Tasmanian School of Business and Economics
University of Tasmania

Discussion Paper Series N 2019-07

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ISBN 978-1-925646-97-9

UNIVERSITY of TASMANIA

Crisis transmission: visualizing vulnerability*

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August 27, 2019

Abstract

This paper develops a means of visualizing the vulnerability of complex systems of financial interactions around the globe using Neural Network clustering techniques. We show how time-varying spillover indices can be translated into two dimensional crisis maps. The crisis maps have the advantage of showing the changing paths of vulnerability, including the direction and extent of the effect between source and affected markets. Using equity market data for 31 global markets over 1998-2017 we provide these crisis maps. These tools help portfolio managers and policy makers to distinguish which of the available tools for crisis management will be most appropriate for the form of vulnerability in play.

Keywords
systemic risk, networks

JEL Classification Numbers
C3, C32, C45, C53, D85, G10

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*Dungey and Volkov acknowledge funding from ARC DP150101716

Introduction

Observed changes in correlation between asset returns during periods of stress have been variously attributed to contagion, spillovers and/or heightened vulnerability of networks. While the literature stretches back as early as King et al. (1994) on spillovers and Allen and Gale (1998) on contagion, the empirical work on networks and systemic risk/ connection is more recent [1]. One of the most important predictions of the network literature demonstrates how financial sector networks can become 'vulnerable'. Shocks may spread dramatically via financial interconnectedness as 'vulnerability' affects otherwise 'robust' networks. Empirical representations show how the networks themselves change over time, between calm and crisis periods, and with the development and growth of emerging capital markets; see for example Billio et al. (2012), Khandani et al. (2013), Demirer et al. (2018a) and Chowdhury (2018). The changing nature of the links between institutions can itself be cast as a measure of contagion; see, Dungey et al. (2017), while spillover indices can be obtained from network adjacency matrices proposed by Diebold and Yilmaz (2009).[2]

This paper presents visualization of crisis transmission pathway in a system of financial network via recursive neural networks, largely known as Artificial Neural Networks (ANN). By considering the largest vulnerabilities in the ANN patterns we produce crisis maps which highlight the least resistance shock transmission pathways at any point in time. They are somewhat analogous to slices of a brain scan lit up by firing neural pathways and as such are easily processed visually. We show how ANN methods relate to the commonly understood VAR representation and hence can be cast as an extension of the vulnerability representations with networks as in Diebold and Yılmaz (2014); Diebold and Yilmaz (2015). The Self Organizing Maps used for this purpose dictates other methods in this area of studies, in that, the maps are produced with a recursive algorithm initiated with random vectors, executing relentlessly until repeating patterns are identified and classified. Self organizing maps are popularized as 'deep unsupervised learning'.

We estimate transmissions from systemic risk estimates, which provides an easily accessible image of the pathways which are most likely to transmit crisis shocks across the system at point in time. This is used to draw two-dimensional maps of how these path-

[1] Systemic risk is the risk inherent in a system of closely connected entities, that can be cast as measure of crisis in the system. That is if triggered, can result in cascading down of the entities forming a global crisis situation. The structure implicit to systemic risk contains the degree of risks transmitted to others from one element and the degree of risks received by the element from others. This allows identification of nodes as either high spreaders or strong receivers within a closed system. The property of receiving shocks from others is closely related to the concept of the varying 'vulnerability' (Allen and Gale, 2000; Gai and Kapadia, 2010; Acemoglu et al., 2015).

[2] See applications and extensions in Yilmaz et al. (2018); Demirer et al. (2018b,c); Yilmaz (2017); Diebold et al. (2017); Diebold and Yilmaz (2015); Diebold and Yılmaz (2014).

ways change as a crisis, and its associated management plan progresses. Further, we contribute in the vein of early warning literature by presenting in-sample predictions of crisis building in our predefined system.

Our aim is to convincingly implement means by which managers of systemic risk can also simulate the effect of alternative intervention paths in a network and have some knowledge of where the most effective interventions may lie given the structure of the network at any point in time. Although we use existing data, managers may decide to randomize inputs, altering expectations or simply feed the networks with predictions to detect alternative transmission pathways. Thus, we specifically acknowledge the conditional nature of the problem, and that intervention strategies may need to be flexible and time-varying, responding to the changing structure of the network and the many alternative possible sources of shocks.

The literature making use of ANN in systemic risk pattern recognition taking advantage of Self Organizing Maps (SOM) is new. Similar application is found only in Sarlin and Peltonen (2013). The approach allows monitoring of channels of crisis transmission, visualizing of vulnerability patterns in a closed system, and proposes an early warning system for possible crisis transmission effects. Betz et al. (2014) shows that SOM has superior prediction properties than traditional latent models based on early learning systems in predicting crises.

We adapt the SOM approach to include estimated unconditional spillover measures into the crisis map - the original Sarlin and Peltonen (2013) maps are calibrated, rather than drawn from estimated relationships. The crisis maps indicate the propagation of a crisis from one position in a space to adjacent locations of the financial stability neighborhood, allowing us to map instabilities throughout connected global markets. More generally, the use of crisis maps allow us to connect the ANN approach to existing concepts of financial stability. Earlier papers using ANN for crisis prediction include Liu and Lindholm (2006); Peltonen (2006); Apolloni et al. (2009); Marghescu et al. (2010); Betz et al. (2014), and for network mapping see Barthélemy (2011); Sarlin and Peltonen (2013); and very recently for the clustering of capital markets with SOM, see Resta (2016). Finally, this system enhances our capacity to recognize the direction of induced vulnerability if a crisis ensues. The maps represent a new frontier in the usage of systemic risk and dynamic network estimates.

This paper uses a balanced sample of 31 equity indices[3]. We classify the markets into five clusters based on commonality in their economic indicators or common experiences with crisis. These are identified as Export Crisis (EC) markets - including markets which are

[3] Australia, Austria, Belgium, Canada, Chile, China, Croatia, Ecuador, France, Germany, Greece, India, Iraq, Ireland, Israel, Japan, Kuwait, Malaysia, New Zealand, Nigeria, Norway, Portugal, Russia, Saudi Arabia, Singapore, South Korea, Sri-Lanka, Thailand, The Philippines, the USA, United Kingdom.

heavily export oriented (oil and non-oil); oil exporters in terms of both emerging (OEE) and developed (OED) markets; European markets directly affected by the Greek crisis of 2010 on-wards (GC), high-yield Asia-Pacific countries directly affected by the Asian crisis of 1997-98 (AC). By inclusion of the USA and Japan identified as conduit countries in global literature (BIS, 1998; Baur and Schulze, 2005), we aim to identify conduit effects in the system. The grouping of countries into each of these categories is shown in Table 1. Together with these indices our network incorporates the West Texas Intermediate (WTI) Oil Price Index for the inclusion of oil market conditions.[4]

The sample period covers 1998 to 2017, capturing multiple episodes of financial stress, including the Asian Financial Crisis of 1997-98, the 1998 Russian Financial and LTCM crises, 2000 Dot-com bubble, 2000 Global Energy Crisis, the terrorist attacks of September 11, 2001, the invasion of Iraq in 2003, the SARS outbreak and third global oil crisis in 2003, the ongoing Gaza conflict, the unrest in 2006 through both North Korean missile tests and the eruption of war between Israel and Lebanon also in 2006, the 2008 Global Financial Crisis and subsequent European Sovereign debt crisis; as well as the 2014 Russian crisis and the 2016 Export crisis. Table 1 provides a brief description of each of these events along with the broad dating conventions. Our results also allow us to focus on the potential emerging risk of a crisis centering on China as an important conduit market as proposed in Elliott (2017); Mullen (2017); Quijones (2017); Mauldin (2017); Friedman (2016); Jolly and Bradsher (2015).

We identify the most crisis-prone markets and explain how the impact of innovations in those markets differ from those in markets which are less crisis-prone. The inclusion of oil exporting markets, during periods where conflict affected oil supplies allows us to examine the sensitivity of the global system to volatility and shocks from these sources.

We address six important questions concerning the time varying nature of systemic risk estimates leading to the detection of crisis transmission patterns. First, we examine whether policy interventions which restrict significant transmission paths help interconnected markets weather shocks. Second, we find that the changing interactions between markets results in changing patterns in risk transmission. Third, we examine whether it is possible to detect which markets are more shock resistant in the sample period from 1998-2017. Fourth, we cut individual pairwise links off from the structural parameter estimates and identify if this reduces vulnerability/resilience. Fifth, we produce time varying crisis transmission pathway maps for a predefined system. We illustrate the changing dynamics in risk transmission, and show how this visualization helps to highlight the contemporaneous contagion and spillover effects using self organizing crisis-maps . Finally, we examine if a completing feedback loop among a cluster spill risks out of the cluster to other clusters Davis et al. (2010), and hence if prediction of such in the patterns

[4]We use S&P GSCI Commodity Return Index for commodity inclusion when applicable.

warns us of ensuing crisis into the system.

We find evidence for both increased resilience in the financial networks corresponding to policy interventions in response to a crisis, and previously resilient markets becoming susceptible to newer shocks. This is particularly clear since the European debt crisis. We also find strong evidence of changing interconnections between markets.

We identify the more resilient markets using dynamic networks and crisis-maps. Finally, we show that while spillover indices strongly indicate the possibility of crisis generation at the end of the sample period, the crisis maps do not indicate forming a feedback loop and does not result in contagion. This demonstrates the usefulness of the crisis maps in complementing the evidence available from spillover indices.

The paper proceeds as follows. Section I presents a brief review of literature. Section II presents the empirical framework and Section III the data set. The results are presented in Section IV, beginning with the system wide connectedness and the associated network among the markets. This sets the stage for subsequent dynamic analysis. We proceed to develop the crisis-map implementation with SOM. Section VI concludes the paper with some remarks concerning the role of this new tool in investment and policy decisions.

Literature Review

Evidence of transmission between markets during crises and the changing size and direction of spillovers poses challenges for diversification and regulatory policy. A substantial literature addresses contagion and volatility spillovers as a mechanism of transmission, particularly in assessing changes in the contemporaneous interdependence among variables (Collins and Biekpe, 2003; Forbes and Rigobon, 2002).[5] A variety of identification approaches to separate contagion, interdependence and volatility spillovers exist (Diebold and Yilmaz, 2015; Acemoglu et al., 2015; Bekaert and Harvey, 1995; Bekaert et al., 2013; Chambet and Gibson, 2008; Eiling and Gerard, 2011; Brooks and Del Negro, 2005; Pukthuanthong and Roll, 2009).

Fernández-Rodríguez et al. (2016) define interconnectedness as a bridge between two crucial visions, 'pure contagion' and 'shock spillover'. Piccotti (2017) argues that there exists a symbiotic relationship in contagion and systemic risk. Endogenous credit and capital constraints turn non-systemic risks to systemic as crisis is propelled through different markets, followed by a reinforcing cycle. The propagation of the crisis itself brings about temporal changes to the aggregate elasticity of temporal substitution affecting asset prices in different markets (Holmstrom and Tirole, 1996, 1997; Kiyotaki and Moore,

[5] While Collins and Biekpe (2003) define contagion as reversals to net capital flow to an economy, Forbes and Rigobon (2002) argue that the correlation between market returns is largely due to common factors, and hence represents interdependence rather than contagion.

1997; Longstaff and Wang, 2012; Elliott et al., 2014; Shenoy and Williams, 2017). Hence, financial contagion increases costs, as the marginal utility of consumption is negatively affected in the short term for long term investors.

While a plethora of studies concerns systemic risk in banking liquidity crisis only, and it is easy to ignore the forming of systemic risk in the equity indices caused by as such in the banking industry; there is a strand of literature connecting the banking and equity market systemic risk transmissions. Myers (1977) describes that as banks and depository financial institutions siphon off large collaterized debts, it drags all other common equities build into such debt portfolios down with it for similar institutions. This leads to systemic decline in equity indices, and as Hanson et al. (2011) conjectures, the resulting fire sales triggered in the equity market is in effect similar to a credit crunch, turning a micro level downturn to a macro crisis. The study of Hanson et al. (2011) cements, that in resemblance systemic markets and systemic financial institutions are not different while facing a global crisis. Diamond and Rajan (2011); Shleifer and Vishny (2010); Stein (2010) further supports this phenomenon by finding intimate connections between credit crunch and fire sale. Among others, Gorton and Metrick (2012); Covitz et al. (2009) cannot distinguish between equity market collapse and a classic bank run on in effect.

Allen and Carletti (2006) outlines that systemic risk does not lead to a cascade if there is proper diversification and no contagion, in both equity markets and in SIFI's [6]. The emergence of a large shock triggers risk transfer between two institutions, two sectors or asset categories (Allen and Carletti, 2010; Billio et al., 2012; Bonaldi et al., 2015; Dungey et al., 2017; Farhi and Tirole, 2017) creating contagion. By definition, contagion is the transfer of systemic risk between two entities or securities, that the conduits connect. This leads to amplification of systemic risk between the entities. Hence, contagion is the catalyst during a crisis that activates systemic risk transmission and vice versa. Khandani and Lo (2011), supports this argument by proposing the 'unwinding hypothesis', that explains systemic risk building in the equity markets with feedback loops forming elsewhere.

Davis et al. (2010) provides empirical evidence of a feedback loop in real sector and asset market reinforcing a secondary feedback loop in the banking sector forming an enormous adverse feedback loop. Stein (2010) and Hanson et al. (2011) further explains this connection with trenching. Most often, institutional investors rely on short term borrowings for buying trenches of securities. Such trenches of assets are produced by entities such as 'structured investment vehicles' that are often affiliated with banks and depository institutions. Such holdings are used to finance overnight collaterized borrowings in the repo market, in form of 'repurchase agreement', that in turn are used by banks for 'deleveraging', reducing cost of raising capital, leading to the formation of a 'shadow banking

[6] Systematically important financial institutions

system'. According to Stein (2010); Hanson et al. (2011) This 'shadow banking system' is to blame for systemic risks in banks to contribute in developing systemic risks for equities and vice versa. More recently, Brunnermeier et al. (2016) provides evidence that, in trenching, common equities for two banks are build into collaterized debt obligations that are traded in repo markets. In the event of an institutional investors failure to roll over financing, leading to essential fire sales drops the market price for the common equity and in turn reduces the value of portfolios maintained by a different bank located in different countries. Here, a contagion formed within the banks contribute to systemic risk building in the equity markets across borders.

It is important to understand that connectedness parameters at large do not indicate risk transmission, but identifies the degree of systemic connections, in our case, across borders. Systemic risk transfer within borders may not lead to a full scale crisis, but risk transfer across borders, as Brunnermeier et al. (2016) suggests, may indicate a diabolic loop, or as highlighted in Farhi and Tirole (2017) a deadly doom loop creating a large scale crisis, that contagion parameters may capture. While contagion parameters captures only the volatility spillovers as suggested in Masson (1998); Khan and Park (2009); Bekaert et al. (2013) that may emerge with large shocks spilling over onto the neighbors corresponding to an event, that is not likely be a systemic event (Dungey and Renault, 2018). We aim to identify the spillovers originating from high degree of systemic risk build up and both the ex ante and ex post development of systemic crisis. This leans more toward financial network studies that is made popular by Dungey et al. (2010b); Billio et al. (2012); Khandani et al. (2013); Anufriev and Panchenko (2015); Acemoglu et al. (2015); Dungey et al. (2017); Demirer et al. (2017) presented in the first half of the paper. The discussion leads to visualization of risk topography approaches of such indicated in (Duffie, 2013) [7] but with a much bigger system. This further contributes to the novelty of the paper.

Extant empirical work explores the buildup of systemic risk in growing markets which experience pro-cyclical credit buffers and financial crises of varying sizes (Dungey et al., 2013, 2007; Antonakakis and Vergos, 2013; Claeys and Vašíček, 2014). The changes in networks between markets following a crisis period may result in higher shock spillover than previously observed (Acemoglu et al., 2015; Dungey et al., 2005, 2007), some of which may be a consequence of bubbles fueled by credit expansion and associated build-up of macroeconomic vulnerabilities (Kaminsky and Reinhart, 1998; Alessi and Detken, 2009; Drehmann et al., 2010; Drehmann and Juselius, 2014). The recessions resulting from the burst of bubbles are shown to be relatively deep and protracted, and feature a slow recovery (Jordà et al., 2013; Hermansen and Röhn, 2017).

Cyclical swings in credit conditions lead to varying degrees of crises stemming from sys-

[7] Duffie (2013) proposes a 10 by 10 by 10 approach, whereas we progress with a 31 by 30 by 30 approach

temic risks in the interconnected capital markets (Gonzalez et al., 2017). In turn this has led to concerns over means for reducing the pro-cyclicality of prudential and capital market regulation (BIS, 2010a,b)[8]. These concerns have led to a heightened interest in how monitoring capital market interconnectedness may help in early detection of buildup in systemic cyclical risks (Hermansen and Röhn, 2017; Kaminsky and Reinhart, 1998; Alessi and Detken, 2009; Bordo and Haubrich, 2010; Drehmann and Juselius, 2014).

In particular, regulators are concerned that the extent to which shocks are amplified across equity markets is directly related to the degree of vulnerability in the network. We address this problem by examining both transmission and vulnerability.

This paper considers a broad set of global equity indices, investigating their complex interconnections. We build on the growing literature on time varying systemic risks, lying within complex market networks, (Giraitis et al., 2016; Diebold and Yilmaz, 2015; Diebold and Yılmaz, 2014) and with theoretical underpinnings in modern economic network theories (Anufriev and Panchenko, 2015; Glover and Richards-Shubik, 2014). We first, make use of the robust DY measure to investigate the contribution of each individual market or market cluster onto all other markets, and highlight events associated with systemic network instability in the empirical evidence.

