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Equity market integration in emerging economies: a network visualization approach

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Abstract

Purpose – The authors examine network features such as connectivity, centrality, adjacency matrices, closeness and betweenness measures through a variety of indicators. The results of the study indicate that over time there is a tendency for markets to integrate and segment due to various factors such as pandemics, financial crises, global trade relations and international investments.

Design/methodology/approach – This paper employs a visualized network technique to study the dynamics of integration and comovements in global equity markets of emerging economies. Daily closing prices of stock market indices of 24 countries from January 2013 to July 2020 are used to construct a minimum spanning tree network (MSTN) and graph network (GN).

Findings – The authors identify India and China as global power hubs and clusters among the emerging economies. India and Bangladesh serve as bridging countries connecting to various other clusters. Bosnia serves as a center in the European region owing to Bosnia's trade relations with neighboring countries. Although Brazil has witnessed the worst recession in the early years of the decade, Brazil has risen to be a central cluster among the Latin American countries. Finally, the authors find that African countries tend to form links with the rest of the world rather than with economies within the Africa continent.

Originality/value – This is the pioneering study that uses network models such as MSTN and GN supplemented with measures of centrality and connectivity to study financial market integration in emerging countries. Against this backdrop, this paper aims to work on a network visualization strategy to examine global stock market integration. The authors also try to use graphs and the spanning trees instead of the correlation models to understand the association between the markets, avoiding the downsides of the existing models. The authors' approach tries to visualize the network integration to examine the interconnectedness in the global stock market.

Keywords Financial integration, Contagion, Minimum spanning tree network, Graph network, Grower distance, Closeness, Betweenness

Paper type Research paper

1. Introduction

Equity market integration includes equity market integration. Overseas equity money flowed into emerging markets as a result of globalization, deregulation, and lower trade barriers. Financial stability and growth are promoted through regulating macroeconomic policy making and developing local financial markets. This strengthened financial connectivity and

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emphasized the impact of major financial crises like the 1997 Asian crisis and the 2008 global financial crises on emerging markets.

Due to increased worldwide exposure, financial market integration has both benefits and drawbacks. They claim that international portfolio diversification works only if it pays off. Diversification gains will tend to dwindle as financial integration and linkages increase. As global returns equalize, further integration reduces the opportunity for foreign portfolio diversification profits. Financial interconnectivity between emerging and established markets grew during the 2008 crisis, according to Lehkonen (2015). The 2007 stock market crash expanded across borders due to financial integration, demonstrating the risks of market integration. On the other hand, with a segmented market structure, crises tend to spread faster.

Previous financial market integration research has relied on econometric methods that focus on system dynamics and heavily on correlation. Even correlation-based systems can have weak correlations, and even fully connected markets can have weak correlations. Multi-factor models have been used to describe global financial integration patterns. We must select relevant elements when developing multi-factor models. The adjusted R-squared values of these models can be used to measure financial integration when some countries have a strong financial representative (Pukthuanthong and Roll, 2009). The evidence for an association-integration link (Bekaert *et al.*, 2005, 2009; Edison *et al.*, 2002) is mixed.

This is the first study to use minimum spanning tree network (MSTN) network and graph network (GN) models with centrality and connectivity measures. Using network visualization, this article will examine worldwide stock market integration. To comprehend market connection, we use graphs and Spanning trees to circumvent the flaws of previous models. Interconnecting global stock markets is our method.

In this regard, Tong *et al.* (2018) created network models like MSTN and GN for developed countries. From 2013 to 2020, we study 24 emerging countries utilizing MSTN, GN, and connectivity indicators. It does it by selecting linkages with the shortest distance or highest correlation. The GN model selects the most correlated graph edges to get a country's Clustering coefficient. Click here for more info about this coefficient.

Several aspects are proven to be crucial in clustering dynamics. Participation in global trade and investment improves ties with partner stock markets. China's massive global investments have made it a major global player. Financial crises and pandemics influence stock market integration. Crisis reduces investor confidence and shrinks stock markets. China lost centrality following the Chinese stock market crash, according to MSTN data. For example, Brazil's recession worsened in 2014.

The remainder of the paper proceeds as follows: Section 2 reviews the relevant literature. Section 3 presents the empirical model and methodology. Section 4 presents the data. Section 5 presents the empirical results and highlights the policy implications of the study. Section 6 concludes.

2. Literature review

Following the October 1987 stock market meltdown, scholars studied worldwide equity market integration. After the 2008 financial crisis, understanding global markets is crucial. Investors are increasingly worried about global financial integration. Based on their research, Friedman and Shachmurove (1997) found the most integrated stock markets to be in the UK Miniature markets aided portfolios more Ferson and Korajczyk (1995). Risk is defined theorem. Capital flow constraints segregated emerging markets. Market integration lowered it.

Huyghebaert and Wang (2010) found minimal equity market integration and consequences on stock prices across seven exchanges in East Asia but not in Mainland China, where exchanges remain separate despite significant financial success. The crisis accelerated market integration, but only briefly. This means longer-term diversification gains in Asia's stock markets. Hong Kong and Singapore stock returns were connected.

Analysis of global equities market integration networks has proven useful. Economic dynamics, systemic risk, and stability are now explained by global financial network linkages (Stiglitz, 2010). Chi *et al.* (2010) studied two-year closing stock price relationships in the US stock market. Stock price fluctuations, returns, and trading volumes were used to create the model's edges. A study by Campbell and Hamao (1992) found that correlation is utilized in finance to analyze asset management and portfolio selection. A structural split in global banking networks was discovered by Minoiu and Reyes (2011). Cross-border bank lending was a country network. On the other hand, node degree and strength explained network density. Fagiolo studied it topologically and statistically (2008). WTW findings varied greatly from BNA outcomes (Albert and Barabási, 2002). Because numerous factors influence edge weights, we must account for variables like currency and GDP (Kossinets and Watts, 2006).

From two perspectives, Chinazzi examines (2013) Assemble nodes and edges to represent web statistics. 2nd, compare crisis intensity across countries using network-based measures (see Blanchard *et al.*, 2010; Berkmen *et al.*, 2012; Lane and Milesi-Ferretti, 2011; Rose and Spiegel, 2011; Frankel and Saravelos, 2012; Giannone *et al.*, 2011, to quote just a few). As stated by Allen and Gale (2000) and Leitner (2005). The findings suggest shock networks. For example, Hale *et al.* (2013) found, connections slow during global financial crises.

Tong *et al.* (2018) mapped global stock market correlations. Daily stock market index values from 57 nations were used to create these graphs and trees. Multiple criteria were used to assess network centrality. Integration of the global financial system and financial markets Campbell and Hamao (1992) used outmoded correlation-based econometric methods. Not right. Since 2008, global financial markets have become more linked, say Tong *et al.* De facto, the US and Europe are losing influence to Asia. Three global stock exchange clusters exist. Later, all clusters become increasingly internationally integrated.

