x, y)$ is 1 if $x = y$ and 0 otherwise. The resolution parameter γ allows weighting the null random model, which can be useful when finding partitions with high modularity. Maximizing modularity with higher values of the resolution parameter often results in more smaller clusters when locating partitions with high modularity. Lower values often result in fewer larger clusters. The original definition of modularity is recovered by setting γ to 1.

iv. *Assortativity*: captures, in a structural sense, the preference of vertices to attach to others that are similar or dissimilar in terms of degree. In our study, we apply three approaches to this measure.

The first one is nominal assortativity, calculated as follows:

$$r = \frac{\sum_i e_{ii} - \sum_i a_i b_i}{1 - \sum_i a_i b_i}, \tag{21}$$

where e_{ij} is the fraction of edges connecting vertices of type i and j, $a_i = \sum_j e_{ij}$, and $b_j = \sum_i e_{ij}$.

The second variant is assortativity, which is based on values assigned to the vertices, defined as:

$$r = \frac{1}{\sigma_o \sigma_i} \sum_{jk} jk\left(e_{jk} - q_j^o q_k^i\right), \tag{22}$$

where $q_i^o = \sum_j e_{ij}$, $q_i^i = \sum_j e_{ji}$, and additionally, σ_q, σ_o, and σ_i are the standard deviations of q, q^o, and q^i, respectively.

The third variant is assortativity degree, which uses the vertex degree (minus one) as the vertex value and is called assortativity.

v. *Edge Density*: The density of a graph is the ratio between the number of edges and the number of possible edges.

4. EMPIRICAL RESULTS

4.1. Data

The selected assets consist of 23 global stock indexes that represent about \$81.3 trillion of the world's GDP in 2022, or in percentage terms, 80.5% of the world's GDP in 2022, according to data from the World Bank and the International Monetary Fund (IMF)[7].Additionally, to enrich and understand financial market dynamics, we included 5 other assets: 1-Gold; 2-Crude Oil; 3-United States 10-Year Government Debt (US10Y); 4-VIX Index (VIX); and 5-Copper. Gold represents a protective asset during crises, especially during economic stagnation with a decrease in long-term interest rates. Crude Oil and Copper are considered by financial analysts and economists as proxy assets that capture global growth prospects. The VIX Index captures the stock market's volatility expectations based on S&P 500 Index options. The United States 10-Year Government Debt (US10Y) is considered the world's safest financial asset, i.e., the risk-free asset. In Table 1, we present the list of financial assets used and additional information about the analyzed assets.

[7] Data from the World Bank is available at https://data.worldbank.org/indicator/NY.GDP.MKTP.CD. The International Monetary Fund data can be found at https://www.imf.org/external/datamapper/datasets.

Table 1 - List of Financial Assets Analyzed

Nº	Country or Asset	Acronym	Stock Index	Ticker	GDP 2022 In Billion US$	Share in Global GDP of 2022
1	South Africa	ZAF	Top 40 Usd Net Tri Index	JN0U	406	0.40%
2	Germany	DEU	Dax Performance-Index	GDAXI	4,072	4.03%
3	Argentina	ARG	Merval	MERV	633	0.63%
4	Australia	AUS	S&P/Asx 200	AXJO	1,675	1.66%
5	Brazil	BRA	Ibovespa	BVSP	1,920	1.90%
6	Canada	CAN	S&P/TSX Composite Index	GSPTSE	2,140	2.12%
7	China	CHN	Hang Seng Index	HSI	17,963	17.78%
8	Singapore	SGP	Sti Index	STI	467	0.46%
9	South Korea	KOR	Kospi Composite Index	KS11	1,665	1.65%
10	United States	USA	S&P 500	GSPC	25,463	25.21%
11	Euro Area	EU	Euro Stoxx 50	STOXX50E	14,041	13.90%
12	France	FRA	Cac 40	FCHI	2,783	2.76%
13	India	IND	S&P Bse Sensex	BSESN	3,385	3.35%
14	Indonesia	IDN	Idx Composite	JKSE	1,319	1.31%
15	Italy	ITA	Ftse Mib Index	FTSEMIB.MI	2,010	1.99%
16	Japan	JPN	Nikkei 225	N225	4,231	4.19%
17	Malaysia	MYS	Ftse Bursa Malaysia Klci	KLSE	406	0.40%
18	Mexico	MEX	Ipc Mexico	MXX	1,414	1.40%
19	New Zealand	NZL	S&P/Nzx 50 Index	NZ50	247	0.24%
20	United Kingdom	GBR	Ftse 100	FTSE	3,071	3.04%
21	Russia	RUS	Moex Russia Index	IMOEX.ME	2,240	2.22%
22	Taiwan	TWN	Tsec Weighted Index	TWII	762	0.754%
23	Turkey	TUR	Bist 100	XU100.IS	906	0.90%
24	Copper	Cooper	Commodity	Copper	NA	NA
25	S&P 500 Volatility Index	VIX	Index	VIX	NA	NA
26	Gold	Gold	Commodity	Gold	NA	NA
27	Crude Oil	Crude_oil	Commodity	Crude_oil	NA	NA
28	US Treasury Bond	US10Y	Sovereign Bonds	TNX	NA	NA

The time series data for the 28 analyzed assets were collected from the Yahoo Finance website. The quotes used are the closing prices. The selected time frame ranges from January 3, 2000, to June 23, 2023, although some series are incomplete throughout the entire period.

The calculation of daily returns was based on the closing price, applying the natural logarithm, as per Equation 23.

$$R_{i,t} = \left[\ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)\right] \times 100 \qquad (23)$$

In Table 2, we present the descriptive statistics of the daily returns of the studied assets.

Table 2 - Descriptive Statistics of Daily Returns on Financial Assets

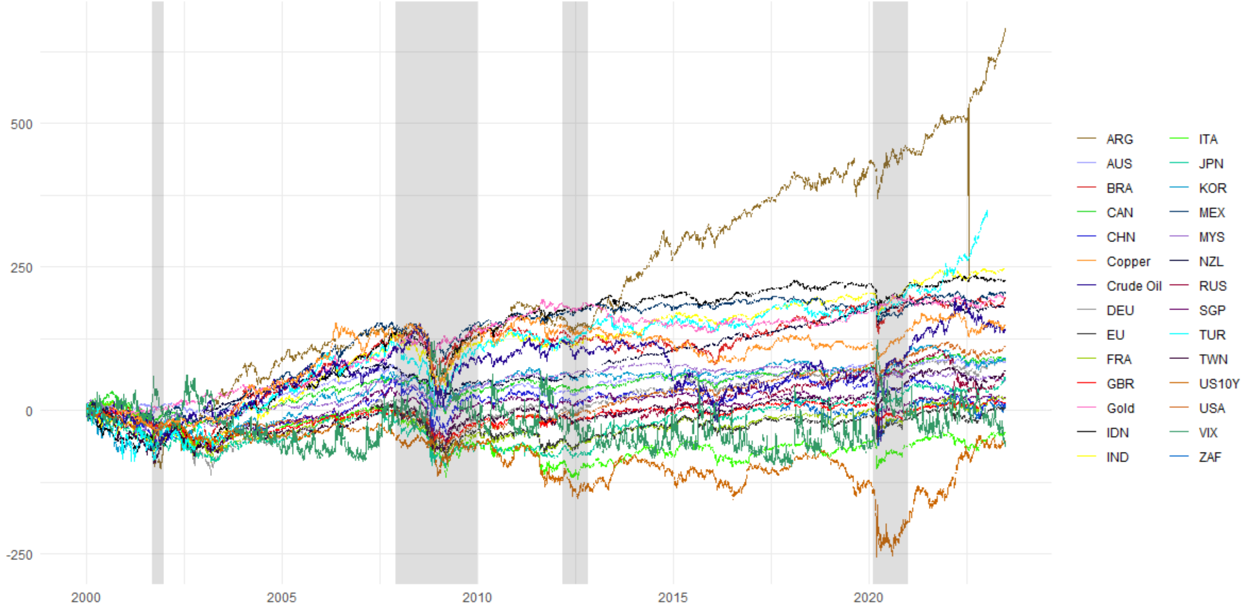
Asset	Nº	Mean (%)	Standard Deviation (%)	Min (%)	Pctl(25) (%)	Median (%)	Pctl(75) (%)	Max (%)
ARG	5,730	0.1158	6.0569	-298.2030	-0.9725	0.1518	1.2649	300.0936
AUS	5,929	0.0140	1.0118	-10.2030	-0.4597	0.0558	0.5395	6.7665
BRA	5,810	0.0336	1.7683	-15.9930	-0.9087	0.0710	1.0463	13.6766
CAN	5,897	0.0146	1.1086	-13.1758	-0.4436	0.0699	0.5424	11.2945
CHN	5,785	0.0015	1.4783	-13.5820	-0.7009	0.0384	0.7488	13.4068
DEU	5,960	0.0143	1.4608	-13.0549	-0.6506	0.0759	0.7372	10.7975
EU	4,069	0.0005	1.4391	-13.2405	-0.6350	0.0395	0.6882	10.4377
FRA	6,000	0.0032	1.4164	-13.0984	-0.6501	0.0434	0.7113	10.5946
GBR	5,927	0.0019	1.1715	-11.5117	-0.5278	0.0483	0.5813	9.3842
IDN	5,709	0.0394	1.2950	-11.3060	-0.5421	0.0958	0.6877	9.7042
IND	5,789	0.0425	1.4294	-14.1017	-0.5986	0.0898	0.7521	15.9900
ITA	5,994	-0.0069	1.5132	-18.5461	-0.7211	0.0598	0.7564	10.8743
JPN	5,752	0.0094	1.4600	-12.1110	-0.7091	0.0507	0.7961	13.2346
KOR	5,790	0.0154	1.4551	-12.8047	-0.6038	0.0706	0.7298	11.2844
MEX	5,892	0.0343	1.2513	-8.2673	-0.5815	0.0556	0.6742	10.4407
MYS	5,756	0.0089	0.8094	-9.9785	-0.3697	0.0227	0.4046	6.6263
NZL	5,042	0.0354	0.7224	-7.9468	-0.3406	0.0695	0.4345	6.9366
RUS	2,532	0.0249	1.5701	-40.4674	-0.5588	0.0510	0.7074	18.2620
SGP	5,872	0.0036	1.0911	-9.0950	-0.4934	0.0214	0.5286	7.5305
TUR	5,762	0.0588	2.0299	-19.9783	-0.9190	0.1192	1.0785	17.7738
TWN	5,761	0.0117	1.3128	-9.9360	-0.5731	0.0550	0.6751	6.5246
USA	5,905	0.0185	1.2469	-12.7652	-0.4895	0.0574	0.5940	10.9572
ZAF	1,435	0.0009	1.8057	-12.8005	-1.0296	0.0763	1.0372	8.5021
Copper	5,729	0.0255	1.7024	-11.6933	-0.8475	0.0188	0.9220	11.7693
Crude_oil	5,732	0.0239	2.6421	-28.2206	-1.2865	0.1086	1.3552	31.9634
Gold	5,724	0.0340	1.0996	-9.8206	-0.4861	0.0449	0.6126	8.6432
US10Y	5,898	-0.0095	2.4790	-34.7009	-1.1510	-0.0613	1.0795	40.4797
VIX	5,905	-0.0100	7.0719	-35.0589	-3.9944	-0.5618	3.3550	76.8245

