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Crisis transmission: Visualizing vulnerability

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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.

1. 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

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[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. (2018a, 2018b); Yilmaz (2017); Diebold et al. (2017); Diebold and Yilmaz (2015); Diebold and Yilmaz (2014).

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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 Yilmaz (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 any point in time. This is used to draw two-dimensional maps of how these pathways 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 the 'state 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 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 to 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

[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.

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

Table 1
Major crisis events. We analyze all events across entire sample period with DY rolling estimates.

Modelling crisis: we summarize important edges found in all conditional spillover figures.

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.
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 times 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	

(*continued on next page*)

Table 1 (*continued*)

Modelling crisis: we summarize important edges found in all conditional spillover figures.

Year	Transmission-markets	Vulnerability-markets	Crisis events
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	
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	
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.

(*continued on next page*)

Table 1 (*continued*)

Modelling crisis: we summarize important edges found in all conditional spillover figures.

Year	Transmission-markets	Vulnerability-markets	Crisis events
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	

spillover effects using self organizing crisis-maps. Finally, we examine if completing a feedback loop for a cluster spill risks to the other clusters Davis et al. (2010), and hence if prediction of such in the patterns warns us of ensuing crisis in 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 in the most recent periods, 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 2 presents a brief review of literature. Section 3 presents the empirical framework and Section 5 the data set. The results are presented in Section 6, 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 9 concludes the paper with some remarks concerning the role of this new tool in investment and policy decisions.

2. 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, 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.

Another strand of literature connects 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 down all other common equities built into such debt portfolios. 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, which turns a micro level downturn to a macro crisis. The study of

[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.

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 markets 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 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 equity markets across borders.

It is important to understand that connectedness measures 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. While contagion measures may capture 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 towards 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 found in (Duffie, 2013)[7] but we propose a much bigger system. This further contributes to the novelty of the current 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., 2007, 2013; 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 buildup 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 relatively deep and protracted, and features a slow recovery (Jordà et al., 2013; Hermansen and Röhn, 2017).

Cyclical swings in credit conditions lead to varying degrees of crises stemming from systemic 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, 2010b).[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 Yilmaz, 2014) that underpins 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 onto all other markets, and highlight events associated with systemic network instability in the empirical evidence.

In identifying crisis transmission pathway patterns 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

[6] Systematically important financial institutions.

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

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

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.

3. 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, $x_t = (x_{1t}, \dots x_{Nt})'$, 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,

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

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

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

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, $\Sigma_{j=1}{}^{N} \theta_{ij}{}^{g}(H) \neq 1$.

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

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

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

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

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-

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

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).

4. 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 nodes in euclidean 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 vectors and randomly generated weight vectors, 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 nodes from the synaptic weight vectors, we find the least distant nodes with input vectors in the neighborhood space, best known as the “Best Matching Units” (BMU). The algorithm works in neighborhood space, so that closer neighbors 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 produce 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% 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 another node in the output vector.

Notably., the iterative backward propagation algorithm has a convergence criterion as it generate weight vectors. 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 relationship with neighbors. 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 the decay function identifying sparsely connected nodes.

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

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

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 $\xi_t = \xi_0 exp^{(-t\lambda^{-1})}$. 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]

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

[10] See Sarlin and Peltonen (2013) for a graphical representation SOM.

[11] The intermediate step offers increased robustness to the crisis-map.

[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.

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

The neighborhood positions of the clusters in the crisis map represent contagion transmission complementing the approach of Sarlin and Peltonen (2013). In the crisis maps the degree of convergence are illuminated with darker to lighter colored grids resembling none to some degree of ensuing crisis. Failure of convergence indicates heightening of non-linearity between nodes, shown with cracks in the topology.

5. 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 price indices for 31 equities 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 estimated returns with 2 day moving average to ameliorate the time zone effect 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 al. (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 2 is a more robust choice, complementing the notion of Spectral Windowing presented in Oppenheim and Schafer (2014); Forbes and Rigobon (2002).

6. 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]

6.1. 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 relationship between different markets have flourished (Demirer et al., 2018a, 2018b; Capponi, 2016; Diebold et al., 2017; Diebold and Yilmaz, 2015; Diebold and Yilmaz, 2014; Yilmaz et al., 2018; 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, 2018). We complement these studies by investigating the dynamics in a multi-cluster representation.

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 individual rolling indices for transmission 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 held 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 Figs. 1–3. 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 Figs. 1–3 with effects of oil inclusion in Figs. 4–6. In Fig. 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

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

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

[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.

