Calm before the storm: an early warning approach before and during the COVID-19 crisis

Raisul Islam

University of Tasmania, Australia

Vladimir Volkov

University of Tasmania, Australia

UNIVERSITY *of* TASMANIA

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Raisul Islam*, Vladimir Volkov*

*Tasmanian School of Business and Economics, University of Tasmania

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Abstract

This paper develops a means of visualising the vulnerability of complex systems of financial interactions resulting from the changing risk tolerance of investors. The investors' risk behavior contributes to the buildup of vulnerability in crisis and in calm periods. We show how both time-varying risk tolerance and spillover indices can be translated into two-dimensional information transmission and crisis transmission maps, respectively. Taken together, the information transmission maps have the advantage of highlighting potential crisis transmission pathways in the crisis transmission maps. These maps provide clear visualization showing information transmission predates crisis transmission drawing from conditional signed spillover and risk tolerance indices computed from equity market data for 31 global markets between 1998 and 2020. We examine if investors' risk preference induces a crisis and to what extent such a predictor may be related to a pandemic. Furthermore, we take a special look at the Covid-19 pandemic and its impact on the dynamics of systemic crisis transmission.

Keywords
Systemic risk, networks, COVID-19

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Corresponding author
Raisul Islam
email: $Islam : raisul.islam@utas.edu.au$

1 Introduction

The many facets of global financial crises have heightened research interests in systemic risk and contagion. In a contagious environment, investors expect higher returns for holding risky assets. Indeed, investor preferences readily change in response to an increase in the degree of total risks in a market as a crisis unveils. In this paper, we investigate inter-temporal changes in investors risk tolerance responding to the degree of systemic risk.

Dynamic information maps are proposed to visualise shifts in investors risk tolerance, contributing to the build-up of systemic risks. Furthermore, we show how to use self-clustering of nonlinear inputs of investor risk preferences across time to identify a crisis. The expectation maximisation/artificial neural network based self-clustering maps highlight information transmission pathways in a pool of markets in response to random stimuli stemming from speculation or fear of crisis. The maps are analogous to slices of brain scans lit up by firing neural pathways and, as such, are easily processed visually. We show that the dynamic maps can be considered an extension of widely acceptable risk estimates, and are easily conceivable by general practitioners in the risk management spectrum. This method improves understanding of the role of frictional networks in dampening resilience of any given country in the global market. We show that investors analyse crisis-related information differently, which changes the corresponding risk tolerance, which generates further vulnerability in the market. Our objective is to allow risk managers to control over information spread in times of crisis, and to simulate the effects of an alternative intervention in the information pathway to detect best possible actions to restrain unprecedented risk speculation exacerbating in any market. This, in turn, helps to manage systemic risk for a recipient market in the system.

The main conjecture is news transmission predates crisis transmission. Here, investor risk tolerance matrices represent a proxy to news transmission that is used in the production of news transmission pathway and, are used to present a comparison with crisis transmission pathway in a two dimensional plateau. Moreover, we provide evidence that past crises are rife with overconfidence and fear. The paper addresses these concerns and model the dynamics in signed risk tolerance corresponding to signed risk matrices, which also produces predictive visual patterns to examine the ability of news transmission to predate a crisis transmission pathway in a system of intricate web of the international markets.

The studies applying self-organising maps (SOMs) as a deep unsupervised learning process to investigate systemic risks is uncommon and fairly new. For example, Resta (2016), presented financial market clusters with SOMs. While Marghescu et al. (2010); Barthélemy (2011); Sarlin and Peltonen (2013) and Betz et al. (2014) popularised the use of SOMs in finance, early papers had applied other artificial neural network methods attempting

to make crisis predictions in a system of financial institutions or markets (Liu and Lindholm, 2006; Apolloni et al., 2009). However, Betz et al. (2014) argued that SOMs have better prediction properties than traditional latent models, and contribute to an early learning system in crises prediction.[1] To our knowledge, this work is the first attempt to investigate an information transmission pathway stemming from vulnerability dynamics with SOMs, indicating the potential of crisis accumulation.

Our dataset encapsulates daily returns of the aforementioned markets from 1997 to 2020. We use a balanced sample of 31 international equity markets: 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, the UK and Venezuela. We further classify our markets into groups based on similarity in macroeconomic fundamentals (or similar traits): export crisis, including markets from leading export (oil and non-oil) countries, oil exporting emerging countries and oil exporting developed countries; Greek debt crisis-affected European markets; and 1997 Asian crisis-affected Asian markets. According to BIS (1998) and Baur and Schulze (2005) the USA and Japan acted as conduits during many of the past events.[2]

Our sample spans 30 episodes of global crisis events which allows to show the difference between all these critical periods. Some of the major crises are 1997-1998 Asian Financial Crisis & the collapse of Thai baht, that resulted in Thailand becoming effectively bankrupt; 1998-2000 Russian financial crisis & devaluation of the ruble followed by Russian Central Bank defaulting on its debt; 2000-2002 Dot-Com bubble & Stock marker crash in 2002 followed by excessive speculations prevalent in 1997-2000; September 2011 terrorist attack on the USA; 2003-2008 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 rising abruptly, exceeding three time the initial price; 2003 when the SARS outbreak is first identified in Guangdong province in China, rapidly becoming epidemic, slowing down economic interactions with China to many markets; 2006 Gaza conflict & Israel-Lebanon war broke out; 2007-2009 Global financial crisis & subprime mortgage crisis followed by 2005 housing bubble burst; 2009-2012: Eurozone crisis emerges in the wake of great recession in the late 2009, when several Eurozone members (Greece, Portugal, Ireland, Spain, Cyprus) failed to bailout over-indebted banks and repay foreign debt; 2014-2017 Russian crisis and the collapse of Russian ruble, followed by economic sanctions imposed on Russia and the collapse of Russian stock markets; 2016

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[1] For studies using SOMs in the field of financial crisis and risk management, see Liu and Lindholm (2006); Peltonen (2006); Apolloni et al. (2009); Marghescu et al. (2010) and Betz et al. (2014), for network mapping see Barthélemy (2011) and Sarlin and Peltonen (2013) and for market clustering see Resta (2016).

[2] For details on the data used and the span of crises in our sample, see Table 1.

Export Crisis as Germany, Chile, France, China, UK and Australia experience historic decline in total exports, followed by a 'oil-glut'; 2015-2016 Chinese crisis when a massive drop in Chinese stock markets resulted in markets terminating transactions in the wake of concerns over a Chinese Crisis; 2013-present Venezuelan Crisis. Termed as the Great depression of Venezuela, the deterioration of major macro economic indicators in Venezuela since 2013 resulted in a significant social and political degradation. The extent of this deterioration is such, that Venezuela topped the misery index 2013, and ranked lowest by the IFC in investing country index. Finally the evolution of the COVID-19 crisis is analyzed.

Facing the onset of COVID-19, at the end of 2019, triggered numerous studies attempting to identify the economic impact of the pandemic. While Mazzoleni et al. (2020); Wang et al. (2020); Yarovaya et al. (2020) recognize the COVID-19 as a black swan and an unforeseeable event, Goodell (2020) contends COVID-19 is foreseeable and hence insurable. Goodell (2020) discusses the papers identifying an emergence of pandemic and predicting its enormous economic losses. Moreover, Goodell (2020) suggests, COVID-19 is directly comparable to a large scale terrorist attack such as the 9/11 attack on the USA, which is localised in its initial manifestation but by design is created to cause a global impact in the investors' moods in the financial markets. Such 'spillover effect' leading to systemic contribution of such localised events into market risks are discussed in Hon et al. (2004); Choudhry (2005); Karolyi (2006); Brounen and Derwall (2010); Nikkinen and Vähämaa (2010); Chesney et al. (2011); Corbet et al. (2018). Interestingly, COVID-19, in its scope and breadth, cannot be directly comparable to a global nuclear disaster only because the outcome of a nuclear disaster is irrelevant as it is not survivable. COVID-19 is survivable despite having different ramifications for different portions of economic spectrum. As the impact of COVID-19 blankets global economies, it is crucial to investigate the spillover effects in the public moods in the international financial markets.

We investigate a 'calm before crisis' phenomenon focusing on the information transmission affecting risk propagation in the pre and during COVID-19 outbreak. We identify the patters that clarify the role of market news and speculations since the COVID-19 recession hit global economies.

- Calmness is prevailing in the dominant international markets, including South Korea, Germany, China, Australia, Belgium, the USA, Canada, Russia, Norway, and Japan. The findings suggest that China is the ground zero of the pandemic which means that an increase in aggregate risk aversion is not different from the other dominant international markets. This is a natural phenomenon related to an imminent economic downturn. It has become evident that the heightening of abnormalities in Chinese economy are mere speculations.

- Vulnerability dampened in the developed markets during the COVID-19 crisis. Naturally, the increased disconnect emerged from the widespread expectation of a crisis trigger. Unlike the disconnects during a systemic event, vulnerability for different markets dampens differently, suggesting the effects of a more localised intervention. Therefore, an exposure risk triggering a contagion is unlikely in this instance.

- Risk aggressiveness and market interconnections heighten for the developing markets. While a higher coupling of markets is related to higher vulnerability, this also indicates the increased market activity in the developing markets and potential spikes in liquidity transferring into these markets despite the COVID-19 outbreak.

- We do not find significant changes in the crisis transmission maps and information transmission maps, during the COVID-19 crisis. Therefore, global markets did not experience significant jumps in the stress classification index. However, we identify cracks in the maps indicating a spike in risk aversion.

- Unlike the results related to the GFC, we do not detect new feedback loops forming and sending random cracks across the maps. This provides additional evidence that the pandemic poses no systemic threat.

In what follows, we present a brief review of the literature in Section 2. Data set is explained in Section 3 followed by presentation of an empirical framework in Section 4. We present the results from signed, unsigned spillovers and risk preference matrices in Section 5. The findings from the self organising maps are shown in Section 6. Next, we discuss the evolution of the markets during the COVID-19 crisis in Section 7 and Section 8, followed by policy implications in Section 9. Section 10 concludes the paper.

2 Literature Review

Piccotti (2017) argued that there exists a symbiotic relationship between contagion and systemic risk.[3] Endogenous credit and capital constraints turn non-systemic risks into systemic risk as crisis propels through different markets followed by a reinforcing cycle. Additionally, crisis propagation brings about temporal changes to 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 all costs, as the

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[3]Financial contagion defines the spread of market disturbances and poses a potential threat for economies by attempting to integrate with international financial system. This also explains the extent to which a local crisis may propagate across neighbours and warrants investigation beyond real economic factors. Conversely, systemic risk suggests the risks that exist within a system of nodes comes from the strength of these nodes.

marginal utility of consumption is negatively affected in the short-term for long-term investors. Consequently, investors short term holding time preference attributes a higher price to contagion (Van Binsbergen et al., 2012, 2013; Belo et al., 2015). Drawing a distinction, Piccotti (2017) suggested that financial contagion may positively affect the marginal utility of consumption corresponding to assets with a longer holding period, subsequently decreasing contagion costs while generating higher returns for risk-takers. In fact we deal with a natural experiment to investigate the degree to which investors' aggregate risk-taking makes a less volatile market more contagious. In other words, we aim to identify if high-risk spillovers are positively associated with high aggregate risk tolerance. In addition, we account for similarity between homogeneous information transmission corresponding to crisis transmission. This similarity may indicate the role of investors' collective risk tolerance in building a crisis.

A plethora of studies has examined emergence of fundamental contagion in the last decade. Fundamental contagion refers to risks that may lie within trade and financial linkages between different economies (Longin and Solnik, 1995; Ang and Bekaert, 1999; Dooley and Hutchison, 2009; Chiang et al., 2017). Goldstein (1998) proposed a 'wake-up call' hypothesis that outlines vulnerability of markets to crisis speculations. Bekaert et al. (2013) provided evidence of 'wake-up calls' causing contagion in the post-GFC period. Intuitively, it is easier to classify market susceptibility by clustering the markets by commonality in fundamentals. We believe the other type of contagion based on investor behaviour is equally important for identifying crisis transmission channels.

Financial contagion studies have taken on greater urgency since the Asian financial crisis of 1997, with little emphasis on investors' risk tolerance as an important factor. In an attempt to catalogue financial contagion papers, Seth and Panda (2018) reviewed 151 studies, only five of which discussed investor-based contagion as a key state variable despite investor overreaction being central to crisis transmission. Chudik and Fratzscher (2011) pointed out that the degree of investors risk tolerance coupled with the tightening of liquidity as a conditional element in crisis, causes differing levels of transmission in both emerging and developed markets. Mondria and Quintana-Domeque (2013) provided empirical evidence that managers' increasing attention to crisis countries heighten crisis transmission. Dungey and Gajurel (2015) rationalised that herding behaviour fraught with asymmetric information generates contagion from the USA to emerging markets. In contrast, Shen et al. (2015) found that Chinese markets receive shocks during crisis, more so from macroeconomic channels in the European markets than from investor based contagion.

Investor-based contagion is primarily caused by dynamics in investors' risk perceptions and risk appetite, which determines how investors re-allocate investments internationally (Masson, 1998; Dornbusch et al., 2000; Forbes and Rigobon, 2002). On the one hand,

dampening risk tolerance may lead to frequent re-balancing of investor portfolios (Kodres and Pritsker, 2002b; Fleming et al., 1998). Conversely, magnification in risk tolerance drives investments towards more riskier asset allocation (Kocaarslan et al., 2017), which simultaneously pushes the prices of risky assets upward. Such contagion resurges due to the restructuring of portfolios by investors, and less so due to market swings (Kumar and Persaud, 2002).

The dynamics in information channels largely drives portfolio rebalancing. Homogeneous information affects investors' risk perceptions, which are induced from cross-market hedging (Fleming et al., 1998) and increasing interconnectedness between markets. However, Kodres and Pritsker (2002b) argued that risk transmission depends highly on information asymmetry coupled with shared macro-economic risks. In this paper, we split our markets based on both shared macro-economic history and macro-economic risks. We order the markets to separate out emerging markets in which information asymmetry may dictate.

Information transmission stimulates active hedging by invoking frequent asset reallocation by investors, which heightens in crisis periods compared to calm periods. This, in turn, increases interdependence (Lehkonen and Heimonen, 2014). Lehkonen and Heimonen (2014) argued that for active investors (e.g., large investment banks) are mostly driven by shorter-term dynamics, whereas passive investors (e.g., individuals, insurance companies and commercial banks) are driven by longer-term dynamics with a higher risk tolerance. Therefore, during stable periods interconnection remains neutral to an extent that hedging in the markets are driven by information symmetry. Conversely, during crisis periods, risk-takers and risk-averse investors alike participate in active hedging in fear of diminishing portfolio values (Kodres and Pritsker, 2002b; Kocaarslan et al., 2017). Aggressive portfolio rebalancing on top of perceived increases in information asymmetry elevate linkages in global networks.

Muir (2017) distinguished between the effects stemming from a financial crisis recession, deep recession and war events and investors' expectations regarding asset values, risk premiums and liquidity in the market. In the vast literature, financial crisis is defined as build-up of systemic risk corresponding to a banking crisis (Shrieves and Dahl, 1992; Sbracia and Zaghini, 2003; Lepetit et al., 2008; Allen and Carletti, 2010; Puri et al., 2011; De Bruyckere et al., 2013; Kalemli-Ozcan et al., 2013; Dungey and Gajurel, 2015). Muir (2017) argued that risk premiums are a more dominant factor than capital during a financial crisis, indicating equities are better determinants of a crisis. Moreover, a bank's liquidity buffer dampens during a recession, deep recession, war-related events and financial crisis alike, creating confusion regarding separating the effects from financial crisis alone. Only swings in the risk premiums are collinear to the degree of financial crisis. Notably, Muir (2017) pointed out that immediately after a crisis, realised returns increase, reversing the drag on wealth; however, this is unlikely in a recession.

