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Quantile coherency networks of international stock markets

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

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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 distributions² 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 horizons³; 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 classification⁵ 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:

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

where for every $j \in \{1, \dots, d\}$ 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 $\Gamma_k(\tau_1, \tau_2) := \left(\gamma_k^{j_1,j_2}(\tau_1, \tau_2) \right)_{j_1, j_2, \dots, d}$, where:

$$\gamma_k^{j_1,j_2}(\tau_1, \tau_2) := \text{Cov}(I\{X_{t+k,j_1} \leq q_{j_1}(\tau_1)\}, I\{X_{t,j_2} \leq q_{j_2}(\tau_2)\}) \quad (2)$$

for $j \in \{1, \dots, d\}$, $k \in \mathbb{Z}$, $\tau_1, \tau_2 \in [0,1]$, 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:

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

where

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

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.

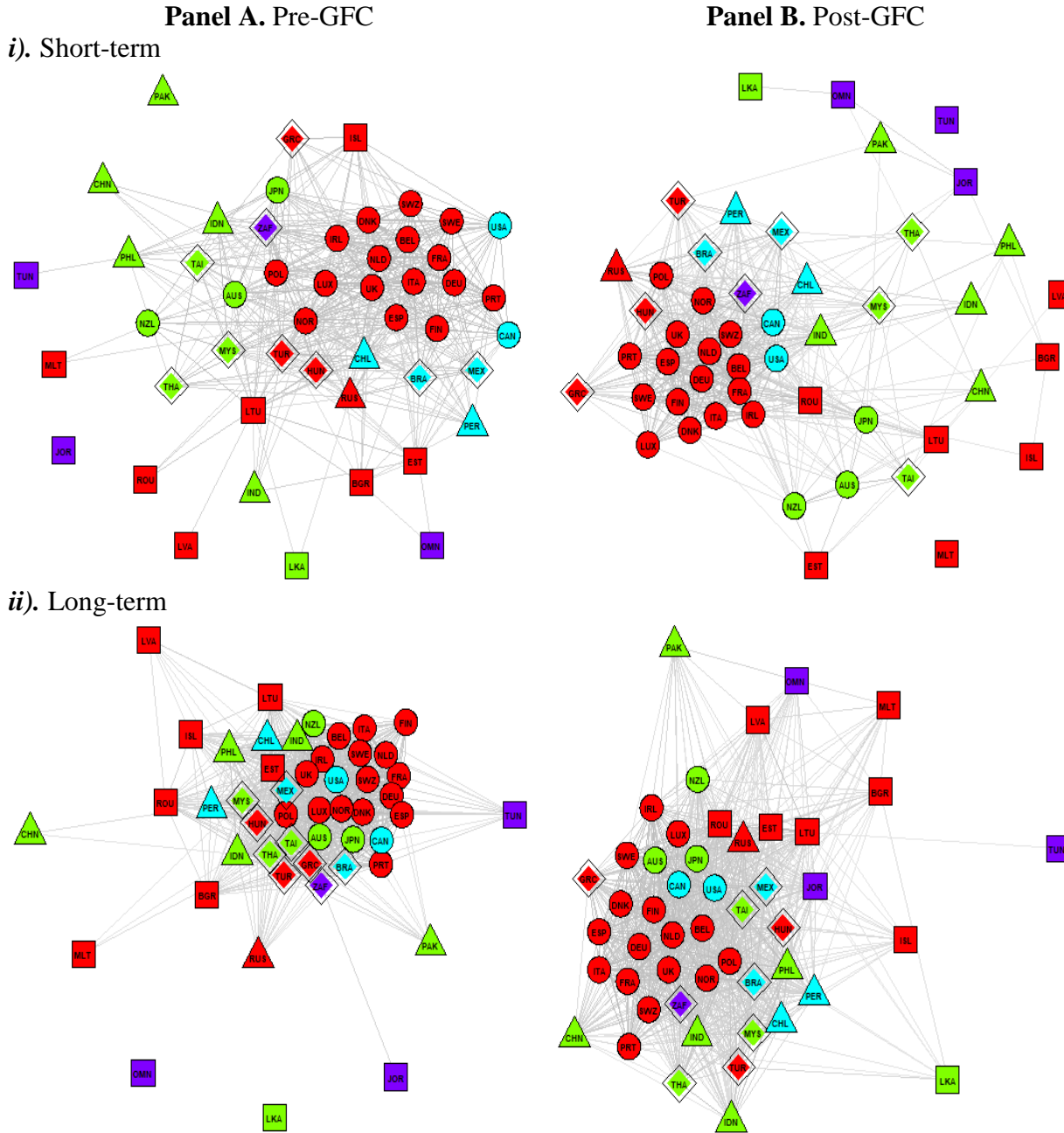


Figure 1. Quantile coherency network – Bearish market conditions (5th percentile)

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.