In identifying crisis transmission pathway pattern while making predictions on crisis buildup we complement Sarlin and Peltonen (2013); Resta (2016). We propose a 'crisis-map' similar to the map of Sarlin and Peltonen (2013), but compiled with connectedness measures. This is a new use of SOM to better understand risk transmission pathway. Earlier, Duffie (2013) proposed a risk topography with a 10 by 10 by 10 approach. We countenance Duffie (2013) by proposing a 31 by 30 by 30 approach. In technical terms, the stress topology in the maps are highlighted with a grid of 30 by 30 classification nodes for each data point in the rolled over unsigned systemic risk index across entire sample period, allowing us to visualize a gradual shift to crisis from non-crisis. The 70-30 split of input data into train and test data allows us to incorporate in sample predictions in the dynamic stress topology, while comparing the crisis occurrences in real time and with unconditional spillover signals.

To our knowledge, no other paper has attempted to detect dynamic stress generation by combining network topology and crisis transmission pathway predictions measured from unsigned systemic risk index.

[8]Basel III has been criticized for failing to address the pro-cyclicality of stock markets and crises (Saurina and Repullo, 2011).

Empirical Framework

The Diebold and Yilmaz (2012) (DY) spillover methodology distinguishes spillovers between markets using VAR forecast error variance decomposition (FEVD). The FEVD matrix is used as the adjacency matrix (or 'connectedness matrix') between N co-variance stationary variables with orthogonal shocks; net pairwise return spillovers between assets form the elements of the bi-variate relationships between the markets in a network. The overall spillover index is formed by adding all the non-diagonal elements of the decomposition.

From a VAR(p) of the form[9]

$$x_t = \sum_{i=1}^{p} \varphi_i x_{t-i} + \varepsilon_t \tag{1}$$

where x_t is a vector of stock returns, $x_t = (x_{1t,...}, x_{Nt})'$, φ_i is a squared parameter matrix and $\varepsilon_t \sim \mathrm{N}(0, \Sigma)$. The corresponding moving average representation is

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i.} \tag{2}$$

in which,

$$A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \ldots + \phi_H A_{i-H}.$$

To circumvent the order variation issue Diebold and Yilmaz (2014) use generalized H-step-ahead forecast error variance decomposition, (where H is user defined), constructed exploiting the generalized VAR framework (GVD) of Koop et al. (1996). This is denoted by $\theta_{ij}^{g}(H)$ and given as

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)} \tag{3}$$

where Σ is the variance co-variance matrix, σ_{jj} is the standard deviation of error term for jth equation, A_h is the coefficient matrix in the infinite moving average representation from VAR. At this stage, $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$.

Normalizing each row of the adjacency matrix gives

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}. \tag{4}$$

By construction $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$. DY index captures the full sample static spillover by measuring the sum of off-diagonal elements as a proportion of

[9] The intercept is suppressed for simplicity and without loss of generality.

the sum of all elements as the system-wide connectedness. The directional spillover index identifies variance spillovers of all other markets to market i as

$$S_{i\leftarrow all}\left(H\right)=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ij}^{g}\left(H\right)}{N}\times 100 \tag{5}$$

and the reverse directional spillover measures volatility spillover from market i to all other markets similarly as $S_{i\rightarrow all}$, generating $\tilde{\theta}_{ji}^{g}\left(H\right)$ parameters.

The net pairwise spillover or pairwise directional connectedness identifies gross shock transmission TO and FROM sample markets. The net spillover between markets i and j is defined as

$$S_{ij}^{net}\left(H\right)=S_{i\rightarrow j}\left(H\right)-S_{j\rightarrow i}\left(H\right). \tag{6}$$

In other words, we compute the transmission and vulnerability matrices from pairwise directional connectedness matrices.

Common network statistics include measures for nodes concerning directional connectedness for links from other nodes as in-degree connectedness and measures of connectedness to other nodes as out-degree connectedness. System-wide connectedness can be measured via mean degree weight measures as in Diebold and Yilmaz (2015).

Crisis-Map Method

With the crisis-map we investigate crisis transmission in global equity indices, by showing how markets evolve during a crisis period. Changes in the location of market clusters in space allows us to identify the possible pathways of lurking crisis in the system.

The self organizing crisis-map makes use of artificial neural network clustering in visualizing the data space. Essentially it implements a non linear projection from a potentially high dimensional input space onto a potentially lower dimensional array of nodes (nodes are also known as neurons in this literature), and as such represents a neural network. In principal, Self Organizing Maps attempt to preserve neighborhood relations by mapping from an n dimensional array of input vectors into a k dimensional array of output nodes. The process applies clustering techniques to assign nodes to their closest cluster via a number of steps. First, a lattice is populated with regular array of randomly generated synaptic weights or centers, in practice initialized with a PCA (Principal Component Analysis) surface. The iterative SOM algorithm, minimizes a loss function scanning across all data points in the input vector, and updates positions on the centers (weights) recursively. The updating process is initiated by reducing the distance, between the input vector and randomly generate weight vector, in other words, the loss function . Although, the position of input vectors remain unchanged, the synaptic weights are associated with nodes in the euclidean space. By finding the least distant input node from the synaptic weight vectors, we find the least distant nodes with input vector in the neighborhood space, best known as the "Best Matching Units" (BMU). The algorithm works in neighbourhood space, so that closer neighbours have greater weight. This eventually results in a surface of weights resembling a sphere around the lattice. Updating and convergence may be achieved by using the usual gradient descent method. Finally, the non-linear structure of the data is fitted optimally around the lattice, shaping a sphere of clusters, that can be presented in a two dimensional grid of nodes [10].

In the process of dimensionality reduction with projection and clustering, SOM method also produces robust predictions in the patterns outlined. The process involves moving nodes across Euclidean space: predictors are organised for nodes (say for example equity indices where each return represents a node) and are grouped into intermediate vectors, which in this case are fewer in number than the initial input vectors[11]. In other words, p distinct training vectors, equivalent to intermediate nodes are selected from the input data. Usually, the training data includes at least 80 percent of the sample data. The problem is represented by two dimensional array of predictions, a process involving random initialization of synaptic weights that we feed into the recursive optimization function, and an updating algorithm until the local minima for the loss function is achieved. The aforementioned updating algorithm leads to output nodes serving as prediction vectors or classifiers in unsupervised clustering. The nodes of the output vectors represent the topology that outlines the structure of the degree of temporal non-linear clustering in the data. The input and output nodes are connected via the weight vectors which project each node in the input vector onto each node in the output vector.

It is notable, that that the backward propagation with random wight generations iterates with a convergence criteria. Hence, patterns produced in this process are much more robust then contemporary methods of clustering in place.

The process proceeds in five steps producing graphical representation of predictions and classifiers. First, a random weight matrix is generated. Second, the algorithm goes on selecting sets of input nodes and updating the weights via backward propagation (the analytic gradients of the weights construct the hidden layers of edges) and then updating the decay function which governs the relationships with neighbours. In each case the Best Matching Unit (BMU) is found by selecting the Euclidean norms, ε. The convergence criterion provides stability in the projection by centering the ε, that is looking for a total zero error. The visualization initiates at this stage with reinforcing of sparcity associated with the decay function.

[10]see Sarlin and Peltonen (2013) for a graphical representation SOM
[11]The intermediate step offers increased robustness to the crisis-map.

The neighborhood around the BMU follows an exponential decay function[12]

$$\sigma_t = \sigma_0 exp^{\left(-t\lambda^{-1}\right)}$$

where, σ_0 is the lattice at time zero, t is the current period and λ is a conditional element. The purpose of the hyper-parameter is to regularize the decay function with penalty for non-convergence, reducing the complexity of the process. In the final stage, weight vectors continuously re-position with neighboring weights changing the most around BMU as reflected by the decay rate. The learning rate ξ decays with $\xi_t = \xi_0 exp^{\left(-t\lambda^{-1}\right)}$. Here, the one-step ahead weight function is represented as,

$$w_{t+1} = \omega_t + \theta_t \xi_t \varepsilon_t.$$

Finally, the neighborhood meets the convergence criteria (zero in theory), resulting in a lower dimensional response vector. The influence rate[13]

$$\theta_t = exp\left(-\frac{\varepsilon_t^2}{2\sigma_t^2}\right)$$

describes the degree of influence for each weight of the response units on the convergence algorithm. This rate is non-zero for the nearest neighbors to BMU and decreasing with distance from BMU.

The neighborhood positions of the clusters in the crisis map represent contagion transmission in the approach of Sarlin and Peltonen (2013). In the crisis maps the degree of convergence are illuminated with darker to lighter colored grids in resembling no economic events to some degree of events that ensues. Failure of convergence represents heightening of non-linearity between nodes, indicated with cracks in the topology.

Data

We collect equity market indices from Datastream, pre-process the source data to control for missing values, estimate spillover indices and subsequently use the spillover indices as source data for 'crisis-maps'. Our raw data are daily dollar denominated stock price indices for 31 equity indices from Asia, Pacific, Europe, Americas and the Middle East[14], for the period beginning from 1st of January, 1998 up until 15th of September, 2017. This period includes at least 10 major episodes of financial stress as documented in Table 1.

We transform the price indices to returns as the first difference of natural logarithms. Following Forbes and Rigobon (2002); Hyndman and Athanasopoulos (2014) we filter

[12] The computational graph of this function takes up a similar structure as that of information processing within our brain neurons, hence the term neural network is loosely used.

[13] This rate substitutes the largely known score function in generalized neural network architecture.

[14] List of the countries is presented in introduction section.

estimated returns with two day moving average to ameliorate the time zone effects on the data. Essentially, the moving average filter concentrates out the sharpest edge points, reducing white noise. This approach underpins much of the predictive and network literature; see for example Joseph et al. (2017); Zhong and Enke (2017); Elliott and Timmermann (2016); Chen et al. (2016); Ferreira and Santa-Clara (2011); Vaisla and Bhatt (2010); Atsalakis and Valavanis (2009); Cont et al. (2001); Granger (1992); Balvers et al. (1990); Fama (1976). Cont et. el. (2001)

Joseph et al. (2017) and Smith et al. (1997) point out that, a moving average (MA) handles discrete time series more subtly than other approaches, despite its simplicity. Hence, we choose the moving average filter for signal processing. The correct choice of window size is important. We conduct multiple trials and find that window size of 2 is the robust choice, complementing the notion of Spectral Windowing presented in Oppenheim and Schafer (2014); Forbes and Rigobon (2002).

Empirical Results

In this section we present the results from estimating interconnectedness between the 31 equity indices with the transmission pathway outlined in crisis-maps.[15]

Dynamic Analysis

To analyze temporal risk associations among the markets, we construct the DY rolling sample indices to assess both transmission and vulnerability. Following Diebold and Yilmaz (2012) we begin by considering a 100 day rolling window to construct the Diebold and Yilmaz Connectedness Index (DYCI). We choose a 10 day ahead horizon, $H = 10$ for the forecast error variance decomposition, also consistent with Diebold and Yilmaz (2012).[16] We retain the important edges by generating signals with 200 day moving average window.

Since the unfolding of the recent Russian ruble crisis leading to the dampening of global exports, investigations into the dynamic contemporaneous relationships between different markets have flourished (Demirer et al., 2018a; Capponi, 2016; Diebold et al., 2017; Diebold and Yilmaz, 2015; Diebold and Yılmaz, 2014; Yilmaz et al., 2018; Demirer et al., 2018c; Liu et al., 2017; Malik and Xu, 2017; Vergote, 2016; Badshah, 2018; Liow, 2015; Andrada-Félix et al., 2018; Ghulam and Doering, 2017; Chiang et al., 2017; Badshah,

[15] A section on static networks is presented in the online Appendix A. Counterfactual rolling plots and counterfactual crisis maps are presented in online Appendix B.

[16] Diebold and Yilmaz (2012) demonstrate that the spillover indexes are not particularly sensitive to the choice of forecast horizon over 4 to 10 days.

2018). We complement these studies by investigating the dynamics in a multi-cluster representation.

Rather than analyzing DY indices for every market individually we classify the sample markets into Asian Crisis (AC), Export Crisis (EC), Greek Crisis (GC), Oil Exporting Emerging (OEE) and Oil Exporting Developed (OED) markets. We construct rolling indices for transmissions and vulnerability and present them jointly.

In Table 1, we model all the crisis events across the sample period using DY rolling indices and find rational for important data points. Table 1 summarizes all the important edges in the figures presented in this section. Here we record the spikes in transmissions and vulnerabilities. Most often, a spike would shift the curves up to a new level and the curves remain upstream until a new spike emerges. This can be hold also for a curve sliding downstream.

We plot the 'TO' and 'FROM' DY indices for AC & EC, OEE & OED and the GC markets together in Figures 1 to 3. Plotting the 'TO' and 'FROM' signals together for transmission and vulnerability allows us to examine whether a higher transmitter also exhibits strong vulnerability; or, if vulnerability is heightened more in response to a local event than a global one. We also examine whether the transmissions and vulnerabilities are counter-cyclical for specific markets. In the following discussion we present a comparative analysis of Figures 1 to 3 with effects of oil inclusion in Figures 4 to 6. In Figure 6 we also include commodity compared to oil for investigating potential risks ensuing from Greek Crisis markets in light of findings outlined in the literature.

In all the cases examined, and for the majority of the time period, the transmission estimates are higher than vulnerabilities. This points out that usually the contribution of own shocks is dominant in explaining variation in any individual market's return, and the total impact of other countries is relatively small. The larger transmissions represent that all the markets are highly interconnected, since the total spillovers to all others can be quite large despite individual (bi-variate pairwise) effect on others is relatively small.[17]

The changing interconnectedness of the markets is clear from the results in Figures 1 to 3. Periods of crisis are distinguished in each of the panels of figures by a widening of the gap between transmission and vulnerability - transmissions tend to be higher and vulnerability - lower. The higher transmissions represent that when a market is experiencing crisis conditions it is more vulnerable to transmission from other markets (this form of increased connectedness is denoted hypersensitivity in Dungey, Milunovich and Thorp, 2010a). The lower vulnerabilities suggest the reduction in the effect of own shocks on others during periods of turmoil.

[17] See Table A1 in online Appendix A.

Asian Crisis

During the Asian crisis of 1997-98 authorities resorted to different intervention strategies to stem the tide of crisis. Thailand adopted a structural adjustment package; Malaysia moved from a floating to fixed exchange rate regime; Indonesia adopted inflation targeting policy and moved to a floating exchange regime; the South Korean currency devalued and eventually floated, see Khan and Park (2009). Conversely, Singapore retained its managed currency float and China did not intervene.

Figure 1, shows transmission and vulnerability indices for the AC markets (India, Malaysia, Singapore, the Philippines, South Korea and Thailand). Our focus is on spillover effects, so own effects are excluded from our discussion. The contrast between the signals for Malaysia and Thailand provides a pertinent example of the features attributed to equity markets during the crises. Thailand is commonly viewed as the originator of shocks for the Asian crisis. This is evident in its heightened transmissions at that time and again in the Global Financial crisis (GFC) period, possibly due to concerns about feedback effects on its economy. We find that both transmission and vulnerability amplifies for Thailand following the 2006 period. In contrast, Malaysia, was highly affected by the Asian Crisis, despite not being a crisis transmitter. It experienced a large increase in its transmissions at that point followed by decline in the relative effect.

The swings are much more substantial for India in the post Asian Crisis period.[18] For both India and the Philippines reversions quickly followed a spike in transmissions in the burgeoning GFC period.

Interestingly, the patterns for both Singapore and South Korea unveils a key finding. The signals point out that both the markets reflect a turning point in vulnerability appearing at the same time, between 2003-2004. Up until this point vulnerability decelerates gradually, rationalizing the benefits of flexible policy interventions in the post Asian crisis period, where a number of IMF programs and reforms were carried out over the late part of the previous decade. Vulnerability continued to amplify past the turning points for these markets.

In the post Asian crisis the decelerating cyclical patterns in crisis transmission and vulnerability supports the emergence of AC markets as safer investment venues relative to some other markets in our sample.

[18]Indian data is sourced from Bombay Stock Exchange (BSE). BSE is not only the largest in the world in terms of a number of listed companies, it is also in the top 10 in the world in terms of market capitalization.

Export Crisis

The second panel in Figure 1 presents the exporting (EC) markets of Germany, Chile, France, China, UK and Australia. Higher transmission and vulnerability in EC markets correspond to the aftermath of drops in exports preceded by the Russian ruble crisis in 2014 following trade sanctions and military actions. Intuitively, the export crisis may also appear from the 2016 crude oil price drop.

We account for several key features extracted from Figure 1 in the vulnerability of systemic risks. We find a brief period of dampening precedes further amplification for Germany at the same point as that of Singapore and Korea. Similar turning point is also detected in Australian pattern but appearing much later. This suggests, that German transition is driven by the same force that exists for Singapore and South Korea, whereas Australian transition reflects emanating GFC. Australia has managed to see slowly reducing vulnerability and increasing transmission over the period. A second key feature is turning points in the curves of the UK and France leading to sharp rise in vulnerability becomes apparent facing European crisis only. Finally, we detect such degree of transitions for China facing the very recent 2015-16 Chinese stock market turbulence.

The Chinese market is fraught with speculations of a crisis in the market(Forum, 2015; Mauldin, 2017; Elliott, 2017; Chiang et al., 2017; Mao, 2009). The speculations are fuelled further with the building up of 2015-16 stock market crash preceding a pronounced rise in both vulnerability and transmission. Moreover, with relatively low vulnerability and high transmission during GFC, Chinese market established exemplary resilience[19]. With the recent deterioration of Chinese resilience, casting risks in Chinese stock markets within systemic risk framework requires further examining before we postulate China to be the ground zero for the next global financial crisis.