Corten (2011) utilized Stata to depict social networks (Wasserman and Faust, 1994; Scott, 2011). It is now widely used to reveal relationships (Freeman *et al.*, 2000). Fintech networks are studied. Stata uses this paradigm to analyze and build networks. However, the MDS and SNA can be used to analyze financial data.

They reflect both strong and weak financial systems. A bankrupt institution's counterparty losses can be easily reduced. Connectivity reduces the chance of infection. A network can be brought down by one institution. Associating institutions can more easily disperse shocks. Robust connectivity reduces the risk of infection but accelerates it. Babus (2016) looked into how banks decide on direct balance sheet links and the risk of contagion. The banking system is more shock tolerant than incomplete networks. In an incomplete network, dependencies are unlikely. To make ex ante optimal financial decisions, you need complete networks! A large network promotes interdependence.

They studied the link between banks credit risk and financial integration from 1988 to 2014. They are linked in banking. Increasing global borrowing, they argue, hurts banks. The implications of a global bank crisis cannot be disregarded due to interconnection. Financial integration was de facto measured by the mean participating banks in inter-bank syndicated loans from 1980 to 2007. Increasing financial interconnectedness causes systemic bank problems. It indicates banking difficulty, they say. The average country's bank is less vulnerable to global financial crises. Bank borrowing increases the risk of economic crisis. Between 1995 and 2010, Inekwe and Valenzuela (2020) examined the impact of financial integration and capital constraints on banking crises in 62 countries. Financial integration raises the risk of a crisis.

3. Model and methodology

A network is the collection of the nodes, and the edges connect them. Each country (i.e. its stock market index) is a node in the global stock exchange network, and the link between them represents the correlation (Table 1). We build two types of networks: MSTNs and GN. Both networks have nodes, edges, and other parameters as shown below. The information carried by nodes differs between MSTN and GN networks. In the MSTN, they represent the country's importance in the network, while in the GN, they represent regional and global clustering.

In the construction of edges between the nodes in the network, the standard social system measurements, such as the separation length, are not straight away relevant. That is because stock exchanges, unlike the asset markets, are frequently conveyed by online automated platforms and would not capture the separation length (Fagiolo *et al.*, 2008). Therefore, we apply the correlation model amongst markets using the everyday stock exchange's index data to ascertain these links. A non-negative correlation-based model is used to interpret the intermarket separation. The above succeeds in the problem of identifying separation in the computerized stock markets. The nodes in the networks are built uniquely in the two representative networks with an Importance Coefficient used to indicate the node's weight in the MSTN and a CC employed in the GN.

3.1 MSTN construction

First, we compute the correlation matrix *Corr(I)* between each pair of countries using daily closing prices of stock market indices for 24 countries. A HashMap *H(C)* is used to store the country codes which are mapped to the country name. The correlation matrix helps us to understand the comovements between countries over time. This graph consists of 276 links making the network noisy and hard to interpret. Therefore, we employ the minimum spanning tree network which filters out only the important links without breaking the connectivity of the network. A minimum spanning tree network is a network of nodes that is connected by selecting the minimum possible edge weights in an undirected weighted graph.

The correlation values in the Corr*(I)* matrix consist of positive and negative values ranging between -1 and 1. In order to resolve the issue of negative values, we convert the *Corr(I)* matrix into a matrix of corresponding Grower distances.

$$D(I) = \sqrt{2(1 - Corr(I))},\ with\, 0 \leq D(I) \leq 2 \tag{1}$$

The grower distances are inversely related to the correlation values. A high correlation between the countries is represented by a short grower distance. The grower distance now represents the edge weight of the minimum spanning tree network instead of the correlation values. Grower distances are best suited to represent edge weights as they are always non-negative, and retain the features of the correlation values.

In order to construct the minimum spanning tree network from the Grower distance matrix, we make use of Kruskal's algorithm to select 23 links that have minimum weights and result in a connected graph. The algorithm greedily selects the minimum edge weight, and adds it to the MST network only if it does not result in a cycle. After applying Kruskal's algorithm, we obtain a vector *Corr(G)* of the Grower distances used in constructing the MSTN. The vector comprises the links that have the largest corresponding correlation values (shortest distances).

Table 1.
MSTN and GN construction description

Description	MSTN	GN
Nodes	Countries	Countries
Links/edges	Grower distance	Grower distance
Length of edges	Values of the grower distance	n/a
Size of the nodes	Importance coefficient	Clustering coefficient

Now that we have identified the important linkages, we turn to the construction of the Importance coefficient to identify the financially important countries. This requires us to revert back to the correlation values. Instead of using the correlation values, we take the reciprocal of the grower distances and introduce the "Inverted Grower distance" $Corr(\hat{I})$ matrix. This matrix is directly proportional to *Corr(I),* but contains only non-negative values. The country links are recovered from the Grower distance matrix *Corr(G)* using the HashMap *H(C).* For these set of countries we take an average of their correlation values from $Corr(\hat{I})$. This represents ρ (Rho), the threshold value for selecting financially important centers.

Importance coefficient captures 2 characteristics of financially important countries. Firstly, a financial center is well connected by links to many other markets. This is captured by constructing a matrix for each country comprising the subset of links from $Corr(\hat{I})$ that have a correlation value greater than the threshold ρ. The number of links for a country m is represented by S_m. A country with more links is considered to be more relevant amongst the global markets. Secondly, an important financial hub has a larger stock market in terms of market capitalization. To identify this, we make use of a country's stock market capitalization as a fraction of the sum of market capitalizations of all the countries in our sample (MC_m).

$$IC_m = S_m * MC_m \tag{2}$$

The importance coefficient helps us understand 2 things. Firstly, it identifies the financially important countries, i.e. countries that have several links, and large market capitalization. Such countries attract international cash flows and investments. Secondly, it reveals comovements between markets. Countries that are strongly integrated with each other tend to move together.

3.2 GN construction

Using the correlations in *Corr(I),* we rank all the correlations in decreasing order, and select the top $x\%$ of correlations. Here we take $x = 25\%$, in order to get a wider selection. We make use of a Clustering Correlation developed by Watts and Strogatz (1998) to calculate the CC_m for each country m in the GN. The clustering coefficient is defined as

$$CCm = \frac{2\Delta m}{N(N-1)} \tag{3}$$

where $N = 24$ represents the number of countries in the network and Δm represents the number of links for each country m.

Using small estimates of x encourages us to better understand the central nations shaping the groups. As the values increment, the number of countries in the cluster begins to increment. The estimations of m reflect what works comparable to the specific system being contemplated. The measure CC was at first brought into the systems, fundamentally the social networks to distinguish little weave bunches with an enormous thickness of interconnections.