The descriptive statistics show that the average daily return is relatively similar among the assets. The standard deviation of Crude Oil, US10Y, and VIX assets is higher compared to the stock indexes, except for the ARG stock index, where the instability in economic policy reflects in high stock market volatility.

The temporal delineation of non-crisis and crisis periods was established through a time-based study, illustrating how these periods impact asset dynamics, highlighting events that consistently disrupted a significant portion of the financial assets in the study.

Therefore, we identified four crisis periods that significantly impacted the analyzed financial assets: 1-September 11 Attacks (09/11/2001 - 12/31/2001); 2-Subprime Crisis (12/01/2007 - 12/31/2009); 3-European Sovereign Debt Crisis (03/01/2012 - 10/31/2012); and 4- The Acute Phase of COVID-19 (02/02/2020 - 12/31/2020). Non-crisis periods intersperse these mentioned crisis periods. In Figure 1, we present the cumulative returns of the assets over time.

Figure 1 - Cumulative Return on Assets (%)



Note: The shaded areas represent the periods of crisis.

In Figure 1, we observed that the shaded areas indeed experienced widespread declines in the returns of the analyzed assets, aligning with the outlined crisis periods in the study. It is noteworthy that the stock index returns of ARG and TUR faced, in addition to the highlighted crises in this study, speculative movements concerning their economies. In Argentina, the Merval index accumulated returns above 600%, and in Turkey, the BIST 100 index accumulated returns above 300%, both within the period from 01/03/2000 to 06/23/2023. However, economic and political instability, coupled with a financially illiquid market and low trading volume, make these assets risky and their real returns uncertain for foreign investors.

Finally, we observed that the other assets accumulated just over 200% return at most during the studied period. In the next subsection, we present the estimations of Bayesian Networks formed by the financial assets in the aforementioned temporal segments.

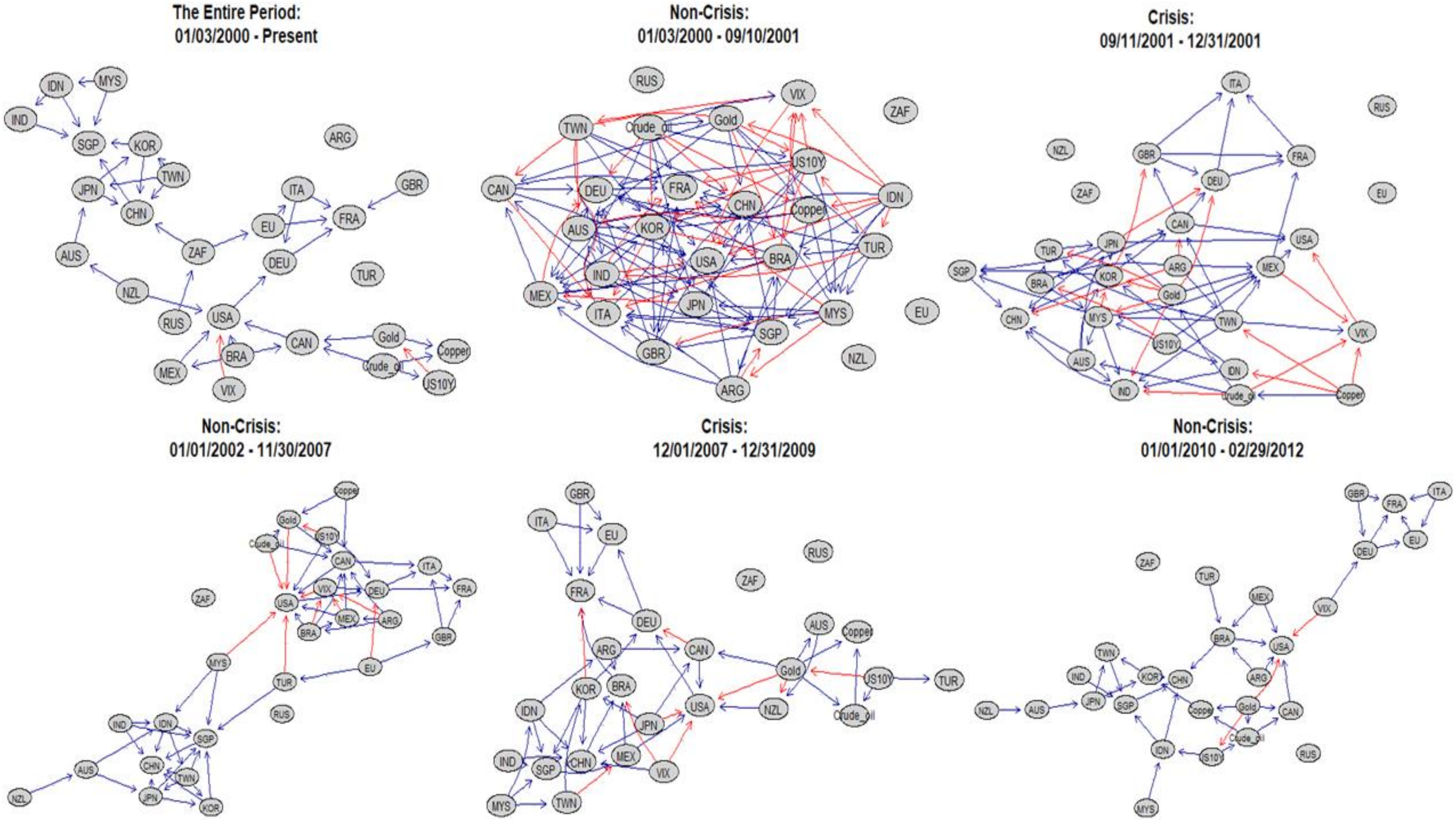
4.2. Estimation of Dynamic Bayesian Networks

We used the logarithm of daily returns from financial assets to estimate Dynamic Bayesian Networks. We conducted Augmented Dickey-Fuller and Phillips-Perron stationarity tests at 1% significance level. All time series of log daily returns from the studied financial assets are stationary, which is an important requirement as pointed out by Nagarajan, Scutari, and Lèbre (2013) for estimating Dynamic Bayesian Networks.

Efron (2007) suggests q-values between 0.05 and 0.15 as feasible choices for estimating networks, with these q-value limits interpreted as a conservative Bayesian factor for interpreting the FDR. To assess result sensitivity, all networks were generated with q-values equal to 0.05, 0.1, and 0.15, and the networks remained unchanged, demonstrating estimation robustness. Finally, the edges represent the direction of partial autocorrelation, with blue indicating positive and red indicating negative associations.

In the first network, we estimated the network considering the entire analyzed period to compare with the non-crisis and crisis periods. The aim was to infer if there is any network formation pattern among the assets. In Figure 2 e Figure 3, we present all the estimated networks over the analyzed period.

Figure 2 - Dynamic Bayesian Networks[8]



The blue edges represent positive partial autocorrelations, while the red edges represent negative partial autocorrelations.

