Baumöhl, Eduard; Shahzad, Syed Jawad Hussain

Working Paper

Quantile coherency networks of international stock markets

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Eduard Baumöhl[a] – Syed Jawad Hussain Shahzad[b*]

Abstract

This paper uses the novel quantile coherency approach to examine the tail dependence network of 49 international stock markets in the frequency domain. We find that geographical proximity and state of market development are important factors in stock markets networks. Both the short- and long-run connectedness significantly increased after the global financial crisis and spillover is higher during bearish market states, highlighting the possibility of contagion effect mainly among developed markets. Frontier and emerging markets are relatively less connected. These findings have implications for international equity market diversification and risk management.

Keywords: quantile coherency, networks, stock markets, extreme negative returns, financial crisis

JEL Classification: C32, C40, G01, G15

[a] *Institute of Economics and Management, University of Economics in Bratislava, Slovakia; Institute of Financial Complex Systems, Masaryk University, Czech Republic; Librade LTD, United Kingdom.*
E-mail: eduard.baumohl@euba.sk

[b] *Department for Management of Science and Technology Development, Ton Duc Thang University, Ho Chi Minh City, Vietnam; Faculty of Finance and Banking, Ton Duc Thang University, Ho Chi Minh City, Vietnam; Montpellier Business School, Montpellier France.*
E-mail: syed.jawad.hussain.shahzad@tdtu.edu.vn
**corresponding author*

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1. Introduction

The post global financial crisis (GFC) period is marked by an adverse investment environment often characterized by high volatility due to shock propagation, mainly originating from advanced economies. In this way, the GFC renewed interest in studying how financial stability can be achieved via better understanding of financial interconnectedness. It is now widely believed that the international stock markets move in tandem, which requires focus and quantifying the tail risk for various investment time horizons. The fundamental reason for this focus on international stock market correlation relies on identifying opportunities to effectively diversify idiosyncratic risk, along with understanding the nature and originators of the crisis, so that policy-makers and researchers might design and implement macro-prudential policy measures worldwide.

The literature on financial connectedness can be classified into network- and non-network-based analysis (see Kara et al., 2015). Network-based approaches, while analyzing and presenting network graphs, use pairwise relationships between financial agents, e.g. institutions, markets or countries. Meanwhile, non-network-based studies use econometric techniques, e.g. principal component analysis, regression analysis or default models to estimate connectedness.[1] Previous studies have mainly focused on the interdependence (Boubaker and Jouini, 2014) and/or contagion between a specific set of countries. For example, Boubaker et al. (2016) find contagion effects from the US equity market to selected developed and emerging stock markets using traditional methods such as cointegration, Granger causality, impulse response functions and variance decompositions. It is not a trivial task however to specify and estimate financial connectedness using conventional models because the network of linkages among international stock markets is complex. Specifically, leptokurtic and skewed distributions[2] of stock market returns show that the underlying dependence structure varies across the distribution, making traditional approaches restrictive and less precise. Shahzad et al. (2018) argues that the traditional approaches may not accurately measure the interdependence in the bearish and bullish market states, because the normality assumption in the joint distribution is not met. It is also important to note that connectedness between international stocks markets may vary across frequencies due to the heterogeneity of multiple agents interacting in these markets. The participants in financial

[1] To understand the developments in financial network studies over last two decades, Marti et al. (2017) provide an excellent and exhaustive review.

[2] Fat tail and negatively skewed financial return series result from factors such as asymmetric transaction costs, information frictions, differences in investors' risk profiles, investment heterogeneity and behavioral biases. As a result, dependence modeling should incorporate the asymmetries in marginal and joint distributions.

markets operate at diverse time horizons[3]; therefore, financial shocks might propagate through markets producing heterogeneous frequency responses. Consequently, it seems reasonable to assume the existence of linkages with various degrees of persistence and, hence, different frequency sources of connectedness among international stock markets. Accordingly, we present and examine the short- and long-run tail dependence network of 49 international stock markets to provide a comprehensive picture of the interconnectedness of world equity markets.

This mapping of tail interdependencies reveals some important factors that determine stock market connectedness, with geographical proximity the most influential (Coelho et al., 2007). Notably, several similarity factors can be apprehended by geographic proximity, such as economic factors (e.g. development, allocation of natural resources, trade and investment partners), cultural factors (e.g. common language, religion), and political factors. Special attention is given to the development level of the stock markets by considering the classification assigned to each. This network analysis identifies markets that play pivotal roles in contagion and those primarily driven by idiosyncratic factors. Since the analysis of stock market dependence is carried out for before and after the GFC period, this study shows how international stock markets' tail interdependencies were affected by the crisis. Furthermore, based on networks, the quantitative evidence indicates an increase in interconnectedness that followed the GFC.

In line with the above discussion, we pose the following three questions to be answered through quantile dependence network analysis:

1. Are geographic proximity and development status of stock markets important factors for international stock market connectedness?
2. Has overall risk propagation among international stock markets increased since the global financial crisis?
3. Are short- and long-term tail dependence dynamics different?

To answer these questions, we build a tail dependence network of international stock markets by estimating the frequency dependence structure in extreme quantiles of the joint distribution through quantile coherency, a novel approach recently proposed by Baruník and Kley (2019). Our contribution thus lies in focusing on dependence among extreme tail returns in the frequency domain, but more importantly, we highlight the benefits of a network approach, which is still not broadly utilized in

[3] The diversity in the time horizons arises because economic agents differ in terms of beliefs, preferences, investment objectives and institutional constraints. Furthermore, they also have distinct levels of information assimilation and risk tolerance.

finance literature. To the best of our knowledge, this methodology has only so far been applied by Baumöhl (2019).

