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Complex Global Interdependencies between Economic Policy Uncertainty and Geopolitical Risks Indices *

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Abstract

We investigate the complex interdependencies of economic policy uncertainty (EPU) and geopolitical risk (GPR) indices between 37 countries. We examine leading and lagging relationships between countries to understand whether one country's EPU or GPR index may affect that of others. Policy uncertainty arises when government policy implementations are uncertain and may intensify economic cycles and substantially affect the economy. Geopolitical risk develops when tensions within a country or between countries affect the ordinary course of business or international relationships. We analyze the monthly index values for EPU and GPR between 1997 and 2020 using the complex Hilbert principal component analysis (CHPCA) to identify leading events associated with essential changes in EPU and GPR indices. CHPCA enables us to construct a weighted and directed network from the correlation matrix. We determine that the most impactful event during this period was the terrorist attack of September 11, 2001, followed by the novel coronavirus 2019 pandemic in 2020, the global financial crisis of 2008, and terrorism and the election of the new president in the United States and the prime minister in the United Kingdom in 2016. We study temporal network dynamics in EPU and GPR indices and observe significant changes in the network before and during these events.

Keywords: economic policy uncertainty, geopolitical risk, complex Hilbert principal component analysis, terrorist attack of September 11, global financial crisis, causality network
JEL classification: C38, D81

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I. Introduction

In this paper, we address the complex interdependences between newspaper-based economic policy uncertainty (EPU) and geopolitical risk (GPR) indices worldwide to identify their correlations and leading and lagging relationships. Policy uncertainty arises when there is doubt concerning the implementation of government policies (Pastor and Veronesi, 2012), and, according to Bernanke (1983), it intensifies economic cycles. Baker, Bloom and Davis (2016) proposed the economic policy uncertainty (EPU) measure and demonstrated that increases in the level of the EPU index have non-negligible repercussions for the global economy.

Caldara and Iacoviello (2018) introduced a geopolitical risk (GPR) index that represents the "risk associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations." They found that entrepreneurs, market participants, and central bank-related individuals consider GPR a key variable that influences investment decisions and stock market behavior and that geopolitical risk is different from EPU and financial market volatility measured by VIX. GPR is associated with events that are likely not endogenous to the business cycles.

Both, EPU and GPR measures have been attracting the attention of researchers in topics such as asset pricing and volatility (Brogaard and Detzel, 2015; Balcilar et al., 2018; Bouras et al., 2019), earnings management (Yung and Root, 2019), corporate investment (Gulen and Ion, 2016; Le and Tran, 2021), corporate debt maturity (Datta, Doan and Iskandar-Datta, 2019; Khoo et al., 2021), corporate cash holdings (Demir and Ersan, 2017; Lee and Wang, 2021), among others. In general, these results suggest that EPU and GPR are informative to market participants. However, there are few studies regarding country's EPU and GPR relationships.

In this paper we propose an analytical method to investigate interconnectedness or leading and lagging relationships between EPU and GPR indices, using a novel CHPCA (Complex Hilbert Principal Component Analysis) methodology (Rasmusson et al., 1981; Horel, 1984; Arai, Yoshikawa and Iyetomi, 2013; Kichikawa, Arai and Iyetomi, 2015; Vodenska et al., 2016; Aoyama et al., 2017), building on Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), Diebold and Yılmaz (2014), and Diebold and Yılmaz (2015), (see, also, Klößner and Sekkel (2014), Balli et al. (2017), Liow, Liao and Huang (2018), and Balli et al. (2021)).

The principal component analysis (PCA), which is applied to an equal-time correlation matrix, does not allow possible leading and lagging structures present in the data to be discovered. CHPCA overcome the problem in PCA. We also introduce the method of rotational random shuffling (RRS), which enables us to separate the correlation into the signal (principal) and noise components. We construct the pseudo-correlation matrix from principal components using only the principal components and call this matrix the principal correlation matrix. The components of the principal correlation matrix are complex numbers; therefore, we can represent these components in terms of amplitude and phase. Hence, we can understand the complex correlation matrix as amplitude correlation matrix and phase correlation matrix.

The amplitude correlation matrix yields a weighted and undirected network. We obtain a directed network by applying the Helmholtz-Hodge (HH) decomposition to the phase correlation matrix to identify leading and lagging relations of the EPU and GPR indices. We consider the leading index as a source and the lagging index as a sink,

The contribution of this study is three-fold. First, it could aid investors in portfolio diversification decisions through the understanding of the dynamics between countries and their mutual influence. Second, it sheds light on the dynamics between large and smaller economies due to the diverse nature of our dataset. Third, the paper contributes to the study of integrated markets, uncovering the interconnectedness between countries to capture early warning signals to avoid disseminating policy uncertainty, geopolitical tensions, or financial crises. Bloom (2017) argues that small economies are likely to be influenced by uncertainty shocks originated in other nations, unrelated to their domestic economy. Our study provides new empirical results regarding policy-induced uncertainty transmission and geopolitical risk transmission on a global scale.

The reminder of this paper is structured as follows. Section II presents the literature review, III details the data, and in Section IV, we explain the methodology. Section V discusses our findings, and Section VI concludes.

II. Literature Review

Uncertainty is recognized as having a meaningful impact on the behavior of the economic agent (Bernanke, 1983; Bloom, 2009). It is relevant to households in their consumption and savings actions, to business managers' decisions regarding investments and employment, to investors' attitudes regarding withdrawing their money or requesting a higher expected rate of return in the face of greater perceived risk, and to policy makers, considering its effect on the real economy. More specifically, its relevance is in line with the stylized facts that uncertainty and consumption/investment co-move, they are inversely related, and when uncertainty spikes, it can lead to a huge decrease in consumption/investment, and once it can reduce them significantly, it is clear why policy makers care about it (Castelnuovo, Lim and Pellegrino, 2017).

A growing interest over the years has occurred in one of its strands, namely the economic policy uncertainty (EPU), since Baker, Bloom and Davis (2016) proposed and made available their EPU measure. According to the authors, it refers to "uncertainty about *who* will make economic policy decisions, *what* economic policy actions will be undertaken and *when*, and the economic *effects* of policy actions (or inaction) – including uncertainties related to the economic ramifications of "non-economic" policy matters, e.g., military actions" (Baker, Bloom and Davis, 2016, p. 1598).

The EPU index of Baker, Bloom and Davis (2016) originally proposed to the United States (US) and then extended to other countries around the world either by the authors or by other academics, offers a valuable contribution to the literature by measuring policy-related economic uncertainty in a way by counting articles containing the terms “uncertain” or “uncertainty”, “economic” or “economy”, and one or more policy-relevant terms from newspaper articles. The authors report that their indices increase during presidential elections, wars, the 2011 debt ceiling dispute, and other relevant dates, while their Vector Autoregressive (VAR) framework shows that increases in the level of EPU have a non-negligible repercussion on the economy for the US and for an international sample. As pointed out by Caggiano, Castelnuovo and Figueres (2020), their findings are relevant from two perspectives: reaffirming that uncertainty can in fact be one of the drivers of changes in real activity in the United States, which is in accordance with other evidences in the literature, and because it sheds light on the distinguished role played by policy uncertainty as a source of movements in real activity.

Using a similar automated text-search procedure, Caldara and Iacoviello (2018) present the geopolitical risk (GPR) index which represents the “risk associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations” (Caldara and Iacoviello, 2018, p. 6). The authors state that GPR is viewed by entrepreneurs, market participants, and central bank related people as the key variable that affects investment decisions and the stock market behavior. Giving support to this understanding, the authors mention the 2017 Gallup survey where over a thousand investors participated and their concerns placed geopolitical risks ahead of political and economic uncertainty. Caldara and Iacoviello (2018) report in their findings that geopolitical risk is a different source of risk from EPU and financial volatility proxied by the VIX index displaying a large amount of non-common variability and is more associated with events that are likely not endogenous to the business and financial cycles and able to pressure them. For instance, they highlight that it does not rise during the dot-com bubble, the 2008 crisis, and presidential elections, whereas either one or both of the two other series do. In contrast, it rises during the Russian annexation of Crimea and other terrorist attacks besides 9/11, while EPU and financial volatility do not.

It is important to note is that this measure has been made available by the authors not only to the US, but to many other countries around the world, making it possible to understand its behavior across the years and economies. One underlying characteristic between EPU and GPR relies on how these measures are constructed; namely, they are newspaper-based indexes available on a monthly basis, allowing for more direct comparisons instead of other quarterly or annual macroeconomic measures. In the GPR case, it relies on counting articles covering geopolitical tensions and risk, such as wars and terror attacks. Once they have been demonstrated to be as of special interest for market participants, one natural extension is to get a better understanding of the countries' policy uncertainties and geopolitical tensions interdependences.

The idea that the economic and financial system around the world is connected beyond the countries' border is no longer new. King and Wadhwani (1990), for instance, constructed a model in which contagion has root on rational agents seeking to infer information from the price behavior in other stock markets. Moreover, the financial crisis that spiked in 2008 is a clear representation regarding this real meaning. Although originated in the subprime mortgage sector in the US, it spread to various regions across the countries. Dooley and Hutchison (2009) and Lehkonen (2015) offer views on the countries' performance in face of the Global Financial Crisis (GFC). Lehkonen (2015) states that market integration is a double-edge sword and stresses that advantages emanating from globalization were put into question, especially during this adverse scenario, given the belief that well-integrated markets contributed to the crisis repercussion into other economies.

Overall, there have been efforts in the literature to investigate the EPU and GPR dynamics in affecting stock market index fluctuations or macroeconomic variables. More specifically, Dakhlaoui and Aloui (2016) investigate the mean return and volatility spillovers from the US EPU and the BRIC (the group of countries composed by Brazil, Russia, India, and China) stock market indices using the cross-correlation function proposed by Cheung and Ng (1996), and their results support the idea that the US EPU is related to these countries' stock market behavior. Das, Kannadhasan and Bhattacharyya (2019) study how shocks to the US EPU, GPR, and the Financial Stress Indicator (FS) affect the mean and variance of emerging stock market returns using a non-parametric causality-in-quantiles technique. Overall, two of their main findings demonstrate that the US shocks influence other stock markets in distinctive ways in the sense of causality and intensity as well as market states, and also that EPU shocks play a more influential role when compared to the other indicators, while the GPR index is more relevant when contrasted to the FS. Colombo (2013), using a structural VAR, shows that a one standard deviation shock in US policy-related economic uncertainty has relevant effects on the European industrial production and consumer prices in the order of -0.12% and -0.06%, respectively, along with a temporary reduction in interest rate, the Euro area EPU increases in response to higher levels of US EPU, and in the short run, the impact of US-related uncertainty is more severe than that of the European counterpart. Caggiano, Castelnuovo and Figueres (2020) show that US EPU shocks have influence on Canadian unemployment rate during boom and busts periods using a nonlinear VAR. The authors identify an asymmetric behavior in the sense that 13% of the variance of the 2-year ahead forecast error of the Canadian unemployment rate is explained during busts, while this effect is only 2% during booms. Moreover, they unveil an 'economic policy uncertainty spillovers channel' through which US EPU affects Canada EPU, which in turn increases the Canadian unemployment rate.