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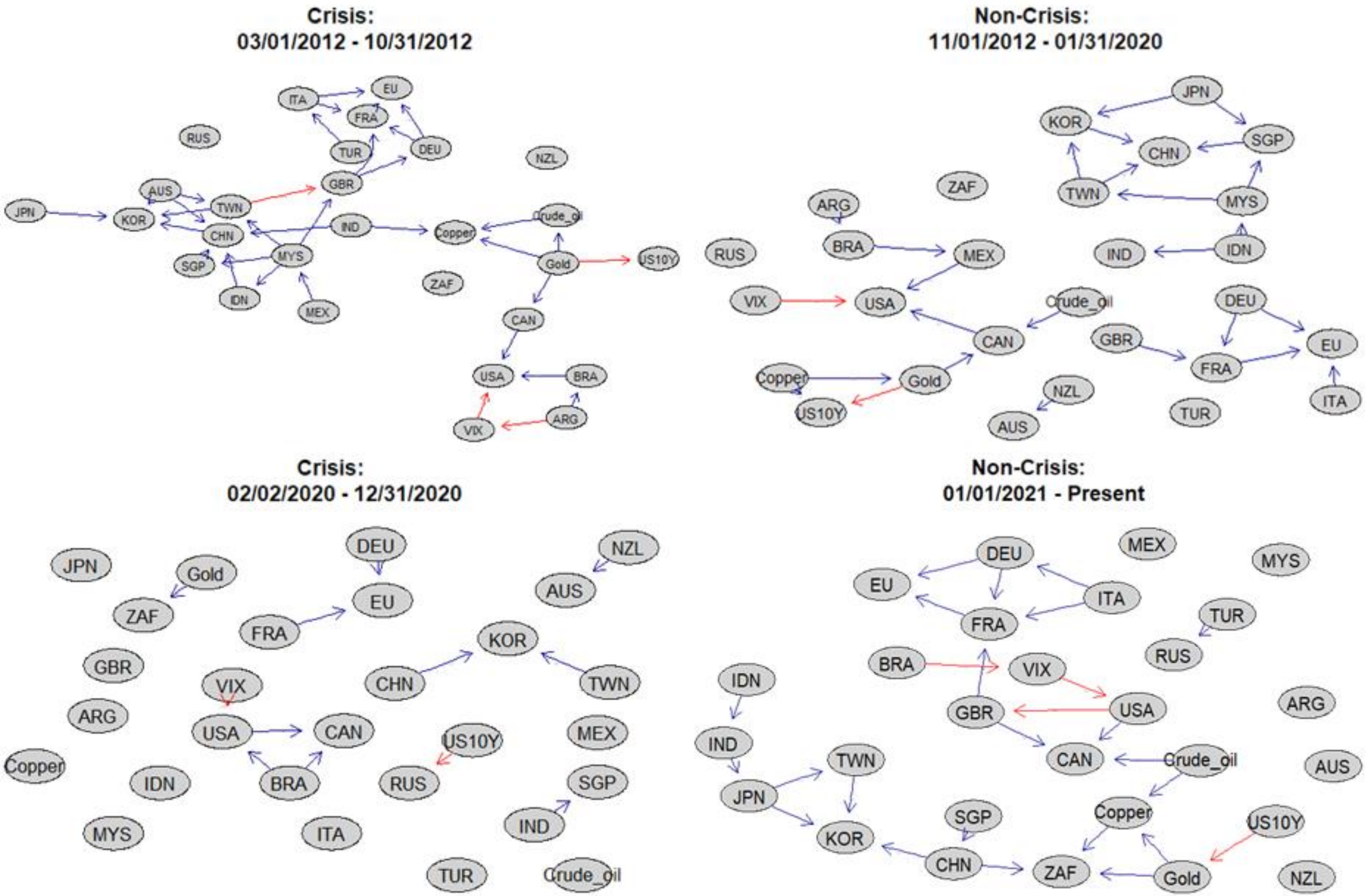
[8] The Dynamic Bayesian Network estimations were conducted in RStudio using the GeneNet package version 1.2.16.

Figure 3 - Dynamic Bayesian Networks (Continued)



The blue edges represent positive partial autocorrelations, while the red edges represent negative partial autocorrelations.

In the first estimated network (Entire Period) from Figure 2, it is evident that financial assets are largely correlated with assets that are geographically close. The initial cluster in the network displays Asia-Pacific assets, with China (CHN) as the main asset. Following this, there is a cluster of European financial assets, with France (FRA) as the main asset and Germany (DEU) acting as a bridge asset, linking to assets in the Americas through the United States (USA). In the Americas, the USA asset is the one receiving the most connections, implying that other assets in the Americas are correlated with variations in the USA asset. It is interesting to note the negative partial autocorrelation of VIX with USA, which is a coherent association because a higher VIX index implies greater aversion to the USA asset, reflecting risk aversion towards the USA asset. The US10Y asset exhibits a negative association with Gold, as expected, since higher US10Y interest rates decrease the attractiveness of Gold, which does not yield interest, and *vice versa*. Finally, Crude_oil shows positive partial autocorrelations with Gold and Copper. It is observed that the economic growth cycle tends to connect these assets, which are essential commodities for the economy (Crude_oil and Copper). Additionally, Gold tends to appreciate when US government bond interest rates are low, especially debt security rates.

The second network in Figure 2 illustrates the dynamics of assets before the September 11 Attacks in the United States (Non-Crisis: 03/01/2000 - 09/10/2001). During this period, financial markets experienced a significant flow seeking better risk-return asymmetries, with the world GDP growing by 4.5% in 2000. The pursuit of risk-return asymmetries demonstrates that geographical regionalization of the network is not evident, besides showing several negative associations signaling possibilities of hedges between assets for investors and portfolio managers. Additionally, in this network, we observe some assets with negative partial autocorrelations with VIX, capturing risk aversion towards the USA asset, reflecting in these negative associations.

In the temporal segment of the September 11 Attacks (Figure 2 - Crisis: 09/11/2001 - 12/31/2001), we notice that the assets USA and CHN remain key assets within the network. Subtly, we observe that assets start to have more associations with geographically proximate assets. The negative associations persist (totaling 16), indicating that even during the crisis and high volatility, hedging positions in assets across different parts of the world were possible. Gold serves as protection during risk aversion periods, especially caused by recession threats. Therefore, we observe that Gold exhibits several negative partial autocorrelations with various financial assets from different geographical regions.

The asset US10Y, typically associated with other commodities (Crude_oil, Copper, and Gold), loses these associations, highlighting the high volatility of financial assets during the September 11 Attacks crisis. Finally, Crude_oil and Copper serve as proxies for economic activity and exhibit negative partial autocorrelations with the VIX, indicating that the prices of these commodities decrease if the risk aversion, captured by the VIX, increases. According to World Bank data, the global GDP growth in 2001 was 2%, representing a slowdown compared to the 4.5% growth in the previous year (2000), with significant contribution from the September 11 Attacks crisis event.

The network formed post-September 11 Attacks (Figure 2 - Non-Crisis: 01/01/2002 - 30/11/2007) makes the geographical regionalization of associations between assets into three major blocks more evident: the Asian-Pacific, the European, and the American, with CHN, DEU, and USA as the primary assets of these clusters, respectively. The MYS asset serves as a bridge between Asia and America, while TUR links Europe and Asia. In the macroeconomic context, World Bank data indicates robust global GDP growth, around 3.7%, and a significant rise in oil prices, from US$21.62 in January 2002 to US$90.62 in November 2007. Consequently, the cost of energy increased, which was captured by the negative association between Crude_oil and USA. Additionally, there is a positive association between US10Y and USA, indicating that lower long-term interest rates, compared to the previous period (03/01/2000 – 12/31/2001), contributed to the traction of equity assets[9].

In the Great Financial Crisis (Figure 2: 12/01/2007 - 12/31/2009), we observe that the USA, the epicenter of the crisis, was located in the center of the graph. This crisis showed the emergence of partial negative autocorrelations not seen in previous networks, such as JPN and USA, KOR and FRA, TWN and MEX, CAN and DEU, and Gold and NZL. These negative associations represent asymmetries for potential investment theses of buying rising assets and selling falling assets. When compared to the September 11 Attacks - when the associations between assets were less regionalized and the negative associations of regionalization were greater - the Great Financial Crisis presented a more regionalized pattern of association among assets. For example, driven by the Chinese economy, Asian assets maintained the pattern of associations pre-Great Financial Crisis.

In the network formed post-Great Financial Crisis (Figure 2: 01/01/2010 - 02/29/2012), the injection of resources by the US government into the financial system and the real economy contributed significantly to the vigorous response of the American economy, which grew by 2.7% in 2010 according to data from the World Bank. This growth had a positive reflection on financial assets, with the USA asset, located in the center of the network, influencing other assets. There was an evident regionalization of assets concerning geographical proximity. Two interesting connections emerged in this network: 1- The VIX asset, whose inverse association with the USA was expected, showed a direct association with DEU, signaling a hedge between USA and DEU assets for investors and portfolio managers; 2- The BRA asset showed positive associations with CHN and USA, the world's two largest economies and Brazil's major trading partners, indicating the Brazilian asset's dependence on the good performance of these countries' assets.

[9] During the Non-Crisis period (01/01/2002 - 11/30/2007), the average US10Y yield was 4.43% per annum compared to a rate of 5.51% per annum in the preceding period (01/01/2000 - 12/31/2001).

The European Debt Crisis (Figure 3: 03/01/2012 - 10/31/2012) generated instability in the global financial market, negatively impacting the number of connections (edges) between the assets in the network. European assets, the epicenter of the crisis, lost connections with other European assets, except for GBR, where TWN and MYS showed inverse and direct associations, respectively, with the mentioned European asset. It was observed that the EU asset induced positive partial autocorrelations with other European assets, indicating that the European Central Bank's liquidity injection positively impacted European financial assets. Finally, financial assets maintained the tendency to associate with assets in close geographic proximity, except for MEX and TWN.

The Post-European Debt Crisis (Figure 3: 11/01/2012 - 01/31/2020) is marked by the return of global GDP growth, averaging 3% between 2013-2019. In the estimated network, we noticed a tendency for a decrease in edges between assets, with almost all associations being positive. This reflects that the growth of the global economy positively impacted risk assets in general. There are only two negative associations: VIX to USA and US10Y to Gold, which are predictable inverse relationships in the financial context. Thus, we see that the network presents few opportunities for hedge construction, given the low presence of inverse associations. It becomes evident that connections between assets are geographically regionalized, indicating a movement already observed in previous networks, which is a kind of "deglobalization" of connections, reducing the search for risk and return asymmetries between assets.

The network formed during the Acute Phase of COVID-19 (Figure 3: 02/02/2020 - 12/31/2020) showed the lowest number of edges among all estimated networks. This fact can be explained by the high unpredictability that the health crisis caused for global financial assets, as the closure of a significant number of commercial establishments and disruptions in global supply chains severely affected the global economy[10] and cash flows of businesses. Nevertheless, we observed that the pattern of geographical regionalization of connections was maintained.

Finally, in the network estimated post-The Acute Phase of COVID-19 (Figure 3: 01/01/2021 - Present[11]), we can observe that connections between assets increase again with the global growth recovery. The pattern of more geographically regionalized connections of assets remains, reducing the possibilities of seeking asymmetries in assets on different continents. It is noteworthy that the CHN asset detached itself from its Asian and Pacific peers due to the slowdown in Chinese GDP growth. This, in turn, shows a trend towards moderate growth, focused on cutting-edge technologies and sophisticated services, rather than growth through infrastructure and construction.

Given the complexity of the interaction among global financial assets, the tools of complex network measures were employed in the analysis of the estimated Dynamic Bayesian Networks (DBNs) in this study.

[10] In 2020, the global GDP contracted by 3.11%, according to data from the World Bank. This contraction represents the largest decline in the 21st century.
[11] We consider the Present Date as 06/23/2023.