Oil Exporting Markets

Now we explore the impact of exogenous factors such as oil indices into the system by examining the changes brought about as well as for robustness in the transmission and vulnerability dynamics for both AC and EC clusters in Figure A4. We account for the heightened systemic risk between China and Germany leading to other EC markets in Figure 1 with robustness delivered in Figure 4. We find that including oil results in systemic risk stemming more from France and the UK than others. Turning to AC markets in the other panel of the same figures, we do not find any substantial up or down swings for the AC markets with the inclusion of exogenous factor. This suggests, Asian markets have better resilience to oil shocks than other markets within systemic risk

[19]This may be presumably due to China's strongly growing domestic economy and timely policy interventions contributing in the economy going upstream facing the Global Financial crisis.

framework.

We show the spillovers of the OED and the OEE markets (OED comprises the USA, Canada, Russia, Norway, Japan and New zealand, while OEE includes the Saudi Arabia, Israel, Iraq, Sri Lanka, Nigeria and Venezuela) in Figure 2. Again, we compare Figure 1 for robustness including oil in Figure 5.

We find acute swings in transmission and vulnerability for Oil Exporting Developed markets highlighted in Figure 2. With the exception of Japan, this is true for Venezuela[20], the USA, Canada, Russia and Norway. We find both Venezuelan and Russian transmissions exceed the aggregate levels during the episodes of US-led Iraq invasion; in the unveiling of GFC, throughout the European debt crisis and the Russian Crisis. We also find that despite continuing increases in Venezuelan amplitudes, resilience in the Russian market intensifies. Additionally, Norwegian market resilience remains stronger relative to the aforementioned markets, but weaker than that of the USA and Canada.

Turning to OEE markets plotted in the second panel of Figure 2, we observe that since the Iraq invasion, Saudi Arabia and Israel have been the highest transmitters and recipients of return shocks, particularly in Middle East. While only a few cycles of transmissions and vulnerabilities are discernible for the Saudi Arabia and Israel during the outbreak of GFC, these pick up dramatically during the period of plunging oil prices in 2016. In the following years vulnerability increases for the Saudi Arabian markets. The remainder of the markets in OEE and OED clusters have been less resilient since the GFC with increasing systemic risk, similar to the results for the EC and GC markets.

The results for including oil shocks in these groups are presented in Figure 5 . We find stronger fluctuations of transmission/vulnerability for Iraq, Kuwait, the Saudi Arabia, Israel, Norway and Russia. Moreover only to Venezuela, Norwegian swings exceed that of the others in these clusters. While Norway shows heightened vulnerability to oil shocks in recent times; prior to the invasion of Iraq, Iraq's responsiveness to oil shocks was highest.

Our results support heightened fragility in energy exporting markets, heralding an increase in systemic risk. We do not find any dampening in the spillovers with the inclusion of oil shocks in Figure 5.

Greek Crisis

A major crisis since the Global Financial Crisis is the European debt crisis, erupting in late 2009, finding its way to major European markets. Studies in this vein suggests, the crisis spread quickly, even before policymakers became aware of the serious troubles facing

[20] Chen et al. (2002) suggests Venezuela is an important representative of Latin American markets. Up until 1999 there was no visible diversification in Venezuelan market due to its high level of integration with other Latin American markets.

the European markets; see for example (Jolly and Bradsher, 2015; Mink and De Haan, 2013; Arghyrou and Tsoukalas, 2011; Jolly and Bradsher, 2015). In Figure 3, we present the dynamic analysis for the GC cluster. Greek, Irish, Portuguese, Croatian and Belgian systemic risk estimates continue to amplify up until 2016. The transmissions for all the markets remain high. In essence, we identify an overall upward shift in the transmissions of GC markets over the 20 years, with heightening vulnerability for Greece, UK, Ireland and Belgium in recent times.

Aiming to explain resilience in the GC markets, we point out key features in vulnerability. Vulnerability remained upstream for Greece, Portugal and Ireland up until the post European Crisis period. We detected a brief dampening in vulnerability only to be picked up much more substantially facing the smaller crises emerging in post European crisis. The recent jump in vulnerability is the highest amplification that heralds a crisis may emanate from within the GC cluster.

The results complement Ghulam and Doering (2017) by identifying higher connectivity of GC markets to EC, CE, OED and OEE markets. The gyrations in GC markets suggest that crisis conditions have not subsided for this cluster. The picture that emerges suggest that a larger crisis may erupt from Greece or other GC markets.

Including Oil and Commodity in Figure 6, we record amplification in overall transmission and vulnerability. This cements the robustness of our analysis while suggesting that GC markets are vulnerable to exogenous shocks to a lesser extent than that of EC, OED and OEE markets.

We again find a turning point of similar degree for Belgium from dampening to magnification appearing at the same time as Germany, Singapore, Korea and some other markets. Next we explain what causes these transitions in vulnerabilities to appear together.

Conduit effects

We detected transitions from dampening of vulnerability to amplification for Germany, Singapore, South Korea and Belgium appearing at the same time in the beginning of 2000 in Figures 1 to 3. We aim to present rationalization for such collinear movements in vulnerability.

In Figure 2, we find the same turning point in the vulnerability curve appears for the USA and Japan at the same time with aforementioned markets, but to a much higher degree then others. BIS (1998) summarizes that the USA and Japan were found to be conduits if not ground zero of earlier crisis events. In light of this discussion, we have detected the conduit effects of the USA and Japan to Germany, South Korea, Sri Lanka, Belgium and Australia. The crises that transpired in the USA from dot comm bubble and the subsequent energy crisis is exerted upon Japan, South Korea, Singapore, Germany, Belgium and Australia resulting in the corresponding transition from low to high vulnerability estimates together at the same point in the plots. This may be due to high volume of trade between these markets with the USA and Japan at one point. In short, we have captured the conduit effects outlined in Baur and Schulze (2005).

Crisis Maps

We now take the DYCI spillover indices generated in the previous section as inputs to produce crisis maps in the form of Self-Organizing Maps.

Using DYCI as the data input rather than historic returns or financial indicators as in earlier papers (Marghescu et al., 2010; Sarlin and Peltonen, 2013; Betz et al., 2014) or log prices in (Resta, 2016) we are able to provide a new way of examining systemic risks, highlighting the interconnectedness and spillovers of the system particularly in representing the paths of vulnerability in the system.

Our main contribution is to present meaningful visualizations of high dimensional inputs. The generated topology of the markets illuminate hidden overlapping and non-linear dependencies. Such technical representation is achieved by defining the topology with SOM Best Matching Units (BMU) discussed earlier.

An important novelty lies in our dynamic (windowed) mapping approach. We disaggregate our original map to thirty-nine (39) successive maps, sampling at roughly 135 rows (semi-annually) for each iteration. We extend the number of replications until all the 5041 rows are mapped. This approach allows us to visualize and examine the changing degree and direction of contagion during different crisis. What lies closest to the spirit of this paper is León et al. (2017) proposing hierarchical clustering of estimates derived from indirect networking methods.

Figure 7 presents the full-sample crisis map generated with SOM using unconditional spillover measures. The horizontal and vertical axes present the markets individually and in clusters. The representation is similar to a heat-map with reordered column positions. The degree of crisis is depicted with lighter to darker colors. The classifications lie between no events (when the convergence in loss function is successful) to events (when loss function is not optimally minimized for as non-linearity heightens in places). Crisis transmission is drawn along the path of events across contemporaneous market links. Additionally, the transmission pathway separates changing stress levels naturally clustered together for all data points.

We interpret the graphs as following. The darker colors represent fissures in a plateau of the mid-colors with occasional lighter colored higher features. To continue the analogy if we consider a shock as some form of flash storm somewhere in the system, then the fissures represent the path into which the storm-water will drain. Deeper fissures will attract more water. This refers to the areas that are most vulnerable. The pathways visible on the plots represent the path of least resistance for shock transmission through the system. For example, in Figure 7, it is clear that the markets from South Korea to Israel on the map are highly vulnerable to a shock from the US (shown on the horizontal axis). We see topographic depressions are deeper as the fissures run across GC to OED clusters. Depressions are deeper again as the crack runs through EC to AC cluster. The dislodging on the plateau forming the fissure represents the vulnerability pathway in the system carrying crisis across the system. Here, Figure 7 gives us a parabolic pattern in the fissures pathway that connect the major topographic depressions. Now we are presented with the question if these fissures are more ephemeral than long lasting.

All these figures representing dynamics in crisis maps over nearly two decades, breaks down to semi-annual time periods in Figure 8, Figure 9, Figure 10 and Figure 11 to show the evolving vulnerabilities of the financial networks. In the first half of 1998, during the Asian crisis, there is a substantial web of fissures connecting many markets in the system. The vulnerability of the system to shocks is evident. This begins to ease in the second half of 1998 and into 1999. Throughout 1999 and 2000, the activity transmission loops at the right hand side of the figures are especially apparent. These maps show the high vulnerability of the OED markets, and increasingly the AC markets to shocks originating from the EC markets. Interestingly, there is little vulnerability to transmission from the US across markets either before or after the dot-com crisis (with the exception of Australia). By 2004, vulnerability to US sourced shocks evinces as a source of global vulnerability (on the left hand side of the figures) and this continues right up until early 2007. However, this does not identify the most vulnerable pathway. Instead, by 2007 markets are most vulnerable to shocks emerging from the EC countries. This possibly reflects the anticipated effects on their economies of the slowdown of the booming demand for exports due to high growth in Asia, perhaps as an indirect consequence of the reduced activity in the US following the crisis. For the following years the primary source of vulnerability in the system remains around the role of shocks from EC markets, and with shocks that affect those markets themselves (across the top of the figures).

Although we have presented how vulnerability pathway, or in other words, crisis transmission pathway in analogy to storm water mounds change along the web of fissure across the plateau, we have detected a common parabolic pattern in the fissures running from end to end throughout the plateau (the system). More coverings open up as new events are triggered and the bedrock is riddled with openings in major events, the running of storm water, drawing an analogy to crisis transmission is temporal. The new cracks fill up quickly, and the system remains with the common pattern in the pathway of crisis transmission over the entire sample period. This is a new finding presented for the first time in the vein of crisis prediction.

There are interesting small surges of vulnerability evident in hot-spots, which we denote sinkholes, in a number of the figures. According to Davis et al. (2010); Khandani et al. (2013) an adverse feedback loop spreads across sectors as deadly doom loop (Farhi and Tirole, 2017) and across international equity markets as diabolic loop(Brunnermeier et al., 2016) . We visualize crises spreading across different clusters in the system as a feedback loop completes circle within a cluster and find such sinkholes appearing in the system in 2004:1 for GC, 2004:2 for OED, 2006:1 and 2006:2 for AC, 2008:2 for GC, 2012:2 for EC and 2014:1 for OEE. Moreover, we find multiple sinkholes appearing in the maps for 2009:1 for GC, OED, OEE; 2010:1 for GC and OED; 2016:2 for EC. However, we are faced with the question on the importance of these sinkholes. Are these sinkholes random appearances? Can we predict crisis forming from these sinkholes?

As per Brunnermeier et al. (2016) diabolic feedback loops transmits risks across capital markets as cascading common equities pooled in SIFIs, indicates a buildup of crisis across national borders. This in turn results in a global contagion. Turning to the first half of 2006, we detect sinkholes creeping up into the system. Can we expect that we will see crisis erupting in the following period? We see rapid dislodging on the plateau in the next period. Moving along, we show new web of deeper fissures opening up along with new sinkholes facing the GFC in 2007. Further, the parabolic pattern in the fissures pathway that remained in calm times, is overlain with many new fissures. Crisis transmitted everywhere along the path of the common pattern. As the effect of crisis subdues, we see these new deeper fissures are filled up and the common parabolic pattern or the common fissure resumes. Again, in 2008 and in 2010 we detect unanticipated sinkholes emerging in the plateau. In both cases, the following period brings in many new openings and fissures with voids exceeding normal times leading to major crisis erupting throughout the system as heightened vulnerability is spread across the system. In the first case, we see a sudden spike in ongoing crisis, and we are faced with the European crisis in the latter case. In all cases examined, we conjecture that the openings into random sinkholes heralds imminent crisis and heightening of transmissions across the system. In the dissemination of a crisis event, the system reverts back to the common parabolic pattern. This is a new presentation in this vein of studies in terms of both long term persistence of commonality in transmission pathway and early warning system.

In contrast, we also capture strong endogenous crisis transmission in our system of dynamic mapping. For example in 2009:1 a strong vulnerability is revealed for AC markets and oil exporting emerging markets, with the sources from the USA, Australia, and India. In 2010:2 there is vulnerability for the USA and Australia from the Asian markets. This is consistent with the resilience of the Asian markets in resisting the effects of the Greek and European debt crises.

In our DY spillover analysis, the total spillover index reached an all-time high by the end of the sample for China. A number of papers focused on China as a potential source market (Chiang et al., 2017; Forum, 2015; Elliott, 2017; Mullen, 2017; Mauldin, 2017; Forum, 2015; Cheng, 2017). However, the full visualizations in the crisis maps do not support the conclusion that China is the source of vulnerability in the system, in fact they point more towards sensitivity to shocks from the GC and OED markets. In February 2018, this view was vindicated in the rapid transmission of shocks from the US sourced drops in the Dow-Jones to the more developed markets of the world, with the patterns largely consistent with the crisis map produced for 2017:1.

A complete counterfactual analysis results for dynamic spillover section and for the crisis maps are presented in online appendix section B.

Policy Implications

One of the most appealing features of the crisis maps is that they are able to display the changing nature of vulnerabilities within a financial system in a readily accessible manner. Despite the usefulness and wide range of applications for the DY adjacency matrix approach, complementary information can be obtained from crisis maps in terms of both the amplification of spillovers and the emergence of specific areas of vulnerability.

The rolling spillover indices and the crisis maps both show that the system can move dramatically. Consequently, the range of tools required by policy makers and portfolio managers needs to be wide. In some instances shutting down a link between two markets may protect other markets, but the results of our counterfactuals suggest that the effects on the overall crisis map are not easily detected. Diagonal fissure lines across the system result from cascades of shocks sourced at an origin market and traveling on via the fissures in the system (eg US to Australia to Japan). The crisis maps highlight both the direct and indirect nature of these relationships. In these cases, co-ordinated actions by many markets may be an appropriate means to short-circuit a crisis. For example, by blocking a pathway, perhaps through policy options such as short sales constraints, or short-term capital movement restrictions.

In other cases sink-holes emerge. These are hot spots where there is a high level of vulnerability for an individual market (or small number of markets) to shocks from a single source (or small set of sources). In this case an apt policy response may be to develop a domestic response to the cause of that vulnerability - possibly involving the traditional repair of macroeconomic fundamentals such as proposed in first generation crisis models; see, for example Eichengreen et al. (1996); Eichengreen and Hausmann (1999); Bordo et al. (2001).[21]

[21] Alternatively the cause may be vulnerability to structural issues such as high reliance on remittances.

Conclusion

In this paper we present return spillover connectedness between major global markets split into multiple categories based on their size, structure and roles played during major financial crises periods. First, we make use of unconditional spillover measures to analyze static networks of markets, and conditional spillover measures to analyze changing interaction of dynamics between major markets. Our analysis not only captures the degree and direction of the episodes affecting 31 international equity markets in the past 20 years, but also allows us to explain how the strengthening of networks are responsible for uncertainties.

This paper proposes a unique way of visualizing the changing vulnerability of a financial network via automated neural networks (ANN), and by filtering on the largest vulnerabilities provides crisis maps. These crisis maps highlight the least resistance shock transmission pathways at any point in time. We show how ANN methods relate to the commonly understood VAR representation and hence can be cast as an extension of the Diebold and Yilmaz (2009); Diebold and Yılmaz (2014) approach.

Time shots provide 'crisis-maps' that detect the changes in vulnerability for markets over time. Not only do we present a complete 'crisis-map' showing a conceptual pathway for shock transmission, but we also give time varying patterns by presenting stepwise windowed stress grids.

We investigate several issues that are central to scientific discourse in the systemic risk tenet of studies. First, we provide evidence of timely intervention leading to reduction of vulnerability and slipping out of crisis for many markets in the past. Second, our results reflect that changing interaction between markets are inducing transmissions that were considered vulnerable in the past, while postulated risky markets are not transmitting risks Third, we demonstrate that AC cluster is more resilient then before. Fourth, we conjecture that cutting links off may increase resilience for some countries in some cases, the aberrations caused in the system instigates larger and quicker crisis transmission in most cases. Fifth, we account for a common and persistent pattern in the pathway of crisis transmission that is only disrupted in crisis periods. Finally, we propose a robust way of crisis prediction with combining existing serving as early warning of crisis. Taken together, these results confirm that the countries in a system alone cannot slip out of an imminent crisis. Crucially, all countries in a system need to come together in order to short-circuit an emerging crisis.

The 'crisis-maps' highlight both the vulnerability and resilience dynamics in the markets examined. With an eye to practical applications, the maps presents an opportunity for investors and financial managers to diversify wealth better, enabling them to predict riskiness patterns in their portfolios. Additionally, our dynamic mapping method of channels of potential vulnerability enables policymakers to adopt proactive measures. Despite arguably underestimating the importance of interconnectedness in the pre-GFC period, policymakers have since realized the importance of identifying and co-ordinating their responses to vulnerability to crises originating elsewhere (León et al., 2017). The patterns observed in the crisis map are a means of visualising vulnerability to policymakers, who may then base their decisions regarding actions towards channels which might be worth restricting or encouraging, to protect individual markets from unfavourable shocks. These tools may help to capture the complexity of the changing nature of integration of world markets, and the changing vulnerabilites that are thrown up over time.

