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# DYNAMIC DISTANCES BETWEEN STOCK MARKETS: USE OF UNCERTAINTY INDICES MEASURES

# DISTANCIAS DINÁMICAS ENTRE LOS MERCADOS DE VALORES: USO DE MEDIDAS DE ÍNDICES DE INCERTIDUMBRE

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**Abstract**

In this study we consider how to more accurately identify the possible impact of systemic risk on spatial dependence related to the most significant financial crises over the last 17 years: the Lehman Brothers bankruptcy, the sub-prime mortgage crisis, the European debt crisis, Brexit and the COVID-19 pandemic which has also affected the financial markets. We analyse two new dynamic distances applied to stock markets based on exogenous criteria known as the World Uncertainty Index (WUI) and our proposed Google Trends Uncertainty Index (GTUI). We address the feasibility and benefits of these dynamic distances compared to an alternative criterion based on hours. Using the new proposed dynamic distance to obtain the Moran's I statistic, we analyse the spatial dependence between the losses of 46 stock markets.

**Keywords:** markets distances, uncertainty index, financial crisis, spatial dependence, stock market

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**Resumen**

En este estudio consideramos cómo identificar con mayor precisión el posible impacto del riesgo sistémico en la dependencia espacial relacionada con las crisis financieras más importantes de los últimos 17 años: la quiebra de Lehman Brothers, la crisis de las hipotecas subprime, la crisis de la deuda europea, el Brexit. y la pandemia de COVID-19 que también ha afectado a los mercados financieros. Analizamos dos nuevas distancias dinámicas aplicadas a los mercados de valores en base a criterios exógenos conocidos como el World Uncertainty Index (WUI) y nuestra propuesta de Google Trends Uncertainty Index (GTUI). Abordamos la viabilidad y los beneficios de estas distancias dinámicas frente a un criterio alternativo basado en horas. Utilizando la nueva distancia dinámica propuesta para obtener la estadística I de Moran, analizamos la dependencia espacial entre las pérdidas de 46 bolsas de valores.

**Palabras clave:** distancias de los mercados, índice de incertidumbre, crisis financiera, dependencia espacial, mercado de valores

## 1. Introduction

We propose a monthly Uncertainty Index for stock markets using the Google Trends tool, Google Trend Uncertainty Index (GTUI). We use this index to calculate dynamic distances between stock markets and analyse the spatial dependence with the Global Moran's I statistic proposed by Moran (1950). Our aim is to analyse, in different financial crisis periods, if systemic risk is reflected in an increase in the spatial dependence between market losses calculated as the negative logarithm of stock returns (see Bolance and Acuña, 2021, for an example of analysis using extreme value dependence with copulas). Market losses were calculated based on the loss function defined in McNeil, Frey, and Embrechts (2015).

Historically, geographical distances have been the most widely used measure for calculating the spatial dependence between regions but, as shown by Acuña et al. (2018), these distances are not valid for analysing spatial dependence between stock markets. An alternative method as proposed by Flavin, Hurley, and Rousseau (2002) as a proxy for the ease of trading was to use the number of overlapping operating hours of stock markets as a measure of trading synchronisation. These authors found that the more hours of common trading, the greater the degree of equity price co-movement. Acuña et al. (2018) showed that overlapping operating hours criterion improves the spatial dependence results obtained using geographical distances.

Uncertainty Indexes have been used recently in the literature because they reflect, either through official reports or internet searches, the concerns of economic and financial agents as well as the general public about events that affect the behaviour of a country's economy. Ahir, Bloom, and Furceri (2019) obtained a quarterly index of uncertainty, called World Economic Uncertainty Index (WUI), which was based on counting the number of times that the words "uncertainty" and its variants appeared in the Economist Intelligence Unit (EIU, https://www.eiu.com/n/) for 143 countries. These authors concluded that the level of uncertainty is significantly higher in developing countries, is positively associated with economic policy uncertainty and stock market volatility and negatively with GDP growth. Baker, Bloom and Davis (2016) calculated a monthly index of Global Economic Policy Uncertainty (GEPU) that was based on the raw count of terms in three categories (economy, policy and uncertainty) divided by the total number of articles in the newspapers of 16 countries that included these terms, the searches being done in the respective native language. Using a similar process, Ghirelli, Perez and Urtasun (2019) obtained their specific Uncertainty Index for Spain. By using Google Trends tool, Weinberg (2020) proposed an Economic Policy Uncertainty Index for the largest economies in the European Union (Germany, France, Italy and Spain). Previously, Castelnuovo and Tran (2017) obtained an economic Google Trend Uncertainty Index for the United States and Australia.

In this paper, based on the WUI and our proposed GTUI, we first calculate two types of dynamic distances between stock markets and analyse their evolution over the last 17 years; specifically, we study how these distances change in the financial crisis periods as systemic risk proxy. Secondly, we use the Global Moran's I statistic to analyse the changes of spatial dependence between international stock markets that have been induced by the various global financial crises over the last 17 years. We identify the month with significant spatial dependence throughout the analysed period and study if during the financial crisis periods of the Lehman Brothers bankruptcy, the sub-prime mortgage crisis, the European debt crisis, Brexit and the COVID-19 pandemic, spatial dependence was more frequent compared to non-crisis periods.

The remainder of the paper is organised as follows. Section 2 presents our distance measures and spatial dependence test. In section 3 we describe the data and empirical analysis of uncertainty indices and spatial dependence. Section 4 offers the conclusions.