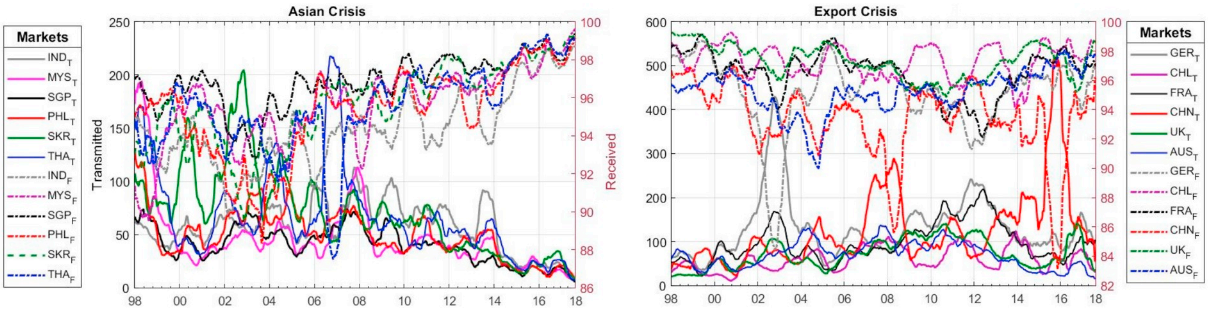


Fig. 1. Asian crisis markets & export crisis markets.
This figure represents a contemporaneous relationship of daily return data for 20 years, for markets categorized within Asian Crisis (AC) and Export Crisis (EC) markets derived from generalized variance decomposition. A detailed description can be found in the 'Asian Crisis' and the 'Export Crisis' subsections under Dynamic Analysis.

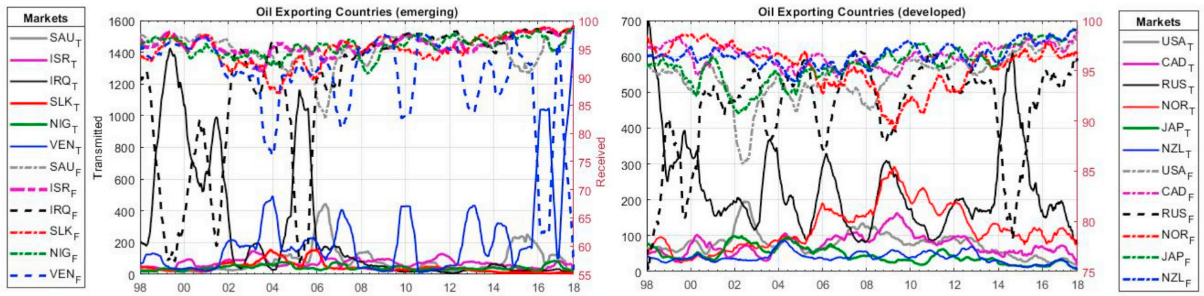


Fig. 2. Oil exporting (emerging) markets & oil exporting (developed) markets.
This figure represents a contemporaneous relationship of daily return data for 20 years, for markets clustered within Emerging Oil Exporting countries (OEE) and Developed Oil Exporting Countries (OED). A detailed description can be found in the 'Oil Exporting markets' and 'Conduit effects' subsections under Dynamic Analysis.

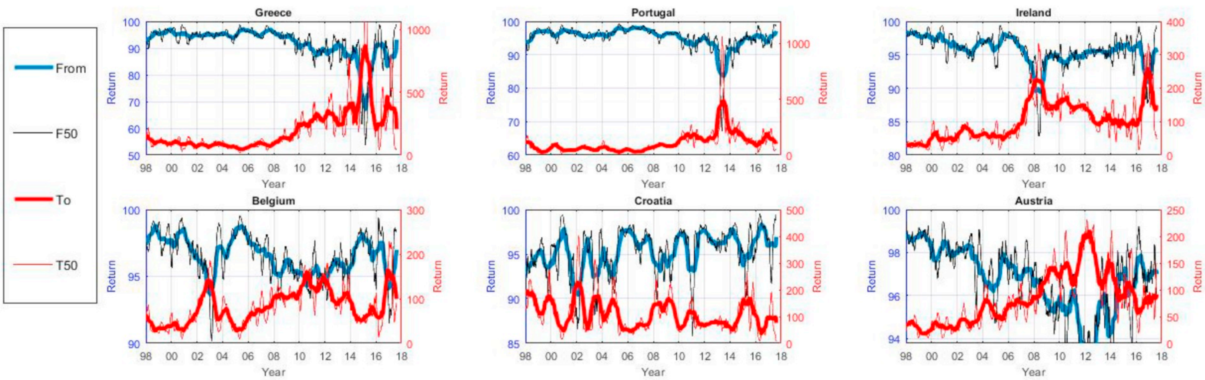


Fig. 3. Greek crisis markets.
This figure represents a contemporaneous relationship of daily return data for 20 years, for sample markets of Greece, Portugal, Ireland, Belgium, Croatia and Austria. A detailed description can be found in 'Greek Crisis' subsection under Dynamic Analysis.
Note: The transmission and the receiving patterns are plot together in all figures, with the same color in both the patterns used for a given country.

points out that usually the contribution of own shock is dominant in explaining variations 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 spillover to all others can be quite large despite individual (bi-variate pairwise) effect on others are relatively small.[17]

The changing interconnectedness of the markets is clear from the results in Figs. 1–3. 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 vulnerabilities – lower. The higher transmissions show when a market experiences crisis conditions it is more vulnerable to transmissions

[17] See Table A1 in online Appendix A.

