The G20 financial market network

Abstract

This paper delves into the dynamically changing financial networks of the G20 markets from 2004 to 2021, taking into account the strength, direction and the statistical significance of the network edges between markets. Investigating the transformations that occur between periods of crisis and periods of recovery will help identify the markets that act as shock-absorbing and shock-spreading nations, as well as the economies that act as bridge markets. This paper empirically estimates the return spillovers and network characteristics across the G20 economies. The entire sample period is subdivided into sub-periods that comprise periods of crisis and recovery. We focus on the transformation of the financial networks prior to and post the global financial crisis of 2007-2009, European debt crisis 2010-2012, world trade friction and Covid-19 pandemic spanning 2018-2021. The financial market network is represented as a graph with nodes representing nations and linkages between them representing the impact that a shock in one economy has on the other. To capture the statistical significance and edge weights we make use of Granger causality tests and the methodology in Diebold and Yilmaz (2014, 2015). We find that during periods of crisis there is an increase in the number of linkages and the financial network grows denser. This impact was more pronounced during the global financial crisis, the world trade friction and covid-19 pandemic of 2020. We discovered that developed markets exhibit more stability with regards to retention of edges between the sub periods as compared to emerging economies. When transitioning into crisis periods, on average the strength of edges added is greater than those removed. The US market is identified as a super-spreader or a conduit with great importance in transferring information from peripheral economies. The EU, Italy and France act as super spreaders of shocks during the course of the European debt crisis. Australia and South Africa are shock absorbers and have high eigenvector centrality. Over the last decade the emerging markets have become more interconnected with the developed economies either through bridge markets such as Mexico or by forming direct links. The G20 set of economies represents a large proportion of important developed and emerging economies that account for a major fraction of world trading activity. Thus it is necessary to study its network from a structural point of view. Investment decisions for diversified portfolios are heavily dependent on understanding the impact of cross-border contagion flows. Previous research work on the G20 financial markets integration utilised the GARCH-BEKK model to study spillover networks. This paper utilises a different methodology based on Granger causality tests, VAR models and Jaccard's statistics to determine the structural characteristics of the network. The findings from this study including transitions in network density, identifying shock-spreading, shock-absorbing and bridge markets will help portfolio managers and researchers in decision making and analysing equity markets.

Introduction

Equity return spillovers form a key component in the study and analysis of financial markets. At its core, return spillover is the process of transmission of information from one market to another. The stock index returns in a market are not only influenced by its own past historical returns but are also impacted by fluctuations in other markets. This transfer between markets is known as return spillover effects. For investment and risk management professionals it is necessary to curb the additional linkage risk that results from spillover effects. Globally diversified portfolios are significantly impacted by international return spillover due to the recent rise in financialization and globalization over the last few decades. Internationally, capital mobility has risen alongside the expeditious development of the global economy previously isolated economies have now integrated with the global economy. But this also leads to an increased chance for the proliferation of risk and contagion across the world. The phenomenon of recent world wide financial crises has led to greater focus on the research of international financial market integration. Cardona et al. (2017) discovered that the recent financial instability in the world arises mainly from a few developed nations and emerging economies. The G20 set of nations is an optimal research case that signifies a group of major emerging and developed economies. The G20 nations represent an international platform for their ministers and central bank governors to meet and discuss important issues related to the 20 major economies. The year 2014 marked the period when the G20 nations accounted for approximately 85% of Gross World Product (GWP), and for roughly 80% of the world trading. Thus, any financial crisis occurring in the G20 economies fairly represents significant shifts in global finance.

Investors and researchers alike have paid a great deal of attention to equity markets. Since the G20 equity markets represent a fairly vast sophisticated system, studying interactions between its entities in a complicated nexus of the financial system by utilising economics methods alone isn't that simple. Therefore it becomes essential for us to analyze the characteristics of the global financial network from a structural perspective. Investigating the structure of the financial network will aid in predicting the consequence of financial contagion. Usually theoretical models attempt to elucidate the reasons behind markets being more correlated during periods of turmoil. Whereas empirical studies investigate the evidence for strengthened links to identify turmoil during a crisis. This is usually examined for an increase in correlation between asset returns. But few researchers have indicated it is not necessary that an increased correlation is a sign of contagion (Corsetti et al., 2001, 2005; Forbes & Rigobon, 2002; Bekaert et al., 2005). The equity return spillover network is a sophisticated network constructed with the nations as nodes. The edges or linkages between countries signify return spillovers. With the global economy developing at a fast paced rate, the financial networks are constantly changing leading to market relationships varying with time. In order to take into consideration these time-varying relationships, we can subdivide the time period into several smaller time spans. This paper is based on a 18-year period from 2004 to 2021 that spans the US subprime crisis, the Eurozone debt crisis and world trade friction for the G20 economies and is further subdivided into five time periods. Bilio et al. (2012) focussed extensively on the net change in the number of statistically significant linkages, whereas the work of Diebold and Yilmaz (2014, 2015) focussed only on the strength of the links but not their statistical significance. This paper seeks to capture both. We apply the widely used Granger Causality test and VAR framework to assess whether the links between markets in each of the five phases are statistically significant, to determine their direction, and the changes that occur across periods. The techniques introduced by Dungey et al. (2018) have been used throughout this paper to create a financial network consisting of links between nodes. Each node represents a nation's stock market index wherein the linkages between the nodes are represented by an adjacency matrix. This matrix comprises the links' direction, strength and statistical significance. This paper has two main contributions. With regards to the methodological aspect, the construction of a spillover network helps in systematically capturing the transfer of spillovers from one G20 stock market to another. The proposed method is used to study the features of return spillover in the G20 markets, and helps find out the significant nodes and the direction of propagation of shocks.

Literature Review

Interconnectedness between financial markets is a double edged sword. Although it has the capacity to instill robustness by absorbing shocks, it can also lead to a greater propagation of shocks. Gai and Kapadia (2010) indicates that financial systems portray a robust-yet-fragile tendency. In a strongly connected system, the counterparty losses of a failing institution are mitigated and absorbed readily by other entities. This risk sharing due to strong connectivity dampens the probability of contagious defaults. But the failure of one institution can trigger contagious defaults in a highly connected system. Shocks are more easily transmitted by institutions that are interconnected leading to a higher chance of widespread contagion. Strong connectivity can dampen the probability of contagion, but it amplifies the spread when it does occur. There have been broad investigations to understand, evaluate and monitor the origins of financial interconnectedness by utilizing a network structure that allows us to uncover the transformations in market structure as various participants withdraw and enter the model. Network analysis tools are an increasingly expanding research area to study changes in financial linkages and ascertain its implications. Allen and Gale (2000) carried out the most well known analysis of financial contagion through direct linkages and network structure. Using networks, they demonstrated that spread of contagion in the banking structure depends critically on the pattern of their interconnectedness. When all banks have equal exposures to each other with equal interbank deposits, the impact of the shock is weakened and mitigated. Thus, a contagion is avoided. But when banks have exposure to only some counterparties, it makes the system fragile. Drawing from their work we make use of networks to create a model of financial linkages that considers the network as a shock propagating source. Numerous studies point to an increase in the network linkages prior to a crisis, and a reduction post the crisis. Minoiu and Reyes (2013) found that a rise in interconnections within a nation and a reduction in interconnections with other nations, is an indicator of a high probability of a banking crisis eventually resulting in turmoil. Connectedness in a country tends to rise prior to a debt or banking crisis, and declines in their aftermath.

A variety of measures have been proposed to study financial interconnectedness. The pioneering work of Allen and Gale (2000) inspired utilisation of network analysis in modelling interconnectedness in financial markets to identify systemic risk propagation. In their study on the Asian financial crisis, Dungey et al. (2016) empirically showed contagion is likely to have greater impacts on stock markets when compared to bond and currency markets. And although contagion is transmitted through developed markets, studying the behaviour of correlation coefficients cannot be used as a metric for detecting contagion. Widely used quantitative network techniques include the vector autoregressive model (Diebold & Yilmaz, 2009; Diebold & Yilmaz, 2014) and Granger causality network (Billio et al., 2012). Both these approaches complement each other. Billio et al. (2012) describes a wide array of econometric methods for measuring connectedness using granger causality tests and principal component analysis to determine a high level of integration in insurance companies, brokers, banks and hedge funds. It is concluded that banks play a larger and more asymmetrical role in transmission of shocks thereby increasing systemic risk. An alternatively used and widely accepted measure is the one suggested by Diebold and Yilmaz (2009). It put forth a novel method (DY 2009) based on forecast-error variance decompositions to calculate return spillover and volatility spillover between different equity markets using a VAR framework. This method makes use of a unified network topology theory and VAR variance-decomposition theory. Decomposition of variance in a VAR framework leads to the construction of directed edges with weights that characterize connectivity in networks and connectedness in the VAR. The original methodology of Diebold and Yilmaz (2009) comes with certain limitations in the model for variance decomposition since it relies on the variables being ordered. This arises because the model adopted the Cholesky factor identification of VARs. This problem is tackled in Diebold and Yilmaz (2012) to make variance decomposition invariant to ordering. The generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998) is used instead of the Cholesky factorization. In order to create a system for network analysis, the basic VAR model is further refined in Diebold and Yilmaz (2014). Previously correlation based measures were used to calculate connectedness. Such measures use pairwise data instead of system wide data points. Diebold and Yilmaz (2014) makes use of decomposition of variance. “Forecast error variance” of variable i is broken down into parts attributed to several other variables from the system. The fractional component of the H-step variance decomposition of variable i stemming from shocks to variable $j$is represented as d_{ij}^{H}. Variance decompositions can be thought of as networks. The matrix D is a network adjacency matrix for variance decomposition. Chowdhury and Hassan (2021) used the spillover index of Diebold and Yilmaz (2014) in order to calculate pairwise return spillovers. This index is based on “Forecast error variance decomposition” on application to a VAR model. The results showed strong connectedness in European Islamic equity markets and weak connectedness Asian Islamic equity markets. Zhou et al. (2012) utilised the Diebold and Yilmaz (2014) “forecast error variance decomposition” method in VAR models to put forth measures concerning the direction and magnitude for volatility spillovers between Chinese equity markets and the rest of the world. Wu (2020) uses both graph theory and a Vector Autoregressive (VAR)-based method to demonstrate that the degree of interconnectivity is high between east and southeast asian countries. But a large portion of the interconnectedness stems from common global factors. The overestimated interconnectedness in East and Southeast Asia is primarily an indication of much greater influences that the global markets have on individual markets. Mensi et al. (2018) measured connectedness between certain regional european markets and global markets and volatility spillovers using Diebold and Yilmaz (2012, 2014) methodology. After having studied the connectivity in the network at different parts of crises, they found increased spillovers to be intensified at the time of crises in support of financial contagion. They also discovered the USA to be a transmitter of shocks, while the rest of the economies were identified as shock receivers. Pradhan et al. (2015) examined the dynamics of macroeconomic variables such as oil prices, economic growth, depth in the stock market and indicators such as real interest rate, inflation rate and real effective exchange rate. To test for Granger causality in G20 countries they utilised a panel vector autoregressive model. Between macroeconomics variables they found the existence of a long run relationship. A complex network of causal relationships was found to exist in the short run.