4.3. Applied Complex Network Measures

We applied 14 measures of complex networks[12], spanning the three classifications of measures suggested by Silva and Zhao (2016). In the category of strictly local measures, we analyzed the degree in three perspectives: the total edges each asset has, the edges entering the asset, and the edges leaving the asset. In Table 3, Table 4 e Table 5, we present the degree of each asset in the respective period.

[12] The calculation of complex network measures was implemented in RStudio using the Igraph package version 1.3.5.

Table 3 - Degree

Degree	ARG	AUS	BRA	CAN	CHN	Copper	Crude_oil	DEU	EU	FRA	GBR	Gold	IDN	IND	ITA	JPN	KOR	MEX	MYS	NZL	RUS	SGP	TUR	TWN	US10Y	USA	VIX	ZAF
The Entire Period: 01/03/2000 - Present	NA	2	3	4	5	2	4	3	3	4	1	4	3	2	3	4	4	2	2	2	1	5	NA	3	2	6	1	3
Non-Crisis: 01/03/2000 - 09/10/2001	7	11	12	8	11	8	10	11	NA	12	8	10	9	10	11	9	14	11	11	NA	NA	12	8	9	11	12	7	NA
Crisis: 09/11/2001 - 12/31/2001	5	6	5	7	6	4	5	6	NA	4	5	8	4	7	3	8	9	8	9	NA	NA	4	4	8	4	4	5	NA
Non-Crisis: 01/01/2002 - 11/30/2007	4	3	5	8	6	2	3	6	3	3	3	5	6	3	4	5	4	5	3	1	NA	8	3	5	3	10	5	NA
Crisis: 12/01/2007 - 12/31/2009	3	2	5	5	7	2	3	5	4	6	2	7	4	2	2	4	6	4	3	3	NA	6	1	3	3	7	3	NA
Non-Crisis: 01/01/2010 - 02/29/2012	2	2	5	3	4	3	4	4	3	4	2	5	4	1	2	3	4	2	1	1	NA	4	1	3	3	6	2	NA
Crisis: 03/01/2012 - 10/31/2012	2	3	2	2	6	3	2	3	3	4	4	4	2	2	3	1	4	1	5	NA	NA	2	1	5	1	3	2	NA
Non-Crisis: 11/01/2012 - 01/31/2020	1	1	2	3	3	2	1	2	3	3	1	3	2	1	1	2	3	2	3	1	NA	3	NA	3	2	3	1	NA
Crisis: 02/02/2020 - 12/31/2020	NA	1	2	2	1	NA	NA	1	2	1	NA	1	NA	1	NA	NA	2	NA	NA	1	1	1	NA	1	1	3	1	1
Non-Crisis: 01/01/2021 - Present	NA	NA	1	3	3	3	2	3	2	4	3	3	1	2	2	3	3	NA	NA	NA	1	1	1	2	1	3	2	3

Table 4 - In-Degree

In-Degree	ARG	AUS	BRA	CAN	CHN	Copper	Crude_oil	DEU	EU	FRA	GBR	Gold	IDN	IND	ITA	JPN	KOR	MEX	MYS	NZL	RUS	SGP	TUR	TWN	US10Y	USA	VIX	ZAF
The Entire Period: 01/03/2000 - Present	NA	1	0	3	4	2	0	2	1	4	0	2	1	1	1	2	2	1	0	0	0	5	NA	0	1	5	0	1
Non-Crisis: 01/03/2000 - 09/10/2001	2	4	7	4	8	3	0	9	NA	12	4	2	0	2	9	5	7	7	4	NA	NA	8	2	1	3	12	6	NA
Crisis: 09/11/2001 - 12/31/2001	0	2	2	4	6	0	1	4	NA	3	2	1	2	6	3	3	5	5	4	NA	NA	3	3	2	0	4	4	NA
Non-Crisis: 01/01/2002 - 11/30/2007	0	1	1	6	6	0	0	4	0	3	1	3	3	0	3	2	2	2	0	0	NA	7	1	1	0	9	3	NA
Crisis: 12/01/2007 - 12/31/2009	1	1	4	3	5	2	2	3	3	6	0	1	1	0	0	0	2	2	0	2	NA	5	1	1	0	6	0	NA
Non-Crisis: 01/01/2010 - 02/29/2012	0	1	3	2	4	2	2	2	2	4	0	0	2	0	0	1	2	0	0	0	NA	3	0	2	1	6	0	NA
Crisis: 03/01/2012 - 10/31/2012	0	0	1	1	5	3	1	1	3	3	2	0	1	0	1	0	4	0	1	NA	NA	1	0	2	1	3	1	NA
Non-Crisis: 11/01/2012 - 01/31/2020	0	1	1	2	3	0	0	0	3	2	0	1	0	1	0	0	2	1	1	0	NA	2	NA	1	2	3	0	NA
Crisis: 02/02/2020 - 12/31/2020	NA	1	0	2	0	NA	NA	0	2	0	NA	0	NA	0	NA	NA	2	NA	NA	0	1	1	NA	0	0	2	0	1
Non-Crisis: 01/01/2021 - Present	NA	NA	0	3	1	2	0	1	2	3	1	1	0	1	0	1	3	NA	NA	NA	1	0	0	1	0	1	1	3

Table 5 - Out-Degree

Out_Degree	ARG	AUS	BRA	CAN	CHN	Copper	Crude_oil	DEU	EU	FRA	GBR	Gold	IDN	IND	ITA	JPN	KOR	MEX	MYS	NZL	RUS	SGP	TUR	TWN	US10Y	USA	VIX	ZAF
The Entire Period: 01/03/2000 - Present	NA	1	3	1	1	0	4	1	2	0	1	2	2	1	2	2	2	1	2	2	1	0	NA	3	1	1	1	2
Non-Crisis: 01/03/2000 - 09/10/2001	5	7	5	4	3	5	10	2	NA	0	4	8	9	8	2	4	7	4	7	NA	NA	4	6	8	8	0	1	NA
Crisis: 09/11/2001 - 12/31/2001	5	4	3	3	0	4	4	2	NA	1	3	7	2	1	0	5	4	3	5	NA	NA	1	1	6	4	0	1	NA
Non-Crisis: 01/01/2002 - 11/30/2007	4	2	4	2	0	2	3	2	3	0	2	2	3	3	1	3	2	3	3	1	NA	1	2	4	3	1	2	NA
Crisis: 12/01/2007 - 12/31/2009	2	1	1	2	2	0	1	2	1	0	2	6	3	2	2	4	4	2	3	1	NA	1	0	2	3	1	3	NA
Non-Crisis: 01/01/2010 - 02/29/2012	2	1	2	1	0	1	2	2	1	0	2	5	2	1	2	2	2	2	1	1	NA	1	1	1	2	0	2	NA
Crisis: 03/01/2012 - 10/31/2012	2	3	1	1	1	0	1	2	0	1	2	4	1	2	2	1	0	1	4	NA	NA	1	1	3	0	0	1	NA
Non-Crisis: 11/01/2012 - 01/31/2020	1	0	1	1	0	2	1	2	0	1	1	2	2	0	1	2	1	1	2	1	NA	1	NA	2	0	0	1	NA
Crisis: 02/02/2020 - 12/31/2020	NA	0	2	0	1	NA	NA	1	0	1	NA	1	NA	1	NA	NA	0	NA	NA	1	0	0	NA	1	1	1	1	0
Non-Crisis: 01/01/2021 - Present	NA	NA	1	0	2	1	2	2	0	1	2	2	1	1	2	2	0	NA	NA	NA	0	1	1	1	1	2	1	0

Table 6 - Global Measures

	The Entire Period: 01/03/2000 - Present	Non-Crisis: 01/03/2000 - 09/10/2001	Crisis: 09/11/2001 - 12/31/2001	Non-Crisis: 01/01/2002 - 11/30/2007	Crisis: 12/01/2007 - 12/31/2009	Non-Crisis: 01/01/2010 - 02/29/2012	Crisis: 03/01/2012 - 10/31/2012	Non-Crisis: 11/01/2012 - 01/31/2020	Crisis: 02/02/2020 - 12/31/2020	Non-Crisis: 01/01/2021 - Present
Diameter	11,3945	3,1372	5,3428	7,9929	7,9109	13,1780	15,1990	7,8956	2,8986	14,1751
Mean_Distance	4,9593	2,0888	2,5890	3,7492	3,5008	4,8894	5,6824	3,0661	1,5851	5,9825
Modularity	0,6123	0,1503	0,3007	0,5241	0,4353	0,5946	0,6023	0,7048	0,8066	0,6530
Assortativity	-0,1119	0,0006	0,0100	-0,0433	-0,1770	-0,2519	-0,3165	-0,2481	-0,0829	-0,1610
Assortativity_Nominal	-0,0475	-0,0449	-0,0479	-0,0483	-0,0482	-0,0482	-0,0515	-0,0489	-0,0706	-0,0530
Assortativity_Degree	-0,2687	-0,0925	0,0159	-0,1952	-0,1478	-0,2533	-0,1150	0,0938	0,1549	0,1333
Transitivity_Net_Global*	0,4242	0,4301	0,2951	0,4643	0,2713	0,3267	0,3176	0,2432	0,4286	0,3571
Edge_Density	0,0600	0,2192	0,1250	0,0892	0,0785	0,0600	0,0583	0,0433	0,0392	0,0514

*Except for this measure, which is categorized as a mixed measure.

