CONTAGION EFFECTS ON FINANCIAL MARKETS RISK

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Abstract
Financial contagion represents a very controversial concept in international finance being one of the most frequently referenced subjects and yet least understood. The literature highlights that shocks and crises can spillover from a country to others through various channels. Although it is hard to determine exactly the cause and channel that lead to the transmission of the initial shock, it is more than clear that these events are encouraged when economies are integrated or in the process of global integration. The core of this study is to capture evidence of financial contagion based on a sample of daily closing prices from 17 different market indices, for the period January 1st, 2007 – October 15th, 2021. We employed the shortfall method for estimating the risk and we built a model within the framework of Bayesian Neural Networks (BNN). Given the results, evidence of contagion was sensed between some of the 17 markets within the sample, however the causality between them differed from the full sample period to the sub-samples periods. Nevertheless, we found that for the sub-sample corresponding to January 1st, 2020 – October 15th, 2021, period that encompasses the global exogenous shock triggered by the COVID-19 pandemic that appeared in Romania at the beginning of 2020, the relationships between global markets were decoupled, contagion being sensed mostly regionally, at the level of the European countries.

Keywords
financial contagion, spillovers, financial markets, pandemic crisis.

JEL Classification
F15, F62, C11, G15, G18

Introduction

Financial contagion represents a phenomenon massively debated in international finance especially since the Asian crisis from 1997. Based on the events from 2007 – 2008, when the US financial crisis hit all around the globe, the concept of financial contagion became of great interest for examination and interpretation. The transmission

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channels and the factors that generate the transmission of financial contagion seem to be at least as powerful nowadays as they were back in the 1990s crises. Since the 1980s, crises were faster and faster transmitted from one country to others in spite of their economic structure, amplitude, location, and other differences compared to the crisis' originating country. Considering that crises move from one country to another, this process seemed to be very similar to the transmission of a disease and in this regard, this phenomenon was called financial contagion. However, the concept of financial contagion does not encompass all the international crises; in other words, not all crises that transfer from one country to another are subject to contagion. The transmission of crises might be caused by various factors such as strong fundamental linkages (financial, real, political linkages, etc.) between certain countries – these causes of transmission are not considered evidence of contagion. Kuusk (2012) considered that the concept of financial contagion is so complex that it can not be associated with only one definition.

The aim of the paper is to analyse the transmission of risk and to capture evidence of contagion during a full sample period, from January 1st, 2007, until October 15th, 2021, that was further split in four sub-sample periods. In this concern, we considered a dataset of 17 market indices, we computed the logarithm of the closing prices, we estimated the risk through the shortfall method and we performed a model within the framework of Bayesian Networks by running the two score-based structure learning algorithms, Hill-Climbing and Tabu Search, at two different significance thresholds, 0.85 and 0.95. Further we applied the Bayesian factor in order to discriminate between the two algorithms and to determine which results are more plausible. This analysis was performed separately for the full sample period and for each sub-sample period.

The paper is organised as follows. The first section presents the distinction between contagion, interdependence and spillovers, the various definitions upon the concept and also our own interpretation for financial contagion. The second section describes the research methodology, the reasons behind it and the data we used in our study. The third section describes the empirical results. The fourth section presents the main results and comments.

1. Financial contagion – conceptual issues

Financial contagion represents a very controversial concept in international finance being one of the most frequently referenced subject and yet least understood. There is a plethora of interpretations and descriptions of financial contagion and finding a couple of scholars that agree on a certain definition is quite impossible. This happens because a wide range of papers started through "our definition is" which represents no more no less than a virtual apology inducing "sorry if you disagree". This approach can be justified because scholars test and look at contagion from different angles while the only general definition that could satisfy all of them is actually very ambiguous: "contagion is given by the shocks propagation between markets, while the transmission of risk is not explained by fundamentals" (Rigobon, 2002). This definition is raising more questions rather than clarifying the concept, for instance: what it means "in excess", what fundamentals are relevant, what kind of shocks are leading to contagion, what markets are rather to be impacted, and the list of questions can continue.