However, there is also an increase in literature seeking to establish connections among countries' EPU and GPR *per se*, which in turn, is closer to our attempt. In terms of EPU, Klößner and Sekkel (2014) investigate whether there is a transmission of economic policy uncertainty among six developed economies (Canada, France, Germany, Italy, United Kingdom, and US), i.e., whether fluctuations in policy uncertainty in one country are able to significantly affect policy uncertainty in other nations and which economies are net uncertainty exporters/importers using a sample from January 1997 to September 2013. To this end, the Diebold and Yilmaz (2009)'s spillover index methodology was adopted, while keeping away from giving any causal reasoning from their findings, but rather shedding light on the overall and pairwise directional connectedness among the economies under analysis. Their findings support that in the full sample period, more than 25% of the countries' EPU behavior is due to spillovers across economies, while the US, followed by United Kingdom, is the most net exporter of uncertainty, and Italy presents the most independent fluctuation. During the financial crisis, their analyses exhibit that the spillover index increases and highlight that not only the EPU is countercyclical, as reported in the literature (Bloom, 2009), but also the overall connectedness between economies, as evidenced in their findings. Moreover, the US was found to play a significant role as a net uncertainty exporter during the crisis period. Balli et al. (2017) extend the results of Klößner and Sekkel (2014) by providing evidence on the spillovers of policy uncertainty across 16 countries and go further by exploring the cross-sectional determinants of these pairwise effects. The authors employ the Diebold and Yilmaz (2012)'s methodology for this purpose. Their results imply that US, Australia, and Canada (US, Australia, and Italy) contribute the most to the mean (volatility) spillover and that variables such as bilateral trade and common language are related to the transmission of net policy uncertainty between countries.

Kang and Yoon (2019) also apply the Diebold and Yılmaz (2014, 2015) spillover approach to the EPU indices of 9 countries and document a high level of policy-induced uncertainty interconnection among them (the total spillover index is on average above 65%) and with the EU found to be the most influential as a net transmitter of policy uncertainty. In addition, their findings highlight the role played by China during the GFC and European debt crisis in which it becomes one of the largest net exporters of spillovers. This finding is also supported by Liow, Liao and Huang (2018), who show that during the GFC, China was a source of policy uncertainty spillover to other economies.

Marfatia, Zhao and Ji (2020) build a global EPU network using a sample of 17 developed and emerging countries. Their methodology is based on a centrality network measured using the minimal spanning tree (MST) and a dependency network using partial correlations, with statistic and dynamic analyses. Overall, the authors' results indicate some geographical connection in which seven countries are directly connected to the US EPU, that the nature and dominance of the EPU network has changed over time, and the US and German EPUs show to be the most relevant in terms of net information flow.

Yang, Luo and Jiang (2021) go one step further and analyze complex networks between EPU and stock market indexes separately and taking both in account. To this end, the authors constructed daily EPU indexes for 17 Asia-Pacific countries and regions for the period between January 2017 and June 2020, and also employed a centrality network using the MST method and a dependency network. Their research findings indicate that China plays a central role in the EPU network as well as the US stock market acts as a relevant intermediary between American and Asian countries. However, when considering a network built upon EPU and stock market indexes jointly, it could be observed that policy uncertainty and stock market behavior in the US represent the most important sources of uncertainties. In this sense, the authors highlight that although China has been gaining space in the contexts analyzed, the US political and financial dominance remains considering the Asia-Pacific region.

Concerning geopolitical risk transmission shocks, the research conducted by Balli et al. (2021) is one of the few from the perspective pursued here and close to ours. Using the Diebold and Yilmaz (2012) spillover measure as well as the methodology of Baruník and Křehlík (2018) to identify short- and long-term GPR transmissions with data over the period from January 1985 to December 2016, they focus on understanding how the GPRs of the countries are transmitted and also employ a gravity model to explain these features. Some of the documented findings point out to a non-negligible level of connectedness (total mean spillover of over 39%) among the 19 countries in their sample, along with the fact that the countries with larger geographic size are also those mainly associated with higher GPR transmission, and the closer the countries are, the higher the spillover among them. On a complementary way, their cross-sectional regressions evidence that variables such as bilateral trade, border sharing, and the distance between countries are relevant in determining the pairwise GPR propagation in the overall analysis. Finally, the total GPR transmission is higher for short-term (up to 3 months) than for long-term (3-100 months), 32% and 7%, respectively. In this sense, the literature also suggests that geopolitical risks exhibit a spillover effect across countries.

III. Data

Our data includes 31 countries; We investigate the EPU indices for 19 countries, and the GPR indices for 18 countries. Six countries (Russia, China, India, South Korea, Colombia, and Brazil) have both the EPU and GPR indices. We investigate 288 monthly time series from January 1997 to December 2020. This dataset is appropriate for our purpose because if we consider more countries, we can only analyze a shorter period. However, to explore a time series from 1985 when the EPU and GPR indices started, we must explore fewer countries.

Figure 1 depicts changes in the EPU index for 19 countries. We display in the indices on the same scale by normalizing each time series to have a mean value and variance equal to zero and one, respectively. The red dots in Fig. 1 indicate the peak of the EPU index for each country. Table 1 depicts the data sources, the year of the highest peaks, the height of the peaks, and the corresponding events for each peak. We used both Reuters and Wikipedia to identify the peak events.

The aforementioned figure and table demonstrate that the EPU indices behave differently in each country. However, there are some similarity. For example, half or more of the countries have peaks in 2020. We might easily imagine that these peaks originated from the coronavirus 2019 (COVID-19) pandemic. In addition, the EPU index increased recently in Europe. The background underlying this tendency is the immigration problem and issues relating to Brexit in the European Union. Meanwhile, the EPU index increased in North America and China because of the trade conflict between two countries. These facts demonstrate that the EPU easily crosses national borders.

In Figure 2, as in the case of the EPU index, we normalized each time series of the GPR index to have the mean value and the variance equal to zero and one, respectively. The red dots in Figure 2 indicate the peak of each country's GPR index. Table 2 depicts the data sources, the years of the highest peaks, the heights of the peaks, and the corresponding events for each peak. We used Reuters and Wikipedia to identify the peak events. The aforementioned figure and table show that the GPR indices behave differently in each country. Remarkably, the GPR index fluctuates around the mean, and there are no common trends like those observed in the EPU index of some countries. This characteristic of the GPR indices is natural because geopolitical risk is strongly associated with geography or religion. Thus, we can expect that the GPR index between adjacent countries are correlated with each other. A typical example is the case of Russia and the Ukraine; the peak of the GPR index for these two countries occurs in March 2014 (i.e., when Russia invaded Crimea).

IV. Methods and Materials

In Section III, we recognized the changes in the EPU and GPR indices, and almost all countries have peaks at different times. In this section, we explain the complex Hilbert PCA to explore the correlation structure of EPU and GPR indices.

A. Complex correlation matrix

We denote time series data of n-th component at time t as $x_{n,t}$. The logarithmic change of time series is defined as follows:

$$r_{n,t} = \log\left(x_{n,t}\right) - \log\left(x_{n,t-1}\right) \ , \tag{1}$$

where $n = 1, \ldots, N$ and $t = 1, \ldots, T$. In this paper, $N = 37$ and $T = 288$. The Fourier transform of Equation (1) is given as follows:

$$r_{n,t} = \sum_{k=0}^{T} \left[a_n\left(\omega_k\right) \cos\left(\omega_k t\right) + b_n\left(\omega_k\right) \sin\left(\omega_k t\right) \right] \ , \tag{2}$$

where $\omega_k = 2\pi k / T \geq 0$. The Hilbert transform of Equation (2) is given as follows:

$$\hat{r}_{n,t} = \sum_{k=0}^{T} \left[b_n\left(\omega_k\right) \cos\left(\omega_k t\right) - a_n\left(\omega_k\right) \sin\left(\omega_k t\right) \right] \ . \tag{3}$$

Equation (3) corresponds to Equation (2) shifted the phase $\pi/2$. Therefore, Equations (2) and (3) are orthogonal to each other. Now, using Equations (2) and (3), we define the complex logarithmic change:

$$\tilde{r}_{n,t} = r_{n,t} + i\,\hat{r}_{n,t} = \sum_{k=0}^{T} c_n(\omega_k) e^{-\omega_k t} \ , \tag{4}$$

where i is an imaginary unit defined by $i^2 = -1$, and $c_n(\omega_k) = a_n(\omega_k) + i\,b_n(\omega_k)$. The right hand side of Equation (4) shows that $\tilde{r}_{n,t}$ rotates in a clockwise direction as time goes on.

The mean value of the complex log return is defined as follows:

$$\langle \tilde{r}_n \rangle = \frac{1}{T} \sum_{t=1}^{T} \tilde{r}_{n,t} \ ,$$

and its variance is defined as follows:

$$\sigma_n^2 = \frac{1}{T} \sum_{t=0}^{T} \left| \tilde{r}_{n,t} - \langle \tilde{r}_n \rangle \right|^2 \ .$$

We normalize the complex logarithmic change defined by Equation (4) to have a mean value equal to zero and a variance equal to one:

$$w_{n,t} = \frac{\tilde{r}_{n,t} - \langle \tilde{r}_n \rangle}{\sigma_n} \ . \tag{5}$$

The matrix with the components given in Equation (5) is called the complex Wishart matrix and is specified as follows:

$$\mathbf{W} = \left[w_{n,t} \right] \ .$$

Thus, the complex correlation matrix is defined as follows:

$$\mathbf{C} = \frac{1}{T}\mathbf{W}\mathbf{W}^{\dagger} \ , \tag{6}$$

where $\mathbf{W}^{\dagger}$ is an adjoint matrix (i.e., transformation and complex conjugate) of $\mathbf{W}$. The components of the complex correlation matrix are represented by the following two equations:

$$\begin{aligned} C_{mn} &= \mathrm{Re}\left(C_{mn}\right) + i\mathrm{Im}\left(C_{mn}\right) \ , \\ &= \left|C_{mn}\right| e^{i\,\varphi_{mn}} \ , \end{aligned}$$

where, φ_{mn} represents the correlation in the phase space. In Section V.D, we will explain how the leading or lagging of the index is derived from φ_{mn}.

