THE CHANGING NETWORK OF FINANCIAL MARKET LINKAGES: THE ASIAN EXPERIENCE

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ABSTRACT

Recent international financial crises highlight the advantages of understanding the global financial system as a network of economies in which cross-border financial linkages are fundamental to the spread of systemic risk. We investigate the changing network of financial markets for six periods from 1995–2016, constructing a network that captures the concepts of the direction of links between markets, the significance of these links, and their strength. Emphasis is placed on the transition of the networks before and after the Asian financial crisis of 1997–1998 and the global financial crisis of 2008–2009. The analysis demonstrates the increase in interconnectedness during periods of stress and the fall in the number of links in postcrisis periods. At the same time, the results reveal a general deepening of the connections of the Asian market with the rest of the world over the past 2 decades. They also suggest that many of these markets have transitioned from being primarily linked to developed non-Asian markets through key bridge markets (such as Hong Kong, China) to developing stronger direct links with these external markets, highlighting the importance of key geographical nodes in market development.

Keywords: Asian markets, financial crises, network

JEL codes: G01, G10, G15

I. INTRODUCTION

Since the Asian financial crisis (AFC) of 1997–1998, Asian markets have become more central in global output production and investment, shifting the center of the financial world steadily eastward (Quah 2011). In the Bank for International Settlements' (BIS) April 2013 Triennial Central Bank Survey, transactions between the Chinese yuan and United States (US) dollar alone accounted for 2.1% of recorded foreign exchange transactions—up from a nonexistent presence in a 1998 survey. In 2016, one-third of the top 15 equity markets by market capitalization were in Asia: in order, Japan; the People's Republic of China (PRC); Hong Kong, China; India; and Australia.

This growing international presence and market development suggests considerable change in the network of financial linkages between countries and regions. This paper examines the development of the Asian markets using new ways of analyzing financial interconnectedness, particularly through network finance, which facilitates clearer understanding of how financial stress transmits between markets.

Theoretical frameworks which support network structures as at least partly responsible for the transmission of financial shocks include Allen and Babus (2009); Gai and Kapadia (2010); and Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015). Data-based empirical work (as opposed to simulations) on the extent and changing nature of global financial networks has since appeared in Billio et al. (2012), Merton et al. (2013), Giraitis et al. (2016), and Diebold and Yilmaz (2015). The inclusion of Asian markets in these networks is less common, although recent literature includes Dungey, Harvey, and Volkov (2017); Giudici and Spelta (2016); Demirer et al. (2015); Wang, Xie, and Stanley (2018); and Raddant and Kenett (2016).

The paper focuses on 1995–2016, a 21-year period covering both the global financial crisis (GFC) and the AFC, and examines the transmission of shocks to market returns between 42 equity markets, divided into five regions (Africa, Asia and the Pacific, Europe, Latin America, and North America, see Table 1 for more detail).[1]

In that 21 years—in addition to increasing global financialization and financial liberalization and the deepening of many markets—markets have experienced several periods of financial crises.

We divide the sample into six distinct periods:

(i) Lead-up to the AFC (3 January 1995–1 July 1997)
(ii) AFC (2 July 1997–31 December 1998)
(iii) Post-AFC (1 January 1999–31 December 2002)
(iv) Lead-up to the GFC (1 January 2003–14 September 2008)
(v) GFC (15 September 2008–31 March 2010)
(vi) Post-GFC (1 April 2010–30 December 2016)

[1] The Asian markets include Australia; Hong Kong, China; India; Indonesia; Japan; Malaysia; New Zealand; Pakistan; the People's Republic of China; the Philippines; the Republic of Korea; Singapore; Sri Lanka; Taipei,China; and Thailand.

Table 1: Markets Grouped by Region

Europe		Asia and the Pacific		Africa		North America		Latin America	
Austria	AUT	Australia	AUS	Egypt	EGY	Canada	CAN	Argentina	ARG
Belgium	BEL	Hong Kong, China	HKG	South Africa	ZAF	United States	USA	Brazil	BRA
Czech Republic	CHL	India	IND					Chile	CHL
Denmark	DEN	Indonesia	INO					Mexico	MEX
Finland	FIN	Japan	JPN						
France	FRA	Malaysia	MAL						
Germany	GER	New Zealand	NZL						
Greece	GRC	Pakistan	PAK						
Hungary	HUN	People's Republic of China	PRC						
Ireland	IRE	Philippines	PHI						
Italy	ITA	Republic of Korea	KOR						
Netherlands	NET	Singapore	SIN						
Poland	POL	Sri Lanka	SRI						
Portugal	POR	Taipei,China	TAP						
Spain	SPA	Thailand	THA						
Sweden	SWE								
Switzerland	SWI								
Turkey	TUR								
United Kingdom	UKG								

Sources: Data from Bloomberg and Datastream (accessed February 2017).

Note that although we are most clearly able to define the lead-up and crisis periods, in each case the postcrisis period contains ongoing crises in other regions or asset markets of the world—the post-AFC period includes the dotcom crisis in the US and a number of South American problems (see Dungey et al. [2010]), while the post-GFC period includes the significant problems in the European sovereign debt markets. We consider both the statistical significance of the potentially changing linkages, their direction, and how they change across periods.

Our empirical application uses data from equity markets. The choice of dataset is controversial in the literature—much of the existing theory revolves around formal bank balance sheet flows. However, there are good reasons to consider links between the prices expressed in other markets. First, the market prices represent market sentiment, even where this may be a misrepresentation of the underlying conditions (such as in bubbles).

Second, as shown in Pesaran and Yang (2016), a system of interconnected quantities—such as flows of goods between firms—can also be expressed in terms of an equivalent form in prices, known in economics as its dual. The form in prices provides a convenient transformation of theories for network connections constructed around financial flows to a more empirically tractable specification expressed in prices.

Finally, there is genuine concern that concentrating analysis on policies to change networks in one specific arena—such as bank liabilities—is likely to simply force shock transmissions into networks that exist in other markets. For example, equity-market linkages are likely to be heightened in the presence of policy initiatives, such as 2016's "Minneapolis Plan to End Too Big to Fail" from the Federal Reserve Bank of Minneapolis, which focuses on absorbing losses in equity markets. If shocks are to be primarily distributed through equity markets, as opposed to increasing debt market financing during periods of stress, then equity markets are likely to become even more important in transmitting stress than in previous periods.

An important contribution from network finance to the management of systemic risk and financial monitoring is the potential to improve the transparency of highly complex systems which make up the both domestic and international financial sectors (see Haldane [2009] and Yellen [2013], for example, and Hughes and Malone [2016] for an industry perspective). Improving understanding of network dynamics may help calm shocks.

If policy makers and actors in the system can anticipate how a network will change when under stress, then perhaps the network can remain "robust" rather than "fragile" when faced with a crisis-triggering shock. Hüser (2015) posits a direct link with the empirical features of robust-but-fragile networks; robust networks can weather random shocks, but when there is a core to the network, direct threats to the core lead to network fragility. Network methods can be used to identify and monitor nodes that are particularly important in spreading shocks. Nodes that build critical bridges between regions may be super-spreaders or super-absorbers and are each important to the policy maker. Critical bridges (or gatekeepers) represent the case where a node forms a link between major groups of markets, where there are relatively few (or no) other pathways that can be easily substituted. The loss of a critical bridge may lead to isolation of part of the network and reduce the ability to absorb or contain shocks. That is, it matters where in the network a shock occurs.

Systemic risk is associated with both too-big-to-fail and too-interconnected-to-fail hypotheses in the literature. There is some debate as to which of these may be more important. For example, Hughes and Malone (2016) prefer to focus on interconnectedness, but most research recognizes that they are two distinct and important effects. The current BIS rules for identifying global systemically important banks include measures to incorporate both effects. Proposals such as the Minneapolis Plan (2016) place the emphasis on equity capital, reasoning that smaller interconnected firms will be more easily managed (presumably the network is closer to random).

Knowledge of the topography of a network will help to provide recommendations for targeted intervention. The strategic intervention in markets to isolate (or inoculate) a particular node may dramatically improve outcomes for the whole system (Hüser 2015). While a random network may have a lower propensity to fail, it may also cascade more dramatically when stressed.

A policy maker will also wish to know the depth of the linkages through which shocks permeate. Currently, the evidence on the average length of "paths" is mixed. Haldane (2009) suggests long paths for interbank transactions, while Gençay et al. (2015) suggest that paths for each node are mainly of degree one (that is, only immediate neighbors). Understanding this is critical to designing appropriate policy actions. For example, short paths for nonsuper-spreaders may be of little importance for systemic risk. Whereas super-spreaders with long tails would be of considerable concern. The paper examines the evidence for super-spreaders and super-absorbers which may mitigate the effects of shocks on others, acting as a form of insurer.

A number of recommended changes to market regulation involve modifying networks in a way that mitigates their complexity and, potentially, dimension (see Haldane [2009]). To even begin to discuss this proposal requires a means of understanding and measuring network performance and characteristics, and the identification of critical links (and potential dominant nodes in the meaning of Pesaran and Yang [2016]).[2] Identifying critical links and dominant nodes will provide a structure so that policy makers can focus their attention on considering how to mitigate systemic risk. However, the risks of altering the topology of one network—and the literature largely focuses on banking and financial institutions—through regulation and monitoring are that the sources of stress may simply shift to another part of the financial system. Arregui et al. (2013) highlight the introduction of tougher capital controls as a risk in exacerbating transmissions in the sovereign debt–bank network; for evidence of these spirals see Dungey, Harvey, and Volkov (2017). Rather than adding to the requirements for large institutions, Markose, Giansante, and Shaghaghi (2012) suggest a tax on super-spreaders, emphasizing the role of interconnectedness. Calls to reduce banks' dependence on raising debt during periods of stress and instead relying on equity market funding, as in the Minneapolis Plan (2016), may well, similarly, heighten transmission in international equity markets.

In reality, the complexity of the financial system is such that multilayered networks are required to capture the many potential forms that links between nodes may take. This field is in its infancy, but Aldasoro and Alves (2017) is a recent application for European banks. Multilayered networks have so far considered multiple balance sheet measures of links between financial institutions but can contribute to the debate in the literature on whether contingent claims or balance sheet data are substitutes or complements for market-based data in understanding network structures. The arguments against market-based data are that this approach omits nonlisted institutions and does not pick up market mispricing (see Arregui et al. [2013]). Rather than ruling out one to justify the other, as in much of the current literature, it is likely that both are informative and that the use of multilayer approaches will enable a richer analysis.

In summary, network analysis may contribute to policy decision making in the following ways:

(i) Improve the transparency of complex systems.
(ii) Identify features of the system (such as centrality, critical nodes).
(iii) Identify too-interconnected-to-fail nodes.
(iv) Provide guidance on where interventions may usefully be applied.
(v) Provide guidance on reducing complexity.
(vi) Consider multilayer interactions and multiple data sources and types.
(vii) Consider the consequences of regulation designed for one network flowing to others.

We find distinct evidence of complex and changing networks over time. The results show that there are clear networks within the Asian region, and between the Asian region and other regional clusters. In this way, the results mirror those of Wang, Xie, and Stanley (2018), which examine a correlation-based network between 57 international equity markets and find distinct evidence of regions.

Both papers find evidence of critical linkages between Asia and the rest of the world's equity markets; consequently, the second half of this paper shifts the focus to the role of markets that act as critical bridges between the region and the rest of the world, and how this has evolved over time. The

[2] Currently, the methodology in Pesaran and Yang (2016) does not simply transform financial markets, due to several structural assumptions in the formation of the dual function. Dominant nodes are similar to nodes that may be both super-absorbers and super-spreaders.

role of the bridge market may be critical to the development of emerging markets, although we show that not all markets choose to go this way.

We categorize the risks for markets in seeking to either find a bridge market to ease the information asymmetry between the global markets and an emerging market, or to choose the role of a bridge market. The empirical evidence from the past 20 years provides instances of markets which seem to have benefited from a relationship with a regional bridge market, those which have chosen not to use a regional bridge but to concentrate on directly accessing the global network, those which have chosen to become a bridge, and what takes place in each of these scenarios during periods of financial stress. Clear advantages exist to protecting emerging markets from crises if they are sheltered behind a regional node, as policy makers can concentrate on protecting that critical link to international markets. Disadvantages to this model may also exist, such as managing the transition to direct integration, and the potential cost to the bridge node of being caught in a crisis not of its own making. Policy makers in each market and region need to weigh the relative risks of each strategy. The next step in this agenda must be to formally test the hypothesis that naturally arises from these results about which of the strategies has the best outcomes for global and regional growth and economic catch-up by less developed economies.

II. LITERATURE REVIEW

The literature on measurement of systemic risk in financial institutions is extensive. Institution-level systemic risk may be thought of either as a financial institution's contribution to the overall systemic risk of the financial system or as the institution's exposure to the overall systemic risk of the financial system. Aggregate systemic risk may also be estimated by calculating the likelihood of a systemwide systemic crisis. Bisias et al. (2012) comprehensively survey systemic-risk measures.

One approach to estimating the impact of individual institutions on aggregate systemic risk uses tail events. For example, the CAViaR model of Engle and Manganelli (2004) and the CoVaR model of Adrian and Brunnermeier (2016). Acharya et al. (2017) propose the "marginal expected shortfall" as the expected losses of an institution when the system as a whole is in distress (marginal expected shortfall can be interpreted as the per dollar systemic risk contribution of this institution). The NYU Stern VLAB project maintains SRISK measures using a weighted average of the institution's marginal expected shortfall and its leverage (Acharya et al. 2017, Brownlees and Engle 2017). Allen, Bali, and Tang (2012) estimate an aggregate systemic-risk measure that incorporates both "variance at risk" and expected shortfall methodologies. They show that their method is bank specific, and that the ability of their indicator to predict crises is contained within the financial institutions data and does not extend to nonfinancial firms.