Our aim is to convincingly implement means by which crisis mangers can simulate the effect of alternative intervention paths in a network and have some knowledge of where the most effective interventions may lie given the structure of the network at any point in time. Thus, we specifically acknowledge the conditional nature of the problem, and that intervention strategies may need to be flexible and time-varying, responding to the changing structure of the network and the many alternative possible sources of shocks.

Discussion

1. We present a filtered static network analysis in online Appendix section A. The filtered static network in gauged from unconditional spillover measures. A static table of generalized variance decomposition matrix is also presented here.

2. We present counterfactual conditional spillovers in figures B1 to B6, in online Appendix section B. The figures are referred in our discussion of dynamic analyses.

3. In an interesting development, we present a 10 basis crisis- classification table (Table C1) and a 900 basis crisis-classification table (Table C2) in the online Appendix C. Table C1 presents summary statistics for within 0-10 range crisis classifications, that is a more simple and tractable presentation of condensed weights for every data point used in the dynamic crisis-maps. Table C2 presents summary statistics for within 0-900 (30 by 30 grid) range crisis classifications, reporting summary statistics of condensed weights for every data point used in the dynamic crisis-maps.The summary statistics are presented for equal number of subsets used as in the dynamic crisis maps. Moreover, The sample data points are split into 70-30 input train and simulated test data points, gauging from rolling vulnerability spillover matrix. This additional section further adds to the robustness, tractability and the predictability of the patterns presented in the paper. In that spirit, the paper serves as a good addition to the early warning literature.

   Tables C1 and C2 adds to the important implications of analyses presented in this paper for early stress detection and subsequent policy decisions neutralizing such stress. While being flexible in the base selection, the updating algorithm applied on vulnerability matrix make accurate predictions for heightened stress generated during 2012, 2015 and 2016. We also detect high stress generation during 1998-1999, 2011-2002, 2006, 2007-2009. Additionally, we produce a 30 by 30 grid stress classification in Table C4. The results complement our findings presented in dynamic analysis and crisis map sections, while also serving as robustness for complete analyses presented in this paper.

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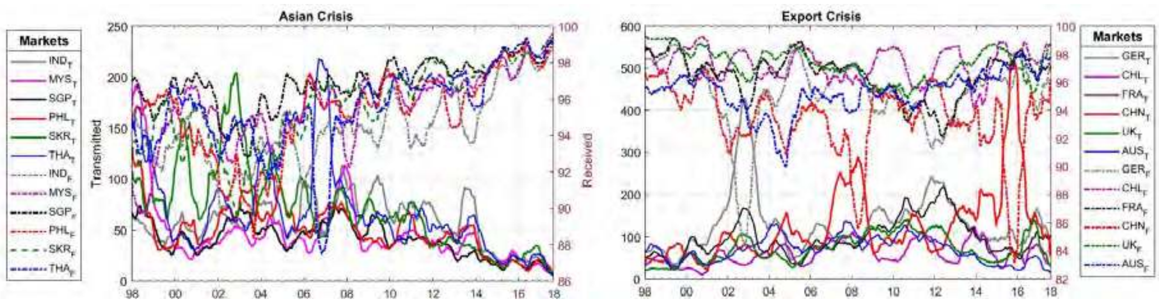


Figure 1: Asian Crisis Markets & Export Crisis Markets

Note: This figure represents contemporaneous relationship of daily return data for 20 years, for markets categorized within Asian Crisis (AC) and Export Crisis (EC) markets derived from generalized variance decomposition.

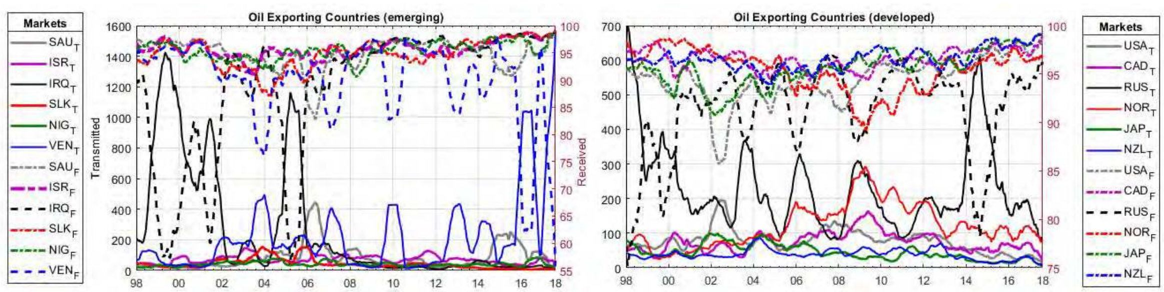


Figure 2: Oil Exporting (Emerging) Markets & Oil Exporting (Developed) Markets

Note: This figure represents contemporaneous relationship of daily return data for 20 years, for markets clustered within Emerging Oil Exporting countries (OEE) and Developed Oil Exporting Countries (OED)

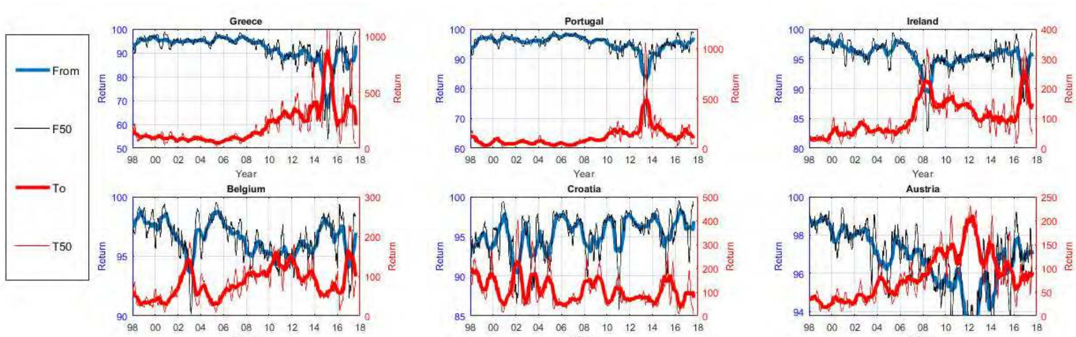


Figure 3: Greek Crisis Markets

Note: This figure represents contemporaneous relationship of daily return data for 20 years, for sample markets of Greece, Portugal, Ireland, Belgium, Croatia and Austria.

Note: For all the plots in this section the transmission and the receiving patterns are plot together, with the same color in both the patterns is used for a given country.

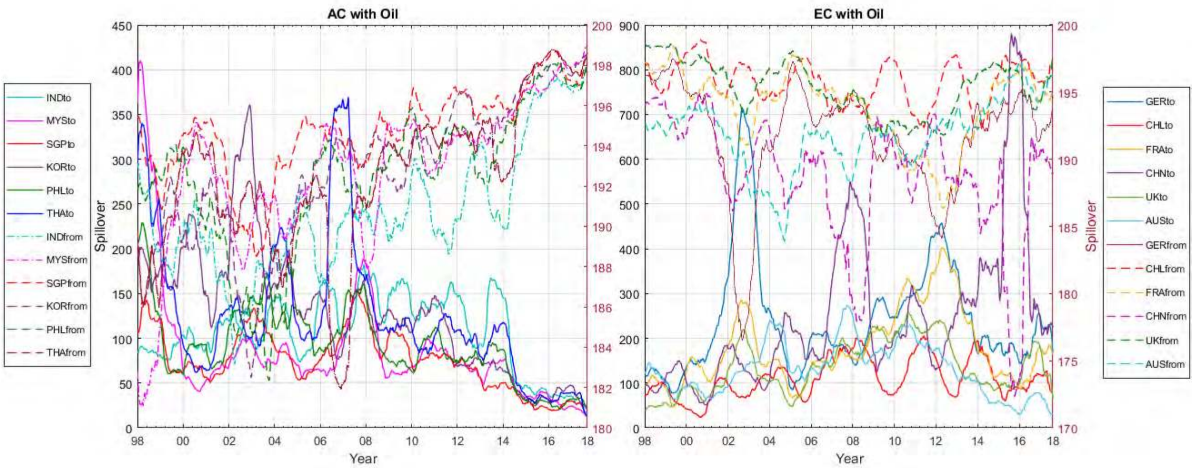


Figure 4: AC-EC spillovers [oil effect]

This figure represents the conditional spillovers with oil index as exogenous to AC and EC blocks.

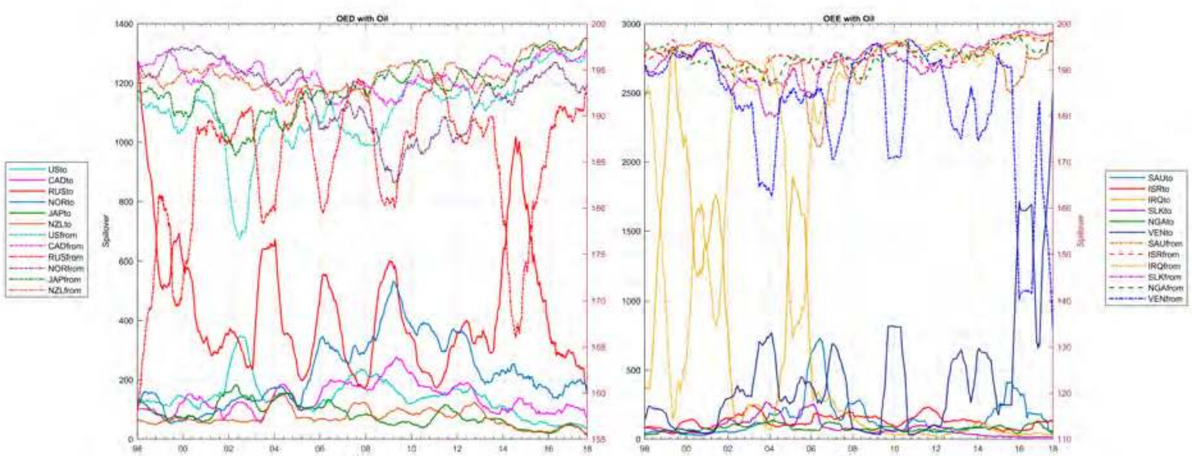


Figure 5: OED-OEE spillovers with [oil effect]

This figure represents the conditional spillovers with oil index as exogenous to OED and OEE blocks.

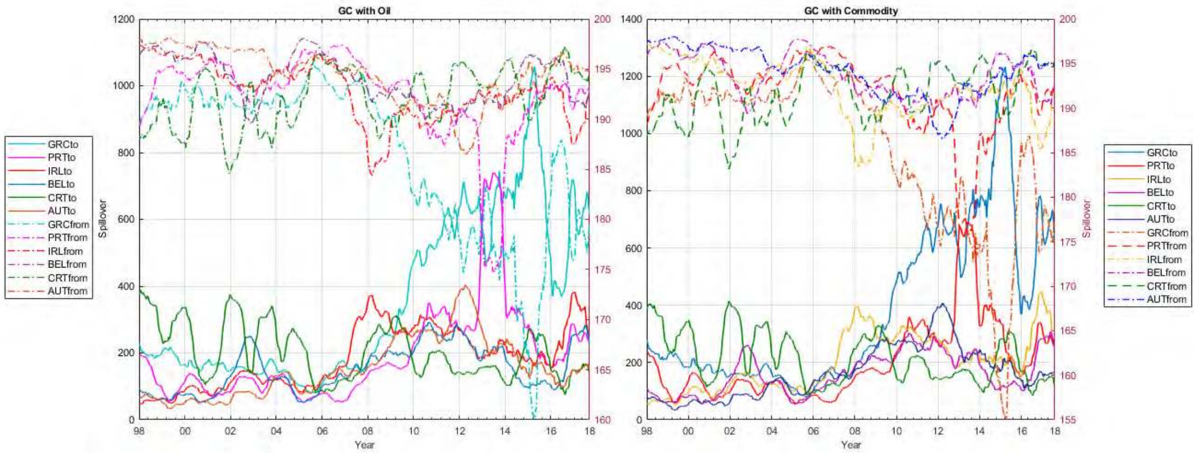


Figure 6: GC spillovers [Oil and Commodity effect]

This figure represent the conditional spillovers with oil and commodity index as exogenous to the sample blocks.

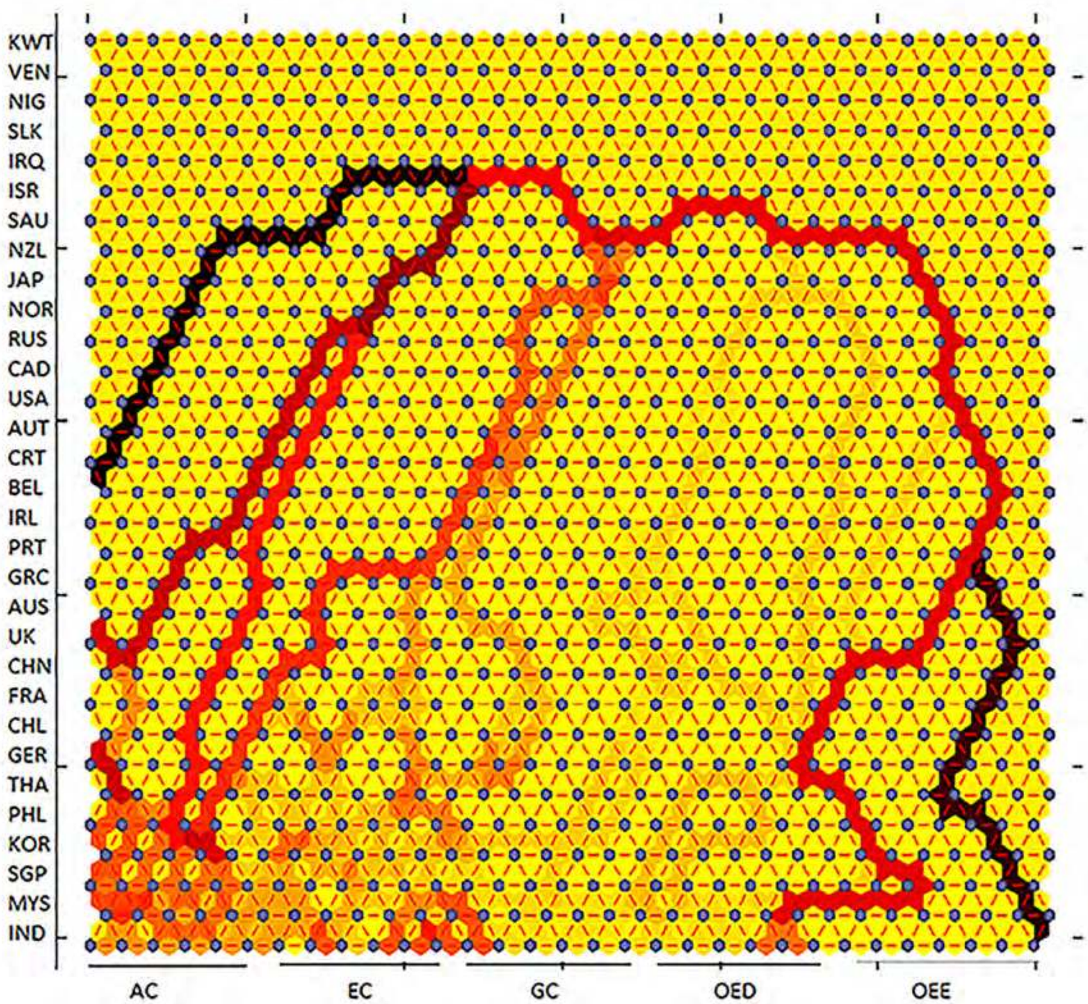
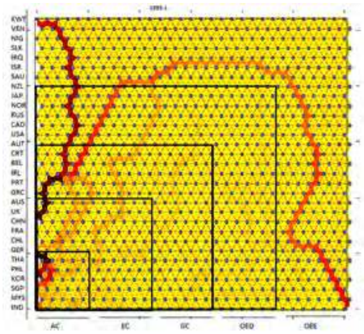


Figure 7: Crisis-Map (full sample period)



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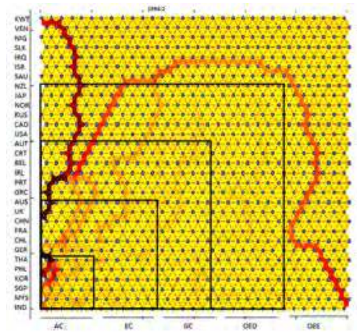

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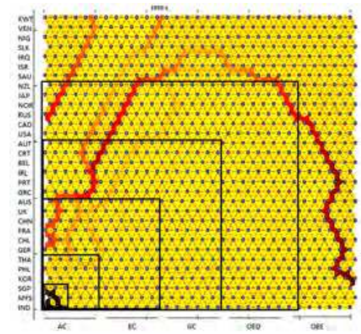

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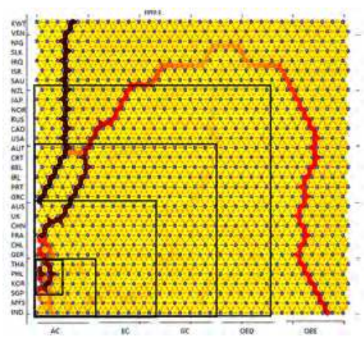