B. *Rotational random shuffling (RSS)*

We can make a completely random complex correlation matrix by constructing the following randomly shuffled Wishart matrix:

$$w_{n,t} \ \rightarrow \ w_{n,\mathrm{rand}[1,T]} \ ,$$

where $\mathrm{rand}[1,T]$ means a random integer from 1 to T without duplication. Thus, the utterly random complex correlation matrix breaks both autocorrelation and cross correlation. Many financial and economic time series feature autocorrelation. Therefore, it is helpful to develop a method that preserves autocorrelation but randomizes cross correlation. Iyetomi et al. (2011a,b) developed the RSS method to construct such a complex correlation matrix (Souma, 2021). In RRS, we shuffle the empirical time-series data rotationally in the time direction and impose the following periodic boundary condition:

$$w_{n,t} \ \rightarrow \ w_{n,\mathrm{mod}[t+\tau,T]} \ ,$$

where $\tau \in [0, T-1]$ is a pseudo-random integer that is different for each n. For example, if $\tau = 37$ for index 1, $\tau = 128$ for index 2, …, $\tau = 287$ for index 36, and $\tau = 71$ for index $N = 37$, the complex Wishart vector, $\boldsymbol{w}_n$ for each index is given by the following:

$$\begin{aligned} \boldsymbol{w}_1 &= \{w_{1,38},\ w_{1,39},\ \ldots,\ w_{1,288},\ w_{1,1},\ w_{1,2},\ \ldots,\ w_{1,37}\} \ , \\ \boldsymbol{w}_2 &= \{w_{2,129},\ w_{2,130},\ \ldots,\ w_{2,288},\ w_{2,1},\ w_{2,2},\ \ldots,\ w_{2,128}\} \ , \\ &\vdots \\ \boldsymbol{w}_{36} &= \{w_{36,288},\ w_{36,1},\ w_{36,2},\ \ldots,\ w_{36,285},\ w_{36,286},\ w_{36,287}\} \ , \\ \boldsymbol{w}_{37} &= \{w_{37,72},\ w_{37,73},\ \ldots,\ w_{37,288},\ w_{37,1},\ w_{37,2},\ \ldots,\ w_{37,71}\} \ . \end{aligned} \tag{7}$$

Therefore, we can construct an RRS complex correlation matrix using Equation (6) with the complex Wishart vectors given by Equation (7). However, we must note that we broke the autocorrelation at the place at which we imposed a periodic boundary condition (i.e., $w_{n,288}, w_{n,1}$).

C. Decomposition of the complex correlation matrix

The PCA for the complex correlation matrix $\mathbf{C}$ derives eigenvalue λ_j and corresponding eigenvector $\boldsymbol{v}_j$, where j represents the ranking of the eigenvalues and corresponding eigenvectors. Thus, if we can obtain the number of principal components n_{p} by applying PCA, we can decompose the complex correlation matrix into its meaningful and noisy part as follows:

$$\mathbf{C} = \sum_{j=1}^{N} \lambda_j \boldsymbol{v}_j \boldsymbol{v}_j^{\dagger} = \sum_{j=1}^{n_{\mathrm{p}}} \lambda_j \boldsymbol{v}_j \boldsymbol{v}_j^{\dagger} + \sum_{j=n_{\mathrm{p}}+1}^{N} \lambda_j \boldsymbol{v}_j \boldsymbol{v}_j^{\dagger} = \mathbf{P} + \mathbf{R} \ , \tag{8}$$

where $\boldsymbol{v}_j^{\dagger}$ is the adjoint vector (i.e., transformation and complex conjugate) of $\boldsymbol{v}_j$. In Equation (8), $\mathbf{P}$ and $\mathbf{R}$ are the principal and noisy parts of the complex correlation matrix, respectively. Therefore, it is reasonable to investigate $\mathbf{P}$ for revealing the properties of the correlation between the indices.

D. Mode signal

A mode signal $\boldsymbol{\alpha}_j$ is a vector with a number of components equal to the length of time series T and defined by the product of $\boldsymbol{v}_j$ and $\mathbf{W}$ as follows:

$$\boldsymbol{\alpha}_j = \boldsymbol{v}_j^{\dagger} \mathbf{W} \ , \tag{9}$$

where $\boldsymbol{v}_j^{\dagger}$ is the adjoint vector (i.e., transformation and complex conjugate) of $\boldsymbol{v}_j$. The mode signal is a useful tool for detecting the sympathetic structure of the time series.

E. Correlation network and Helmholtz-Hodge (HH) decomposition

As previously stated, it is reasonable to investigate $\mathbf{P}$ to reveal the characteristics of the correlation between the indices. The elements of $\mathbf{P}$ are written as follows:

$$P_{mn} = |P_{mn}| \, e^{i\,\theta_{mn}} \ ,$$

where $\arg(P_{mn}) := \theta_{mn} \in [-\pi, \pi)$. Generally, $P_{mn} \neq 0$. Therefore, the network constructed from $\mathbf{P}$ is a fully connected complete graph in which the weights of the links are given by complex numbers. However, it is natural to expect the characteristics of the correlation to be found in the large $|P_{mn}|$. Therefore, we set a lower bound (i.e., $|P_{mn}| > P_{\mathrm{min.}}$). However, if we take too large a value of $P_{\mathrm{min.}}$, the network obtained becomes a disconnected network. Thus, we must keep the value of $P_{\mathrm{min.}}$ in an appropriate range. Similarly, we must keep the value of θ_{mn} in an appropriate range (i.e., $|\theta_{mn}| < \theta_{\mathrm{max.}}$) to construct a connected yet not dense network. Thus, we define the constrained principal correlation matrix as follows:

$$\tilde{\mathbf{P}} := \mathbf{P} \quad \text{with} \quad |P_{mn}| < P_{\mathrm{min.}} \text{ and } |\theta_{mn}| < \theta_{\mathrm{max.}} \ . \tag{10}$$

We expect that the network constructed from Equation (10) will be the backbone of the correlation network.

The Helmholtz-Hodge (HH) decomposition aims to clarify the leading and lagging relationships between indices. In the HH decomposition, θ_{mn} represents the flow from index m to index n and decomposes θ_{mn} into two parts as follows:

$$\theta_{mn} = \theta_{mn}^{(\mathrm{c})} + \theta_{mn}^{(\mathrm{g})} \ ,$$

where $\theta_{mn}^{(\mathrm{c})}$ corresponds to the circular flow defined by the following:

$$\sum_{n=1}^{N} \theta_{mn}^{(\mathrm{c})} = 0 \ . \tag{11}$$

Meanwhile, $\theta_{mn}^{(\mathrm{g})}$ corresponds to the gradient flow defined by the following

$$\theta_{mn}^{(\mathrm{g})} = \gamma_{mn} \left(\phi_m - \phi_n\right) \ , \tag{12}$$

where ϕ_n is the HH potential and assigns the leading and lagging relationships to the indices. Here, γ_{mn} is an adjacency matrix given as follows:

$$\gamma_{mn} = \begin{cases} 1 & \text{If } \theta_{mn} \neq 0 \\ 0 & \text{otherwise} \end{cases} \ .$$

Using Equation (12), we can rewrite Equation (11) as follows:

$$\sum_{n=1}^{N} \left[\theta_{mn} - \gamma_{mn} \left(\phi_m - \phi_n\right)\right] = 0 \ . \tag{13}$$

Thus, we obtain ϕ_n by solving Equation (13).

V. Results

We apply the method explained in Section IV to the EPU indices for 19 countries and the GPR indices for 18 countries during 288 months from January 1997 to December 2020. We then focus on the correlation network before the September 11 attacks, the correlation network before the global financial crisis (GFC), and the correlation network in the second half of 2016.

A. Correlation matrix and eigenvalues

The left panel of Figure 3 depicts the distribution of elements of the complex correlation matrix. In this figure, the abscissa corresponds to the real axis, and the ordinate corresponds to the imaginary axis. This figure shows that the distribution is skewed with a fat tail in the range of large real numbers. In addition, this figure shows that the distribution is symmetrical to the real axis by definition of the complex correlation matrix.

Figure 4 depicts the scree graph for the eigenvalues. In this figure, the abscissa represents the ranking of eigenvalue j, and the ordinate represents the magnitude of eigenvalue λ_j. The red line with dots corresponds to the distribution of the eigenvalues derived from the complex correlation matrix constructed from the data. The slope of this red curve sharply changes in the range $3 \lesssim j \lesssim 7$. Thus, in ad-hoc human judgment, the number of principal components differs from person to person. Therefore, it is necessary to develop a method to automatically extract the principal component. The blue line with the absolute error bars represents the distribution of the eigenvalues derived from the RRS complex correlation matrix. We simulated 10 times to obtain this blue curve and calculated the mean value and the absolute error. By comparing the red and the blue curves, we can confirm that the first and second eigenvalues are apparently the principal components (i.e., $n_{\mathrm{p}} = 2$).

Therefore, using $n_{\mathrm{p}} = 2$, we obtain $\mathbf{P}$ from Equation (8). The blue dots in the left panel of Figure 3 depict the distribution of the elements of $\mathbf{P}$. In this figure, the red dots are the components of $\tilde{\mathbf{P}}$ with $P_{\mathrm{min.}} = 0.086$ and $\theta_{\mathrm{max.}} = 0.1 \times \pi$. In Section V.D, we will construct the correlation network from this value of $\tilde{\mathbf{P}}$.

B. Principal eigenvectors

The left panel of Figure 5 depicts the distribution of the eigenvector corresponding to the first eigenvalue. In this figure, the abscissa corresponds to the real axis, and the ordinate corresponds to the imaginary axis. Unlike the case of the real correlation matrix, the components of the eigenvector are distributed on a complex plane. The round flags correspond to the EPU indices, and the square flags correspond to the GPR indices. To obtain this figure from the nature of the eigenvectors, we imposed the constraint that the imaginal part of the GPR index of Brazil is equal to zero. In this figure, the essential quantities are the absolute value and the argument of the complex. The absolute value represents the strength in the component of the eigenvector. Therefore, the EPU index of the United States is the most dominant. In addition, the EPU indices (round flags) have a significant absolute value compared with the GPR indices (square flags), except for the GPR index of China. This result indicates that almost all the EPU indices are significant in the first eigenvector. Meanwhile, the argument of the complex represents the leading and lagging relationships. As mentioned in Equation (4), as time progresses, each index rotates in a clockwise direction. Therefore, the GPR index of Thailand is the most leading, and the GPR index of the Ukraine is the most lagging. However, almost all of the indices have a similar value to the argument of the complex. This result indicates that almost all indices are comoving.

The right panel of Figure 6 depicts the distribution of the eigenvector components corresponding to the second eigenvalue. Similar to the case shown in the left panel of Figure 5, we imposed the constraint that the imaginal part of the GPR of Brazil is equal to zero. In this figure, the EPU indices and GPR indices are distributed in almost opposite directions (i.e., the argument of the complex of the EPU indices and the GPR indices are approximately equal to π). Therefore, it is difficult to decide which index group is leading or lagging. Significantly, the eigenvectors corresponding to the second eigenvalue are constructed from the EPU and GPR indices' group structure.

C. *Mode signal*

Figure 7 depicts the mode signal. In this figure, the abscissa represents the years, and the ordinate represents the square values of the mode signals. The black line shows the sum of all of the square values of mode signals as follows:

$$|\alpha_t|^2 = \sum_{j=1}^{37} |\alpha_{j,t}|^2 \ ,$$

where $\alpha_{j,t}$ is defined by Equation (9). Here, we used the square value of the mode signal because the mode signal components are given by a complex number. The red line and the blue line in this figure correspond to the first mode signal $|\alpha_{1,t}|^2$ and the second mode signal $|\alpha_{2,t}|^2$, respectively. We drew the mode signals from the 3rd to the 37th thin and gray lines. This figure indicates that almost all of the significant peaks are explained by the first mode signal.