## 2. Dynamic distances and spatial dependence

We propose the calculation of two alternative distances between countries based on two uncertainty indices: the WUI and the GTUI. The former is a quarterly index that is calculated for 143 countries by counting the number of times the words “uncertain”, “uncertainty” and “uncertainties” are mentioned in the EIU (Economist Intelligence Unit) country reports (see Ahir et al., 2019). The latter is a monthly index that is specifically designed for our study.

The EIU reports discuss the main political and economic developments in each of the 143 countries analysed, together with an analysis of the political and economic conditions. A team of analysts from each country and a central editorial team of the EIU are employed to do this. For the WUI to be comparable between different countries, the frequency of words by country and quarterly report is divided by the total number of words in this report and multiplied by 1000.

The highest peaks of the WUI coincide with the following events: the second Gulf war (2003), the attacks of September 11 (2011), the European debt crisis (2009), the referendum of the United Kingdom in favour of Brexit and the presidential election in the United States (2016), the border control crisis in Europe and the ARS-CoV-2 outbreak (2019) and with the weather phenomenon El Niño. These peaks of uncertainty tend to be more synchronised between developed economies and between economies whose countries have closer commercial and financial ties. Furthermore, a lower uncertainty has been observed in developed economies.

In our financial context, the WUI has some limitations. Firstly, we only have quarterly information. Secondly, this index only works with the word “uncertainty” and some variants of it. Using Google Trends, we propose an alternative index that can be obtained monthly and, in addition to the word “uncertainty” used in the WUI, it includes other relevant words related to the financial markets trends.

### 2.1. Google Trends Uncertainty Index

The Google Trends is a Google Labs tool that shows the most popular searched terms using the Google search engine. This tool gives information related to the frequency with which a search for a particular term is carried out in various regions of the world and in various languages. The available data range from 2004 to date.

The Google Trends Uncertainty Index (GTUI) is based on the idea that economic agents, represented by internet users, search for information online when they are not sure. This implies that the frequency of searching for terms that may be associated with future and possible bad events is high when the level of uncertainty is high. To obtain the specific index for each country, we select a broad set of keywords that are often cited in the Federal Reserve Beige Book for the U.S. and the Reserve Bank Statement on Monetary Policy. English is chosen as the common language since it is the mostly widely used language in the world. The words of interest that are selected, related to financial markets and the crisis events that have occurred in recent years, are the following: "austerity", "bankruptcy", "dollar", "financial crisis", "recession", "risk", "stock exchange", "share price", "stock market" and "uncertainty'. The Google Trends tool enables us to find out the percentage search frequency of each of these words by country and period. In our study, $45$ countries and $46$ stock indices (2 for USA) are analysed monthly. These countries and stock indices are listed in Table 4 in the Appendix. Each country is labelled using the two first digits notation. The frequency of words per country and period are added to obtain our proposed monthly GTUI.

## 2.2. Global Moran's I statistic

Since this study focuses on spatial dependence measures to analyse how markets are interconnected, the specification of the linkages matrices for each period $t$ between stock markets is important; these matrices are called $W_t$ and in our case are $46 \times 46$. For calculating the elements of $W_t$ we use the criteria defined by Asgharian, Hess, and Liu (2013) based on constructing a contiguity matrix $C_t$ between markets. This matrix indicates how contiguous market $j$ to market $i$ in period $t$ is, according to a measure of distance (or similarity) between both countries. We then define the matrix $C_t$ using distance criteria as proposed in this study.

Let $D_{ijt}$ be a measure of distance between countries $i$ and $j$ at period $t$. The elements $C_{ijt}$ in $C_t$ are given by:

$$C_{ijt} = 1 - \frac{D_{ijt} - min_j D_{ijt}}{max_j D_{ijt} - min_j D_{ijt}} \qquad \forall \quad i \neq j \ \ t = 1, \ldots, T. \tag{1}$$

This definition of contiguity ensures that all elements of $C_t$ lie between 0 and 1; if $C_{ijt}$ is near $0$ the longest distance is from country $i$ to country $j$ and if $C_{ijt}$ is near $1$ the shortest distance is between country $i$ and country $j$. Moreover, $C_{ijt}$ is not necessarily symmetric; it could be that country $j$ is an important neighbour for country $i$ (i.e., $C_{ijt}$ is close to 1) but country $i$ may be unimportant for country $j$ (i.e., $C_{ijt}$ is close to 0). The linkages matrix or spatial weights in the matrices $W_t$ are obtained from $C_{ijt}$ through row standardisation such that, for each row $i$, $\sum_j W_{ijt} = 1$.

Through the GTUI we can obtain a monthly distance matrix between countries. Let $GTUI_{it}$, $i = 1,...,46$ be the value of the uncertainty index for the stock market $i$ in the period $t$, then the distances between pairs of stock markets are defined as:

$$D_{ijt} = |GTUI_{it} - GTUI_{jt}|, \ \forall i \neq j \ \ t = 1,...,T. \tag{2}$$

Alternatively, the WUI can also be used to calculate distances between stock markets. However, this uncertainty index is available quarterly and to calculate monthly spatial weights we assume that the WUI is constant throughout the three months of each quarter.