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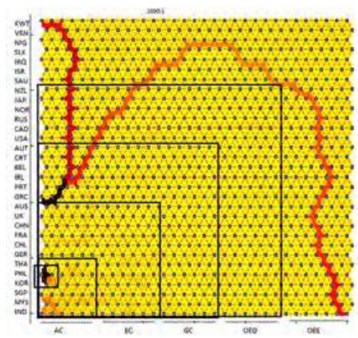

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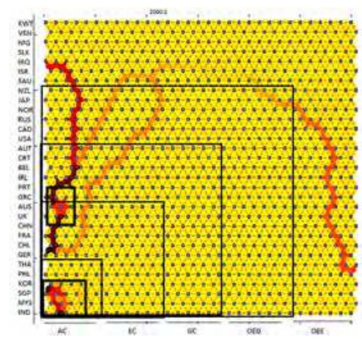

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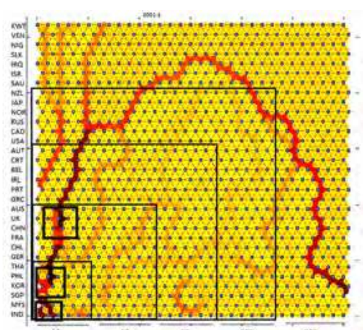

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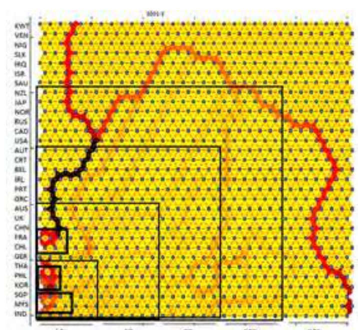

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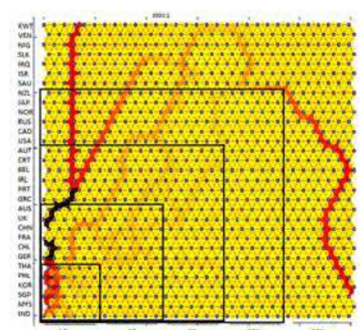

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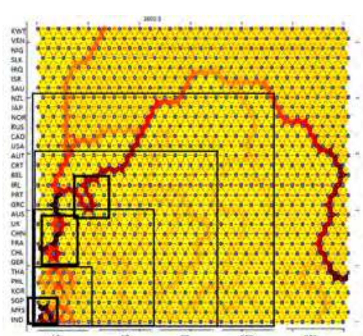

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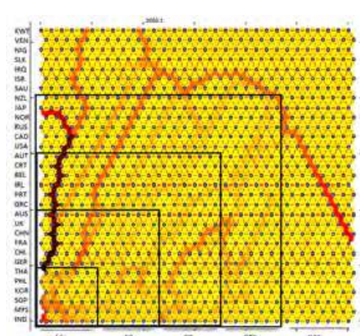

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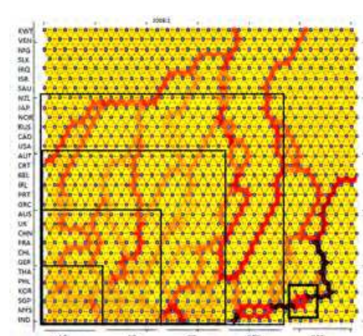
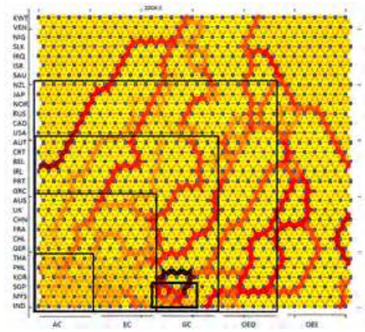


((l)) 2003:2

Figure 8: Dynamic crisis transmission maps from 1998-2003



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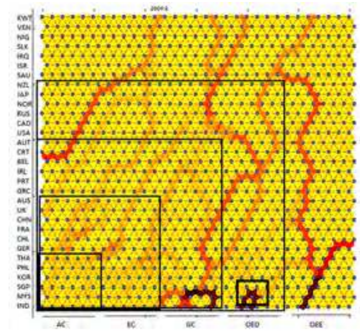

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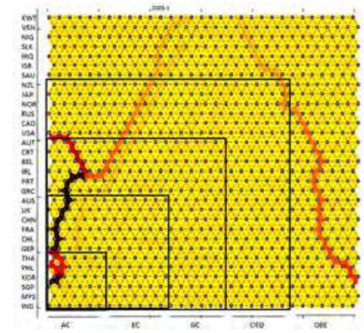

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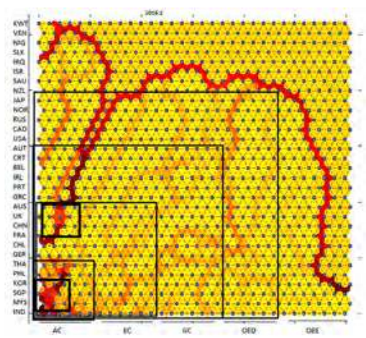

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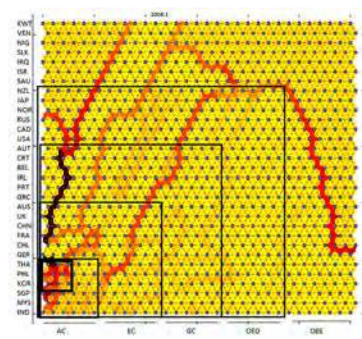

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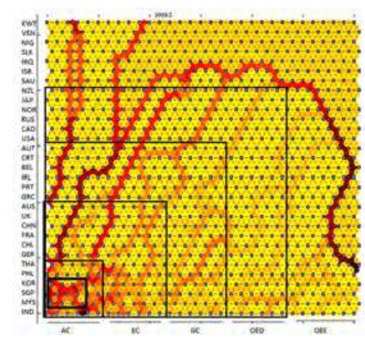

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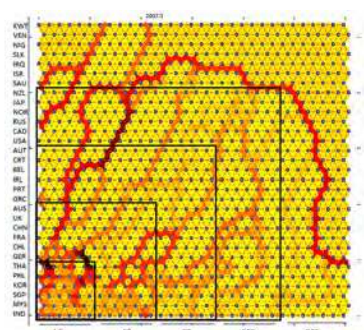

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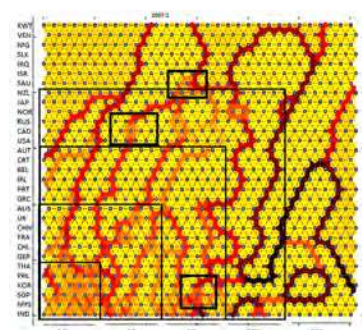

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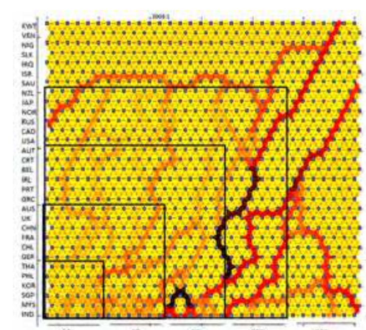

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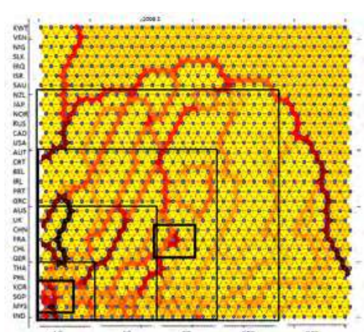

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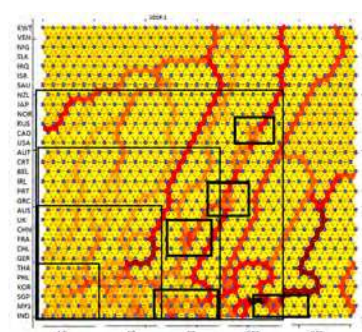

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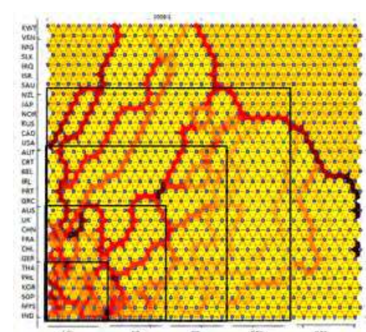
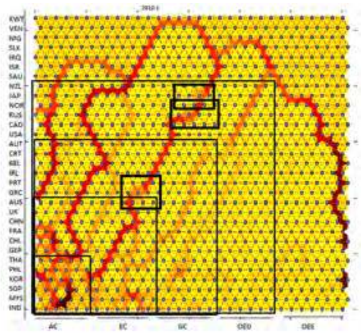


((l)) 2009:2

Figure 9: Dynamic crisis transmission maps from 2004-2009



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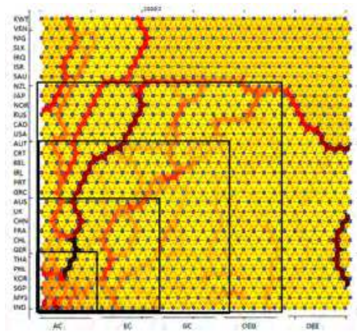

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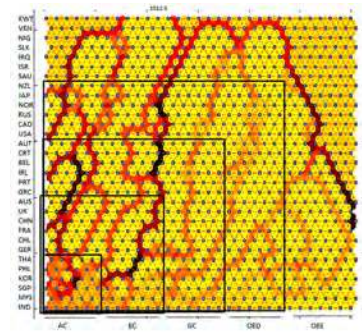
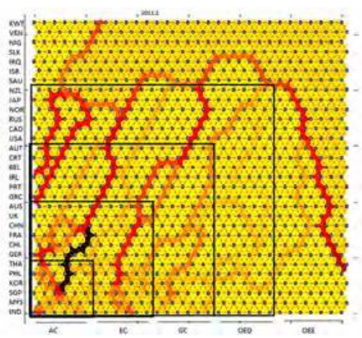


((c)) 2011:1



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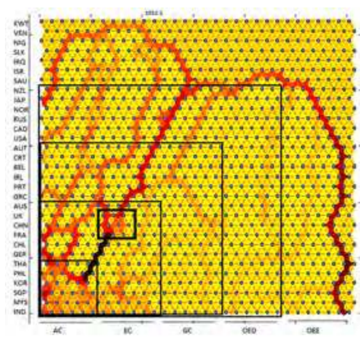

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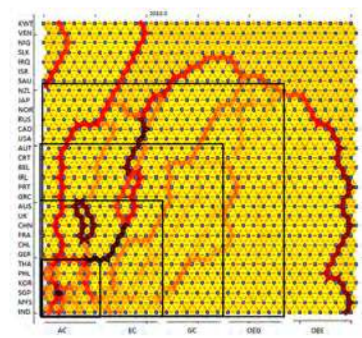

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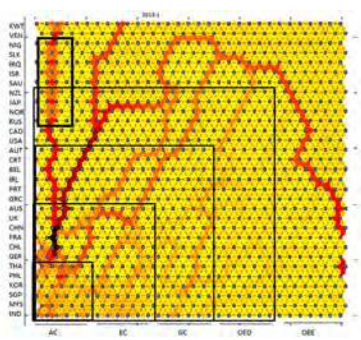

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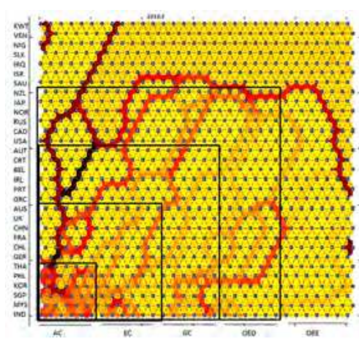

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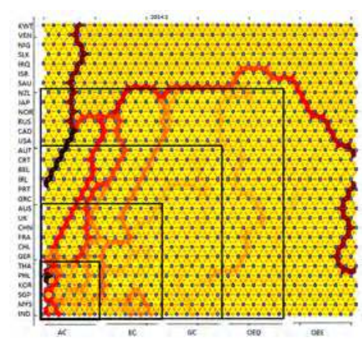

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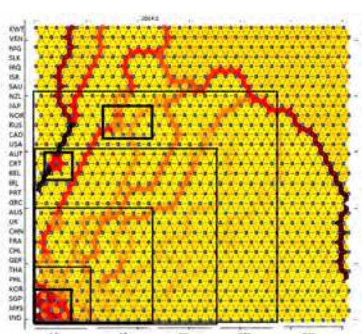

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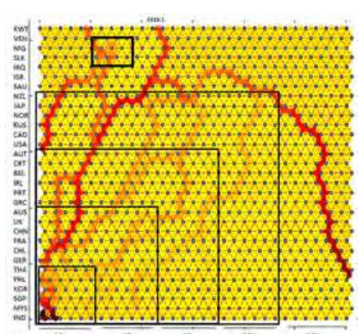

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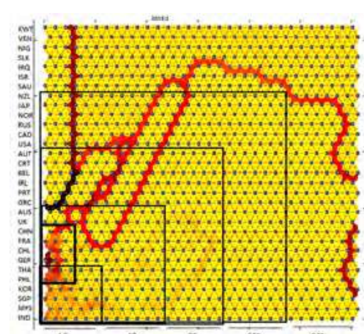
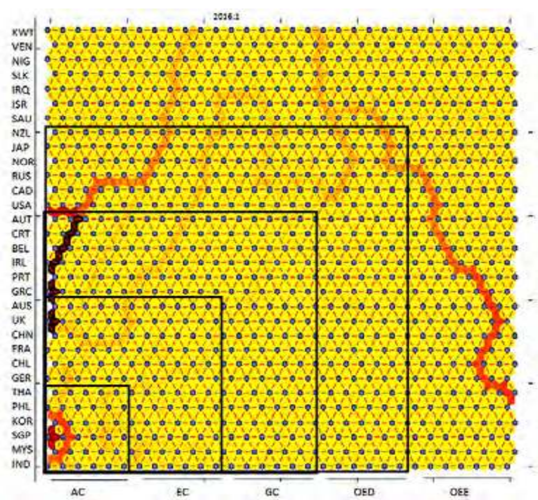


((l)) 2015:2

Figure 10: Dynamic crisis transmission maps from 2010-2015



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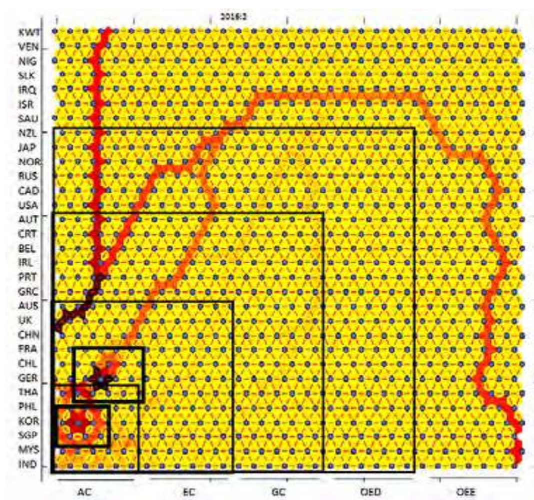

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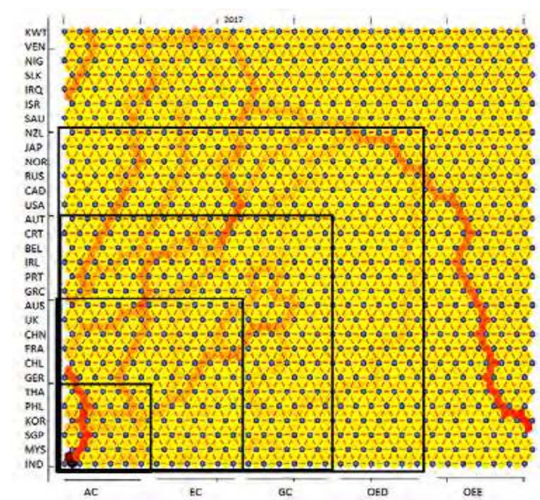

((c)) 2017:1

Figure 11: Dynamic crisis transmission maps from 2016-2017(Crisis Prediction)