In our analysis, we find that (a) European developed markets are the most connected markets; (b) emerging and frontier markets are (apart from a few exceptions) still not strongly connected, even after the GFC; (c) geographical proximity matters, especially in propagating negative shocks; and (d) stock market connectedness increased after the GFC, from both short- and long-term perspectives and for extreme positive and extreme negative returns. In general, our results are in line with extant literature on stock market networks (e.g., Coelho et al., 2007; Baumöhl et al., 2018; Wang et al., 2018). However, we also contribute to the growing body of literature focusing on lower tail dependence (e.g., Poon et al., 2003; Rodriguez, 2007; Bollerslev et al., 2013; Wen et al., 2019), which is of particular interest not only to investors, but also to policy makers, for identifying and managing systemic risk and financial crises.

The remainder of the paper is structured as follows. Section 2 explains the data and methodology. Section 3 discusses the results and Section 4 provides the concluding remarks.

2. Data and methodology

Our dataset comprises the daily data of 49 international stock market indices from January 1, 2001 to December 18, 2018, a total of 4,687 daily observations for each country. Since we only focus on the network topology of stock markets, without considering the perspective of an international investor, our data are expressed in local currency terms.[4] The selected international stock markets represent all regions of the world classified as per the World Bank lending groups. We classify the regions into four major groups, namely Europe (27 countries), Asia (12 countries), Americas (6 countries) and Middle East & Africa (4 countries). The FTSE annual country classification[5] represents the development status of stock markets and the sample has 21 developed, 9 advance emerging, 8 secondary emerging and 11 frontier stock markets. As the focus is to examine changes in tail dependence dynamics since the global financial crisis, the sample is divided into pre- and post-GFC sub-samples, with the sample period from January 1, 2001 to August 29, 2008 considered pre-GFC and November 3, 2008 to December 2018 post-GFC. We intentionally exclude September-October 2008 data to avoid the exceptionally high volatility at the peak of the GFC.

[4] It is highly likely that the international investor may hedge currency risk should the aim be to have only stock market exposure.

[5] https://www.ftse.com/products/downloads/FTSE-Country-Classification-Update-2018.pdf.

The returns are calculated as natural logarithmic differences between two consecutive trading days. To manage differences in countries' holidays, days when the returns of more than 20% of the sample (10 countries) are equal to zero are excluded. This adjustment reduces the sample size to 4,522 days. Similarly, distortions from differences in countries' time zones (non-synchronous bias) are managed by the standard procedure of computing two-day rolling-average returns (see Forbes and Rigobon, 2002). Table A.1 in the appendix lists the regions, categories, countries, corresponding ISO code, Bloomberg ticker and individual descriptive statistics of 49 stock market indices for the sub-periods before and after the GFC. The differences in mean and standard deviations between the two periods (see Figure A.1) and across individual stock indices (Table A.1) are significant. The mean and standard deviations are, not surprisingly, higher after the GFC.

The quantile cross-spectral analysis proposed by Baruník and Kley (2019) provides a measure of general dependence emerging from quantiles of the joint distribution in the frequency domain. It is of interest to examine the dependence network among international stock markets by placing more focus on the periods of large negative values (the lowest percentiles of the joint distribution) than the periods of large positive values (upper percentile). Furthermore, it is important to discern the dependence structure in the short- and long-term. The quantile coherency measure allows for this.

Baruník and Kley (2019) define a measure of dynamic dependence between two stationary processes X_{t,j_1} and X_{t,j_2}, the so-called quantile coherency kernel, as follows:

$$\mathfrak{R}^{j_1,j_2}(\omega;\ \tau_1,\tau_2) := \frac{\mathfrak{f}^{j_1,j_2}(\omega;\ \tau_1,\tau_2)}{\left(\mathfrak{f}^{j_1,j_1}(\omega;\ \tau_1,\tau_2)\ \mathfrak{f}^{j_2,j_2}(\omega;\ \tau_1,\tau_2)\right)^{1/2}} \tag{1}$$

where for every $j \in \{1,\ldots,d\}$ and $\tau \in [0,1]$, $\mathfrak{f}^{j_1,j_2}$ is the quantile cross-spectral density and $\mathfrak{f}^{j_1,j_1}$ and $\mathfrak{f}^{j_2,j_2}$ are the quantile spectral densities of processes X_{t,j_1} and X_{t,j_2}, respectively. These are estimated from the Fourier transform of the matrix of quantile cross-covariance kernels $\Gamma_k(\tau_1,\tau_2) := \left(\gamma_k^{j_1,j_2}(\tau_1,\tau_2)\right)_{j_1,j_2,\ldots,d}$, where:

$$\gamma_k^{j_1,j_2}(\tau_1,\tau_2) := Cov\left(I\{X_{t+k,j_1} \le q_{j_1}(\tau_1)\}, I\{X_{t,j_2} \le q_{j_2}(\tau_2)\}\right) \tag{2}$$

for $j \in \{1,\ldots,d\}$, $k \in \mathrm{Z}$, $\tau_1,\tau_2 \in [0,1]$, and $I\{A\}$ is the indicator function of event A. As argued by Baruník and Kley (2019), by letting k vary we can obtain important information about the serial dependence, and by choosing $j_1 \neq j_2$ we can obtain important information about the cross-section dependence. In the frequency domain, this yields the so-called matrix of quantile cross-spectral density kernels:

$$\mathbf{f}(\omega;\ \tau_1, \tau_2) := \left(\mathfrak{f}^{j_1,j_2}(\omega;\ \tau_1, \tau_2)\right)_{j_1, j_2, \dots, d} \tag{3}$$

where

$$\mathfrak{f}^{j_1,j_2}(\omega;\ \tau_1, \tau_2) \coloneqq (2\pi)^{-1} \sum_{k=-\infty}^{\infty} \gamma_k^{j_1,j_2}(\tau_1, \tau_2)\ e^{-ik\omega} \tag{4}$$

Quantile coherency is estimated via the smoothed quantile cross-periodograms. For more detail see Baruník and Kley (2019). In this paper, we extract quantile coherency matrices for two percentiles, corresponding to extreme negative returns (5th percentile) and extreme positive returns (95th percentile). We consider two frequencies: short-term (5 days) and long-term (250 days). The entire analysis is performed in R.