After the 1997 Asian crisis when the importance of the phenomenon called contagion grew up significantly, other concepts such as spillover and interdependence appeared. In order to be able to understand what contagion is, one needs to understand first of all what these concepts represent; so this is exactly what this section is meant for, to clearly describe and define the concepts of contagion, spillover and interdependence.

By starting from the general sense of the word, interdependence refers to "the fact of depending on each other". In this sense, in the field of economics and finance interdependence on financial markets refers to a significant level of correlation between two or more international markets which actually means a significant level of dependency between financial markets. Interdependence was analysed by various scholars such as Asgharian and Bengtsson (2006), Asgharian and Nossman (2011), Liu (2012), who argued that this phenomenon can occur as "cross-border spillover of extreme shocks" due to the real or trade linkages between countries. Other authors considered that interdependence is not only about trade linkages and spillovers. For instance, Edwards and Susmel (2003) and Larsson (2007) analysed to what extent the relationship between the factors that can increase the volatility of different financial assets is relevant. Forbes and Chinn (2004) and Wälti (2011) drew their analysis upon interdependence by considering as explanatory variables the level of economic and monetary integration. From a broader perspective, as Beirne and Gieck (2012) argued, interdependence could be described as the linkage between the assets classes (stocks, bonds and currency) on average, on a certain period of time.

Besides the phenomenon of interdependence, Shinagawa (2014) argued that the changes in policies, as well as the shocks in one market, have a certain level of impact in other markets; this impact represents the so-called financial market spillovers. Spillovers have been assessed in the specific literature from different viewpoints by taking into account different variables and various samples of data. Scholars who analysed this concept were Forbes and Rigobon (2002), Bunda et al. (2010), Didier et al. (2010), Forbes (2012) and so on. Shinagawa (2014) also analysed this concept and considered that spillovers are transmitted through four different channels, namely: the bilateral portfolio investment, bilateral trade, home bias and country concentration.

The concept of contagion can be found in various domains but its clearest sense exists in medicine. From an epidemiologic and biologic viewpoint, contagion means the transmission of a virus or a disease from one individual/organism to others by contact. In other words, in order to be infected with a virus, an individual/organism needs to contact another individual/organism that is already carrying the virus. Based on its epidemiological sense, in the field of economics and finance contagion refers to "the fact of economic problems on one country, region, etc. spreading to another". According to Pericoli and Sbracia (2003, p. 9-11), the most common and used definitions for the concept of financial contagion in the specific literature are:

- "Contagion represents a relevant increased likelihood of a crisis to occur in a country, conditional on a crisis that occurred in another country."
- "Contagion happens at the moment when asset prices volatility spillovers from the country where the crisis originates, to other countries."
- "It can be considered contagion when the asset prices comovements between certain countries are not caused by fundamentals."
- "Contagion represents a relevant increase in prices and quantities comovements between markets, conditional on a crisis happening in one country."
- "Shift contagion happens when the channel of transmission of shocks becomes stronger."

By looking at the definitions mentioned above we can see that they start from a general, ambiguous framework to a narrower one. At the same time, as we can see from the description of the three concepts, the distinction between them is very soft and thin. As Rigobon (2019) argued, the definition of each of the concepts changes along with the model used for analyses because they all are "model- and belief-dependent".

In order to classify the large list of definitions and interpretations, Rigobon (2002) drew up their taxonomy. He considered that definitions of financial contagion can be split in two categories, namely: (1) the definitions that refer to this phenomenon as being an increase in the speed of transmission of shocks and (2) the definitions that refer to the type of transmission channels for shocks. The supporters of the second category are the ones who put the accent on the type of propagation mechanism and on how much of the shock is transmitted through the specific transmission channels. According to the literature, contagion is considered to be the proportion of a shock which is transmitted through any transmission channel other than the trading one.