Table 1: Major crisis events

Modelling crisis			
Year	Transmission- Markets	Vulnerability-markets	Crisis events
1998:1	Malaysia, The Phillipines, Croatia, Russia, Japan	Greece, , Portugal, Ireland, Austria, USA, Japan, Venezuela	**1**. 1997 Asian Financial Crisis continues. **2**. Sourcing from the collapse of Thai baht, resulting in Thailand becoming effectively bankrupt.
1998:2	Malaysia, India, The Philippines, Singapore, Australia, Chili, Norway	Malaysia, Greece, , Portugal, Ireland, Belgium, Croatia, Austria, Japan, Venezuela	**1**. 1998 Russian Financial crisis- Devaluation of the ruble followed by Russian Central Bank defaulting on its debt **2**. 1998 Oil price crash follows
1999:1		Malaysia, The Phillipines, Singapore, South Korea, Greece, , Portugal, Ireland, Croatia, Austria, Canada, Russia, Norway, Japan, Iraq, Sri Lanka, Nigeria, Venezuela	Ecuador financial crisis followed by Brazilian Financial crisis and South American economic crisis, effecting many of the GC countries and spreading through the oil markets into Oil dependent countries.
1999:2	USA, Russia, Iraq, Nigeria	Malaysia, The Phillipines, South Korea, Germany, France, Greece, Portugal, Ireland, Austria, Saudi Arabia, Nigeria, Venezuela	1998-1999 Russian Financial Crisis continues.
2000:1	India, South Korea, UK, France, Australia, Croatia, Canada, New Zealand, Israel	Malaysia, The Phillipines, Greece, Portugal, Ireland, Belgium, Croatia, Austria, Saudi Arabia, Israel, Venezuela	**1**. Early 2000s recession effecting Euroopean Union , the USA (commencing). **2**. Japan's 1990s recession (the lost decade) continues.
2000:2		Malaysia, Singapore, Chili, Greece, Portugal, Ireland, Austria, Russia, Saudi Arabia, Venezuela	The dot com bubble leading to dot comm stock market crash, effecting the USA and Canada mostly.
2001:1		Singapore, South Korea, China, Greece, Portugal, Ireland, Austria,USA, Canada, Russia, New Zealand, Saudi Arabia, Iraq, Sri Lanka, Nigeria	The dot com crash continues.
2001:2	Chili, Japan, Iraq, Nigeria	Greece, Portugal, Ireland, Austria, Canada, Russia, Japan, Venezuela	**1**. Early 2000s recession continues. **2**. Japan's 1990s recession (the lost decade) continues.
2002:1	India, Croatia,Japan, Sri Lanka, Nigeria	Greece, Portugal, Ireland, Austria, Russia, Iraq	**1**. The dot com crash continue.s **2**. Japan's 1990s recession (the lost decade) continues.
2002:2	South Korea, Belgium,USA, Canada	India, Chili, Greece, Portugal, Ireland, Croatia, Austria, Russia	**1**. US Stock marker crash in 2002 followed by excessive speculations prevalent in 1997-2000 led from the September 2011 terrorist attack on US. **2**. Enron bankruptcy , Tyco and Worldcom scandals effected energy stocks around the globe emerging from the USA .
2003:1	Singapore, South Korea, Germany, UK, France, Croatia, Saudi Arabia	India, Greece, Portugal, Ireland, Austria, Canada, Russia	**1**. The dot com crash continues. **2**. Japan's 1990s recession continues.

continue on the next page

Table 1: Major crisis events

	Modelling crisis		
Year	Transmission- Markets	Vulnerability-markets	Crisis events
2003:2	The Philippines, Singapore, Russia, Sri Lanka	India, China, Greece, Portugal, Ireland, Iraq, Nigeria	**1**. Global energy crisis- Increasing tensions in Middle East together with rising concerns over oil price speculations followed by a significant fall of US dollar , resulted in oil prices rise abruptly, exceeding three time the price at the beginning. **2**. SARS outbreak : First identified in Guangdong province in China, rapidly took an epidemic form worldwide, slowing down economic interactions with China to many markets.
2004:1	The Philippines, Australia, Chili,USA, Canada, New Zealand, Nigeria, Venezuela	India, South Korea,Greece, Portugal, Ireland, Croatia,USA, Japan, Israel, Venezuela.	**1**. Global energy crisis continues. **2**. The dot com crisis continues. **3**. Japan's 1990s recession continues.
2004:2	Croatia, Japan	Greece, Portugal, Ireland, Venezuela	Petrocurrency effect subdues
2005:1	South Korea, China, Iraq	Singapore, Germany, France, Greece, Portugal, Ireland, Belgium, Canada, Russia, Japan, New Zealand, Sri Lanka, Nigeria, Venezuela	**1**. Global energy market starts to recover. **2**. With petrocurrency effect subsiding, this period sees a buoyant global stock markets.
2005:2		Singapore, South Korea, Germany, Australia, Chili, Greece, Portugal, Ireland, Croatia, Canada, Venezuela	
2006:1	South Korea, Russia, Norway,Japan, Saudi Arabia, Saudi Arabia, Sri Lanka	Singapore, Greece, Portugal,USA, Iraq, Venezuela	The GAZA conflict emerges, amplifying the energy crisis.
2006:2	India, UK, Canada, Nigeria	The Philippines , South Korea, Greece, Portugal, Japan	
2007:1		India, The Philippines, South Korea, Greece, Portugal, Canada, Japan, Saudi Arabia, Israel, Sri Lanka, Nigeria	Global Financial Crisis (GFC) emerges
2007:2	Thailand, The Philippines, India, The Singapore, South Korea, UK, Australia, Chili, Ireland,USA, Canada, New Zealand, Saudi Arabia, Israel, Venezuela	Thailand, Greece, Portugal, Canada, Russia, Norway, New Zealand	
2008:1	China, Chili, Ireland, Belgium, Saudi Arabia		**1**. The Global financial crisis continues. **2**. Post 2008 Irish banking crisis ensues.
2008:2	India, Croatia	Singapore, Thailand, Australia	

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Table 1: Major crisis events

Modelling crisis			
Year	Transmission- Markets	Vulnerability-markets	Crisis events
2009:1	Croatia, Austria, Canada, Russia, Norway, New Zealand, Israel, Venezuela	China, Australia, Ireland, Belgium, Japan, Saudi Arabia, Sri Lanka, Venezuela	**1**. 2008 -2011 Icelandic financial crisis leads to credit crisis in UK, hurting the euro-zone areas to some extent. **2**. Russian crisis: the great recession in Russia begins resulting in a full fledged economic crisis in Russia. **3**. Spanish financial crisis/ Great Spanish depression begins. **4**. Eurozone crisis/ Greek crisis: In the wake of Great recession in the late 2009 , several Eurozone members (Greece, Portugal, Ireland, Spain, Cyprus) failed to bailout over-indebted banks and repay foreign debt. 2009-2010 Venezuelan banking crisis unearths.
2009:2	India, Singapore, Germany, UK, Nigeria	China, Chili, Norway	The post 2008 Irish banking crisis leaves German and French banks exposed , having enormous foreign claims in Greece, Ireland, Portugal, Italy, Spain (Greek crisis countries).
2010:1	Belgium	India, The Philippines, Croatia,USA, Canada, Japan, New Zealand, Israel, Nigeria	
2010:2	UK, France, Australia, Portugal, Croatia	The Philippines, Singapore, Venezuela	**1**. Eurozone crisis/ Greek crisis deepens. **2**. Spanish financial crisis/ Great Spanish depression further fuels in the European sovereign debt crisis. **3**. Venezuelan banking crisis continues. **4**. Spanish financial crisis/ Great Spanish depression continues.
2011:1	The Philippines, Portugal, Japan, New-Zealand	Russia, Norway, Sri Lanka, Venezuela	**1**. Eurozone crisis heightens. **2**. Great Spanish depression contributes in the worsening of Eurozone crisis.
2011:2	India, Belgium, USA, Saudi Arabia, Israel	China, Croatia, New Zealand, Venezuela	Heightening Eurozone crisis, Spanish crisis, Venezuelan crisis reinforces feedback loops across global financial markets, recoupling emerging energy dependent and oil exporting country's markets. This in turn, reinforces risk transmissions back into the USA.
2012:1	Germany, UK, France, Chili, Greece, Austria, Canada	Singapore, South Korea,USA, Japan, Nigeria, Venezuela	Eurozone crisis continues
2012:2	Germany, UK, France, New Zealand, Nigeria	India, Singapore, South Korea, Chili	

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Table 1: Major crisis events

Modelling crisis			
Year	Transmission- Markets	Vulnerability-markets	Crisis events
2013:1	Greece, Portugal, Ireland, Venezuela	India, Austria, Canada, Norway, New Zealand	Eurozone crisis continues
2013:2	India, Chili, Austria, Russia, Norway	Germany, France, Croatia, Japan	Eurozone crisis continues
2014:1	India, Chili, Austria, Russia, Norway	Germany, France, Croatia, Japan	Commodity price drops with the slowdown in Chinese economy, also contributing into a large scale Brazilian economic crisis.
2014:2	Russia		**2014-2015 Russian Financial crisis**: Following economic sanctions on Russia, plummeting global oil prices, devaluation of Russian ruble and fire sale of Russian assets all contributed in the development of a major financial crisis in Russia.
2015:1	Greece, Croatia, Austria, Saudi Arabia, Nigeria, Venezuela	Chili, Belgium, Austria, Canada, Norway, New Zealand, Israel, Nigeria, Venezuela	
2015:2	China, Canada	India, The Philippines, South Korea,USA, Russia, Japan	Corresponding to Russian Financial crisis, stock market in the USA starts to decline.
2016:1	China, Venezuela	India, The Philippines, Singapore, South Korea, France, Australia, Greece, Portugal, Belgium, Austria,USA, Russia, Norway, Japan, Saudi Arabia, Sri Lanka, Nigeria	**1**. **Export Crisis**: Germany, Chile, France, China, UK, Australia among others experience historic decline in total exports to others, followed by the so-called oil-glut. **2**. **Chinese crisis**: A massive drop in Chinese stock markets results in markets terminating transactions in the wake of concerns over a Chinese Crisis, that eventually took the shape of a global meltdown. **3**. January 2016 global meltdown resulting from fire sales of Chinese assets brought down the European and the USA stock markets
2016:2		Greece, Portugal, Croatia, Austria, Russia, Japan	
2017:1	UK, Australia, France, Chili, Greece, Portugal, Ireland, Belgium, Croatia, Austria, Japan, New Zealand, Israel, Nigeria, Venezuela	China, Russia, Japan, New Zealand	2016 global meltdown continues
2017:2		China, Australia, Chili, Ireland,USA, Canada, Russia, Japan, New Zealand, Saudi Arabia, Nigeria, Venezuela	

Appendix: Crisis transmission: visualizing vulnerability

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August 27, 2019

Appendix A: Static filtered networks

In this section, we present the unconditional spillover generated from 31 equity markets and draw dynamic filtered financial networks. The financial networks highlight the highest transmitters and receivers in aggregate terms. For better visualization we present spatial maps showing the highest to lowest transmitters and receivers identified with unconditional spillover measures.

Static Network

The estimated connectedness results for the full sample of 31 indices is shown in Table A1. An element in the i^{th} row and j^{th} column of the matrix gives the percentage contribution of the 10 day ahead forecast error variance decomposition to market i by market j. It clearly shows that the main source of shocks to each market are via own shocks on the main diagonal. Spillovers between markets are given by the off-diagonal elements. The total directional connectedness (from all others excluding own shocks) to i is found in the far right column of the table. The total connectedness to all others (excluding own shocks) from j is found in the bottom row of the column. These are the components of the DY index represented over the entire sample period.

Estimated vulnerability network plots, are shown in Figure A1 and Figure A2. The edges in these figures represent Euclidean distance between the nodes. We further filter both of the network plots to retain only the important linkages in the system. We use dynamic filtering[1] of the static networks to retain links where the strength is over 100 and 50

[1] We use the force directed algorithm proposed by Fruchterman and Reingold (1991). This method

percentage basis points, respectively in Figure A1 and Figure A2. We select the cutoff points by estimating the averages of weights in percentage basis points and then consider the upper points in the range. This allows us to concentrate on the important network components of the system.

An appeal of the dynamic filtering is that it allows a more granular approach in explaining the degree and direction of changing systemic risks within networks. Figure B1, represents the links only when the shock transmission from the source nodes are higher than a maximum threshold of 100 points. The picture that emerges from the dynamic filtering highlights that Germany, Norway, Russia, Belgium, Canada, Sri-Lanka and the USA are the main transmitting markets. Specifically, the highest spillovers come from Germany and the USA to Australia, India and Iraq. The USA spills its shock to China, and Germany transmits shocks to New Zealand.

Usefully, when we explain the degree of transmissions between two nodes with GVD weights, the euclidean distance between nodes account for the speed of transmission. We find that, while Germany transmits a higher degree of risk to Japan and Kuwait than Australia, euclidean distance suggests that a crisis transmits faster to Australia and Kuwait from Germany then to Japan. In other words, Japan will have more time to shift policies resisting the crisis reaching Japanese markets in the case of a crisis erupting in Germany, while Australia and Kuwait have considerably less time. The node locations also indicate that, oil exporting markets in Middle East are highly vulnerable in terms of both degree and direction of crisis emerging from the USA and to a lesser degree from Russia. Interestingly, China is highly vulnerable only to a crisis erupting from the USA.

Figure A2 depicts vulnerabilities characterized by spillovers 'FROM' other markets. We filter out shock received from the source nodes if higher than maximum threshold (50 percentage basis points). Figure A2 shows that Australia, Belgium, Austria, Germany, New Zealand and the UK are the most vulnerable to crises generated elsewhere. Some evidence is also provided on high vulnerability for China, Iraq, Kuwait, Sri Lanka and Canada. Figure A2 further shows that vulnerability nodes spread out further than transmission nodes. We interpret this as demonstrating the vulnerability of major markets to others, implying that with the emergence of a crisis, all markets will fall victim where the speed of transmission will vary with node distance.

Two dimensional networks represent a good way for presenting complicated estimates. Yet, information is suppressed for limitations in the dimensions. We overcome these limitations by producing interactive three dimensional networks.[2] With three dimensional

is interactivity in terms of capturing changes between forces, and has a strong theoretical foundation influenced by Multidimensional Scaling (MDS) theories. For more details see Fruchterman and Reingold (1991).

[2]These results are available upon request.

networks, we find China and most middle eastern markets are close to each other while all other nodes are clustered in regards to both transmission and vulnerability.

The network representations hold important information to aid with policy and investment decisions. The euclidean distance illustrating speed of transmission should allow policy makers laying out plans to stay away from critical nodes.

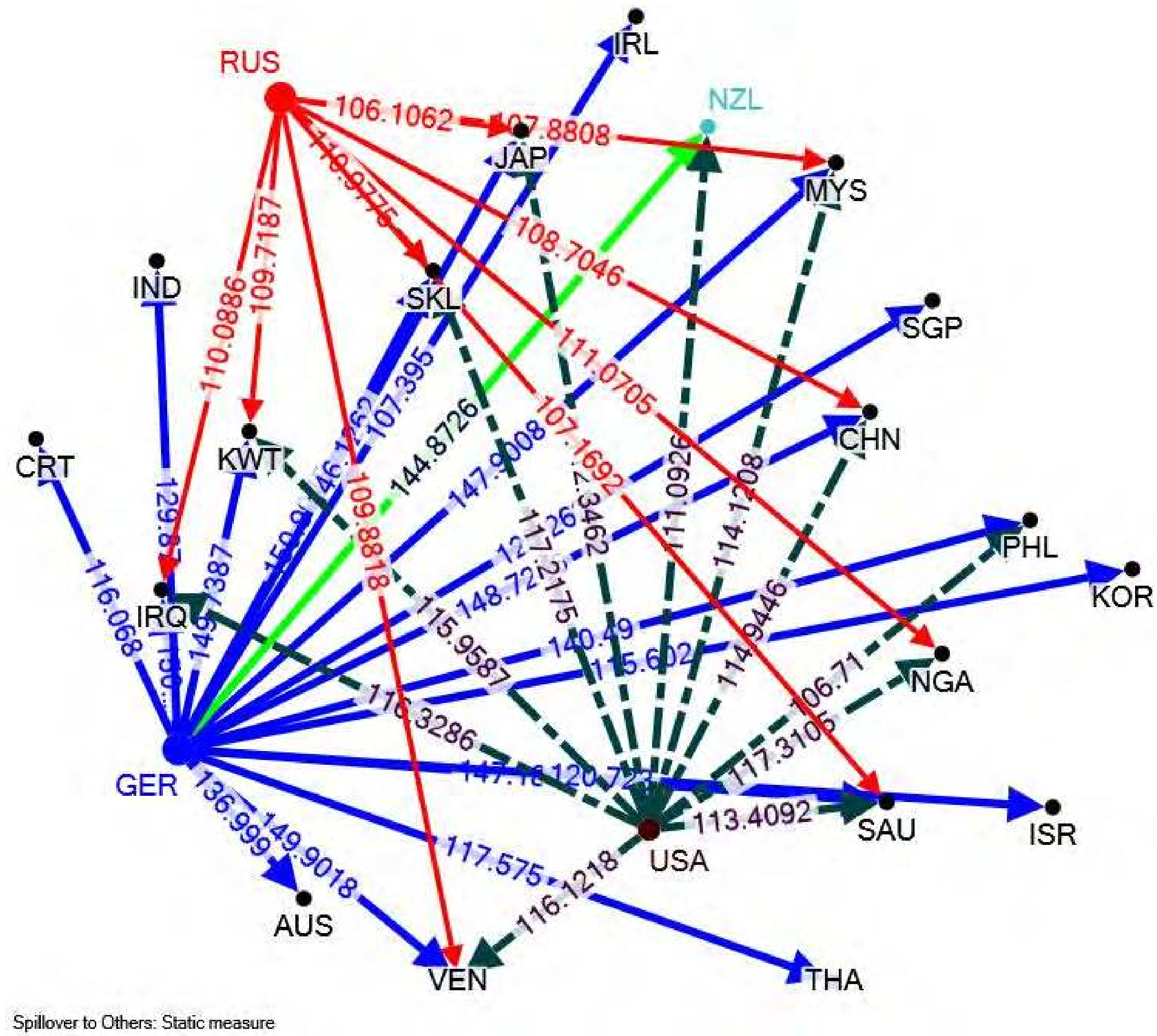
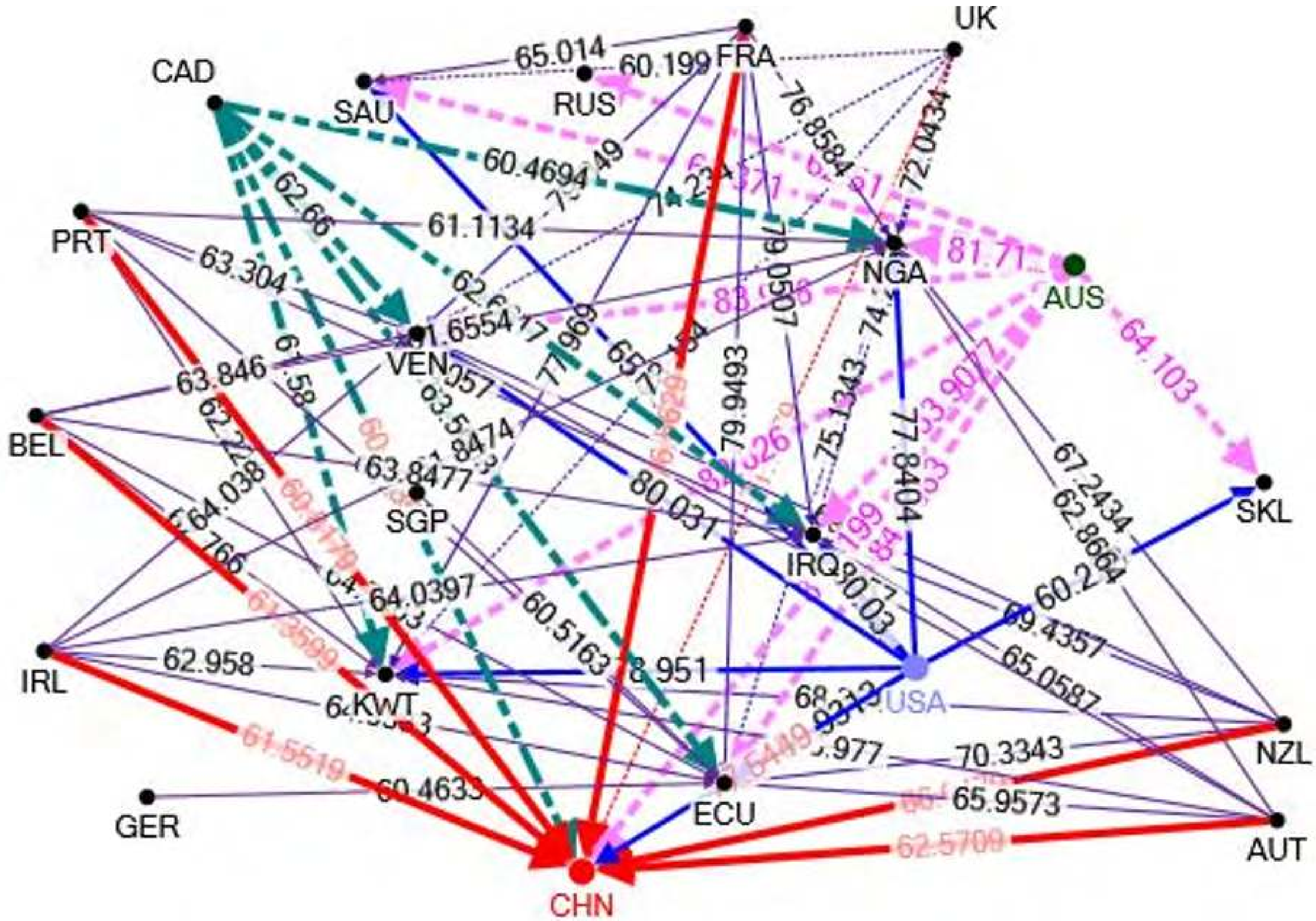