3. Results

We start our analysis by examining the coherency between joint distributions of stock market returns at lower percentile (5%), that is, the relationship among the extreme negative returns. This relationship is of particular interest to investors and policy makers, as it determines how contagion spreads among international markets.

Figure 1 captures four networks of extreme negative return coherency, i.e. for the two periods examined (pre-GFC and post-GFC) and two frequencies (short-term and long-term). In Table A.2 we present two centrality measures for these networks, i.e. degree and closeness centrality.

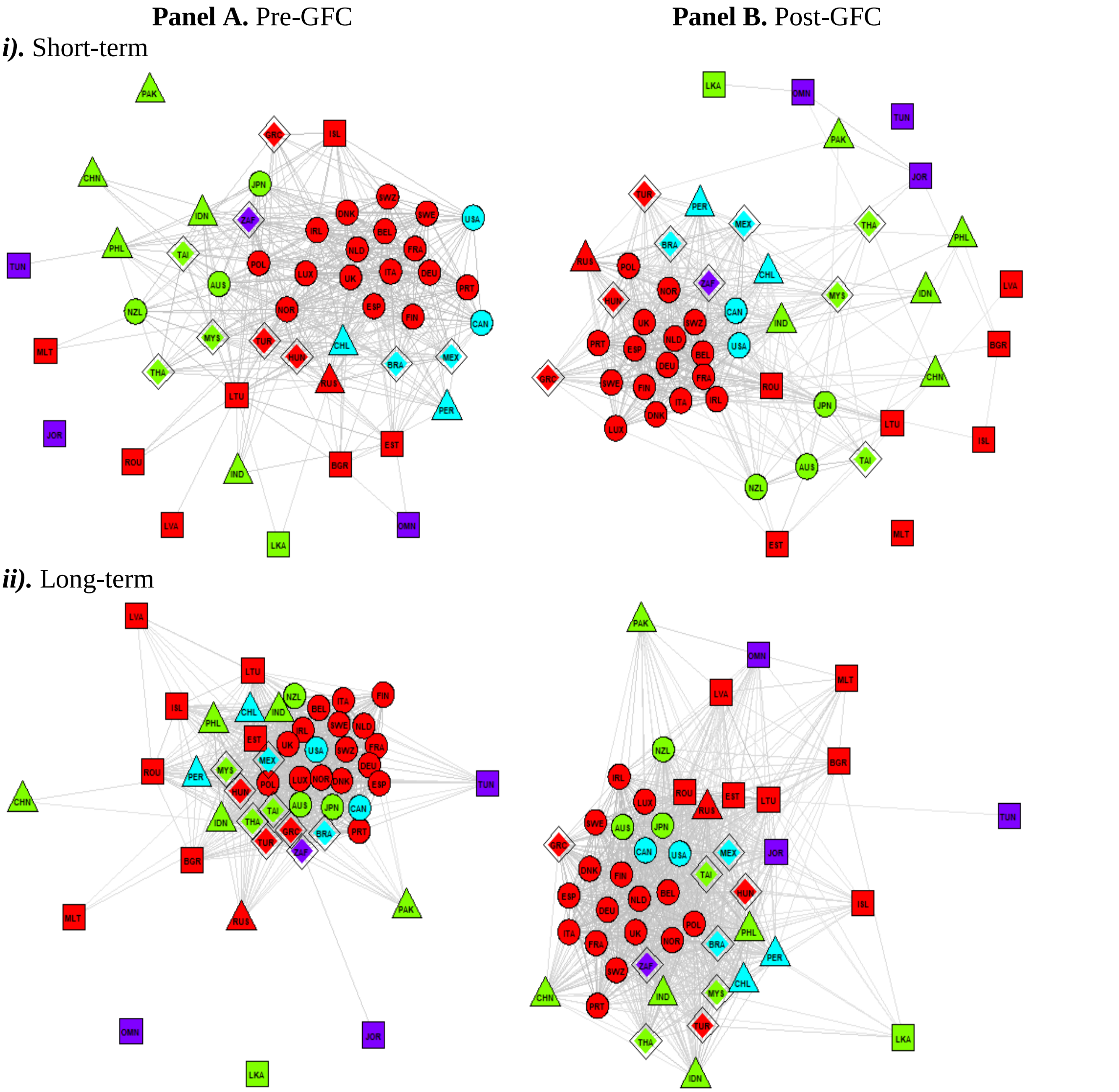


Figure 1. Quantile coherency network – Bearish market conditions (5th percentile)

Notes: The quantile coherency measure is used as the input for the adjacency matrix and the network is built using an extended version of the force-directed layout suggested by Fruchterman and Reingold (1991), minimizing the Euclidian distance between the nodes (stock markets). Red nodes represent Europe (27 countries), green Asia (12 countries), light blue Americas (6 countries) and dark blue Middle East & Africa (4 countries). The shape of the node indicates the development category: circle = developed; diamond = advance emerging; triangle = secondary emerging; square = frontier.