The Moran's I statistic at period $t$ is defined as (see Moran, 1950):

$$I_t = \frac{N}{S_{0t}} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} W_{ijt}(l_{it}-\bar{l}_t)(l_{jt}-\bar{l}_t)}{\sum_{i=1}^{N} (l_{it}-\bar{l}_t)^2}, \tag{3}$$

where $N = 46$, $S_{0t}$ is the sum of all the spatial weights $W_{ijt}$, $\forall i \neq j$ and $l_{it}$ are the loss of the index $i$ in period $t$, that are equal to negative log-returns, $l_{it} = -log\left(\frac{P_{i,t+1}}{P_{i,t}}\right)$, where $P_{i,t}$ is the value of stock index $i$ in period $t$. In alternative studies the spatial weights matrix is discretised, only those areas whose continuity coefficients are greater than the mean or median of all these coefficients are considered neighbors (see Asgharian et al., 2013). In this paper, taking into account that finanial markets have a global behaibour and that systemic risk has global effect, we decided to use continuous weights matrix, that give more weight to those more similar markets, according to the distance criterion.

The asymptotic distribution of $I_t$ is Normal with mean and variance known (Moran, 1950) and we can therefore perform the test of positive global spatial dependence for each period $t$.

The inference suggested by the global Moran's I statistic is based on the assumption that the data are independent and identically distributed (iid). Regarding non-normality, Griffith (2010) concludes that the assumption of normality is not essential for the asymptotic properties of the Moran's I statistic.

## 3. Empirical analysis

We analyse the spatial dependence between monthly losses of 46 stock indices of 45 countries, which are listed in Table 4 of the Appendix and which shows that USA is the only analysed country with two stock indices. The data cover the period from January 2004 to March 2021 and take into account different events that carried a systemic risk: Lehman Brothers bankruptcy in September 2008, the sub-prime mortgage crisis between 2007 and 2009, the European debt crisis (Euro debt) since the end of 2009 until mid 2014, Brexit in June of 2016 and the COVID-19 pandemic since March 2020. In Table 1 we show the beginning and end of these crisis periods.

Table 1
*Crisis Periods*

| | **Sub-prime** | **Euro debt** | **Brexit** | **COVID-19** |
|---|---|---|---|---|
| **Beginning** | 31/08/2007 | 30/06/2010 | 30/06/2016 | 29/02/2020 |
| **End** | 30/06/2009 | 30/06/2014 | 31/01/2020 | 31/03/2021 |

Before beginning the analysis, we plotted the uncertainty index GTUI in Figure 1, the plot of the WUI is shown in the Figure 6 of the Appendix. The top part of both Figures represents the values of the indices; the darker the shading, the higher the value. In the bottom part of both Figures the mean of the index for all countries is plotted and the box-plots of the Uncertainty Index for each country are shown on the right. For the WUI we only have data up to the last quarter of 2020 and we assume that for each observed quarter the index value is constant over all three months. At first glance, it is evident that both indices behave differently. We compare the GTUI in Figure 1 with the filtered series of losses using the ARMA-GARCH models shown in Table 4 in the Appendix. The filtered series are free of the temporal component, i.e. they take independent values, which guarantees the properties of the inference that is presented at the end of this section and compares different periods. For each month, we test the spatial dependence between the random components of the series, this dependence implies a greater systemic risk.

The filtered series are plotted in Figure 2 and, comparing with Figure 1 and Figure 6 of Appendix, it can be seen that our GTUI captures market uncertainty better than the WUI. In Figure 3 we plot the GTUI for each country with the overall mean of its confidence interval at 95% confidence level, showing a similar behaviour in all analysed countries, especially in the periods of most uncertainy.

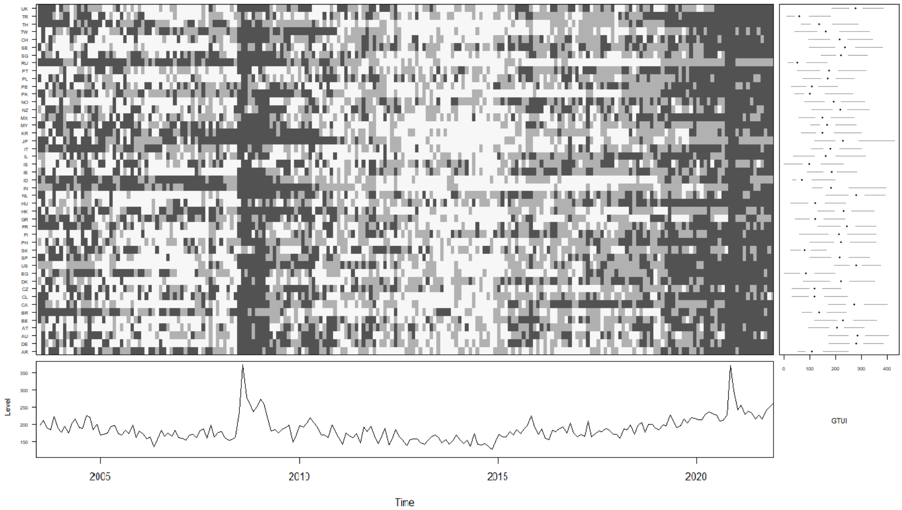


*Figure 1*. Values of the Google Trend Uncertainty Index for Each Country (at top) - The Darker the Shading, the Higher the Value - and plot of the Mean Index (at bottom). The Box-Plots of the GTUI for Each Country are shown on the Right