Figure 8 depicts the comparison of $|\alpha_{1,t}|^2$ (red line) and the global economic uncertainty (GEPU) index (green line). The GEPU index is a gross domestic product (GDP-) weighted average of the national EPU indices of 21 countries: Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States (see, `https://policyuncertainty.com/global_monthly.html`). We normalized both $|\alpha_{1,t}|^2$ and the GEPU index to a mean value equal to zero and a variance equal to one to draw the same range of the magnitude. Here, we quoted some specific events written in the original figure of the GEPU. As previously explained, the EPU indices in Figure 1 and the GPR indices in Figure 2 show that the change in the indices and the peaks of the indices depend on the country. However, the first mode signal (i.e., the red line in Figure 8) indicates that the most impactful event was the September 11 attack in 2001. The second was the COVID-19 pandemic in 2020. The third was the GFC, represented by events such as the bankruptcy of Lehman Brothers in 2008. The fourth occurred in the second half of 2016, for example, terrorist attacks such as the 2016 Islamic State of Iraq and the Levant (ISIL) bombing of Karrada, the election of a new prime minister in the United Kingdom and a new president in the United States, the Nice truck attack in France, and the Turkish *coup d'état* attempt. However, in the GEPU index (i.e., the green line), the most impactful event was the COVID-19 pandemic.

D. *Correlation network and the Helmholtz-Hodge (HH) potential*

Figure 9 depicts the HH potential. In this figure, the abscissa corresponds to the index number, n, and the ordinate corresponds to the HH potential ϕ_n. The round flags correspond to the EPU indices, and the square flags corresponds to the GPR indices. To obtain this figure, we used $\tilde{\mathbf{P}}$ with $P_{\text{min.}} = 0.086$ and $\theta_{\text{max.}} = 0.1 \times \pi$. If index n is leading, the corresponding ϕ_n has a low value. Therefore, a downward direction represents leading. However, if the index n is lagging, the corresponding ϕ_n has a high value. Therefore, an upward direction represents lagging. Thus, in this figure, the most leading index is the EPU index of Brazil, and the most lagging index is the GPR index in the Ukraine.

From the HH potential ϕ_n, we can recognize the leading and lagging relationships between the indices. However, we cannot understand which index affects which by analyzing only the leading and lagging relationships. The correlation network with direction and weight overcomes this problem. Figure 10 depicts the correlation network constructed from $\tilde{\mathbf{P}}$ with $P_{\text{min.}} = 0.086$ and $\theta_{\text{max.}} = 0.1 \times \pi$. To obtain this figure, we first constructed a connected and weighted network without direction by tuning $P_{\text{min.}}$. Next, by tuning $\theta_{\text{max.}}$ we obtained a connected and weighted network with direction. We assigned the direction of the links based on the HH potential. Namely, we drew arrows from the leading (the low value of ϕ_n) index to the lagging (the high value of ϕ_m) index. In this figure, the green directed links connect each EPU index; the blue ones connect each GPR index; and the red ones connect EPU and GPR indices. The thickness of the links is proportional to the weight given by $|\tilde{P}_{mn}|$.

From the viewpoint of the rapid propagation of risk between the EPU and the GPR indices, the most rapid propagation is from the EPU index of Brazil, which is the most leading of the EPU indices, to the GPR index of Mexico through the EPU index of Greece. In the other direction, the most rapid propagation is the direct propagation from the GPR index of Saudi Arabia, which is the most leading of the GPR indices, to the EPU index of Australia.

Furthermore, we also applied cluster analysis developed in the field of network science to the directed and weighted correlation network and obtained two clusters surrounded by thin curved lines. One of these clusters consists of only EPU indices, and the others consist of all GPR indices and the EPU index of China.

Table 3 depicts the ratio of the types of links calculated based on the number of links. This table demonstrates that the EPU indices are densely interconnected, and the GPR indices are also densely interconnected. However, the connections between EPU and GPR indices are sparse. Table 4 depicts the ratio of the types of links calculated from the weight of the links. Like in the case of Table 3, the EPU indices are strongly connected to each other, and the GPR indices are also strongly connected to each other. However, the connections between the EPU and GPR indices are weak.

E. September 11, 2001 terrorist attacks

We investigate 4 years of data before the September 11 attack (i.e., the 48 months from September 1997 to August 2001) to understand whether the historical EPU and GPR dynamics could insight into events and developments that might have lead to this tragic event.

Figure 11 depicts the HH potential before the September 11 attack. In this subsection, we use a $\tilde{\mathbf{P}}$ with $P_{\text{min.}} = 0.14$ and $\theta_{\text{max.}} = 0.38 \times \pi$. In this figure, except for the EPU index of Ireland, the HH potential for every index is distributed in a narrow range (i.e., $-0.5 \lesssim \phi_n \lesssim 0.5$). The average value of the HH potential for the EPU indices is $\phi_{\text{EPU}} = 0.105$ ($\phi_{\text{EPU}} = 0.033$, if we exclude the EPU index of Ireland) and that for the GPR indices is $\phi_{\text{GPR}} = -0.105$. Therefore, as a whole, the GPR index leads the EPU index during the period preceding the terrorist attacks on September 11, 2001.

Figure 12 depicts the correlation network before the September 11 attack. This network consists of three clusters of EPU indices, that of the GPR indices of the Philippines, Singapore, and Thailand, and that of the GPR indices without these three countries. In Figure 12, the cluster of EPU indices and the cluster of GPR indices without these three countries are connected by more thick and red lines than in Figure 10.

We can quantitatively confirm this intuition in Tables 3 and 4. These tables demonstrate that the ratio of red links from EPU indices to GPR indices is greater than in the case when we used all terms from January 1997 to November 2020. In addition, the ratio of both the EPU index to the GPR index and the GPR index to the EPU index is almost the same.

F. The Global financial crisis (GFC)

As in the case of the September 11 attack, we investigate 4 years of data before the GFC (i.e., 48 months from September 2004 to August 2008). Here, we define the GFC as the month of the bankruptcy of Lehman Brothers Holdings Inc. (i.e., September 15, 2008). In this subsection, we use a $\tilde{\mathbf{P}}$ with $P_{\text{min.}} = 0.15$ and $\theta_{\text{max.}} = 0.42 \times \pi$. Figure 13 depicts the HH potential before the GFC and shows an uneven distribution. The average value of the HH potential for the EPU index is $\phi_{\text{EPU}} = -0.004$ and that for GPR is $\phi_{\text{GPR}} = 0.004$. Therefore, as a whole, the EPU index leads the GPR index.

Figure 14 depicts the correlation network before the GFC. This network consists of four clusters. The largest cluster contains 17 countries, which include the GPR index without South Africa, Indonesia, the Philippines, and Thailand and the EPU index of India, Australia, and Greece. The EPU index of India propagates to the EPU index of five countries (i.e., Germany, Ireland, Australia, the United States, and Colombia) and the GPR index of seven countries (i.e., Israel, India, Saudi Arabia, Mexico, Colombia, Venezuela, and Brazil). The EPU index of Greece affects the EPU index of two countries (i.e., Italy and India) and the GPR index of six countries (i.e., Turkey, Israel, Korea, Saudi Arabia, Argentina, and Colombia). The EPU index of Australia affects the GPR index of Argentina. The GPR index of China connects to all 13 GPR indices contained in this largest cluster. The next largest cluster contains 15 countries and consists of the EPU index without India, Australia, or Greece. In this cluster, the most leading country is Brazil, which connects to the EPU index of 13 countries. The hub in this cluster is the EPU index of Japan, which connects to the EPU index of 11 countries and the GPR index of five countries.

In Figure 13, the HH potential shows that the GPR index of South Africa is the most leading index. However, the correlation network shown in Figure 14 indicates that the effect of risk propagates only to the GPR index of the Philippines and then does not propagate anymore. Figure 14 contains more thick red links than does Figure 10. We can quantitatively confirm this intuition by examining Tables 3 and 4. These tables show that the ratio of red links from the EPU index to the GPR index is larger than when we used all terms from January 1997 to November 2020. In addition, the ratio of the EPU index to the GPR index is more significant than that of the GPR index to the EPU index.

G. Around the latter half of 2016

In this subsection, we investigate 4 years around the latter half of 2016 (i.e., 48 months from October 2014 to September 2018). We use a $\tilde{\mathbf{P}}$ with $P_{\mathrm{min.}} = 0.008$ and $\theta_{\mathrm{max.}} = 0.24 \times \pi$. Figure 15 depicts the HH potential and shows an uneven distribution. The average value of the HH potential for the EPU index is $\phi_{\mathrm{EPU}} = -0.004$ if we exclude Ireland, and that for the GPR index is $\phi_{\mathrm{GPR}} = -0.008$. Therefore, the GPR and EPU indices are moving together as a whole.

Figure 16 depicts the correlation network around the latter half of 2016. This network consists of two clusters. The largest cluster contains the EPU index of all countries and the GPR index of the Philippines. The GPR index of the Philippines connects to the EPU index of six countries (i.e., the United Kingdom, Australia, China, India, Japan, and Canada) and the GPR index of two countries (i.e., Turkey and Israel). The largest hub in this cluster is the EPU index of the United States, which connects to the EPU index of 13 countries (the EPU index excluding Ireland, the Netherlands, Russia, Colombia, and Chile) and the GPR index of three countries (i.e., India, China, and the Philippines). The next largest hub in this cluster is the EPU index of Korea, which connects to the EPU index of 12 countries (the EPU index excluding the Netherlands, Russia, Spain, the United States, Colombia, and Chile) and the GPR index of three countries (i.e., India, China, and the Philippines). The next largest cluster contains the GPR index of 17 countries (the GPR index without the Philippines). The largest hub in this cluster is the GPR index of India connecting to the EPR index of seven countries (i.e., France, Germany, Greece, the United Kingdom, Australia, China, and Brazil) and the GPR index of 12 countries (the GPR index excluding Korea, Indonesia, Thailand, Malaysia, and Argentina). The next largest hub in this cluster is the GPR of Korea, connecting to the EPU index of six countries (i.e., France, Greece, the United Kingdom, Australia, China, Brazil) and the GPR index of nine countries (i.e., Russia, India, China, Saudi Arabia, the Philippines, Mexico, Colombia, Venezuela, and Brazil).

Figure 16 contains more thick red links than does Figure 10. We can quantitatively confirm this intuition by examining Tables 3 and 4. These tables show that the ratio of red links from the GPR index to the EPU index is greater than when we used all terms from January 1997 to November 2020. In addition, the ratio of the GPR index to the EPU index is more significant than that of the EPU index to the GPR index.

VI. Summary and Discussion

This paper investigated the correlation between the EPU and GPR indices of 31 countries; 19 countries for the EPU index and 18 countries for the GPR index. Six countries (Russia, China, India, South Korea, Colombia, and Brazil) have both EPU and GPR indices. We explored 288 monthly time series from January 1997 to December 2020. The application of CHPCA to the complex correlation matrix extracted two significant components. We constructed the principal complex correlation matrix from those two components. Using the HH potential, we obtained a weighted and directed correlation network from this principal complex correlation matrix. The direction of the links in this network is from the leading indices to the lagging indices. We applied cluster analysis to the network and determined the structure of the clusters. Our investigation of all data derived two clusters; an EPU index cluster without China and a GPR index cluster without the EPU index of China. We also calculated the mode signals and found that the significant peaks are the September 11 attack in 2001, the COVID-19 pandemic in 2020, the GFC in 2008, and the second half of 2016.