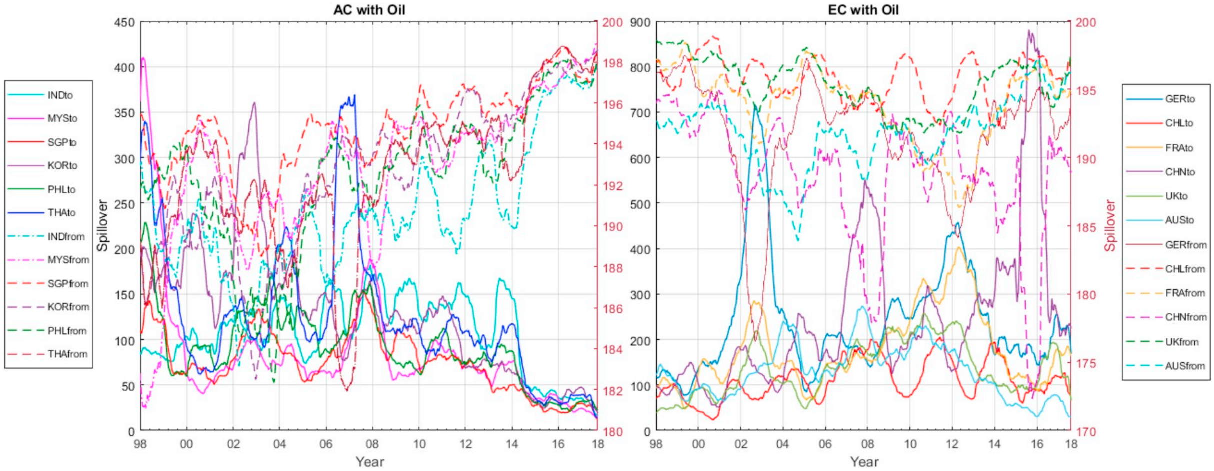


Fig. 4. AC-EC spillovers [oil effect].
This figure represents the conditional spillovers with oil index as exogenous to AC and EC blocks. A detailed description can be found in 'Oil Exporting markets' subsection under Dynamic Analysis.

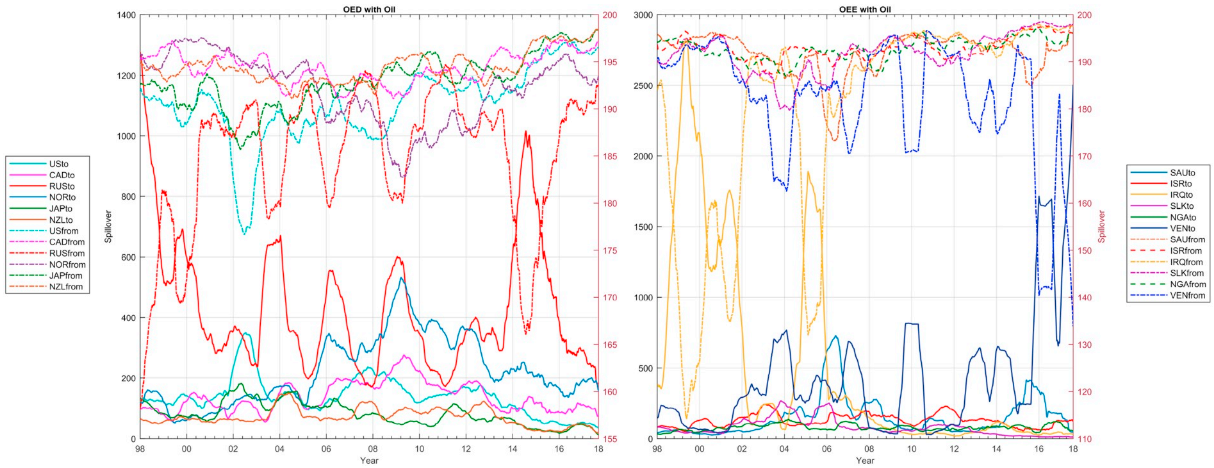


Fig. 5. OED-OEE spillovers with [oil effect].
This figure represents the conditional spillovers with oil index as exogenous to OED and OEE blocks. A detailed description can be found in 'Oil Exporting markets' subsection under Dynamic Analysis.

coming from other markets (this form of increased connectedness is denoted hypersensitivity in Dungey et al., 2010a). The lower vulnerabilities suggest the reduction in the effect of own shocks onto others during periods of turmoil.

6.2. 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.

Fig. 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 also evident in its heightened transmissions at that time and again in the Global Financial crisis (GFC) period modelled in Fig. 1, during the periods of increasing concerns over 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.