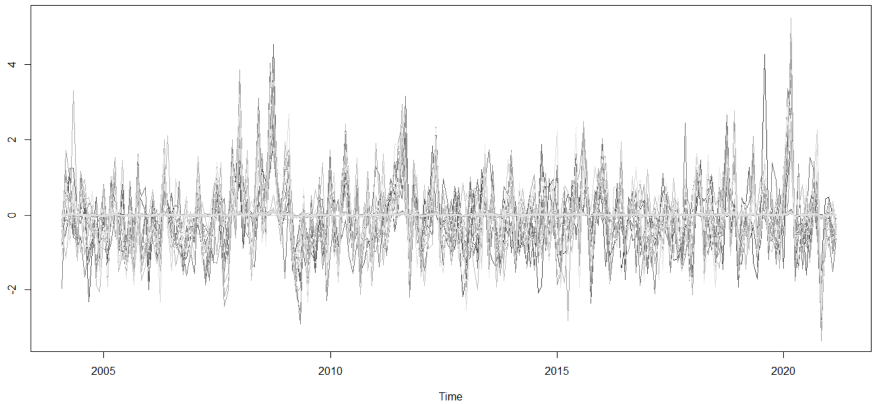


*Figure 2*. Filtered Losses for the 46 Stock Indices

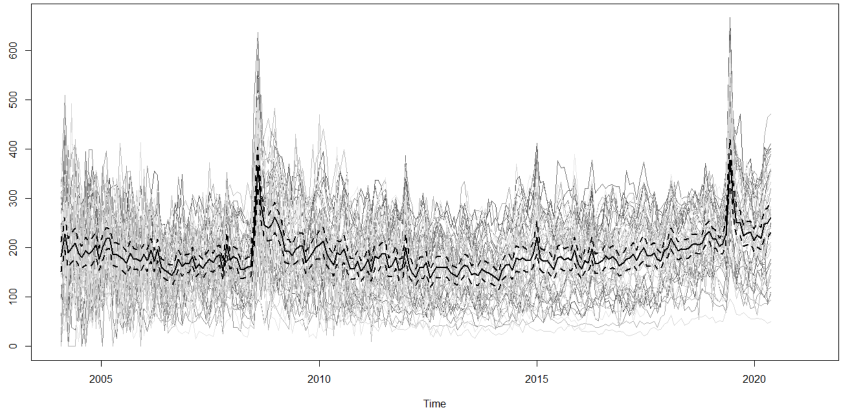


*Figure 3.* GTUI for the 45 Countries, Mean (the thickest line) and 95% Confidence Intervals of the Mean (dashed lines)

Focusing on the right part of Figure 1, it can be seen that the countries that reached highest GTUI values are Japan followed by Australia. The periods showing the highest GTUI values are at the time of the sub-prime mortgage crisis and the COVID-19 pandemic.

With the aim of analysing how these distances change in the different crisis periods we carry out a hierarchical cluster using complete linkage with the distance matrix obtained at the beginning and end of each crisis period; the dendograms are shown in the Appendix (Figures 7, 8, 9 and 10). We see that, in all cases, using a "Height" between 0.10 and 0.20, three groups can be formed that change at different moments of time. The summary of the groups is shown in Table 2. At the beginning of the sub-prime mortgage and Euro debt crises Japan was isolated from the other countries. The same situation occurred for United Kindong at the beginning of the Brexit period. At the end of the Brexit period and in the last month analysed during the COVID-19 pandemic the isolated countries were Russia and Netherlands.

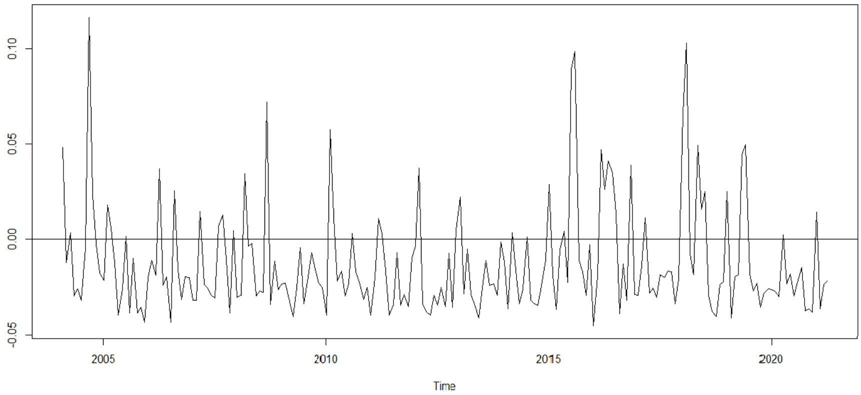


*Figure 4*. Moran's I Statistic for Spatial Dependency

In Figure 4 we show the monthly time serie of the Moran's I statistic for spatial dependency, that was defined in expression (3). This index detects greater spatial dependence throughout the crisis periods (see Table 1), that are also associated with the most similir behavior between markets acording to the GTUI.

In Figure 5 we summarise the results of the monthly Moran's I test of spatial dependence based on GTUI distances. We compare the crisis periods (in grey and framed with a thick black line) and non-crisis periods (in white). For each crisis and non-crisis period the months with significant spatial dependence at 10% level are marked in black. The same figures using WUI distances and overlapping hours criterion are shown in the Appendix (Figures 11 and 12). These figures shows that spatial dependence is more significant using the GTUI distances.