We applied our method to the 4 years of data before the September 11 attack (i.e., 48 months from September 1997 to August 2001) and found three clusters. The largest cluster consists of all of the EPU indices, and the next largest cluster consists of the GPR index of 15 countries. The connection between these clusters is more robust than when we used all the data from 1997 to 2020, and the HH potential suggested that the GPR index led the EPU index. We also applied our method to the 4 years of data before the GFC (i.e., 48 months from September 2004 to August 2008) and found four clusters. The largest cluster consists of the

EPU index without Australia, Greece, India, and Russia, and the next largest one consists of the GPR index with Australia, Greece, and India. The connection between these clusters is more robust than the September 11 attack, and the HH potential suggested that the EPU index leads the GPR index. In addition, we applied our method to the 4 years around the latter half of 2016 (i.e., 48 months from October 2014 to September 2018) and found two clusters. The largest cluster consists of the EPU index with the GPR index of the Philippines, and the next largest one consists of the GPR index without the Philippines. The connections from the GPR index to the EPU index are twice as great as that of the EPU index to the GPR index, and the HH potential suggested that the EPU and GPR indices are almost comoving.

Once policy uncertainty and geopolitical tensions have been documented to significantly impact the market participants' decisions and influence economic activity, our empirical results are useful as early warning signals of possible changes across countries. More specifically, aware that fluctuations in the index of a determined country (or group of countries) can disseminate to your economy, policymakers, firms, and investors could use our findings to monitor the global (relevant) environment.

However, this study is not exempt from limitations. It may be the case that the index we relied on for a given country does not fully capture the environment in terms of policy uncertainty. For instance, Brazil's EPU is constructed upon terms found only in one specific newspaper (i.e., Folha de São Paulo). Meanwhile, the geopolitical risk measure is based on leading international newspapers circulating in the United States, United Kingdom, and Canada but does not consider the local press of the other countries in the sample (country-specific newspaper). Hence, an interesting avenue for future studies is the extension of the data source.

Moreover, the EPU and GPR indices allow us to investigate qualitative aspects of society and the economy. Quantitative data, such as the gross domestic product (GPD), plays an essential role in economics. However, qualitative data such as textual data are even more abundant than quantitative data. Therefore, future researches could skillfully integrate quantitative and textual data to become more critical. More precisely, the current EPU and GPR indices should be considered semi-qualitative. This is because these indices are derived from textual data by counting the number of occurrences of certain words. Thus, this method ignores the polarities of textual data, for instance, whether the situation is worsening or improving. We expect that natural language processing based on machine learning will overcome this problem.

REFERENCES

Aoyama, Hideaki, Yoshi Fujiwara, Yuichi Ikeda, and Wataru Souma. 2017. *Macro-econophysics: new studies on economic networks and synchronization.* Cambridge University Press.

Arai, Yuta, Takeo Yoshikawa, and Hiroshi Iyetomi. 2013. "Complex principal component analysis of dynamic correlations in financial markets." In *Intelligent Decision Technologies.* 111–119. IOS Press.

Baker, Scott R, Nicholas Bloom, and Steven J Davis. 2016. "Measuring economic policy uncertainty." *The quarterly journal of economics*, 131(4): 1593–1636.

Balcilar, Mehmet, Matteo Bonato, Riza Demirer, and Rangan Gupta. 2018. "Geopolitical risks and stock market dynamics of the BRICS." *Economic Systems*, 42(2): 295–306.

Balli, Faruk, Gazi Salah Uddin, Hasan Mudassar, and Seong-Min Yoon. 2017. "Cross-country determinants of economic policy uncertainty spillovers." *Economics Letters*, 156: 179–183.

Balli, Faruk, Hatice Ozer Balli, Mudassar Hasan, and Russell Gregory-Allen. 2021. "Geopolitical risk spillovers and its determinants." *The Annals of Regional Science*, 1–38.

Baruník, Jozef, and Tomáš Křehlík. 2018. "Measuring the frequency dynamics of financial connectedness and systemic risk." *Journal of Financial Econometrics*, 16(2): 271–296.

Bernanke, Ben S. 1983. "Irreversibility, uncertainty, and cyclical investment." *The quarterly journal of economics*, 98(1): 85–106.

Bloom, Nicholas. 2009. "The impact of uncertainty shocks." *econometrica*, 77(3): 623–685.

Bloom, Nicholas. 2017. "Observations on uncertainty." *Australian Economic Review*, 50(1): 79–84.

Bouras, Christos, Christina Christou, Rangan Gupta, and Tahir Suleman. 2019. "Geopolitical risks, returns, and volatility in emerging stock markets: evidence from a panel GARCH model." *Emerging Markets Finance and Trade*, 55(8): 1841–1856.

Brogaard, Jonathan, and Andrew Detzel. 2015. "The asset-pricing implications of government economic policy uncertainty." *Management Science*, 61(1): 3–18.

Caggiano, Giovanni, Efrem Castelnuovo, and Juan Manuel Figueres. 2020. "Economic policy uncertainty spillovers in booms and busts." *Oxford Bulletin of Economics and Statistics*, 82(1): 125–155.

Caldara, Dario, and Matteo Iacoviello. 2018. "Measuring geopolitical risk." *FRB International Finance Discussion Paper*, , (1222).

Castelnuovo, Efrem, Guay Lim, and Giovanni Pellegrino. 2017. "A short review of the recent literature on uncertainty." *Australian Economic Review*, 50(1): 68–78.

Cheung, Yin-Wong, and Lilian K Ng. 1996. "A causality-in-variance test and its application to financial market prices." *Journal of econometrics*, 72(1-2): 33–48.

Colombo, Valentina. 2013. "Economic policy uncertainty in the US: Does it matter for the Euro area?" *Economics Letters*, 121(1): 39–42.

Dakhlaoui, Imen, and Chaker Aloui. 2016. "The interactive relationship between the US economic policy uncertainty and BRIC stock markets." *International Economics*, 146: 141–157.

Das, Debojyoti, M Kannadhasan, and Malay Bhattacharyya. 2019. "Do the emerging stock markets react to international economic policy uncertainty, geopolitical risk and financial stress alike?" *The North American Journal of Economics and Finance*, 48: 1–19.

Datta, Sudip, Trang Doan, and Mai Iskandar-Datta. 2019. "Policy uncertainty and the maturity structure of corporate debt." *Journal of Financial Stability*, 44: 100694.

Demir, Ender, and Oguz Ersan. 2017. "Economic policy uncertainty and cash holdings: Evidence from BRIC countries." *Emerging Markets Review*, 33: 189–200.

Diebold, Francis X, and Kamil Yilmaz. 2009. "Measuring financial asset return and volatility spillovers, with application to global equity markets." *The Economic Journal*, 119(534): 158–171.

Diebold, Francis X, and Kamil Yilmaz. 2012. "Better to give than to receive: Predictive directional measurement of volatility spillovers." *International Journal of forecasting*, 28(1): 57–66.

Diebold, Francis X, and Kamil Yılmaz. 2014. "On the network topology of variance decompositions: Measuring the connectedness of financial firms." *Journal of econometrics*, 182(1): 119–134.

Diebold, Francis X, and Kamil Yılmaz. 2015. *Financial and macroeconomic connectedness: A network approach to measurement and monitoring.* Oxford University Press, USA.

Dooley, Michael, and Michael Hutchison. 2009. "Transmission of the US subprime crisis to emerging markets: Evidence on the decoupling–recoupling hypothesis." *Journal of International Money and Finance*, 28(8): 1331–1349.

Gulen, Huseyin, and Mihai Ion. 2016. "Policy uncertainty and corporate investment." *The Review of Financial Studies*, 29(3): 523–564.

Horel, John D. 1984. "Complex principal component analysis: Theory and examples." *Journal of Applied Meteorology and Climatology*, 23(12): 1660–1673.

Iyetomi, Hiroshi, Yasuhiro Nakayama, Hideaki Aoyama, Yoshi Fujiwara, Yuichi Ikeda, and Wataru Souma. 2011*a*. "Fluctuation-dissipation theory of input-output interindustrial relations." *Physical Review E, Statistical, Nonlinear, and Soft Matter Physics*, 83(1): 016103.

Iyetomi, Hiroshi, Yasuhiro Nakayama, Hiroshi Yoshikawa, Hideaki Aoyama, Yoshi Fujiwara, Yuichi Ikeda, and Wataru Souma. 2011*b*. "What causes business cycles? Analysis of the Japanese industrial production data." *Journal of the Japanese and International Economies*, 25(3): 246–272.

Kang, Sang Hoon, and Seong-Min Yoon. 2019. "Dynamic connectedness network in economic policy uncertainties." *Applied Economics Letters*, 26(1): 74–78.

Khoo, Joye, et al. 2021. "Does geopolitical uncertainty affect corporate financing? Evidence from MIDAS regression." *Global Finance Journal*, 47: 100519.

Kichikawa, Yuichi, Yuta Arai, and Hiroshi Iyetomi. 2015. "Complex principle component analysis on dynamic correlation structure in price index data." *Procedia Computer Science*, 60: 1836–1845.

King, Mervyn A, and Sushil Wadhwani. 1990. "Transmission of volatility between stock markets." *The Review of Financial Studies*, 3(1): 5–33.

Klößner, Stefan, and Rodrigo Sekkel. 2014. "International spillovers of policy uncertainty." *Economics Letters*, 124(3): 508–512.

Le, Anh-Tuan, and Thao Phuong Tran. 2021. "Does geopolitical risk matter for corporate investment? Evidence from emerging countries in Asia." *Journal of Multinational Financial Management*, 62: 100703.

Lee, Chien-Chiang, and Chih-Wei Wang. 2021. "Firms' cash reserve, financial constraint, and geopolitical risk." *Pacific-Basin Finance Journal*, 65: 101480.

Lehkonen, Heikki. 2015. "Stock market integration and the global financial crisis." *Review of Finance*, 19(5): 2039–2094.

Liow, Kim Hiang, Wen-Chi Liao, and Yuting Huang. 2018. "Dynamics of international spillovers and interaction: Evidence from financial market stress and economic policy uncertainty." *Economic Modelling*, 68: 96–116.

Marfatia, Hardik, Wan-Li Zhao, and Qiang Ji. 2020. "Uncovering the global network of economic policy uncertainty." *Research in International Business and Finance*, 53: 101223.

Pastor, Lubos, and Pietro Veronesi. 2012. "Uncertainty about government policy and stock prices." *The journal of Finance*, 67(4): 1219–1264.

Rasmusson, Eugene M, Phillip A Arkin, Wen-Yuan Chen, and John B Jalickee. 1981. "Biennial variations in surface temperature over the United States as revealed by singular decomposition." *Monthly weather review*, 109(3): 587–598.

Souma, Wataru. 2021. "Characteristics of Principal Components in Stock Price Correlation." *Frontiers in Physics*, 9: 104.

Vodenska, I., H. Aoyama, Y. Fujiwara, H. Iyetomi, and Y. Arai. 2016. "Interdependencies and causalities in coupled financial networks." *PLoS ONE*, 11(3): e0150994.

Yang, LI, Jingqiu Luo, and Yongmu Jiang. 2021. "Policy uncertainty spillovers and financial risk contagion in the Asia-Pacific network." *Pacific-Basin Finance Journal*, 67: 101554.

Yung, Kenneth, and Andrew Root. 2019. "Policy uncertainty and earnings management: International evidence." *Journal of Business Research*, 100: 255–267.