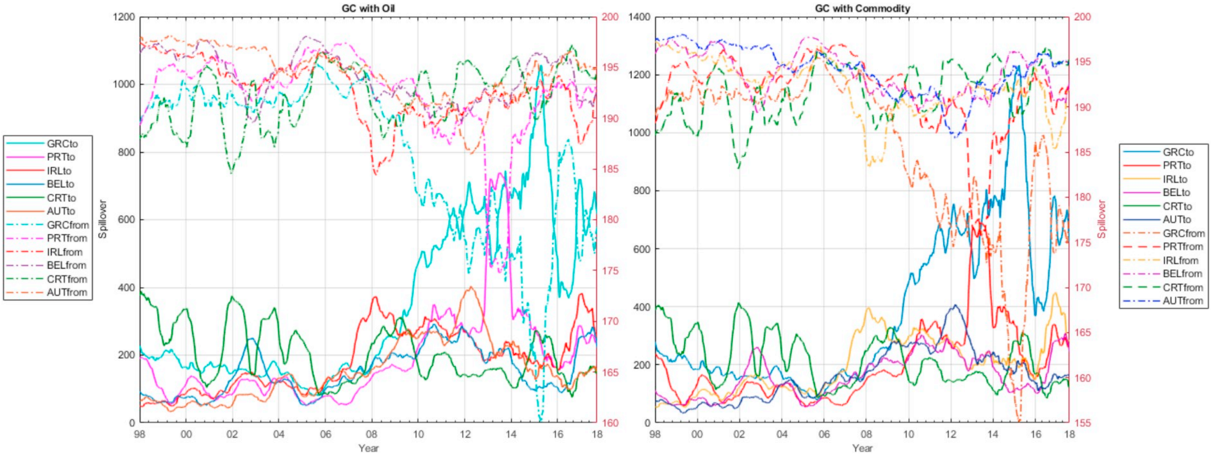


Fig. 6. GC spillovers [oil and commodity effect].
This figure represent the conditional spillovers with oil and commodity index as exogenous to the sample blocks. A detailed description can be found in 'Greek Crisis' subsection under Dynamic Analysis.

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 and 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.

6.3. Export crisis

The second panel in Fig. 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 Fig. 1 in the vulnerability of systemic risks. We find a brief period of dampening that precedes further amplification for Germany at the same point as that of Singapore and Korea. Similar turning point is also detected in the 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 sees 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 over an ensuing crisis (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.

6.4. 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 Fig. A4.[20] We account for the

[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 terms of market capitalization.

[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.

[20] See online Appendix A, Fig. 4.

heightened systemic risk between China and Germany leading to other EC markets in Fig. 1 with robustness delivered in Fig. 4. We find that oil inclusion results in systemic risk stemming more from France and the UK than others. Turning to AC markets in the other panel of the same figure, 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 a systemic risk 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 Fig. 2. Again, we compare Fig. 1 for robustness including oil in Fig. 5.

We find acute swings in transmission and vulnerability for Oil Exporting Developed markets highlighted in Fig. 2. With the exception of Japan, this holds for Venezuela,[21] 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 recent Russian ruble 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 Fig. 2, we observe that since the Iraq invasion, Saudi Arabia and Israel have been the highest transmitters and recipients of return shocks, particularly in the Middle East. While only a few cycles of transmissions and vulnerabilities are discernible for 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 Fig. 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 were 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 Fig. 5.

6.5. 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 the European markets; see for example (Jolly and Bradsher, 2015; Mink and De Haan, 2013; Arghyrou and Tsoukalas, 2011; Jolly and Bradsher, 2015). In Fig. 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 the 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, 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 Fig. 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 from dampening to magnification appearing for Belgium at the same time as Germany, Singapore, Korea and some other markets. Next we explain what causes these transitions in vulnerabilities to appear together.

6.6. Conduit effects

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

In Fig. 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 for earlier crisis events. In light of this discussion, we have detected the conduit effects of the USA and

[21] 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.