Lee et al. (2015) also invoked the phenomenon of risk aversion to explain the determining factors of risk premiums. They argued for the importance of investors' risk preferences to determine asset pricing, active reallocation of assets in a portfolio and the varying degree of risk management. Hurd et al. (2011) suggested that active portfolio reallocation is determined mostly by systematic variations in assets, reflecting investorsâĂŹ risk preferences. The lack of empirical evidence concerning risk preference during crisis provides a natural experiment for us to disentangle the dynamics of risk aversion in association with exogenous shocks and systemic risk effects. By doing so, we gain further insights into the role and evolution of the degree of investors' risk preferences in the pre, during and post-crisis periods.

The information channel is imperative to separate out the crisis propagation pathway, similar to risk premiums corresponding to investors' expectations about the market and overreactions to crisis-related information (Malmendier and Nagel, 2011; Barberis et al., 2015). Thus, financial crisis is better identified using investors' expectations of the market than using risks associated with bank liquidity.

Most recently, the importance of information flow in the build-up of financial crisis was explained with 'order-disorder phase transition', a term adopted by Bossomaier et al. (2018). During stable periods, markets become disordered due to heterogeneity in investors' information-based decision-making process. In contrast, both exogenous and endogenous crises stimulate coordinated and collective decision-making with individual investors, bringing more order to the market. Here, endogenous crisis is likely to represent an amplification in mutual information sharing among investors (Matsuda et al., 1996; Gu et al., 2007; Barnett et al., 2013) .

A predictive indicator that would amplify before transitioning into a crisis is longed for in the literature. In line with that purpose, our information transmission maps visually discern endogenous and exogenous crises. Exogenous crises are mapped with small reinforcing circles as laid out in Muir (2017), whereas the abnormalities in nonlinear clustering represented with contrasting colours indicate endogenous crises. The economic prior underlying the closed circles address the undirected cyclic graph, a process involving a unique neural connectedness feeding off each other within random patterns. The identification of unique cycles bears some evidence, but only if such cyclic shapes suggest the onset of a crisis propagation, which is analogous to a ripple effect.

3   Data

We draw on daily dollar denominated stock price indices for 31 equity markets from Asia, the Pacific, Europe, the Americas and the Middle East for the period 1 January, 1998 until 09 June, 2020. Our data are sourced from Thompson Reuters Datastream.

The descriptive statistics on the filtered data is presented in Table 2. We do not find significant correlation in the residuals, ruling out inconsistency in our sample data.

We estimate returns using first difference of natural logarithms. As suggested by Forbes and Rigobon (2002) and Hyndman and Athanasopoulos (2014) we scale down the time zone difference by filtering our data with two day moving averages. In principal, moving averages filtering reduces white noise optimally by focusing out the sharpest edge points. This guideline follows the relevant network and finance literature (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, 2001; Granger, 1992; Balvers et al., 1990; Fama, 1976).

The importance of using equity returns in empirical studies for distinguishing the properties between indicators has been discussed in detail in the relevant literature. While Cont (2001) focused on non-linearity and persistence, Granger (1992) pointed out the non-stationary properties of financial data. In the past, Fama (1976) provided evidence of daily returns being more non-Gaussian compared to intra-day returns. Recently, asset returns have been reported by Joseph et al. (2017) to have non-Gaussian, time-varying, persistent characteristics with smooth compact support over low-frequency spectral content. In contrast Zhong and Enke (2017); Wollschlager and Schäfer (2016); Joseph et al. (2011); Atsalakis and Valavanis (2009); Joseph and Larrain (2008) contended that daily returns are highly non-linear, volatile and negatively skewed. Despite the scientific discourse, the benefits of using asset returns with appropriate pre-processing outweighs its harms in financial economics.

Additionally, filtering with MA is well supported by the literature. As Joseph et al. (2017) suggested that MA filtering increases the quality for both continuous or discrete time series in both time and frequency domains. Smith (1997) also provides evidence of MA handling discrete time series with greater accuracy but in a less complicated manner.

Research into systemic risk and predictive modelling widely uses asset return indicators, and applies both non-parametric self-learning techniques and parametric statistical methods (Joseph et al., 2017; Zhong and Enke, 2017; Joseph et al., 2016; Elliott and Timmermann, 2016; Chen et al., 2016; Ferreira and Santa-Clara, 2011; Vaisla and Bhatt, 2010; Atsalakis and Valavanis, 2009; Cont, 2001; Granger, 1992; Balvers et al., 1990). We complement Joseph et al. (2017, 2016); Atsalakis and Valavanis (2009) and Zhong and Enke (2017) by pre-processing our data with an appropriate window choice with the aim to avoid aberrations caused by discontinuations in returns data. We complement Oppenheim and Schafer (2014) and Forbes and Rigobon (2002) who reported the best results with window size 2; this also underpins the 'spectral windowing' theory.

4 Empirical framework

In this section, we estimate risk tolerance parameters using a univariate GARCH in mean model for each of the returns indices in the sample to understand the degree to which the transmission is received by the index in the interconnected network. In other words, we are examining if the swings in vulnerability during a crisis period are led by investors' risk preference at any given time. In what follows, we estimate unsigned spillover indices and model risk in daily returns with respect to estimated vulnerability indices.

To begin with, we need to estimate the vulnerability indices from unsigned spillover indices. The Diebold and Yilmaz (2012) proposed n-step ahead forecast error variance decomposition matrix in a VAR framework categorises unsigned connectedness between N covariance stationary variables with orthogonal shocks. Here, the summation of all non-diagonal elements produce estimates of transmissions and vulnerabilities of i with respect to j. The form of VAR(p) is as follows

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

Here x_t is a return vector $x_t = (x_{1.t,.....}x_{N.t})'$, φ is a $N \times N$ parameter matrix in this model and $\tilde{\varepsilon}_t$, N(0, Σ); while

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

is the moving average representation where

$$A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \ldots + \phi_P A_{i-p}$$

and rewriting this gives

$$x_t = \sum_{i=0}^{\infty} (A_i P) \left(P^{-1} \varepsilon_{t-1} \right) = \sum_{i=0}^{\infty} (A_i P) (\tilde{\varepsilon}_{t-i}) = \sum_{i=0} \tilde{A}_i \tilde{\varepsilon}_{t-i}$$

P is a lower triangular Cholesky factor. Diebold and Yilmaz (2012) exploits generalized VAR framework originally proposed by Koop et al. (1996) and calibrates the current model using KPPS H-step-ahead FEVD that circumvents the ordering issue. Denoting this by $\theta_{ij}^g (H)$ gives

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

The variance-covariance matrix is $\sum$, the standard deviation of residuals is a_{jj}, the moving average (infinite) coefficient from VAR is denoted by A_h and e_j is a selection vector. Yet, $\sum_{j=1}^{N} \tilde{\theta}_{ij}^g (H) \neq 1$, further normalization gives

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

After normalization $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$, and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$. We fetch the unconditional spillovers measuring off-diagonal elements added up proportional to all elements added up. The unconstrained directional return spillover of all to i is constructed as

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

and in the opposite direction with $S_{i \rightarrow all}$ for all parameters $\tilde{\theta}_{ji}^{g}(H)$.

Now, with spillover indices in hand the vulnerability index is obtained. We estimate the dynamics between return and risk with a bivariate GARCH-M model presented here. We begin by estimating the expected return of indices regarding its risk when exogenous shock from return spillover received from others $r_{spilloverfrom,t}$ is added to the following model.

$$\mu_{i,t} = \gamma_0 + \gamma_1 r_{spilloverfrom,t} + \varphi \sigma_{i,t}^{\rho}$$

Later we re-analyse the model with $r_{oil,t}$ to examine the effect of return shocks corresponding to the oil index with

$$\mu_{i,t} = \gamma_0 + \gamma_1 r_{oil,t} + \varphi \sigma_{i,t}^{\rho}$$

The uni-variate GARCH in mean model is

$$\sigma_{i,t}^{2} = \alpha_0 + \alpha_1 v_{i,t-1}^{2} + \beta_1 \sigma_{i,t-1}^{2}$$

where $v_{i,t} = r_{i,t} - \mu_{i,t}$. The parameters to estimate here are $\theta = \{\gamma_0, \varphi, \rho, \alpha_0, \alpha_i \beta_i\}$. Here $\rho > 0$, the estimated parameter φ gives us Risk Aversion if $\varphi > 0$, Risk Neutrality if $\varphi = 0$ and Risk Taking if $\varphi < 0$. The parameters are estimated by maximising the negative log-likelihood function

$$\ln l_t(\theta) = -\frac{N}{2} \ln(2\pi) - \frac{1}{2} \ln \sigma_t^2 - \frac{1}{2} \ln z^2,$$

with the standardised residual $z_{i,t} = \frac{v_{i,t}}{\sigma_{i,t}}$. We perform tests of risk-neutrality using the Wald test by testing the restriction $\varphi = 0$. Here, the null hypothesis is $H_0 : \widehat{\varphi}_{i,t} = 0$ against the alternative hypothesis $H_1 : \widehat{\varphi}_{i,t} > 0$. We perform our analysis N times, generating risk aversion indices alongside the significant test results. With forward propagation we compute vulnerability indices for each market. In the next, we show how to obtain the signed spillover index which complements the risk aversion indices.

4.1 Generalized Historic Decomposition (GHD)

Dungey et al. (2017) proposed a signed spillover index, that overcome the limitations of unsigned spillover indices proposed by Diebold and Yilmaz (2012). This signed spillover

discerns both the magnification and dampening effects of contemporaneous shocks in the markets compared to unsigned estimations. Here, A_{ij} measures the connectedness elements due to shocks in j related to the fraction of variation of i. We use a VAR discussed in the previous section to estimate moving average parameters A_j and to obtain impulse responses IRFs. The historical decomposition matrix at time $t + j$ is estimated as

$$GHD_{t+j} = \sum_{i=0}^{j-1} IRF_i \odot A_{t+j-i} + \sum_{i=j}^{\infty} IRF_i \odot A_{t+j-i}, \tag{1}$$

where IRF_i are one unit impulse responses (non-orthogonalised), $\odot$ is the Hadamard product between two matrices. GHD measures the signed weights of shocks by simply estimating impulse responses weighted by residuals. We extract the TO and FROM signed spillovers from row and column elements of matrix GHD. In what follows, we generate self-organizing maps (SOM) that rely on neural networks estimated from risk aversion indices.

4.2 Dynamic-mapping

We examine the effect of information propagation in exacerbating a crisis for a market facing a high degree of systemic risk with multiple levels of risk sensitivity using self-organizing information maps (henceforth $SOM^{information}$). The changing position of nodes during N recursive estimation illustrates the direction of information propagation that may lead to a heightening of systemic risks in the following period.

$SOM^{information}$ is a class of deep unsupervised clustering that meets expected minimisation criteria across weights. Presented with input nodes (in this case risk aversion indices with systemic risk as a covariate) across two-dimensional Euclidean space, the classic backwardâĂŞforward propagation, in linear combination with nonlinear functions, project estimated weights drawn from least distances with expected cluster centres onto a compressed space of squared dimension. This process is initialised with multi-nominal probabilistic distribution. In summary, the recursive process outlined in the computations group the input arrays into intermediate arrays, reducing the dimension of inputs. Convergence results in lower-dimensional classifiers/outputs. Overall, the SOM method clusters nonlinear inputs better than K-means clustering. (Clark et al., 2014; Kohonen, 1998)[4]

The algorithm starts from the principal component surface populating a lattice with an array of random /stochastic gradient weights.[5] Next, the recursive optimisation converges to local minima scanning across all data points and, in doing so, updates centres

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[4]K-means clustering remains better in clustering linear inputs.

[5]The weights are assigned onto each data point in the input vector. The process involving activation of objective function is a multi-class generalisation process. Optimising the objective function, known as network training, is analogous to polynomial curve fitting as the target vector is Gaussian. The algorithm

on the lattice. The convergence is reached when least distant outputs from input nodes by changing of their weights is achieved and is denoted the 'best matching units' (BMU) (the analytic gradients of the weights construct the popularised hidden layers of edges). In other words, the nearest neighbours are assigned higher weights in a neighbourhood space, resulting in the centres forming a sphere around the lattice. In the process, BMUs are computed in a two-dimensional space by minimising Euclidean norm, gradually forming a sphere of nodes, in which the distance between nodes i and j is computed as $\varepsilon = \sqrt{\sum_{j,i=0}^{n}(v_i - \omega_j)^2}$. Finally, a map is retrieved by presenting the sphere in a two-dimensional grid of neurons to which the non-linear structure in input data is optimally fitted.

The 'sequential processing' of the algorithm ensures that each weight is updated with its corresponding input nodes and propagated backwards in the base using the updating function,

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

The updates are scaled with the learning rate and influence rate σ_t for curve fitting. Finally, the influence rate[6] depicts the influence of each weight on the classifiers:

$$\theta_t = e^{\left(-\frac{\varepsilon^2}{2\sigma_t^2}\right)}$$

The influence rate assigns non-zero units for BMUs and decreases if the distance between the nodes in BMUs increase. This is analogous to multi-nomial probabilistic classification.

We generate an information map following the methods suggested by Sarlin and Peltonen (2013). Upon nonlinear convergence, the maps resemble sparsity, no event illuminate with lighter colours. Failure to do so presents a high degree of nonlinear cycles, represented by the darker regions. The picture that emerges shows an event is transpiring in the information transmission pathway compared to no events occurring. Technically, this map is known as 'iris flower map' clustering, which is observed with darker colours compared to converging clusters with lighter colours. Here, (x, y) locations represent the positions of the markets' nodes in the two-dimensional representation.

5   Empirical results

Now we conjecture which macro-economic factors determine the dynamic co-movement of global markets in times of crisis. This discussion leads to the argument that volatility

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is targeted to minimise the loss function (target-prediction) by updating gradients of node weights in a sequential process of backward-forward propagation.

[6]This rate substitutes the popularised score function in generalised neural network architecture.

amplification in the market during crisis indicates a dilemma on the proportion of contagion identifying crisis propagation relative to other macro-economic factors (Kocaarslan et al., 2017). Recent studies have attempted to explain financial contagion, and investor sentiment has made its way into recent empirical research (Corsetti et al., 2005; Boyer et al., 2006; Chiang et al., 2007; Syllignakis and Kouretas, 2011; Celık, 2012). Kodres and Pritsker (2002a) pointed out that information asymmetry is minimal in calm periods and leads to reduced hedging activities. In contrast, investors expect positive jumps in information linkage dynamics during crisis periods. Further, the selective shifting of funds across global markets and alternative investment areas, such as oil, eventually heightens systemic risks for any given market. Recently, Kocaarslan et al. (2017) stated that important macro-economic factors may only affect crisis propagation in global markets through investors' expectations of information linkage and reactions to information dynamics.

In this section, we contribute to this strand of literature by presenting the dynamics of investors' risk perception corresponding to signed spillover indices across crisis and calm periods. We also produce dynamic information maps explaining information linkages during such periods. These findings, combined with systemic risk analysis, improves understanding of crisis propagation across the markets.

We classify our markets into Asian crisis (AC), Greek crisis (GC), export crisis (EC) markets, oil exporting developed (OED) and oil exporting emerging (OEE). We present the signed risk neutrality indices juxtaposed against signed spillovers (TO and FROM), respectively, in Figure 1, Figure 2, Figure 3, Figure 4 and Figure 5. In doing so, we examine the dynamics in investors' risk tolerance corresponding to the degree of transmission and vulnerability in any given period. Hence, we understand how readily available information corresponding to dynamics of postulated crisis changes in investors' risk tolerance. Further, the order of the clusters is maintained in the axes of dynamic maps capturing the information transmissions.