Figure A1: Static Network- Major contributors

Note: Edge arrow size indicate directional connectedness To others. The weights of networks are labeled on the edges. Here, the vertexes are filtered out based on weights between 100-150 percentile point. The maximum edge weight is 150 percentile point.



Spillover From: Static Analysis

Figure A2: Static Network- Major receivers

Note: Maximum threshold is considered to be edge weight over 50 percentile point. The maximum edge weight is 100 percentile point.

Table A1: Generalized Variance Decomposition Matrix

To	USA	AUS	IND	JAP	MYS	NZL	SGP	PHL	KOR	SLK	THA	NGA	VEN	KWT	From IRQ	SAU	CHN	ISR	CAD	GRC	PRT	IRL	BEL	HRV	AUT	RUS	NOR	GER	CHL	UK	FRA	Total
USA	16.74	1.491	2.877	0.548	0.551	1.791	4.386	0.725	3.569	0.025	2.846	0.041	0.018	0.057	0.073	0.666	0.117	7.281	28.98	3.962	6.170	7.647	13.76	3.219	10.91	6.956	15.59	30.34	17.67	18.54	24.22	231.8
AUS	3.471	13.44	6.869	6.479	4.034	14.78	11.43	3.559	9.143	0.115	8.428	0.127	0.034	0.107	0.115	1.014	1.992	4.549	19.70	5.852	7.980	7.503	12.09	8.008	18.10	8.309	24.07	16.52	19.23	16.04	17.81	270.9
IND	1.055	0.075	58.46	0.562	1.015	0.404	2.883	0.964	2.519	0.199	2.971	0.197	0.013	0.101	0.059	0.331	0.446	2.439	3.668	1.329	1.635	1.521	2.561	1.025	2.433	3.186	2.195	4.449	7.207	2.221	4.240	112.3
JAP	2.006	0.108	0.466	49.06	0.648	0.132	2.564	0.471	3.341	0.079	1.779	0.077	0.004	0.068	0.104	0.445	0.175	0.543	3.942	0.618	0.457	0.401	1.278	0.522	1.136	1.293	0.968	3.421	3.862	1.882	3.879	85.74
MYS	0.932	0.044	0.048	0.295	65.35	0.037	3.389	1.517	1.272	0.038	4.502	0.016	0.033	0.013	0.026	0.071	0.092	0.676	2.679	0.156	0.652	0.239	1.310	1.536	0.703	2.415	1.006	0.916	4.108	0.628	2.011	96.72
NZL	2.162	0.075	0.613	0.023	0.081	27.37	1.339	0.447	0.450	0.261	1.087	0.087	0.002	0.050	0.018	0.189	0.027	1.224	6.044	1.396	2.173	1.941	3.861	2.163	3.699	1.588	3.842	5.727	5.562	3.509	4.928	81.94
SGP	1.490	0.065	0.142	0.732	0.217	0.117	37.24	2.308	2.296	0.431	9.439	0.015	0.095	0.064	0.012	0.037	0.175	1.533	4.853	0.996	0.692	0.709	2.638	0.603	1.529	2.855	2.318	2.983	5.619	2.412	3.594	88.22
PHL	1.845	0.101	0.496	0.473	0.173	0.164	1.159	53.47	1.222	0.104	5.557	0.079	0.007	0.154	0.021	0.129	0.098	1.702	4.686	0.581	0.955	1.034	3.650	0.704	1.718	1.959	2.001	3.632	8.744	2.162	3.676	102.4
KOR	2.425	0.464	0.740	1.429	0.162	0.270	1.742	0.502	56.44	0.088	2.489	0.175	0.016	0.133	0.025	0.361	0.503	1.887	6.693	1.032	1.566	1.245	4.656	0.972	1.480	3.082	2.096	8.230	7.657	3.914	7.142	119.6
SLK	0.104	0.008	0.093	0.134	0.047	0.121	0.035	0.009	0.063	88.22	0.072	0.118	0.006	0.115	0.030	0.223	0.063	0.125	0.237	0.045	0.223	0.175	0.599	0.591	0.227	0.152	0.644	0.401	0.825	0.453	0.107	94.26
THA	1.096	0.108	0.084	0.409	0.254	0.276	0.548	0.784	1.002	0.037	68.24	0.043	0.009	0.063	0.007	0.122	0.392	0.546	4.325	0.455	0.69	0.596	2.003	0.954	0.481	2.026	1.035	1.978	8.504	0.885	2.929	100.8
NGA	0.069	0.063	0.012	0.048	0.031	0.053	0.019	0.044	0.006	0.041	0.032	96.00	0.023	0.037	0.045	0.502	0.055	0.034	0.168	0.059	0.100	0.097	0.182	0.137	0.024	0.225	0.123	0.154	0.149	0.068	0.094	98.70
VEN	0.185	0.248	0.097	0.413	0.019	0.274	0.184	0.137	0.637	0.092	0.108	0.028	97.34	0.012	0.015	0.379	0.889	0.632	1.336	0.978	4.262	0.256	0.395	0.184	0.618	0.706	0.539	0.579	3.156	2.395	0.556	117.6
KWT	0.101	0.229	0.286	0.196	0.101	0.108	0.353	0.252	0.009	0.709	0.114	0.206	0.003	95.64	0.003	0.789	0.122	0.664	0.072	0.249	0.382	0.474	0.176	0.269	0.418	0.982	0.138	0.356	0.126	0.288	0.646	104.4
IRQ	0.208	0.094	0.079	0.208	0.125	0.173	0.136	0.145	0.408	0.458	0.470	0.419	0.005	0.190	96.95	1.178	0.095	0.806	0.103	0.501	0.346	0.181	0.495	0.621	0.651	0.515	0.367	0.656	2.235	0.148	0.443	109.4
SAU	0.223	0.017	0.169	0.134	0.032	0.024	0.296	0.152	0.338	0.154	0.040	0.028	0.001	0.024	0.015	82.68	0.257	0.414	1.303	0.389	0.403	0.336	0.665	0.396	0.658	0.800	1.696	0.873	0.995	0.517	0.540	94.57
CHN	0.101	0.050	0.049	0.196	0.018	0.003	0.089	0.208	0.045	0.103	0.019	0.012	0.001	0.005	0.017	0.105	94.24	0.134	0.401	0.205	0.065	0.223	0.772	0.192	0.263	0.122	0.152	0.791	1.305	0.109	0.207	100.2
ISR	1.335	0.189	0.698	0.089	0.047	0.039	0.440	0.274	0.262	0.067	0.137	0.010	0.005	0.019	0.011	0.329	0.124	46.60	5.150	1.854	2.242	1.952	3.264	2.019	4.128	2.812	5.862	6.935	3.995	3.464	6.674	101.0
CAD	1.153	0.311	0.511	0.160	0.133	0.123	0.899	0.124	0.417	0.072	0.230	0.056	0.012	0.013	0.001	0.089	0.013	0.704	34.17	1.322	2.304	0.975	3.481	2.244	3.840	3.202	8.616	6.499	6.483	4.375	5.363	87.91
GRC	2.857	0.034	0.629	0.022	0.082	0.286	1.019	0.131	0.239	0.093	0.085	0.042	0.007	0.017	0.034	0.119	0.187	1.409	6.257	53.38	8.376	5.483	12.45	4.563	10.10	2.789	7.043	16.75	7.628	5.774	12.22	160.1
PRT	1.588	0.089	0.539	0.011	0.012	0.067	0.328	0.082	0.386	0.029	0.106	0.029	0.002	0.015	0.003	0.021	0.068	0.666	2.930	1.156	33.47	5.540	12.78	3.982	12.50	1.716	6.809	16.94	6.702	6.194	17.21	131.9
IRL	3.342	0.277	0.655	0.250	0.015	0.228	1.408	0.278	0.814	0.003	0.494	0.056	0.008	0.017	0.016	0.494	0.109	1.442	6.312	1.558	1.744	32.75	11.13	2.581	8.032	2.568	5.512	12.45	6.578	9.331	9.241	119.7
BEL	2.144	0.179	0.675	0.023	0.044	0.118	0.695	0.173	0.458	0.012	0.101	0.033	0.001	0.003	0.003	0.203	0.089	0.936	4.252	0.900	0.970	0.857	32.91	1.893	5.363	1.249	4.582	14.89	4.558	5.828	10.74	94.90
HRV	1.898	0.041	0.494	0.358	0.080	0.071	0.809	0.137	0.224	0.267	0.181	0.006	0.006	0.040	0.018	0.394	0.009	0.971	2.464	0.538	0.970	1.034	2.341	67.09	2.855	1.707	2.059	3.449	4.841	0.975	2.175	98.52
AUT	1.965	0.193	1.035	0.007	0.012	0.217	1.105	0.129	0.579	0.047	0.253	0.041	0.008	0.016	0.009	0.305	0.027	0.657	4.749	1.199	1.329	1.349	4.034	0.836	31.77	2.930	6.844	5.322	6.124	2.635	3.617	79.35
RUS	2.391	0.088	0.860	0.258	0.219	0.585	1.288	0.519	0.255	0.544	0.071	0.193	0.008	0.038	0.015	0.090	0.243	0.400	9.777	0.674	1.137	0.300	2.014	2.184	2.418	75.29	5.104	6.429	11.71	4.427	2.286	131.8
NOR	3.252	0.316	1.001	0.224	0.009	0.208	1.071	0.308	0.649	0.082	0.384	0.074	0.006	0.014	0.014	0.327	0.087	0.987	10.16	1.652	1.832	1.241	4.853	1.461	2.352	2.185	40.47	7.899	6.159	4.569	5.528	99.37
GER	3.090	0.322	0.996	0.173	0.073	0.227	1.011	0.107	0.748	0.019	0.313	0.040	0.005	0.012	0.003	0.242	0.048	1.937	6.104	1.409	1.817	1.525	5.608	1.182	3.202	2.395	2.849	37.32	5.308	5.100	13.38	96.57
CHL	0.693	0.105	0.166	0.051	0.040	0.061	0.205	0.046	0.066	0.091	0.119	0.083	0.001	0.014	0.004	0.077	0.006	0.376	1.247	0.218	0.389	0.287	1.239	0.337	0.373	0.489	0.850	1.522	69.95	0.732	1.133	80.97
UK	3.444	0.488	1.074	0.202	0.054	0.398	1.297	0.228	0.889	0.013	0.504	0.050	0.008	0.043	0.003	0.248	0.061	1.503	7.437	1.637	1.929	1.848	5.853	1.247	3.801	2.167	3.777	8.037	5.227	22.53	6.341	82.34
FRA	3.403	0.416	1.043	0.192	0.087	0.438	1.193	0.162	0.937	0.007	0.324	0.037	0.008	0.023	0.003	0.322	0.052	1.849	6.836	1.742	2.201	1.521	5.439	1.205	3.344	2.252	3.273	8.669	5.072	2.905	17.78	72.73
Total	66.78	19.73	81.97	63.36	73.77	49.17	80.57	68.41	89.69	92.51	111.5	98.43	97.70	97.13	97.67	92.48	100.8	85.63	197.1	88.05	89.46	81.24	158.5	114.9	139.1	140.9	162.4	235.1	247.3	135.0	190.7	

Appendix B

Counterfactual Analysis

Counterfactual conditional spillovers

Counterfactuals invoke causal relations alternative to the existing association by modifying past inputs. However, without access to controlled experimental conditions true counterfactuals are almost impossible to perform in the literature. While critiques of counterfactuals postulate that altering causal relations may generate erroneous results (Dawid, 2000), the advocates of counterfactual analysis provide evidence of its usefulness, in that, results drawn from alternatives may help actions to mitigate undesirable consequences from crisis conditions elsewhere in the network (Pearl, 2000, 2002). We present counterfactual experiment results in this light.

We execute our counterfactual experiments by constraining selected effects in transmission process, specifically by constraining a number of the largest identified bi-variate pairwise linkages to zero. In policy terms we link this to a policy intervention designed to halt transmission between two nodes.

The *first counterfactual* considers the case where all the large links either receiving or transmitting identified as being over 100 basis points are set to zero. We then re-estimate the spillover indices with those links set to zero and all other link values from the original VAR retained.

We begin by presenting counterfactual dynamic conditional spillovers that marks crucial changes with counterfactuals in Figure B1 and in Figure B2. Not all counterfactual estimates capture substantial deviation from findings in non-counterfactuals.

We find transmissions around global financial crisis only amplifies for Australia, Israel, Japan, South Korea and New Zealand when these market's links with Germany is turned off. The transmissions for these market's exceed that of with all existing links. Interestingly, the American transmissions spike up only when its link with New Zealand is turned off. Seemingly, cutting links off, specifically with Germany, heightens risk transmissions for all markets.

We focus on interesting findings with vulnerability spillovers when we turn individual pairwise links off. We show that the entire Japanese vulnerability curve shifts down, or in other words, Japanese market becomes stronger as we turn its link off with the USA. Similarly, we show that Malaysian market becomes stronger when we cut its link off with the USA. Put together, it is an interesting finding to see that strong links with the USA market increases crisis related vulnerability for several countries that are the closest trade partners to the USA as well. We do not extract similar deviations neither in vulnerability nor in transmission by conditioning on any other associations.

Moreover, two notable findings are presented here. We identify that the overall transmission and vulnerability for Australia amplifies for the entire cycles if Australian links to both the USA and Germany is turned off. Also, We find the USA vulnerability increasing substantially only when the links to New Zealand is turned off. It is evident from the results that the USA market interdependence to New Zealand is stronger then others in the cluster. This significant interdependence for both markets maybe attributable to the phenomenal alternative investments between the USA and New Zealand as major energy exporters in the same cluster.

The findings in Figure B1 and in Figure B2 supports our argument that limiting exposure to certain markets may exacerbate systemic risks for others while serving as the dynamic robustness of the unconditional connectedness presented in the dynamic analysis section of the paper.

Crisis-maps

Now we set two conditions in counterfactuals. In *counterfactual one* we turn all big links off altogether to re-examine changes in transmission pathways in crisis-maps. Then, in *counterfactual two* we turn individual pairwise associations off for all markets as before [3]. These serves the purpose of explaining, if controlling for all big transmissions substantially changes the transmission pathways while allowing us the flexibility to examine changes in fissures with individual associations. Consequently, this either yields new information or proves robustness in the visualizations.

We present full-sample crisis map generated with *counterfactual one* in Figure B3 and with *counterfactual two* in Figure B4.