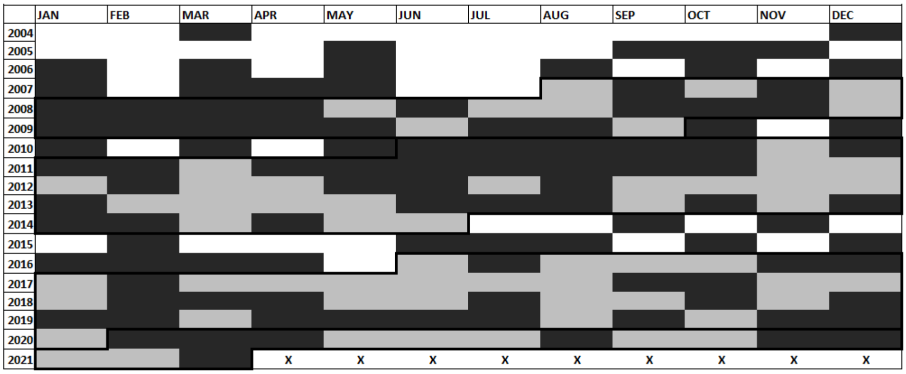


*Figure 5*. Monthly Results for Moran's I Test of Spatial Dependence with GTUI Distances. The Crisis Period is in grey, the Non-Crisis Period in White and Significant Spatial Dependence at 10% Level in Black (the Months Outside the Analyzed Period are marked with x)

Table 2
*Groups of Countries obtained with Hierarchical Cluster with Distances based on GTUI*

| | **Sub-prime** | **Euro debt** | **Brexit** | **COVID-19** |
|---|---|---|---|---|
| | **Beginning of crisis period** | | | |
| **Group 1** | HU,EG,RU,CZ SK,PE,TR | IS,BR,EG,HU ID,PK,PE,RU TR | AR,BR,CL,CZ GR,HU,IN,MY MX,PE,KR,TW TH | GR,IS,ID,RU SK,TR |
| **Group 2** | AR,AT,BE,BR CA,CL,DK,FI FR,GR,IS,ID IE,IL,IT,JP MY,MX,NL,NZ NO,PK,PL,PT RU,KR,ES,SE TW,TH | AU,AT,CA,DK FR,GB,DE,NL NZ,NO,SG,ES TW,US | EG,ID,PK,RU SK,TR | AU,CA,DK,DE NL,SE,GB,US |
| **Group 3** | AU,DE,HK,IN PH,SG,CH,UK US | AR,BE,CH,CL CZ,FI,GR,HK IN,IE,IL,IT MY,MX,PH,PL PT,SK,KR,SE CH,TH | AU,AT,BE,CA DK,FI,FR,DE HK,IS,IE,IL IT,JP,NL,NZ NO,PH,PL,PT SG,ES,SE,CH US | AR,AT,BE,BR CL,CZ,EG,FI FR,HK,HU,IN IE,IL,IT,JP MY,MX,NZ,NO PK,PE,PH,PL PT,SG,KR,ES CH,TW,TH |
| **No Group** | JP | JP | GB | |
| | **End of crisis period** | | | |
| **Group 1** | AU,IN,JP,NL US | AR,DE,EG,GR IS,MX,NL,PE PK,RU,TH | AU,BE,CA,DK FI,FR,DE,NL PH,ES,SE,CH TH,GB,US | BR,CL,CZ,EG GR,IS,ID,PE SK,TR |
| **Group 2** | AR,BE,CA,DK FI,FR,GR,HK NZ,PK,PH,SG KR,ES,SE,CH UK | AT,AU,BE,CA FI,FR,GB,NZ SE,US | AR,AT,BR,CL EG,HK,HU,IN IE,IL,IT,JP MY,MX,NZ,NO PK,PE,PL,PT | AR,ES,HU,IL IT,IE,PL,TH TW,JP,MY,KR MX,PK |
| **Group 3** | AT,BR,CL,CZ DK,EG,HU,ID IE,IL,IT,IS MY,MX,NO,PE PL,PT,RU,SK TW,TH,TR | BR,CH,CL,CZ DK,ES,HK,HU IE,IL,IN,IT JP,KR,MY,NO PH,PL,PT,SG SK,TW | CZ,GR,IS,ID SK,TR | AT,AU,BE,CA CH,DE,DK,FI FR,GB,HK,IN NO,NZ,PH,PT SE,SG,US |
| **No Group** | | | RU | NL,RU |

Based on GTUI we calculate a dynamic distance between countries using expression (2).

Using GTUI distances, in Table 3 we compare the proportions of months with spatial dependence in crisis and non-crisis periods and test if these proportions are larger for a crisis period than for a non-crisis period. The last column in Table 3 shows the p-values associated with the statistic for testing equality of the proportions in crisis and non-crisis periods against the alternative - that in a crisis period this proportion is greater than in a non-crisis period. The results shows that, taking into account all crises periods, spatial dependence tends to increase (p-value=0.08). The sub-prime is the crisis period with the most spatial dependence, i.e., in these periods there was more contagion between markets and, therefore, the systemic risk increases.