We clearly demonstrate the changing interconnectedness affecting investors' risk tolerance. We use risk tolerance, risk preference, risk sensitivity and aggregate risk behaviour interchangeably for the remainder of the paper. Periods of crisis can be distinguished by the widening gaps between transmission and vulnerability. A discerning feature in the figures is the higher gaps that are exerted on dynamic risk tolerance during crisis periods, indicating that investors' risk preference readily changes with the degree to which a crisis is interconnected. In general, high-level risk-taking is derived from the figures during turmoil periods, which is consistent with Dungey et al.'s (2010a). The heightening in risk-taking may indicate the contribution of investors' heightened reaction during a crisis period, which contributes to exacerbating the crisis transmission and accompanying amplifications in vulnerability. This finding is in line with the suggestions outlined by (Chudik and Fratzscher, 2011; Mondria and Quintana-Domeque, 2013).

5.1 Asian markets

In this section, we examine the signed spillovers against the risk neutrality index presented in Figure 1 to discover whether investors' aggressiveness affects the degree of systemic risk in the AC markets cluster. In this cluster, we include India, the Philippines, Malaysia, Thailand, Singapore and South Korea. These countries' markets are selected to investigate the systemic risk dynamics corresponding to multiple events of crisis since the Asian financial crisis. We further postulate crisis originating from investors' risk preference, driven by accessible crisis-related information.

First, for India and the Philippines, we find both markets laid dormant in terms of investors' aggressiveness, except for the periods leading from the 1997 Asian financial crisis. Both markets remain vulnerable to changes in other markets while the corresponding risk aversion remain dominant. Further, we find that while vulnerability plunges for India in the periods following the GFC, the transmissions pick up. However, the Indian investors remain mostly risk averse. It is only after the European crisis that Indian investors' risk tolerance amplifies. We discern similar patterns all the more for the Philippines. However, in Figure 6 we find the p value from the Wald test remains in the region of not rejecting the null of risk neutrality in the Asian financial crisis, but starts to shift towards the region against the null of risk neutrality. We find this holds more so for the Philippines in the post-GFC period. Both markets cement the notion that markets may remain vulnerable even with low risk tolerant investors. Additionally, higher risk tolerance may further fuel risk transmissions to other markets.

Next, from the signed spillover indices we find that vulnerability dominates in Malaysia and Thailand across the sample period. The only exception is a strong upswing in transmission from Thailand in the post-European crisis period. The investors in both markets largely demonstrate strong risk neutrality. The graphs show a pull towards risk-taking during and after the GFC. This corresponds to a Wald significance test lying around the risk neutrality region, with the significance curve moving away from risk neutrality only after the GFC.

Then, we identify strong contrast in the risk tolerance for Singapore and South Korea. Despite similarity in the transmission and vulnerability derived from signed spillover indices for both markets, investors in Singapore are highly aggressive compared to investors from South Korea, who are mostly risk averse in the post-GFC period. This leads to higher vulnerability for Singapore compared to South Korea. Moreover, a more significant shift from the null of risk neutrality with accompanying jumps from these two markets show investors become either more risk averse or more risk aggressive.

In all cases from Figure 1, we find that Asian investors transition from risk neutral to risk-taking with the heightening of accompanying vulnerability, especially after the GFC.

5.2 Export markets

In this section, we discuss the cluster representing countries affected by plunging total exports since 2016. We consider Germany, France, Australia, China, Chile and the UK. We investigate the signed systemic risk indicators while also presenting in Figure 2 investors' risk positions in these markets, which we believe are responsible for higher systemic risks.

First, we find both vulnerability and transmissions for Germany and France are mutually exclusive. The degree of transmission for Germany remains higher than for France, especially during the GFC. Conversely, France remains resilient in the post-European debt crisis, which contrasts with German patterns. Although, Figure 2 depicts a higher risk tolerance for France comparing to Germany, Figure 6 shows a diminishing significance for risk tolerance in Germany, and investors in both markets are predominantly neutral across the sample.

Next, the Australian transmission is intense across important crisis periods, especially during the GFC and, more recently, at the onset of Chinese crisis. The accompanying vulnerability levels indicate that with jumps in risk transmissions, Australia becomes more susceptible to in-shocks. While the corresponding investor sensitivity seems to lean towards high-risk preferences among investors, risk significance indicates that investors respond with higher aggregate risk tolerance. This corresponds to jumps in risks, and even more so in the post-GFC period. Overall, Australian investors prefer to remain risk neutral in calm periods.

Furthermore, we find China becomes more resilient, especially during the recent Chinese crisis. We identify the strengthening of such resilience when compared to a similar combination of transmission and vulnerability during the GFC. Investors' aggregate risk tolerance decreases in the risk preference index, with the corresponding significance index depicting a shift towards the direction of risk aversion, while risk neutrality remains highly significant.

Turning to the remainder of the markets in this cluster, Chile and the UK both remain resilient to negative in-shocks. However, this is dictated by stronger transmissions from the UK, as the UK market nodes are located near high-risk markets, referred elsewhere. Risk preference in the Chilean market turns towards the extreme, although a significance test does not hold. For Chile, significant risk-taking is evident during tumultuous times only. In contrast, risk-taking as an aggregate behaviour dominates over the British market in the risk preference index, which is in line with the gauged significance, especially since the onset of the GFC.

In all the markets discussed in Figure 2, the patterns accord well with the fact that risk-taking increases corresponding to amplifications in systemic risk propagation during

periods of turmoil, with investors remaining neutral in other times. In other words, investors' access to crisis-related information fuels herding or risk tolerance further in the market. This, in turn, propagates stronger shocks to other markets by building up systemic risks, consequently serving as a propagation channel for future crises.

5.3 Markets related to Greece

In Figure 3, we demonstrate the spillovers from countries that were primarily affected by the European crisis, coupled with risk neutrality estimates. The countries are Greece, Portugal, Ireland, Belgium, Croatia and Austria. Jumps in the risk tolerance curve correspond well with signed spillover indices, signifying its importance in driving the dynamics in the degrees of systemic over time.

The risk preference index for Croatia, Austria and Ireland depicts opposing directional changes in the pre- and post-GFC periods. As the GFC unfolds, the Croatian risk preference index shows amplification in risk tolerance. In contrast, Austria and Ireland markets respond with a dampening risk tolerance. The significance curves support the patterns presented here by showing the curves moving away from the null of risk neutrality for Croatia and moving towards risk neutrality for Austria and Ireland. The corresponding gaps in the spillovers with the risk preference curves widen. This explains that higher risk-taking prior to a crisis fuels systemic risks further during a crisis despite investors' changing preferences when faced with a crisis. We conjecture that higher risk aversion during crisis results the markets falling further into a disaster. This is particularly true in the pre-GFC era; we identify a strong dampening of risk tolerance during each crisis period that is preceded by amplitudes in risk tolerance as shown in Figure 3. The corresponding systemic risk estimates demonstrate sharper swings in recent years, especially in transmissions from Croatia.

From Figure 3, initially we find a commonality in the risk sensitivity patterns of Portugal and Belgium because both the countries' investors are leaning naturally towards risk aversion from high-level risk-taking prior to the GFC. Nonetheless, the significance index presented in Figure 6 shows inconsistent risk aversion significance for Belgium, while depicting consistent significance for Portugal. This leads to build-up in resilience and corresponding gradual deceleration in transmission of risks from these markets, which affirms that an overall shift of investors' sentiment towards lower risk tolerance may lead to less propagation of shocks across markets.

Finally, examining the Greek curves, we find that investors in Greece are predominantly risk averse, especially since the USA subprime crisis sends the European markets into a downward spiral. We also show that despite Greece being a strong transmitter of shocks at the onset of European crisis, multiple austerity measures push the transmission

down while simultaneously amplifying Greece's vulnerability to the rest of the world. In response, the high risk taking investors become risk neutral.

We suggest several points from this cluster. First, we show that a complete shift from risk aggressiveness to risk neutrality comes about due to a crisis, leading to resilience building for the concerned market. Second, we demonstrate that markets in this block are more vulnerable and investors are mostly risk averse. Third, we observe that repeated austerity measures suppress the transmission coming out from Greece, turning its investors risk neutral but at a cost of resilience to in-shocks. Next, we discuss oil exporting markets for both emerging and developing countries.

5.4 Oil exporting markets

Now, we discuss the countries that dominate the global oil markets. We cluster the countries in terms of economy sizes and characteristics. The OED cluster consists of the markets from the USA, Canada, Russia, Norway, Japan and New Zealand, and we discuss them in Figure 4. The OEE cluster comprises Saudi Arabia, Israel, Iraq, Sri Lanka, Nigeria and Venezuela, which we in Figure 5.

In Figure 4, we show that both Norway and New Zealand are both more resilient than others in this cluster. While Norway remains a big spreader, we find that since the GFC, New Zealand is becoming increasingly like a spreader. Consequently, New Zealand's vulnerability soars with the accompanying increase in risk tolerance among investors. In contrast, Norwegian investors show a diminishing pattern of risk tolerance. The significance index is consistent with the Norwegian pattern of risk preference, and is less consistent with the pattern emerging from New Zealand.

In terms of investorsâĂŹ risk tolerance, the Japanese and Canadian markets contrast sharply with the Russian market. In Figure 4, we show that both Japanese and Canadian investors are high risk takers for most part of the sample period. Moreover, the significance test on risk sensitivity for the Japanese market gives increasing support towards Japanese investors becoming high risk takers since the GFC. However, this does not hold for the Canadian and Russian markets. Additionally, for both the Japanese and Canadian markets, the corresponding transmissions outweigh vulnerability. However, the Japanese swings are sharper in both directions compared to Canada, mostly during a global event. In contrast, the Russian investors are risk averse, and since the post-Russian crisis in 1998, the degree of transmission and vulnerability starts falling. Russian systemic risks did not amplify during the GFC; moreover, transmissions from Russia flatten out since 2008. In all cases, vulnerability remains low for these markets. Hence, we can conclude that with increasing risk tolerance, Japanese investors are contributing in the markets' ascending vulnerability since the global meltdown. Conversely,

Russian and Canadian investors are less and play an important role in cooling down the risk propagation into their own markets.

Finally, we find a phenomenal amplification in the transmission swings from the USA during global meltdown, before it reverts back to normal level. Thereafter, we do not see such intensity in the vulnerability swings of the USA. Investors from the USA remain risk takers with brief intermissions towards risk neutrality in post-turmoils across the sample period. Figure 6 suggests that USA investors are becoming more risk tolerant again as the economy recovers from the meltdown.

Turning to the OEE markets, we can suggest unequivocally that investors in all the markets are largely less risk tolerant, at least up until the emergence of the European crisis. We find the only exceptions are for Israel when the GFC erupts, and for Iraq in the post-GFC period. We also find a slowing down of transmission and vulnerability levels in recent years for all the Middle Eastern markets. However, Figure 5 shows that increases in vulnerability accompanies a heightening of risk tolerance for Nigeria since the European crisis. Conversely, the Venezuelan market drops flat with the economy spiralling down and, as such, only transmissions emit with liquidity flight. Risk neutrality for this market indicates little or no market activities, which may also hold for Iraq.

In all, we find that increases in vulnerability alone generally cannot be associated with lower risk tolerance, but may play an important role in subduing a transpiring crisis. However, transmission and vulnerability both amplify if investors in the markets facing a crisis are high risk takers. We conjecture that an increase in aggregate risk tolerance is caused more by friction, which increases systemic risk taking.

6 Self-organising maps

6.1 Crisis transmission maps

In this section, we present a visualisation of a least-resistant shock transmission pathway in the network of our markets, which can be considered an extension of vulnerability detection in network finance. This method proposes an easy visualisation of the complex structure of holistic associated network in our sample markets by producing maps similar to slices of brain scans lit up by firing neural pathways. We further compare the least resistant shock transmission pathway with the neural pathway lit up by changes in investor sentiments corresponding to information available to the investors at any point. By doing so, we provide evidence of an information transmission pathway preparing the way for crisis transmission across the adjacent pathways.

We contribute to the literature by producing visualisations of high-dimensional inputs by

condensing matrices of both signed spillover gauges and signed risk neutrality measures into the meaningful self-organising clusters SOM^{crisis} and $SOM^{information}$, respectively. We begin by slicing the complete rectangular matrix into 40 successive windows, yielding a total of 80 maps capturing the dynamics in the association of crisis build-up and the underlying changes in information transmission. In Figure 7, Figure 8, Figure 9, Figure 10 we present the dynamic crisis transmission maps produced with signed spillover matrices and in Figure 11, Figure 12, Figure 13, Figure 14 we present the signed risk sensitivity indices gauged with multivariate GARCH optimisation. In the SOM dynamic representations, the horizontal and vertical scales give the individual markets and the markets in their respective clusters.

We propose to interpret the SOM^{crisis} by drawing on an analogy of a plateau: mild dark colours represent fissures in the plateau, while the degree of vector quantisation are represented by light-dark-coloured neural pathways across the map. In addition to this interpretation, if shocks evincing a crisis are analogous to a flash storm in the system, then the rainwater naturally infiltrates through the fissures and sinkholes. Hence, the visible pathways represent the least-resistant pathway of crisis or crisis-related information transmission. In other words, a higher degree of risk build-up or substantial changes in investor sentiments about the market are condensed out with darker colours, for such extreme conditions are scaled with strong prior gauges in the SOM process.

Figure 7, Figure 8, Figure 9 and Figure 10 depict the dynamics in crisis maps, with splicing of the sample time frame to semiannual crisis maps produced each time from the signed spillover gauges, which show the evolving vulnerability in the changing networks. Since the first half of 1998, the Asian financial crisis spurs a complicated web of fissures connecting networks that emerge, corresponding to a crisis. We find coverings open up, outlining vulnerability surges from Asia to the European markets, Australia and China. Additionally, fissures creep up along the Greek crisis to the OEE markets across the plateau, forming an italic 'v' shape. The picture that emerges may reflect the effects on these economies of the slowdown of global resource trade with Asia. This complex feature begins to ease out in the first half of 2001, forming fissures that give a parabolic pattern running across the entire plateau. A key to this visualisation is this pattern, predominant in all calm periods, forming ground water mounds running from end to end. In the advent of a crisis, we find that, in keeping with our analogy, coverings open up and the flash storm (i.e., unprecedented shocks) gives rapid dissipation of ephemeral ground water mounds into lower discharge areas. In other words, new depressions in the plateau underscore vulnerability transmitting from sources to predominantly less vulnerable markets. In such circumstances, the common parabolic pattern in the fissures become less visible. We outline some of such changes in the local topographic depressions.

During the first half of the dotcom bubble crisis, a stream passes through a crevasse with

a significant void. This is evident in the OED plot axes and continues right up across AC and GC until the latter half of 2002, shifting the crevasse carrying storm-water from the AC to GC blocks in the axes.

Facing the USA mortgage-backed securities crisis, the fissure changes shape from the common parabolic pattern to the italic 'v' pattern, and is also found earlier during the Asian financial crisis. This highlights the predictive power of the changing shapes on the plateau, indicating imminent, large-scale crises. As the crisis emerges into a full-scale global crisis, the bedrock in our plateau (analogous to systems of VAR) becomes riddled with openings. From a bird's eye view, the topographic depressions indicate the sheer fragility of the entire plateau, reaching a melting point corresponding to global meltdown.