The contribution of a firm to systemic risk may be measured as either the value of the cooperation of the firm in the system—Tarashev, Borio, and Tsatsaronis (2010) estimate systemic risk contribution by calculating the Shapley value of a financial institution—or, more commonly, the loss of the system due to an institutional default.[3] Chan-Lau (2010) estimates the difference between the aggregate loss distribution of the financial system when a financial institution defaults and the aggregate loss distribution of the financial system when a financial institution is solvent and creates a capital charge for institutions which are deemed "too-connected-to-fail." A related concept is the

[3] The Shapley value comes from game theory and indicates the value of an entity in achieving a cooperative solution. This is extended to the concept of contribution to systemic risk in this paper.

insurance premium for the case of a systemwide tail event, estimated as the Distress Insurance Premium by Huang, Zhou, and Zhu (2012). The systemic risk contribution of a financial institution is then the marginal contribution of the financial institution to the overall risk premium. Capuano (2008) estimates the “option implied probability of default,” which estimates the default probability of the financial system using equity-option data. Segoviano Basurto and Goodhart (2009) estimate a systemic-risk measure that utilizes the system's multivariate density function and allows for the calculation of the distress contributed to the system by a single financial institution, as well as distress between banks. Finally, Giglio (2011) derives a system default probability based on credit default swap data.

Aggregate systemic risk may also be estimated using stress test methodologies as practiced by a number of central banks and international regulators; see BIS (2009). Duffie (2013) advises regulators to concentrate on important financial institutions and their reactions to different stress scenarios. For each situation, a financial institution calculates the profit or loss on its positions for each counterparty to which it has the largest exposure, relative to all other counterparties. Alternatively, Alfaro and Drehmann (2009) propose modeling stress around gross domestic product (GDP) shocks. This method models GDP growth as an autoregressive process, as the authors note that GDP growth typically drops prior to a banking crisis.

Another set of methods estimates aggregate systemic risk by measuring the illiquidity of financial institutions. Hu, Pan, and Wang (2013) examine arbitrage capital in the market and its effect on the price differences of US Treasuries. During crises, less arbitrage capital is available, and yields on Treasuries are more volatile. Khandani and Lo (2011) measure the liquidity of equity markets using the profitability of buying losers and selling winners. When this method is more profitable, the markets are less liquid. They also examine changes in the Kyle (1985) lambda, which calculates the volume required to move the price of a given stock by $1. Finally, another set of measures examines hedge funds, including that in Getmansky, Lo, and Makarov (2004); Chan et al. (2005, 2006); and Pojarliev and Levich (2011). Each of these measures uses hedge fund data to examine the liquidity of financial markets.

Another stream of literature uses some form of balance sheet analysis; including contingent claims, as in Lehar (2005); Gray, Merton, and Bodie (2007); and Gray and Jobst (2011), and the interbank market in Giraitis et al. (2016). Fender and McGuire (2010) focus on group-level balance sheet risk and how cross-border linkages of financial institutions can create shocks from one country to another. There is strong cross-over between the approaches of these papers and those directly in the network finance literature.

Finally, a growing body of literature examines aggregate systemic-risk measures through network connections. The theoretical network literature is large, but recently Acemoglu et al. (2015) have provided a modeling framework to motivate the relationships between financial institutions and real economy firms in the form of networks, and Diebold and Yılmaz (2014) have shown the mapping between the network approach and vector autoregression methods. Chan-Lau, Espinosa, and Solé (2009) examine the network externalities of bank failures through a matrix of between-institution exposures. Simulations calculate the effect on the financial system of a bank's default, allowing designation of systemically important financial institutions. Billio et al. (2012) propose a principal components analysis method to augment bivariate network links established through Granger causality. Principal component analysis is used to extract the commonality of returns among financial institutions, and increases in this value are associated with increasing systemic risk. Kritzman et al.

(2011) also use a principal component analysis methodology to estimate the common components of systemic distress. Network analysis techniques are being rapidly adopted from areas such as biology and computational science, including the use of the PageRank algorithm, which powers internet search engines, in Dungey, Luciani, and Veredas (2018) and van de Leur, Lucas, and Seeger (2017), and spanning trees in Anufriev and Panchenko (2015).

The closest current works to this paper that include Asian markets are Wang, Xie, and Stanley (2018), who examine connectedness between 57 global markets from 2005–2014, and Raddant and Kenett (2016), who consider a network of stocks across 15 countries, including six from our focus group of Asian markets. Raddant and Kenett (2016) find that Asia is relatively disconnected from the rest of the world markets and while country-based nodes are formed there is little evidence of a regional cluster (ultimately we find this is unsurprising given their choice of Asian markets). Wang, Xie, and Stanley (2018) use a spanning tree approach and find that Japan forms a critical bridge node to the rest of Asia, consistent with our findings below for the later part of our sample.

III. NETWORK MEASURES AND APPROACH

This paper contributes a new way of examining the changes in financial networks over time. We test for changes in the existence, number, and strength of links between financial markets. The results show the developing profile of Asian financial markets in a global network over a 20-year period containing two important periods of crisis. We compare the evolution of the network before, during, and after two different crises (AFC in 1997–1998 and GFC in 2008–2009) and provide statistical evidence based on weighted networks and Jaccard similarity coefficients to assess the impact of the crises along with the increasing interconnectedness of Asian markets. Our focus on evidence for the changing number and strengths of links (or edges) between the nodes (equity markets) in the network differentiates the work from those which focus exclusively on the net change in the number of statistically significant links, such as Billio et al. (2012) or solely on the strength (but not statistical significance) of the linkages, such as Diebold and Yilmaz (2014, 2015).

Our approach extends existing work by implementing an adjacency matrix which incorporates the spillover strengths filtered by the statistical significance of the links. In this way, we omit spuriously large but insignificant links. We consider not only the net change in links between nodes, but also the evolution of the Jaccard similarity coefficient, which provides information on the number of retained links between sample periods. The changing nature of the network leads us to consider not only the degrees and centrality measures of the networks, but also to an analysis of the number and strength of links that are extinguished and those that are formed. For example, in terms of the weighted completeness of the network, a result that may at first appear as a net increase in links may in fact represent a reduction in strong linkages and proliferation of weaker links.

Our approach embeds existing definitions of contagion within a network representation of systemic risk. In particular, when links fail between nodes during periods of stress, this is evidence of the form of contagion proposed in Gai and Kapadia (2010), when the breakdown of the network results from contagion due to failing counterparty arrangements. Alternatively, when new links are formed between nodes during periods of stress, this increases the number of connections, akin to the traditional Forbes and Rigobon (2002) definition of markets becoming more interconnected during crises. To date, the literature finds evidence of both of these contagion routes but does not effectively reconcile them into a single framework. That is the aim of this background paper.

The paper draws on the methodological approaches developed in Dungey, Harvey, and Volkov (2017) in developing a network of financial linkages between nodes (represented by country index equity market data) where the links between them (edges) are determined by an adjacency matrix, which includes both the direction and strength of those links and a measure of their statistical significance. The relative strengths of the links is determined by using the Diebold and Yilmaz (DY) (2009, 2014) forecast error variance decomposition approach—whereby the sources of observed volatility in each return are attributed to shocks in source nodes. The DY approach has the advantage of allowing the researcher to vary the horizon of shock examined. We couple this with the Granger-causality approach of authors such as Billio et al. (2012) who consider the statistical power of the existence of links between nodes. If one node Granger-causes the other at a statistically significant level (selected by the researcher) then this link is indicated as existing in the network. If the Granger causality is not significant, then the link is nonexistent. In this way, we use the Granger-causality approach to weed the spuriously large (poorly estimated) linkages from the adjacency matrix provided by the DY approach. It combines measures of existence, direction, and size of the edges.

Methodology

To measure the connectedness between entities, we identify statistically significant relations among them by applying Granger-causality tests to establish the edges of the network nodes. The directionality of the relationships is found from these tests. Granger-causality tests suggest causality if past values of one time series, Y_i, stock return series in our case, contain information that help forecast another return series, Y_s.

These causality links can be assessed using a vector autoregression

$$Y_t = c + \sum_{j=1}^{p} \Phi_j Y_{t-j} + \varepsilon_t \tag{1}$$

where p is the number of lags, and Φ_j and c are parameters of the model. The Wald statistic to test for Granger causality between stock returns has the form:

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

in which Y is the matrix of independent variables from (1), $vec(\widehat{\Pi})$ denotes the row vectorised coefficients of $\widehat{\Pi} = [\Phi_1, \dots, \Phi_k]$, $\hat{V} = T^{-1} \sum_{t=1}^{T} \widehat{\varepsilon_t}\, \widehat{\varepsilon'_t}$ and e is the $k \times 2(2k+1)$ selection matrix defined as

$$e = \begin{bmatrix} 0 & 1 & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & 1 & \cdots & 0 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 1 & \cdots & 0 & 0 & \cdots & 0 & 0 \end{bmatrix} \tag{3}$$

Each row of e picks one of the coefficients to set to zero under the noncausal hypothesis $Y_i \to Y_s$. Then, Granger-causality test results can be summarized as binary entries of matrix

$$A = [a_{ij}] \tag{4}$$

where,

$$a_{ij} = \begin{cases} 0, if\ Y_i\ does\ not\ Granger\ cause\ Y_j \\ 1, if\ Y_i\ Granger\ causes\ Y_j \end{cases} \tag{5}$$

The direction of the edges is only one aspect of the relationship between entities in the network. Another important aspect is the strength of the relationship, which we examine by assigning weights, W_{ij}, to each of the significant relationships existing in the network. We use the Diebold and Yilmaz (2009) framework of a generalized variance decomposition to obtain these weights and to obtain the weight matrix $W_{ij} = \left[w_{ij} \right]$. The spillover measure is based on forecast error variance decompositions. Suppose that the contribution of shocks to variable *j* to the *H* step ahead generalized forecast error variance of entity i, $\theta_{ij}^{g}(H)$, is represented by

$$\theta_{ig}^{g}(H) = \frac{V_{jj}^{-1} \sum_{h=0}^{H-1} \left(e'_i B_h V e_j\right)^2}{\sum_{h=0}^{H-1} \left(e'_i B_h V B'_h e_j\right)} \tag{6}$$

where, *H* = 1, 2, 3,..., and *V* is the variance covariance matrix for the error term ε_t, V_{jj} is the standard deviation of the *j* 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 $B_i = \phi_1 B_{i-1} + \phi_2 B_{i-2} + \cdots + \phi_k B_{i-k}$ with B_0 an $n \times n$ identity matrix and $B_i = 0$ for $i < 0$. Each entry of the generalized variance decomposition is normalized by the row sum as

$$w_{ij} = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{n} \theta_{ij}^{g}(H)} \tag{7}$$

where $\sum_{j=1}^{n} w_{ij} = 1$ and $\sum_{ij=1}^{n} = n$. We denote the values defined in (7) as DY weights.

The structure of the weighted network can be defined by combining matrices *A* and *W*. As a result, the adjacency matrix $\tilde{A}$ is defined as

$$\tilde{A} = A \odot W \tag{8}$$

where $\odot$ is the Hadamard product. Elements of adjacency matrix $\tilde{A}$ capture the connectedness between entities conditional on significant causal linkages between them. Henceforth, we will call them GDY weights. The systemwide completeness of the network is measured as

$$C = \frac{\sum_{i,j=1_{i \neq j}}^{n} \tilde{a}_{ij}}{\sum_{i,j=1_{i \neq j}}^{n} w_{ij}} \tag{9}$$

in case of a large shock in any part of the network.

Interest in this paper centers on the changing nature of the network over the sample period. In particular, the adjacency matrix may change due to changes in the weight matrix, *W*, and/or the significant entries in the matrix *A*. The changes in the *A* matrix link the specification directly to the literature assessing links during crises; for example Granger, Huang, and Yang (2000) assess changing Granger-causality links in the Asian markets between 1986 and 1998 . To illustrate how this may apply in the current framework, consider the example of linkages between a pair of assets in a two-node example (we stress that this is for illustrative purposes—the Granger-causality relationships used in the empirical application are drawn from the vector autoregression model of the entire system with a Wald test approach as outlined in equations [2] to [3]). Consider a bivariate vector autoregression with one lag between Y_{1t} and Y_{2t}

$$Y_{1t} = c_1 + \vartheta_{11} Y_{1t-1} + \vartheta_{12} Y_{2t-1} + \varepsilon_{1t} \tag{10}$$

$$Y_{2t} = c_2 + \vartheta_{21} Y_{1t-1} + \vartheta_{22} Y_{2t-1} + \varepsilon_{2t} \tag{11}$$

which can be compactly written in matrix form as

$$Y_t = c + \Theta Y_{t-1} + \varepsilon_t \tag{12}$$

where Y_t is the vector $[Y_{1t}\ Y_{2t}]'$, c is the 2x1 vector of constants, Θ is the 2x2 matrix of coefficients and ε_t is the 2x1 vector of residuals.