Figure 4 - Authority Scores

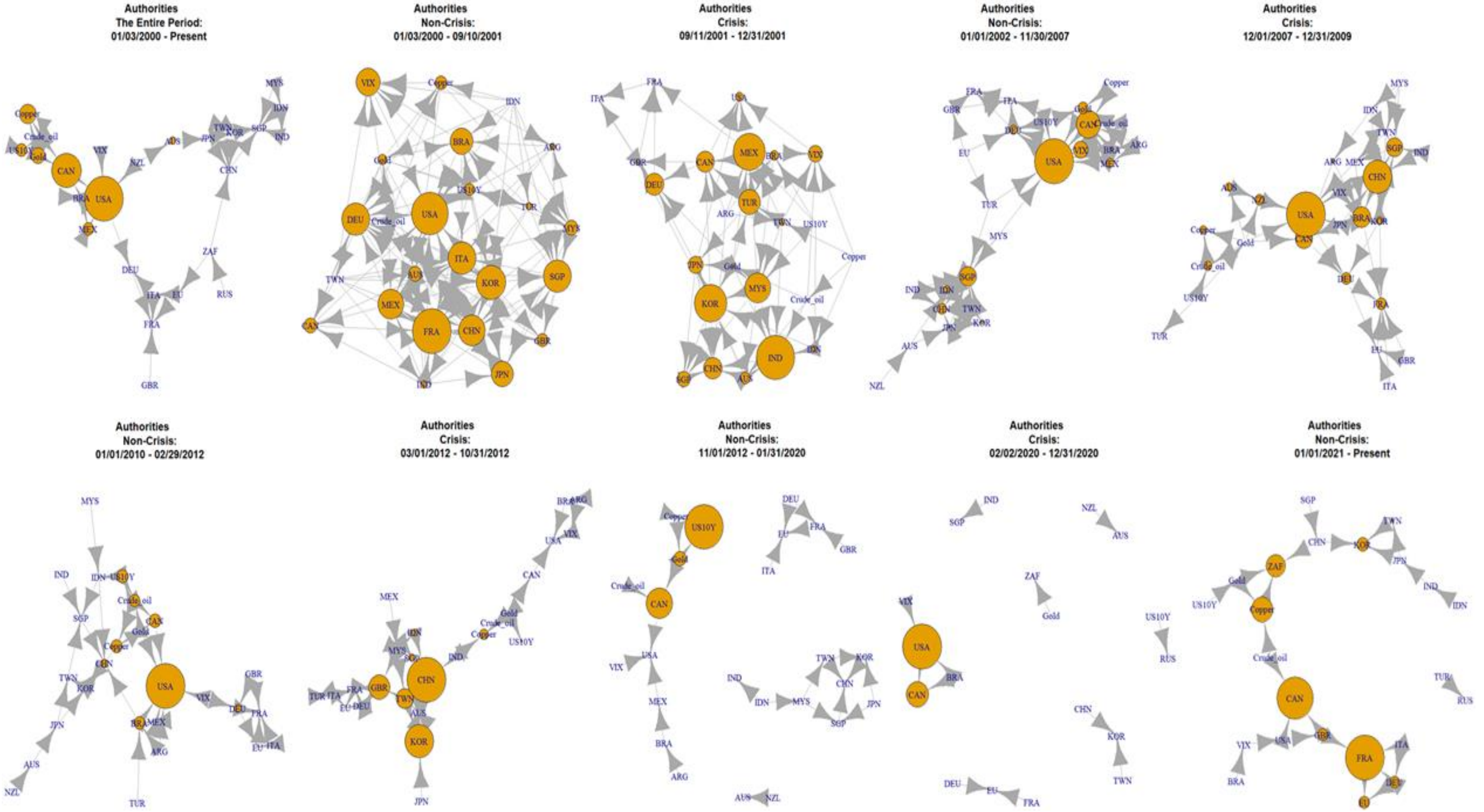


Figure 5 - Hub Scores

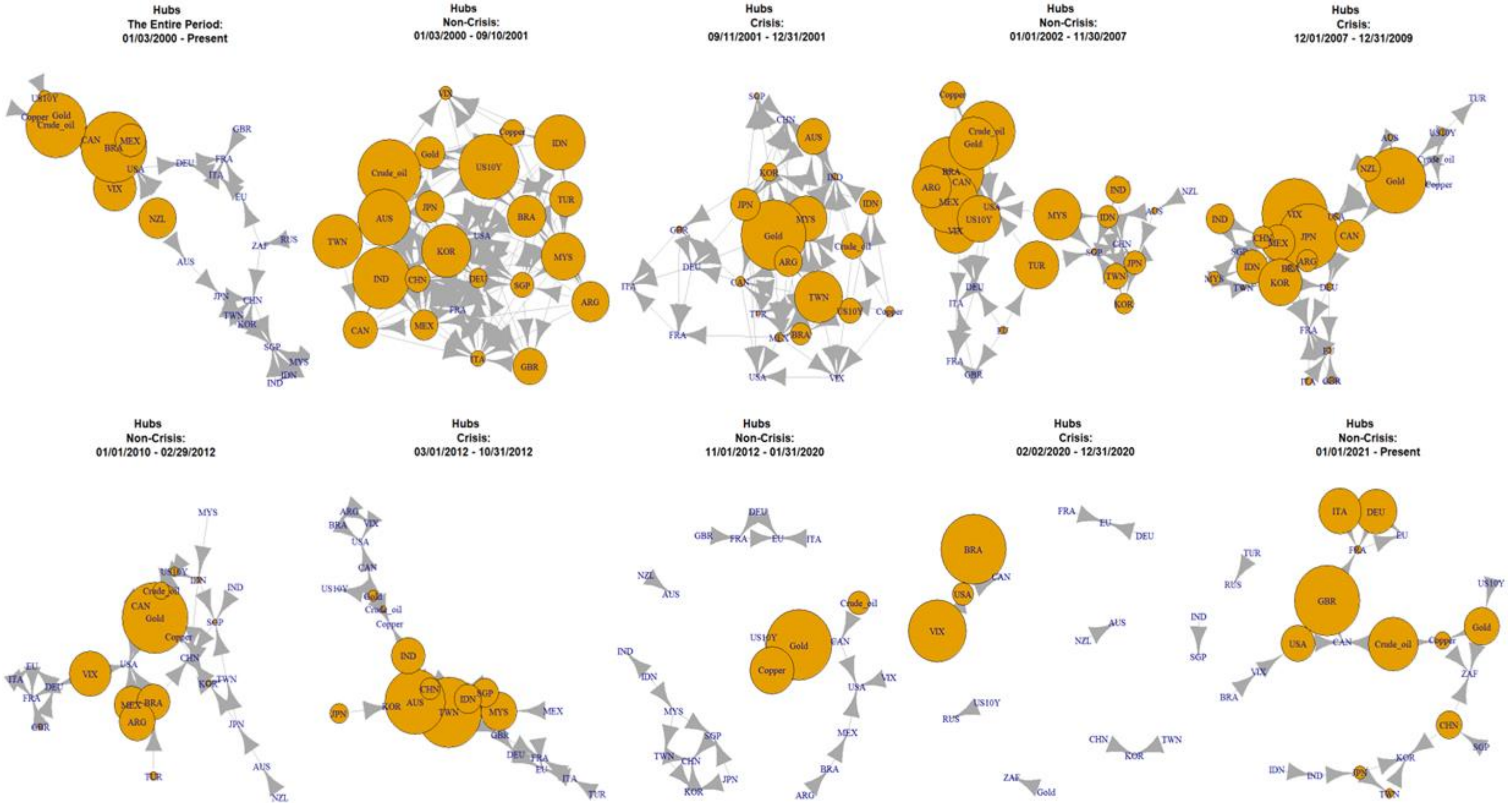


Figure 6 - Coreness

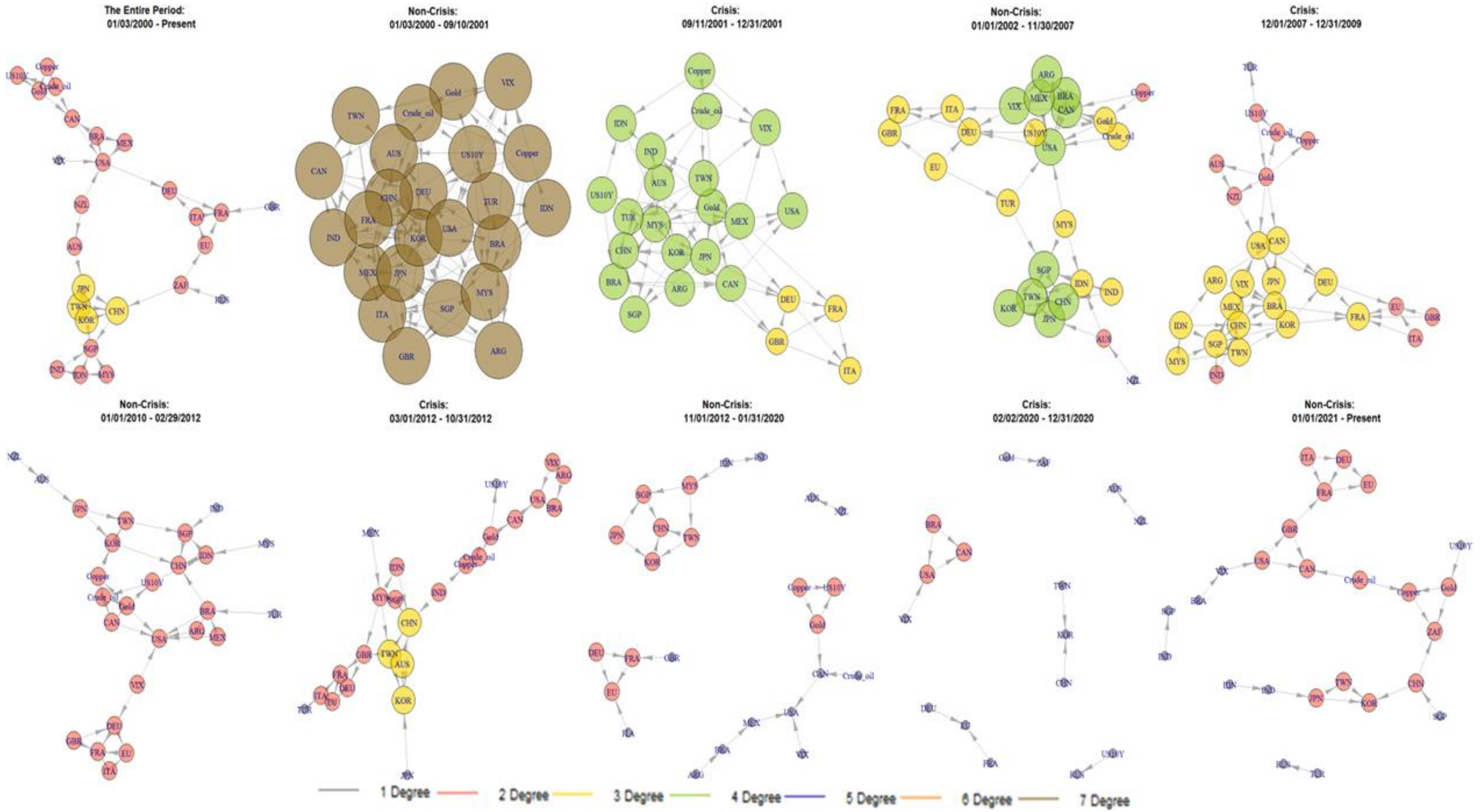
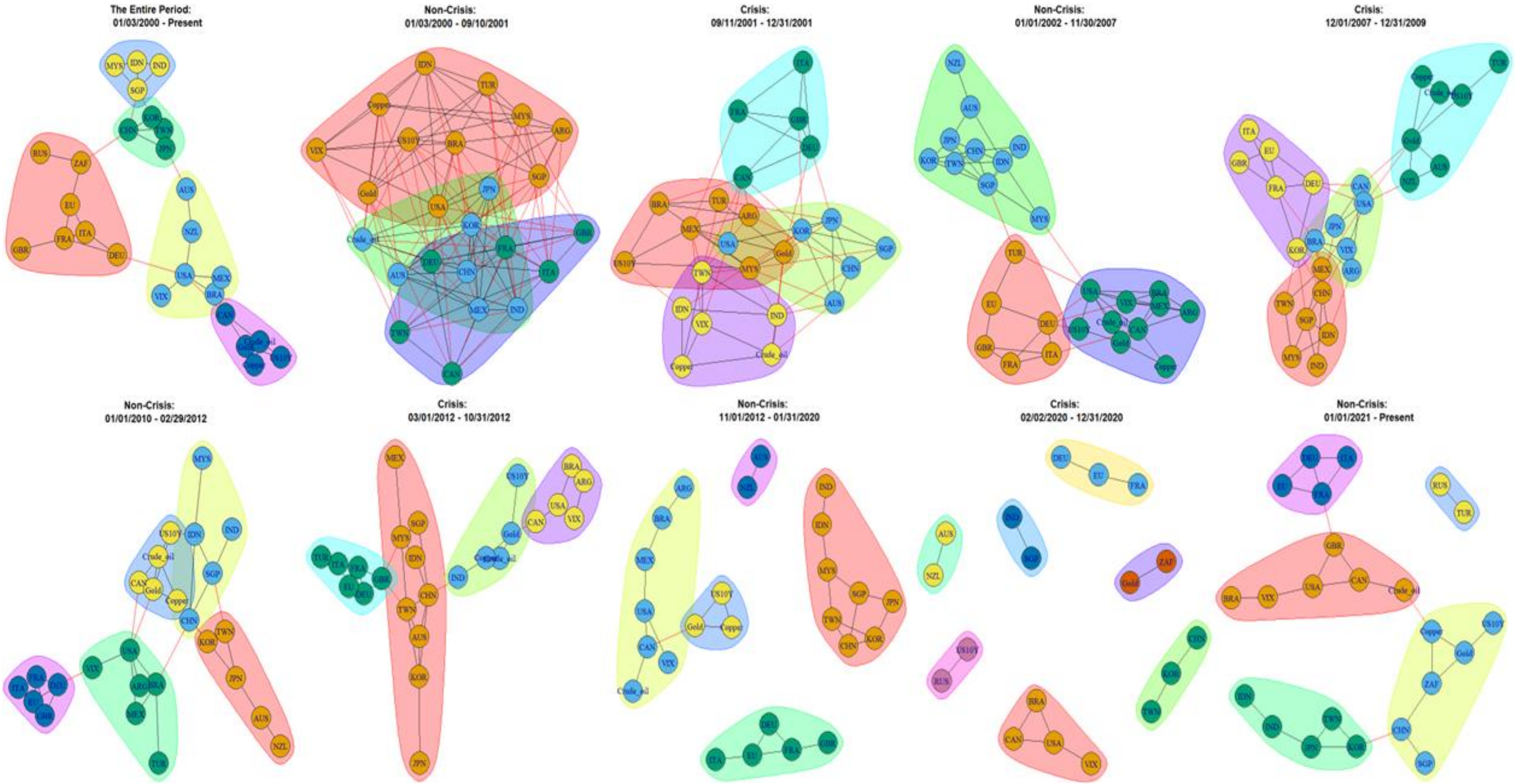


Figure 7 - Communities



The red edges represent connections between individuals from different communities, while the black edges represent connections between individuals within the same community.

Analyzing the Degree of Assets from Table 3, it is observed that CHN and USA, representing the financial assets of the world's largest economies, have the highest number of edges throughout the period (line 1). The asset SGP shows the same number of edges as CHN, indicating that Singapore's financial system, crucial to the Asian region, is strongly integrated into international financial markets. Typically, connections (Degree) expand during non-crisis periods. However, in the chronological series of the periods studied, there was a reduction in edges between the assets.

In Table 4, the In-Degree metric represents the edges entering the asset. Hence, assets CHN and USA receive more connections due to the significance of their economies, except that the Chinese economy loses some traction in the last two periods due to the shift in the direction of its economic growth engine. Assets CAN, DEU, and FRA have a significant number of edges connecting to them. The first is due to its geographical proximity to the American economy and having major companies exporting mineral commodities. The second and third, being the first and second largest economies in the Eurozone, determine the dynamics of financial flows and Europe's growth. Finally, SGP had several connections until the pre-COVID-19 period due to the sophisticated financial center in Asia, acting as a bridge for investments in other assets in the region.

The Out-Degre, in Table 5, highlights the connections leaving the asset. Considering financial theory, it is inferred that more peripheral assets exhibit greater connections towards the more representative assets in the network. The multiple edges from the commodities Crude Oil and Gold connect to other assets, which is explained by the fact that these two commodities serve as proxies for measuring activity, in the case of Crude Oil, and allocation for protection, in the case of Gold.

We employed mixed measures to analyze the formed networks. The first measures, Authority Scores, and Hub Scores, are two complementary approaches to understand the centrality of financial assets within the estimated networks, serving as effective measures for acyclic networks, as is the case with our networks. In Figure 4 and Figure 5, we present the Authority Scores and Hub Scores for the estimated networks, respectively.

In Figure 4, the first network, which considers the entire period, presents the asset USA as the highest authority. The United States, being the primary economic and military power in the world, significantly influences the global economic dynamics, and its financial assets receive substantial resource inflows from the rest of the world. CAN behaved as another authoritative asset because the Canadian stock market comprises major mineral commodity companies, crucial inputs for economic growth.

The mineral commodities Copper and Gold also emerged as relevant points of authority. The former is an important input for economic activity, serving as a proxy for economic growth, while the latter acts as a safe-haven asset and diversification within investment managers' portfolios. Finally, there is the US10Y, a lesser point of authority, indicating that the risk-free asset has a significant influence on determining portfolio allocation.