4. Source of data and description

For our analysis, we have used daily closing prices of stock market indices of 24 emerging economies from January 2013 to July 2020. The following are the list of the countries that are a part of the analysis (Table 2).

The data were obtained from World Bank resources. We divide the data into four subperiods: to make it easier to read. During these 8 years, numerous major economic

Table 2.
Country and stock market index description

S.No	Region	Country	Name of the index	Abbreviation
1	Europe	Budapest	Budapest SE	BUX
2	Europe	Bosnia and Herzegovina	BIRS	BIRS1
3	Europe	Bulgaria	BSE SOFIX	SOFIX
4	Europe	Croatia	CROBEX	CRBEX
5	Europe	Poland	MSCI Poland	MIPL00000PPL
6	Europe	Russia	NASDAQ OMX Russia 1	NORUX15
7	Europe	Serbia	Serbian USD	SRXUSD
8	Europe	Ukraine	WIG Ukraine	WIGUA
9	Asia	Bangladesh	Dhaka stock exchange 30	DS30
10	Asia	Mongolia	MNE Top 20	MNETOP20
11	Asia	China	Shanghai composite	SSEC
12	Asia	India	BSE Sensex 30	BSESN
13	Asia	Indonesia	Jakarta stock exchange composite index	JKSE
14	Asia	Thailand	SET index	SETI
15	Asia	Philippines	PSEI composite	PSEI
16	Asia	Sri Lanka	MSCI Sri Lanka	MILK00000PLK
17	Asia	Saudi Arabia	Tadawul All share index (TASI)	TASI
18	Asia	Malaysia	MSCI Malaysia	MSCI
19	America	Brazil	Brazil index	IBRX
20	America	Colombia	Columbia stock exchange (COLCAP)	COLCAP
21	America	Mexico	MSCI Mexico	MIMX00000PUS
22	Africa	Egypt	Egyptian exchange 30 (EGX 30)	EG
23	Africa	Morocco	Morocco all share (MASI)	MU
24	Africa	South Africa	MSCI South Africa	ZA

conflicts and financial crises happened globally. Our research will examine the impact of these shocks on global stock market integration. Asia, Africa, Europe, and America are considered emerging countries. To make the results easier to read, we combined two years into one. As a result, we may focus on changes in the country's position in the network rather than on timeline residuals. Though we divide the time period into chunks, we look at the overall effect. If a country has many indices, we use the one that matches the analysis period (Table 3).

In the subsequent section, the following acronyms have been used:

H(C): *HashMap of country codes*

Corr(I): *correlation matrix*

Corr($\hat{I}$): *inverted grower distance*

S_m: *Number of links greater than threshold*

ρ: Threshold

Corr(G): grower distance

$MC_{m:}$ Market cap ratio

5. Empirical results and discussion

We use the MST network and GN to explore the components of long-run correlations among our 24 financial exchanges. Even more explicitly, we look at (1) whether or not various emerging markets across the globe will bring about comprehensive proposition connectivity

Year	Events	Scale
2013	Ukrainian Crisis	Continental (Europe): Economy of Ukraine shrank by 8%. Economic sanctions by the western countries resulted in Russian Financial Crisis
2014	Crude Oil Crisis	International
2014	Brazilian Economic Crisis	Country wide crisis
2014	Russian financial crisis	International. RTS index (USD) declined by 30%. Affected the currencies of most of the post-Soviet States. Credit Rating was lowered to BB+
2015	Greek debt crisis	Continental (Europe): Huge debt levels
2015	Black Monday in China	International: China Index down by 8.5%, Japan by 4.6%, European Countries by 4–5%, USA by 4% single day decline
2015	Stock market selloff	International: SSE fell by more than 45% in 2 months. Result of a combination of economic recessions and crises
2018	Turkish currency and debt crisis	Major continental, minor international impact
2019	US-China Trade War	International
2019	Middle East Crisis	Scrapping Iranian nuclear deal
2020	Stock Market crash	International: Reasons: COVID-19 pandemic, recession, oil prices drop

Table 3.
Timeline of major financial events from 2013 to 2020

patterns; (2) the integration amongst countries; (3) the clustering of nodes, that is, whether or not countries are moving together or apart from one another and the dynamics of the global financial network, furthermore, (4) the central markets of clusters in both local and global structures.

5.1 General results from MSTN

The MSTN features explicit network centers that can help answer the first two questions, while the GN's static structure can help answer the latter two. However, countries from different regions may be included in the same GN cluster. Both the GN and MSTN networks use bridge nations to connect multiple geographical local clusters. Table 4 outlines the Stata network. The network's nodes represent the network's countries (24), and the model's average density looks to be 0.08. There are 22 linkages between the nodes. Some components are not connected, resulting in some clusters in the network.

We study the GN network with x = 25% (Figure 1). We chose 25% GN since the sample set of countries is tiny and any value less generates few outcomes to analyze. This filter results in a mix of core nations with considerable connectedness, and smaller clusters will inevitably converge into a bigger one. The constructed network reveals the relationships between the nations that are dispersed (detached) outside of a cluster. The clustered countries are responsive to both the x percent filter and the period. Russia, a key focal point until 2015, lost its prominence due to the Russian Financial Crisis. The major pattern is that countries with significant worldwide domination and exceptional economic growth, which lost prominence during the crisis, regained its post-crisis. Due to the outstanding economic and financial performance of Asian countries, we may notice a movement in the clustering of nations from American-African to European-Asian.

Nodes	24
Edges	22
Density	0.08

Table 4.
Basic results

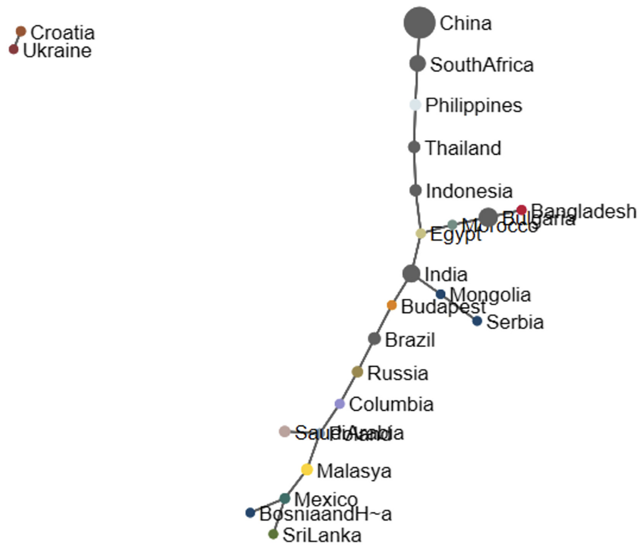


Figure 1.
A MSTN network representing the global stock market integration

5.2 General results from GN

While GN network results are more static, MSTN results are dynamic to reflect network structure changes during the analysis time. They aid in studying the MSTN's connectivity between countries (Selecting the edges that are significant). The influence sphere (node size) and the length of the linking edges show the results. The estimated IC values show the country's network supremacy. The IC values indicate the country's stock market's influence on the entire network/sub-network. During the Russian financial crisis, the size of the node and the link between Russia and most nations shrank. The shocks from the previous country's turmoil affected the more integrated countries hard. This effect extends to other countries, affecting their influence sphere. To test this hypothesis, we can look at how closely linked countries move together when faced with shocks. Bridge countries assist connect local and global stock market networks as well as geographical clusters. These countries link many local clusters to integrate the global stock market. Because they are connected to various countries, their stock market is less susceptible to shocks and is not badly harmed. As a result, they tend to stay in the same location in the network.