Table 3
*Frequencies and Proportion of Month with Spatial Dependence and p-values Associated with the Test of Equality of Proportion against Greater Proportion in Crisis Periods*

| | **Frequency** | **Proportion** | **p-value** |
|---|---|---|---|
| **Sub-prime** | 17 | 0.65 | 0.03 |
| **Euro debt** | 28 | 0.57 | 0.09 |
| **Brexit** | 21 | 0.48 | 0.37 |
| **COVID-19** | 7 | 0.50 | 0.35 |
| **Total crisis** | 73 | 0.55 | 0.08 |
| **Total non-crisis** | 33 | 0.45 | |

## 4. Conclusions

We have shown that our proposed Google Trend Uncertainty Index is a good indicator of financial instability. Periods with higher values of GTUI are associated with financial crisis periods and with higher losses. Dynamic distances based on GTUI allow us to improve the statistical significance of the Moran's I statistic for testing spatial dependence. We observe how events related to systemic risk increase the global spatial dependence between the analysed 46 stock markets, i.e. the dependence is stronger between stock markets with similar GTUI than between markets with different GTUI and, furthermore, this dependence increases in crisis periods when the values of the GTUI are higher. This behaviour cannot be detected with the WUI based distances neither with hours overlapping criterion.

## Appendix

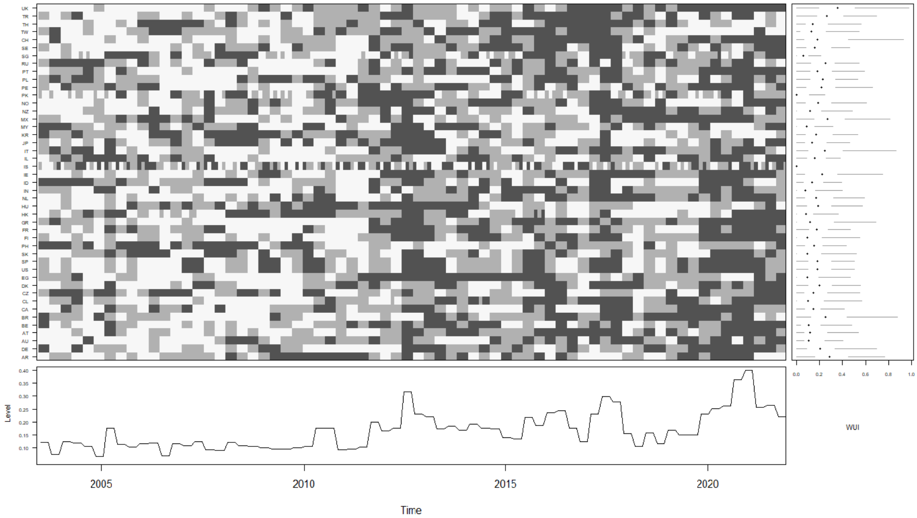


*Figure 6*. Values of the World Uncertainty Index (at top) - the Darker the Shading, the Higher the Value - and Plot of the Mean Index (at bottom). The Box-Plots of the WUI for each Country are shown on the Right