The Granger-causality test is essentially a test of significance of the off-diagonal elements of the coefficient matrix in (12). That is, whether ϑ_{12} and/or ϑ_{21} are nonzero. To extend this to evidence for contagion and the changing nature of networks, we may consider comparing these coefficients across two sample periods. 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.

We use the Jaccard similarity coefficient to examine just how many of the edges identified in each subsample are retained between samples. Papers such as Billio et al. (2012) are concerned only with the net formation of new links, but we find that it is important to consider the gross movements to obtain a clearer picture. The Jaccard similarity coefficient considers what portion of the edges in two networks are formed by the same edges, and is formed as a ratio of the intersection of the sets of links in two networks, *Q* and *R*, to the union of the sets of links in two networks as follows:

$$J(Q,R) = \frac{n(Q \cap R)}{n(Q \cup R)} = \frac{n(Q \cap R)}{n(Q) + n(R) - n(Q \cap R)} \tag{13}$$

When the statistically significant links in *A* are weighted by DY weights, it is possible that the *W* matrix may change between periods. In this way the completeness of the network (as per equation [9]) may change, either due to changes in the number of links, and/or changes in the relative strength of those links. As we will show, this effect seems to be important in distinguishing the nature of the evolving network and seems to be particularly the case in understanding the transition from the build-up to a crisis and the crisis itself.

IV. DATA AND STYLIZED FACTS

The dataset includes 15 Asian daily equity market indices (in local currencies) for 1995–2016 from Bloomberg. These are augmented by the daily (closing) equity market indices for 27 other economies, all listed by region in Table 1. Unit root tests reveal the usual characteristics of stationary returns in each series. The analysis is conducted using demeaned returns (as the mean is usually extremely close to zero and, as we are focused on variance decompositions, this assumption is innocuous). Analysis of the complete network, consisting of 42 nodes, forms the initial benchmark for the study.

To construct our network, we use the data with its recorded closing time date. The choice of time zone treatment can have dramatic effects, no one choice is dominant due to the complications of wanting to test for two-way causality. Other researchers have used the dates as provided with the data (Wang, Xie, and Stanley 2018), averaged data over consecutive days (Forbes and Rigobon 2002) or used time-matched data series (Kleimeier, Lehnert, and Verschoor 2008). Although the last of these is arguably the most appropriate, it is difficult to obtain this data for the markets examined here and to control for problems associated with out-of-local trading time liquidity effects (most markets have different price-impact effects during local and nonlocal trading). The averaging procedure used by Forbes and Rigobon (2002) clearly introduces a moving average bias into the problem, and, with Granger-causality testing, produces additional problems with the performance of the statistic. And the use of lagged or nonlagged samples is dogged by argument as to whether this introduces or reduces noise in the process. Sensitivity analysis to different choices of date-lagging produced important differences; the most pronounced of these is that when US data are lagged there is virtually no evidence of transmission from the US to Asia, which seems at odds with our understanding of international financial markets and the transmission of shocks. Consequently, this paper uses the convention of actual day dating in its analysis.

We first proceed to examine the evolution of the unweighted and weighted networks over the sample period and then to augment this analysis with scenarios based around alternative clusterings of markets, as per the Asian Development Bank member countries and the role of regional groupings including the Association of Southeast Asian Nations (ASEAN) with other regions across the globe.

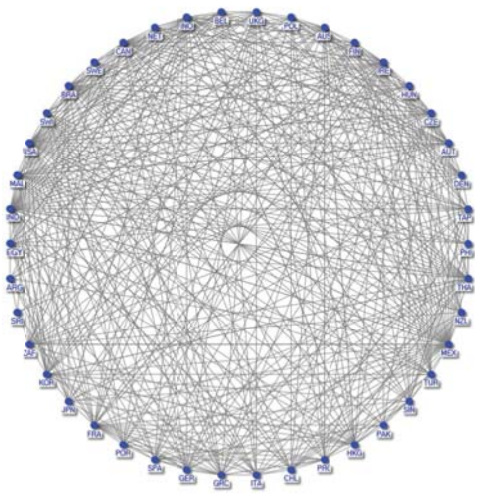
V. RESULTS AND ANALYSIS

Panel A of Figure 1 shows the statistically significant links between each of the country nodes in the sample using just the Granger-causality test results over the entire sample period (1995–2016). It immediately points to the complexity of the relationships between nodes—there are 1,722 ($= 42!/40!$) possible connections between the nodes. It is evident that the markets involved are heavily interconnected, but it is difficult analytically to say more from this diagram.

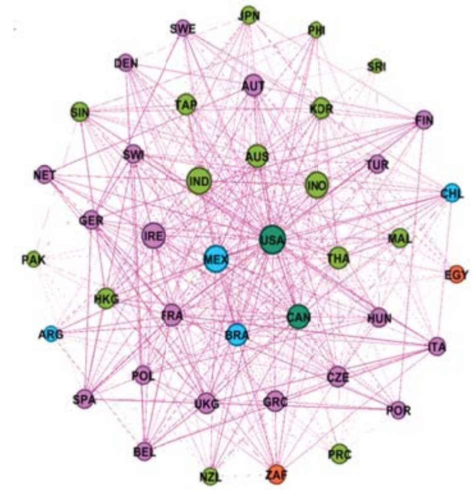
In panel B of Figure 1, the unweighted network is represented with the Granger-causality results grouped regionally (using the groupings in Table 1). The primary focus of this paper is the Asian economies, which are represented in light green, primarily to the left of the figure. The sizes of each node reflect the number of links in and out of that node—for example, it is evident that the US has many connections over the sample period.

Figure 1: Evolution of Network Plots for Entire Sample with Different Network Modeling Choices

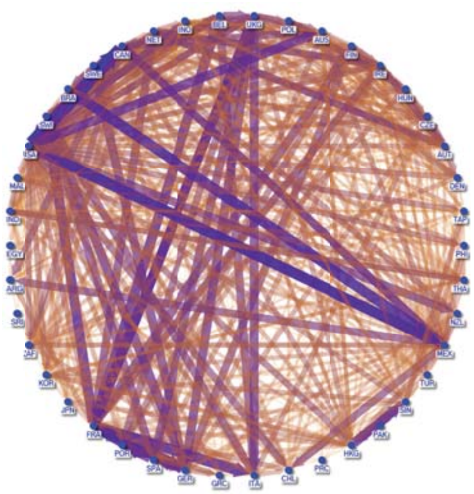
A. Unweighted circle plot



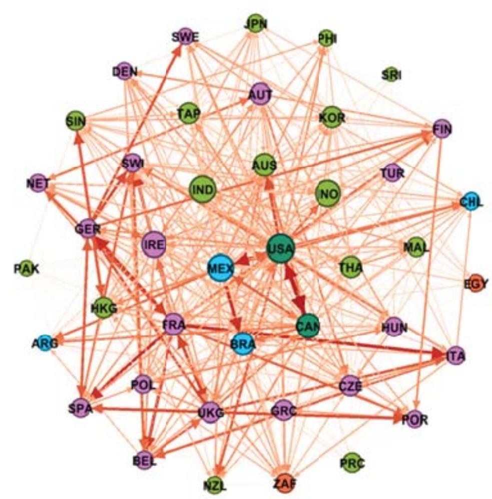
B. Unweighted with regions indicated



A. Weighted circle plot



B. Weighted with regions indicated



Notes: Sample period is from 1 March 1995–30 December 2016. Regions are color-coded as Africa (orange), Asia (light green), Europe (magenta), North America (dark green), South America (blue). Regional groupings and country codes are defined in Table 1. The figure displays the returns-based network of 42 equity markets. Edges were calculated using bivariate Granger-causality tests between markets at the 5% level of significance.
Sources: Data from Bloomberg and Datastream (accessed February 2017).

The methodological section of the paper showed how we augment these simple directional graphs with weights drawn from the DY method to obtain a weighted directional network of the nodes. Panels C and D of Figure 1 provide the weighted network equivalents of panels A and B of Figure 1. It identifies both the nodes with the largest connections and with statistically significant links. Some nodes are relatively isolated—in this picture, Pakistan is a relatively isolated node, while Sri Lanka is an end node (that is, it is joined by only a few edges to other nodes in the system). The diagram also illustrates the clear, relatively strong significance of the relationships between the European markets in the sample, particularly those which are members of the euro area. The linkages between the markets are also directional, as given by the arrows at the ends of each edge—while some are double-ended, implying Granger causality in both directions (such as Hong Kong, China and Singapore), others are not (the link between Thailand and Malaysia is shown running in one direction only).

The thickness of the lines in panels C and D indicates the relative strength as well as statistical significance of the links. Thus, it is immediately evident that the US and France are strongly connected to others (a similar role for France is found in Wang, Xie, and Stanley [2018]). Within the Asian focus of this paper there are clearly strong links between Hong Kong, China and the US, and slightly less so for Hong Kong, China and Canada. Hong Kong, China is also strongly linked to Malaysia and Singapore, as well as slightly less strongly to a raft of other economies. Other distinctly strong linkages occur between European countries such as Finland and Sweden, the United Kingdom and Italy, and so on. The links between the European countries are stronger (in DY weights) than those detected for most of the Asian economies, which is probably unsurprising as many of them were members of a common currency union for a large part of the sample period.

A distinct disadvantage of Figure 1 is the span of the sample covered. There have been many changes in world financial markets in this period—including the introduction of the euro; the float of many Asian currencies; increasing financialization of emerging markets in Africa, Asia, and South America; more liberated international capital markets; and capital deepening in many areas. In addition there have been several financial crises.

We consequently divide our sample into six subsample periods. Each of Figures 2–4 has panels A–F representing the networks in each of these six phases. The phases are selected based primarily on a desire to examine how the network of Asian markets has changed over the sample period. The sample periods are divided as represented in Table 2, Figure 2 illustrates the unweighted networks, with panels A–F corresponding to phases 1 to 6.

Table 2: Time Series Observation in Each Subsample Period

Phase	Period	Represents	Observations
All Phases	1 Mar 1995–30 Dec 2016		5,738
Phase 1	1 Mar 1995–1 Jul 1997	Pre-AFC period	650
Phase 2	2 Jul 1997–31 Dec 1998	AFC period	391
Phase 3	1 Jan 1999–31 Dec 2002	Post-AFC	1,042
Phase 4	1 Jan 2003–14 Sep 2008	Lead-up to the GFC	1,287
Phase 5	15 Sep 2008–31 Mar 2010	GFC	602
Phase 6	1 Apr 2010–30 Dec 2016	Post-IMF program approval in Greece	1,761

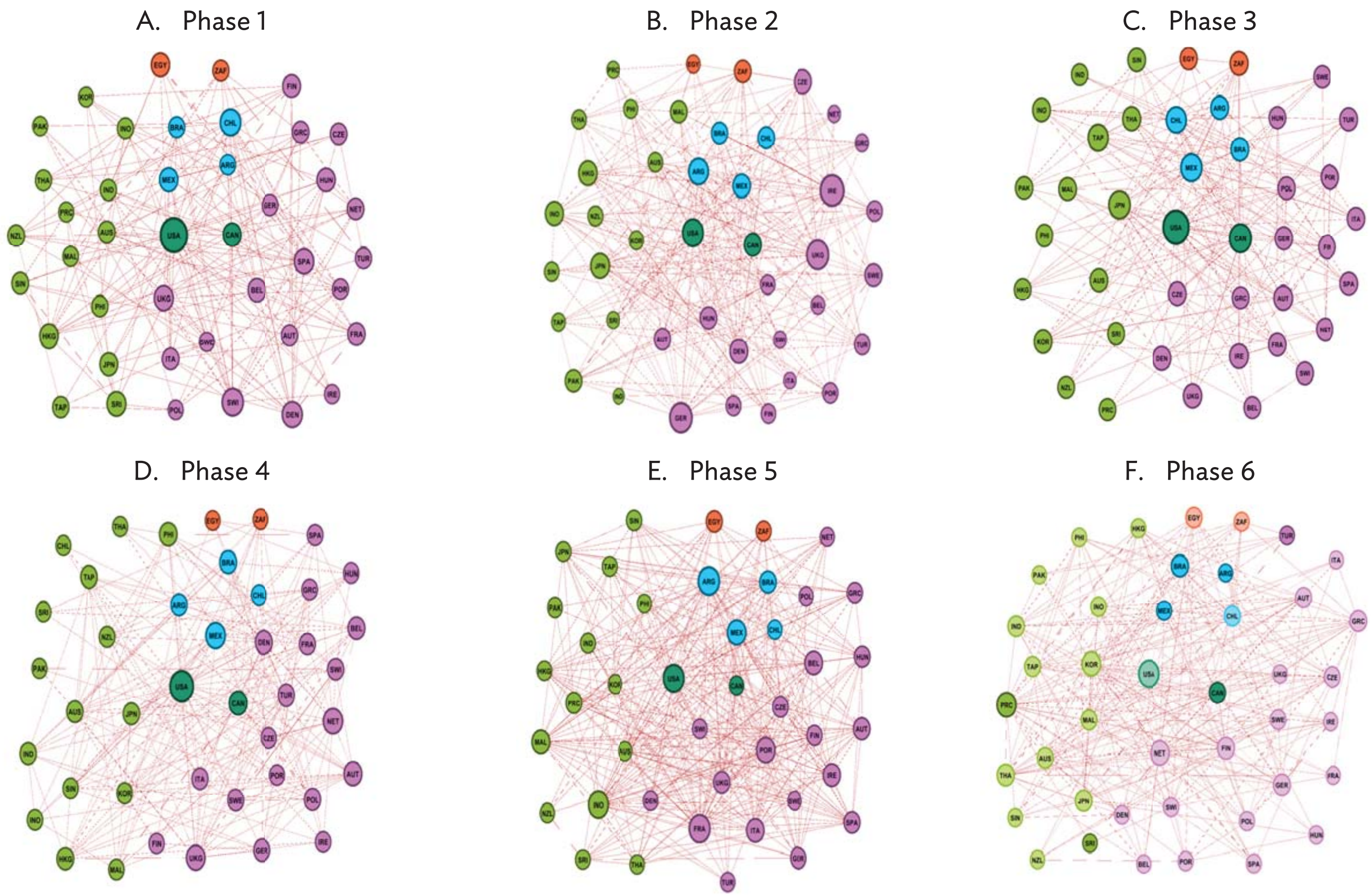
AFC = Asian financial crisis, GFC= global financial crisis, IMF= International Monetary Fund.
Sources: Data from Bloomberg and Datastream (accessed February 2017).