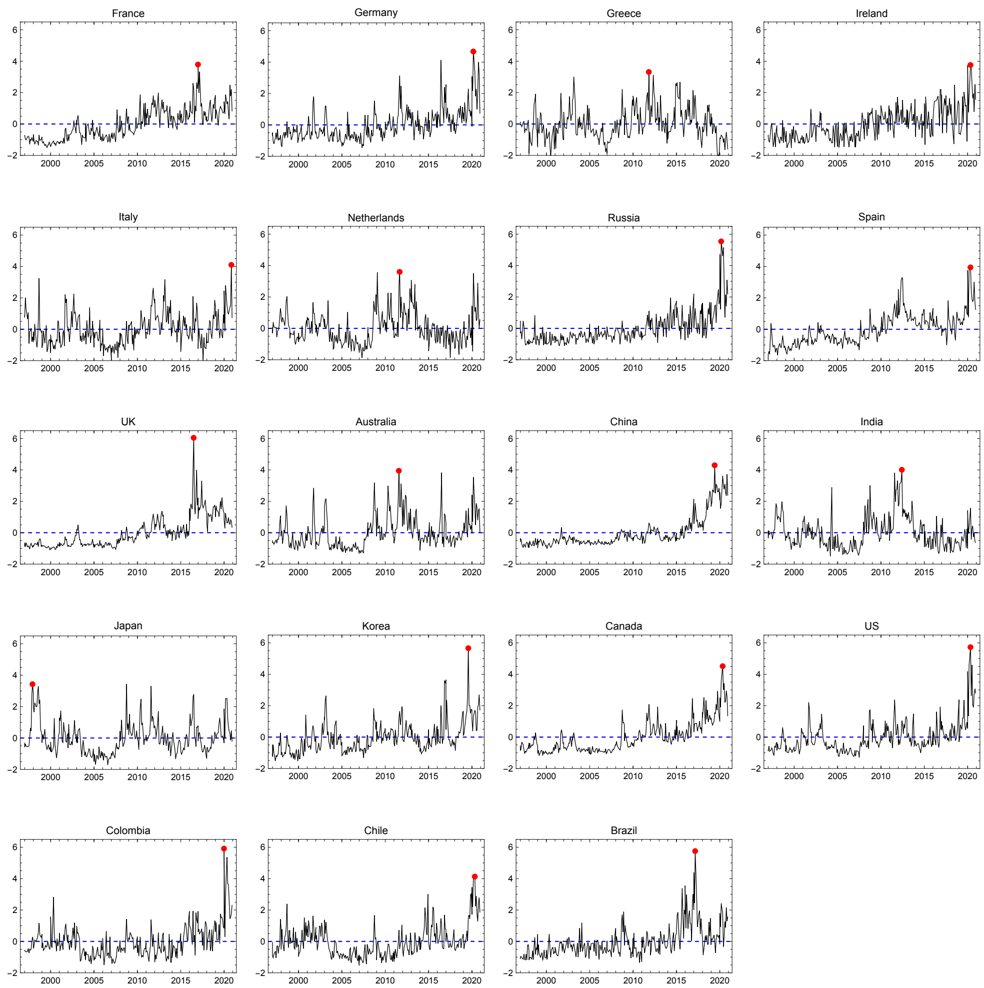

Figure 1. Change in EPU indices for 19 countries. The red dot in each figure indicates the peak of time series.

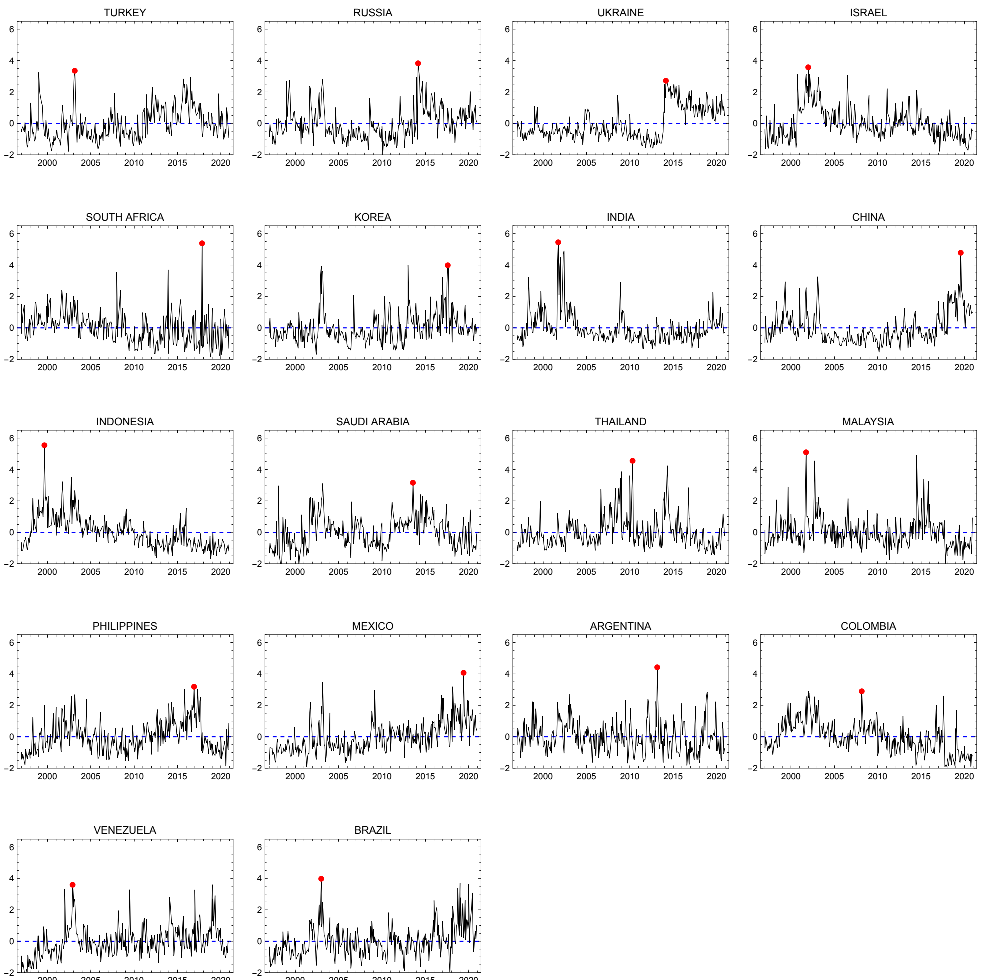

Figure 2. Change in GPR indices for 18 countries. The red dot in each figure indicates the peak of time series.

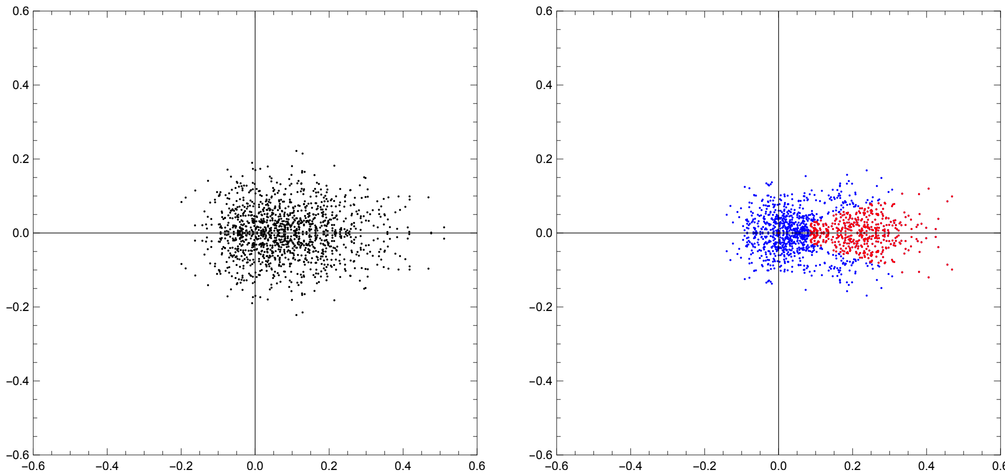

Figure 3. Distribution of the elements of complex correlation matrix $\mathbf{C}$ (left panel), $\mathbf{P}$ (blue dots in the right panel), and $\tilde{\mathbf{P}}$ (red dots in the right panel).

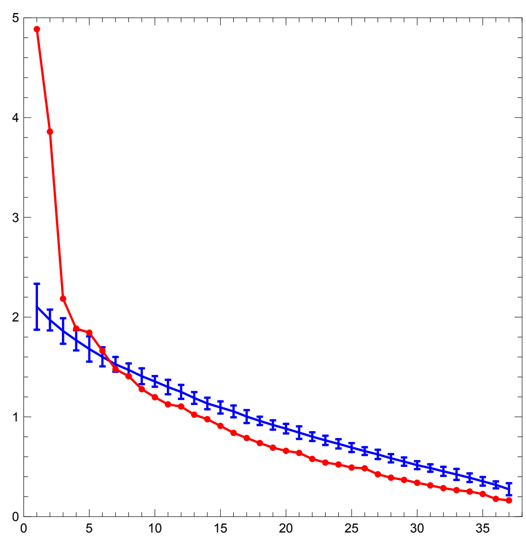

Figure 4. Scree graph of the complex correlation matrix given by Equation (6) (red line) and that of a rotationally and randomly shuffled complex correlation matrix (blue line).

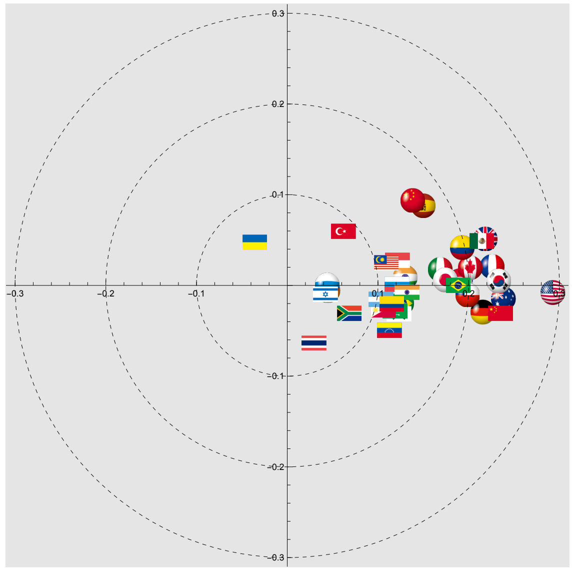

Figure 5. Distribution of the components of the eigenvector corresponding to the first eigenvalue.

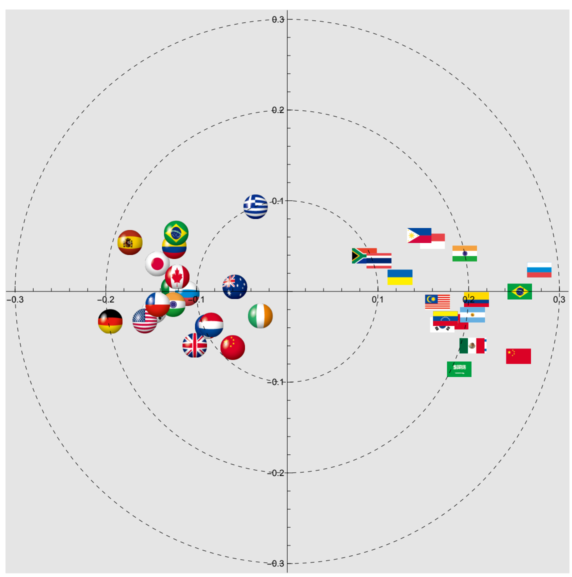

Figure 6. Distribution of the components of the eigenvector corresponding to the second eigenvalue.