Table 4
*Data Filtering ARMA-GARCH Models*

| Country | Label | Index | Model |
|---|---|---|---|
| ***Argentina*** | AR | MERVAL | *ARMA(0,0)-GARCH(1,1)* |
| ***Australia*** | AU | S&P-ASX200 | *ARMA(0,0)-GARCH(1,1)* |
| ***Austria*** | AT | ATX | *ARMA(1,0)-GARCH(0,0)* |
| ***Belgium*** | BE | BEL20 | *ARMA(1,0)-GARCH(0,0)* |
| ***Brazil*** | BR | BOVESPA | *ARMA(0,0)-GARCH(0,0)* |
| ***Canada*** | CA | S&PTSX | *ARMA(0,0)-GARCH(1,1)* |
| ***Chile*** | CL | IPSA | *ARMA(0,0)-GARCH(1,1)* |
| ***CzechRep*** | CZ | PX | *ARMA(1,0)-GARCH(0,0)* |
| ***Denmark*** | DK | OMX | *ARMA(1,0)-GARCH(0,0)* |
| ***Egypt*** | EG | EGX30 | *ARMA(1,0)-GARCH(0,0)* |
| ***Finland*** | FI | OMXH25 | *ARMA(1,0)-GARCH(0,0)* |
| ***France*** | FR | CAC40 | *ARMA(0,0)-GARCH(1,1)* |
| ***Germany*** | DE | DAX | *ARMA(0,0)-GARCH(0,0)* |
| ***Greece*** | GR | ATH | *ARMA(1,0)-GARCH(0,0)* |
| ***HongKong*** | HK | HANGSENG | *ARMA(0,0)-GARCH(1,1)* |
| ***Hungary*** | HU | BUX | *ARMA(1,0)-GARCH(0,0)* |
| ***Iceland*** | IS | ICEX | *ARMA(1,0)-GARCH(0,0)* |
| ***India*** | IN | BSESENSEX30 | *ARMA(0,0)-GARCH(1,1)* |
| ***Indonesia*** | ID | IDX | *ARMA(1,0)-GARCH(0,0)* |
| ***Ireland*** | IE | ISEQ20 | *ARMA(1,0)-GARCH(0,0)* |
| ***Israel*** | IL | TA35 | *ARMA(0,0)-GARCH(1,1)* |
| ***Italy*** | IT | FTSEMIB | *ARMA(0,0)-GARCH(0,0)* |
| ***Japan*** | JP | NIKKEI225 | *ARMA(0,0)-GARCH(1,1)* |
| ***Malaysia*** | MY | KLCI | *ARMA(0,0)-GARCH(0,0)* |
| ***Mexico*** | MX | IPC | *ARMA(0,0)-GARCH(0,0)* |
| ***Netherlands*** | NL | AEX | *ARMA(0,0)-GARCH(1,1)* |
| ***New Zealand*** | NZ | S&PNZX10 | *ARMA(0,0)-GARCH(0,0)* |
| ***Norway*** | NO | OSEAX | *ARMA(1,0)-GARCH(0,0)* |
| ***Pakistan*** | PK | KARACHI100 | *ARMA(0,0)-GARCH(0,0)* |
| ***Peru*** | PE | IGBVL | *ARMA(1,0)-GARCH(0,0)* |
| ***Philippines*** | PH | PSEI | *ARMA(0,0)-GARCH(0,0)* |
| ***Poland*** | PL | WIG20 | *ARMA(0,0)-GARCH(1,1)* |
| ***Portugal*** | PT | PSI20 | *ARMA(1,0)-GARCH(0,0)* |
| ***Russia*** | RU | RTSI | *ARMA(1,0)-GARCH(0,0)* |
| ***Singapore*** | SG | STI | *ARMA(0,0)-GARCH(0,0)* |
| ***Slovakia*** | SK | SAX | *ARMA(1,0)-GARCH(0,0)* |
| ***SouthKorea*** | KR | KOSPI200 | *ARMA(0,0)-GARCH(0.0)* |
| ***Spain*** | SP | IBEX35 | *ARMA(0,0)-GARCH(0,0)* |
| ***Sweden*** | SE | OMXS30 | *ARMA(0,0)-GARCH(0,0)* |
| ***Switzerland*** | CH | SMI | *ARMA(0,0)-GARCH(1,1)* |
| ***Taiwan*** | TW | TWII | *ARMA(1,0)-GARCH(0,0)* |
| ***Thailand*** | TH | SET | *ARMA(1,0)-GARCH(0,0)* |
| ***Turkey*** | TR | BIST100 | *ARMA(0,0)-GARCH(0,0)* |
| ***UK*** | UK | FTSE100 | *ARMA(0,0)-GARCH(1,1)* |
| ***USA*** | US | DOWJONES | *ARMA(0,0)-GARCH(1,1)* |
| ***USA*** | US | S&P500 | *ARMA(0,0)-GARCH(1,1)* |

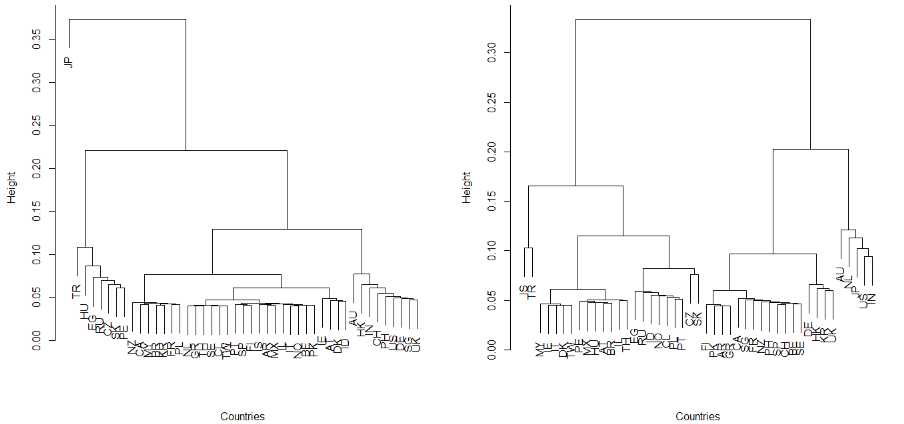


*Figure 7*. Dendogram at Beginning of Sub-Prime Mortgage Crisis(Left) and End of Sub-Prime Mortgage Crisis (Right)

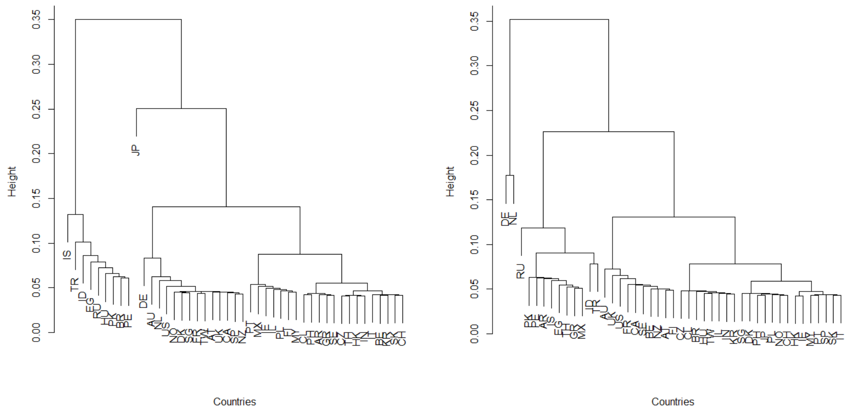


*Figure 8*. Dendogram at Beginning of Euro Debt (Left) and End of Euro Debt (Right)