This concept is used to compute shortest nodes. The average shortest path length and the diameter are calculated for the largest component of the network. The average shortest path can be considered as a proxy measure for the efficiency of information or shock transportation in the financial network. Nodes in this network: 231 (Table 5). 2 Nodes are cut off from the rest. No more than ($24 \times 23/2$) pathways are possible. The network's 231 paths yield an average shortest path of 5.57.

Table 5.
Shortest path

Nodes	24
Paths (largest component)	231
Diameter (largest component)	13
Average shortest path (largest component)	5.57

This metric shows how the countries in the integrated network are connected using distance (Grover Measure employing correlation) as a proxy. From this, we can conclude that any market shock or information travels via 5 countries. The shortest path has more nodes, therefore the shock is less across the network. Therefore, their stock market is less susceptible to shocks and is not badly harmed. As a result, they tend to stay in the same location in the network.

The greatest component's diameter is 13. This is another way to quantify graph size. It represents the network's linear size. The graph has 24 nodes and a diameter of 13, which is more than half the number of nodes. This represents the network's connectivity. Based on this, the emerging market network is linear, with little clustering around some nodes. In economic terms, any information or shock generated by a market has a linear dissipation, affecting one or two markets connected to it, with little diffusion to many emerging markets. Prone to shock and not badly harmed as a result, they tend to stay in the same location in the network.

5.2.1 Components of the network. The number of components of the network gives an analysis of the countries that are connected with some of the nodes but are isolated with the rest. The central nodes mostly affect the countries that are surrounding them to a much greater degree based on the Grover distance measure and not so much with the rest of the countries.

The network has two components, the largest of which has 22 countries (Table 6). The other component consists of two countries isolated from the rest of the MST network's growing countries. From this, we can deduce that most countries in the component cluster, and that clusters impact each other. Croatia and Ukraine are separated from the main component. They are connected to each other but not to the rest of the global stock markets, so any shocks in these nations do not have a substantial impact on the larger cluster of developing countries. Because of the weak integration of the production factor markets, trade integration, and economic instability, the rest of the developing countries are not financially connected to these two isolated countries (Derado, 2009).

5.2.2 Adjacency matrix/socio-matrix analysis. As seen in the graph below (Figure 2), the social matrix describes how distinct nodes/indices in the deep web interact with each other using measurements like as centrality, Grover distance, and correlation. The adjacency matrix is a square matrix that shows whether or not components are nearby. The graph shows if the two network nodes are connected using this matrix. If the two nodes are connected, 1 is displayed, otherwise 0. This symmetrical matrix is based on the correlation of index prices between two nodes. The adjacency matrix and the socio-matrix are the same in this graph since it is unweighted and undirected.

From the above figure (Figure 2) we can observe the interaction of various nodes with the other and observe the clustering around the nodes (e.g. India, Bangladesh). This matrix not does not explicitly mention whether the interaction is because of the importance or the bridging between the clusters, but it does represent the interactions among the countries. This can be used to understand the connectivity of one country with another. As we can see from the graph, the length of the adjacency list has a maximum value of 3 and the average

Component	Freq.	Percent	Cum.
1	22	91.67	91.67
2	2	8.33	100
Total	24	100	

Table 6. Components of the network

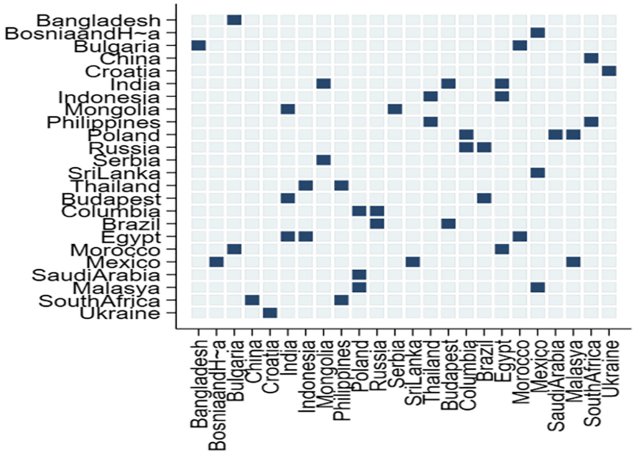


Figure 2.
Adjacency matrix/
socio-matrix

value is 1.83 nodes connected to each country. This suggests that every country on an average, is connected to 2 countries in the MSTN network.

5.2.3 Degree centralization. The degree of centrality is the number of edges or links from one node to the other. Since this is a symmetric and an undirected graph, the number of in-degrees is the same as the number of out-degrees.

As shown in the table, the highest degree node has 4 nodes associated with it. The other degrees are 2 or 1. Most countries are connected to two additional countries (12) (Table 7). This tells us how central some nodes are compared to the others. The more nodes a country has, the more connections it has to others. Only four countries are connected to three other countries, showing that the developing market network is linear. 3-Degree centrality countries are India, Egypt, Poland, and Mexico. This suggests that these countries are relatively well connected to other emerging countries and play a key role in the network's shock absorption or shock generation. The greater the country's degree of centrality, the greater its shock absorbing and shock passing capacity. As a result, any shock caused in these countries quickly spreads to other countries, allowing for faster recovery. So any significant shock hits two countries connected to it and then spreads slowly throughout the network with an average impact of 1.83/vertex.

However, Table 8 shows the countries' average degree for 2013–2020. To comprehend how a country became an absorber, we must examine period degree Table 8. Philippines, India, Mexico, and Egypt had better connection in 2013. In 2015–16, countries like Brazil, Thailand, Mongolia, Saudi Arabia, and Egypt were more interconnected. In 2017–2018, a broader network of marketplaces connected Serbia, Philippines, and Bulgaria. As a result, the network connections are not static but highly dynamic, and none of the Adobe connectivity listed above will be prevalent in the future.