To avoid complications in naming our choice of periods in the literature, particularly for choosing end points of each sample, we refer to each of these subperiods simply as phases within the total sample. Table 2 indicates the number of time series observations in each subsample. The total number of observations in the whole sample is 5,738; in each subsample, the number of observations varies, with Phase 2 the lowest (391), and Phase 6 the highest (1,761). However, some of these phases strongly correspond with periods of interest.

Phase 1 represents the period in the lead-up to the Asian crisis of 1997–1998 and Phase 2 covers the generally accepted duration of that crisis (see Dungey, Fry, and Martin [2006]). Phase 4 covers the recognized lead-up to the GFC pre-2008, and Phase 5 the usual period of the GFC itself (see Dungey et al. [2015]). Consequently, Phases 1 and 4 both represent periods of lead-up to crisis, Phases 2 and 5 are periods of crisis, and Phases 3 and 6 are to some extent recovery periods, although this is clouded by the dotcom crisis in 2001 in Phase 3 and the stress in sovereign debt markets post-2010. Our area of interest is to examine not only the networks in those periods, but also the transitions which occur in these networks between the different phases. In this way, we will generalize about the number of characteristics of networks as they enter and exit crisis conditions. Our findings are reinforced by those for the large network (107 nodes) of credit default swap issuers examined in Dungey, Harvey, and Volkov (2017), even though market coverage in that paper was more specifically geared toward individual financial institutions and sovereign issuers rather than the equity market indicators used here.

The next stage of analysis is to examine the changing nature of the network over time, the importance of particular sources of shock, and a geographical examination of the relationship of non-Asia to the region and within Asia relationships.

Figure 2: Evolution of Unweighted Networks



Notes: Sample period is from 1 March 1995–30 December 2016. Regions are color-coded as Africa (orange), Asia (light green), Europe (magenta), North America (dark green), South America (blue). Regional groupings and country codes are defined in Table 1. The figure displays the returns-based network of 42 equity markets. Edges were calculated using bivariate Granger-causality tests between markets at the 5% level of significance.

Sources: Data from Bloomberg and Datastream (accessed February 2017).

A. Changing Network Links Over Time

Figures 3 and 4 illustrate the changing nature of the weighted financial network over the six phases defined in the previous section. Table 3 provides the associated network statistics which aid our analysis.

Table 3: Statistics Used for Analysis of Network Structures (All Countries)

Panel A

	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	Phase 6
Average strength	0.0260	0.0235	0.0236	0.0276	0.0260	0.0225
Number of edges	210	305	214	237	389	306
Completeness	0.2570	0.2252	0.1820	0.2034	0.2734	0.1990

Panel B

Edges Formed

Phase 1–Phase 2	Phase 2–Phase 3	Phase 3–Phase 4	Phase 4–Phase 5	Phase 5–Phase 6
0.0194	0.0169	0.0208	0.0225	0.0211
264	159	180	306	233
0.1608	0.0968	0.1163	0.1864	0.1424

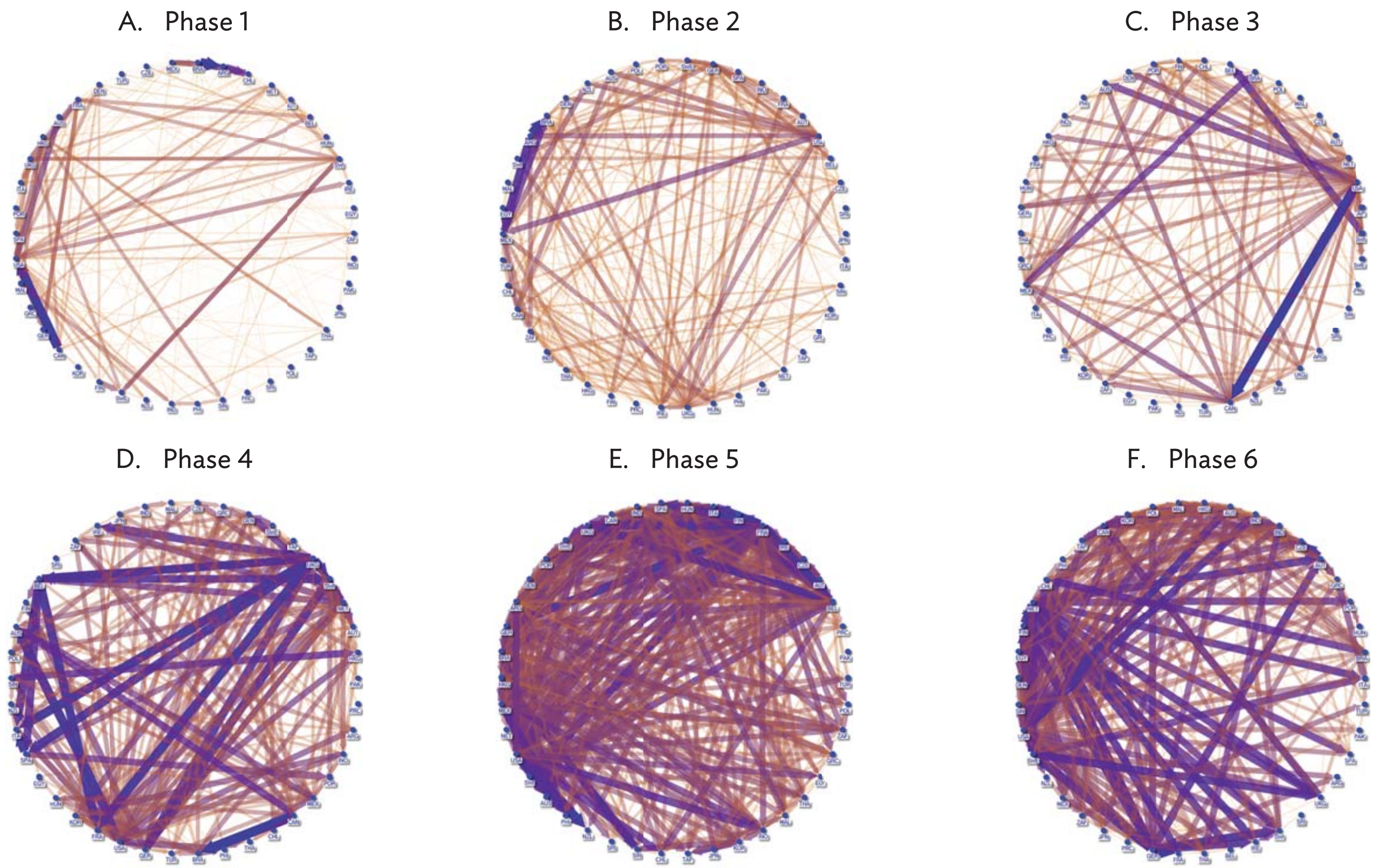
Edges Removed

Phase 1–Phase 2	Phase 2–Phase 3	Phase 3–Phase 4	Phase 4–Phase 5	Phase 5–Phase 6
0.0206	0.0196	0.0180	0.0207	0.0229
169	250	157	154	316
0.1640	0.1536	0.1020	0.0994	0.1957

Notes: The average link strength is estimated from the connectedness of each respective network. The number of edges was calculated using bivariate Granger-causality tests between network nodes (entities).
Sources: Data from Bloomberg and Datastream (accessed February 2017).

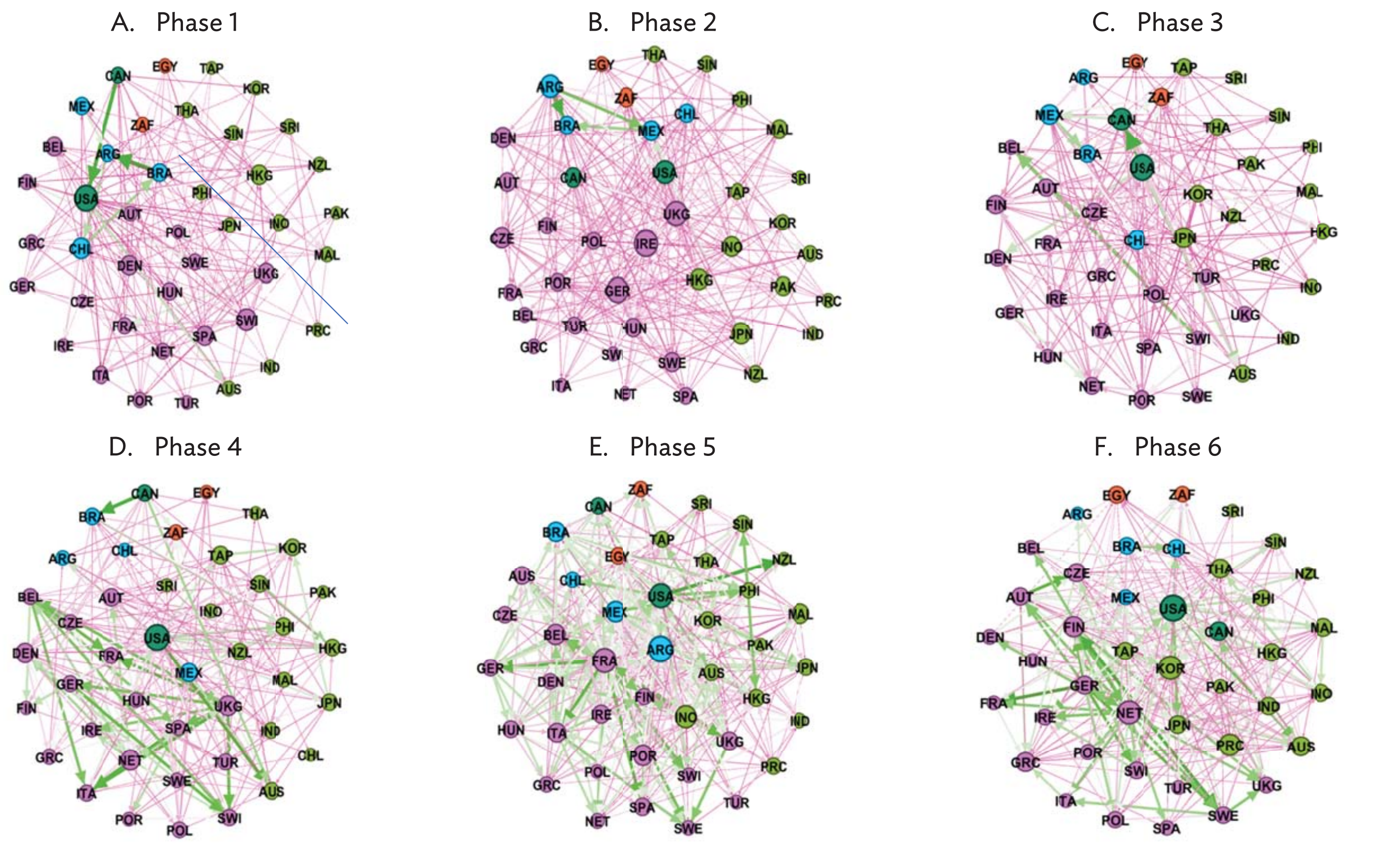
The first impression from panels A–B in each figure is that the density of the network has changed substantially over time. The figures give the impression of becoming darker and thicker—that is, more connected, in a similar manner to the changes noted by Billio et al. (2012) and Merton et al. (2013) for several forms of financial intermediaries in the US and European markets. However, Table 3 reveals that the number of statistically significant edges in the network has grown less monotonically than the panels may suggest. In Phase 1, 210 of the possible 1,722 linkages were statistically significant. This is only 12.2% of all the possible linkages. However, this number grew dramatically, by 45% to 305 links in Phase 2, before returning close to the precrisis period numbers in Phase 3. In Phase 4, the build-up to the GFC, the number of links increased in the system, up by 10%, but in Phase 5 the number of links jumped dramatically to 389, an increase of almost 65%. After that period, the links decreased again but remained at about the same level in Phase 6, as was evident in the crisis of 1997–1998.

Figure 3: Evolution of Weighted Networks



Notes: The figure displays the returns-based network of 42 equity markets from 1 March 1995–30 December 2016. Country codes are defined in Table 1. Edges were calculated using bivariate Granger-causality tests between markets at the 5% level of significance. The thickness of the lines indicates the average relative strength of each market.
Sources: Data from Bloomberg and Datastream (accessed February 2017).