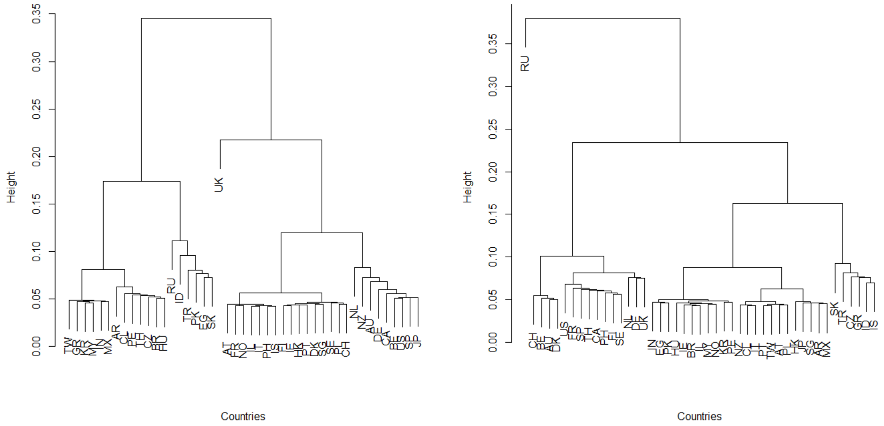


*Figure 9*. Dendogram at Beginning of Brexit (Left) and End of Brexit (Right)

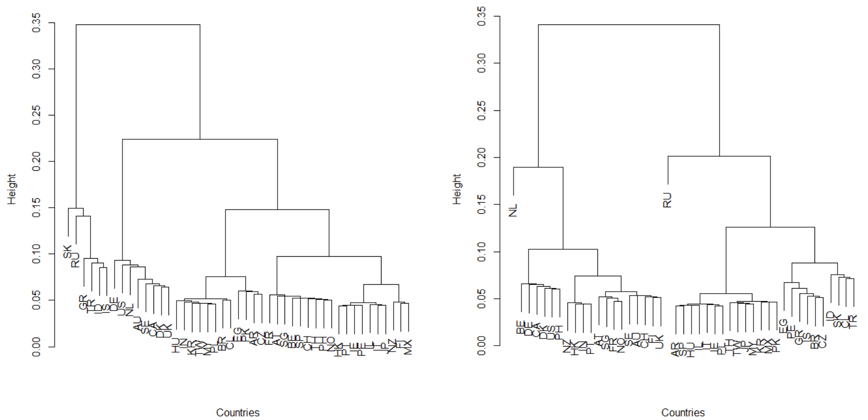


*Figure 10.* Dendogram at Beginning of COVID-19 (Left) and End of COVID-19 (Right)

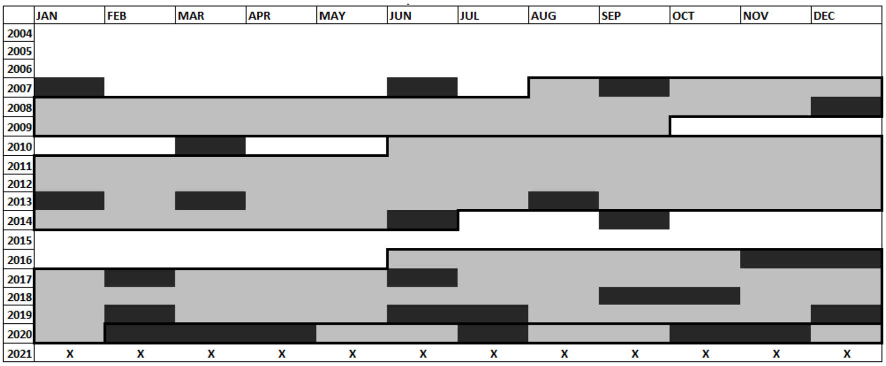


*Figure 11*. Monthly Results for Moran's I Test of Spatial Dependence with WUI Distance. The Crisis Period is in Grey, the Non-Crisis Period in White and Significant Spatial Dependence at 10% Level in Black (the Months Outside the Analyzed Period are marked with x)

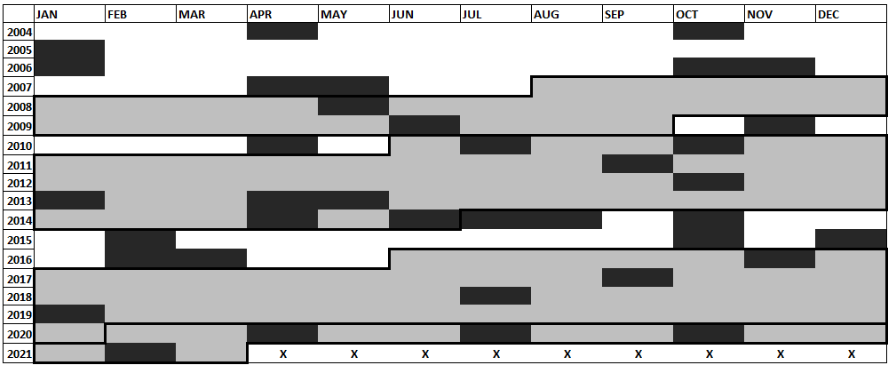


*Figure 12*. Monthly Results for Moran's I Test of Spatial Dependence with Hours Overlapping Criterion. The Crisis Period is in Grey, the Non-Crisis Period in White and Significant Spatial Dependence at 10% Level in Black (the Months Outside the Analyzed Period are marked with x)

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