From a short-term perspective, the sum of degree centrality is 906 in the pre-GFC period and 988 in the post-GFC period. Note that the maximal number of all possible links in our analysis is 1,176 (N*(N–1)/2) and the maximal sum of degree centrality is 2,352; in such cases a network would be complete. We can see that in times of market turmoil, the negative returns have a strong tendency to spread through the stock markets around the world. Some exceptions are a few secondary emerging (China, Pakistan) and frontier markets (Latvia, Malta, Romania, Jordan, Oman, Tunisia, Sri Lanka), which before the GFC had less than 4 connections to other stock markets. Notably, we can see the clustering of colours and shapes, which represent geographical proximity and development level, and it is clearly evident that these factors play a major role in extreme connectedness among international stock markets.

On average, the number of links in the network (degree centrality) is 18.49 in the pre-GFC and 20.16 in the post-GFC period. This result suggests a slight increase in stock market connectivity. However, when we look at individual markets, there are some notable differences. The most significant changes are reported for Iceland, which drops from 18 links to 2 after the GFC. On the other hand, the connectivity of Romania increases from 3 to 31 links after the GFC.

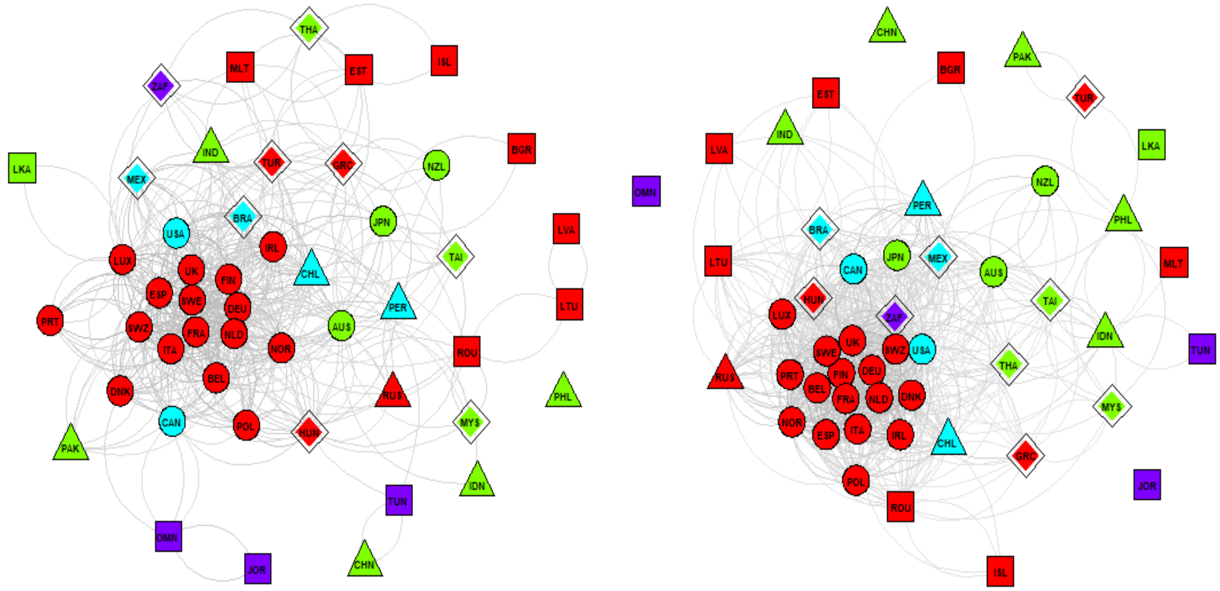
The most influential markets (based on closeness centrality) are those from developed European countries (closeness over 4). One may argue that this result might be, although partially, driven by the over-representation of European markets in our sample. However, when we look at other markets, most of them exhibit very similar closeness centrality (over 3). All these results indicate that networks based on extreme negative returns are highly connected.

What we see from a long-term perspective is two disconnected vertices (isolated markets – Sri Lanka and Oman) and a few markets with very few connections before the crisis. Overall, the network is highly connected, with the sum of 1,560 degree centrality before and 1,832 after the GFC. It is apparent that after the crisis, the network connectivity significantly increases; the average degree centrality being 37.39 and the average closeness 0.6.

To obtain a broader perspective, we also present results for extreme positive return coherency (Figure 2 and Table A.3). From the network visualization it is clear that positive returns are not as propagated as negative. Short-term connectivity before the crisis is rather low (9.8 links on average) and is also not that strong after the crisis (13.88 links on average). From a long-term perspective, after the crisis there is a significant increase in degree centrality (from 9.02 links to 20.94 links on average), but still much less than in the case of coherency among extreme negative returns. The average closeness centrality is also lower, even in the long-term. These results clearly show that extreme negative shocks propagate among international stock markets to a greater extent than their positive counterparts.