Figure 4: Evolution of Weighted Networks with Regional Groupings



Notes: Sample period is from 1 March 1995–30 December 2016. Regions are color-coded as Africa (orange), Asia (light green), Europe (magenta), North America (dark green), South America (blue). Regional groupings and country codes are defined in Table 1. The figure displays the returns-based network of 42 equity markets. Edges were calculated using bivariate Granger-causality tests between markets at the 5% level of significance.

Sources: Data from Bloomberg and Datastream (accessed February 2017).

The Jaccard statistics, which compare the networks in a phase to that in the previous phase, summarize one aspect of the changing numbers of linkages (Table 4). The first row of Table 4 indicates the proportion of links that existed in the earlier period which were removed in the transition to the next period. The second row indicates the proportion of links which formed between the two phases as a proportion of the latest phase's links. In this way, we can see the composition of the elements of the Jaccard statistic listed in the third row of the column. The Jaccard statistics are low; that is, relatively few links are common between two phases. This is partly because the network is growing significantly in number of links over the sample period, with 45% more links in Phase 6 than Phase 1, and this growth results in a reduction in the Jaccard statistic by construction. The first two rows show that, in general, the network exhibits greater stability, in terms of the retention of edges, as time progresses. Setting aside the postcrisis period of Phase 6, it is apparent that the proportion of links lost during each of the sample shifts is falling, from 80% to 65%. The edges are becoming more likely to be retained over the sample period. The growth of the network is still apparent, however, in that the drop of the number of new links as a proportion of the total in each phase remains relatively more stable, at or over 75% of each phase.

Table 4: Jaccard Statistics for All Countries in the Sample
(%)

	Phases				
	1–2	2–3	3–4	4–5	5–6
Edges removed as proportion of Phase *t*-1	80.48	81.97	73.96	64.98	81.23
Edges formed as proportion of Phase *t*	86.56	74.30	75.95	78.66	76.14
Jaccard statistic for all edges	8.65	11.85	14.47	15.29	11.74

Sources: Data from Bloomberg and Datastream (accessed February 2017).

The transitions around the GFC period, involving Phase 5, paint a picture complementary to the analysis above. During Phase 5 a relatively lower proportion of existing links in Phase 4 have been retained, and the many that are formed during the crisis period are subsequently not retained in Phase 6. Thus, the crisis period sees an increase in density consistent with the high degree of net formation of new links, consistent with the dominance of the Forbes and Rigobon (2002) form of contagion.

The result of examining the transition from the build-up in precrisis to crisis period is that there is a rapid increase in the number of statistically significant edges in the network—supporting the idea that during periods of stress the markets become more interconnected. This is consistent with the literature finding considerable evidence of contagion.[4]

The average link is weaker in the crisis period than the lead-up to the crisis period. Panel B of Table 3 shows how this evolves. The top part of the panel describes the mechanism of formation of edges between each of the phases and the bottom section describes the edges removed. A relatively large number, on average, of weaker edges were formed (264 edges formed of average strength 0.0194) while a smaller number of stronger edges were removed (169 edges removed of average strength 0.0206). Dungey, Harvey, and Volkov (2017) observe declines in the average strength of the links between the periods leading up to the crisis and the crisis periods themselves for credit default swap markets.

[4] In our analysis, sample variances are separately controlled in the different phases, thus the changes in correlation are not a symptom of the changing variance. See Forbes and Rigobon (2002).

A similar pattern is observed in the transition between the pre-GFC period and the crisis itself in comparing the results for Phases 4 and 5. In this case, there were 306 links formed between Phase 4 and 5 and 154 links removed. That is, the number of links formed outweighs the number of links removed (and note that the total number of links recorded in Phase 5 was 389, so that a full 64% of the links in Phase 4 were removed in Phase 5). The Jaccard statistic for Phase 5 compared with Phase 4 is 11.74% (Table 4). The new links in this case were on average slightly stronger than those removed, and the completeness statistics for the network increase due to both higher average strength of the link and a higher number of links.[5]

The net change in the number of edges reported is not sufficient to characterize the changing nature of the network. Edges removed are just as important as edges formed in understanding the transmission of crises—these are both forms of contagion between markets. The complications of using completeness statistics to understand the evolution of a network are also revealed—completeness may fall due to increased number of edges being outweighed by the fall in their average strength as in the AFC example, or it may rise due to the overwhelming increase in the number of edges, which is the case for the GFC period. Knowing which edges are removed may be critical—for example, the collapse of Bear-Stearns in 2007. Policy makers will clearly wish to understand both the possibilities for removed edges and formed edges in periods of stress and have alternative plans available for each.

The postcrisis periods in the sample also reveal interesting contrasts. Both periods also include crisis periods in other parts of the network—in Phase 3, the dotcom crisis, and in Phase 6, the European debt crisis—making it difficult to classify these two periods as clearly postcrisis conditions. However, the transitions from the main crises of focus in this analysis are instructive. From Phase 2 to Phase 3, the number of links is reduced, as it is from Phase 5 to Phase 6. That is, after our main crisis period, the number of edges falls. In the first case, from Phase 2 to Phase 3, this is achieved by reducing the number of links (loss of 250 links and gain of only 159) and a lower average strength in the new links than those which are removed. These factors both contribute to a lower completeness statistic in Phase 3 than in the previous period. Similarly, in the transition from Phase 5 to Phase 6, more links are removed than formed. The links which are removed are stronger than those formed, contributing to a lower completeness statistic in Phase 6.

Identifying which of the links exist prior to a crisis, are lost during the crisis, and then reformed in the postcrisis period has policy implications. Were these linkage losses due to deliberate isolation of nodes or due to their vulnerability? To address this question more specifically we turn to the analysis of the links between nodes themselves.

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[5] The reason the average strength of links in panel A of Table 3 is lower in Phase 5 than Phase 4, but the formed edges between Phases 4 and 5 are stronger than the removed edges in panel B is that they represent slightly different options for calculation. Panel A gives the average strength as the sum of the weighted Granger links over the possible links. Panel B gives the removed strengths as the sum of the removed links weighted by the t-1 period weights over the changed number of links (that is, an incremental Granger matrix) and the formed strengths are given as the sum of the weighted links formed, weighted with the current period weights, over the sum of the formed links (that is, an incremental Granger matrix). Thus, in panel A the results are only about time t data, whereas panel B involves weights from both the previous and current periods. This accounts for the apparent analytical differences.

B. Changing Involvement of Nodes Over Time

As shown in Table 3, not only does the net number of linkages between nodes change between subperiods, but this also masks changes in the existence of specific linkages. Table 5 provides descriptive statistics of the form of the network in each phase. The first statistics are the degree of the network-in-degree is the number of links which directionally point toward each node, out-degree is the number of links pointing away from each node.

The average in-degree and out-degree for the network over the entire sample period is given in the first panel of Table 5 and shows that the means are identical. However, the median in-degree for the network exceeds the median out-degree and has a much lower standard deviation—the range of the out-degree for each node is far higher. While for the entire sample every node has an in-degree of at least 5, meaning that each node receives transmissions from at least 5 other nodes, directly, the maximum in-degree is 18. In contrast, not all nodes transmit shocks (a minimum out-degree of zero).

To consider the changing nature of the in-degree and out-degree, Figure 5 provides a bar chart of the numbers of nodes with out- and in-degree respectively, by 5-degree intervals for each phase. The light blue section of each column of Figure 5 is the number of nodes recording 5 or fewer edges (including zero) in that phase, with subsequent categories rising in increments of 5. It is immediately apparent that in-degree by phase has lower numbers of nodes with fewer connections than out-degree by phase. This is marked during the crisis Phases 2 and 5, which have the fewest nodes registering low in-degree or out-degree. This means that the nodes which are connected during the periods of stress have links to more other nodes than those connected during periods of less stress. The in-degree for any node involved in the system is never above 15, indicating that each node receives shocks from sources which are specific, and perhaps identifiable, paths. However, the out-degree for each phase is more diverse. Table 5 shows that the maximum out-degree generally rises over the sample, but the figures reveal the extent to which the distribution of higher connected nodes increases in times of stress. In Phases 2 and 5 there are discernibly more nodes involved with a higher out-degree. That is, they are involved in transmitting shocks to (more) other nodes. However, this does not necessarily mean that they are source nodes for the shocks.

Shocks may transmit between nodes through other nodes. A measure of the extent of this effect is the "betweenness" centrality, which effectively assesses the substitutability of a node. This measures the number of times a given node acts as part of the shortest path between two other nodes. It helps to determine how important a node may be in transmitting information through a network. A node with a normalized betweenness centrality measure of one is involved in the shortest path between all nodes in the network, and hence its removal could be of substantial importance for the network. (This node does not obviously need to be the biggest in the network or the source of a shock. Bear-Stearns forms a good example of this type of risk during the GFC.) A market with a betweenness measure of zero is unimportant in retaining the network.

Table 5 shows that the average betweenness centrality of the network rises dramatically in Phase 3 of the sample but, in Phase 5, it drops from the previous precrisis sample period. Betweenness clearly differs across the phases, pointing to the different structures of core nodes during the different periods, as will be discussed below.

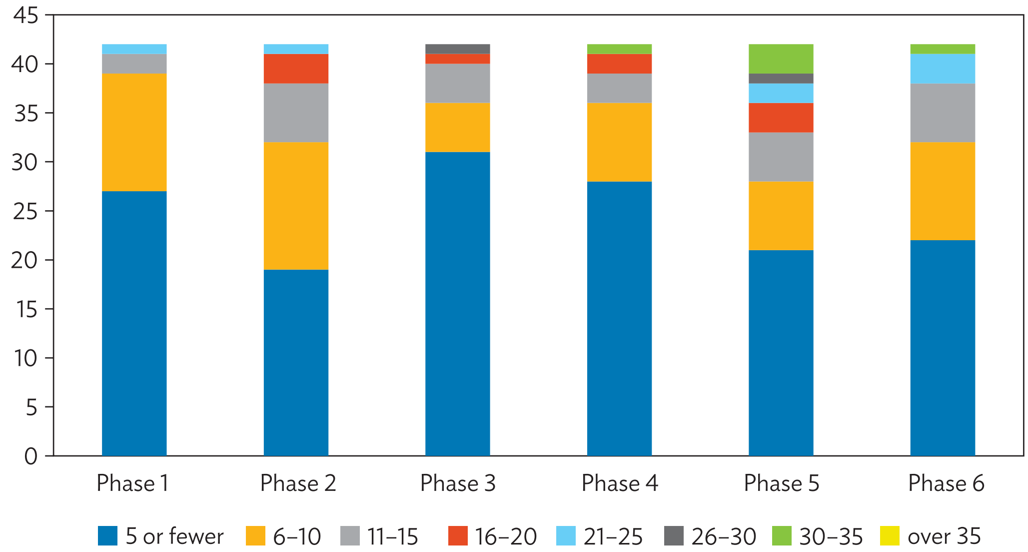
Table 5: Summary Statistics of Various Network Measures (All Countries)

	Mean	Med	Std. Dev	Min	Max
	All Phases (1 Mar 1995–30 Dec 2016)				
In-Degree	11.52	11.00	3.27	5.00	18.00
Out-Degree	11.52	8.00	9.18	0.00	37.00
Betweenness Centrality	21.00	12.84	21.18	1.32	90.41
Eigenvector Centrality	0.02	0.02	0.01	0.01	0.04
	Phase 1 (1 Mar 1995–1 Jul 1997)				
In-Degree	5.00	5.00	2.55	0.00	10.00
Out-Degree	5.00	4.00	3.85	1.00	22.00
Betweenness Centrality	36.71	22.88	43.35	3.78	227.12
Eigenvector Centrality	0.02	0.02	0.01	0.01	0.06
	Phase 2 (2 Jul 1997–31 Dec 1998)				
In-Degree	7.26	7.00	3.19	0.00	14.00
Out-Degree	7.26	6.00	5.52	0.00	22.00
Betweenness Centrality	28.48	19.59	27.28	1.90	105.77
Eigenvector Centrality	0.02	0.02	0.01	0.01	0.04
	Phase 3 (1 Jan 1999–31 Dec 2002)				
In-Degree	5.10	5.00	2.18	1.00	10.00
Out-Degree	5.10	4.00	5.28	0.00	28.00
Betweenness Centrality	36.19	17.42	53.48	0.00	307.61
Eigenvector Centrality	0.02	0.02	0.01	0.00	0.06
	Phase 4 (1 Jan 2003–14 Sep 2008)				
In-Degree	5.64	6.00	2.43	0.00	12.00
Out-Degree	5.64	4.00	5.91	0.00	31.00
Betweenness Centrality	33.43	21.29	43.67	0.00	263.65
Eigenvector Centrality	0.02	0.02	0.01	0.01	0.06
	Phase 5 (15 Sep 2008–31 Mar 2010)				
In-Degree	9.26	9.00	2.96	1.00	15.00
Out-Degree	9.26	5.50	9.49	0.00	35.00
Betweenness Centrality	24.71	10.56	38.47	0.52	196.03
Eigenvector Centrality	0.02	0.02	0.01	0.00	0.05
	Phase 6 (1 Apr 2010–30 Dec 2016)				
In-Degree	7.29	7.00	2.99	0.00	13.00
Out-Degree	7.29	5.00	7.40	0.00	34.00
Betweenness Centrality	28.14	14.52	43.21	0.00	211.56
Eigenvector Centrality	0.02	0.02	0.01	0.01	0.05

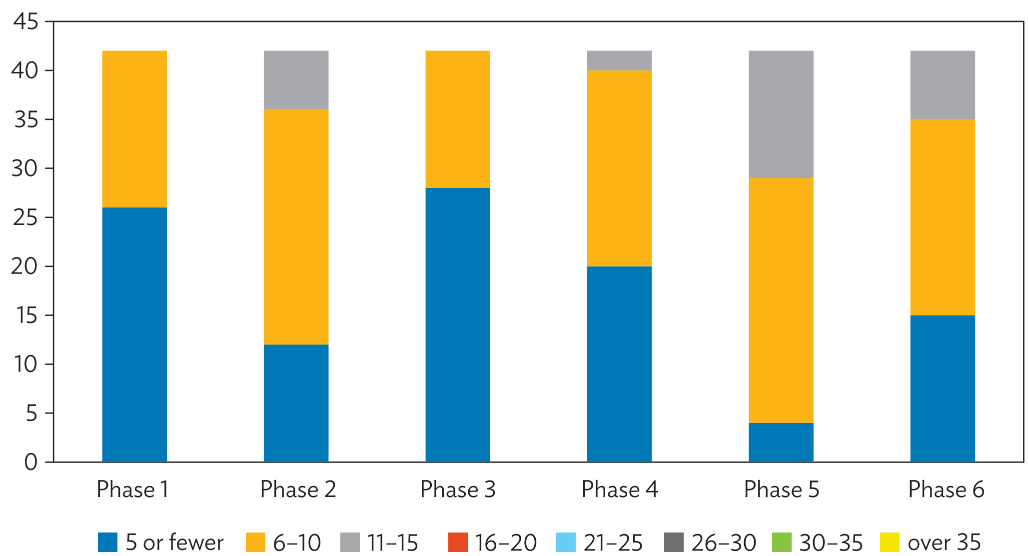
Note: We use the network measures of in-degree, out-degree, betweenness centrality, and eigenvector centrality to capture the centrality of a country's position in the global financial network and its closeness to all other countries in these networks.
Sources: Data from Bloomberg and Datastream (accessed February 2017).