In order to reach a narrower description of the phenomenon known as financial contagion, one needs to closely look at the past literature for better seeing to what definitions did the contagion models conduct. Rigobon (2002) stated that "a lot of people consider that whenever an emerging country sneezes, the other developing markets around the world are most probably going to suffer from acute pneumonia". Actually, based on the previous crises, it does not necessarily matter how good or balanced fiscal/external accounts countries might have, to some extent they would all be impacted by a global shock. Rigobon (2002) drew up a simple description of the concept by splitting it in two different categories, namely pure and shift contagion. Pure contagion can be defined by the propagation of shocks from one market to others through any transmission channel except the trading or real ones, while shift contagion can be described by an increase in the shocks propagation mechanism.

Based on the wide literature on the concept of contagion we can remark that there are different opinions upon what it truly represents. In this sense, we intend to give our own opinion on the concept and stick to this definition in building our model. The various models in past literature proved that risk exists as long as countries and markets are interconnected. Starting from this point and from the idea that markets are always interrelated, not just in periods of bubbles and crises, we can consider that contagion is a continuous process. For instance, if we consider the real channel of shocks transmission, more precisely the trading linkages, disruptions exist all the time in both business as usual periods and turmoil periods.

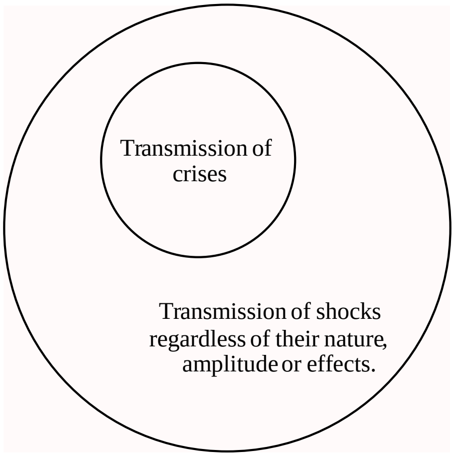


Figure no. 1: The narrow and broad senses of contagion

By synthetizing the vast literature, we can extract a broad sense of contagion and a narrow one as depicted in figure no. 1. We can see that the narrow sense stands in the idea that contagion represents the transmission of crises, meaning that it can only be available during periods of financial turmoil. The broad sense is more general and it stands in the idea that contagion represents the transmission of shocks regardless of their endogenous or exogenous nature, their amplitude and effects.

Continuously in our paper we are going to approach the broad sense of contagion. In this regard, we consider that contagion is a continuous process that exists in both business as usual periods and turmoil periods. At the same time, we consider that financial contagion is present not only between different markets, but also inter-market, from a different segment to another.

2. Research methodology

The core of our study is to find how risk and shocks were transmitted from one market to others at a global level and to capture evidence of contagion on a large sample period, January 1st, 2007 – October 15th, 2021, and in four different sub-sample periods, namely January 1st, 2007 – December 30th, 2009; January 1st, 2010 – December 30th, 2015, January 1st, 2016 – December 30th, 2019; and January 1st, 2020 – October 15th, 2021. In order to approach this issue, we built a sample of 17 countries from all over the globe and we implied the closing prices of stocks on a daily basis. The indices that were used are global market indices and the data we used in the analysis is public and was taken from Yahoo Finance (https://finance.yahoo.com/). In order to estimate the risk for all the four sub-sample periods and for the full sample period, we implied the expected shortfall method. Based on the samples and databases, we built our model by using Bayesian Networks. We decided to use this model because it is a probabilistic one and gives us the possibility to analyse and represent uncertainty and risk. Moreover, the Bayesian Networks models conditional dependence further generating the causation and the direct or indirect relationships between the exogenous and endogenous variables, and it allows us to see how risk can spread from one market to others considering that, after all, this is what contagion is about.