Panel A. Pre-GFC **Panel B.** Post-GFC

i). Short-term



ii). Long-term

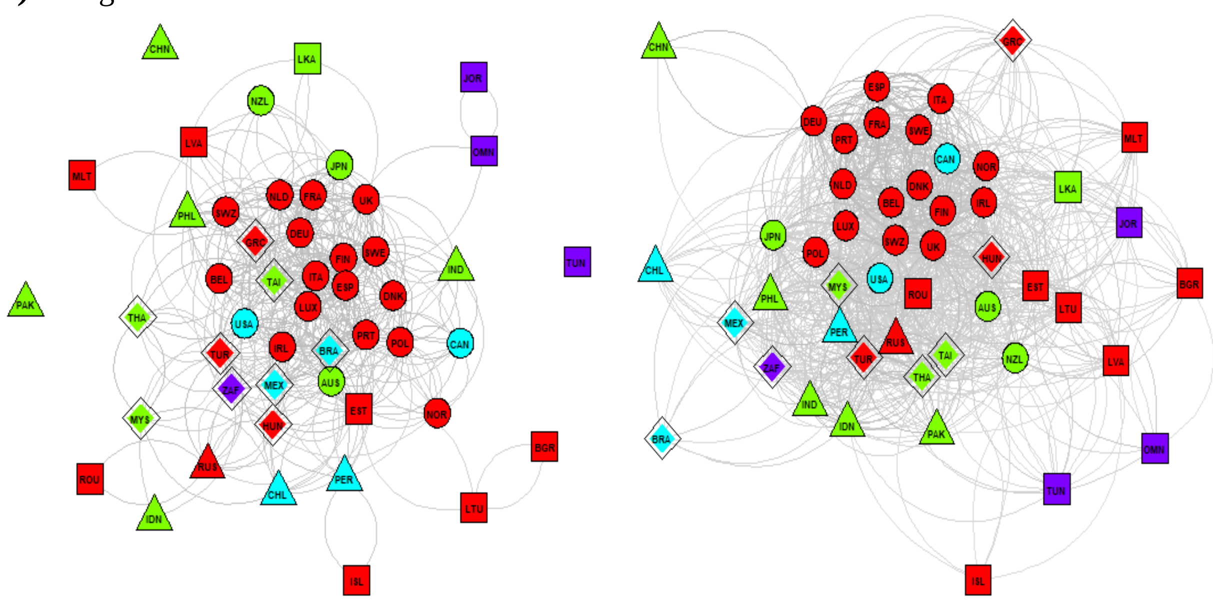
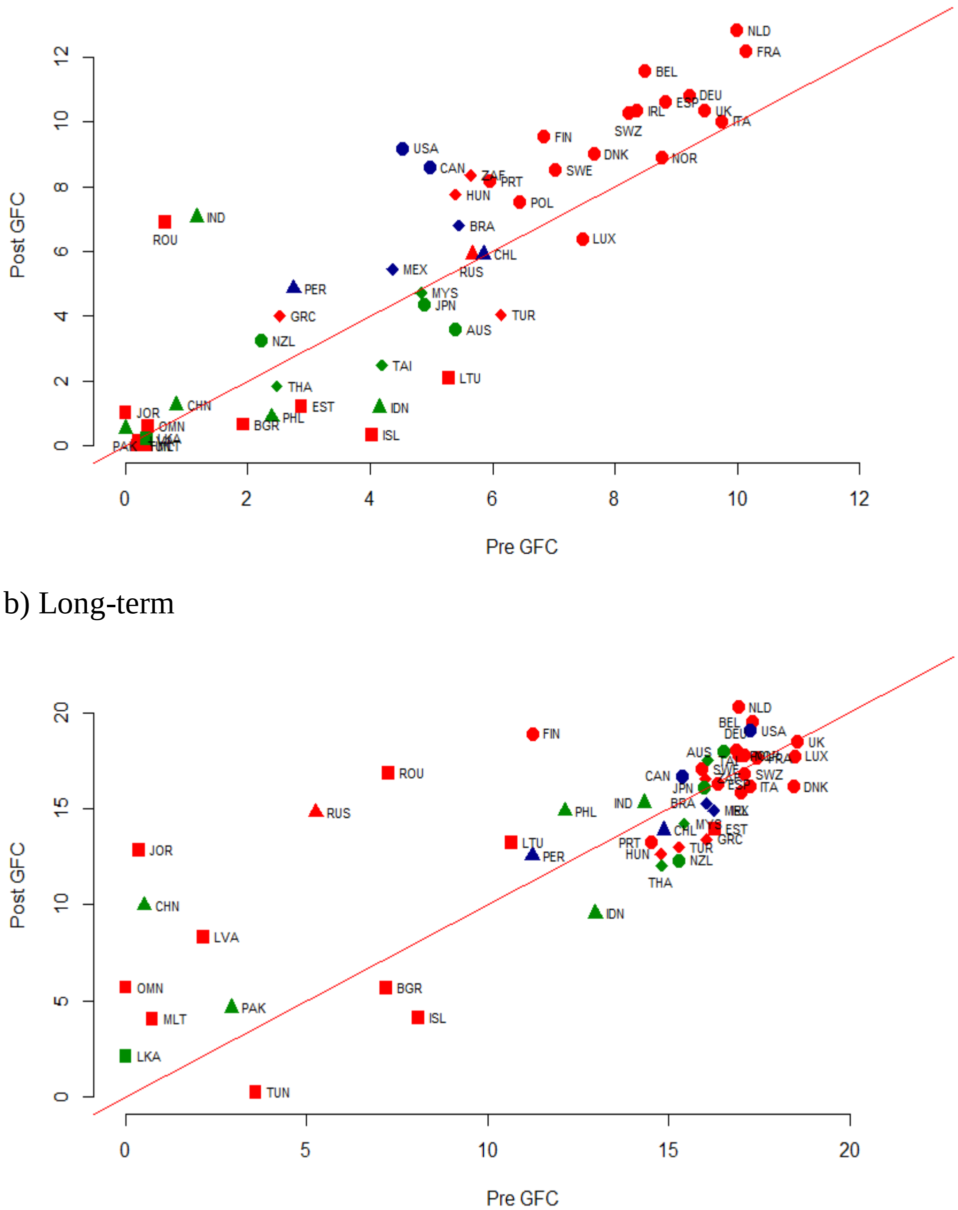


Figure 2. Quantile coherency network – Bullish market conditions (percentile 0.95)

Notes: The quantile coherency measure is used as the input for the adjacency matrix and the network is built using an extended version of the force-directed layout suggested by Fruchterman and Reingold (1991), minimizing the Euclidian distance between the nodes (stock markets). Red nodes represent Europe (27 countries), green Asia (12 countries) light blue Americas (6 countries) and dark blue Middle East & Africa (4 countries). The shape of the node indicates the development category: circle = developed; diamond = advance emerging; triangle = secondary emerging; square = frontier.