In recent studies pertaining to financial connectedness of G20 countries, researchers have adopted sophisticated graph theory to build networks for volatility spillover . Zhang et al. (2020) examined volatility spillovers, elements influencing it and the spatial correlation relationship between them across the G20 equity market. The GARCH-BEKK model was used in constructing volatility networks and estimating the volatility spillover. When compared to emerging economies, it was found that the markets which are developed tend to be more impactful in times of turbulence. Emerging economies exhibit greater sensitivity to volatility shocks as compared to the developed markets in the same time period. And network connectivity was observed to be the strongest during the financial crisis. A complex spillover network was constructed by Liu et al. (2017) using the GARCH-BEKK model to analyse the volatility spillovers among G20 economies. Results demonstrated the proliferation of fluctuations was quick in spreading amongst the G20 nations. Within the G20 network Korea was identified as the largest transmitter, while Brazil was the largest recipient.

Our empirical methodology utilises the network structure technique ideated by Diebold and Yilmaz (2011) to calibrate connectedness in financial assets for G20 markets based on decomposing variance of the h-step-ahead forecasts from a vector autoregressive model and a method for modelling causality proposed by Billio et al. (2012). These methodologies have the capacity to calculate the level of interconnectivity and the impacts of transmission of stress for the nations being investigated. But the nature of this study is different from the existing literature in analysing the changes in the nature of the financial networks over different time periods. It constructs a directed network with edge weights corresponding to return spillovers. This is an improvement on Diebold and Yilmaz (2014, 2015) as well as Billio et al. (2012). The former uses a weighted technique taking into account statistically insignificant linkages whereas the latter makes use of an unweighted methodology. This study seeks to determine the essential linkages that were discarded or created over different periods.

Methodology

Network's structural characteristics are used to study the evolution of financial networks over time. Count of links and their edge weights can be monitored to investigate for any change occurring in their characteristics. This approach has been suggested in Dungey et al. (2018), Diebold and Yilmaz (2014, 2015), and Billio et al. (2012). The changes in the Jaccard similarity coefficient has been taken into consideration. This provides information regarding the number of linkages that have been retained between the sample periods. For example, there could be a case wherein there exists an overall increase in the number of links. But the underlying cause could be attributed to a proliferation of weaker links and a reduction in the stronger links.

The network is constructed using vector autoregression (VAR) models through two main steps. The first step involves capturing the relationship existing among equity markets. In this method, Granger Causality test is used to decide whether the links are statistically significant or not. The second step is to identify the weights of the edges following the method outlined in Diebold and Yilmaz (2014, 2015). The comprehensive network model constructed will provide a thorough understanding about the financial network for G20 countries and the evolution of linkages over time.

Construction of graph edges using granger causality test

The degree of interconnectivity among different entities can be evaluated by first identifying the links having statistical significance. This is achieved through Granger causality tests. This test suggests causality in case the historical values of a time series, Y_i, in our case the equity return series, contains some data that will aid in predicting some other stock return series, Y_s. This will help to establish the network edges and their directionality.

$$Y_t = c + \sum_{j=1}^{k} \phi_j Y_{t-j} + \varepsilon_t \qquad (1)$$

where k refers to the lag value and ϕ_j and c are model parameters

The test for Granger causality between stock returns is carried out using wald statistic:

$$WT = \left[e\, vec(\widehat{II})\right]' \left[e(V \otimes \widehat{(Y'Y)}^{-1})e'\right]^{-1} \left[e\, vec(\widehat{II})\right] \qquad (2)$$

where the matrix Y is contains explanatory variables from Eq. (1), $e\, vec(\widehat{II})$ represents the row vector coefficients of $\widehat{II}$ = $\left[\phi_1, \phi_2, .. \phi_k\right]$, $\widehat{V} = T^{-1} \sum_{t=1}^{T} \widehat{\varepsilon_t}\widehat{\varepsilon_t}'$ and e denotes the k × 2(2 k + 1) selection matrix. Every row of e has one of the coefficients set to zero under the non-causal hypothesis $Y_i \rightarrow Y_s$The Granger causality test results are presented in binary matrix format

$$A = \left[a_{ij}\right] \qquad (3)$$

where,

a_{ij}= 0 , when return in country i does not Granger cause return in country j

1 , when return in country i Granger causes return in country j (4)

This establishes the edges in the network

Network connectedness

In order to signify the strength the links, we assign weights W_{ij} to all the important relationships that are present in the network. In the Diebold and Yilmaz (2009) methodology, a generalized variance decomposition has been utilized to calculate the weights. The matrix of weights is obtained as W_{ij}. Forecast error variance decompositions help arrive at the spillover measure. Response of country i to shocks to variable j is given by the H step ahead generalized forecast error variance decomposition $\theta_{ij}^{g}(H)$ as follows

$$\theta_{ij}^{g}(H) = \frac{V_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i^{'} B_h V e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i^{'} B_h V B_h^{'} e_i\right)} \tag{5}$$

where, H takes on values 1,2,3,.. so on. V represents the variance covariance matrix for the error term ε_t, V_{jj} is the standard deviation of the j th error term and e_i is the selection vector with one as the i th element and zero otherwise. The coefficient matrices, B_i, obey the recursion $B_i = \phi_1 B_{i-1} + \phi_2 B_{i-2} + \dots + \phi_k B_{i-k}$ with B_0 an n × n identity matrix and $B_i = 0$ for $i < 0$.

Normalization of the entries of the generalized variance decomposition by the row sum is carried out as follows

$$w_{ij} = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{n} \theta_{ij}^{g}(H)} \tag{6}$$

The values mentioned in the above equation are defined weights and form the entries of the DY matrix. The combined weighted matrix can be constructed by taking the Hadamard product of matrices A and W. This results in the adjacency matrix $\overline{A}$

$$\overline{A} = A \odot W \tag{7}$$

where the Hadamard product is signified by ⊙

The components in the adjacency matrix $\overline{A}$ represent the connectivity among entities conditional on significant causal linkages between them. These elements will be referred to as GDY weights. Next, the completeness of the total network is calculated by

$$C = \frac{\sum_{i,j=1,\, i\neq j}^{n} \overline{a_{ij}}}{\sum_{i,j=1,\, i\neq j}^{n} w_{ij}} \quad (8)$$

In this study we are concerned about the varying network structure across the sample time durations. The adjacency matrix $\overline{A}$ may modify due to changes pertaining to the weight matrix, W, and the significant entries in the matrix A. Any change in matrix A links the specification directly to literature assessing links during crises. To demonstrate its application in the present model, consider the case of a 2 node network in which edges connect a pair of nodes. Let us take into consideration a bivariate VAR(1) model

$$Y_{1t} = c_1 + \vartheta_{11} Y_{1t-1} + \vartheta_{12} Y_{2t-1} + \varepsilon_{1t} \quad (9)$$

$$Y_{2t} = c_2 + \vartheta_{21} Y_{1t-1} + \vartheta_{22} Y_{2t-1} + \varepsilon_{2t} \quad (10)$$

this is written concisely in matrix format as follows

$$Y_t = c + \Theta Y_{t-1} + \varepsilon_t \quad (11)$$

where Y_t is the vector $\left[Y_{1t}\, Y_{2t}\right]'$, c represents the vector containing constants and has dimensions 2 × 1 vector of constants, Θ has dimensions 2 × 2 and contains coefficients. ε_t is a 2 × 1 residual vector. The test of Granger causality is essentially a test of statistical significance of ϑ_{12} and ϑ_{21} , the off-diagonal elements of the coefficient matrix in Eq. (11). If, in period 1, ϑ_{12} is statistically significant, but in period 2 it is not, then the link has been lost between the two periods—consistent with contagion through breakdown of linkages as per Gai and Kapadia (2010). Alternatively, if the link ϑ_{12} is insignificant in period 1, but significant in period 2, then the evidence is consistent with contagion through the formation of new linkages, such as in the Forbes and Rigobon (2002) approach.

Jaccard similarity coefficient

The Jaccard similarity coefficient is a statistic that helps identify the similarity and diversity in data samples. The Jaccard similarity coefficient helps us to determine retention of edges from one subsample to the next. In research works like Billio et al. (2012) the emphasis is solely on how many new linkages are formed on the whole. However in order to get a clear picture it is equally necessary and crucial to take into account the gross movements. Jaccard's coefficient checks the fraction of links in two sample networks that are constructed from the same linkages. Consider two sample networks Q and R. Jaccard similarity coefficient is calculated as a fraction. The numerator is the set consisting of the intersection of Q and R. The denominator is the union of the sets of edges.

$$J(Q, R) = \frac{n(Q \cap R)}{n(Q \cup R)} = \frac{n(Q \cap R)}{n(Q) + n(R) - n(Q \cap R)}$$

In matrix A, since the edges having statistical significance are weighted corresponding to DY weights, the matrix W tends to change between periods. This can cause changes in the network's completeness, arising from modifications in the count of linkages, or even modifications to the linkages' relative strength. The impact is worth noting as it helps us in differentiating the characteristics of the dynamically changing structure and is important in understanding the transition from the stable periods prior to the crisis to the financial turmoil itself.

Data

The set of data comprises 19 daily closing prices of stock market indices (dollar denominated) spanning the period 2004-2021 from Morgan Stanley. This includes the daily closing spot price of all the G20 nations. The stock indices' closing price must be synchronized pairwise. In case of a missing observation for a particular day on one index, the data points for the same date on all the remaining indices are deleted. This analysis is conducted by computing the returns as the difference of natural logarithms of consecutive stock index prices as $r_{it} = ln(p_{i,t}) - ln(p_{i,t-1})$ where $p_{i,t}$ is country i's equity index price at time t; $p_{i,t-1}$ is country i's equity index price at time $t - 1$.

The entire sample period captures several market conditions like bear and bull markets, as well periods of recovery, thereby having a wholesome representation. Dungey et al. (2015) advises on demarcation of crisis period in order to detect contagion during crisis. The sample period is broken down into sub periods consisting of the following five stages: the first stage captures the duration leading to the US subprime crisis. The second stage captures the global financial crisis of 2008. The third stage covers the Eurozone debt crisis. The fourth stage is the period of recovery, and the fifth stage captures world trade friction and Brexit. The aim here is to investigate the topological changes in the network over the course of these stages, and the occurrence of transformations in return spillover models from one stage to another. The findings in this study are based on the Akaike information criterion (AIC) in the VAR(2) model.