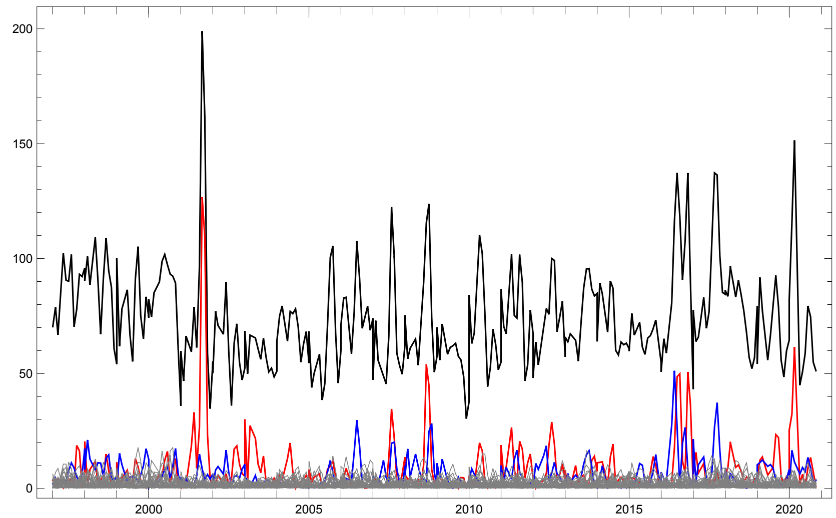

Figure 7. Comparison of the sum of mode signals (thick black line), the first mode signal (thick red line), the second mode signal (thick blue line), and mode signals from 3 to 37 (thin gray lines).

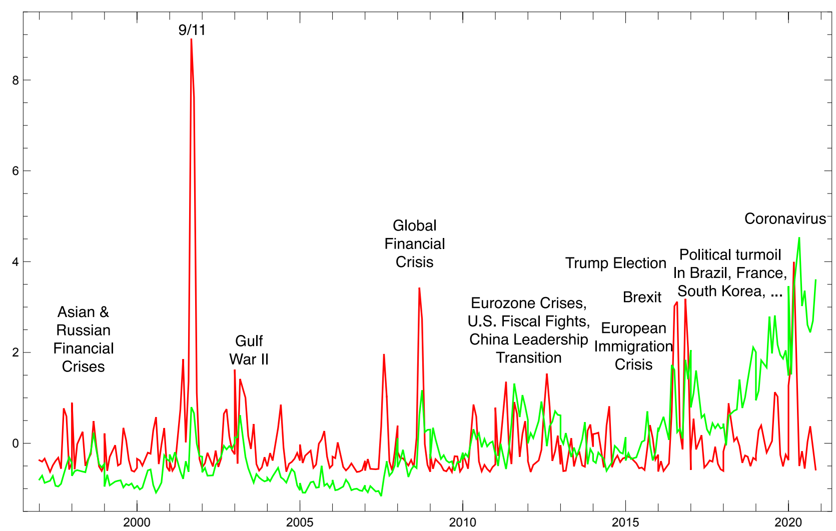

Figure 8. Comparison of the first mode signal (red line) and the GEPU (green line).

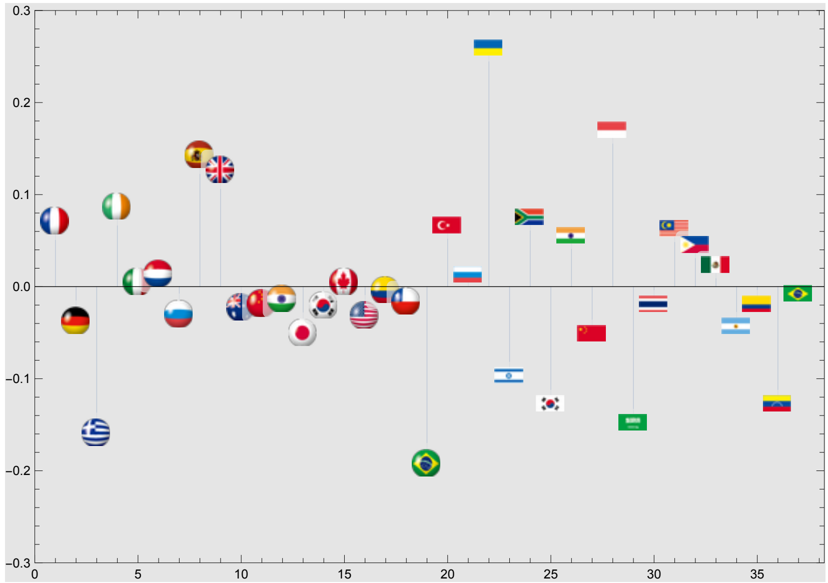

Figure 9. Helmholtz-Hodge potential from January 1997 to December 2020.

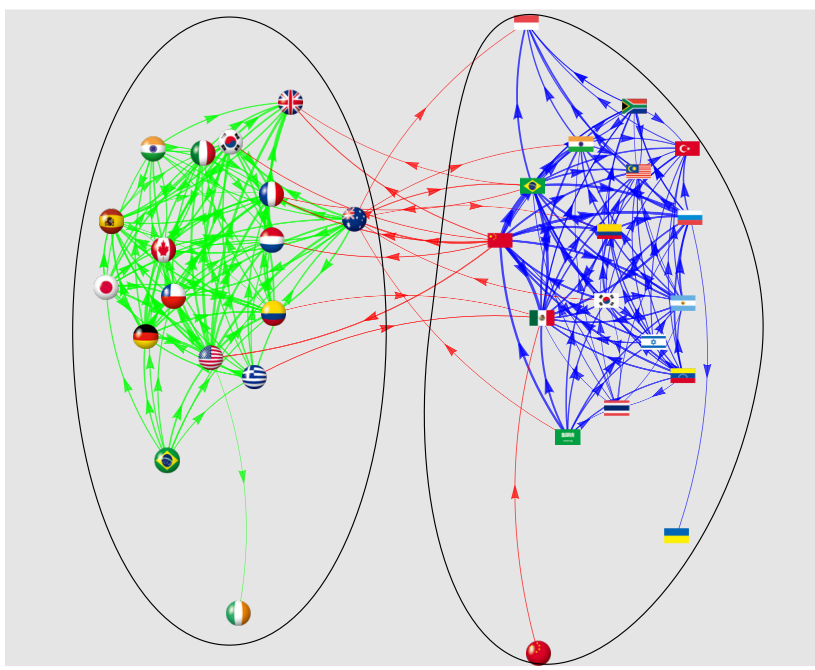

Figure 10. Correlation network from January 1997 to December 2020.

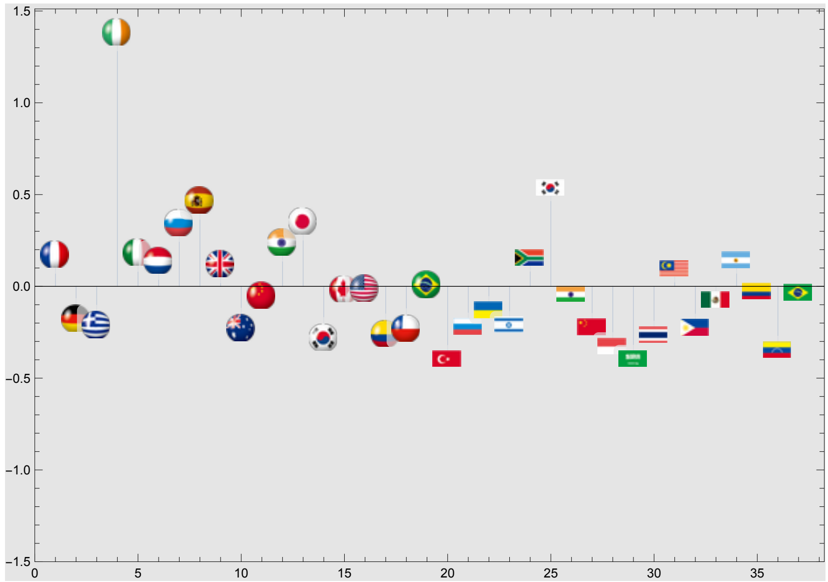

Figure 11. Helmholtz-Hodge potential for 4 years before the September 11 attacks.

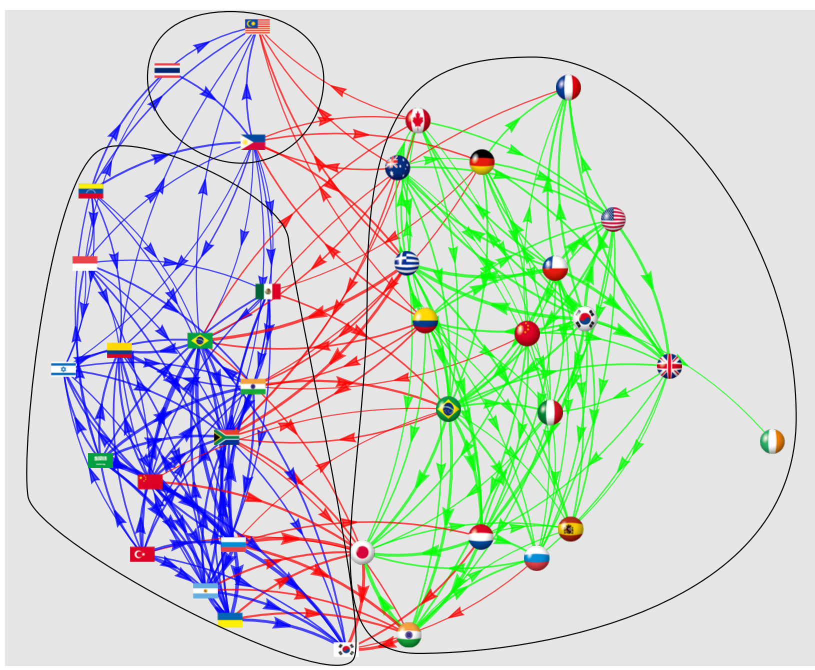

Figure 12. Correlation network for 4 years before the September 11 attacks.