The parabolic pattern in the fissures is lost again with European crisis emerging in 2010. The plateau cracks open, creating a new crevasse with significant voids from GC continuing right up to the OED markets. The parabolic pattern in the fissures re-emerge in early 2011, and remain up until late 2014 when the topography begins to change shape. Since early 2015, cracks and sinkholes continue to open up in the areas underneath the parabolic pattern with a new web of fissures creeping up unlike before. Although it seems the dislodging of the bedrock is more severe in the OED to AC and in the AC to OED and GC, late 2017 especially shows a complete melting point with deep cracks running all across the plateau. Next, we try to discover whether investors' access to information precede crevasse formation by using a similar analogy with the information transmission maps.

7   Information transmission maps

According to Wilcox and Fabozzi (2013), the complex network of feedback loops in interconnected financial markets is naturally disguised by frictions in the system. The issue of erratic market operations leading to the build-up of systemic risks across, not only investments but also multiple investors, is better understood through the collective sentiments of a network of investors. The essence of this network is that the system is acyclical and, hence, has signals (e.g., the many types of information that investors use as a 'rule of thumb' to take selling and buying decisions, including expected returns on investment, asset prices, trading volume and expected credit worthiness) that naturally pass through intermediaries. In doing so, the signals that are transmitted out of these channels are overlain with frictions, as those intermediaries may choose to transmit signals that accumulate above a threshold. This leads to similar directions in investors' actions. The resultant investor herding behaviour amplifies the effect of a positive feedback loop, which can be considered a contagion of investors' actions. Moreover, together with the lack of an early warning approach that makes anticipatory control ineffective and the risks borne

out of the investors' collective actions, the erratic explosions in the corresponding investor activity turns systemic. Consequently, the system is introduced with bubbles and crashes (Wilcox and Fabozzi, 2013).

Now we may explain how this environment leads to an adverse feedback loop. According to Davis et al. (2010), a shock causes a decline in economic activities with an adverse feedback loop. The loss of asset values and decline in profits result in increasing default rates in the real sector and an amplification in loan losses for the intermediaries. Hence, the drag on the buffer of resources that intermediaries can drawdown with the falling markets, contributes increasing business cycle volatility and the tightening of liquidity available in both the market and real sector. Consequently, what follows is a further drop in asset values and profits, sending the sector into a downward spiral.

All this provides us with a natural foundation from which to investigate and visualise an information transmission (i.e., signal with frictions) pathway with investors' changing degree of risk tolerance. This may allow us to predict the crisis transmission pathway, forming a possible early warning system. In what follows, we present dynamic $SOM^{information}$, and examine if we can derive crisis generation indicators that correspond with SOM^{crisis} presented earlier.

Again, drawing on the analogy of a plateau with mid-colours and occasional lighter-coloured higher features, the interpretation of $SOM^{information}$ is somewhat different than the interpretation for SOM^{crisis} for two reasons. First, there is an immense network of fissures running wildly across the plateau with $SOM^{information}$. This suggests that market participants are always riddled with intense information, regardless of crisis or calm periods. Hence, those speculators with a lack of knowledge may analyse crisis predictions differently, generating positive and adverse feedback loops as well as reinforcing cycles. Second, a crevasse would indicate collective risk tolerance resulting from varying levels of intermediation and signal processing by speculators, indicating that liquidity is being drawn out of the markets. In contrast, risk-taking is analogous to a crevice in our discussion, which may precede a crisis or may deepen as a crisis unfolds. This is because while amplifications in signals represent risk aversion, risk tolerance is highlighted by a dampening in the neutrality index. Hence, despite the common parabolic pattern of fissures in the plateau housing the smaller crevices and gaping crevasses, the interpretations may change entirely for the maps in figures Figure 11, Figure 12, Figure 13, Figure 14.

In the second half of 1998, burrows and crevices are at the bottom left corner of the $SOM^{information}$ topography, highlighting that the risk tolerance of Asian investors dominates AC markets during this period. In the subsequent period, the first half of 1999 depicts reinforcing cycles in risk aversion sentiments followed by risk-taking in the developed markets (OED) coming about from the Asian investors. Both these periods accord well with the SOM^{crisis} topography outlining crisis transmission from the AC to OED

markets. The shifting of portfolios from the crisis-ridden Asian markets to the OED markets shows new corresponding crises transpiring in the OED markets, consistent with the active hedging phenomenon and leading to elevated market linkages (Kodres and Pritsker, 2002b; Kocaarslan et al., 2017).

Facing the dotcom bubble, emerging deep crevasses running across the OED region on the top left corner of the plateau scar the topographic formation. This portrays the dampening of risk tolerance that corresponds to events unfolding in the OED markets, and may lead to the riskier allocation of assets, as suggested by Kocaarslan et al. (2017). This in turn, raises the prices of risky assets, emanates investor-based contagion and may also lead to new crisis formation in the SOMcrisis maps. This is especially apparent in the first half of 2001. As the SOM^{crisis} maps show, Asian investors pulling investments out of the OED markets correspond to a gaping new crevasse creeping up in the OED zone. Hence, the predictability between the SOM^{crisis} maps and $SOM^{information}$ maps provides us with the early warning system for which we aimed. This also holds for Lehkonen and Heimonen (2014) theory that in crisis periods, homogeneous information transmission triggers active hedging, leading to frequent asset reallocation. This, in turn, induces interdependence. Additionally, this process addresses a crucial network problem. The maps lay out the role of Asian investors in propagating a crisis emerging from the OED cluster into the EC cluster, and underscores the importance of a middle node in transmitting a crisis from A to B.

Both the $SOM^{information}$ and SOM^{crisis} maps revert to somewhat a similar parabolic pattern, which is slightly more wedged in for $SOM^{information}$ maps, which continues until the onset of the GFC. During this period, a yawning crevasse runs across the OEE markets, highlighting a high level of risk intolerance for mostly the Middle Eastern markets that coincides with the greatest turmoils, including war breaking out in this region with the US-led Iraq invasion. This is of no surprise; such events would force investors to pull resources out, and the emerging pattern depicts this loss of risk tolerance.

With the dynamic maps rolling into the periods marking the advent of the GFC, the bottom right corner of the plateau begins to form a twiggy crevasse that opens up into a dark void, signifying the full cycle of the GFC. As the GFC subsides, the crevasse fills up, resembling the very beginning of its formation before disappearing completely. During this period, the bottom left corner of the $SOM^{information}$ maps depict visible topographic depressions as holes and burrows. Here again, we draw on an analogy to the changing dynamics of patterns in risk tolerance that $SOM^{information}$ illuminates. The imminent GFC, which can also be observed as the scars forming up on the SOM^{crisis} landscape, marks a time of high-risk evasion in the OED markets and risk-taking among European and Asian investors. It is possible that the realisation of crisis fear among investors. Eventually, the GFC swings into full cycle, forcing OED investors to become risk-takers

while European and Asian investors become risk averse following a flow of capital out of the OED into the EC and AC markets. This results in gaping crevasses creeping up across the EC and AC markets located in the SOM^{crisis} maps in the latter half of 2007, as the heightening sense of potential crisis in this region transmits crisis into these markets.

The mere visibility of the scars opening up in the $SOM^{information}$ maps, along with the transpiring European debt crisis, creates deep crevasses running across the GC and OED markets in the SOM^{crisis} maps. With the Greek austerity measures taking effect, these crevasses fill up, corresponding to the deepening of scars into new crevasses in the $SOM^{information}$ maps. This suggests that investors across the GC and OED markets resort to dodging risk, leading to amplifications in crises in 2010 as observed in the SOM^{crisis} pattern. Investors become risk-takers again as the crisis subsides. This continues up until the second half of 2012, when investors eventually begin to avert risks again confidence as builds up in the GC and OED markets. Consequently, this triggers another phase in this crisis across the affected markets, as investors pull resources out. Risk tolerance reaches its minimum for the GC and OED markets in the first half of 2016. These patterns are consistent with the feedback loop argued by Wilcox and Fabozzi (2013) and Kocaarslan et al. (2017), who showed that a crisis does not subside despite investors becoming risk averse. Investors react by making risky investment decisions, which pushes the already high prices of risky assets even higher and assumes lower returns than risk. As a result, the second half of 2016 scars the plateau with widening crevasses and deep sinkholes. This time crisis is predominant in the OED markets, and is transmitted to other markets and the area adjacent to the GC markets to form multiple reinforcing cycles that affect Asia more than the other markets.

The outcome of the maps produced in Figure 7, Figure 8, Figure 9, Figure 10, Figure 11, Figure 12, Figure 13, Figure 14 is further reinforced in Table 3 and Table 4. Both of these tables provide additional insights, as they display the summary statistics of 900 basis classification indices generated from the risk perception matrix and signed spillover (vulnerability) matrix. Combining the results from both these tables, it is evident that an amplification in risk tolerance precedes crisis generation. Moreover, amplification in the vulnerability of markets heightens risk tolerance, forming a diabolic feedback loop. An agent-based diabolic feedback loop is concentrated out for 1998, 2001, 2002, 2003, 2004, 2006, 2007, 2008, 2009, 2011, 2012, 2013, 2014, 2015 and 2017. The efficacy of the method's predictive capacity is laid out in the prediction segment of these tables. These tables show that in the periods immediately before crisis amplifies, investors with public information attempt to prevent investment losses by pulling capital out of the markets. Coupled with fire sales and the depreciating value of cross-border assets, this reinforces a worsening spiral in market. Therefore, these findings provide evidence for the significance of our approach as an early warning system.

In summary, we have observed that deciphering the $SOM^{information}$ maps helps us to make predictions in the SOM^{crisis} maps, and both the systems feed off each other. Hence, these models connect well to deliver us an early warning system. This system allows us to devise and interpret one model to make predictions on the other.

In the next section, we take a granular approach and present the impact of COVID-19 outbreak in investors risk preference and a crisis propagation pathway.

8   Impact of COVID-19

The outbreak of COVID-19 that was identified in February 2020 pushed many major economies towards a recession. According to the World Bank, while global GDP contraction exceeded 5.2% advanced economies are expected to shrink by 7% and emerging economies are expected to shrink by 2.5% when the before the epidemic is neutralised (Kose et al., 2020). The DJIA, FTSE 100 index, London stock exchange and Tokyo stock exchange dampens respectively by 12.93%, 9.99%, 24.80% and 20% recording maximum losses in a single day. The unfolding of the crisis brought about by COVID-19 has led to a wave of studies in the global literature. In the current tenet of the studies, Akhtaruzzaman et al. (2020) and Corbet et al. (2020) focus on contagion, Baker et al. (2020) and Ramelli and Wagner (2020) focus on stock market crashes, Sharif et al. (2020) and McKibbin and Fernando (2020) focus on the economic impacts of the crisis and Zhang et al. (2020) focus on global financial markets as a whole. While Yarovaya et al. (2020) provide evidence of the absence of herding behavior under COVID-19 in the cryptocurrency market, Conlon and McGee (2020) provides evidence of cryptocurrency markets' failure in providing a safe heaven for investment. In this section, we take a granular view in the pre and during COVID-19 periods and examine investors' risk preferences facing COVID-19.

Figure 15 provides contour plots of risk preference matrices and vulnerability to systemic risk matrices. From the contour plot of risk preference matrix it is evident that South Korea, Germany, China, Australia, Belgium, the USA, Canada, Russia, Norway, Japan, Israel and Sri Lanka experience drops in risk taking among investors. The market calmness mostly in the advanced markets indicates the fear of economic downturn that grips the investors facing stringent physical distancing measures in place to battle the spread of virus, which, in effect, stunting business activities and growth in these economies. In contrast, developing economies and emerging economies thrive as many of these countries do not adopt stringent measures such as the developed economies. This market sentiment complements the predictions presented in the June 2020 World Bank report (Kose et al., 2020). The importance of the risk preference matrix is highlighted when we observe the vulnerability to systemic risk matrix presented in figure 15. The systemic risk matrix

suggests, vulnerability dampens for almost all the markets in the sample, which indicates heightening disconnect between the markets. Such resilience building is due to expectations regarding the trigger of global crisis and the degree of shocks emanating from interventions within the markets which simply reduced the systemic risk and connectivity between the markets except for the USA and its neighboring markets such as Canada. This also proves that the COVID-19 impact is less systemic in nature and the ongoing crisis is emerging due to idiosyncratic exogenous shocks corresponding to heterogeneous interventions and not due to exposure risk, that may trigger a contagion.

Similarly, Figure 16 provides the SOM^{crisis} transmission maps and the $SOM^{information}$ transmission maps in the post and during COVID-19 outbreak. The $SOM^{information}$ maps do not change substantially from earlier periods, except for more cracks indicative of heightening of risk aversion. The consistency in patterns signal no substantial heightening in the stress classifications corresponding to these periods. More cracks signify jumps in the degree of risk aversion that complements our findings from contour plots. Most importantly, we do not see changes in inter-connectivity. The SOM^{crisis} transmission maps also do not indicate formation of any new feedback loops or dissemination of the common patterns erupting into random signals across the space. This highlights the difference between the systemic risk maps during a systemic crisis and a non-systemic crisis. Systemic crisis transmission maps gauging from the systemic risk parameter indices capture the effects of systemic crisis more accurately and are not overshadowed by events that are not systemic to the market.

An important revelation is, while COVID-19 outbreak originates in China, we do not observe any extreme market movements in China being a ground zero to the pandemic. Similar to major global markets, we observe market calmness prevailing China as a potential indicator of a future crisis. However, such an indication is not different to South Korea, Germany, Australia, Belgium, the USA, Canada, Russia, Norway, Japan, Israel and Sri Lanka markets. This finding clearly shows the position of Chinese market against the many speculations that grip the pandemic news.

9 Policy implications

Another appealing feature in both the 'crisis maps' and 'information transmission maps' is that they show the changing dynamics in vulnerability corresponding to risk tolerance within a system of markets in a readily accessible manner. Although we are able to extract important information related to the intertwining nature of the markets and risk tolerance across these markets with unsigned and signed spillover analysis and signed risk neutrality computed from a structural VAR framework, the 'crisis maps' propose complementary information that outlines a vulnerability transmission pathway. When presented

along with the information transmission stream flowing out of the collective sentiment in investor networks, these results lay out a pathway for vulnerability transmission. Hence, we present an early warning system of contagion without having to exploit systemic risk estimates.

This provides an additional tool for policymakers and active portfolio managers. The web of fissures across the system results from a cascade of shocks emerging out of an origin and travelling on via the network of fissures in the system (e.g., Greece to China and to Australia). Understanding this association is a key for taking appropriate actions in preventing a crisis. For example, instead of taking a more drastic approach, such as blocking a pathway through outright bans on short selling or capital movement restrictions, regulators can take a more moderate approach, controlling news borne out of mere speculation or syndication, which may probably stop a crisis from happening in the first instance.

In other cases, suddenly emerging sinkholes suggest a high degree of vulnerability for an individual market or group of markets to shocks from a small set of sources. Thus, a domestic response to the cause of the crisis may involve repairing macro-economic fundamentals with traditional approaches, as proposed by Eichengreen et al. (1996); Eichengreen and Hausmann (1999) and Bordo et al. (2001).

10 Conclusion

In this paper, we contributed to the systemic risk literature by providing an early warning predictor, that does not require a state of art crisis period demarcation technique to detect potentially emerging crisis. We propose an approach, identifying agents risk sentiments corresponding to episodes of crisis or potential information regarding an imminent crisis. We provide dynamic information transmission maps that allow regulators to identify points of most effective intervention in the public information transmission pathway halting a potential for speculative attacks in the market or mere syndication. This helps to address a long standing issue: knowing how crisis spreads is not enough, but knowing how to stop is the aim.