By taking a deeper look in the literature, it can be noticed that the Neural Networks method can be used for studying various forms of contagion at the market level, the banking sector and so on. Recently, it has been a spread of using this method in finding evidence of contagion, for instance Paltalidis et. al. (2015) used Neural Networks to analyse systemic risk and the propagation of contagion in the banking system within the Eurozone. On the same path, Ouyang et. al. (2020) measured systemic risk and the propagation of contagion in the Chinese banking industry. Li et. al. (2019) intended to distinguish between systematic and idiosyncratic contagion by employing the network-based method and by analysing Chinese financial institutions. Xiaofeng and Zhe (2008) used the Fuzzy Neural Networks to analyse financial contagion and to capture dynamical interdependence within the stock markets of Hong Kong, China and the USA. Ahelegbey, Giudici and Hashem (2021) used the Network VAR models in order to measure contagion arising from financial markets and the banking system. Among other scholars, Guidolin et al. (2017) also used the method to analyse the cross-asset mechanisms of contagion, Chong and Klüppelberg (2018) argued how the Bayesian Networks method can be used in order to identify financial contagion channels, Herculano (2018) used the same method in order to examine the relevance of financial contagion in the US banking system, and Zhang and Zhuang (2021) also used this method to analyse the spread of herd behavior between a sample of markets.

In what regards the method that we chose for the estimation of risk, we decided to use the expected shortfall method (ES) for each single sample period rather than the standard value at risk method (VaR). This happened due to the fact that the ES implies a certain property that generates more robust results. According to Acerbi and Tasche (2002), a risk measure should imply four important properties in order to be coherent, namely monotonicity (meaning in case a portfolio generates a certain return which is higher than another's regardless the market, it implies a lower level of risk), translation invariance (meaning in case a certain amount of money is added to a portfolio, the risk associated to that specific portfolio is decreased by that amount), homogeneity (it refers to maintaining the weights; in case the size of a portfolio increases with a certain factor, the risk is going to be multiplied by the same particular factor) and subadditivity (meaning the risk level of two merged portfolios has to be lower than the sum of their individual risk). In this regard, when distinguishing between the VaR and ES methods it is important to take into account that the subadditivity property can only be reached by the ES method.

In our particular case for analysing contagion, the decision to estimate risk through the ES method is based on the subadditivity property that it fulfils. In analysing contagion, it is important to take into account that we actually analyse a sample of more than one market where assets from different markets are merged, and that we look at the general risk, not at the individual risk implied by each single asset.

In order to understand our model, first of all it is important to understand the methodology behind it, namely what it means a Bayesian Networks model and how it works. In this regard, we will further detail in this section the probabilistic model known as Bayesian Networks.

From a methodological point of view, the Bayesian Networks model is based on the mathematical theorem of Bayes, also known as Bayes' Rule, that is normally used to determine the conditional probability of certain events based on relevant historical knowledge. This theorem is considered to be the basis of the inference approach that was further called Bayes' inference. In this regard, from a Bayesian viewpoint the Bayesian Networks model is meant to extend the standard networks models that use the bootstrapping approach to quantify uncertainty, approach that is known as posterior inference (Rao, 2014). Given its employability, this theorem is used in different fields, especially medicine and finance, where it is used to model risk and to forecast the probability of certain outcomes.

The Bayesian Networks model stands in the categorisation of joint probability distributions of random variables over finite sets. As Nguyen (2013) stated, the Bayesian Networks is one of the most used models in machine learning, diagnosis and data mining. Its notoriety comes from the fact that the Bayesian Networks model implies a strong evidence-based interference which is somehow related to human intuition. According to Rao (2014), Bayesian Networks represent a model that illustrates the interrelationships between certain random variables in the form of conditional distributions. In this type of model, the random variables generate different values any time they are accessed; this process is known as sampling. This is possible because the variables have different statistical properties that change over time and the generated values depend on the probability distribution associated to the random variable. In this regard, the only information and knowledge we have upon the variables' behavior is given by historical data. In Bayesian Networks the variables are given by the so-called nodes, while the arcs between the nodes represent the linkages, more precisely the conditional dependencies or independencies between the variables. In this regard, the model appears in the form of a Directed Acyclic Graph (DAG), where the nodes and arcs depict the structure of the conditional distributions.