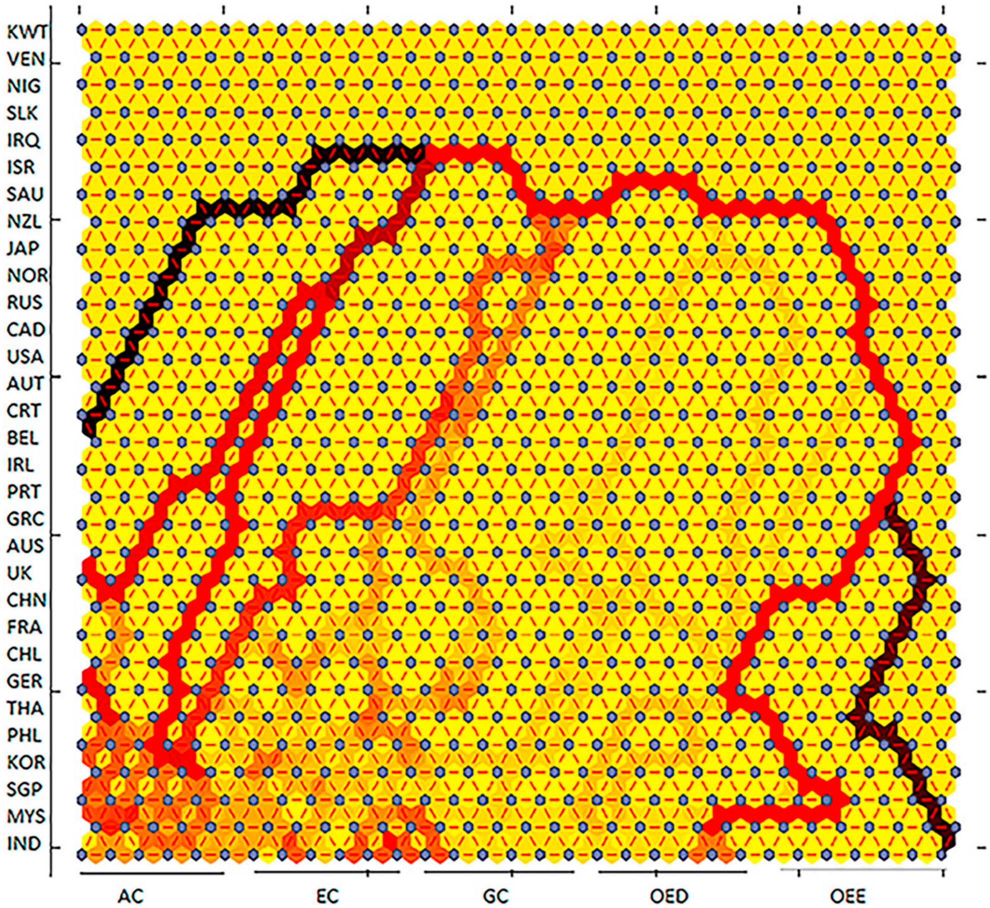


Fig. 7. Crisis-Map (full sample period). Maps generated with SOM gauging raw data from DY unconditional spillover transmission measures with 70–30 splits on the full sample period for all vectors. A detailed description is outlined in 'Crisis Maps' section.

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 has exerted transitions from low to high vulnerability regions for Japan, South Korea, Singapore, Germany, Belgium and Australia. This may be due to high volume of trade between these markets with the USA and also with Japan at some point. In short, we have captured the conduit effects outlined in Baur and Schulze (2005).

7. 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 raw input data 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.

Fig. 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 Fig. 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, Fig. 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 Figs. 8, 9, 10 and 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).

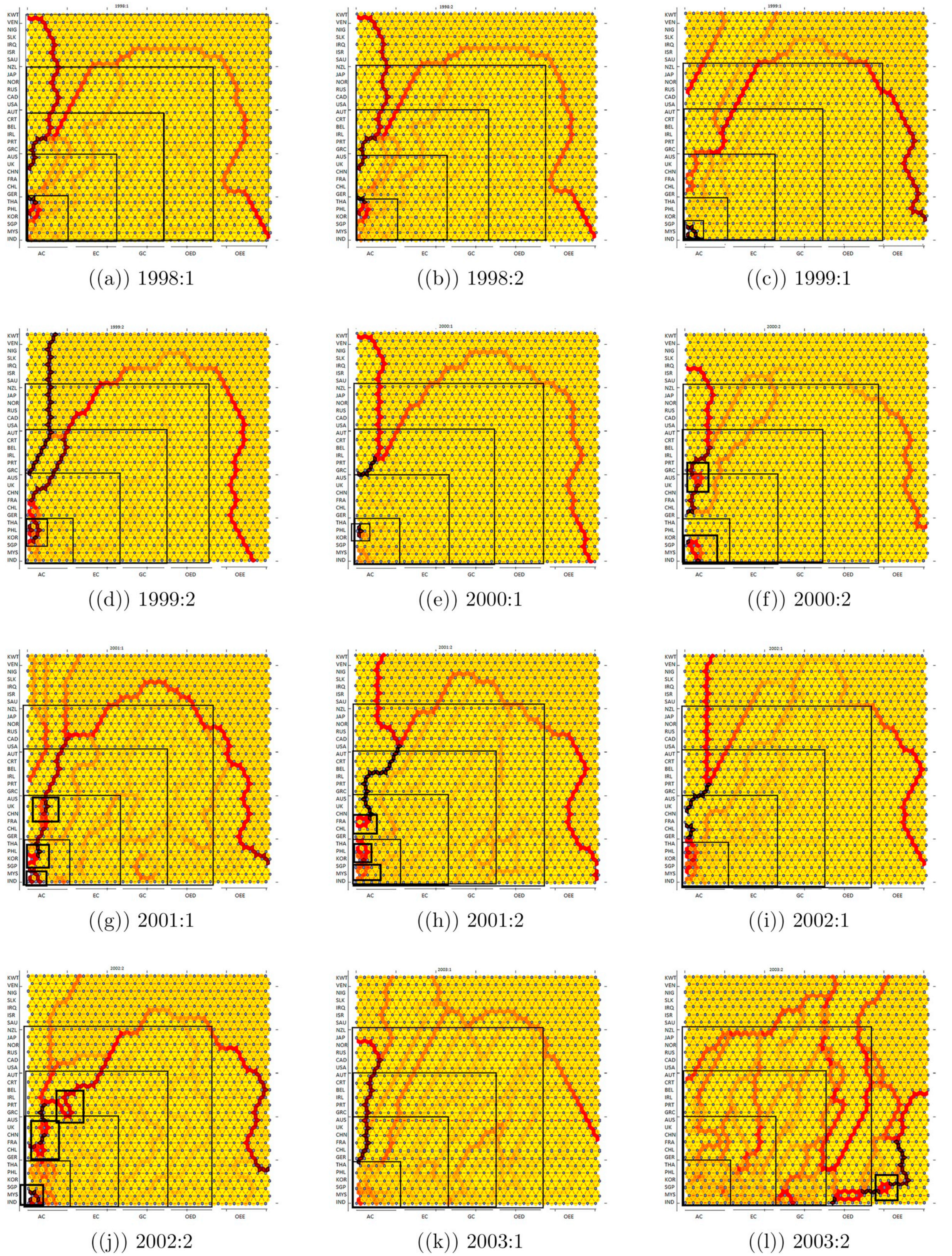
Although we have presented how vulnerability pathway, or in other words, crisis transmission pathway in analogy to storm water mounds change along the web of fissure across the plateau, we have detected a common parabolic pattern in the fissures running from end to end throughout the plateau (the system). 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 transmit 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 prevalent 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 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