Figure 5: Figures for In-Degree and Out-Degree by Phases

A. Out-degree by Phase



B. In-degree by Phase



Note: See Table 2 for the phases and their corresponding time periods.
Sources: Data from Bloomberg and Datastream (accessed February 2017).

Eigenvector centrality is also an indicator of proximity between nodes. The eigenvector centrality of each market is determined by the eigenvector centralities of the markets to which it is connected. That is, eigenvector centrality of country i , ev_i, is given by, $ev_i = \frac{1}{\lambda}\sum_j A_{ij}\ ev_j$, where λ is a constant that provides a nontrivial solution and A_{ij} is an adjacency matrix; see Bonacich (1972) and Chuluun (2017). In this way eigenvalue centrality is a measure of connectedness in the entire market network. Although it has a similar form to the PageRank algorithm used in assessing systemic risk in Dungey, Luciani, and Veredas (2018) and van de Leur, Lucas, and Seeger (2017), because eigenvalue centrality is based on eigenvalues which do not vary much between phases, the eigenvalue centrality measure does not move between the phases. This points to the importance of understanding the measures which are being used; the relatively unchanging eigenvalues is consistent with Pesaran and Yang (2016) who find that the wholesale trade sector is the dominant economic sector over multiple samples in a real economy network. (Unlike in their form, there is no individual node with an eigenvalue of greater than 0.5 in our sample that can be considered statistically dominant.) There is little information content in the eigenvalue centrality measure for assessing the changing nature of a network of nodes in financial markets over time. Table 6 provides the betweenness centrality, closeness centrality, and eigenvalue centrality figures for each individual node assessed over the entire sample. It is evident that there is no great variation in the closeness and eigenvalue centrality measures across different economies. In contrast, Wang, Xie, and Stanley (2018) derive a variety of centrality and closeness measures for 57 international equity markets and observe patterns consistent with crisis periods, although the range of their statistics does not vary greatly over time.

Table 6: Completeness Statistics for the Whole Sample
(All Phases: 1 March 1995–30 December 2016)

Vertex/Economy	In-Degree	Out-Degree	Betweenness Centrality	Eigenvector Centrality
Argentina	7	4	6.5658	0.0113
Australia	18	13	24.3210	0.0309
Austria	14	13	32.6658	0.0261
Belgium	11	7	9.6903	0.0189
Brazil	11	19	36.7235	0.0318
Canada	11	24	52.5183	0.0360
Chile	12	6	9.7601	0.0211
Czech Republic	15	10	20.6217	0.0252
Denmark	9	6	4.4163	0.0197
Egypt	9	7	6.6775	0.0174
Finland	12	7	8.1179	0.0217
France	10	19	53.7337	0.0275
Germany	11	9	8.4845	0.0213
Greece	7	18	21.7494	0.0239
Hong Kong, China	17	8	18.1500	0.0259
Hungary	12	9	15.3452	0.0235
India	11	6	9.2375	0.0195
Indonesia	15	28	56.8902	0.0381
Ireland	10	29	58.3729	0.0352

continued on next page

Table 6 *continued*

Vertex/Economy	In-Degree	Out-Degree	Betweenness Centrality	Eigenvector Centrality
Italy	9	9	11.1405	0.0217
Japan	13	29	50.0405	0.0344
Malaysia	15	6	14.3542	0.0235
Mexico	5	37	76.6419	0.0406
Netherlands	10	7	1.3214	0.0158
New Zealand	9	6	9.0325	0.0185
Pakistan	6	5	4.4446	0.0108
People's Republic of China	6	16	12.7719	0.0204
Philippines	10	2	1.8190	0.0163
Poland	15	4	8.2548	0.0228
Portugal	13	1	2.4349	0.0176
Republic of Korea	18	9	15.7321	0.0271
Singapore	13	8	12.9077	0.0222
South Africa	14	7	17.6159	0.0235
Spain	13	7	11.3760	0.0221
Sri Lanka	6	0	1.8586	0.0068
Sweden	9	4	2.8124	0.0177
Switzerland	14	5	10.1012	0.0210
Taipei,China	13	13	19.8328	0.0260
Thailand	16	12	25.2410	0.0279
Turkey	11	7	10.1564	0.0208
United Kingdom	14	11	17.6546	0.0281
United States	10	37	90.4137	0.0398

Sources: Data from Bloomberg and Datastream (accessed February 2017).

Thus far we have established that: (i) the number of connections between nodes changes between phases, (ii) that some edges are removed from the system while (iii) some edges are formed each time, (iv) that the connectedness of nodes as measured by in-degree and out-degree changes in what appears to be a discernible way, increasing during periods of stress, (v) the nodes which are more or less involved in the network during various phases may change, and that (vi) measures of centrality do not provide definitive information about changing financial networks during periods of stress. This information is gleaned from the summary measures of the network for each phase. We turn now to examining individual nodes.

C. Spreaders and Absorbers

We are particularly interested in identifying four types of nodes, and whether different nodes change their role during periods of stress and calm. The four types of nodes are: super-spreaders, super-absorbers, periphery-spreaders, and periphery-absorbers. Super-spreaders are those markets which absorb shocks and distribute them to many other nodes; generally, they will have a substantially higher out-degree than in-degree. Super-absorbers are markets which are subject to many shocks but do not distribute them widely; generally, they will have a substantially lower out-degree than in-degree. A greater discrepancy between the in-degree and the out-degree of each node places it more firmly into the super-spreader or super-absorber category. Periphery-spreaders originate shocks to many markets but do not receive a great deal of in-links. They can be viewed as a specific form of the super-spreaders, the key difference being that the in-degree is relatively small. Periphery-absorbers are markets which absorb shocks but do not pass them on; they are a specific form of super-absorbers where the key is the very low out-degree.

The most obvious super-spreader in the sample is the US (Table 7). It routinely has more out-degrees than in-degrees. The central role of the US in global financial markets is well documented, and here our evidence seems to strongly support the center and periphery argument of Kaminsky, Reinhart, and Vegh (2003), where developed financial markets act as a conduit for the transmission of shocks from other periphery markets.

Table 7: Connectedness of Markets: Vertex Centrality in Return-Based Network

	All Phases		Phase 1		Phase 2		Phase 3		Phase 4		Phase 5		Phase 6	
Vertex	Out	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out	In
Argentina	4	7	2	9	18	5	4	4	5	3	35	12	0	3
Australia	13	18	4	4	4	7	4	7	5	9	1	14	7	13
Austria	13	14	3	5	5	10	7	6	11	4	12	9	8	8
Belgium	7	11	6	9	6	3	1	5	7	6	17	12	0	7
Brazil	19	11	3	10	6	9	4	8	8	5	12	14	14	0
Canada	24	11	6	4	12	5	16	6	11	1	1	15	9	10
Chile	6	12	11	7	9	7	11	6	2	3	2	10	8	7
Czech Republic	10	15	4	1	9	11	4	9	3	6	7	9	9	10
Denmark	6	9	10	6	10	9	6	4	10	9	4	9	3	6
Egypt	7	9	7	0	3	6	2	5	0	5	10	7	9	6
Finland	7	12	6	2	2	9	5	10	1	4	5	10	13	11
France	19	10	5	6	1	10	3	5	4	7	33	9	1	5
Germany	9	11	4	5	15	14	3	2	8	4	11	5	13	5
Greece	18	7	4	4	7	1	1	4	3	6	6	7	11	10
Hong Kong, China	8	17	7	9	11	9	1	8	7	6	3	15	3	13
Hungary	9	12	7	5	3	13	1	5	1	7	8	10	1	5
India	6	11	3	3	0	5	0	3	5	6	4	8	10	6
Indonesia	28	15	3	7	13	6	4	5	2	4	27	9	5	11
Ireland	29	10	1	4	22	10	7	4	2	5	15	7	2	10
Italy	9	9	4	9	1	5	3	5	5	7	17	8	1	5
Japan	29	13	6	1	15	6	15	4	6	7	5	12	12	5
Malaysia	6	15	2	6	6	10	4	3	2	7	18	8	7	11
Mexico	37	5	7	5	10	8	14	4	17	0	22	8	4	5
Netherlands	7	10	4	6	0	7	4	8	16	5	0	11	23	9
New Zealand	6	9	4	4	4	8	1	5	3	10	1	4	0	5
Pakistan	5	6	1	3	13	3	3	4	0	3	2	1	1	5
People's Republic of China	16	6	1	4	4	3	1	2	0	3	8	8	23	4

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Table 7 *continued*

	All Phases		Phase 1		Phase 2		Phase 3		Phase 4		Phase 5		Phase 6	
Vertex	Out	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out	In
Philippines	2	10	3	3	4	6	0	4	10	5	0	12	2	10
Poland	4	15	1	5	1	12	2	10	5	6	0	6	4	9
Portugal	1	13	3	6	7	6	7	8	1	5	22	8	4	6
Republic of Korea	9	18	2	4	6	4	4	7	2	11	2	14	21	11
Singapore	8	13	4	4	7	4	4	3	1	12	6	9	1	8
South Africa	7	14	3	5	4	12	5	8	2	7	5	8	3	8
Spain	7	13	9	7	5	7	4	5	3	6	9	11	3	5
Sri Lanka	0	6	8	0	7	0	1	2	0	4	3	8	1	2
Sweden	4	9	1	9	5	12	2	4	4	4	2	8	6	8
Switzerland	5	14	12	8	1	6	2	3	5	7	3	7	5	10
Taipei,China	13	13	3	1	5	4	11	1	10	6	4	10	8	7
Thailand	12	16	3	5	2	9	5	6	1	3	2	12	14	7
Turkey	7	11	3	3	6	7	4	5	4	8	2	5	2	4
United Kingdom	11	14	8	7	20	8	6	3	14	7	11	11	1	11
United States	37	10	22	5	16	9	28	4	31	4	32	9	34	5

Sources: Data from Bloomberg and Datastream (accessed February 2017).

The in-degree and out-degree measures for individual markets are recorded in Table 7. The first two columns present the out-degree and in-degree of each of the nodes for the entire sample of the network. It is evident that the greatest number of out-degrees is recorded for the US, consistent with our designation of a super-spreader. The fewest links are recorded by Sri Lanka, which, we noted previously, is an isolated node. The maximum in-degree is received by the Republic of Korea, while the minimum in-degree is recorded by Mexico.

All three members of the North American block of markets (Canada, Mexico, the US) show properties of being super-spreaders across the sample. However, in Phases 5 and 6, Canada in fact acted as an absorber, as for the first time in the sample it had few links leaving the market compared with the number of entrants. In this it joined Australia as a developed market which absorbs shocks from numerous sources but does not distribute to as many. Other countries, such as Argentina, play a mixed role. During both the crisis periods, Phases 2 and 5, Argentina became an important super-spreader, Figure 3 illustrates that this includes links to other South American markets; but outside of those times, Argentina does not play a distinct role in spreading shocks.

To summarize the role of the super-spreaders, super-absorbers, and peripheral spreaders, and peripheral absorbers, Table 9 provides a breakdown of the markets identified in the sample. To construct this table, we used the selection rules laid out in Table 8 and applied these to each market:

Table 8: Definition of Spreaders and Absorbers

Define: x = (out-degree − in-degree)

	x<0	x>0
Out-degree < 3	Peripheral-absorber	
In-degree <3		Peripheral-spreader
Absolute (x) >6	Super-absorber	Super-spreader

Source: Authors.

The cut-off points for differentiating these types of absorbers have been chosen on an ad-hoc basis in this table, based on visual analysis by the authors. Further work to examine the sensitivity and explanatory power of different variables to alternative definitions is warranted in future work.