Table 7.
Degree of centrality for the overall network

Degree of freedom	Freq.	Percent	Cum.
1	8	33.33	33.3
2	12	50	83.3
3	4	16.67	100
Total	24	100	

Country	2013–14	2015–16	2017–18	2019–20	Delta 2014–15	Delta 2016–17	Delta 2018–19
Bangladesh	1	1	3	1	0	2	−2
Bosnia	1	2	1	1	1	−1	0
Brazil	2	3	1	1	1	−2	0
Budapest	1	2	1	3	1	−1	2
Bulgaria	2	2	4	2	0	2	−2
China	1	1	2	1	0	1	−1
Croatia	2	2	1	4	0	−1	3
Columbia	2	2	1	1	0	−1	0
Egypt	3	3	2	1	0	−1	−1
India	3	2	2	2	−1	0	0
Indonesia	2	1	3	3	−1	2	0
Malaysia	2	1	1	2	−1	0	1
Mexico	3	2	1	2	−1	−1	1
Mongolia	1	3	1	2	2	−2	1
Morocco	1	1	1	1	0	0	0
Philippines	5	2	5	2	−3	3	−3
Poland	1	3	1	3	2	−2	2
Russia	2	1	1	2	−1	0	1
Saudi Arabia	2	3	1	2	1	−2	1
Serbia	2	2	5	1	0	3	−4
South Africa	3	1	1	2	−2	0	1
Sri Lanka	1	1	1	2	0	0	1
Thailand	1	4	3	2	3	−1	−1
Ukraine		1	3	2	1	2	−1

Note(s): Delta year1-year2 represents the difference in the degree centralization of a market from year 1 to year 2

Table 8. Degree of centrality of the countries for different time periods

5.2.4 Closeness. According to Freeman *et al.* (2000), the centrality measure, Closeness gives greater ranks to nodes that are nearer to independent nodes from their component/segment (the arrangement of reachable nodes) by taking the inverse of the standard briefest ways as an extent of proximity. That is, the closeness centrality for vertex i is portrayed as follows:

$$\frac{|V| - 1}{\sum_{j \neq i} Dij} \tag{4}$$

This indicates how vertices with shorter standard path lengths obtain greater centrality scores than those further distant from their part. In the table, India is connected to other continents via Budapest, Egypt, and Magnolia, occupying the top three spots (Table 9). These results show that the shocks caused by the former country are predominantly felt by the latter. They show the countries' clustering inside the network. Most of the top countries are Asian source countries linked to others. So, Asian countries dominate network movements. Almost every Asian country is represented in the table. This indicates that these countries' markets are closer in terms of index price movement, explaining the markets' proximity.

5.2.5 Betweenness and eigenvector centrality. Betweenness measures a node's efficiency in transmitting shocks by counting how many times it produces an entity in the shortest path between two other nodes. As a result, removing a node with high betweenness could have a major influence on the network. Betweenness centrality delivers higher centrality values for nodes that are closer to the shortest paths connecting various vertices. Let Pab represent the

Table 9.
Degree of closeness

	Source	Target	degree ~ e	degree ~ t	closen ~ e	closen ~ t
1	Egypt	Morocco	0.294	0.192	0.138	0.113
2	Philippines	South Africa	0.167	0.147	0.091	0.077
3	India	Budapest	0.248	0.188	0.142	0.134
4	Budapest	Brazil	0.188	0.155	0.134	0.125
5	Indonesia	Egypt	0.170	0.294	0.117	0.138
6	India	Egypt	0.248	0.294	0.142	0.138
7	Indonesia	Thailand	0.170	0.149	0.117	0.102
8	Bulgaria	Morocco	0.195	0.192	0.099	0.113
9	Mongolia	Serbia	0.137	0.073	0.120	0.100
10	Philippines	Thailand	0.167	0.149	0.091	0.102
11	India	Mongolia	0.248	0.137	0.142	0.120
12	Bangladesh	Bulgaria	0.064	0.195	0.087	0.099
13	Russia	Brazil	0.119	0.155	0.118	0.125
14	Mexico	Malaysia	0.169	0.121	0.085	0.094
15	Poland	Malaysia	0.161	0.121	0.103	0.094
16	Russia	Columbia	0.119	0.108	0.118	0.110
17	Sri Lanka	Mexico	0.054	0.169	0.077	0.085
18	Bulgaria	Ukraine	0.195	0.100	0.099	0.090
19	Poland	Columbia	0.161	0.108	0.103	0.110
20	Bosnia and ~ a	Mexico	0.052	0.169	0.078	0.085
21	China	South Africa	0.051	0.147	0.071	0.077
22	Poland	Saudi Arabia	0.161	0.051	0.103	0.093
23	Croatia	Ukraine	0.046	0.100	0.082	0.090

number of shortest routes from a to b. Let Pab(k) be the length of the shortest path from a to b including k. At that point following Anthonisse (1971) furthermore, the betweenness centrality measure for vertex k is characterized as:

$$\sum_{i \neq j \neq k \neq i} \frac{Pij(k)}{Pij} \tag{5}$$

To standardize, we isolate by (|V | – 1) (|V | – 2), the most considerable number of ways that a given vertex could lie on between sets of different vertices. The betweenness measure is used to identify the nodes in the network with more significant centrality measures, i.e. the vertices that lie on the more significant proportion of shortest paths. The betweenness is highest for Egypt, India, and Russia and Budapest (Table 10). These nodes are of central importance in each of the components as they are the central nodes in the shortest distance centrality.

Drawing from the conclusions from closeness and centrality measures, we can conclude that Asian and Russian form epicenters of financial crises and result in contagion. Amplification of crises arises when epicenters are well integrated in the network. This is in accordance with the findings in Kali and Reyes (2010).

5.3 Discussions on the global network integration using MSTN and GN networks

We aim to look at the results from 2013 to 2020. Based on these facts, we can observe that the network integration has changed significantly over time (Figure 3). The data show that over time, nations like India, Mexico, and South Africa have become key impact nodes in the network, influencing or being influenced by a huge number of markets (Paul and Mas, 2016). As seen by the heat maps, the CC has shifted from Europe to Asia due to the tremendous growth of trade and financial investments into and out of Asia (Click and Plummer, 2005).