To sum up, Figure 3 highlights the differences among the strength (as a node centrality measure) of the markets before and after the GFC, extracted from quantile coherency networks of extreme negative returns. From another perspective, it is apparent that (a) European developed markets are the most connected and their influence increased after the GFC; (b) overall stock market connectedness increased after the GFC, from both short- and long-term perspectives; and (c) emerging and frontier markets are (apart from a few exceptions) still not strongly connected, even after the GFC.

a) Short-term



b) Long-term

Figure 3. Scatter plot of node centrality (strength) of stock markets before and after the GFC (5th percentile)

4. Concluding remarks

In this paper, we apply a recently proposed connectedness measure, which allows us to analyze the interrelationships among 49 stock markets from around the world. We bring a new perspective by analyzing stock market co-movements at various percentiles and frequencies. Through the novelty of the method used and by setting the entire analysis into the network framework, we shed additional light on overall stock market connectedness. Our most profound result is that extreme negative shocks propagate among international stock markets to a larger extent than their positive counterparts. We also find that development stage of stock markets plays vital role because we find that developed markets are more connected both before and after global financial crisis. This higher dependence can be seen as a challenge to pricing efficiency of these markets. On the other hand, lack of interdependence of frontier and emerging stock markets with developed stock markets highlight the potential of former markets for diversification and risk management purposes. Our analysis is based of bivariate measures of coherence and, hence, we don't control for the global common factors, we leave this interesting extension for future works.

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Appendix

Table A.1. Basic information and statistics on selected stock indices

					Before the GFC (January 2001 – August 2008)				After the GFC (November 2008 – December 2018)			
Region[a]	Category[b]	Country	ISO code	Bloomberg Ticker	Mean	Std. Dev.	Skewness	Kurtosis	Mean	Std. Dev.	Skewness	Kurtosis
Europe	D	Belgium	BEL	BEL20	-0.01	0.87	0.11	10.11	0.01	0.89	-0.75	8.60
	F	Bulgaria	BGR	SOFIX	0.12	1.23	0.46	21.35	-0.01	0.84	-1.42	22.06
	D	Denmark	DNK	KFX	0.01	0.81	-0.53	5.15	0.03	0.95	-0.47	9.02
	F	Estonia	EST	TALSE	0.07	0.76	-0.14	6.14	0.03	0.79	-0.01	15.02
	D	Finland	FIN	HEX	-0.02	1.30	-0.40	7.00	0.01	0.97	-0.22	6.06
	D	France	FRA	CAC	-0.02	0.98	-0.04	6.60	0.01	1.01	-0.28	7.46
	D	Germany	DEU	DAX	-0.01	1.08	-0.32	6.40	0.02	1.00	-0.31	7.28
	AE	Greece	GRC	ASE	-0.01	0.91	-0.20	5.26	-0.06	1.58	-0.43	6.12
	AE	Hungary	HUN	BUX	0.05	0.95	-0.20	4.10	0.03	1.12	-0.24	14.32
	F	Iceland	ISL	ICEXI	0.06	0.70	-0.52	6.49	-0.04	1.73	-24.95	760.80
	D	Ireland	IRL	ISEQ	-0.02	0.90	-0.42	6.68	0.02	1.02	-0.90	12.17
	D	Italy	ITA	FTSEMIB	-0.03	0.86	-0.26	6.73	-0.01	1.20	-0.42	6.51
	F	Latvia	LVA	RIGSE	0.06	1.12	-2.22	42.67	0.03	0.87	0.04	13.84
	F	Lithuania	LTU	VILSE	0.08	0.68	-0.13	5.57	0.02	0.77	-0.84	35.33
	D	Luxembourg	LUX	LUXXX	0.01	0.82	-0.77	11.40	0.00	0.97	-0.65	8.88
	F	Malta	MLT	MALTEX	0.00	0.64	0.26	10.08	0.01	0.43	0.38	9.90
	D	Netherlands	NLD	AMX	-0.03	1.05	-0.11	8.25	0.02	0.94	-0.57	8.59
	D	Norway	NOR	OBX	0.05	0.88	-0.73	5.19	0.03	0.98	-0.65	10.80
	D	Poland	POL	WIG	0.02	1.07	-0.03	3.98	0.00	1.01	-0.30	7.10
	D	Portugal	PRT	BVLX	-0.01	0.68	-0.51	6.03	-0.02	0.98	-0.44	6.99
	F	Romania	ROU	BET	0.13	1.15	0.31	6.95	0.03	1.02	-0.93	16.85
	E	Russia	RUS	CF	0.11	1.32	-0.45	4.94	0.04	1.33	-0.68	21.04
	D	Spain	ESP	IBEX	0.01	0.90	-0.15	5.17	-0.01	1.12	-0.28	7.03
	D	Sweden	SWE	OMX	-0.01	1.07	-0.07	4.75	0.02	0.95	-0.15	7.87
	D	Switzerland	SWZ	SMI	-0.01	0.87	-0.25	7.79	0.01	0.81	-0.64	14.80
	AE	Turkey	TUR	XU100	0.07	1.67	-0.05	6.16	0.04	1.09	-0.50	6.86
	D	UK	UK	UKX	-0.01	0.78	-0.24	6.54	0.01	0.81	-0.29	10.42
Middle East & Africa	F	Jordan	JOR	JOSMGNFF	0.08	0.77	-0.52	8.62	-0.03	0.51	-1.72	21.17
	F	Oman	OMN	MSM30	0.08	0.59	-0.33	9.85	-0.03	0.74	-2.04	41.16
	AE	South Africa	ZAF	JALSH	0.06	0.86	-0.23	4.46	0.03	0.82	0.01	7.87
	F	Tunisia	TUN	TUSISE	0.04	0.40	0.60	10.38	0.03	0.43	-0.95	18.26
Asia	D	Australia	AUS	AS51	0.02	0.60	-0.30	9.71	0.00	0.73	-0.50	7.50
	E	P. R. of China	CHN	SHSZ300	0.00	1.15	0.02	6.26	0.00	1.04	-0.78	8.51
	E	India	IND	NIFTY	0.05	1.16	-1.43	12.45	0.04	0.89	-0.11	14.44
	E	Indonesia	IDN	JCI	0.08	1.03	-0.83	6.93	0.04	0.91	-0.70	12.52
	D	Japan	JPN	NKY	-0.01	0.97	-0.16	4.06	0.02	1.07	-0.53	12.20
	AE	Malaysia	MYS	FBMKLCI	0.02	0.67	-1.03	9.88	0.02	0.47	-0.20	6.57
	D	New Zealand	NZL	NZSE50FG	0.03	0.51	-0.21	4.96	0.04	0.48	-0.75	8.41
	E	Pakistan	PAK	KSE100	0.09	1.11	-0.49	6.36	0.05	0.79	-0.58	6.87
	E	Philippines	PHL	PCOMP	0.03	0.98	0.34	8.78	0.04	0.88	-0.68	10.01
	F	Sri Lanka	LKA	CSEALL	0.09	1.03	0.08	26.56	0.03	0.62	0.34	8.24
	AE	Taiwan	TAI	TWSE	0.00	1.03	-0.25	4.85	0.02	0.79	-0.31	7.96
	AE	Thailand	THA	SET	0.04	0.95	-0.62	9.26	0.04	0.83	-0.98	14.22
Americas	AE	Brazil	BRA	IBOV	0.06	1.25	-0.44	3.85	0.02	1.15	-0.15	8.33
	D	Canada	CAN	SPTSX	0.02	0.67	-0.47	4.81	0.01	0.78	-0.73	14.53
	E	Chile	CHL	IPSA	0.05	0.52	-0.58	6.03	0.03	0.61	-0.09	12.08
	AE	Mexico	MEX	MEXBOL	0.07	0.92	-0.19	4.81	0.02	0.84	-0.20	10.81
	E	Peru	PER	IGBVL	0.12	0.93	-0.58	8.76	0.01	1.07	-0.37	18.05
	D	USA	USA	SPX	-0.01	0.74	-0.13	5.29	0.03	0.83	-0.70	11.93