Table 9 makes evident that over the different samples, the number of spreaders and absorbers increases—which simply represents the more connected network. Two countries particularly stand out as ones that swap roles between periods of stress and nonstress. Both Argentina and Ireland are super-spreaders in the crisis periods of Phases 2 and 5 but revert to being super-absorbers during other periods. The constant presence of the US as a super-spreader is accompanied by Japan, which is a spreader (either super or peripheral) in each period except Phase 4. (Recall that Phase 4 represents the early part of the 21st century when the Japanese economy was not synchronized with other Organisation for Economic Co-operation and Development or global economies—Farrell et al. [2005] note a diminishing role for Japanese markets in this period.) Distinct roles for several European markets emerge in the later parts of the sample; particularly post-Phase 3 after the formal introduction of the euro area. France and Italy are each super-spreaders during the GFC, but not during the surrounding phases, while Germany emerges as a super-spreader in both postcrisis periods of Phases 3 and 4. The perhaps unexpectedly different roles of the German and French markets are consistent with the results in Wang, Xie, and Stanley (2018), who attribute the centrality of the French markets within Europe as due to the presence of the World Federation of Exchanges in Paris.[6]

Rather than being isolated or negligible (as in the analysis of Farrell et al. [2005]), the Asian region markets are clearly identifiable as a presence in the network. While Japan is evident throughout, Asian markets are more generally identified as spreaders or absorbers from Phase 3 onward—that is, in the post-Asian crisis period. The emergence of Hong Kong, China and Singapore as super-absorbers is particularly important (Hong Kong, China from Phase 3 onward, and Singapore in Phases 3 and 6). New Zealand also emerges as an absorber in this period. Interestingly, these are all some of the most developed markets in the region, although the New Zealand market is small by global standards. This role of super-absorber is evident as they form bridges between the numerous in-linkages from Asian economies and fewer out-linkages transporting the effects to the global markets.

The analysis of the changing in- and out-degree of the network considers that not only are the numbers of links in the network changing, but also that the nodes that are most connected change. The next stage in this research agenda is to explore whether these changes in out-degree and in-degree can be systematically related to characteristics of the markets involved.

[6] If this hypothesis is correct, then there are significant gains to a market from co-location with an international organizational body.

Table 9: Spreaders and Absorbers by Phase

	Phase 1		Phase 2		Phase 3		Phase 4		Phase 5		Phase 6	
Vertex	S	A	S	A	S	A	S	A	S	A	S	A
Argentina		SA	SS						SS			PA
Australia										SA		
Austria												
Belgium						PA						SA
Brazil											SS	
Canada					SS					SA		
Chile								PA		PA		
Czech Republic	PS											
Denmark												
Egypt	SS					PA		PA				
Finland	PS			SA				PA				
France									SS			PA
Germany					SS						SS	
Greece						PA						
Hong Kong, China						SA				SA		SA
Hungary				SA		PA		PA				PA
India						PA						
Indonesia			SS					PA	SS			
Ireland		PA	SS					PA	SS			SA
Italy									SS			PA
Japan	PS		SS		SS			PA			SS	
Malaysia		PA							SS			
Mexico									SS			
Netherlands										SA		PA
New Zealand								SA		PA		
Pakistan		PA	SS					PA	PS			PA
People's Republic of China		PA				PA					SS	
Philippines										SA		SA
Poland		PA								PA		
Portugal								PA	SS			
Republic of Korea		PA						SA		SA	SS	
Singapore								SA				SA
South Africa								PA				
Spain												
Sri Lanka	SS		SS			PA		PA				
Sweden		SA		SA		PA						
Switzerland				PA		PA						
Taipei,China					SS					SA		
Thailand				SA				PA			SS	
Turkey										PA		PA
United Kingdom			SS								SS	
United States	SS		SS		SS				SS		SS	

A = absorber, PA = periphery absorber, PS = periphery-spreader, S = spreader, SA = super-absorber, SS = super-spreader.
Sources: Data from Bloomberg and Datastream (accessed February 2017).

D. Role of the Association of Southeast Asian Nations Markets

Figure 6 presents the network between the Asia and Pacific markets with the ASEAN markets aggregated to a single block to examine the evolution of the network between both ASEAN and the rest of the Asian block, as well as the rest of the world.[7]

Figure 6 shows the importance of the link between Hong Kong, China and the ASEAN markets over the whole period—each of the phase diagrams show that this link remains prominent throughout the subsamples. These links primarily run from ASEAN markets to Hong Kong, China—as previously covered this reflects the role of Hong Kong, China (and Singapore, which is included in the ASEAN sample) in connecting Asian markets to the rest of the world.

Across the differing phases, there is a transformation of the structure of the network involving ASEAN and Asian markets, which seems to reflect the increasing development and deepening of the markets dominating the effects of crisis and noncrisis periods. Early in the sample, in Phase 1, there are noticeably fewer links to ASEAN economies than later in the sample—the links are mainly from or to developed markets rather than other developing Asian markets. Notably, Japan is not connected directly to ASEAN in this period. During Phase 2, there is a distinct change, in that inward links to ASEAN from other Asian markets begin to appear, from the PRC and the Republic of Korea. Japan remains directly unconnected.

In Phase 3, post-AFC, the US is clearly central to the distribution around the network. The links from other markets continue to develop, with Japan, Pakistan, and Taipei,China connecting, although the Republic of Korea has dropped the association it had during the crisis period of Phase 2. The PRC is also connecting to the network through its non-Asian connections but has the role of an end node in this network, a position also occupied by Sri Lanka.

In the build-up to the GFC during Phase 4, the network shows the ASEAN markets having stronger links than previously, with a similar group of markets as the previous phase. The Indian market, which was previously not directly linked with ASEAN markets, is now present; Pakistan remains relatively isolated.

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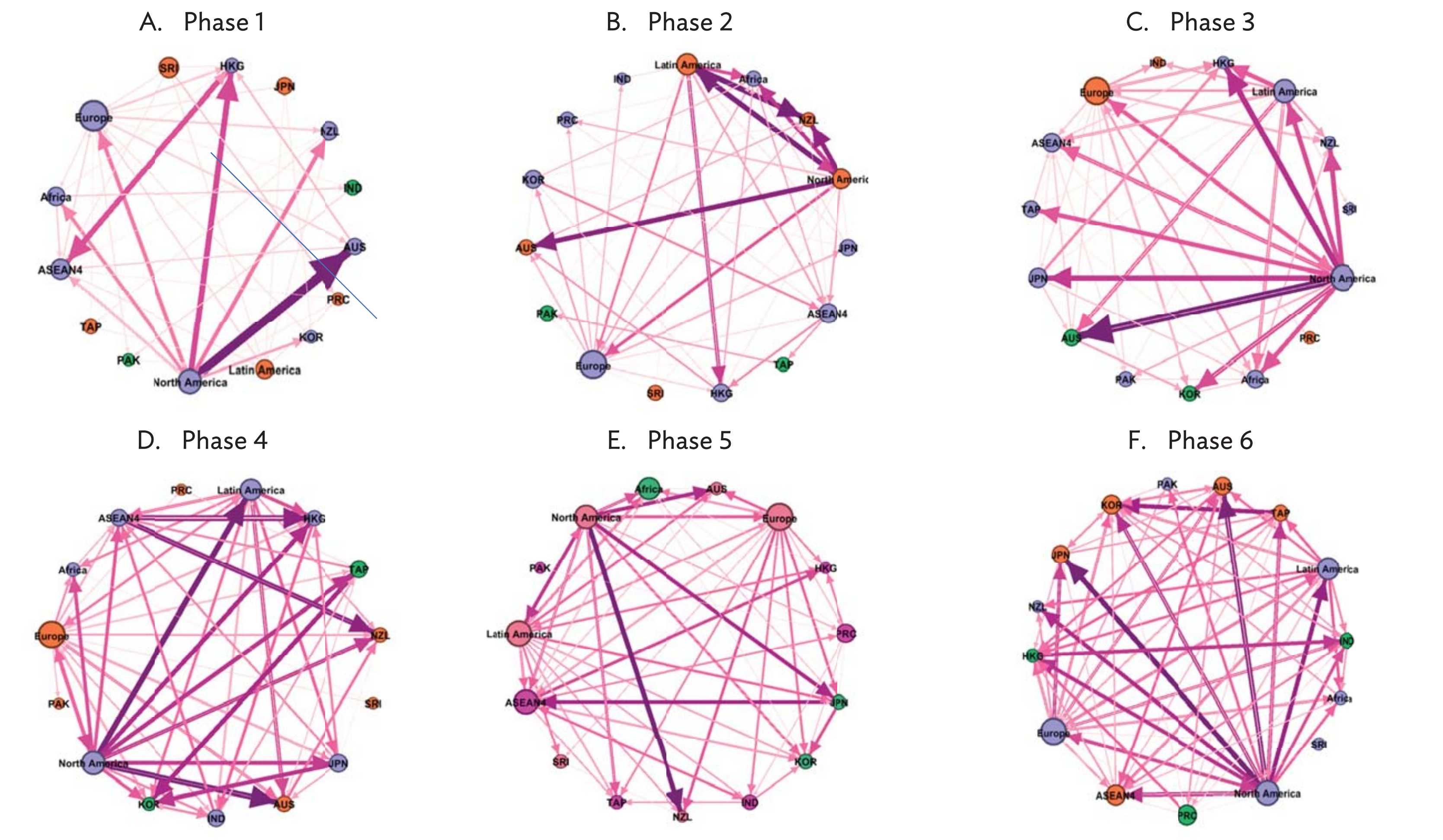
7 In this empirical exercise, ASEAN markets are characterized by Indonesia, Malaysia, the Philippines, and Thailand, i.e. ASEAN4 markets.

Figure 6: Evolution of Weighted Networks with Regional Groupings Highlighting the Association of Southeast Asian Nations and Asian Markets



ASEAN = Association of Southeast Asian Nations.

Notes: ASEAN4 includes Indonesia, Malaysia, the Philippines, and Thailand. The figure displays the returns-based network of 42 equity markets from 1 March 1995 to 30 December 2016. Edges were calculated using bivariate Granger-causality tests between markets at the 5% level of significance. The thickness of the lines indicates the average relative strength of each market (or regional grouping). The size of the nodes increases with the number of outward links of each respective market (or regional grouping). Regional groupings and country codes are defined in Table 1.

Sources: Data from Bloomberg and Datastream (accessed February 2017).

During the GFC itself, Phase 5, the network is dramatically different from the previous phase. Having subsumed the density of links between European, North American, and Latin American markets into regional nodes, it is apparent that during this period there is an important role for the transmission of shocks from the North American markets to ASEAN through Japan, less so from Australia than previously, and not at all from New Zealand.[8] The critical paths from the rest of the world to Asian markets have changed so that Japan has a gatekeeper role that was not evident previously. The PRC is now more evidently directly and strongly linked to ASEAN markets and North America, so there are both direct and indirect links between Asian and the PRC markets.

In the final phase, the PRC has continued to increase the number of evident direct links to other nodes in the network, and ASEAN markets are clearly an important hub in terms of the number of linkages coming in to the ASEAN node. There are also substantial numbers of weaker links from ASEAN to other Asian markets, such as Australia; Hong Kong, China; India; Japan; and the Republic of Korea. Note in this final network, ASEAN markets transition into becoming more integrated into the international network in a markedly different way from Phase 1 and the subsequent two phases. During the GFC it appears that the Asian markets matured to become more clearly interconnected with other major regions, both through the hubs of ASEAN; Hong Kong, China; and Singapore; and more directly by links to major regions outside.

The conclusion of this analysis is that ASEAN markets are part of the bridge between the market regions of Asia, Europe, and the Americas. Consequently, there is a role here for ASEAN markets as a core for systemic risk in the Asian region, and many links are filtered through ASEAN and Hong Kong, China markets. Other markets are less clearly hubs for connections with the rest of the world; however, this has changed over the last phases as Asian markets have become more completely connected to other regions of world markets.

VI. POLICY IMPLICATIONS

Based on the results, additional individual analysis of the evolution of network connections for each individual country, and the observations from Raddant and Kenett (2016), we look at policy options at both a regional and country level.

A. Regional Level

(i) **Supporting regional development**. A clear feature which differentiates our analysis from others is the far greater scale of Asian markets included. Although other studies find that Asian markets are relatively isolated in their networks, we find evidence of distinct regional groupings, particularly around the ASEAN markets and the bridge market of Hong Kong, China. Our narrative of the more peripheral markets supports the idea that in the early stages of the network many of these markets first connected to the rest of the world through the bridge of the regional cooperation organizations, such as ASEAN, which may have provided a filter for informing the rest of the world about the developments in these markets.

Bridge markets can provide a way in which second degree links are available to relatively unconnected nodes—for example, in Phase 1, Sri Lanka and Thailand connect to the US

[8] The Latin American sample includes Argentina, Brazil, Chile, and Mexico. See Table 1 for more on the regional groupings.

and Germany through Hong Kong, China. Support is provided by overcoming information asymmetries between the international markets and the domestic market. Over time, a number of markets have followed this pattern and gone on to form their own significant direct links with the rest of the world markets and are no longer primarily connecting through ASEAN, such as Indonesia and Taipei,China. This points to a potentially important role for cooperation in regions to support developing markets, helping lift the participation of millions of citizens into access to international finance and thus growth opportunities.