- First, we showed how to compute investors' risk tolerance. The risk tolerance indices depict herding induced from potential public information on crisis preceding a crisis and amplifying the effects of crisis. As such, risk tolerance can be a proxy for the public information transmission index. We found that Asian investors are becoming more risk-takers in the most recent periods, which is implicit in potentially contagious Asian markets. With the exception of UK and Singaporean investors, those from other markets are more risk neutral. However, erratic behaviour escalates

prior to a crisis. Interestingly, when crisis is imminent, investors become risk averse, which explains their reluctance in making new investments. Coupled with fire sales and capital flights, this deepens the effects of an ensuing crisis.

- Next, we demonstrated how to use information transmission maps to analyze signed dynamic public information transmission (risk tolerance) indices. The dynamic crisis transmission maps provide predictive visual patterns in the maps comparing to crisis transmission maps. We conclude that immediately before a crisis, investors turn to be risk averse. Contagion transmission runs along the information pathway and passes through the plateau. Hence, the risk aversion pathway precedes the crisis transmission pathway and provides a means to detect crisis earlier.

- We investigate the influence of COVID-19 on the global markets and show how its impact on systemic transmission and risk preferences is different from that of a systemic crisis.

This finding will allows regulators to short circuit crisis transmission by intervening into the public information transmission pathway. Further, regulators can dig deeper into the potential nature of what sourcing information transmission and wield control over speculation or planned syndication. The maps make potential information transmission pathway more conspicuous. In the aftermath of the GFC, policymakers came together in realising the importance of identifying vulnerability to crises originating elsewhere and in coordinating actions to prevent such transmissions.

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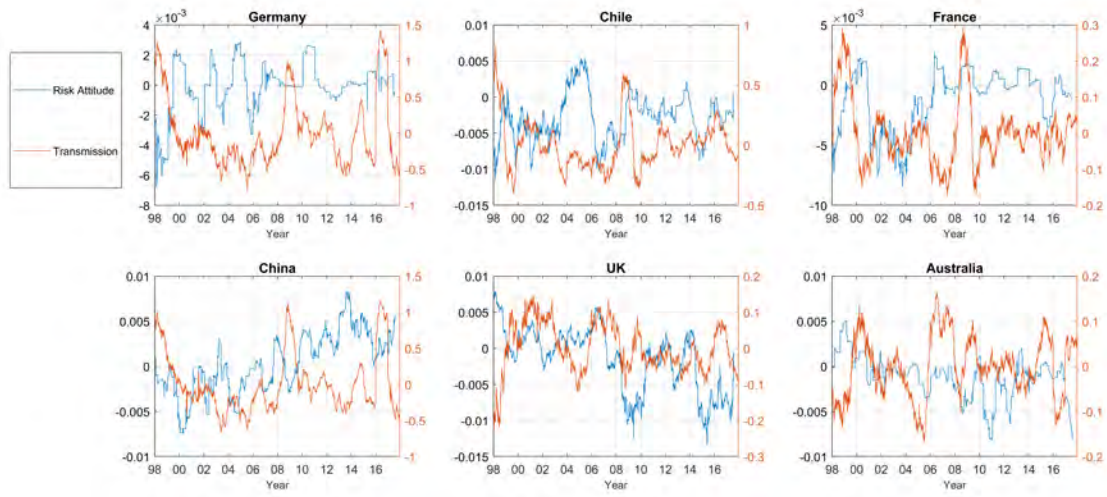# 11 Appendix

11.1 Figures
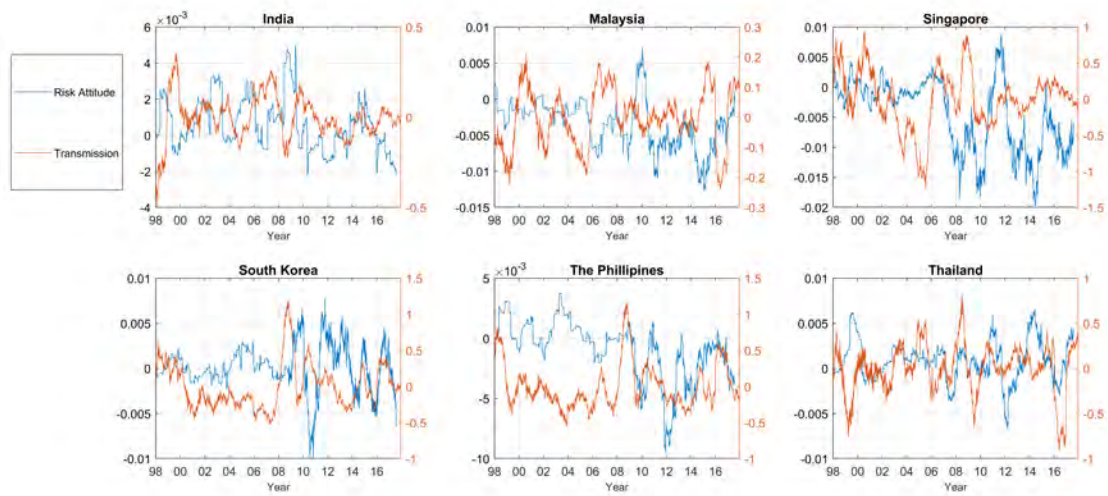
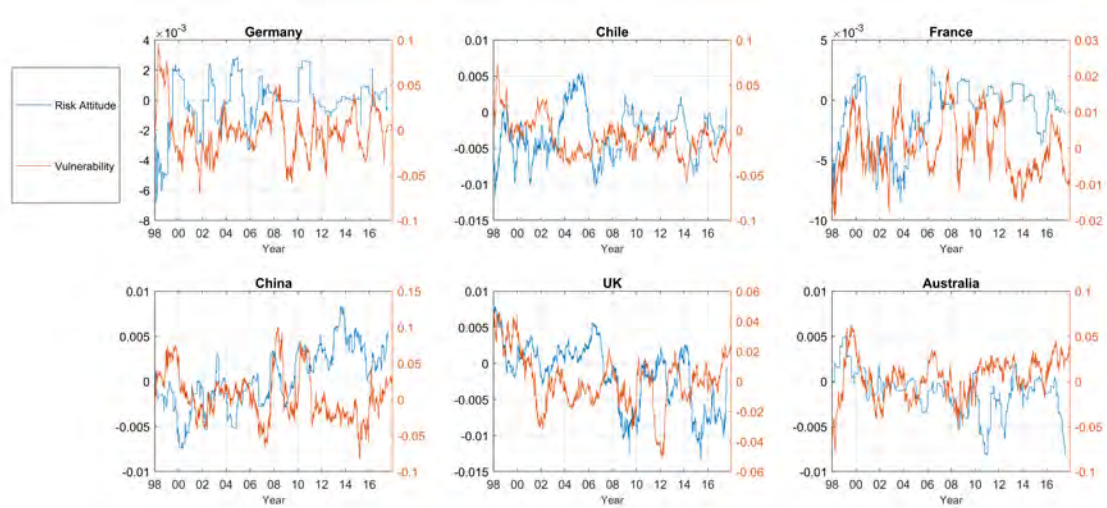(a) Asian crisis markets with transmission
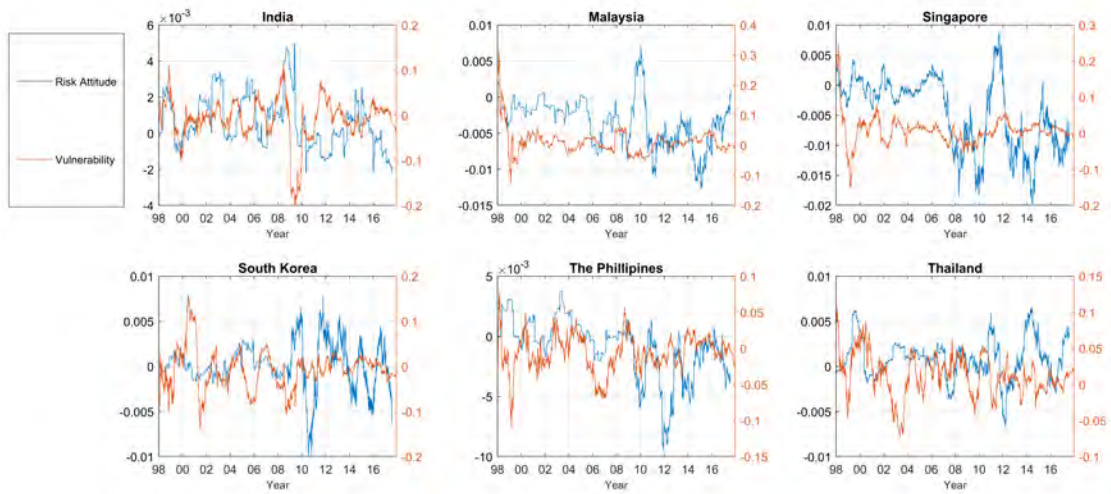
(b) Asian crisis markets with vulnerability
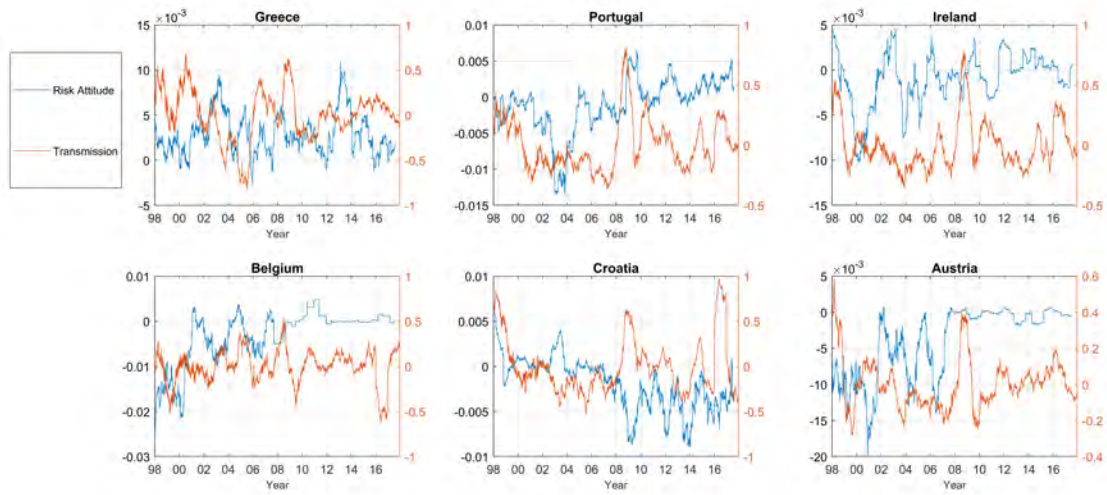
Figure 1: Asian crisis markets

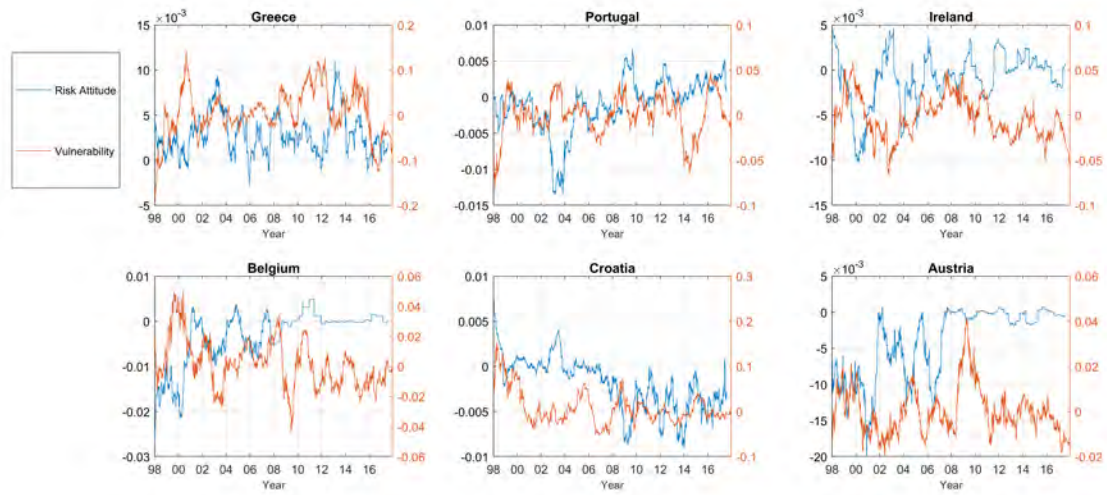(a) Export crisis markets with transmission

(b) Export crisis markets with vulnerability
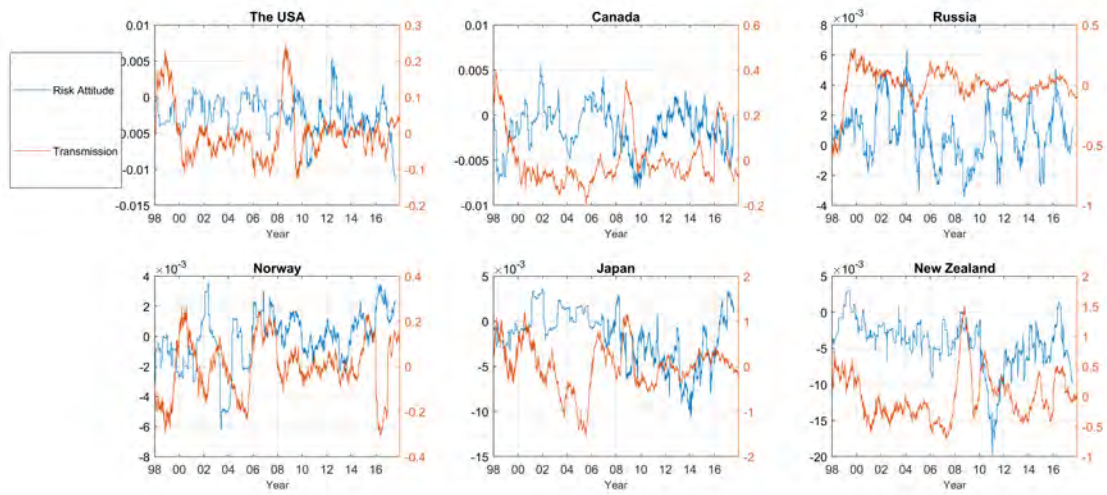
Figure 2: Export crisis markets

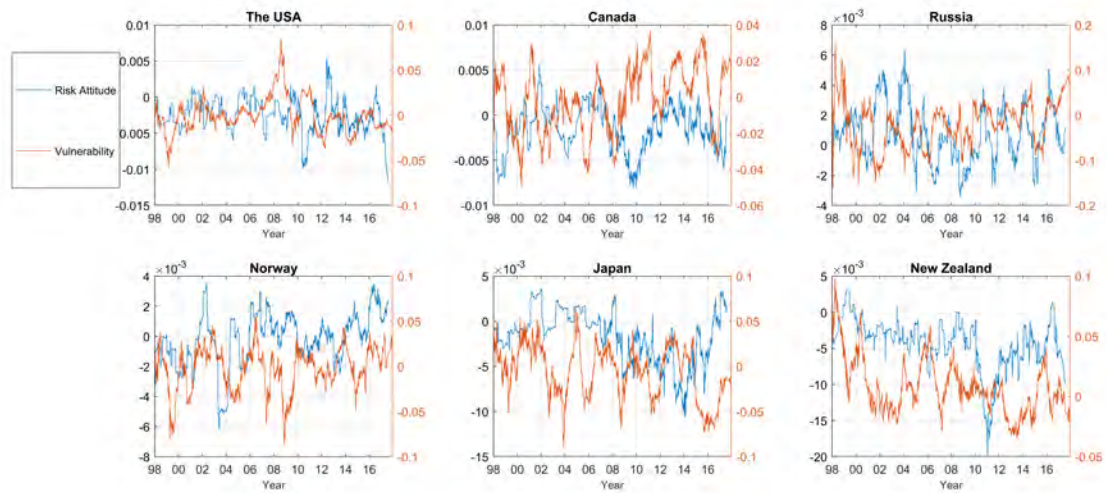(a) Greek crisis markets with transmission