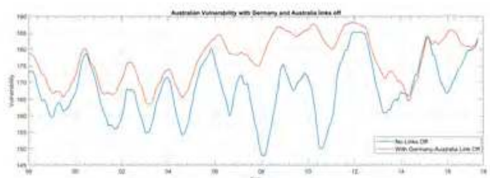
The picture that emerges from examining the full sample maps with the first restrictions applied, is the fissures running left to right in Figure B3 replicates the pattern of fissures produced with all links existing as found in Figure B7 of the main body of the paper, but with voids deeper then Figure B7, carrying more storm water deposits (higher degree of shocks) within them. This demonstrates that controlling for big transmissions, the parabolic pattern in the transmission pathway is not hindered. Additionally, the figures suggest that with *counterfactual one* severity of crisis intensifies while makes evident the robustness of earlier crisis maps.

In contrast, Figure B4 lays out full sample map with only Germany-Australia links off. It

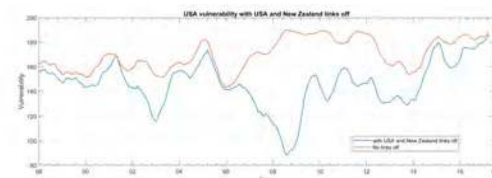
[3] In the spirit of capturing shocks received by home country, we only present maps with Germany-Australia links off here. However, maps with all other links off, or any specific links off can be produces and supplied upon request.

is clear that the plateau is riddled with openings into deeper voids, and with new cracks emerging within the parabolic pattern running from Germany to OED cluster, through the GC cluster. This illustrates that with one major link off triggers crisis spreading all over. This only reinforces the argument that we need to be cautious in selecting what links to turn off if we want to short circuit an imminent crisis instead of exacerbating it.

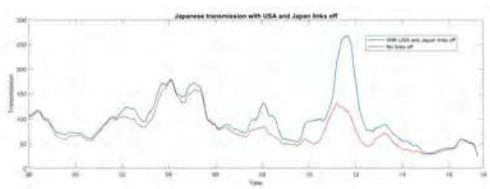
We conclude that even if we shut off big links all together we retain some degree of persistence in the patterns and the patterns remain predictable. Shutting off random links only results in lose control over the patterns.



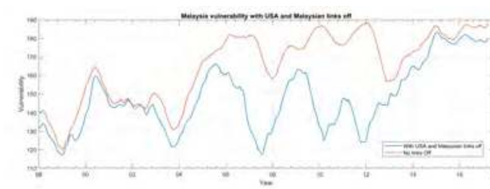
(a) Australian vulnerability:GER-AUS links off



(b) USA vulnerability:USA-NZL links off



(c) JAP vulnerability:USA-JAP links off



(d) MYS vulnerability:USA-MYS links off

Figure B1: Highest variations with individual links off

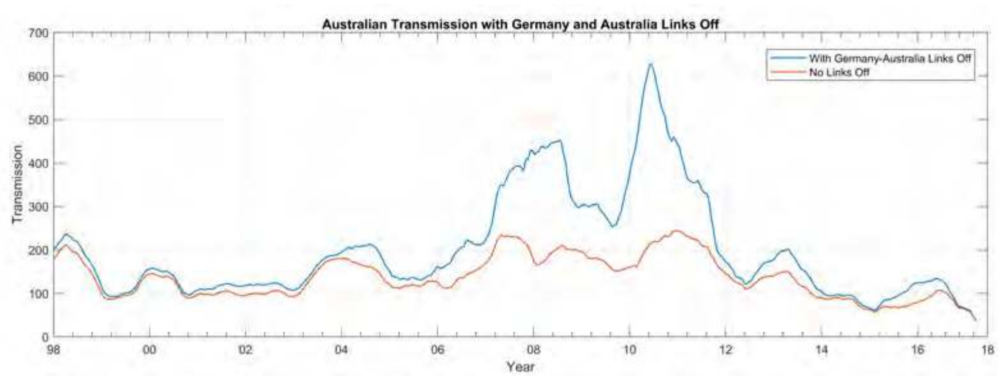


Figure B2: Australian Transmission with GER-AUS individual links off

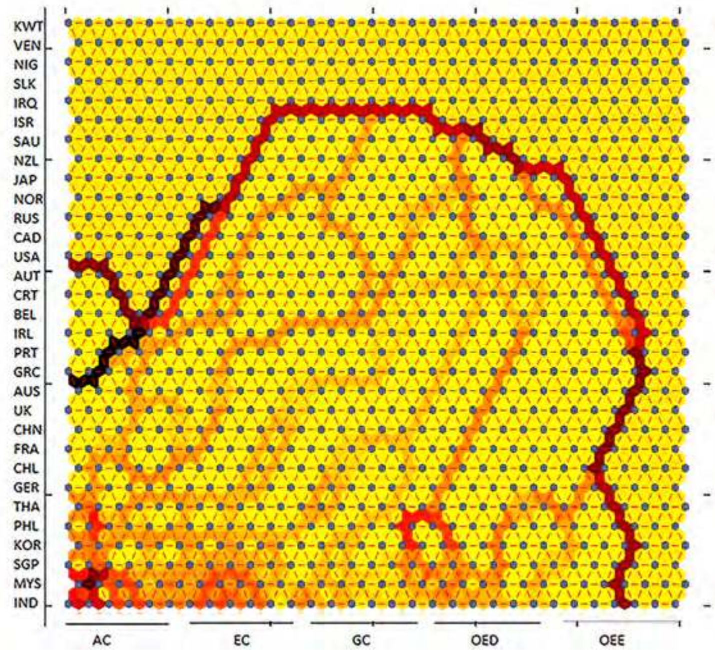


Figure B3: Counter-factual Full Sample Crisis Map. This figure represents a full sample crisis-map for the complete period, with all big links off from bi-variate pairwise 'TO' estimates

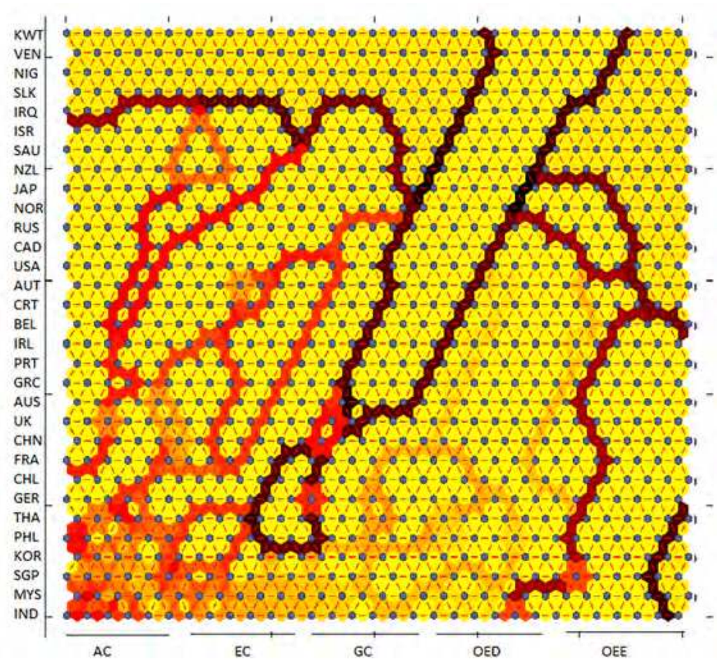
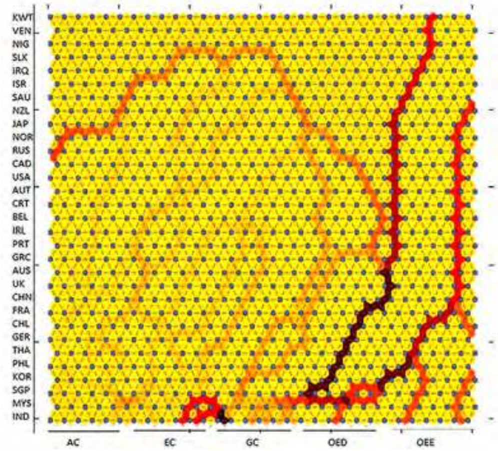
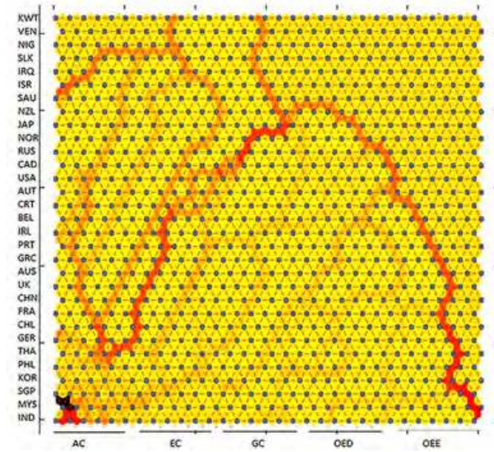


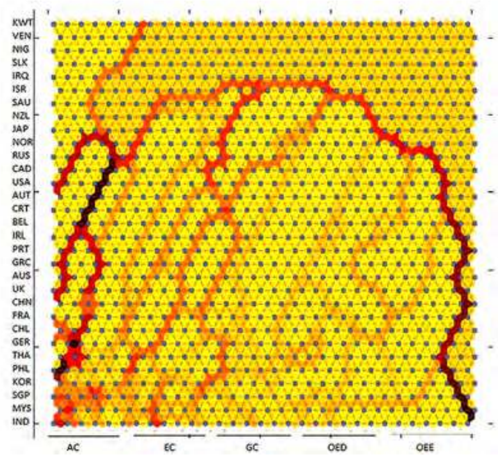
Figure B4: Counter-factual Full Sample Crisis Map with only Germany -Australia link off. This figure represents a full sample crisis-map for the complete period, with Germany - Australia links off from bi-variate pairwise 'TO' estimates



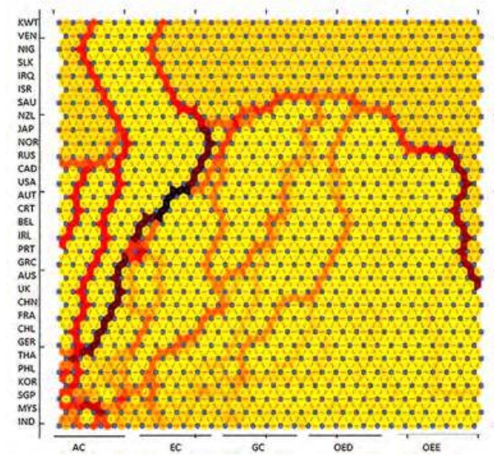
(a) 2008:1



(b) 2012:2



(c) 2008:1



(d) 2012:2

Figure B5: Change in global crisis transmission controlling for Australia and Germany link, compared to controlling for all links in the post GFC and EC period

Appendix C

In this section, we include a 10 basis crisis classification table, and a 900 basis gauged from the SOM classification matrix. We generate a 0-10 degree range crisis classification in Table C1 and 0-900 degree range crisis classification in Table C2 gauging from vulnerability matrix, for each data points across rolling samples. We use a 70-30 split for test simulations based on training input. We then aggregate the classification vector into 39 subsets in compliance with the window size selection for dynamic 'crisis-maps'. We present summary statistics for each subset in tables C1 and C2. Table C2 presents the summary statistics of generated classification weights forming the dynamic crisis maps. Table C1 presents a simple range showing the robustness of self organizing maps gauging from spillover indices. In addition, both the tables demonstrate the applicability of a class of deep unsupervised learning classification on a conditional spillover index for crisis prediction.

In our training sample, sample data spanning across years 1998 to 2011:1 is included. The test simulation makes in sample predictions for 2011: 2 to 2017:1.

We find high degree of stress accumulation for 1998:2, 1999:1, 1999:2, 2001:2, 2002:1, 2006:1, 2007:1, 2007:2,2008:1, 2008:2, 2009:1, 2010:2, 2011:1. What is more, the test simulations make accurate predictions for stress generated in the years 2012, 2015 and 2016. The summary statistics shown in this table complements our findings in dynamic analysis and dynamic crisis-map sections. Also, the tables add to the robustness, tractability and the predictability of the patterns presented in the paper.

Table C1: Summary Statistics of 10 basis crisis classification

Actual	1998:1	1998:2	1999:1	1999:2	2000:1	2000:2	2001:1	2001:2	2002:1	2002:2	2003:1	2003:2	2004:1	2004:2	2005:1
Min.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1st Qu.	1.00	6.00	5.00	6.00	1.00	5.00	5.00	6.00	6.00	1.00	4.00	5.00	1.00	1.00	4.00
Median	3.00	7.00	7.00	6.00	4.00	6.00	6.00	7.00	7.00	5.00	5.00	5.00	4.00	5.00	6.00
Mean	3.92	5.95	**6.22**	6.19	3.55	5.50	5.24	**6.40**	**6.65**	4.50	4.64	5.12	3.78	4.75	5.19
3rd Qu.	7.00	7.00	7.00	7.00	6.00	7.00	7.00	7.00	7.00	7.00	7.00	6.00	6.00	7.00	7.00
Max.	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00

Actual	2005:2	2006:1	2006:2	2007:1	2007:2	2008:1	2008:2	2009:1	2009:2	2010:1	2010:2	2011:1
Min.	1.00	1.00	1.00	1.00	3.00	1.00	3.00	3.00	1.00	1.00	1.00	1.00
1st Qu.	1.00	8.00	5.00	8.00	8.00	4.00	8.00	3.00	3.00	3.00	3.00	4.00
Median	6.00	8.00	5.00	8.00	8.00	6.00	8.00	9.00	3.00	3.00	6.00	9.00
Mean	4.65	**7.58**	5.78	**7.90**	**8.15**	6.17	**8.08**	**6.98**	5.20	5.39	**6.84**	**6.96**
3rd Qu.	7.00	8.00	8.00	9.00	10.00	9.00	10.00	10.00	8.00	9.00	10.00	9.00
Max.	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00

Prediction	2011:2	2012:1	2012:2	2013:1	2013:2	2014:1	2014:2	2015:1	2015:2	2016:1	2016:2	2017:1
Min.	3.00	3.00	3.00	4.00	1.00	1.00	1.00	1.00	4.00	1.00	1.00	1.00
1st Qu.	3.00	6.00	4.00	5.00	4.00	4.00	4.00	4.00	6.00	8.00	4.00	4.00
Median	3.00	9.00	6.00	5.00	4.00	4.00	6.00	5.00	9.00	8.00	5.00	5.00
Mean	5.17	**8.35**	5.92	5.59	4.94	4.86	5.37	5.45	**8.01**	**7.94**	5.30	4.95
3rd Qu.	8.00	10.00	6.00	6.00	6.00	6.00	6.00	6.00	10.00	9.00	9.00	7.00
Max.	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00

Table C2: Summary Statistics of 900 basis crisis classification

Actual	1998:1	1998:2	1999:1	1999:2	2000:1	2000:2	2001:1	2001:2	2002:1	2002:2	2003:1	2003:2	2004:1	2004:2	2005:1
Min.	51.00	3.000	19.00	8.000	2.000	11.00	37.00	39.00	59.00	21.00	48.00	25.00	129.00	45.00	80.00
1st Qu.	421.0	181.0	253.0	127.0	309.0	92.00	322.0	256.0	317.0	243.0	280.0	266.0	287.0	247.0	382.0
Median	536.0	430.0	535.0	348.0	561.0	460.0	456.0	533.0	544.0	377.0	543.0	610.0	524.0	601.0	548.0
Mean	**550.0**	436.0	**515.2**	353.5	500.9	360.3	502.9	509.1	**523.2**	428.0	464.9	506.6	**530.8**	524.8	497.7
3rd Qu.	780.0	699.0	790.0	455.0	696.0	532.0	846.0	751.0	729.0	675.0	679.0	802.0	713.0	844.0	616.0
Max.	959.0	871.0	950.0	945.0	937.0	869.0	953.0	961.0	896.0	931.0	955.0	944.0	955.0	934.0	868.0

Actual	2005:2	2006:1	2006:2	2007:1	2007:2	2008:1	2008:2	2009:1	2009:2	2010:1	2010:2	2011:1
Min.	28.00	36.00	12.00	6.000	24.00	1.000	13.00	43.00	83.00	64.00	1.000	7.000
1st Qu.	198.0	222.0	175.0	305.0	345.0	228.0	85.00	462.0	185.0	385.0	142.0	126.0
Median	453.0	371.0	390.0	517.0	504.0	415.0	252.0	633.0	412.0	660.0	254.0	308.0
Mean	463.4	**470.6**	392.3	**513.8**	**563.2**	464.7	345.2	**607.2**	**498.2**	**545.9**	413.6	431.3
3rd Qu.	775.0	762.0	588.0	683.0	821.0	795.0	553.0	849.0	902.0	707.0	678.0	712.0
Max.	920.0	949.0	946.0	957.0	941.0	914.0	900.0	952.0	951.0	927.0	948.0	958.0

Prediction	2011:2	2012:1	2012:2	2013:1	2013:2	2014:1	2014:2	2015:1	2015:2	2016:1	2016:2	2017:1
Min.	30.00	64.00	30.00	1.000	4.000	102.0	17.00	1.000	33.00	70.00	16.00	5.000
1st Qu.	298.0	214.0	234.0	279.0	167.0	475.0	211.0	337.0	106.0	268.0	290.0	205.0
Median	404.0	466.0	442.0	478.0	411.0	566.0	440.0	489.0	301.0	506.0	406.0	389.0
Mean	475.7	**485.3**	480.1	**494.4**	439.6	**573.4**	457.9	**524.4**	362.4	507.4	491.1	445.2
3rd Qu.	736.0	698.0	673.0	720.0	786.0	758.0	741.0	726.0	604.0	725.0	788.0	741.0
Max.	956.0	960.0	912.0	925.0	921.0	937.0	954.0	957.0	951.0	908.0	951.0	910.0

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