Starting from the Bayes' Theorem, the Bayesian Networks models came to life. Pearl (1988) considered that Bayesian Networks are graphical models that can be defined through a finite set of random variables, for instance $X = \{X_1,...,X_N\}$, that describe certain entities which are associated to the nodes of the DAGs. Scutari (2007) considered that Bayesian Networks can be defined from two perspectives, namely (1) a network structure described through a DAG where each node $v \in V$ is corresponding to a random variable X_i and (2) a "global" probability distribution X with parameters

θ that can be split in various "local" probability distributions with their own parameter set $(\theta_{X_1},...,\theta_{X_N})$, based on the arcs generated in the DAG. The scope of the network structure is to identify and visually represent the relationships of conditional independence between the variables used in the model by factorizing the global distribution through graphical separation. It is important to mention that the union of the parameters of each single "local" probability distribution needs to be smaller than the parameter $\theta(\cup\theta_{X_1} < \theta)$, because a significant amount of parameters are fixed due to the fact that the variables they correspond to are independent.

$$P(X) = \prod_{i=1}^{N} P(X_i \mid \prod{}_{X_i}) \qquad (1)$$

where:

$$\prod{}_{X_i} = \{parents\ of\ X_i\}$$

In our analysis where we intended to capture evidence of contagion between various international markets, we decided to use the Discrete Bayesian Networks (BNs). This approach fitted best the scope of our analysis because we used discrete data, not continuous data, where the nodes were multinomial random variables. At the same time, the analysis was a purely data-driven process, meaning that we let the data talk by itself. According to Heckerman et al. (1995), Discrete Bayesian Networks (BNs) imply that both X and X_i are multinomial random variables. At the same time, the parameters of the "local" distributions are the conditional probabilities of X_i taking into account the configuration of its parents' values. The values of the parents of X_i are normally displayed as a conditional probability table of each single random variable. The "local" probability distributions are given by the following formula:

$$X_i \mid \prod{}_{X_i} \approx Mul(\pi_{ik|j}) \qquad (2)$$

where:

$$\pi_{ik|j} = P(X_i = k \mid \prod{}_{X_i} = j)$$

The analyses in the framework of Bayesian Networks provide various tools for different data analysis aspects. For instance, as Schad et al. (2021) considered, one important feature of Bayesian analysis is given by the fact that it allows to quantify based on probabilistic ways, the data evidence generated through distinct models. In this way, through Bayesian analyses, more precisely through the so-called Bayes factors, it can be established what model is more plausible and reliable compared to another one. The Bayes factors can be implemented and used in order to quantify the evidence in favour of one model compared to another. In literature this issue was analysed by various scholars, such as Jeffreys (1939) who was the first to establish the thresholds for interpreting the results generated through Bayes factors, Kass and Raftery (1995), Gronau et al. (2017), Schönbrodt and Wagenmakers (2018) and so on. Schad et al. (2021) considered that the Bayes factor represents a measure of relative evidence and implies the comparison of the predictive performance of one model over another. The Bayes factor can be expressed as the ratio of marginal likelihoods for the conditional joint probability distributions:

$$BF_{AB} = \frac{P(x \mid M_A)}{P(x \mid M_B)} \quad (3)$$

where:

BF_{AB}, indicates whether data on M_A is more probable over the data on M_B.

In this regard, based on Schad et al. (2021), the results can be interpreted based on the thresholds established in the literature:

- if the value of the Bayesian factor is higher than +80 (+100), the first method (M_A) is more plausible than the other;
- if the value of the Bayesian factor is smaller than -80 (-100), the second method (M_B) is more plausible than the other;
- if the value of the Bayesian factor is "close" to 0, meaning the values are in-between the above mentioned predetermined thresholds, the data evidence of the two algorithms is inconclusive.