(b) Greek crisis markets with vulnerability

Figure 3: Greek crisis markets

(a) Oil exporting developed markets with transmission

(b) Oil exporting developed markets with vulnerability

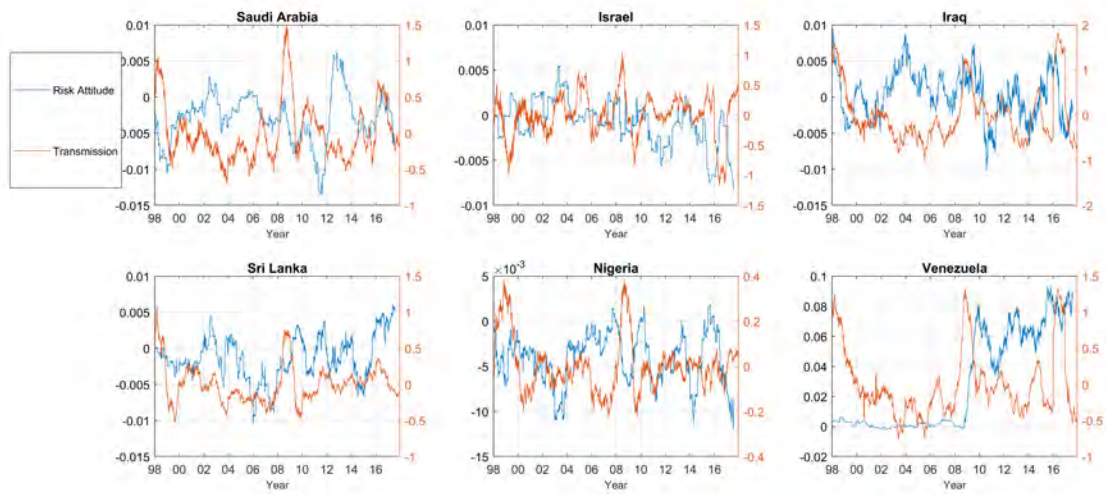Figure 4: Oil exporting developed markets

(a) Oil exporting emerging markets with transmission
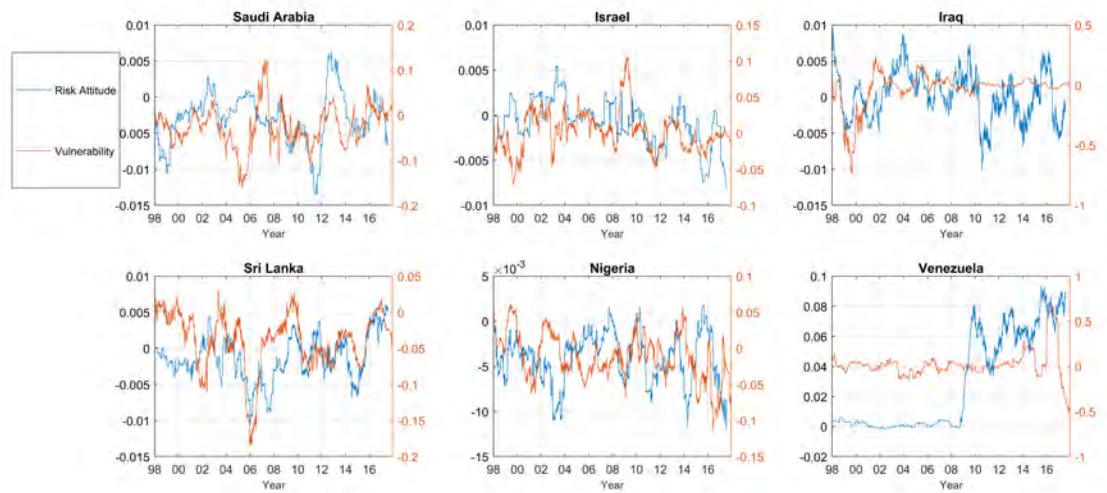
(b) Oil exporting emerging markets with vulnerability

Figure 5: Oil exporting emerging markets
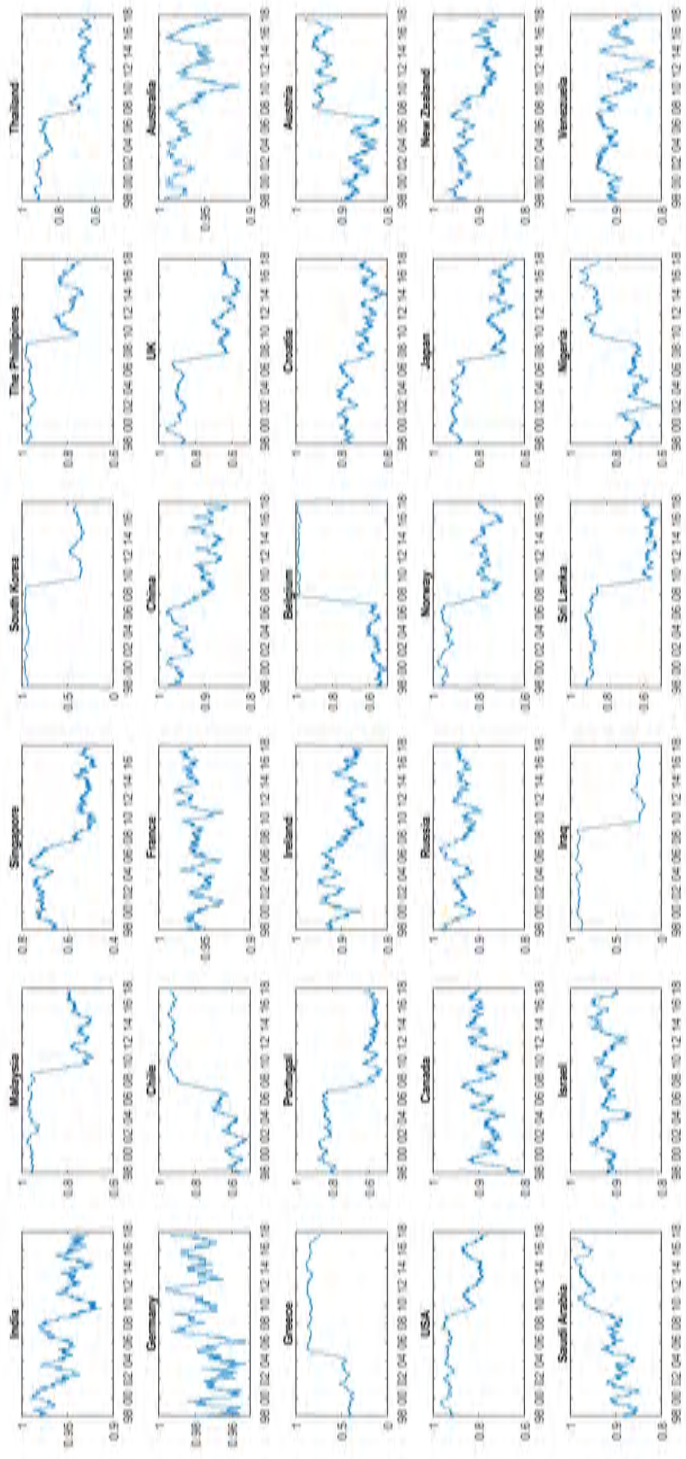
Figure 6: The Wald test results for risk neutrality

This plot shows the Wald significance test outcome across time, with no risk preference in the null and risk aversion or risk taking as alternatives

(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

Figure 7: Dynamic crisis transmission maps from 1998-2003

(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
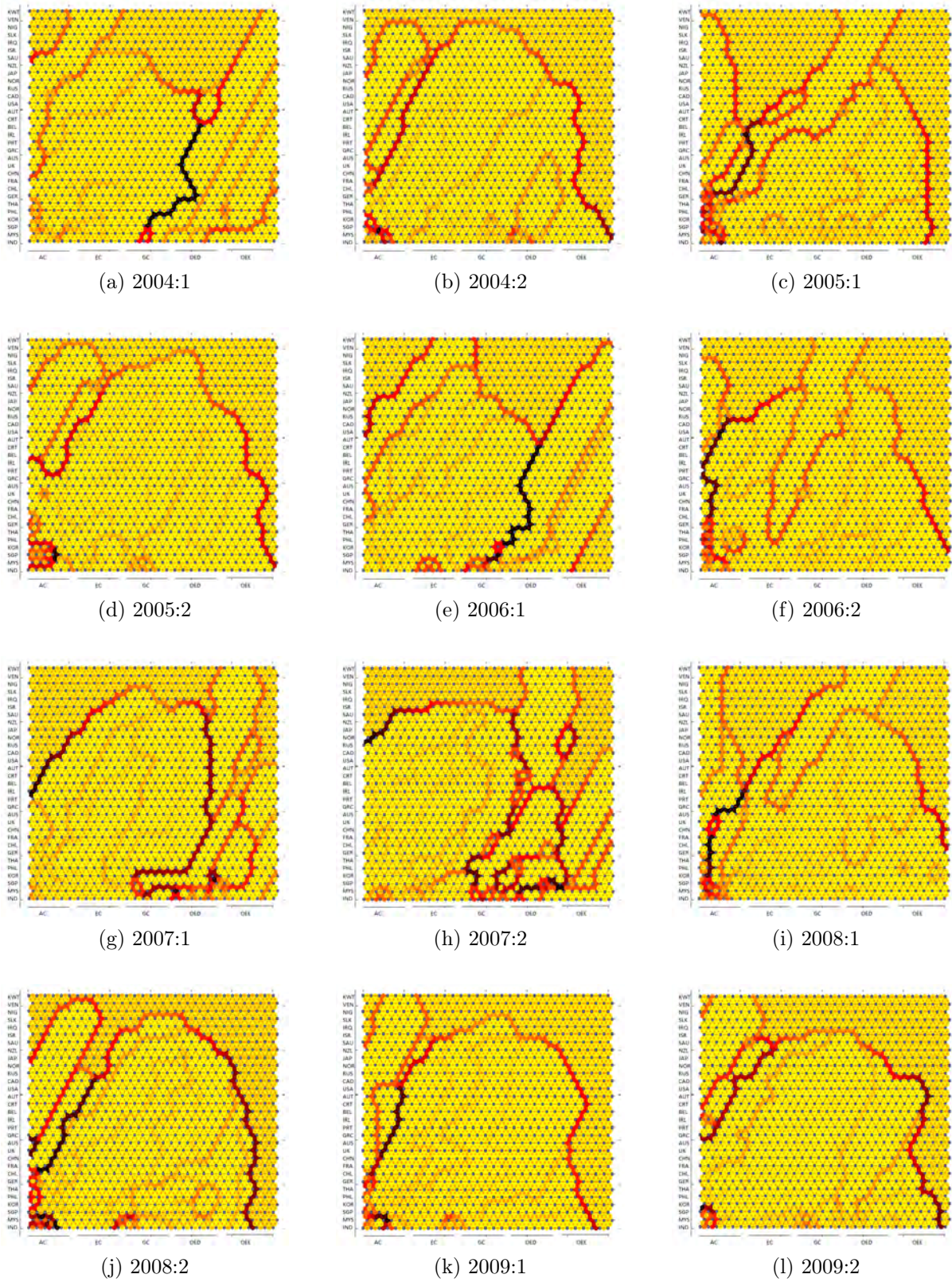
Figure 8: Dynamic crisis transmission maps from 2004-2009

(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

Figure 9: Dynamic crisis transmission maps from 2010-2015
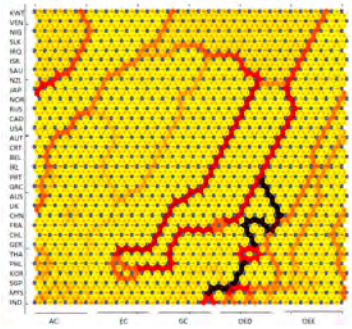
(a) 2016:1