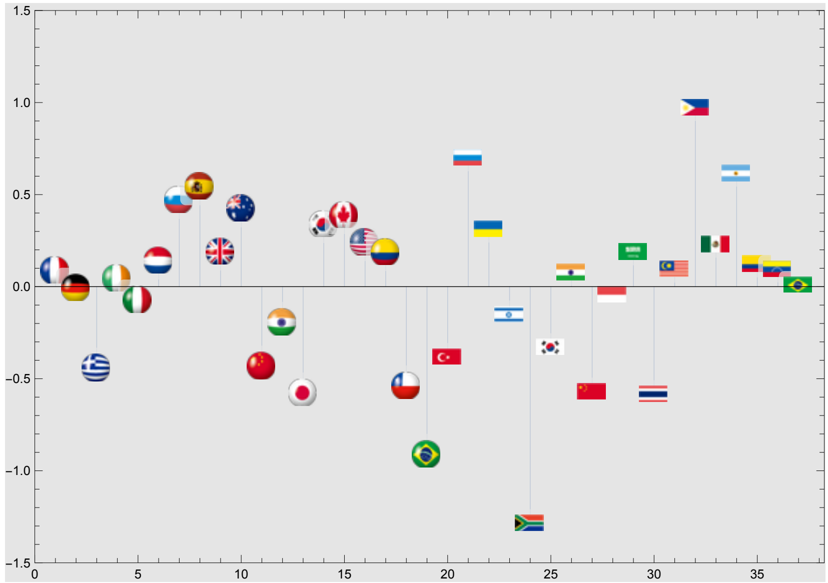

Figure 13. Helmholtz-Hodge potential for 4 years before the global financial crisis.

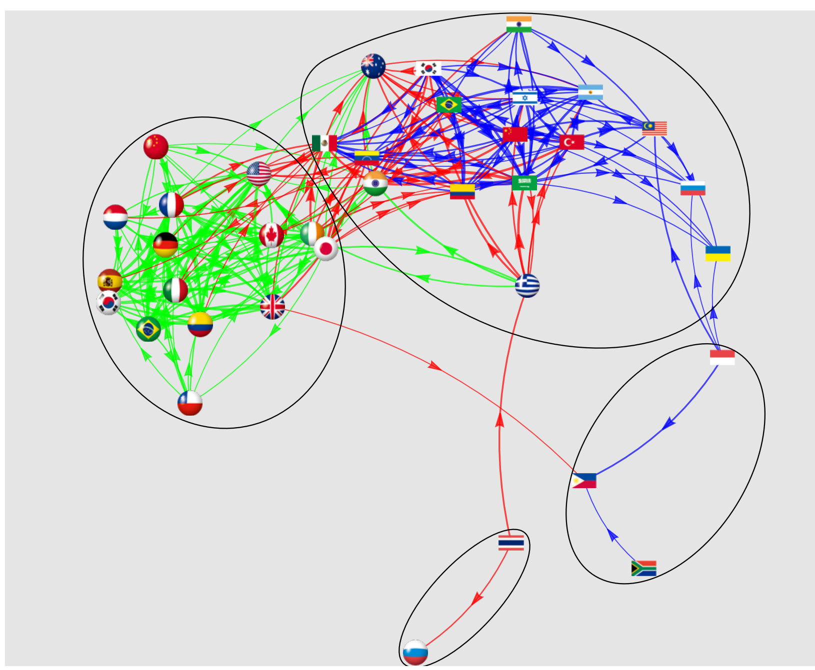

Figure 14. Correlation network for 4 years before the global financial crisis.

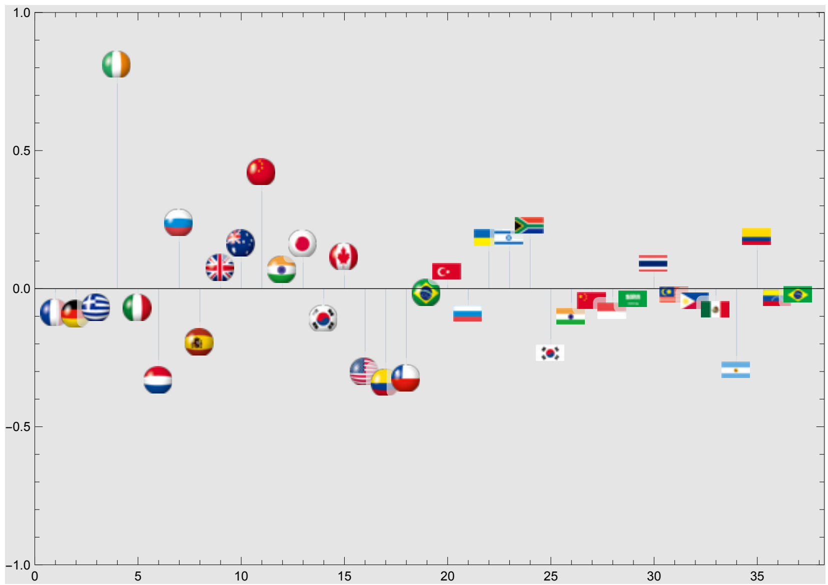

Figure 15. Helmholtz-Hodge potential for 4 years around the second half of 2016.

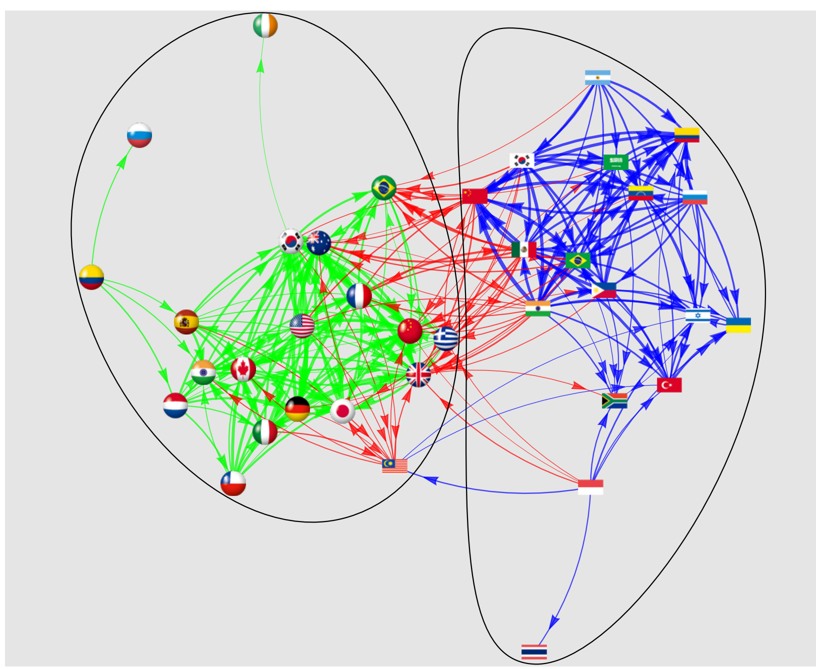

Figure 16. Correlation network for 4 years around the latter half of 2016.

Table 1—Data source, peak of time series, and corresponding event of EPU indices for 19 countries.

County	Data Source	Peak	Hight	Event
France	Le Monde, Le Figaro for France	App-2017	3.83	Presidential election
Germany	Handelsblatt, Frankfurter Allgemeine Zeitung for Germany	Mar-2020	4.71	Coronavirus
Greece	Kathimerini	Nov-2011	3.36	Debt crisis
Ireland	The Irish Times	May-2020	3.79	Coronavirus
Italy	Corriere Della Sera, La Stampa	Nov-2020	4.12	Coronavirus
Netherlands	Algemeen Dagblad, NRC Handelsblad, De Telegraaf, Trouw, De Volkskrant	Sep-2011	3.65	European debt crisis
Russia	Kommersant	Mar-2020	5.58	Coronavirus
Spain	El Mundo, El Pais	May-2020	3.98	Coronavirus
UK	The Times of London, Financial Times	Jul-2016	6.09	Brexit
Australia	Daily Telegraph, Courier Mail, The Australian, The Age, The Advertiser, Mercury, Sydney Morning Herald, The Herald Sun	Aug-2011	3.97	High Australian dollar
China	South China Morning Post	Jun-2019	4.32	Intensification of trade friction between the U.S. and China
India	Economic Times, the Times of India, the Hindustan Times, the Hindu, the Statesman, the Indian Express, the Financial Express	Jun-2012	4.05	High inflation and large twin deficits (budget deficit and current account deficit), rupee depreciation
Japan	Yomiuri, Asahi, Mainichi, Nikkei	Dec-1997	3.46	Financial system crisis
South Korea	Donga Ilbo, Kyunghyang, Maeil Economic (from 1995), Hankyoreh, Hankook Ilbo, Korea Economic Daily (from 1995)	Aug-2019	5.70	Deterioration of Japan-Korea relations
Canada	The Gazette, The Vancouver Sun, The Toronto Star, The Ottawa Citizen, The Globe and Mail, Canadian Newswire	May-2020	4.55	Coronavirus
US	USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the Houston Chronicle, the WSJ	May-2020	5.76	Coronavirus President Trump
Colombia	El Tiempo	App-2020	5.94	Coronavirus
Chile	El Mercurio, La Segunda	May-2020	4.16	Coronavirus
Brazil	Folha de Sao Paulo	Mar-2017	5.77	

Table 2—Data source, peak of time series, and corresponding event of GPR indices for 18 countries.

County	Data Source	Peak	Hight	Event
Turkey	11 national and international newspapers:	Mar-2003	3.40	Non-participation in the US-led coalition of
	The Boston Globe, Chicago Tribune,			the willing in the Iraq war
Russia	The Daily Telegraph, The Globe and Mail,	Mar-2014	3.87	Russia invades Crimea
Ukraine	The Guardian, Los Angeles Times,	Mar-2014	2.75	Russia invades Crimea
Israel	The New York Times, The Times,	Jan-2002	3.62	Deterioration of the Middle East Peace Process
South Africa	The Wall Street Journal,	Nov-2017	5.42	Confusion relating to the publication
	The Washington Post			"The President's Keepers"
Korea		Aug-2017	4.03	North Korea crisis
India		Oct-2001	5.48	India-Pakistan relations
China		Aug-2019	4.81	China-United States trade war
Indonesia		Sep-1999	5.58	East Timorese crisis
Saudi Arabia		Aug-2013	3.18	Related to Syrian civil war
Thailand		May-2010	4.58	Thai political protests
Malaysia		Oct-2001	5.12	Anthrax attacks, Response to Afghanistan
Philippines		Dec-2016	3.22	President Rodrigo Duterte's policy
Mexico		Jun-2019	4.13	Illegal Immigration
Argentina		Mar-2013	4.45	Referendum to the inhabitants of the Falkland Islands about the sense of belonging to the UK. First Argentinian pope.
Colombia		Mar-2008	2.93	2008 Andean diplomatic crisis
Venezuela		Dec-2002	3.63	Venezuelan general strike of 2002-2003
Brazil		Jan-2003	4.00	The birth of Brazil's first full-scale left-wing government

Table 3—The ratio of the types of links derived from the number of links

Time	EPU → EPU (%)	EPU → GPR (%)	GPR → EPU (%)	GPR → GPR (%)
Entire term	49.15	2.99	4.27	43.59
Before 9.11	41.80	9.43	8.61	40.16
Before GFC	44.44	13.25	11.54	30.77
Latter half of 2016	42.58	7.42	15.23	34.77

Table 4—The ratio of the types of links derived from the weight of links

Time	EPU → EPU (%)	EPU → GPR (%)	GPR → EPU (%)	GPR → GPR (%)
Entire term	52.83	1.66	2.80	42.72
Before 9.11	41.36	8.64	8.21	41.79
Before GFC	37.70	10.05	8.19	44.07
Latter half of 2016	48.27	4.13	9.52	38.08