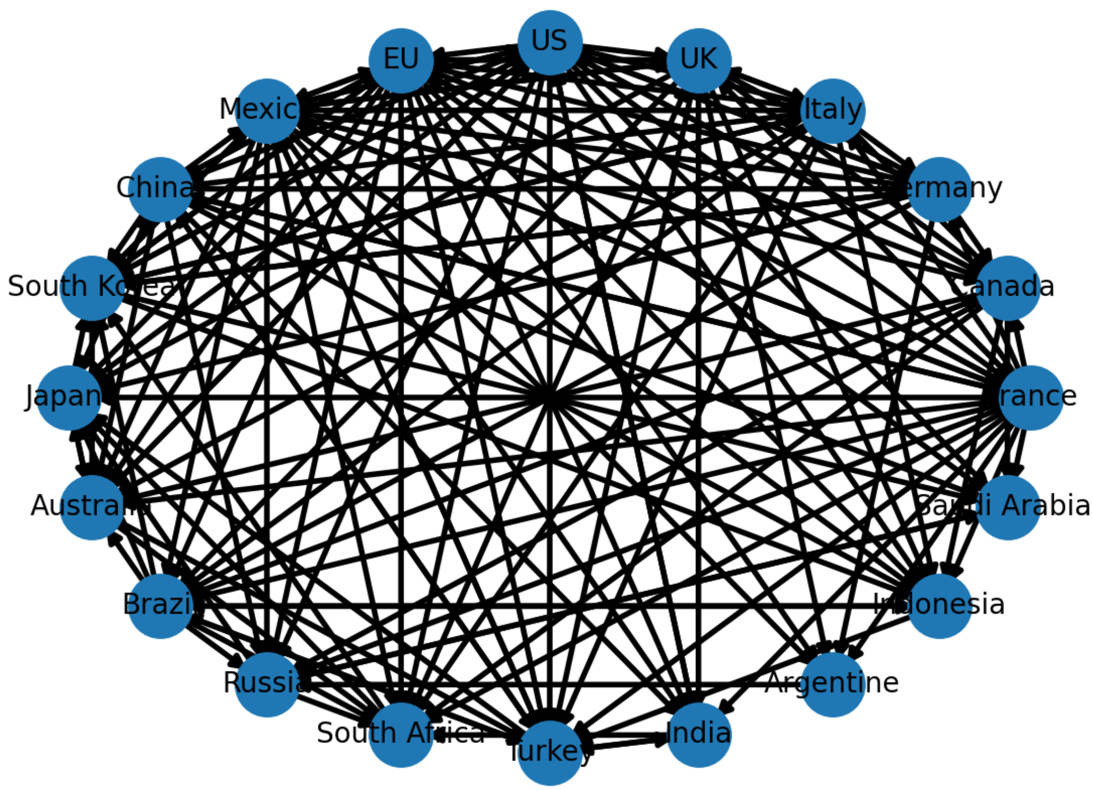
Empirical Findings

Descriptive statistics

The return is calculated by collecting daily stock index prices and computing the difference of natural logarithms of consecutive index prices as: $r_{it} = ln(p_{i,t}) - ln(p_{i,t-1})$. We come across some intriguing statistics, as has been mentioned in Table 3 of the Appendix. China has the highest mean return, while Italy with the lowest mean return is the only country with a negative mean return. Argentina has the greatest deviation or dispersion (2.46%), while the United States has the lowest (1.19%). The skewness of the entire series is towards the left and all the series are leptokurtic with a kurtosis value of above 3. This points towards a strong effect of the crisis on these economies. It indicates that these equity returns are non-normal distributions but have leptokurtosis. Appendix Table 4 contains the results from the standard augmented Dickey-Fuller and it implies that the series are stationary with large negative values at 1% significance levels.

Analysis of results

Figure 1: Graph network for the entire time period from 2004 to 2021



After utilising Granger causality tests to identify statistically significant links, the edges are augmented with the DY weights over the entire time period from 2004 to 2021. This is represented by the weighted directed network in Figure 1. The large number of linkages emanating from the EU and the USA goes to show that they have many connections. Saudi Arabia and Argentina are end nodes or nodes having few edges connecting it to the rest of the network, having very little influence. Some links are bidirectional implying Granger causality in both directions. These include pairs such as

Italy-Korea, USA-mexico and Japan-China. Pairs of countries having a unidirectional edge comprise France-Canada and Indonesia-Turkey.

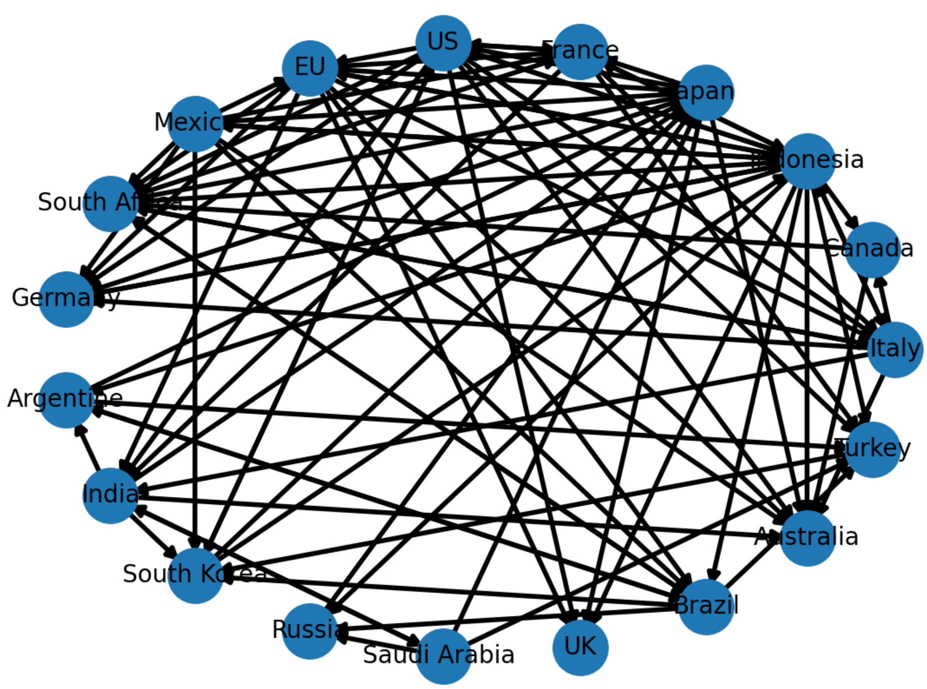
The entities of the DY matrix in Table 5 of the Appendix depicts the strength of the edges. The link from the EU to Italy is the strongest since it has the highest DY weight. Overall, European economies exhibit strong relationships between them owing largely to the union and common currency for a significant part of the sample's time duration.

Time varying changes in network

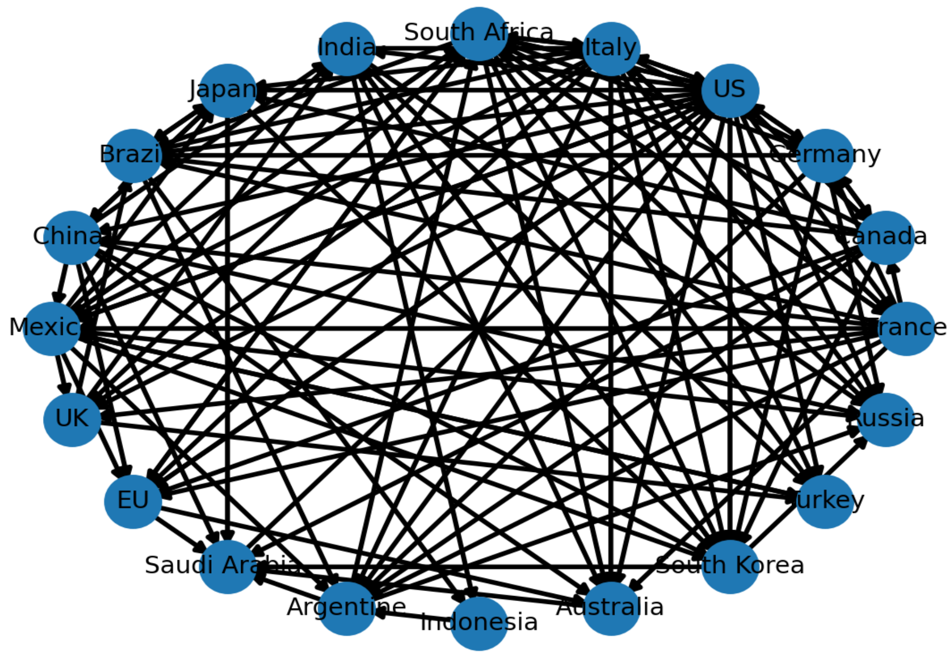
The sample period is subdivided into smaller periods covering the 2008 financial crisis, the Eurozone debt crisis, a recovery period and friction in global trade. The changes in the financial network over the course of the five stages are depicted in Figure 2

Figure 2: Changes in the evolving network over five stages

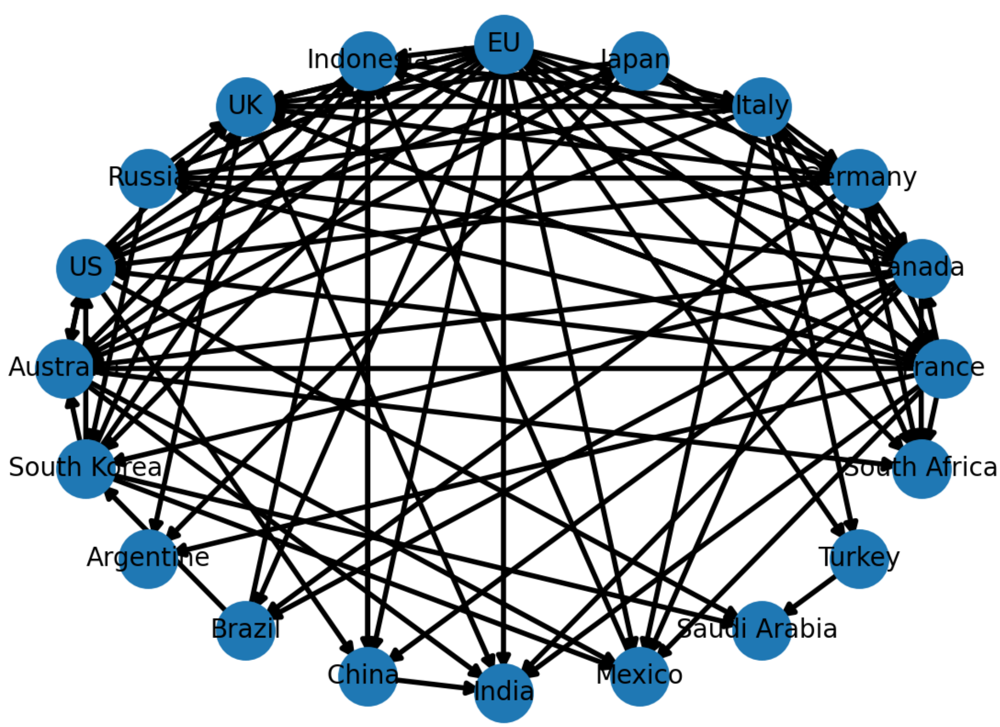
Phase 1:



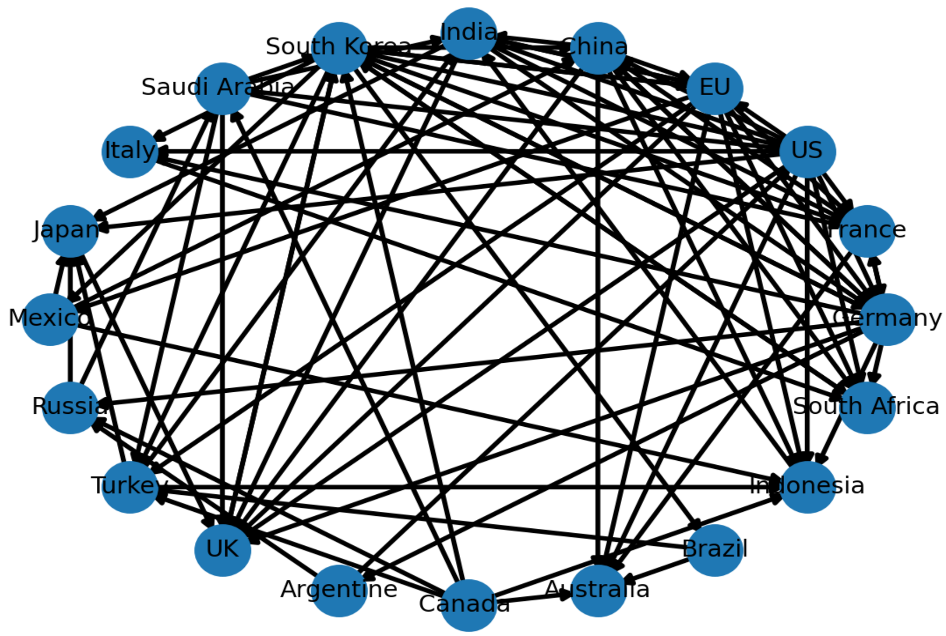
Phase 2:



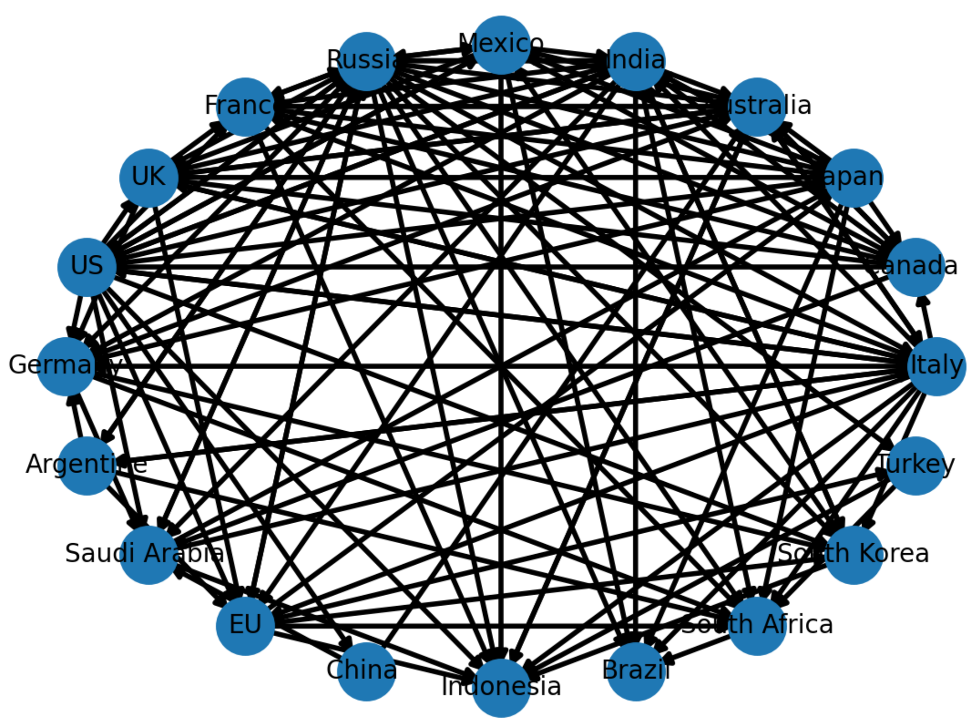
Phase 3:



Phase 4:



Phase 5:



The evolution of the financial network over the five sample periods is depicted in Figure 2. The transition to a denser and darker graph network indicates increased connectivity, consistent with existing literature from Dungey et al. (2018). The network statistics contained in Appendix Tables 7 and 8 highlight the changes that have occurred in the network's density. The Jaccard similarity coefficient is used in comparing network structures in two consecutive periods. In Appendix Table 8, row 1 captures the fraction of edges removed when transitioning from phase t-1 to phase t, as compared to the edges existing in the previous phase t-1. After the transition to phase 2, it is evident that there is a fall in the proportion of edges lost from one phase to another. Row 2 captures the fraction of edges which were newly constructed when transitioning from phase t-1 to phase t, as compared to the edges of the latest phase t. Overall, the formation of new edges is quite stable over the time duration. Row 3 contains the Jaccard similarity coefficient calculated as the proportion of common links between the two phases to the total number of links over the two phases. The low values of this statistic indicate that comparatively only a few edges were common in the phase transitions. The Jaccard statistic (Table 8) was the highest for the transition from phase 3 to phase 4 with a value of 20.54%.

Phase 1 to 2 includes the transition from the pre-crisis period to the global financial crisis. Phase 2 retains comparatively a small fraction of the edges in phase 1. Most of the edges that were formed during the crisis period of phase 2 are not retained in phase 3. This increased construction of new links resulting in high network density during periods of crisis is in alignment with the contagion form in Forbes and Rigobon (2002). In times of turmoil, financial markets tend to show increased connectivity. Transitioning to the crisis period from the pre-crisis phase demonstrates a sharp rise in statistically significant links. These findings are in alignment with existing literature on evidence related to contagion. Increased connectivity in G20 economies during crisis periods was observed by Zhang et al. (2020).

Panel A of Appendix Table 7 describes the formation and removal of edges during the transitions. In the transitions leading up to phase 2 and phase 5, there was a significant increase in the number of edges added. Additionally, the newly formed edges were slightly stronger on average in comparison to the ones removed. Panel B of Appendix Table 7 shows that in the phases covering the 2008 financial crisis and the European debt crisis the average edge strength was higher as compared to the other periods. This is in contrast to Dungey et al. (2018) which identified a decline in the edges' average strength for CDS markets when strong linkages were replaced by weaker edges during periods of stress.

Evolution of the network cannot be summarized by assessing the changes in the number of links alone. In order to understand how crises are transmitted, the links lost are equally essential as the ones formed. Using the statistic for completeness isn't the best way to study the changes occurring in the network. Increase in number of links accompanied by a large fall in strength of links could result in a fall in the completeness statistic. On the contrary, a rise in the number of links alone could result in increased completeness. Therefore, from the perspective of policy makers and investment managers it is necessary to take into account both - edges formed as well as edges removed. Policy implications arise when distinguishing between edges that existed prior to a crisis and those that were removed during the course of the crisis and then restored. Whether the edges were removed because of vulnerability or isolation can be determined from the Jaccard statistic. The low value of this statistic indicates that overall only a few edges existing pre-crisis continue to exist post-crisis and there is no return of the network to its pre-crisis condition.

Phase 3 of the network could be viewed as a recovery period from the global financial crisis for most countries. But this includes times of turmoil for other entities of the network, since European nations were greatly affected by the Eurozone debt crisis. This makes it difficult to precisely classify phase 3 as a recovery or crisis period. Still, our analysis is focussed on the main crises. During the European debt crisis the level of integration amongst the European markets increased. This was marked by a doubling of the number of linkages between the EU, Italy, France, Germany and UK. But apparently in the following years spanning over the Brexit referendum, there was a drop in the degree of financial integration. This is consistent with the findings in Tilfani et al. (2020) which suggested that the decreased levels of integration arose out of fear, uncertainty and doubt prevalent amongst investors.

Phase 4 is a relatively calmer period for almost all the G20 countries. Reduction in edges when transitioning from phase 3 to phase 4 is indicative of a fall in number of links post the major crisis (gain of 55 edges and loss of 63 edges) coupled with weaker average strength in the newly formed edges as compared to the ones lost.

Appendix tables 10 and 11 contain the centrality measures for betweenness and eigenvectors. Betweenness captures the degree of effectiveness of a node in the transmission of shocks by keeping track of the count when a particular node forms an entity in the shortest path between another pair of nodes. Removing a node with high betweenness could have a significant impact on the network because such a node has great importance in shock transmission. The average value of betweenness centrality has small fluctuations between phases, indicating minor structural changes in the nodes. In phase 2 of the global financial crisis, US and South Africa register the highest centrality. Zhang et al. (2020) had identified South Africa to have the highest betweenness during the subprime crisis.

The centrality measure of eigenvectors captures connectivity throughout the financial network and the eigenvalues do not change much between periods. Australia and South Africa consistently register an above average eigenvector centrality measure. Overall there isn’t much variation in the centrality measures across all the different countries.

Figure 3: Betweenness centrality

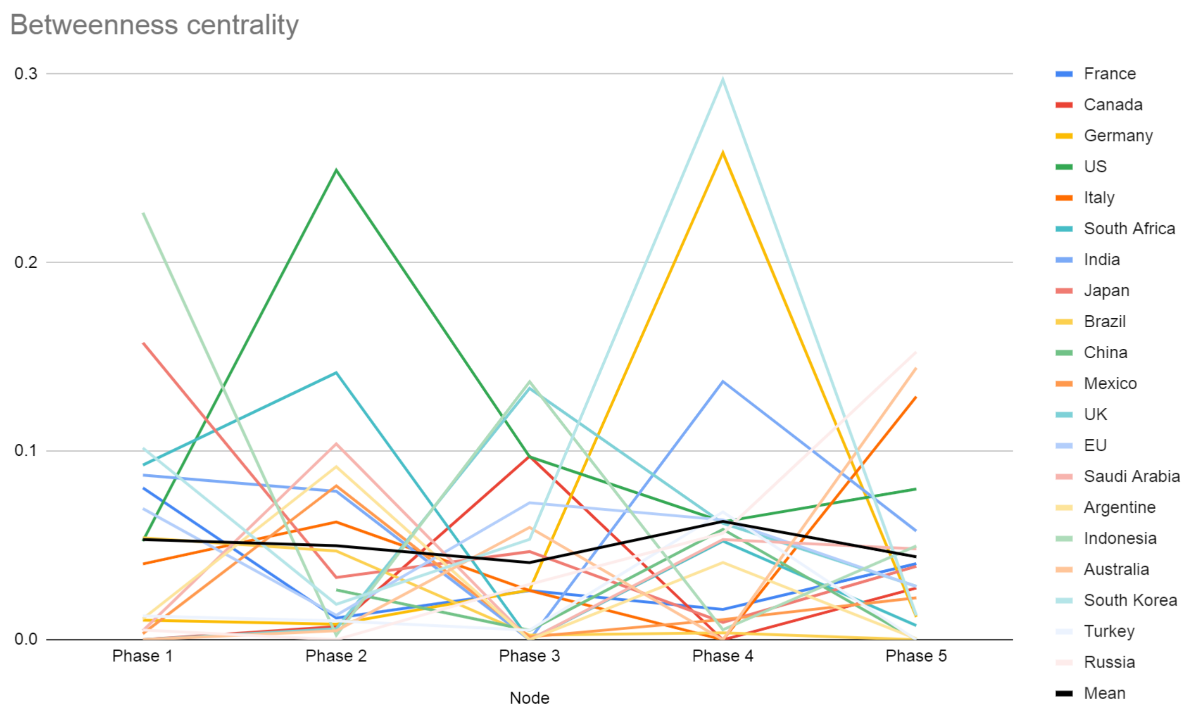
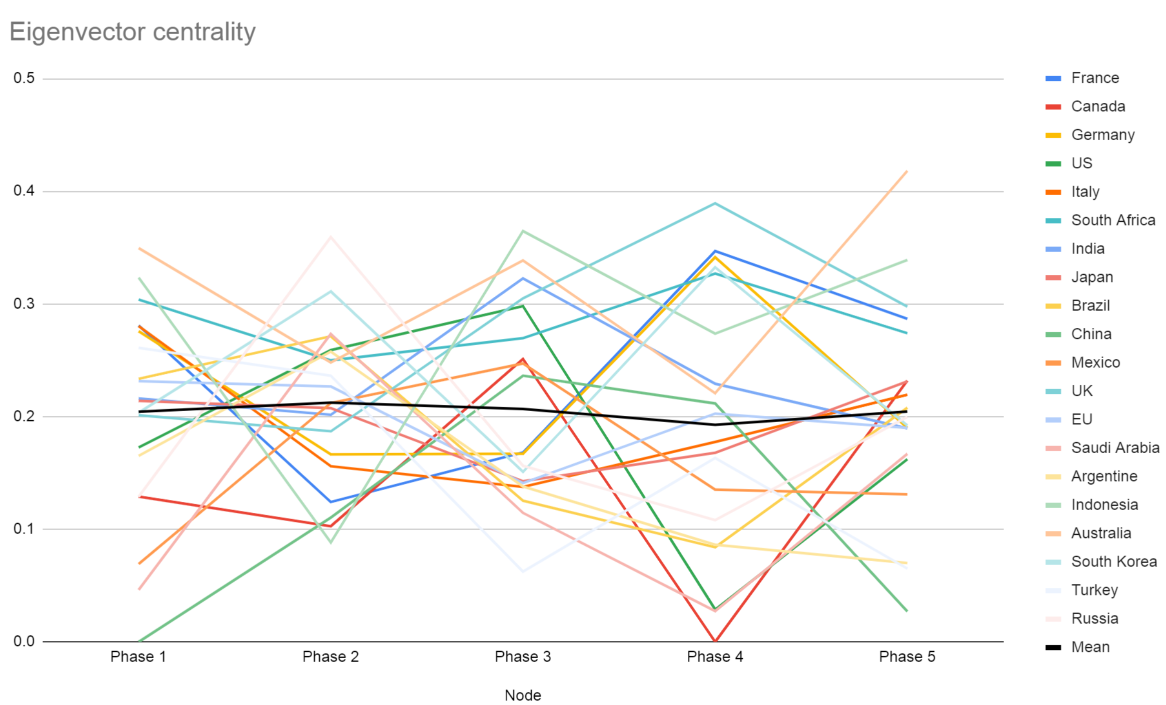