Notes: Statistics are calculated from raw data (i.e., before filtering).
[a] Regions are based on World Bank lending groups.
[b] FTSE Russell as at September 2018. D = Developed; AE = Advanced Emerging; E = Secondary Emerging; F = Frontier markets (FTSE Annual Country Classification Review).

Table A.2. Network centrality – bearish state (5th percentile)

	Short-term				**Long-term**			
	pre-GFC		post-GFC		pre-GFC		post-GFC	
	Degree	Closeness	Degree	Closeness	Degree	Closeness	Degree	Closeness
BEL	28	0.398	32	0.415	39	0.743	45	0.759
BGR	10	0.274	4	0.191	26	0.484	21	0.425
DNK	30	0.386	30	0.370	39	0.809	41	0.656
EST	15	0.293	6	0.251	41	0.740	43	0.600
FIN	25	0.370	29	0.383	32	0.577	43	0.737
FRA	27	0.432	35	0.421	38	0.741	40	0.683
DEU	26	0.419	30	0.404	37	0.741	41	0.712
GRC	11	0.300	19	0.275	41	0.734	41	0.567
HUN	24	0.354	30	0.342	38	0.687	40	0.563
ISL	18	0.308	2	0.170	28	0.501	17	0.379
IRL	31	0.403	34	0.396	39	0.749	41	0.662
ITA	28	0.423	28	0.388	38	0.734	39	0.637
JOR	0	0.000	5	0.221	1	0.383	44	0.554
LVA	1	0.201	1	0.146	8	0.389	30	0.479
LTU	24	0.359	11	0.261	35	0.560	41	0.594
LUX	30	0.382	25	0.323	41	0.811	46	0.703
MLT	2	0.213	0	0.000	3	0.343	15	0.396
NLD	30	0.431	33	0.433	39	0.734	42	0.770
NOR	33	0.431	30	0.371	38	0.772	43	0.710
OMN	2	0.217	3	0.164	0	0.000	22	0.417
POL	29	0.367	29	0.337	41	0.758	43	0.725
PRT	23	0.357	27	0.357	36	0.687	38	0.565
ROU	3	0.241	31	0.338	24	0.515	46	0.695
RUS	26	0.354	26	0.301	19	0.450	43	0.621
ZAF	23	0.366	32	0.360	41	0.734	41	0.678
ESP	28	0.427	28	0.397	36	0.730	39	0.649
SWE	23	0.388	25	0.365	37	0.715	43	0.671
SWZ	24	0.404	30	0.398	38	0.749	40	0.669
TUN	1	0.166	0	0.000	13	0.413	1	0.250
TUR	28	0.360	21	0.275	41	0.705	41	0.567
UK	29	0.438	29	0.395	40	0.817	42	0.718
AUS	25	0.348	17	0.280	41	0.744	43	0.717
CHN	4	0.238	7	0.237	2	0.336	34	0.490
IND	6	0.249	33	0.330	37	0.687	40	0.636
IDN	20	0.319	6	0.232	38	0.632	31	0.494
JPN	22	0.345	20	0.318	39	0.713	42	0.653
MYS	22	0.343	25	0.304	43	0.705	43	0.607
NZL	9	0.307	17	0.267	39	0.704	40	0.549
PAK	0	0.000	3	0.188	11	0.414	17	0.412
PHL	12	0.274	5	0.205	36	0.613	44	0.608
LKA	2	0.199	1	0.121	0	0.000	9	0.343
TAI	19	0.328	12	0.266	41	0.740	45	0.723
THA	11	0.310	10	0.256	38	0.700	37	0.543
BRA	24	0.337	30	0.324	39	0.725	43	0.631
CAN	20	0.336	31	0.366	37	0.718	42	0.674
CHL	26	0.360	28	0.308	39	0.690	42	0.597
MEX	19	0.321	26	0.299	40	0.737	42	0.629
PER	14	0.284	22	0.297	35	0.579	42	0.546
USA	19	0.313	30	0.385	38	0.766	44	0.759
average	18.490	0.320	20.163	0.295	31.837	0.627	37.388	0.600
min	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.250
max	33.000	0.438	35.000	0.433	43.000	0.817	46.000	0.770