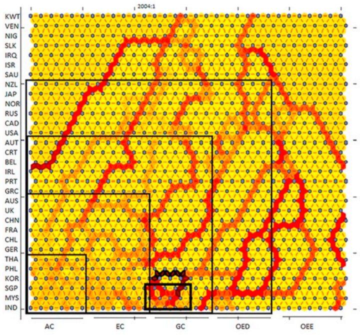
((a)) 1998:1 ((b)) 1998:2 ((c)) 1999:1

((d)) 1999:2 ((e)) 2000:1 ((f)) 2000:2

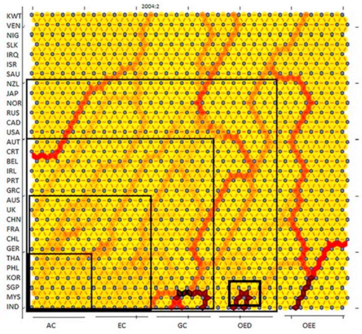
((g)) 2001:1 ((h)) 2001:2 ((i)) 2002:1

((j)) 2002:2 ((k)) 2003:1 ((l)) 2003:2

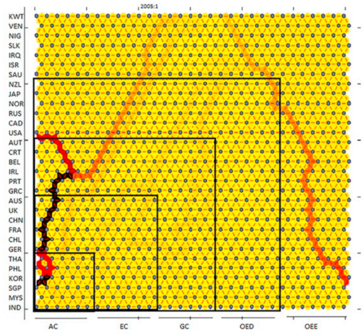
Fig. 8. Dynamic crisis transmission maps from 1998 to 2003. Maps generated with SOM gauging raw data from DYCI transmission with 70–30 splits on sub-periods. A detailed description is outlined in 'Crisis Maps' section.