During the non-crisis period (Figure 4: 01/03/2000 - 09/10/2001), trade liberalization, globalization of financial markets, and free capital flow contributed to various possibilities of interconnectivity within global financial markets, resulting in multiple authorities within the network.

In the non-crisis period post-September 11 Attacks (Figure 4: 01/01/2002 - 11/30/2007), we see the asset USA as the greatest authority in the network, what is explained by the favorable global economic conditions and its possession of a range of globally leading companies across various sectors, attracting investment flows into its equity assets. The asset CAN also held authority within the network due to a commodity boom during this period, benefiting several Canadian commodity-exporting companies listed in its stock market. In the Asian context, assets CHN and SGP emerged as authorities.

In the post-Great Financial Crisis period (Figure 4: 01/01/2010 - 02/29/2012), the massive stimuli initiated by the U.S. government, both in fiscal policies involving substantial investments in the economy and in monetary policies through the Federal Reserve's purchase of financial assets, propelled the American economy significantly. This had a substantial impact on the asset USA, which emerged as the greatest authority in the network. Additionally, towards the end of the commodities boom, asset CAN, the commodities Crude Oil and Copper (both indicative of economic activity), and the asset US10Y stood out as authorities. The first three were influenced by the commodities cycle, while US10Y reflected the low risk aversion during this period.

In the last two non-crisis periods (Figure 4: 11/01/2012 - 01/31/2020 and 01/01/2021 - Present), there was a significant reduction in connections (edges). Assets USA, CAN, and Gold were the authorities in the first period, while assets FRA, CAN, and Copper were the authorities in the second period. Particularly in the post-Acute Phase of COVID-19 (01/01/2021 - Present), the boom in agricultural and mineral commodity prices had a positive impact on stock markets that have companies involved in producing or extracting these commodities.

The first period of crisis, September 11 Attacks (Figure 4: 09/11/2001 - 12/31/2001), demonstrates that the United States was the epicenter of the crisis resulting from the terrorist attack on September 11. This crisis triggered a capital flight from the United States (due to the uncertain direction of its economy) towards other regions, resulting in multiple points of authority in different geographical areas.

In the second crisis period, the Great Financial Crisis (Figure 4: 12/01/2007 - 12/31/2009), the asset USA is the most authoritative point. Despite the 2.59% contraction in GDP in 2009[13], the liquidity injection promoted by the U.S. government contributed to sustaining the economy and equity assets, what is reflected in the asset USA. China, a significant engine of economic growth during this period, positively affected its financial asset CHN, making it the second authority. Finally, we have assets BRA and SGP as authorities in the network, which might have positively influenced the profitability of their companies and attracted resources to their financial assets due to their significant relations with China.

[13] According to World Bank data.