Figure 4: Eigenvector centrality



Absorbers and Spreaders

	x < 0	x > 0
Outdegree < 3	Peripheral absorber (PA)	
Indegree < 3		Peripheral spreader (PS)
Absolute (x) > 6	Super absorber (SA)	Super spreader (SS)

Define: x = (outdegree − indegree)

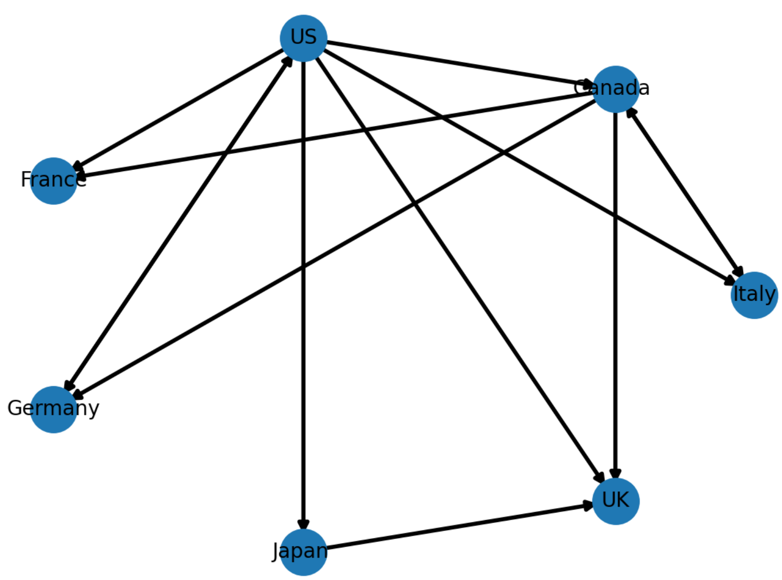
Peripheral absorbers, super absorbers, peripheral spreaders and super spreaders are the four classifications of nodes that will help in detecting change in the type of nodes over phases of turmoil and recovery. Peripheral absorbers are nodes with a low outdegree and are involved in absorbing shocks without passing them forward. Super absorbers don't spread shocks widely, despite being subjected to several. They are identified as nodes having a larger indegree as compared to outdegree. Peripheral spreaders are the shock-generating sources but aren't subjected to many themselves due to a small indegree. Super spreaders are the nodes responsible for absorbing as well as distributing shocks to several other nodes. Their outdegree far outweighs their indegree. The super absorber and spreaders are characterised by nodes which have stark differences between outdegree and indegree. From Appendix Table 9, in agreement with Rapach et al. (2013) it is evident that the US is the most obvious super spreader. In accordance with Kaminsky et al. (2003) a developed market such as the US forms a key channel to transmit shocks from peripheral economies. Along with the US, France and Italy also acted as super spreaders during the 2008 financial crisis. The role of the French market is consistent with findings from Wang et al. (2018), who claimed that the centrality of France within Europe could be attributed to the existence of the World Federation of Exchanges in Paris. In phase 3 over the course of the European debt crisis, Italy, France and the EU act as super spreaders. The gradual increase in the number of absorbers and spreaders over the later phases is indicative of the network becoming more integrated.

Appendix Table 6 contains the network characteristics presenting the indegree and outdegree pertaining to every nation. Clearly, the US has one of the greatest records and thus aligns with the definition of it being a constant super spreader. Argentina and Saudi Arabia being isolated nodes have the least number of edges. Table 9 contains the detailed classification of nodes as absorbers or spreaders. Both Australia and South Africa act as absorbers in times of crisis and stability. This is in support of the findings in Liu et al. (2017) which states that Australia isn't very sensitive to external shocks.

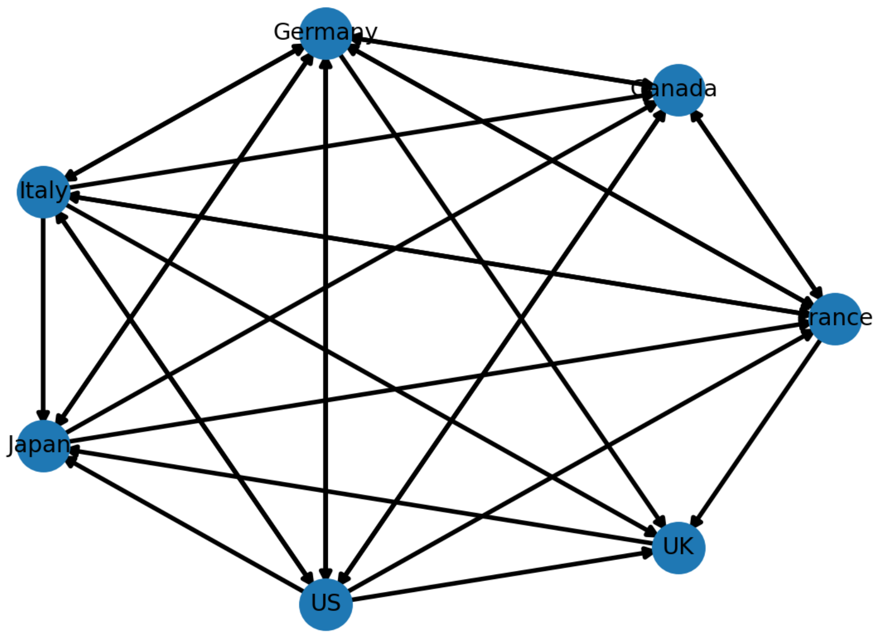
Focus on the developed and emerging economies

From Appendix Tables 12 and 14, we see that the developed economies have higher edge strength as compared to the emerging markets. When moving from pre-crisis to crisis periods, edges having a lower average strength are replaced by a greater number of edges having higher strength. Developed countries have a higher value of Jaccard statistics indicating that a proportionately greater number of edges are retained from one phase to another as compared to the emerging economies. Relatively isolated nodes like Argentina and Saudi Arabia have very little impact on the other G20 nations. This indicates that in comparison to emerging economies developed markets tend to be more influential, in accordance with Zhang et al. (2020).

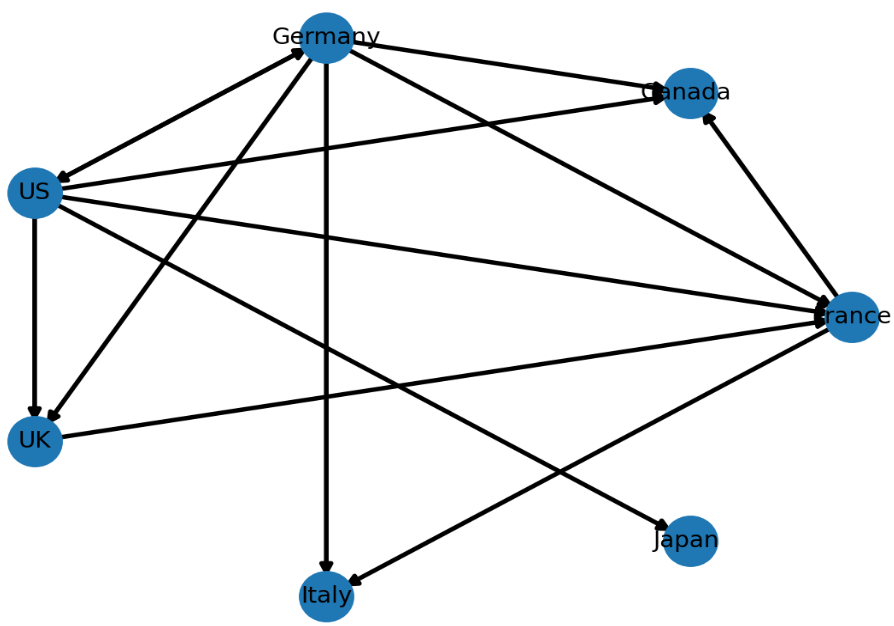
Figure 5: Developed markets
Phase 1:



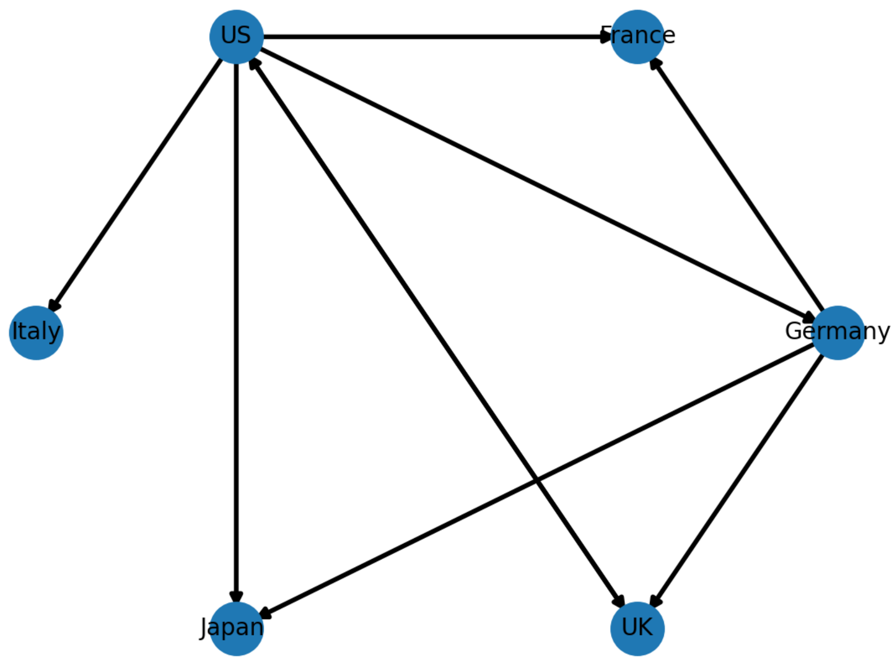
Phase 2:



Phase 3:



Phase 4:



Phase 5:

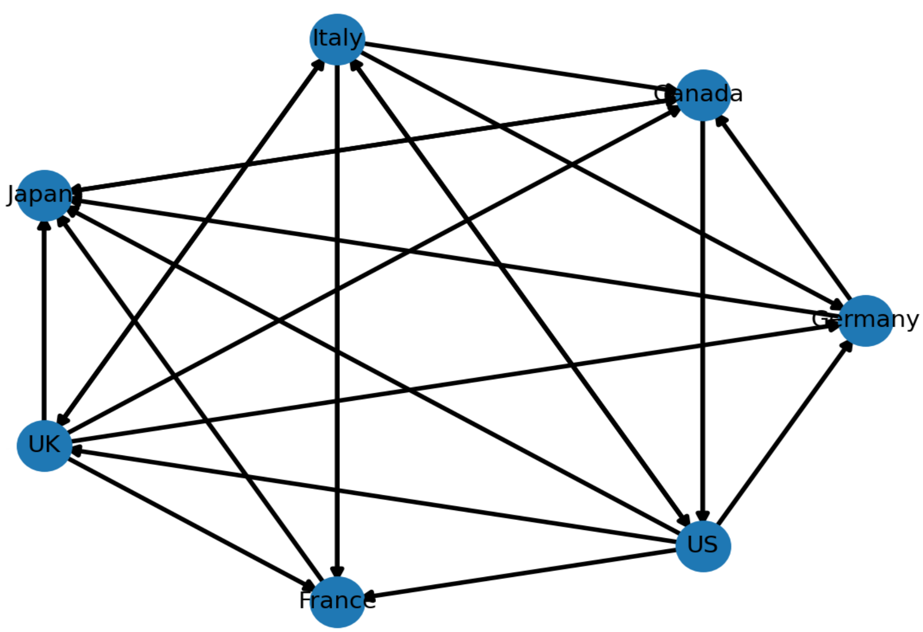


Figure 5 depicts the subnetwork of developed G20 economies with its statistics and network characteristics mentioned in Table 12. The transformation in the network structure of the developed markets over the different subperiods involves the increasing deepening and development of the markets reflecting the dominating effects of crisis periods in phases 2 and 5.

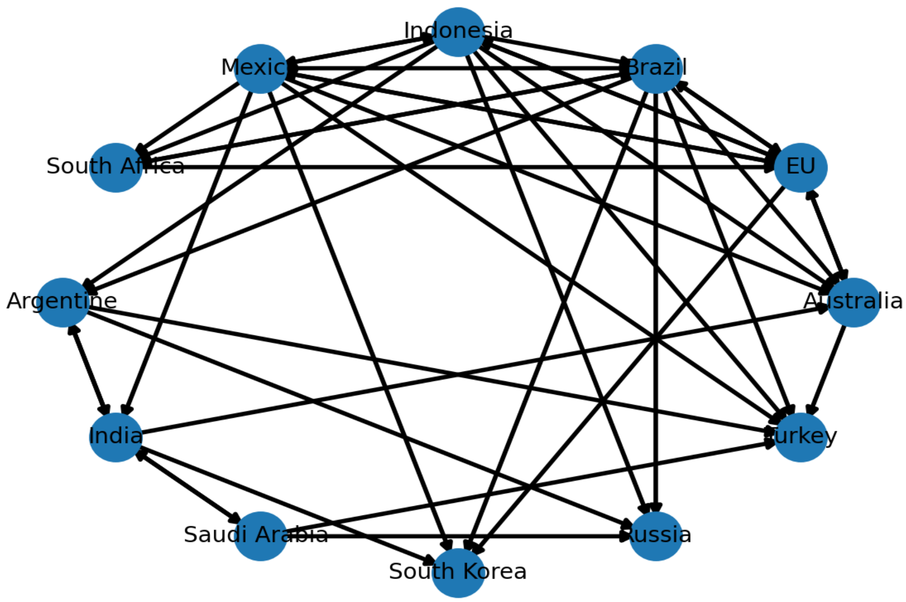
There are links going from the US to every other developed market in each of the phases indicating that the US is the most significant node amongst developed G20 nations. Out of the edges emanating from the US, the dominant ones include linkages with developed economies - Canada and Japan, and to the emerging market of Australia. Through all the phases the US has a consistent large influence on Japan. In the case of Japan it is interesting to note that even though it is strongly linked to the US, it does not act as a bridge for shocks to transmit into Asian markets. Farrell et al. (2005) noted the diminished synchronization of the Japanese economy with other OECD or global economies during this period of the early 21st century.

Australia is largely a shock absorber and receives links from the US, Canada and Japan. It has minimal impact on the European markets. In phase 1 prior to the global financial crisis, it is clearly evident that in the sparse network, the US has the maximum number of connections. This is supported by the high betweenness centrality value for the US (table 13). The European markets of Germany, Italy and UK are relatively more isolated. Progressing into the second phase covering the global financial crisis, the network becomes denser as compared to the previous phase. With the outgoing links from the US to other markets remaining strong, the onward transmission of these shocks to the European markets is more pronounced. In phase 3, the network density decreases relatively. Over the period of the European debt crisis, Germany became the dominant node with the strongest linkages. The recovery period of phase 4 undergoes a further reduction in network density with the US once again becoming the dominant node. Phase 5 has greater connectedness with the maximum number of bidirectional linkages. In this phase Canada and the US have the strongest links. The betweenness centrality is highest for the US during the pre crisis periods of phase 1 and phase 4.

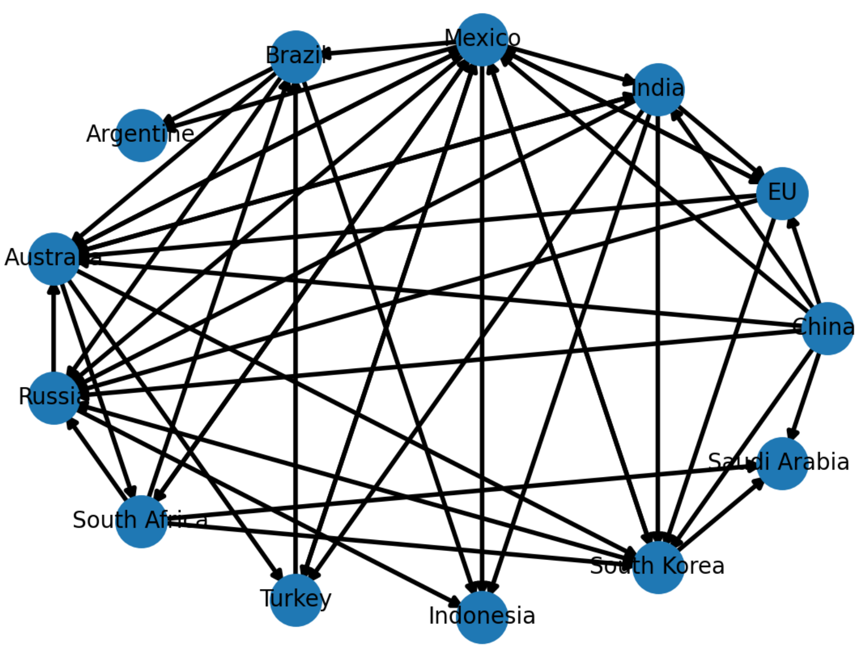
This implies that the US constituted the most important node in information transmission between developed markets over the pre crisis periods.

Figure 6: Emerging markets

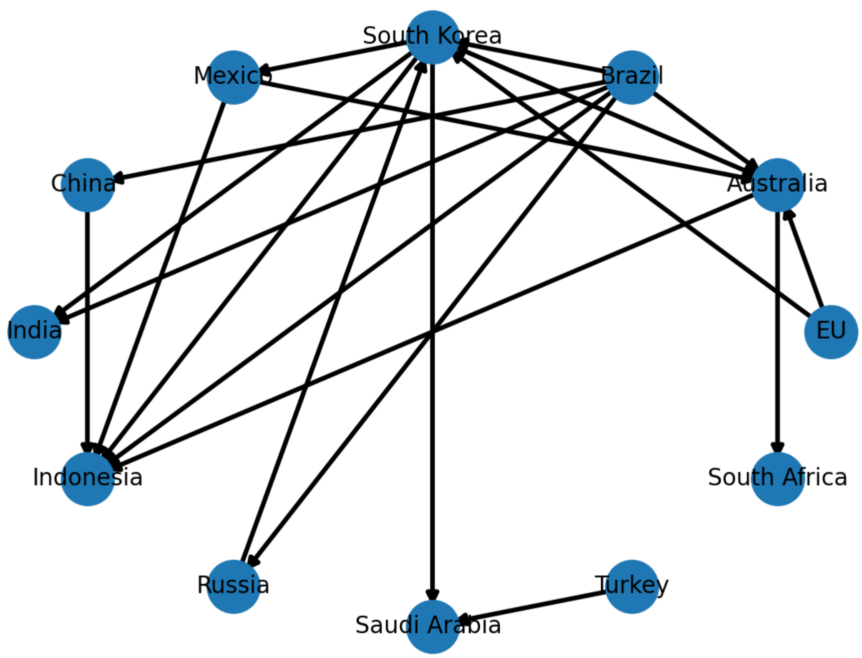
Phase 1:



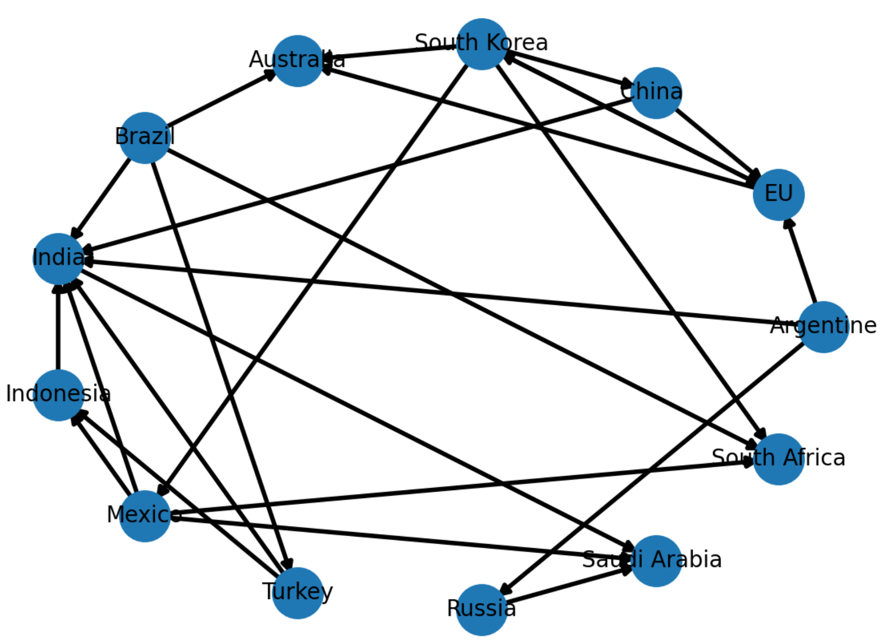
Phase 2:



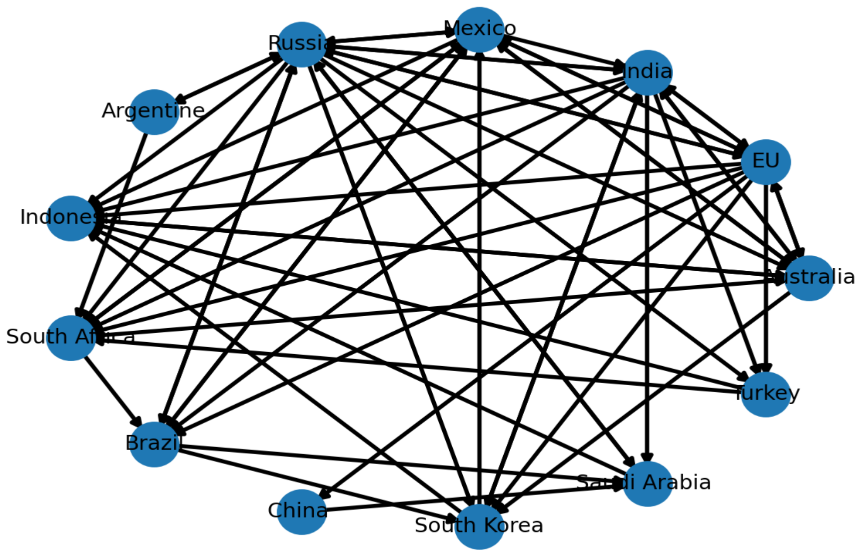
Phase 3:



Phase 4:



Phase 5:



In phase 1 Brazil has the maximum number of edges with the highest strength while the EU is the most significant node with respect to information transmission amongst emerging countries. Most of the emerging countries - China, South Korea, Russia, South Africa, Turkey - do not have much of an impact in transmitting shocks to other countries. This is similar to results in Liu et al. (2017) and Zhang et al. (2020) which claim that emerging economies aren't very influential as compared to developed markets. Progressing into phase 2, the network of the emerging countries is significantly impacted by the global financial crisis. There appears to be a distinct change with Mexico becoming the central dominant node during the global financial crisis. From Appendix table 5 it is clear that in phase 2, out of all the emerging countries, the US has the strongest linkage with Mexico. From table 15 we can conclude that Mexico has the highest betweenness centrality during the global financial crisis. Thus, it is the most important node in transmitting information amongst the emerging markets. Since Mexico facilitates the transmission of shocks from the US to the emerging markets it can be classified as a bridge market. The role of bridge markets is often crucial to the development of emerging economies although some countries directly access international markets without going through a bridge market. However, this result is in contradiction to Liu et al. (2017) which states that Mexico has very little influence on other G20 economies. In phases 3 and 4, post the global financial crisis, the network grows sparse and there is a drop in the association that existed during the previous crisis period. China mostly occupies the position of an end node in this network. The network during phase 5 grows denser and is quite different from the previous phases. Over the build-up in phase 5, the network has increased density with strong linkages. There is a spike in the betweenness centrality measure with Russia taking on the role of most important transmitter. In this last phase, Russia has continued to increase the direct linkages to other markets in the network. Alongside the Russian market, the Indian market, which was previously not so heavily linked with emerging nations, now is strongly integrated. India and Russia have direct links to each of the developed G20 markets. They clearly form an important hub for transmitting shocks from the emerging economies to the developed markets. In this final phase, Indian and Russian economies transform, integrating into the international network in a way markedly different from the previous phases. Over the course of the global financial crisis, it seemed that the emerging markets were maturing and becoming more connected with other important regions, through Mexico and by direct links to regions outside. Emerging markets are gaining traction in the international network. The last phase has led to emerging economies becoming more strongly connected to other markets of the world.

Conclusion

In this paper we have analysed the characteristics of the return spillovers network for G20 markets. The data consists of stock market returns over the period from 2004 to 2021 by sub-dividing it into five smaller periods to gain a better understanding of the dynamics. The methodology entails using Granger causality tests to assess statistical significance and the vector autoregressive (VAR) model to gauge the impacts that a shock in one country has on the other countries.

Firstly we investigate the stock market equity return spillover effects among G20 economies by the VAR model and construct graph networks for the same. There is an increase in financial integration during periods of crisis and a fall in connectivity during recovery periods. Stronger connectedness is represented by a denser network and higher average edge strength. When transitioning into crisis periods, the increase in the number of linkages in the network is accompanied by replacement of weaker edges by stronger edges. The indegree and outdegree of nodes are used to identify shock spreaders or markets that amplify the information transmission. The US acted as a super-spreader of shocks over most of the phases. The EU, Italy and France were responsible for spreading shocks during the period of the European debt crisis.

We compute network centrality measures of betweenness and eigenvector to study the status and impact of each equity market. Across all phases Australia and South Africa have high values of eigenvector centrality. Both these nations also act as shock absorbers, lessening the influence of external shocks.

Finally we draw comparisons between the developed and emerging G20 markets. Developed markets tend to be more impactful as their networks have a higher average edge strength. During the global financial crisis, Mexico is observed to have a high betweenness amongst the emerging markets. Its strong link to the US, makes it a bridge market that helps in transferring shocks from the US to other G20 emerging economies. Over the course of the last phase Russia and India form a large number of links leading to the G20 emerging markets becoming more integrated. It is necessary and meaningful for investors and policy makers to acknowledge the factors affecting contagion and financial integration of stock markets. This will aid portfolio managers to hedge risks and modify their strategies beforehand on the basis of external or internal influencing factors.

Appendix

Table 1: G20 markets

	Country	Stock market index
Developed	United Kingdom	UKX Index
	France	CAC Index
	Canada	SPTSX Index
	Italy	FTSEMIB Index
	US	SPX Index
	Australia	AS51 Index
	Germany	DAX Index
	Japan	NKY Index
Emerging	China	SSE50 Index
	India	NIFTY Index
	Brazil	IBOV Index
	Saudi Arabia	SASEIDX Index
	South Africa	JALSH Index
	Indonesia	JCI Index
	Turkey	XU100 Index
	Argentina	MERVAL Index
	Russia	IMOEX Index
	Korea	KOSPI Index
	Mexico	MEXBOL Index

	European Union	EURO STOXX Index

Table 2: Duration of sample periods

Stage 1	Pre-crisis of global financial crisis	2004/01/01 to 2007/08/09
Stage 2	2008 global financial crisis	2007/08/10 to 2009/12/31
Stage 3	Eurozone debt crisis	2010/12/08 to 2012/12/31
Stage 4	Recovery period, Brexit referendum	2013/01/02 to 2017/12/31
Stage 5	World trade friction, Covid-19 pandemic	2018/01/02 to 2021/08/04

Table 3: Descriptive statistics

	Mean	Std dev	Variance	Skewness	Kurtosis	Observations
Canada	0.0002313	0.0137964	0.0001903	-0.8988678	17.27249	4,589
France	0.0001429	0.015211	0.0002314	-0.2177635	12.33961	4,589
Germany	0.0003281	0.0149361	0.0002231	-0.2603183	11.3548	4,589
Italy	-5.99E-06	0.0169392	0.0002869	-0.5888685	13.08736	4,589
Japan	0.0002324	0.0137913	0.0001902	-0.3903135	9.124589	4,589
UK	0.0000745	0.0134787	0.0001817	-0.3867808	15.73135	4,589
US	0.0003374	0.0119439	0.0001427	-0.5803691	17.97123	4,589
Argentina	0.0000844	0.0246579	0.000608	-5.012845	123.0479	4,589
Australia	0.0002142	0.0148415	0.0002203	-0.9185742	12.98356	4,589
Brazil	0.0002892	0.0233164	0.0005437	-0.552399	11.09473	4,589
China	0.0004985	0.0166961	0.0002788	-0.3111909	7.327734	4,589

India	0.0004038	0.016252	0.0002641	-0.3506315	14.14453	4,589
Indonesia	0.0004152	0.015808	0.0002499	-0.6639045	12.86367	4,589
South Korea	0.0003427	0.0163459	0.0002672	-0.443301	19.68916	4,589
Mexico	0.0002929	0.0160656	0.0002581	-0.3677791	10.09403	4,589
Russia	0.0002259	0.022117	0.0004892	-0.2934795	17.86737	4,589
Saudi Arabia	0.0003505	0.015724	0.0002472	-1.304527	20.5101	4,589
South Africa	0.0002695	0.0178888	0.00032	-0.4498269	8.631397	4,589
Turkey	0.0000841	0.0220078	0.0004843	-0.6042482	8.948563	4,589

Table 4: ADF unit root test for stationarity

ADF test for unit root				
	Test statistic	1% Critical	5% Critical	10% Critical
Canada	-56.143	-3.43	-2.86	-2.57
France	-60.161	-3.43	-2.86	-2.57
Germany	-58.273	-3.43	-2.86	-2.57
Italy	-59.271	-3.43	-2.86	-2.57
Japan	-66.877	-3.43	-2.86	-2.57
UK	-59.609	-3.43	-2.86	-2.57
US	-66.922	-3.43	-2.86	-2.57
Argentina	-57.974	-3.43	-2.86	-2.57

Australia	-57.32	-3.43	-2.86	-2.57
Brazil	-58.284	-3.43	-2.86	-2.57
China	-58.405	-3.43	-2.86	-2.57
India	-58.341	-3.43	-2.86	-2.57
Indonesia	-52.527	-3.43	-2.86	-2.57
South Korea	-54.687	-3.43	-2.86	-2.57
Mexico	-50.055	-3.43	-2.86	-2.57
Russia	-57.963	-3.43	-2.86	-2.57
Saudi Arabia	-56.402	-3.43	-2.86	-2.57
South Africa	-56.342	-3.43	-2.86	-2.57
Turkey	-55.438	-3.43	-2.86	-2.57

Table 5: G20 composite weighted network for the entire sample period

	Canada	France	Germany	Italy	Japan	UK	US	EU	Argentine	Australia	Brazil	China	India	Indonesia	South Korea	Mexico	Russia	Saudi Arabia	South Africa	Turkey
Canada	0	0.0694	0.0653	0.0589	0	0.0764	0.0876	0.0721	0	0	0	0	0	0	0	0.0641	0	0	0	0
France	0	0	0	0	0	0.0953	0.0568	0.1145	0	0	0	0.0034	0	0	0	0.0493	0	0	0	0
Germany	0	0.1121	0	0.0961	0	0.0917	0.0583	0.1142	0	0	0	0.0033	0	0	0.0246	0.049	0	0	0	0
Italy	0	0.1146	0	0	0	0.0909	0.0519	0.1171	0	0	0	0.003	0	0	0.0201	0.0457	0	0	0	0
Japan	0	0.0619	0.0635	0	0	0.0602	0.0802	0.0676	0	0.0412	0.0422	0.0067	0	0	0	0	0.0322	0	0.0404	0.0233
UK	0	0.0991	0	0.0829	0	0	0.0611	0.0959	0	0	0	0	0	0	0	0.0516	0	0	0.0719	0