(ii) Regional level protection. Regional fostering of this nature also has advantages in providing a level of protection for these markets during periods of crisis. If there is a bridge market that is critical in connecting a region to international markets, then it is much easier to sever that one link or a limited number of links and protect a large part of the regional system than if all components are individually linked. Most likely this relates to the stage of development of the market, because as markets reach a greater stage of maturity and form more direct relationships with the rest of the global markets, they will increasingly need to have more sophisticated regulatory oversight and tools.

(iii) Concentration of market power. A disadvantage of encouraging a regional approach to development may be the concentration of market power in the bridge market. Although this is a possibility, as there are clear advantages to the bridge market in mediating between asymmetric information situations (where the rest of the world is less informed about the developing market) as markets develop, this should be naturally eroded by the incentives to develop direct relationships to avoid these costs.

B. Individual Country Level

Individual countries face several options in accessing international financial markets to foster growth, while still being wary of protecting themselves during periods of stress.

(i) Align with a regional bridge node (or nodes). Recommended for markets in early stages of development, this strategy allows a market to connect with the international financial markets supported by a known node which can mediate the information asymmetry between the developing node and the international market. The advantage of this approach for the developing market is that it reduces the initial costs of overcoming the information asymmetry—only one node needs to be educated about the developing node to access their connections to the rest of the world. One such strategy could be to attach to a super-spreader node. Choosing the node with which to establish such a relationship is not trivial. In the data, a couple of strategies are evident. One is to form regional groupings to act as bridges, such as ASEAN markets. This clearly has advantages in terms of regional cooperation and potentially better understanding and alignment of the information asymmetries; and could be seen as typified by the actions of markets such as the Republic of Korea in the dataset.

(ii) Form a bridge with a dominant super-spreader market directly. This type of relationship is typified by the two fastest-growing large economies, India and the PRC. India developed relationships with the international network initially through its relationships with the United Kingdom (reflecting historical associations). The PRC has tended to foster its connections outside the Asian region as a matter of priority prior to building the relationships with the Asian nodes. An observation from the data is that this seems to be a relatively slower way in which to integrate with the world network directly—although slower integration may itself also be a policy choice.

(iii) Playing the role of a bridge. A market may have the opportunity to play the role of a bridge between developing nodes and the rest of the global network. This has advantages in that there are premia to be made from exploiting the information asymmetry between the global markets and the more isolated node. It will contribute to the global importance of the bridge market in the network, presumably increasing turnover and influence. The disadvantage seems to be that if the node itself is involved in a crisis, a consequent loss of trust may be very damaging to the future formation of such relationships. A key illustration of this seems to be in the reduction in connectedness of the Hong Kong, China market as a bridge after the Hong Kong, China crisis in 1998.

(iv) Avoid becoming a bridge. Some markets may also choose not to engage in the risk of acting as a bridge node, but to wait until other market nodes are more fully engaged with the entirety of the network before establishing links. This seems to be the nature of the relationship between Japan and the other Asian markets. Such an approach protects a node from the possibility that it may become a conduit for the transmission of crises originating in emerging markets to the rest of the world, and subsequently inflict loss on its local economic agents.

(v) Isolating markets. An advantage of aligning with a bridge node is that during periods of stress it is simpler to cut off these bridge relationships to protect the domestic market. The greater the degree of relationships between a market and other world markets the more difficult it is to isolate during periods of stress. There are costs and benefits from being able to isolate the market node. A case in point is the Malaysian experience, where, pre-AFC, the degree of connectedness for Malaysia was relatively high for an Asian market at that time. However, the actions to protect Malaysia during the Asian crisis seemed to result in considerable contraction in its connectedness with the rest of the world markets for several more phases (particularly until these restrictions were lifted and relationships re-established). It may be damaging to ongoing relationships to disconnect during periods of stress—although it is hard to quantify the relative costs and benefits of these actions.

Informing these choices, we observe the following characteristics of the behavior of markets within the network during periods of crisis, both originating elsewhere and in their home environment. The perceived probability of undergoing either a homegrown policy or political crisis are critical inputs in how a market chooses to engage with the rest of the network, and what choices are offered by the existing nodes on how it may engage (that is, which markets may be willing or not willing to engage as bridge markets for a developing node).

(vi) Growing despite crisis. If a node is not itself directly involved in a crisis, a market may simply continue to grow its network steadily, despite chaos surrounding it. In this way, being off to the side of the network can result in being protected, and in fact may allow a market to benefit from others' difficulties in establishing direct linkages, as in Taipei,China and Republic of Korea during the GFC.

(vii) Weathering a home-grown crisis. Just as crises come in many forms, the outcomes following the responses to crises seem to come in different forms for the nodes involved. For example, in the case of Thailand, which was relatively well connected for an Asian market pre-AFC, the subsequent period was characterized by a contraction in its network relationships, which took time to rebuild. On the other hand, the Republic of

Korea—which arguably was not an instigator of the crisis in 1998 but was a victim of the various forms of contagion which affected it at the time—was forced into significant market liberalization by the terms of the International Monetary Fund programs it was involved in, and has continuously grown its integration into world markets ever since. This is clearly not a predetermined path, however, as Indonesia had a very different experience (probably mitigated by point vi).

(viii) **The role of domestic political stress.** Part of the reason for information asymmetry and uncertainty can revolve around political or civil stress in an economy. This is evident for Sri Lanka and Thailand. The timing of political unrest coincides with a reduced rate of formation of relationships between these nodes and the rest of the markets. Forming international financial connections may not be a resource priority during these periods, while the investment risk may also simply be too high for international investors.

The overall aim of economic policy-making bodies is to increase the welfare of citizens. While we generally assume that greater integration into international financial markets will help to achieve this, it does expose the domestic economy to financial crises originating elsewhere. The choice to seek either a relationship with a bridge node, or indeed to become a bridge node, is one that can be mutually beneficial, but the data suggests it is not clearly so. Some markets have chosen this route while others have chosen only to connect only after sufficient development of either their own markets or other nodes, thereby initially avoiding regional bridges. The variables which influence this choice seem likely to be related to: risk aversion of the individual markets, stage of development, current rate of economic growth, appetite for capital, economic size, and perhaps political uncertainty. Casual analysis suggests that (relatively) small emerging markets with lower than potential rates of growth and unmet capital needs will benefit from forming an alliance with a regional bridge as a conduit to greater capital integration. Those which choose to take on the role of bridge markets benefit from the opportunity for increased growth and exploitation of the information asymmetry. Economic geography implies that for many that ability to exploit the information asymmetry is likely to lie within regions. And the formation of bridge nodes through a group of markets, such as ASEAN markets, seems to form a reasonable means of the group nodes sharing the risk of crises originating from the developing nodes. A formal theoretical model of these relationships, and the determining factors for the emergence of the alternative paths evident in the data is scope for ongoing work.

VII. CONCLUSIONS

Network diagrams improve the transparency of financial interrelationships and provide a more compelling picture of the complexity of these relationships, and the potential length and plethora of pathways between nodes, than simple tables of correlation analysis ever can. The unweighted network filters for nonstatistically significant connections, meaning that the potentially spuriously large connections are omitted from the weighted network.

The evolution of the network over the sample period clearly indicates the growing internationalization and interconnectedness of Asian markets. We highlight instances where this has occurred through the interaction of markets with local or regional core or gatekeeper nodes, particularly Hong Kong, China; Singapore; and the ASEAN economies.

Over time, however, the linkage is increasingly direct between most Asian markets and other major regions. We hypothesize that this is because the development of new markets may benefit from the support (or existence) of geographically localized hubs or centers that help establish the role of an emerging market within the global markets. On the other hand, there is also evidence of large markets, such as India, emerging to become more interconnected with global markets without significant use of a geographically based hub—in the Indian case this may be a consequence of strong historical links to British institutional structures. However, this hypothesis remains to be formally tested.

The contribution of the gateway or core markets within a region to the development of emerging markets is a strong argument against proposals to develop policies to remove these features from networks—that is, to reduce complexity and increase the randomness of the network. Doing so may have detrimental effects on the development and deepening of emerging markets, which appear to “grow” into maturity by establishing their own direct links with nonregional markets through the legitimacy of first transmitting through regional hubs. This is critical for regions with significant untapped financial deepening—a structure which may be beneficial to already developed markets may limit opportunities for those that are emerging.

A core of markets to support regional financial development may be aided by the formal economic cooperation of strategic players. For example, the results show that while Singapore and Hong Kong, China played important roles as gatekeepers for many Asian markets, when the ASEAN economies are aggregated, their developing role in the world financial markets, and as a gatekeeper group of markets, is clear.

Considering the role of core groups in a region in assisting the development of emerging members is a strong policy recommendation when developing interventions to protect (or even form) regional cores, and for policy actions to inoculate those cores during crisis periods, thus protecting a substantial part of the network. Akin to arguments surrounding the vulnerability of economies undergoing a transition from fixed to floating exchange rate regimes to currency crises, the period of developing financial market deepening in other financial assets may also be accompanied by vulnerabilities that require extra vigilance on the part not only of the individual economies involved, but also on the regional and international financial community.

It is clearly necessary to examine the direction, strength, and evolution of links in a network. Examining net links, and changes in net links, omits valuable information about the sustainability of individual links and the changing importance of individual nodes. A few critical nodes (in our data, Argentina and Ireland) play the unusual role of switching between super-spreader during periods of stress and a super-absorber during periods of calm. Markets with these properties deserve to be watched carefully, with inoculation plans in place for adapting to changing circumstances (for example, restrictions on flows to and from those markets).

There are also markets which seem to be reliably either super-spreaders (the US) or super-absorbers. Super-absorbers are valuable allies in the bid to reduce the transmission of shocks between markets. These markets are also those that perhaps deserve particular attention, because if they were to break down, the system might become disproportionately less stable as shocks propagate through the more expansive routes (this is a form of the robust-but-fragile nature of the network).

All this points to the complexity of the financial networks in place, and indeed their evolution. However, it does not necessarily support means to reduce this complexity. Instead, the complexity reveals a rich tapestry of relationships that underpin the development of financial markets and the distribution of shocks. We propose that the first step is to understand this complexity.

The disadvantages of reducing complexity (that is, trying to enact policies that force a more random structure on the network) include that this may restrict or reduce the potential for emerging markets to develop in the shortest possible time frame. The role of a regional hub in developing financial markets appears to be important, as revealed by the results for ASEAN economies—although this requires formal testing across other emerging market economies. The results in this paper support the development of policies aimed at inoculation of important nodes. Indeed, there is a significant danger that constraining the form of one network through regulation may simply lead to the unwanted transmissions through another network that connects economies. For example, increased capital requirements on banks tie banking networks and sovereign bond networks more closely together and increased equity requirements have the potential to do the same for banking networks and equity markets. This also raises the somewhat more difficult proposition of policy coordination across different arms of the policy-making community, ensuring the coordination of financial regulation with monetary and fiscal policy making.

The single dimension of this network in terms of the asset markets considered is a limitation of the results. The financial links between economies are certainly more complex than those established simply through equity markets. The challenge to researchers and policy makers is to develop analytically tractable tools that reveal the complexity of the multiple layers of financial interconnectedness between economies through different asset markets and potentially different players. Sovereign bond networks will differ from equity market networks (see Dungey, Harvey, and Volkov 2017). Real economy networks such as trade networks, or input–output production networks as in Pesaran and Yang (2016), will be tied to financial networks, but the weights on the nodes are likely to be quite different, and may involve nodes which are not included in all layers. In the future, understanding the roles of nodes in different layers of the network may help to understand how effective policy interventions may be targeted at nodes that play critical roles in transmitting between layers to contain crisis events (or even to spread crisis events in a way that reduces their impact on individual layers and/or nodes).

The overall policy relevant findings from this report are the following:

(i) A map of the complexity of the interactions between the financial markets of Asia and the rest of the world.
(ii) A snapshot and analysis of how these networks change over time including the findings that
  (a) the complexity allows for the development of emerging markets, with seeming support from regional core/gateway nodes;
  (b) and while policies to reduce complexity may seem attractive they do not take into account the different stages of development of different nodes in the network.
(iii) Some nodes (and the future network as a whole) may benefit from having a gatekeeper relationship with another (more developed) node.
(iv) Policy interventions that protect important core nodes during times of stress are likely to prove beneficial to the stability of the whole system. Gatekeeper nodes also have the attractive feature of being able to potentially isolate a whole section of the network from chaos elsewhere.
(v) Emerging markets may choose to participate in the network by forming relationships with bridge nodes, which can help to overcome information asymmetries; alternatively, larger markets may wait until they are sufficiently internally developed to bypass this stage.
(vi) Markets may choose to become bridge nodes for emerging markets depending on whether the gains from doing so outweigh the potential risks.

We demonstrate that the gatekeeper nodes can change over time, as can designation of super-spreaders and super-absorbers. During periods of stress, some of these changes are dramatic. Consequently, regular monitoring of the network structure and the development of more frequently updated networks will help policy makers identify the changing role of nodes. This includes both the changing nature of the vulnerability of an individual node and the contribution each makes to systemic risk.

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The Changing Network of Financial Market Linkages: The Asian Experience

Asian markets have developed deeper connections with the rest of the world over the past 2 decades. They have transitioned toward stronger direct links to developed non-Asian markets, from less direct links through key bridge markets (such as Hong Kong, China). This paper investigates this changing network of financial markets for six periods from 1995 to 2016, emphasizing the direction, significance, and strength of links between markets. It focuses on transitions before and after the Asian financial and global financial crises, and shows that interconnectedness increases during periods of stress and falls in postcrisis periods.

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