During the European Sovereign Debt Crisis (Figure 4: 03/01/2012 – 10/31/2012), the asset CHN is the highest authority due to the economic growth in the Asian region, with China being the main exponent. Another point of authority in this region is the asset KOR, due to its dynamic economy and export of high-value-added products. In this case, Korean companies may have benefited from the economic growth in the Asian region, led by China.

In the last crisis period, the Acute Phase of COVID-19 (Figure 4: 02/02/2020 - 12/31/2020), the asset USA emerges as the authority in the network, owing to the monetary easing promoted by the Federal Reserve (Fed), which supported risk assets and contributed to the strong performance of technology companies during this period.

The Hub Scores are the second centrality approach employed in the study. A high Hub Score indicates many good authorities. In this pattern, we observed that the Hubs are financial assets from both emerging and developed economies that are not among the top five largest economies in the world. Additionally, we identified commodities, the US10Y, and the VIX as important Hubs. The insight is that the dynamics of the Hubs relate to a country's economic growth perspective and the size and liquidity of the financial market. In other words, these Hubs diversify the portfolios of major global investors, representing bets with good risk-return asymmetries when compared to the financial assets of the largest economies. See Figure 5.

The third mixed measure employed is the Coreness of the estimated networks, which highlights subgroups within networks with the same number of connections. In other words, individuals with higher Coreness scores are grouped in the network core, while others are on the periphery. He et al. (2012) summarize that Coreness progressively identifies the inner cores and analyzes the network by layers, revealing the structure of different layers. See Figure 6.

In the first network covering the entire period studied (Figure 6: 01/01/2000 - Present), the Coreness of the Asia-Pacific region shows a denser Coreness, with assets CHN, KOR, JPN, and TWN having 3 connections, indicating that the economic growth of this region (average annual growth of 7.83% between 2000-2021, according to World Bank data) had a positive impact on the region's financial assets.

From the other estimated networks separated into periods of non-crisis and crisis in chronological order, we infer that connections between financial assets have decreased over time, especially after the Great Financial Crisis, where we no longer identified Coreness with four or more connections. As found in other measures, Coreness also captured the process of financial asset deglobalization towards more regionalized networks, emphasized by geographical proximity.

The fourth mixed measure we used in the study was Global Transitivity, where we noticed that the number of triangles in the networks does not show a clear trend. However, if we analyze this measure along with the three other mixed measures presented earlier, we can ascertain that these triangles are formed by assets that are closer geographically. See Table 6 line 7.

The global measures employed in our study were 7. In Table 6 , we can observe the evolution of these aforementioned measures.

The first two global measures in Table 6 are Diameter and Mean_Distance. We observed that over the periods, there is a trend of increasing values for these measures. In other words, there is a decrease in edges between assets throughout the estimated networks. Therefore, to reach from one side to the other of the network (Diameter) or to connect with a particular asset, the reduction in edges in the estimated networks over time reduces the possible paths, impacting the increase in these measures. Finally, it is noteworthy that the Acute Phase of COVID-19 Crisis (02/02/2020 - 12/31/2020) impacted each country's economies differently and at different stages, causing a significant decrease in edges within the network. Consequently, Diameter and Mean_Distance had their lowest values during that period.

Our third global measure is Modularity, which measures the strength of the division of a network into modules. Therefore, high modularity implies dense connections among nodes within modules but scarce connections among nodes in different modules. We observed a clear upward trend in modularity across the analyzed periods, supporting the evidence of geographical regionalization of connections among financial assets.

The fourth, fifth, and sixth global measures implemented in our study are Assortativity, Nominal Assortativity (Assortativity_Nominal), and Degree Assortativity (Assortativity_Degree). The assortativity measure assesses whether a network prefers certain connections or not. Positive coefficients indicate that vertex pairs in the network have vertices at the ends with similar degrees, while negative values indicate ends with different degrees. The three measures calculated for each analyzed period predominantly show negative coefficients, as expected for financial market networks. Additionally, Silva, De Souza, and Tabak (2016) found a negative assortativity coefficient for financial asset networks.

The seventh calculated global measure is Edge_Density, the ratio between the number of edges and the number of possible edges, showing a decreasing trend across the analyzed periods. This evidence is supported by two major factors: 1-A slowdown in global growth negatively impacting the potential cash generation of companies, reflected in their stock prices; 2-The deglobalization of financial markets towards more geographically regionalized connections among financial assets, contributing to reducing the theoretical maximum quantity of possible connections among these assets.

4.3.1. Building Communities among Financial Assets

Given the evidence found in the estimations of Dynamic Bayesian Networks and in the measures of Complex Networks indicating a deglobalization of financial assets, resulting in more geographically regionalized communities, we constructed communities of financial assets over time using the algorithm suggested by Clauset, Newman, and Moore (2004) to find the greatest modularity for each network. See Figure 7.

The first community formed is from the network estimated over the Entire Period (Figure 7: 01/01/2000 - Present), where we observe the formation of 5 communities: two consisting of Asian countries, one of European and African countries, one of countries from the Americas and Oceania, and one involving commodities, USA10Y, and CAN. Overall, even considering all the series, there is a clear regionalization of communities by assets geographically close. Additionally, the edges connecting different communities are few (7), indicating that opportunities for hedging and portfolio diversification have become scarcer.

During September 11 Attacks (Figure 7: 09/11/2001 - 12/31/2001), the number of asset communities expands when compared to the immediately preceding period (Figure 7: 01/03/2000 - 09/10/2001), with 4 communities during this crisis period. Additionally, connections between different communities contract slightly, but they still present several interesting risk-return asymmetries in allocation during that crisis.

During the Great Financial Crisis (Figure 7: 12/01/2007 - 12/31/2009), the formed communities were four, with one community formed solely by commodities (Gold, Crude_oil, Copper), US10Y, NZL, AUS, and TUR. This demonstrates that this crisis severely impacted the real economy and commodities, as well as the US10Y, indicators for global growth. In perspective, in the first four estimated networks (two non-crisis and two crisis periods), there is a trend of geographical regionalization of connections between assets (black edges) and a reduction in connections between different communities (red edges).

In the five periods of non-crisis (Figure 7: 01/03/2000 - 09/10/2001; 01/01/2002 - 11/30/2007; 01/01/2010 - 02/29/2012; 11/01/2012 - 01/31/2020; and 01/01/2021 - Present), the pattern of connections among assets within the same community becomes more pronounced, while connections between different communities decrease drastically. The aspect of geographical proximity among financial assets is emphasized in the formation of communities, showing a clear trend of connections between assets within the community.

During the European Debt Crisis (Figure 7: 03/01/2012 - 10/31/2012), the pattern of connections between assets remained consistent, i.e., with connections among assets within the same community. We observed that during these periods, the four communities formed clearly follow a geographical proximity among countries, with two exceptions: MEX belonging to the community of Asian and Oceanic countries, and IND belonging to the community of commodities and US10Y.

The communities formed during the Acute Phase of the COVID-19 (Figure 7: 02/02/2020 - 12/31/2020) show connections only among members of the same community, emphasizing the trend of communities being formed by assets geographically close. A peculiarity of this crisis is that each country addressed the health pandemic with different measures, which consequently impacted the stages of economic recovery in diverse ways, reflecting in financial assets disparately. Thus, the estimated Dynamic

Bayesian Network for this period showed few statistically significant connections that served as the basis for identifying these asset communities.

4.4. Econometric Model Estimation on Panel Data

In view of the numerous complex network measures calculated, the econometric model in static panel data was applied to explain the profitability of financial assets. The dependent variable is represented by the average of daily log-returns for the periods analyzed. The independent variables were the complex network measures previously presented and calculated in the study. Equation 24 presents the model to be estimated.

$$\begin{aligned} Y_{i,t} = {} & \beta_0 + \beta_1 H\_S_{i,t} + \beta_2 A\_S_{i,t} + \beta_3 Kc_{i,t} + \beta_4 D_{i,t} + \beta_5 D\_in_{i,t} + \beta_6 Diam_t \\ & + \beta_7 M\_Dist_t + \beta_8 Modul_t + \beta_9 Asso\_N_t + \beta_{10} Asso_t + \beta_{11} Asso\_D_t \\ & + \beta_{12} Tr\_Net\_G_t + \beta_{13} Ed\_Den_t + \mu_i + \varepsilon_{i,t}. \end{aligned} \tag{24}$$

Where:
$Y_{i,t}$: Dependent variable represented by the average of daily log-returns for the periods;
$H\_S_{i,t}$: Hub Score;
$A\_S_{i,t}$: Authority Score;
$Kc_{i,t}$: Coreness;
$D_{i,t}$: Degree;
$D\_in_{i,t}$: In-Degree;
$Diam_t$: Diameter;
M_Dist_t: Mean Distance;
$Modul_t$: Modularity;
$Asso\_N_t$: Assortativity_Nominal;
$Asso_t$: Assortativity;
$Asso\_D_t$: Assortativity_Degree;
$Tr\_Net\_G_t$: Global Transitivity;
Ed_Den_t: Edge_Density;
μ_i: Individual Fixed Effect;
$\varepsilon_{i,t}$: Random Error.

In Table 7, we present the estimation of the model with complex network measures explaining the profitability of financial assets. We can observe that the global measures, *Diam* and *M_Dist*, were statistically significant at 5%. The estimated coefficient for the variable *Diam* is positive, and for the variable *M_Dist*, it is negative. We can interpret that an increase of one unit in *Diam* is associated with a 0.0555 percentage point increase in the profitability of financial assets, while an increase of one unit in *M_Dist* is associated with a decrease of 0.1638 percentage points in the profitability of financial assets. We understand that a larger network diameter (*Diam*) implies a greater possibility of seeking risk-return asymmetries throughout the formed network, as well as better diversification. On the other hand, if the mean distance (*M_Dist*) between assets decreases, we comprehend that the potential paths to reach a specific asset decrease. Consequently, the search for risk-return asymmetries or short-term hedging diminishes, negatively impacting the profitability of financial assets.

The *Modul* (Modularity) was statistically significant at 5%. Its association indicates that an increase of one unit of modularity is associated with a reduction of 0.6262 percentage points in asset returns. That is, higher modularity implies increasingly smaller clusters of financial assets, reducing opportunities for arbitrage and the pursuit of asymmetries between markets that enable significant returns.