US	0.0975	0	0.0715	0	0	0	0	0	0	0.0364	0	0	0.0196	0	0.0226	0.0755	0	0	0	0
EU	0	0.1138	0	0	0	0.0915	0.0596	0	0	0	0	0.0036	0	0	0.0228	0.0495	0	0	0	0
Argentine	0	0.0471	0.044	0	0	0.0476	0	0.0496	0	0	0	0	0	0	0	0.0575	0	0	0	0
Australia	0.0706	0.0634	0	0.0525	0.0222	0	0.0717	0.0674	0	0	0.052	0.0092	0	0	0.047	0.0561	0	0	0	0
Brazil	0.0735	0.0597	0.0566	0.0496	0	0.0615	0	0.0615	0	0	0	0	0	0.0175	0	0.0845	0	0	0	0.0361
China	0	0.0233	0	0	0.0183	0	0.0257	0.0256	0	0	0	0	0	0	0	0	0	0	0	0.0153
India	0	0.0488	0	0	0	0.0482	0.0477	0.053	0	0	0	0.013	0	0	0	0.0498	0	0	0	0.0372
Indonesia	0.049	0.0439	0	0.0346	0	0.0448	0.047	0.0467	0	0	0.0491	0.0114	0	0	0.0543	0.0546	0	0	0	0
South Korea	0	0	0.0535	0.0411	0.0357	0	0.0496	0.0543	0	0	0.0479	0.0169	0	0	0	0.0551	0	0	0.0621	0
Mexico	0	0.0659	0	0	0	0.0643	0.0784	0.0676	0	0	0	0.0053	0	0	0.0303	0	0	0	0	0.0378
Russia	0.063	0.0666	0	0	0	0	0.0437	0.0666	0.0225	0	0.0514	0.005	0	0	0	0.0528	0	0.0036	0	0
Saudi Arabia	0.024	0.0223	0	0	0	0	0.0261	0.0229	0	0	0	0.0037	0	0	0.0165	0	0.0189	0	0	0
South Africa	0.063	0.0769	0	0.0629	0	0	0.0503	0.075	0	0.0504	0.0549	0	0.0261	0	0	0.0608	0.0476	0	0	0
Turkey	0	0.0612	0	0.0498	0	0.0598	0.0419	0.0621	0	0.0344	0.0516	0.0038	0.0295	0.023	0	0.0584	0	0	0	0

Table 6: Network characteristics

	Phase 1			Phase 2			Phase 3			Phase 4			Phase 5		
Node	In	Out	x	In	Out	x	In	Out	x	In	Out	x	In	Out	x
Canada	2	2	0	3	9	6	6	8	2	0	6	6	6	5	-1
France	6	5	-1	3	11	8	4	12	8	7	2	-5	7	5	-2
Germany	6	1	-5	5	6	1	5	7	2	6	9	3	6	5	-1
Italy	5	6	1	4	14	10	3	10	7	3	1	-2	6	13	7
Japan	7	6	-1	6	4	-2	2	4	2	5	1	-4	7	7	0
UK	4	0	-4	5	3	-2	8	5	-3	8	1	-7	8	5	-3
US	3	12	9	7	17	10	6	5	-1	2	12	10	5	14	9
EU	5	8	3	7	4	-3	3	16	13	4	10	6	6	6	0
Argentine	3	3	0	8	3	-5	3	0	-3	1	2	1	2	5	3
Australia	8	0	-8	7	1	-6	7	6	-1	6	0	-6	12	5	-7
Brazil	5	5	0	8	3	-5	3	2	-1	1	2	1	6	0	-6
China	0	0	0	3	8	5	4	2	-2	4	8	4	1	2	1
India	5	5	0	5	6	1	6	0	-6	6	5	-1	6	13	7
Indonesia	7	14	7	2	1	-1	8	4	-4	7	1	-6	10	1	-9
South Korea	5	3	-2	9	3	-6	4	6	2	7	10	3	6	3	-3
Mexico	1	9	8	6	10	4	6	1	-5	2	3	1	4	8	4
Russia	3	1	-2	9	0	-9	4	4	0	3	2	-1	7	18	11
Saudi Arabia	1	4	3	7	1	-6	3	0	-3	2	6	4	6	4	-2
South Africa	7	4	-3	7	12	5	6	0	-6	6	1	-5	9	1	-8
Turkey	6	1	-5	6	1	-5	2	1	-1	5	3	-2	2	2	0

Table 7: Network statistics

Panel A

	Number of edges formed	Average strength of edge formed	Number of edges removed	Average strength of edge removed
Phase 1 to 2	88	0.05172045455	60	0.03823833333
Phase 2 to 3	58	0.05319482759	82	0.04907926829
Phase 3 to 4	55	0.03051636364	63	0.05651269841
Phase 4 to 5	88	0.04750227273	51	0.04141764706

Panel B

	Average edge strength	Total edges
Phase 1	0.04434382022	89
Phase 2	0.05440603448	117
Phase 3	0.05817096774	92
Phase 4	0.04206470588	84
Phase 5	0.04710819672	121

Table 8: Jaccard similarity coefficient as percentage

	Phase 1 to 2	Phase 2 to 3	Phase 3 to 4	Phase 4 to 5
Edges removed as proportion of Phase t − 1	67.41573034	70.08547009	68.47826087	60.71428571
Edges formed as proportion of Phase t	75.21367521	63.04347826	65.47619048	72.72727273
Jaccard statistic for all edges	16.38418079	19.42857143	20.54794521	19.18604651

Table 9: Absorbers and Spreaders

	Phase1	Phase 2	Phase 3	Phase 4	Phase 5
Canada				PS	
France		SS	SS	PA	
Germany	PA				
Italy		SS	SS	PA	SS
Japan			PS	PA	
UK	PA			SA	
US	SS	SS		SS	SS
EU			SS		
Argentine			PA	PS	PS
Australia	SA	PA		PA	SA
Brazil			PA	PS	PA
China			PA		PS
India			PA		SS
Indonesia	SS	PA		PA	SA
South Korea					
Mexico	SS		PA	PS	
Russia	PA	SA		PA	SS
Saudi Arabia	PS	PA	PA	PS	
South Africa			PA	PA	SA
Turkey	PA	PA	PA		PS

Table 10: Betweenness centrality

Node	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5
France	0.08055	0.01155	0.026096	0.016082	0.040346
Canada	0	0.006948	0.097295	0	0.02742
Germany	0.01042	0.008236	0.026413	0.258236	0.01213
US	0.052358	0.248977	0.097027	0.062622	0.079896
Italy	0.040221	0.062427	0.026096	0	0.12897
South Africa	0.092661	0.141569	0	0.052339	0.007535
India	0.087267	0.078704	0	0.13694	0.057651
Japan	0.157485	0.03302	0.046735	0.009211	0.038965
Brazil	0.054033	0.047076	0.002437	0.003655	0
China		0.026441	0.004971	0.058528	0
Mexico	0.003268	0.081628	0.001559	0.010721	0.022285
UK	0	0.005799	0.133309	0.061793	0.02833
EU	0.06961	0.01304	0.072636	0.063548	0.028272
Saudi Arabia	0.004902	0.103899	0	0.053119	0.048215
Argentine	0.011127	0.091743	0	0.040936	0.000585
Indonesia	0.226438	0.002437	0.136866	0.005361	0.049756
Australia	0	0.004755	0.0596	0	0.144228
South Korea	0.101683	0.018839	0.053241	0.297027	0.012905
Turkey	0.012645	0.00999	0.005068	0.067739	0
Russia	0.005135	0	0.029362	0.05653	0.152629

Table 11: Eigenvector centrality

Node	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5
France	0.280771	0.12413	0.168114	0.346884	0.286767
Canada	0.128978	0.102637	0.251065	1.62E-10	0.231803
Germany	0.275755	0.166479	0.166999	0.34138	0.189967
US	0.172552	0.25899	0.297942	0.028679	0.162128
Italy	0.280289	0.155844	0.137551	0.177476	0.219369
South Africa	0.303769	0.249859	0.269528	0.326944	0.273956
India	0.216047	0.201536	0.322533	0.229115	0.189504
Japan	0.213944	0.20748	0.142567	0.167807	0.231155
Brazil	0.233473	0.27122	0.12523	0.083992	0.207745
China	0	0.110294	0.236229	0.211622	0.027061
Mexico	0.069088	0.21203	0.247088	0.135167	0.131022
UK	0.201103	0.186907	0.304949	0.389275	0.297554
EU	0.23134	0.226672	0.140981	0.202576	0.189967
Saudi Arabia	0.046163	0.273318	0.114517	0.027289	0.16693
Argentine	0.165138	0.257641	0.137905	0.086239	0.06994
Indonesia	0.323338	0.088286	0.364578	0.273512	0.338993
Australia	0.349477	0.247875	0.338501	0.220727	0.4181
South Korea	0.203447	0.310964	0.150885	0.332484	0.192044
Turkey	0.260987	0.236266	0.062394	0.163278	0.065033
Russia	0.128839	0.359235	0.156293	0.108025	0.199665

Table 12: Network statistics for developed markets

	Average edge strength	Total edges
Phase 1	0.08236153846	12
Phase 2	0.1344689655	29
Phase 3	0.1571461538	13

Phase 4	0.1159	9
Phase 5	0.1302809524	21

	Number of edges formed	Average strength of edge formed	Number of edges removed	Average strength of edge removed
Phase 1 to 2	19	0.1379368421	3	0.0597
Phase 2 to 3	1	0.1683	17	0.1218411765
Phase 3 to 4	3	0.08673333333	7	0.1678857143
Phase 4 to 5	15	0.1388066667	3	0.1713

	Phase 1 to 2	Phase 2 to 3	Phase 3 to 4	Phase 4 to 5
Edges removed as proportion of Phase t − 1	25	58.62068966	53.84615385	33.33333333
Edges formed as proportion of Phase t	65.51724138	7.692307692	33.33333333	71.42857143
Jaccard statistic for all edges	32.25806452	40	37.5	25

Table 13: Betweenness centrality for developed markets

Node	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5
France	0	0.072222	0.083333	0	0.006667
Canada	0.166667	0.044444	0	0	0.456667
Germany	0.133333	0.144444	0.016667	0	0.015
Italy	0	0.022222	0	0	0.025
Japan	0	0.166667	0	0	0.175
US	0.233333	0.038889	0.033333	0.25	0.473333
UK	0	0.011111	0	0.1	0.015

Table 14: Network statistics for emerging markets

	Average edge strength	Total edges
Phase 1	0.06275714286	42
Phase 2	0.0704625	48
Phase 3	0.07377	20
Phase 4	0.056208	25
Phase 5	0.06988666667	60

	Number of edges formed	Average strength of edge formed	Number of edges removed	Average strength of edge removed
Phase 1 to 2	28	0.05741428571	24	0.044525
Phase 2 to 3	10	0.06391	18	0.06791842105
Phase 3 to 4	18	0.05093333333	13	0.06883076923
Phase 4 to 5	47	0.06943617021	14	0.05072857143

	Phase 1 to 2	Phase 2 to 3	Phase 3 to 4	Phase 4 to 5
Edges removed as proportion of Phase t − 1	57.14285714	37.5	65	56
Edges formed as proportion of Phase t	58.33333333	50	72	78.33333333
Jaccard statistic for all edges	28.57142857	17.24137931	18.42105263	18.05555556

Table 15: Betweenness centrality for emerging markets

Node	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5
Australia	0.141667	0.149874	0.05	0	0.127778
EU	0.248485	0.003409	0	0.083333	0.118939
Brazil	0.091667	0.025505	0	0	0.045076
Indonesia	0.043182	0	0	0	0.02399

Mexico	0.075	0.235227	0	0.05303	0.106692
South Africa	0	0.025884	0	0	0.074495
Argentine	0.043939	0	0	0	0
India	0.20303	0.022096	0	0.034091	0.094318
Saudi Arabia	0.007576	0	0	0	0.085227
South Korea	0	0.039394	0.104545	0.098485	0.005682
Russia	0	0.018939	0	0.003788	0.308333
Turkey	0	0.017551	0	0.007576	0
China	0	0	0	0.007576	0.001894

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