	Source	Target	betwee ~ e	betwee ~ t	eigenv ~ e	eigenv ~ t
1	Egypt	Morocco	0.613	0.300	0.478	0.333
2	Philippines	South Africa	0.166	0.087	0.105	0.058
3	India	Budapest	0.601	0.498	0.448	0.278
4	Budapest	Brazil	0.498	0.474	0.278	0.176
5	Indonesia	Egypt	0.300	0.613	0.292	0.478
6	India	Egypt	0.601	0.613	0.448	0.478
7	Indonesia	Thailand	0.300	0.237	0.292	0.177
8	Bulgaria	Morocco	0.245	0.300	0.268	0.333
9	Mongolia	Serbia	0.087	0.000	0.249	0.111
10	Philippines	Thailand	0.166	0.237	0.105	0.177
11	India	Mongolia	0.601	0.087	0.448	0.249
12	Bangladesh	Bulgaria	0.000	0.245	0.119	0.268
13	Russia	Brazil	0.443	0.474	0.117	0.176
14	Mexico	Malaysia	0.170	0.237	0.037	0.050
15	Poland	Malaysia	0.372	0.237	0.076	0.050
16	Russia	Columbia	0.443	0.403	0.117	0.086
17	SriLanka	Mexico	0.000	0.170	0.017	0.037
18	Bulgaria	Ukraine	0.245	0.087	0.268	0.149
19	Poland	Columbia	0.372	0.403	0.076	0.086
20	Bosnia and ~ *a*	Mexico	0.000	0.170	0.017	0.037
21	China	South Africa	0.000	0.087	0.026	0.058
22	Poland	Saudi Arabia	0.372	0.000	0.076	0.034
23	Croatia	Ukraine	0.000	0.087	0.066	0.149

Table 10.
Degree of betweenness and eigenvector centrality

South Africa has always been a key market in Africa, followed by Egypt. The IC heat maps show that the markets in America and Africa have lost relevance, and their importance coefficient is lower than the markets in Europe and Asia. In the figures, we can see that markets like India, Bangladesh, and Mexico have been key bridge nations since they lack IC at the regional level and connect to other clusters via CC.

Post 2016, China and India have become more dominant in the Asian markets of developing countries. India has steadily improved its status and is currently the second most prominent country in Asia. Most Middle Eastern countries have been at the top of the GN network because their oil markets influence the entire world (Tong *et al.*).

In terms of dominance, we can see that Asia and the Middle East emerging countries have surpassed the rest of the global financial network in 2018. Major events like the Global Financial Crisis, Middle East Oil Crisis, and Chinese Stock Market Crash have changed the way global financial markets are integrated. Others became bridge countries connecting distinct clusters, and several linkages were broken and rejoined with other regional markets. Some countries have a high bridge importance but a low IC or clustering coefficient, but they connect two clusters. We can also see changes in country clustering before and after the crisis (Figure 4). The relevance of clustering around certain countries is lost during the crisis and regained afterward. Because the research solely covers emerging markets, most of the crisis repercussions are on industrialized nations not included in the network. Egypt, India, China, and Mexico have all acted as bridge countries connecting diverse regional market clusters.

In the Asian region, India ranked third in the MSTN IC results for 2013–2014 and 2015–16 (Figure 5). A concentration in centrality and clustering may be seen in India's recent rapid expansion, which has drawn many foreign investors from developed and emerging countries. Bangladesh has a huge CC value connecting the regional stock market. It has served as a link between the global market and the Asian cluster. In the Asian market, India has the largest average range of IC, followed by Saudi Arabia because to its dominance in the oil markets

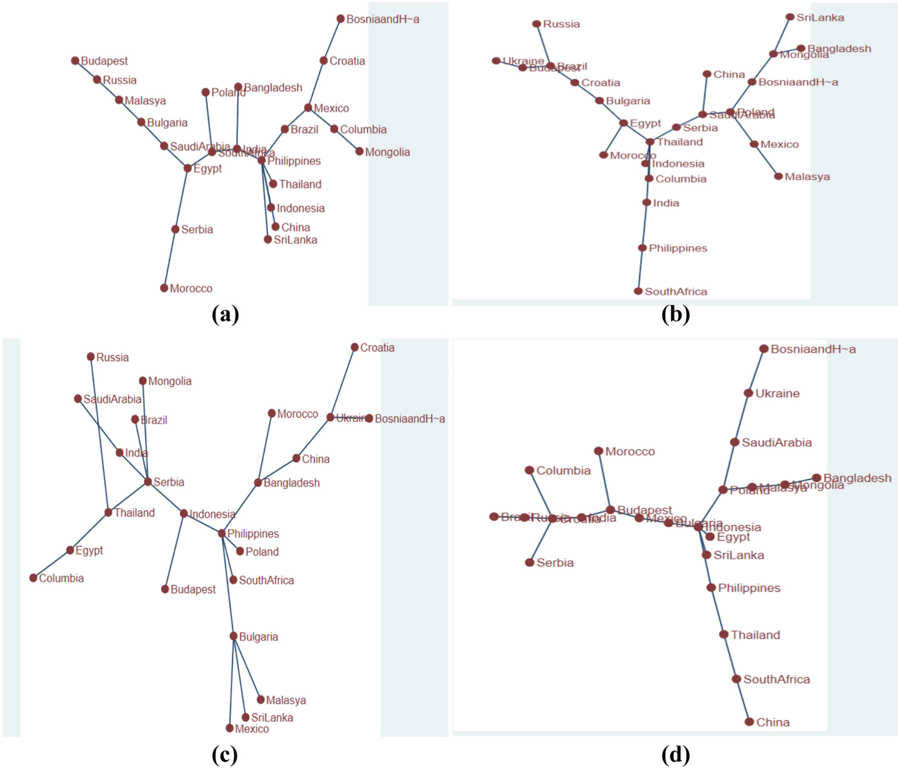


Figure 3.
MSTN network for the period 2013 to 2020

(Espinoza *et al.*, 2011), and then countries like Russia, Philippines, and Indonesia. A higher IC score shows a country's financial importance in the global market. India is also the third largest emerging market in terms of IC, behind China and Saudi Arabia. This demonstrates the growing importance of Asian markets in global financial markets. It is also generally established that larger financial markets attract more foreign investments due to their free economic environment and low trade barriers (Demirgüç-Kunt and Levine, 1996; Krugman, 1999; Bevan *et al.*, 2004).

Also, China has had one of the world's fastest rising GDPs. It has made large investments in other nations and hence has many international relations. After the Chinese stock market crisis in 2015, it rose to the top of the list of all countries. China has witnessed extraordinary expansion since 2015 and has a considerable index in the worldwide market. Despite the country's low IC, increasing CC numbers since 2015 reveal regional ties. As evidenced by its ICs and ranks, the MSTN statistics suggest China and India to be the global network's financial hub and motor.