Table 7 - Base Model Estimation

Independent Variable: Ln_mean_asset_return		
	Coefficient	**Std. Error**
H_S	0.0175	(0.0217)
A_S	0.0221	(0.0226)
Kc	-0.0187	(0.0132)
D	0.0035	(0.0062)
D_in	-0.0015	(0.0033)
Diam	0.0555**	(0.0208)
M_Dist	-0.1638***	(0.0571)
Modul	-0.6262**	(0.2288)
Asso_N	6.956***	(0.9956)
Asso	0.1588	(0.1480)
Asso_D	0.3509***	(0.1081)
Tr_Net_G	1.011***	(0.2223)
Ed_Den	-2.619***	(0.9288)
Fixed-Effects:	--	
ID	Yes	
Standard-Errors Clustered by:	ID	
Observations:	217	
R^2:	0.33607	
Within R^2:	0.24904	

Signif. codes: 0 '***' 0.01 '**' 0.05 '*' 0.1 ' ' 1

The measures *Asso_N* (Assortativity Nominal) and *Asso_D* (Assortativity Degree) were significant at 5%. Both variables, *Asso_N* and *Asso_D*, show a direct association with asset returns. We infer that higher value of *Asso_N* indicate a greater propensity for financial assets to associate with assets having the same degree, which indicates increased opportunities for short-term returns and higher liquidity, allowing quick entry and exit from positions. On the other hand, the *Asso_D* variable, which demonstrates the propensity for an asset to connect with an asset of a lower degree than itself, indicates that these lower-degree assets are not the main connections for higher-degree assets. However, they can offer opportunities for complementing resource allocation, albeit with a more limited influence on higher degree assets.

The transitivity (*Tr_Net_G*) showed a positive coefficient and significance at 5%. We can interpret that an increase in *Tr_Net_G* by one unit is associated with a 1.011 percentage point increase in financial asset returns. Economically, this implies that an increase in triangles within networks creates more connections between financial markets. During periods of global growth, these triangles (connections) enhance return possibilities across various assets, while during times of stress, they can serve as hedges in positions.

The last significant measure at 5% in the model is *Ed_Den* (Edge_Density), which showed a coefficient inversely related to the return of financial assets. The inverse association indicates that an increase in network connections creates possibilities for greater diversification, potential transaction costs, and significant information asymmetries.

4.4.1. Estimations Considering Non-Crisis and Crisis Events

As our study examined the networks formed during non-crisis and crisis periods, investigating how the measures of complex networks behaved in these respective periods, we created two panels. The first panel included the non-crisis periods, and the second comprised the crisis periods to verify how the calculated measures contributed to explaining the returns of financial assets. In Table 8, we present the estimations.

Table 8 - Model Estimation by Episode Type

Sample	**Model 1: Non-Crisis**		**Model 2: Crisis**	
Independent Variable:	**Ln_mean_asset_return**		**Ln_mean_asset_return**	
	Coefficients	**Std. Error**	**Coefficients**	**Std. Error**
H_S	-0.0272	(0.0182)	0.0289	(0.0458)
A_S	-0.0380	(0.0290)	0.0337	(0.0450)
Kc	0.0043	(0.0144)	-0.0253	(0.0409)
D	0.0001	(0.0097)	0.0069	(0.0143)
D_in	0.0050	(0.0052)	-0.0120	(0.0103)
Diam	-0.0503***	(0.0090)	0.1501***	(0.0409)
M_Dist	0.1611***	(0.0296)	-0.4698***	(0.1286)
Modul	0.5448***	(0.1341)	-0.3860**	(0.1622)
Asso_N	27.88***	(8.8910)		
Fixed-Effects:	-----------------------------------		----------------------------------	
ID	Yes		Yes	
S.E.: Clustered by:	ID		ID	
Observations:	124		93	
R^2:	0.55536		0.43494	
Within R^2:	0.51482		0.14874	

Signif. codes: 0 '***' 0.01 '**' 0.05 '*' 0.1 ' ' 1

When we analyze the non-crisis episode (Model 1) in Table 8, the network measure of diameter (*Diam*) remained significant at 5%, and its association with asset returns becomes inverse. We intuit that the inverse association shows that in non-crisis periods, the network tends to expand its connections and its diameter, which can generate transaction costs for entering/exiting assets and numerous asymmetries between markets, making it difficult for economic agents to choose better allocations.

The Mean Distance (*M_Dist*) remains statistically significant at 5%, and the coefficient becomes positive during non-crisis periods. We can interpret that an increase of one unit in *M_Dist* is associated with a 0.1611 percentage point increase in the returns of financial assets. From an economic standpoint, during non-crisis periods, the network tends to increase its connections, particularly among financial assets associated with economies showing positive growth prospects. Consequently, investors and portfolio managers can enhance their global asset allocation diversification and seek risk-return asymmetries that compensate trade-offs without the need to resort to highly risky assets within the formed networks.

The last two statistically significant variables at 5% are *Modul* and *Asso_N*. Therefore, during non-crisis periods, the connections among community members and the probability of associating with similar assets increase. This scenario creates an environment for allocating opportunities within communities and greater ease in unwinding positions in assets.

In the crisis episodes (Model 2) from Table 8, we observed that three measures were statistically significant at 5%.

The first one is the diameter (*Diam*), and its coefficient is positive. We infer that, during certain crisis moments, networks expand due to contagion or some assets might present lower risk. Hence, these two factors might be capturing the positive dynamics of the coefficient.

The second measure is the *M_Dist*, which presented a negative coefficient, indicating that during times of crisis, there is a generalization of volatility and risk among the financial assets in the network. Therefore, the cost of allocating or seeking trade-offs becomes riskier.

The third one is the modularity (*Modul*), whose coefficient is negative. That is, an increase of one unit in modularity is associated with a reduction of 0.3860 percentage points in the return of financial assets. During times of crisis, the formed communities become denser, meaning that assets have more connections with other assets within the same community. This makes it difficult to find asymmetry and diversification in assets from other communities.

5. CONCLUSION

This study aimed to investigate the intricate dynamics of interdependence within global financial markets, encompassing 23 countries whose stock indexes accounted for approximately 80% of the world's GDP in 2022. Additionally, five significant financial assets were analyzed: Gold, Crude Oil, 10-year US Treasury Bonds, Volatility Index (VIX), and Copper. To conduct this analysis, we opted to employ the technique of Dynamic Bayesian Networks, enabling us to model and interpret the interactions among these financial assets over the period from 03/01/2000 to 06/23/2023.

The estimation results revealed that financial assets demonstrate significant correlations with geographically proximate assets and predominantly display positive partial autocorrelations (connections) throughout most of the analyzed period. This suggests that, in the long term, financial markets tend to move in the same direction, although this interdependence dynamic might change in the short term. During non-crisis periods (5 periods), we observed a trend of reduced connections among assets, with positive partial autocorrelations among geographically close assets. This decrease in negative partial autocorrelations indicates a decline in hedging opportunities and the pursuit of risk-return asymmetries among assets in the short term, impacting portfolio managers and investors (see Figure 2 and Figure 3).

On the other hand, for policymakers, this information provides insights into how their decisions can impact or potentiate these interactions within networks, especially in economically relevant countries.

During crisis periods (4 periods), such as the September 11 Attacks (09/11/2001 - 12/31/2001) and the Subprime Crisis (12/01/2007 - 12/31/2009), connections extend beyond geographical borders, generating a complex network of partial autocorrelations among assets from different regions. These partial autocorrelations are mostly positive, driving targeted movements, yet negative partial autocorrelations also emerge, which could be explored to yield returns through buy and sell operations. In the last two crises, the European Sovereign Debt Crisis (03/01/2012 - 10/31/2012) and The Acute Phase of COVID-19 (02/02/2020 - 12/31/2020), the geographic regionalization of connections (partial autocorrelations) among assets becomes more evident, and the number of connections decreases when compared to previous crises. This dynamic complicates the search for risk-return asymmetries by portfolio managers and investors, making the trade-off for global asset diversification more challenging.

The analysis of the estimated Dynamic Bayesian Networks revealed that the asset USA holds significant authority in almost all networks, regardless of whether it is a crisis or non-crisis period. This prominence is partly due to the presence of highly dynamic companies in its index and the resilience of the American economy. On the other hand, the Hubs are numerous and vary according to each network, but we identified a pattern where they are assets from emerging economies or they are not among the world's top 5, as well as commodities, US10Y, and VIX. These serve as strategic short-term allocations for global managers in the quest for risk-return asymmetries, considering the economic scenario outlined.

Considering other measures of complex networks employed, a reduction in network density (Figure 6 and Table 6) was notable over time, as well as a higher regionalization, where financial assets formed communities with their geographically close peers, with few or almost no connections with assets from other communities (Figure 7). The main finding of this study revealed a phenomenon of 'deglobalization' in global financial markets, making it more challenging for portfolio managers and investors to identify risk-return asymmetries outside the regionalized communities. This trend increases the trade-off when analyzing and investing in new markets.

For policymakers impacting financial markets, it becomes essential to focus on policies tailored to regional specificities and characteristics. The contemporary multipolar world is also reflected in current financial markets, and therefore, policies that take the particularities of each region into account are of utmost importance.

In the context of econometric estimations to explain the profitability of financial assets, we observe that the measures Diameter (*Diam*), Average Distance (*M_Dist*), and Modularity (*Modul*) emerge as significant variables in both non-crisis and crisis periods. Thus, portfolio managers and investors interested in using the concept of complex networks to understand the dynamics of financial markets should consider these measures as potential indicators. For policymakers, such measures can serve as barometers to gauge the effects of policies and regulations on the financial market, which is increasingly interconnected regionally and with limited connections to geographically distant financial markets.

Finally, for future work, we suggest applying machine learning concepts to estimate future network patterns based on daily return data of the studied assets, as well as the estimated complex network measures over time periods. This approach could provide additional insights into the dynamics of financial markets and their complex interactions.

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