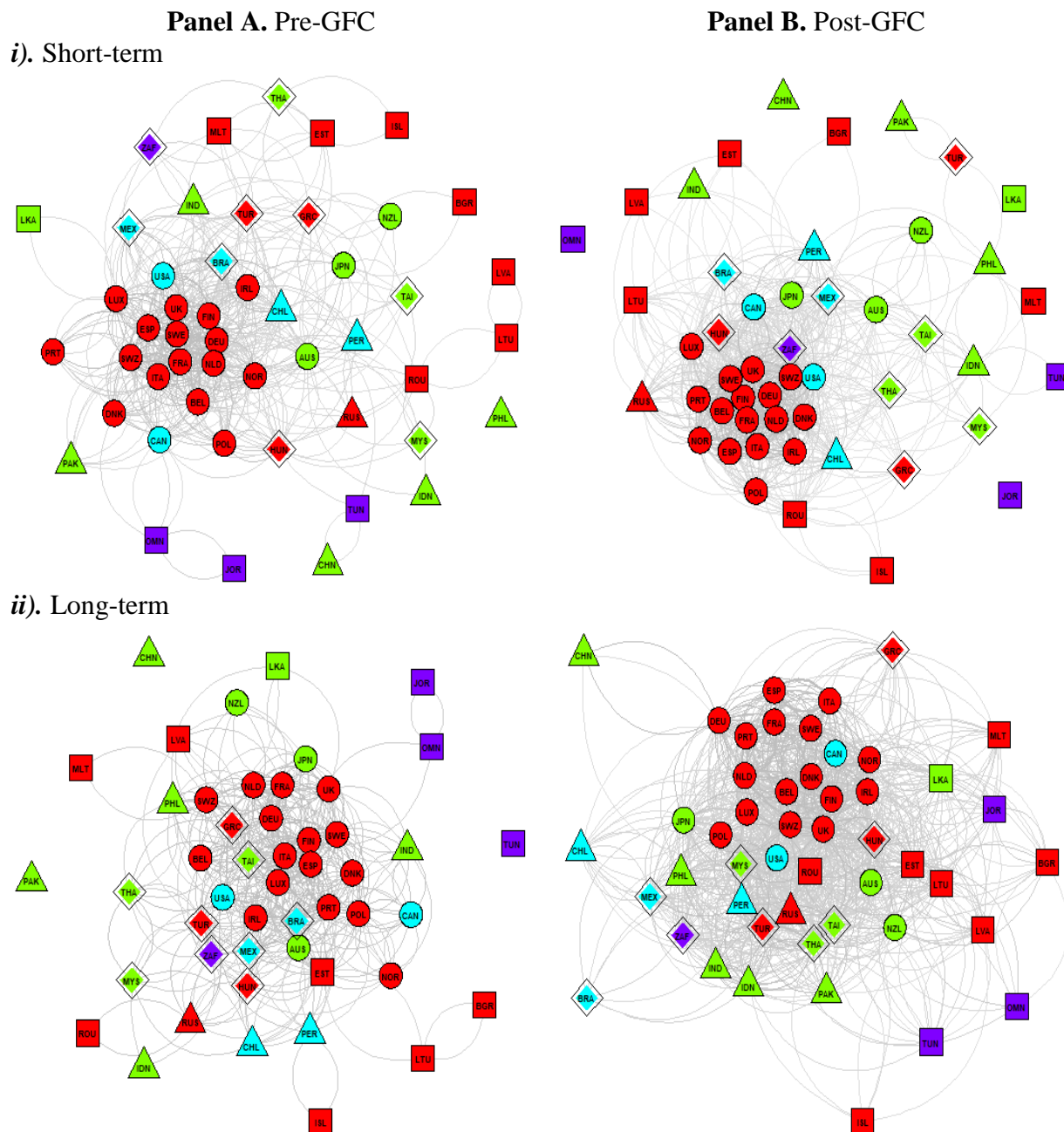


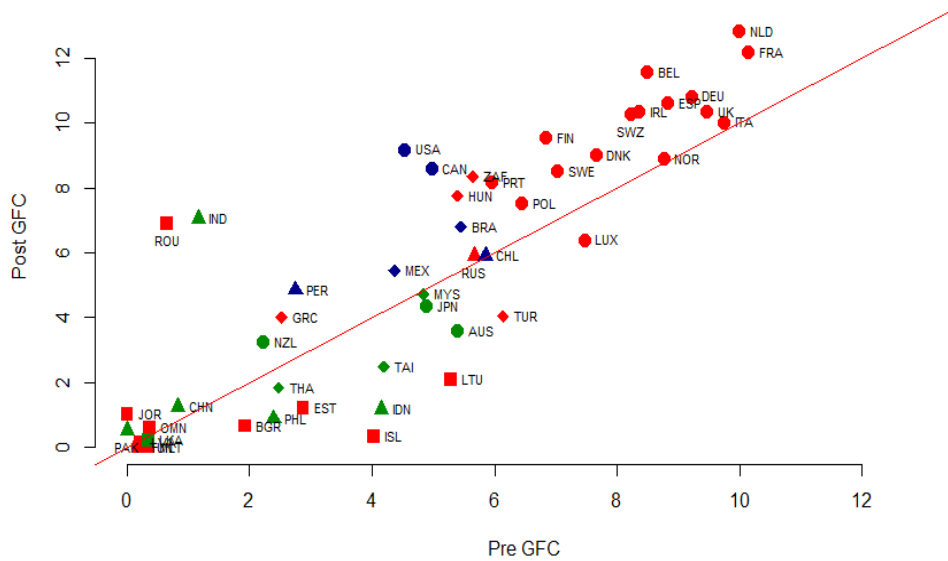
Figure 2. Quantile coherency network – Bullish market conditions (percentile 0.95)

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

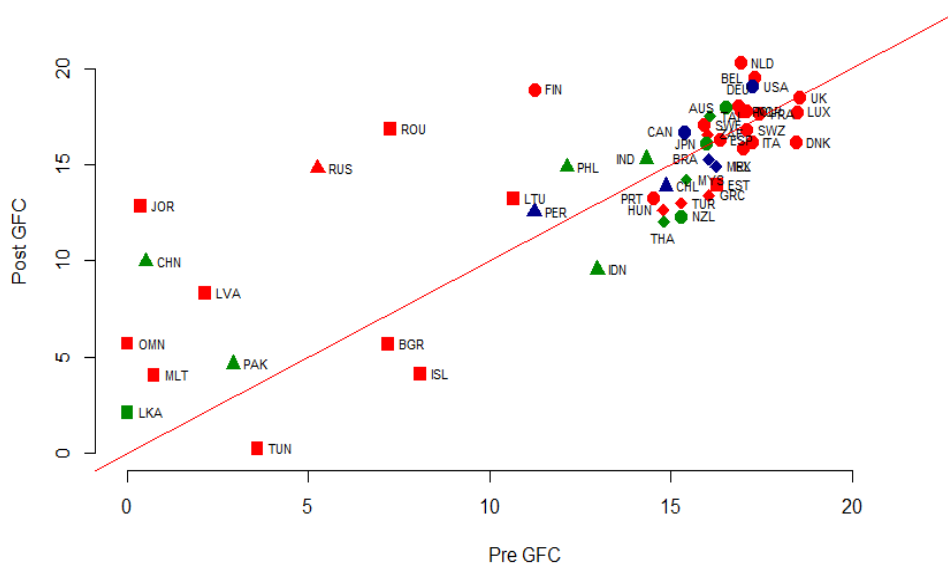


Figure 3. Scatter plot of node centrality (strength) of stock markets before and after the GFC (5th percentile)

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

| Region ^a | Category ^b | Country | ISO code | Bloomberg Ticker | Before the GFC (January 2001 – August 2008) | | | | After the GFC (November 2008 – December 2018) | | | |
|----------------------|-----------------------|----------------|----------|------------------|--|-----------|----------|----------|--|-----------|----------|----------|
| | | | | | 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 |
| Americas | 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 |
| | 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 |