Table A.3. Network centrality – bullish state (95th percentile)

	Short-term				**Long-term**			
	pre-GFC		post-GFC		pre-GFC		post-GFC	
	Degree	Closeness	Degree	Closeness	Degree	Closeness	Degree	Closeness
BEL	18	0.283	25	0.371	10	0.322	34	0.488
BGR	1	0.142	1	0.153	1	0.150	8	0.295
DNK	13	0.243	23	0.327	10	0.326	34	0.467
EST	3	0.166	3	0.184	13	0.348	25	0.418
FIN	22	0.310	25	0.369	18	0.389	31	0.485
FRA	25	0.336	25	0.382	14	0.370	21	0.458
DEU	21	0.325	27	0.368	15	0.362	23	0.415
GRC	10	0.222	9	0.234	12	0.325	11	0.315
HUN	12	0.240	23	0.287	6	0.297	28	0.433
ISL	1	0.112	2	0.188	1	0.191	3	0.251
IRL	15	0.251	19	0.318	11	0.350	30	0.443
ITA	21	0.311	23	0.348	23	0.415	20	0.413
JOR	1	0.126	0	0.000	1	0.172	11	0.314
LVA	1	0.098	2	0.182	4	0.264	11	0.317
LTU	2	0.128	10	0.235	2	0.212	19	0.362
LUX	18	0.267	23	0.311	22	0.398	24	0.407
MLT	4	0.190	1	0.175	1	0.213	8	0.320
NLD	26	0.334	26	0.373	14	0.342	27	0.476
NOR	16	0.260	21	0.329	7	0.267	29	0.432
OMN	3	0.166	0	0.000	2	0.242	4	0.290
POL	12	0.242	19	0.284	12	0.363	27	0.407
PRT	7	0.231	27	0.327	15	0.355	21	0.401
ROU	5	0.193	14	0.236	1	0.194	27	0.411
RUS	5	0.202	14	0.276	7	0.278	24	0.393
ZAF	4	0.200	31	0.364	11	0.313	15	0.350
ESP	22	0.320	22	0.340	17	0.385	21	0.406
SWE	22	0.319	27	0.384	18	0.406	24	0.423
SWZ	17	0.303	25	0.338	12	0.336	32	0.476
TUN	2	0.158	1	0.148	0	0.000	8	0.289
TUR	10	0.225	2	0.129	13	0.346	30	0.436
UK	22	0.313	29	0.379	13	0.349	37	0.537
AUS	17	0.242	13	0.248	14	0.360	30	0.409
CHN	1	0.112	0	0.000	0	0.000	2	0.285
IND	7	0.201	3	0.188	7	0.290	18	0.370
IDN	1	0.156	7	0.242	1	0.217	18	0.375
JPN	6	0.226	18	0.278	11	0.319	24	0.405
MYS	3	0.191	5	0.213	4	0.248	31	0.431
NZL	3	0.193	4	0.203	3	0.257	19	0.363
PAK	4	0.195	1	0.096	0	0.000	13	0.360
PHL	0	0.000	4	0.191	9	0.303	21	0.383
LKA	1	0.163	0	0.000	2	0.224	21	0.366
TAI	5	0.183	11	0.245	21	0.400	25	0.418
THA	3	0.157	11	0.256	6	0.293	26	0.425
BRA	16	0.263	14	0.262	20	0.407	4	0.275
CAN	11	0.243	19	0.313	8	0.303	23	0.404
CHL	15	0.250	16	0.270	5	0.266	9	0.295
MEX	9	0.236	15	0.277	10	0.315	19	0.370
PER	5	0.215	12	0.278	5	0.272	22	0.397
USA	12	0.279	28	0.352	10	0.330	34	0.446
average	9.796	0.219	13.878	0.250	9.020	0.287	20.939	0.390
min	0.000	0.000	0.000	0.000	0.000	0.000	2.000	0.251
max	26.000	0.336	31.000	0.384	23.000	0.415	37.000	0.537