During the crises, the countries' power diminished, but quickly restored. For example, China lost centrality in 2015 because to the Chinese stock market calamity, but swiftly regained it due to its size and ability to self-recover. It has recently lost its prominence owing to the COVID-19 Crisis. The same holds true for India. During 2015–2016, the country lost its centrality owing to internal challenges, but swiftly regained it. The global pandemic has diminished the importance of most countries in the MSTN results for 2019–20. Other literature supports this, as most countries desire to insulate themselves from foreign

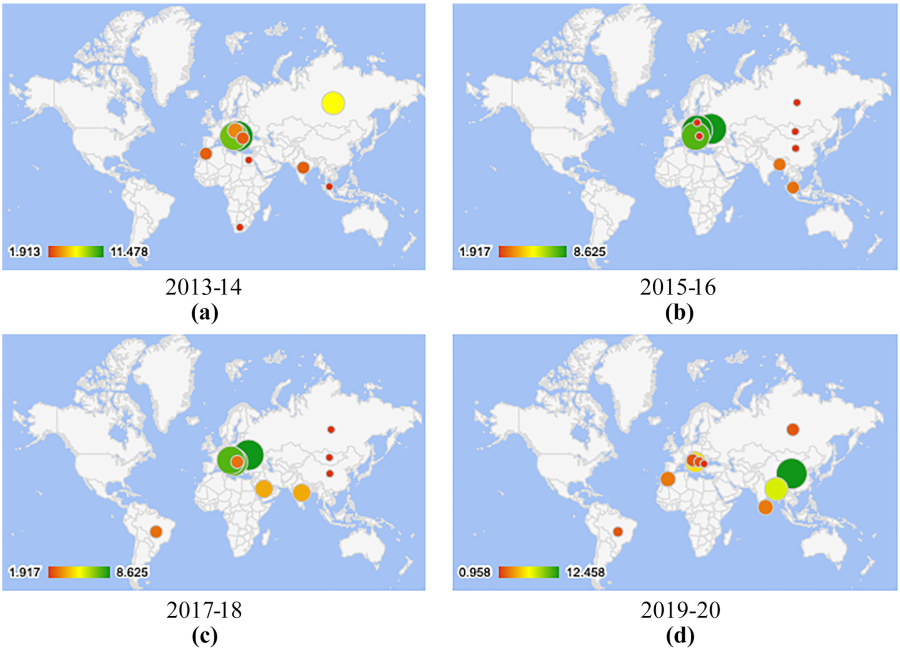


Figure 4.
Heat map representing the CC of the countries

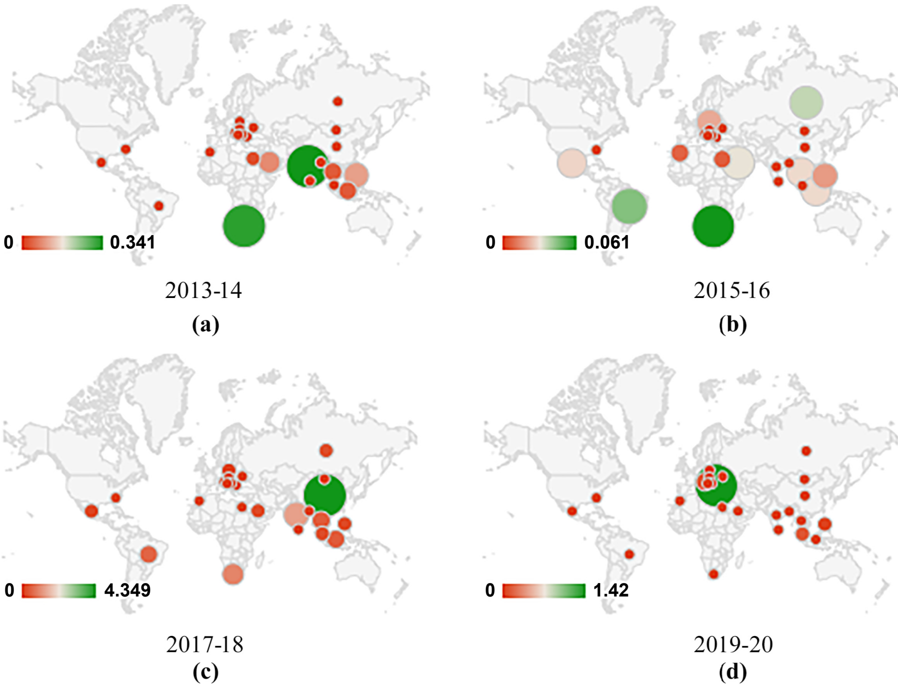


Figure 5.
Heat map representing the IC of the countries

influences. Due to the Russian Financial Crisis in 2014–2015, Russia lost its relevance and its CC began decreasing in 2015. It had been serving as a bridge country connecting Asia with Europe and Africa. The IC countries have moved from African-American to Asian countries that have done well.

However, as shown in Appendix Tables A1 and A2, the continental clustering results for Africa are not very significant. Due to their significant commercial relations, African countries tend to associate more with the rest of the world than among themselves. Despite South Africa's financial linkages to the US and Europe, the GN data show little. South Africa's significance coefficient in the MST network shows Africa's importance in the network.

Our MSTN's most noteworthy IC is South Africa, however it is not territorial. The CC gauges an economy's linkages, while African countries like South Africa have fewer. Economists contend that endogenous characteristics rather than external links drive economic performance in Africa (Enisan and Olufisayo, 2009; King and Levine, 1993; Tong *et al.*, 2018). This is because other African states are more widely scattered and geographically linked (especially to the European group). As a result, this district lacks a middle. Africa's countries are more scattered and linked to other regional hubs than key clusters.

Brazil's economy rules Latin America. In the last decade, Brazil outpaced the BRICS as one of the world's fastest growing economies. Due to 2014s crisis, the Brazilian CC declined from 2013 to 2016 and barely recovered in 2017. In 2014–2016, FDI decreased and GDP fell by 8%. China's faltering economy compounded Brazil's two-year negative growth.

B&H has kept CC even with its challenging post-war political structure and uneven economic model in Europe. The World Bank's 2016–2020 Country Partnership Framework helped Bosnia's public sector grow. The 2008 financial crisis slowed many European economies. Serbia was affected hard. Floods and a downturn in trade with adjacent countries hit agriculture and household demand hard in 2014. Post-2014 decline in CC reflects these causes. It has since improved financial stability and competitiveness.

5.4 Policy implications the global network integration using MSTN and GN networks

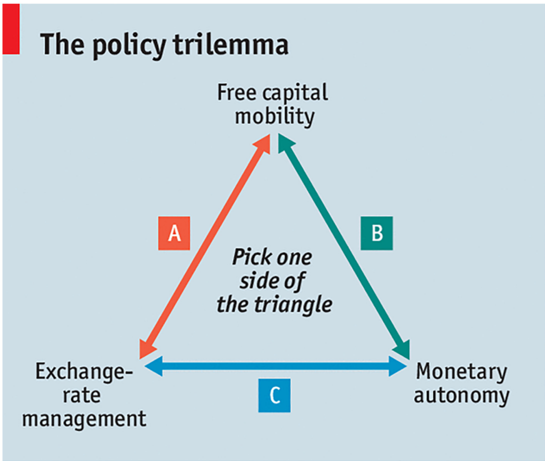
Opening up of emerging markets to international flows of currency and global trade has important implications on monetary policy making. Globalization and liberalization has presented policy makers with a fresh dilemma (Figure 6).