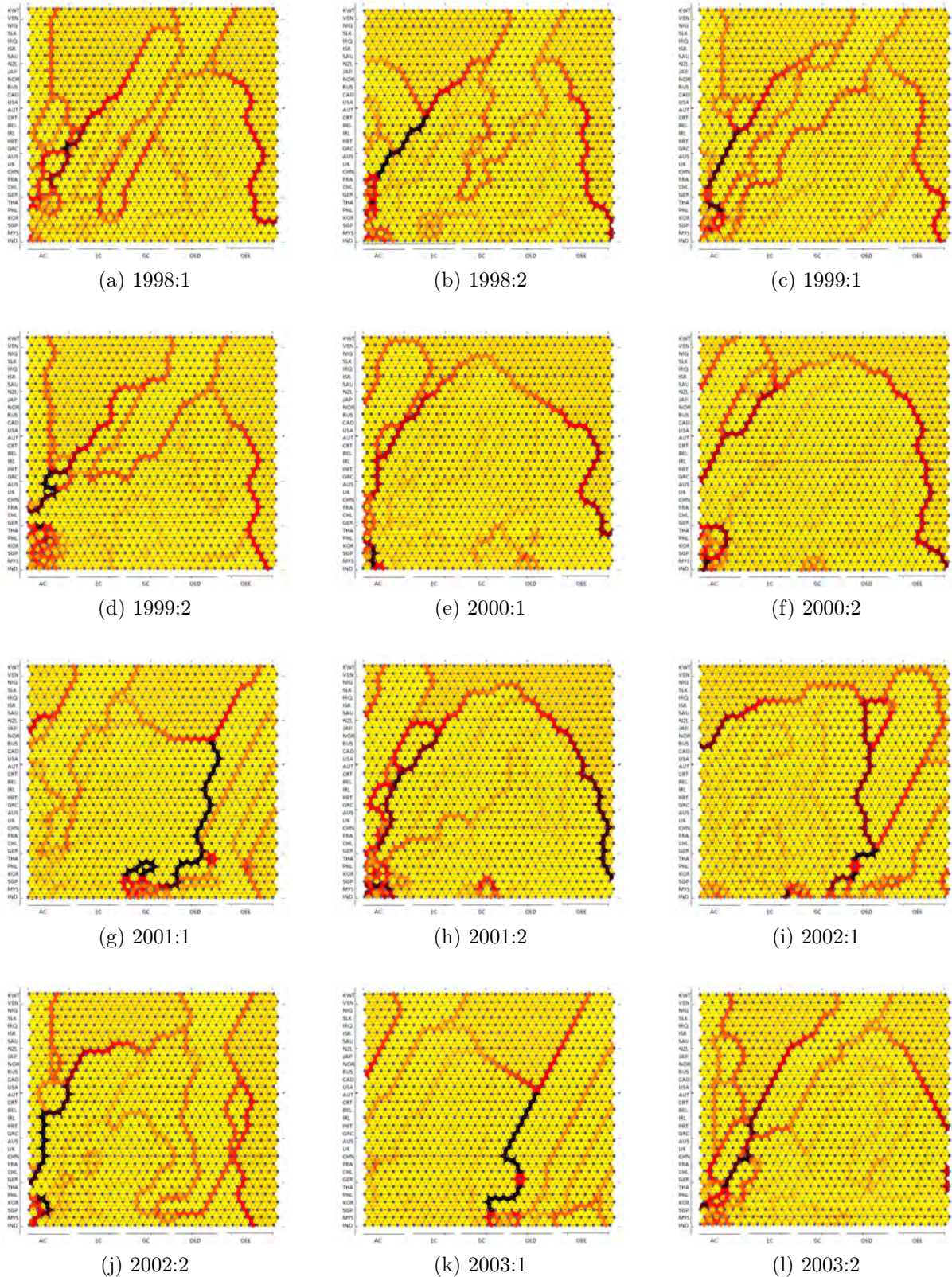(b) 2016:2

(c) 2017:1
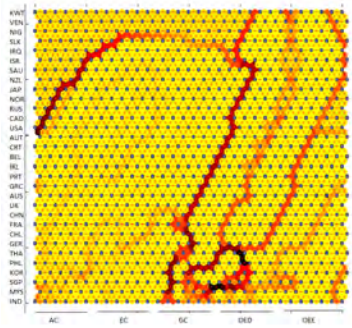
(d) 2017:2

Figure 10: Dynamic crisis transmission maps from 2016-2017

(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
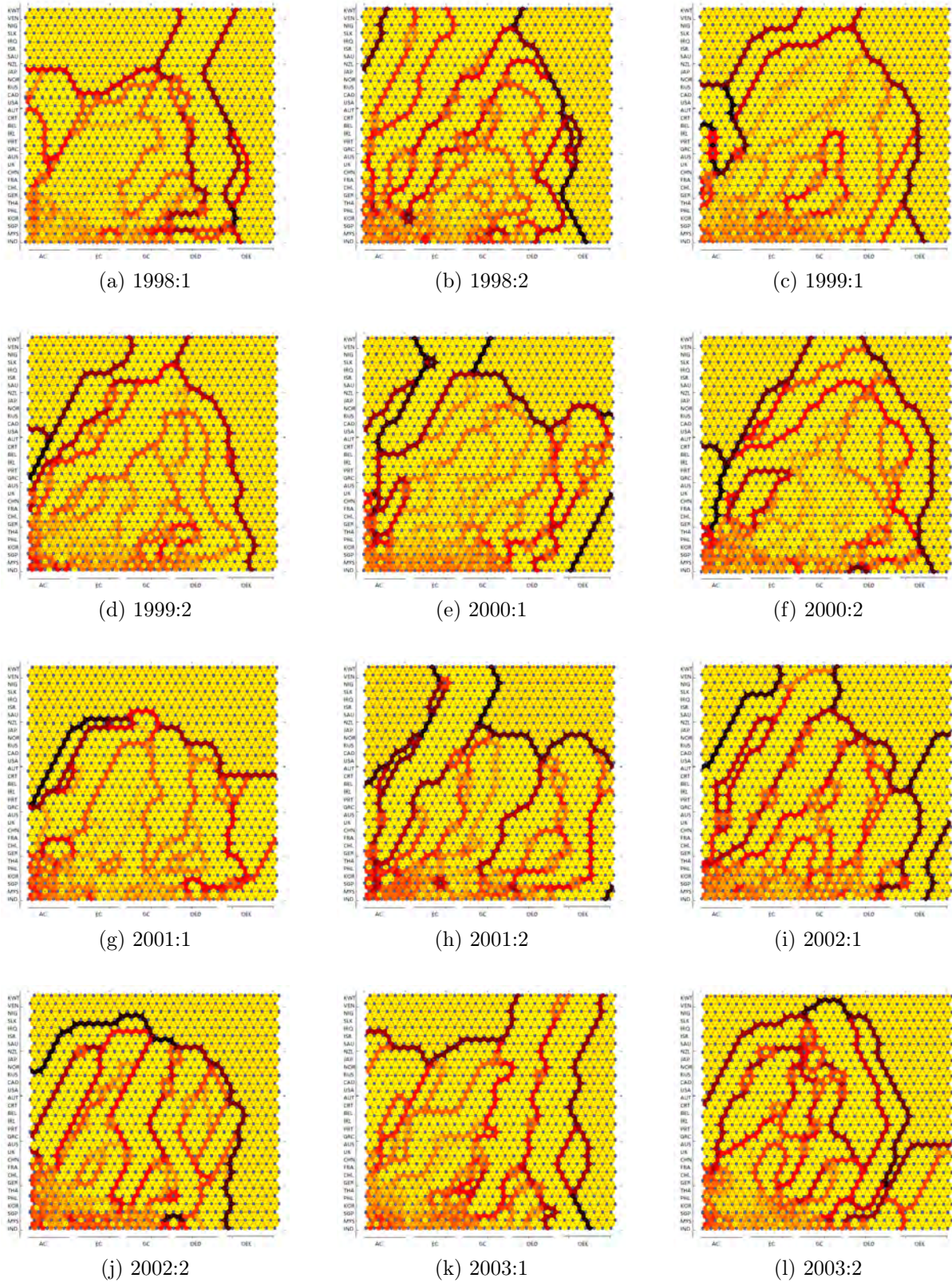
Figure 11: Dynamic information transmission maps from 1998-2003

(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
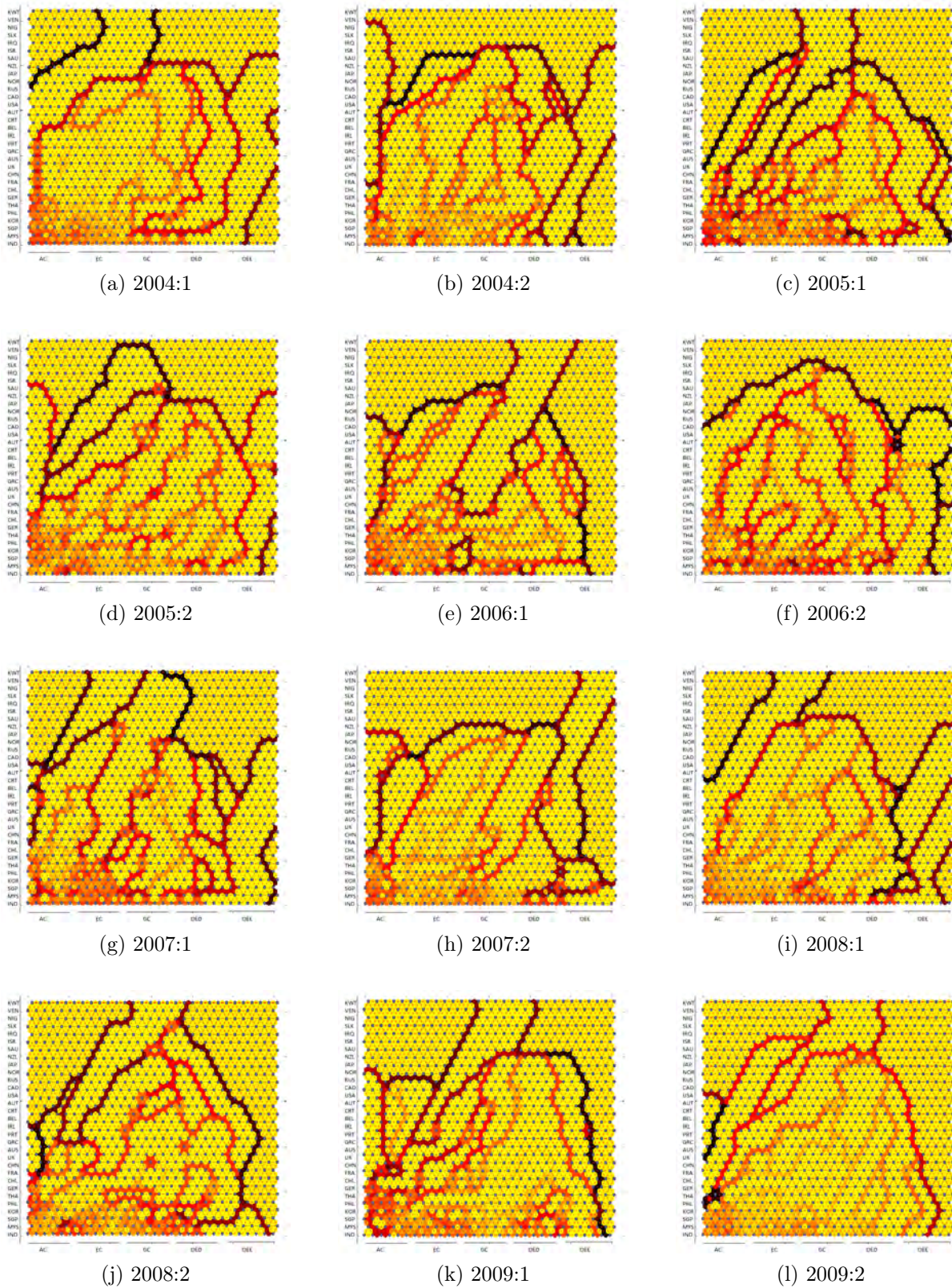
Figure 12: Dynamic information transmission maps from 2004-2009

(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
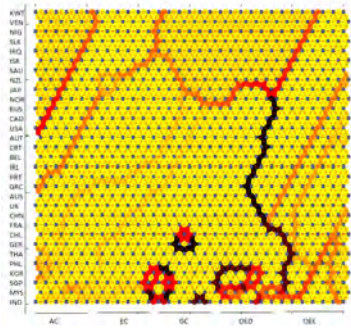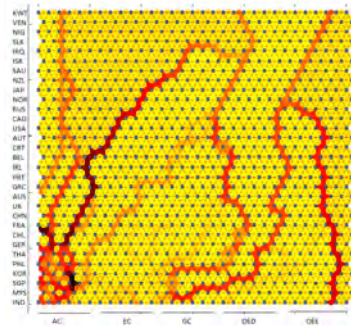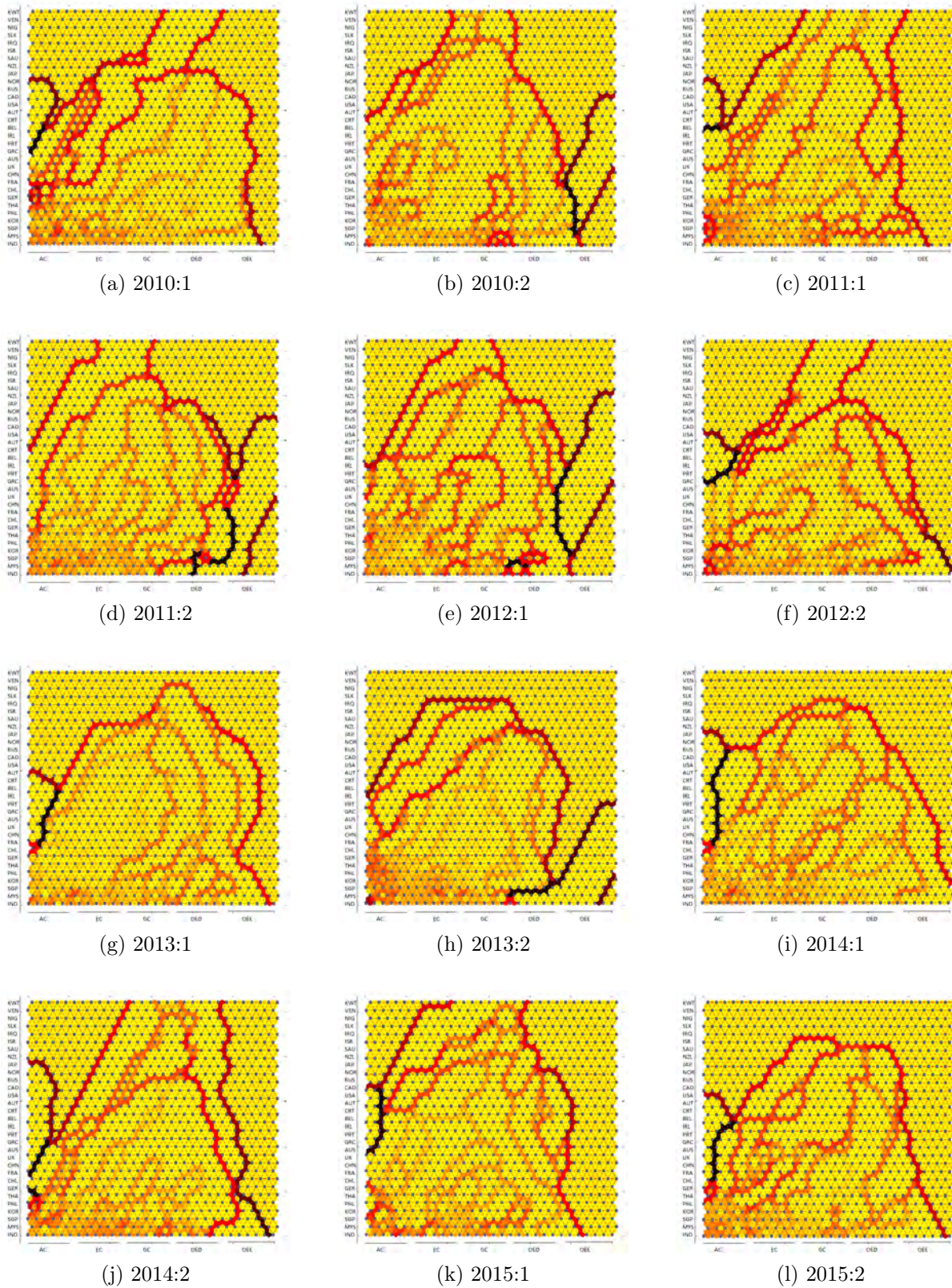
Figure 13: Dynamic information transmission maps from 2010-2015
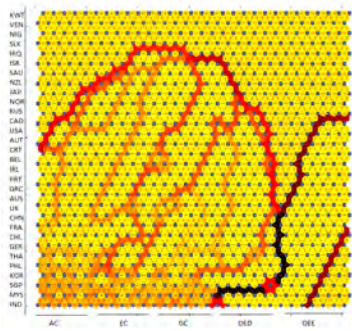
(a) 2016:1
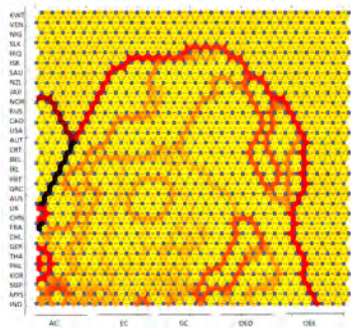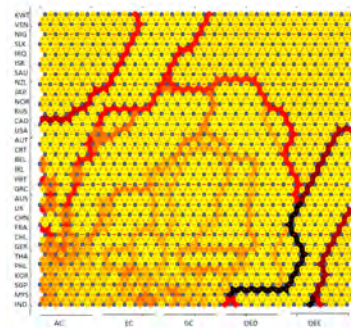
(b) 2016:2