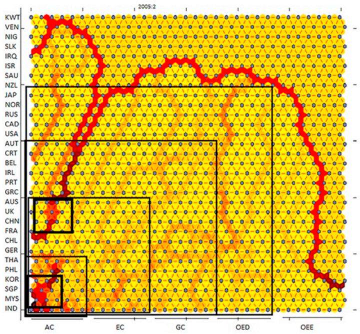
((a)) 2004:1



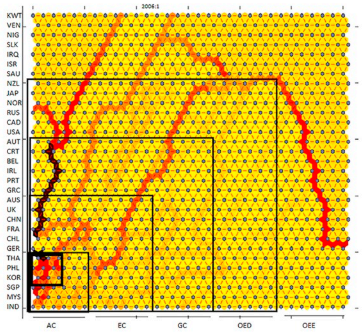
((b)) 2004:2



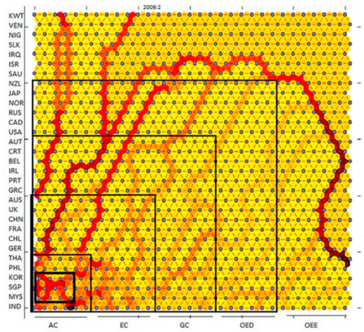
((c)) 2005:1



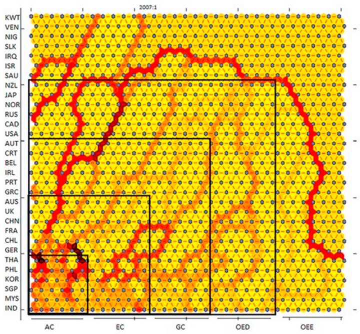
((d)) 2005:2



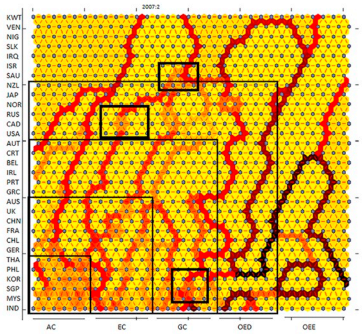
((e)) 2006:1



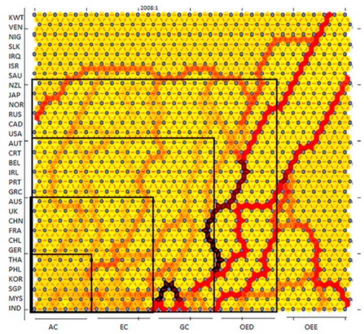
((f)) 2006:2



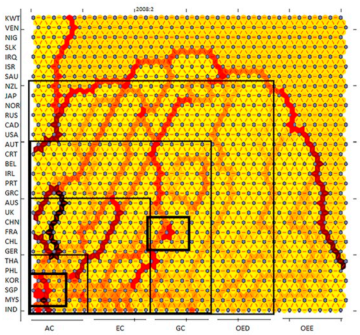
((g)) 2007:1



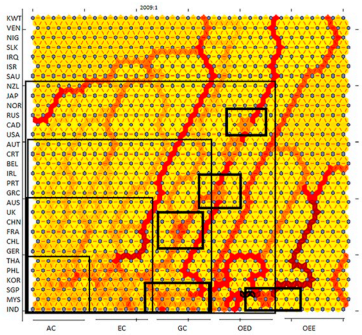
((h)) 2007:2



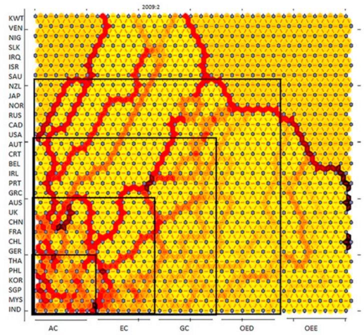
((i)) 2008:1



((j)) 2008:2

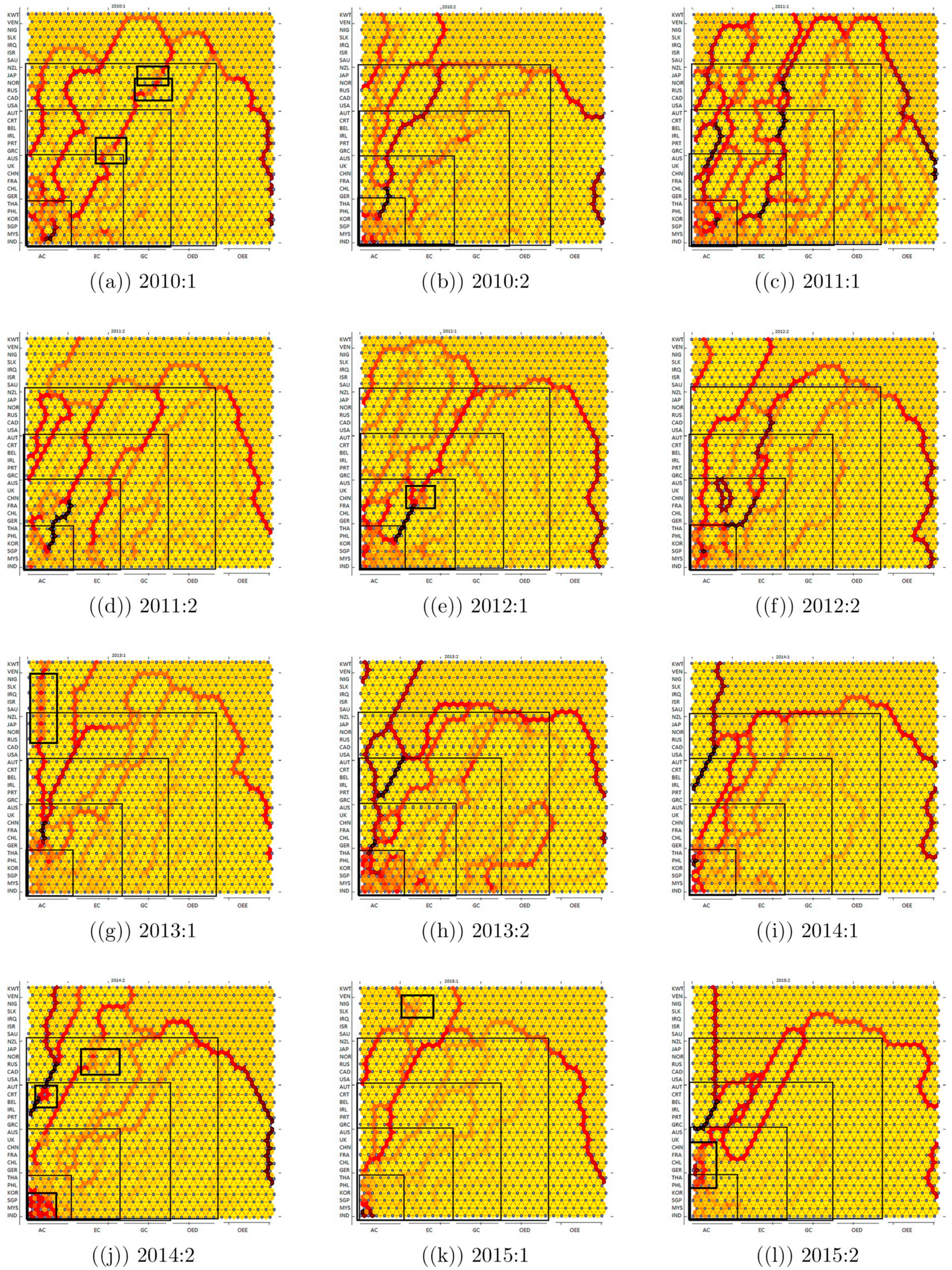


((k)) 2009:1



((l)) 2009:2

Fig. 9. Dynamic crisis transmission maps from 2004 to 2009. Maps generated with SOM gauging raw data from DYCI transmission with 70–30 splits on sub-periods. A detailed description is outlined in 'Crisis Maps' section.



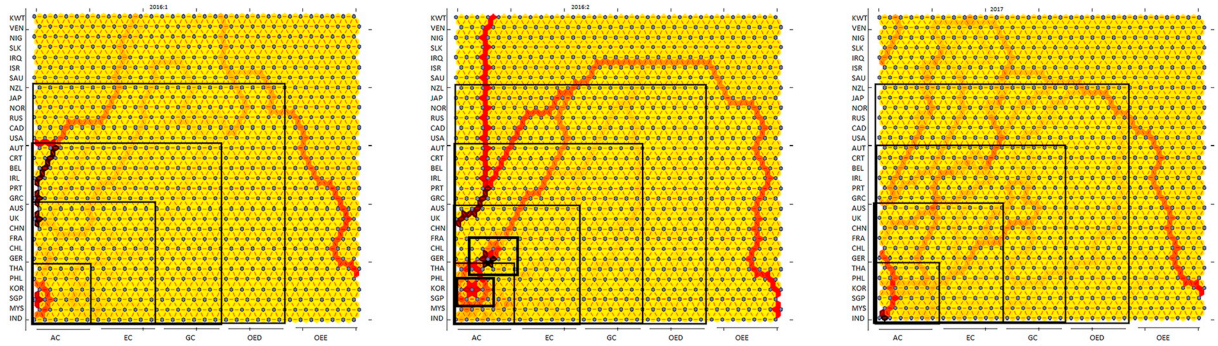
((a)) 2010:1 ((b)) 2010:2 ((c)) 2011:1

((d)) 2011:2 ((e)) 2012:1 ((f)) 2012:2

((g)) 2013:1 ((h)) 2013:2 ((i)) 2014:1

((j)) 2014:2 ((k)) 2015:1 ((l)) 2015:2

Fig. 10. Dynamic crisis transmission maps from 2010 to 2015. Maps generated with SOM gauging raw data from DYCI transmission with 70–30 splits on sub-periods. A detailed description is outlined in 'Crisis Maps' section.



((a)) 2016:1 ((b)) 2016:2 ((c)) 2017:1

Fig. 11. Dynamic crisis transmission maps from 2016 to 2017(Crisis Prediction). Maps generated with SOM gauging raw data from DYCI transmission with 70–30 splits on sub-periods. A detailed description is outlined in ‘Crisis Maps’ section.

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 shocks to the more developed markets of the world (corresponding to significant drops in Dow Jones), reflected in the predictive patterns in the crisis maps 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.

8. 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 and as such co-ordinated actions 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).[22]

9. 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 Yilmaz (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 for many markets in the past. Second, our results reflect that changing

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

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 scenarios. In so doing, the aberrations caused in the system instigates larger and quicker crisis transmission in most simulations. Fifth, we account for a common and persistent pattern in the pathway of shock transmission that is only disrupted with the eruption of strong crises. Finally, we propose a robust way of crisis prediction 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 visualizing 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.

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[23].

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pacfin.2019.101255.

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