Exchange rate stability, monetary policy independence, and financial integration are options for economies but not all three. The Mundell Fleming trilemma: trade, finance, and investment transactions across borders have a significant impact on exchange rate policy decisions. On one hand, policymakers can manage domestic interest rates while limiting inflation. Or they can choose to let go of monetary policy authority in favor of exchange rate regulation. India, Brazil, and South Africa have chosen an open economy with monetary policy autonomy over exchange rate control. Saudi Arabia, on the other hand, has chosen a fixed exchange rate, keeping the Saudi Riyal anchored to the USD. A stable currency rate attracts overseas investors and enterprises. China's third policy mix is a pegged exchange rate, independent monetary policy, and largely closed financial markets.

Global capital flows and commodities prices are more volatile in emerging markets. This affects the exchange rate and can cause economic shocks. So developing countries struggle to entirely abandon exchange rate stability. The only way to do this is to monitor financial integration.

6. Conclusion

A minimal spanning tree model and a graphical network for eight years for 24 nations utilizing daily closing stock market prices are used to analyze the global financial network.



Source(s): The Economist

Figure 6.
Policy implication–the policy trilemma

We compare the findings of the basic correlation model and the graphical model. No actual exchange platform is required to offer distance measures in our report, unlike past financial networks. We can analyze more online data by using two interconnected correlation-based networks. These visual networks present a more relaxed exploration of time changes. The network's dynamic nature allows us to better examine connectivity and model alterations.

Our views seem to align with past research on stock market integration. We discovered that markets move in clusters, adapting to shocks and errors caused by economic pressures in some countries. We study how closeness, significance, and clustering affect the network in real-time. We discover that the Asian markets have improved tremendously over time to dominate the computed outcomes. The clusters moved from Europe to Asia.

China and India have become regional as well as network focal centers in Asia. India and Bangladesh are the primary regional bridge countries connecting the Asian cluster. Bosnia has become one of the most important countries in Europe due to its trading links. Despite the greatest recession, Brazil regained its position. Due to their slow growth, African countries tend to form local clusters. Surrounding countries of the crisis-hit countries are heavily impacted, and this influence spreads across the network. We also find the shortest pathways and the degree of centrality of shocks in the network. The graphs show that the countries move together through time, whereas countries isolated tend to stay still.

This study can be extended to assess the integration of emerging economies with developed economies. We can comprehend how a developing economy's transition to a mature economy affects its neighbors. We can connect an economy's topological timeline with similar economies to see the parallels and contrasts in the paths taken by those countries in similar settings.

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Appendix

Country	Region	2013–14	2015–16	2017–18	2019–20	Average rank
Egypt	Africa	0.0224	0.0064	0.0317	0.0109	9.5
SouthAfrica		0.3207	0.0607	0.9416	0.0000	3.5
Morocco		0.0000	0.0074	0.0292	0.0000	10.5
Brazil	America	0.0000	0.0449	0.5495	0.0025	5.25
Mexico		0.0000	0.0271	0.1567	0.0000	8.5
Columbia		0.0000	0.0000	0.0657	0.0000	10.5
Malaysia	Asia	0.0000	0.0000	0.2494	0.1174	8
Philippines		0.1015	0.0172	0.2139	0.0421	6.5
Thailand		0.0332	0.0281	0.4439	0.0055	5.25
China		0.0000	0.0000	4.3490	0.0000	7.5
India		0.3411	0.0000	1.2913	0.0000	6
Indonesia		0.0326	0.0280	0.4267	0.0000	6.5
Russia		0.0000	0.0365	0.2734	0.0000	6.5
SaudiArabia		0.0811	0.0313	0.2180	0.0000	6.25
Bangladesh		0.0000	0.0000	0.0425	0.0000	10.75
SriLanka		0.0000	0.0000	0.0056	0.0000	11.75
Mongolia		0.0000	0.0000	0.0000	0.0000	12.5
Bulgaria	Europe	0.0000	0.0000	0.0000	1.4196	10.75
Croatia		0.0000	0.0000	0.0014	0.1211	10.5
Poland		0.0000	0.0199	0.1052	0.0000	9
Budapest		0.0000	0.0014	0.0177	0.0000	11.25
Ukraine		0.0000	0.0000	0.0009	0.0000	12.25
Serbia		0.0000	0.0000	0.0000	0.0000	12.5
Bosnia		0.0000	0.0000	0.0000	0.0000	12.5

Table A1.
Year wise IC results

Table A2.
Year wise CC results

Region	2013–14	CC	2015–16	CC	2017–18	CC	2019–20	CC
Africa	Budapest	3.8261	Morocco	0.9583	Egypt	1.9167	Morocco	2.8750
	Bulgaria	2.8696	SouthAfrica	0.9583	Morocco	0.0000	Egypt	0.9583
	SouthAfrica	1.9130	Egypt	0.0000	SouthAfrica	0.0000	SouthAfrica	0.9583
America	Egypt	1.9130	Mexico	1.9167	Brazil	2.8750	Brazil	1.9167
	Russia	6.6957	Columbia	0.9583	Mexico	0.0000	Columbia	0.0000
	India	2.8696	Brazil	0.9583	Columbia	1.9167	Mexico	0.9583
Asia	Serbia	11.4783	China	1.9167	Indonesia	0.9583	China	12.4583
	Malaysia	1.9130	Malaysia	2.8750	Malaysia	0.0000	Bangladesh	7.6667
	Bosnia	9.5652	Bangladesh	2.8750	India	3.8333	SriLanka	2.8750
	Morocco	2.8696	Indonesia	0.9583	SaudiArabia	3.8333	Russia	1.9167
	Bangladesh	1.9130	Philippines	0.0000	China	1.9167	India	0.9583
	China	1.9130	Thailand	0.0000	Thailand	1.9167	Indonesia	0.9583
	Croatia	1.9130	Mongolia	1.9167	Bangladesh	0.0000	Philippines	0.9583
	SriLanka	1.9130	Russia	1.9167	Philippines	0.0000	Thailand	0.9583
	Columbia	0.9565	SriLanka	1.9167	Mongolia	1.9167	Mongolia	0.9583
	SaudiArabia	0.9565	India	0.0000	Russia	1.9167	Malaysia	0.9583
	Indonesia	0.9565	SaudiArabia	1.9167	SriLanka	0.0000	SaudiArabia	0.0000
Europe	Mongolia	0.9565	Budapest	8.6250	Croatia	7.6667	Poland	0.9583
	Philippines	0.9565	Croatia	0.9583	Bosnia	7.6667	Ukraine	0.9583
	Poland	0.0000	Poland	1.9167	Budapest	1.9167	Budapest	0.9583
	Thailand	0.0000	Serbia	1.9167	Bulgaria	0.0000	Serbia	1.9167
	Brazil	0.0000	Ukraine	8.6250	Poland	0.0000	Bulgaria	0.9583
	Mexico	0.0000	Bosnia	7.6667	Ukraine	8.6250	Bosnia	5.7500
			Bulgaria	0.0000	Serbia	2.8750	Croatia	1.9167