(c) 2017:1
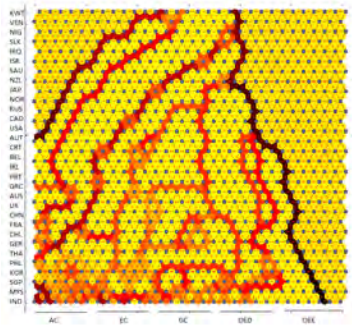
(d) 2017:2

Figure 14: Dynamic information transmission maps from 2016-2017
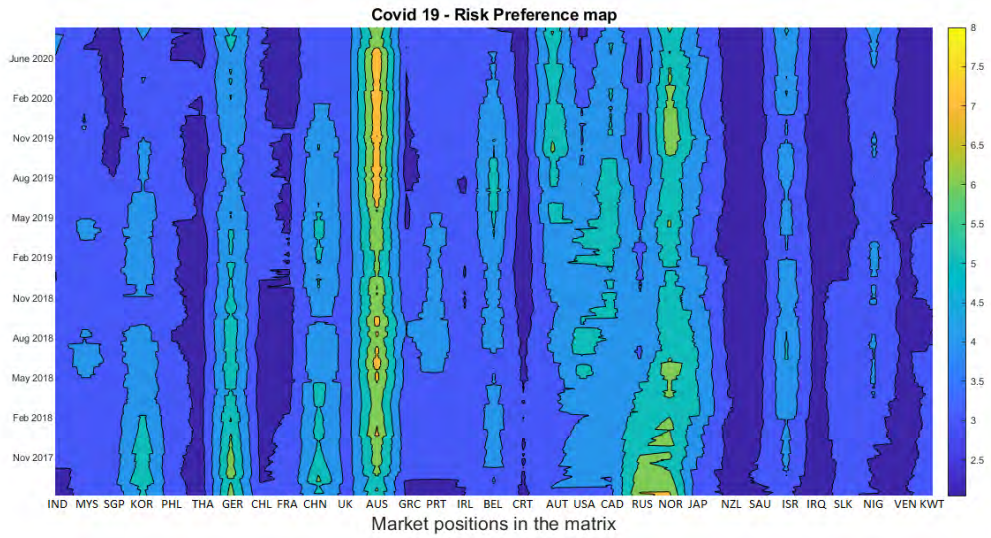
(a) COVID-19 impact on Risk Preference
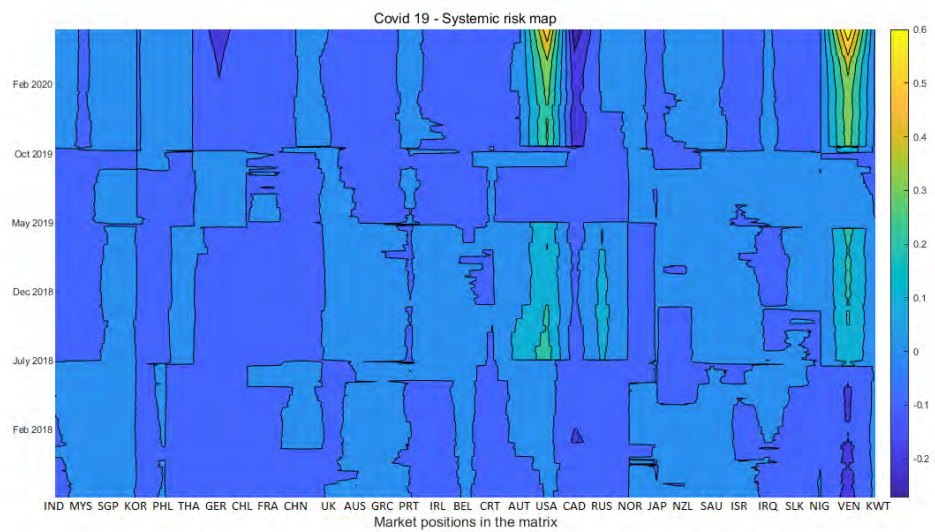
(b) COVID-19 impact on Systemic Risk

Figure 15: COVID-19 contour plots

(a) IT-2018:1   (b) IT-2018:2   (c) IT-2019:1

(d) IT-2019:2   (e) IT-2020:1   (f) SR-2018:1

(g) SR-2018:2   (h) SR-2019:1   (i) SR-2019:2

(j) SR-2020:1
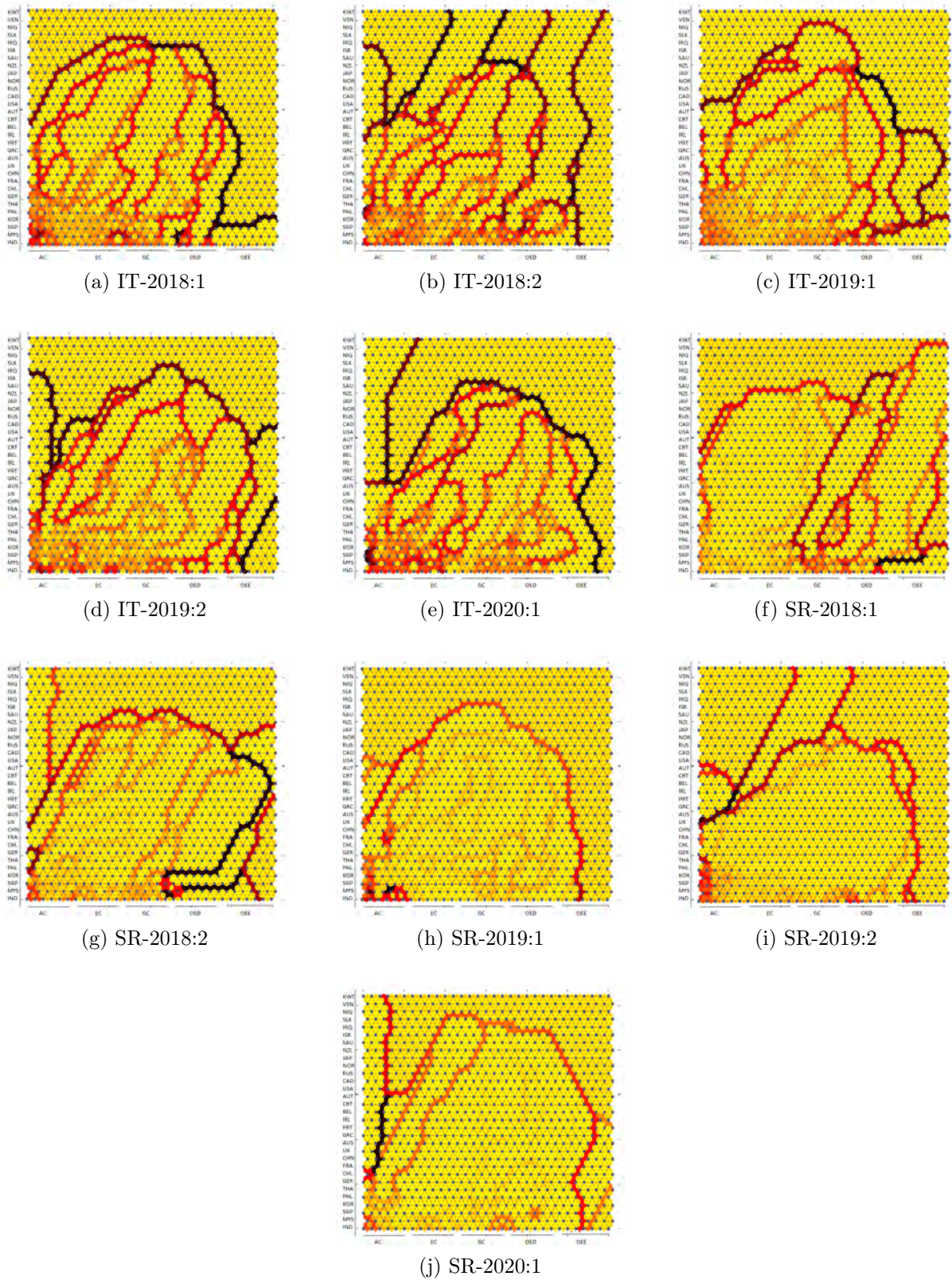
Figure 16: Dynamic information transmission and crisis transmission maps pre and during COVID-19

Table 1: Countries by analytical group

| Exporters | Commodity Exporters | Oil Exporters | Greek Crisis | Asian Crisis | Conduit Countries |
EC	CE	OE	GRC	AC	CC
Australia	Australia	Canada	Austria	Australia	Japan
China	Canada	Ecuador	Belgium	China	USA
Chile	France	Iraq[7]	Croatia	India	
Germany	Japan	Israel	Greece	Malaysia	
Nigeria	New Zealand	Kuwait	Ireland	Philippines	
Norway	UK	Nigeria	Portugal	Singapore	
Russia		Saudi Arabia		South Korea	
Saudi Arabia		Venezeula		Sri Lanka	
South Korea		USA		Thailand	

Table 2: Descriptive Statistics

Descriptive Statistics	USA	AUS	IND	JAP	MYS	NZL	SGP
Min	-6.629	-8.364	-9.852	-8.239	-19.017	-5.406	-8.848
Max	6.202	8.107	10.783	6.618	17.587	5.138	8.071
Median	0.049	0.069	0.106	0.037	0.022	0.062	0.047
Mean	0.018	0.021	0.038	0.009	0.019	0.017	0.026
Standard Deviation	0.817	1.026	1.244	0.965	1.105	0.832	0.993
JB test p Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Critical Value	5.951	6.008	6.043	6.015	5.986	5.992	5.983
	PHL	KOR	SLK	THA	NIG	VEN	KWT
Min	-8.23	-12.50	-9.95	-10.25	-17.09	-145.75	-62.81
Max	13.890	12.320	11.797	15.888	6.777	20.320	62.554
Median	0.044	0.000	0.000	0.029	0.000	0.008	0.0043
Mean	0.024	0.044	0.025	0.034	0.007	-0.003	0.012
Standard Deviation	1.181	1.514	0.858	1.321	1.129	3.557	1.871
JB test p Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Critical Value	6.019	5.975	5.987	5.988	6.005	5.995	5.996
	IRQ	SAU	CHN	ISR	CAD	GRC	PRT
Min	-41.219	-10.573	-7.863	-6.253	-9.432	-10.350	-7.060
Max	40.780	7.914	6.493	6.506	7.828	8.331	7.494
Median	0.000	0.008	0.020	0.063	0.084	0.064	0.039
Mean	0.027	0.022	0.036	0.028	0.019	-0.012	-0.008
Standard Deviation	2.508	1.013	1.243	0.986	0.985	1.523	1.041
JB test p Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Critical Value	6.003	5.948	6.010	5.996	6.012	5.964	5.986

Descriptive Statistics

Descriptive Statistics	IRL	BEL	CRT	AUT	RUS	NOR	GER	CHL	UK	FRA
Min	-11.5	-6.9	-11.2	-7.5	-16.8	-10.8	-6.7	-6.2	-9.7	-6.9
Max	5.9	5.8	11.6	8.19	13.8	7.3	7.1	8.3	7.1	6.7
Median	0.07	0.05	0.03	0.07	0.06	0.07	0.07	0.05	0.04	0.07
Mean	0.01	0.02	0.01	0.02	0.021	0.016	0.02	0.03	0.01	0.02
Standard Deviation	1.06	0.95	1.16	1.01	1.809	1.258	1.14	0.82	0.94	1.02
JB test p Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Critical Value	5.98	6.02	5.96	5.97	5.97	6.03	6.03	5.94	5.95	6.0

Table 3: Summary Statistics of 900 basis agents risk perception 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.	4.00	5.00	6.00	3.00	13.00	13.00	3.00	33.00	10.00	2.00	24.00	10.00	16.00	7.00	34.00
1st Qu.	214.0	194.0	190.0	242.0	191.0	207.00	219.0	275.0	207.0	275.0	281.0	262.0	192.0	190.0	336.0
Median	441.0	415.0	444.0	528.0	409.0	422.0	465.0	472.0	434.0	463.0	441.0	394.0	423.0	528.0	
Mean	**471.0**	463.8	462.9	511.1	437.1	451.6	**479.2**	**494.4**	443.7	**492.8**	482.7	**485**	452.1	455.6	**545.6**
3rd Qu.	744.0	712.0	716.0	744.0	647.0	689.0	727.0	703.0	692.0	721.0	688.0	743.0	716.0	732.0	800.0
Max.	956.0	957.0	954.0	957.0	955.0	952.0	957.0	960.0	939.0	959.0	952.0	961.0	953.0	956.0	952.0

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.	26.00	5.00	5.00	6.00	3.00	21.00	3.00	8.00	26.00	16.00	10.00	3.00
1st Qu.	172.0	200.0	207.0	232.0	271.0	207.0	247.00	214.0	258.0	190.0	257.0	185.0
Median	378.0	382.0	462.0	430.0	579.0	432.0	435.0	492.0	526.0	380.0	471.0	411.0
Mean	408.6	428.6	**469.5**	473.6	**525.6**	461.9	478.3	483.5	**506.4**	428.8	504.6	420.0
3rd Qu.	529.0	629.0	695.0	727.0	756.0	716.0	709.0	744.0	748.0	672.0	799.0	630.0
Max.	960.0	957.0	946.0	957.0	960.0	952.0	960.0	955.0	957.0	959.0	960.0	952.0

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.	14.00	27.00	6.00	6.00	22.00	8.0	6.00	5.000	5.00	1.00	6.00	28.00
1st Qu.	229.0	175.0	180.0	260.0	242.0	230.0	201.0	199.0	247.0	228.0	261.0	
Median	422.0	371.0	462.0	505.0	471.0	479.0	440.0	414.0	471.0	441.0	458.0	440.0
Mean	**465.7**	430.7	463.2	**491**	476.9	**484.3**	467.5	456.8	490.4	483.6	460.9	**477.8**
3rd Qu.	717.0	647.0	705.0	727.0	723.0	765.0	752.0	678.0	805.0	744.0	658.0	695.0
Max.	957.0	957.0	958.0	957.0	957.0	952.0	956.0	951.0	956.0	951.0	960.0	947.0

Table 4: Summary Statistics of 900 basis signed risk 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.	4.00	1.00	2.00	1.00	12.00	10.00	10.00	1.00	1.00	14.00	14.00	9.00	6.00	1.00	2.00
1st Qu.	215.0	282.0	230.0	200.0	216.0	240.00	267.0	203.0	298.0	240.0	206.0	262.0	283.0	230.0	280.0
Median	461.0	508.0	507.0	500.0	435.0	488.0	457.0	454.0	533.0	519.0	472.0	501.0	533.0	426.0	573.0
Mean	476.9	**495**	497.5	482.9	435.4	475.9	480	461.4	**520.2**	491.8	**468.7**	507.7	**513.5**	459.1	513.8
3rd Qu.	748.0	708.0	761.0	716.0	646.0	708.0	710.0	720.0	748.0	716.0	728.0	761.0	762.0	701.0	714.0
Max.	961.0	944.0	961.0	959.0	955.0	951.0	948.0	951.0	959.0	961.0	941.0	961.0	946.0	957.0	957.0

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.	11.00	8.00	2.00	11.00	1.00	6.00	5.00	3.00	6.00	1.00	2.00	22.00
1st Qu.	250.0	174.0	247.0	243.0	236.0	227.0	250.00	198.0	257.0	228.0	202.0	238.0
Median	500.0	360.0	510.0	505.0	496.0	481.0	499.0	372.0	496.0	484.0	461.0	420.0
Mean	491.4	482.4	485.5	**493.6**	475.3	**491.2**	**485.2**	428.8	**486.8**	471.1	458.9	443.8
3rd Qu.	713.0	701.0	714.0	722.0	697.0	758.0	745.0	716.0	726.0	699.0	693.0	679.0
Max.	953.0	961.0	940.0	961.0	960.0	956.0	959.0	961.0	956.0	959.0	956.0	939.0

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.	6.00	20.00	1.00	1.00	1.00	18.0	11.00	1.000	5.00	1.00	5.00	16.00
1st Qu.	231.0	259.0	233.0	259.0	247.0	243.0	279.0	293.0	234.0	227.0	247.0	287.0
Median	462.0	483.0	474.0	506.0	535	491.0	496.0	513.0	505.0	432.0	410.0	492.0
Mean	489.6	**495.2**	464.7	492.2	**506.8**	493.3	491.2	511.3	498.9	455.6	446.9	**512.7**
3rd Qu.	767.0	746.0	679.0	748.0	770.0	746.0	713.0	699.0	762.0	697.0	669.0	752.0
Max.	961.0	936.0	958.0	945.0	958.0	952.0	961.0	959.0	961.0	960.0	961.0	945.0