Data

We proposed through this study to analyse and to represent the transmission of risk and to look for evidence of contagion during a full sample period and four sub-sample periods that encompass the global financial crisis from 2007-2009 (January 1st, 2007 – December 30th, 2009), the post-crisis period (January 1st, 2010 – December 30th, 2015), the tranquil period (January 1st, 2016 – December 30th, 2019) and the pandemic crisis that started in 2020 (January 1st, 2020 – October 15th, 2021), triggered by the appearance of the COVID-19 (coronavirus). We intended to draw a comparison between the results in order to apprehend the transmission of shocks; however, we did not have a specific and clear theory. In this regard, we opened a theoretical discussion apart from the empirics but based on the empirical results, and we built an auto-realizing anticipation. Our contribution is detailed in the following steps. The first step in building our model was to set up the database. We took public data from Yahoo Finance, namely the daily closing prices for the full sample and sub-sample periods for 17 global market indices: S&P 500, DAX Performance-Index, FTSE 100, Nikkei 225, IBOVESPA, MERVAL, Hang Seng Index, Straits Times Index, CAC 40, BEL 20, IBEX 35, FTSE MIB Index, SMI PR, S&P/ASX 200, G&P/TSX Composite Index, S&P/NZX 50 Index Gross and FTSE Bursa Malaysia KLCI.

For setting up the database, we performed our analysis by computing the logarithm of the daily closing prices and by estimating the risk based on the expected shortfall method separately for each single sample period. The database was ready after synchronizing the results by cutting the non-available information; we further obtained 2707 observations for the full sample, 570 observations for the first sub-sample (2007-2009), 1066 observations for the second sub-sample (2010-2015), 741 observations for the third sub-sample (2016-2019) and 319 observations for the last sub-sample (2020-2021). After obtaining synchronized series, we performed the Bayesian Networks model (BNN). We further applied the bootstrapping procedure for the two BNN score-based structure learning algorithms, namely the Hill Climbing and the Tabu Search (Scutari, 2019), for which we employed two significance thresholds, 0.85 and 0.95. We performed this analysis separately for the full sample period and for each sub-samples.

3. Empirical results

The key for understanding the model stands in the generated directed acyclic graphs (DAGs). We applied the Bayesian Networks model for the 17 global market indices that were mentioned earlier and we found that the markets were correlated in the full sample period (January 1st, 2007 – October 15th, 2021), and in each single sub-sample periods (as depicted in figures no. 2-11). However, at this point we did not take into account the bootstrap for either of the BNN two algorithms. In this case, we cannot visualise the propagation sense and the strongest potential linkages between the indices (in other words, the causality), because it is the bootstrap procedure that generates the DAGs that depict the strongest relationships.

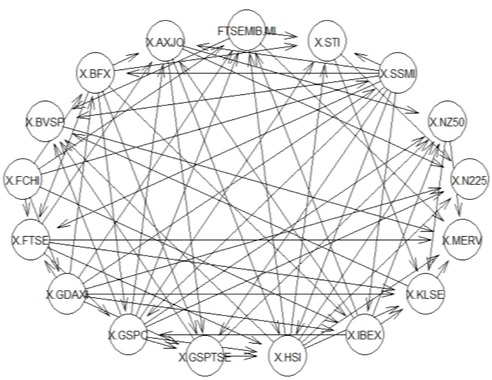


Figure no. 2: Score-Based Learning Algorithms Hill-Climbing for 2007-2021

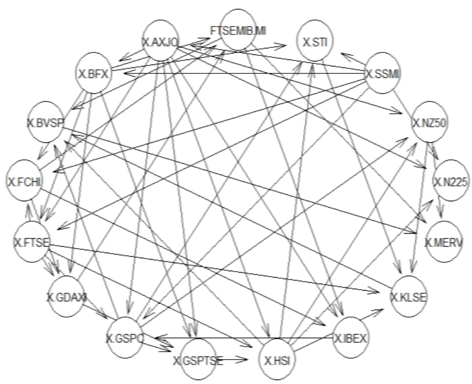


Figure no. 3: Score-Based Learning Algorithms Tabu-Search for 2007-2021

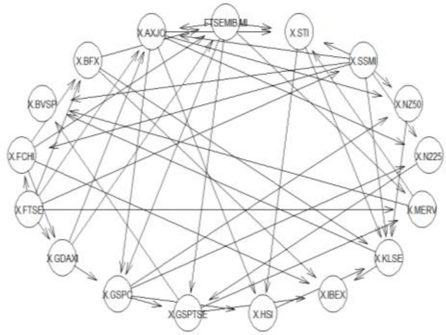


Figure no. 4: Score-Based Learning Algorithms Hill-Climbing for 2007-2009

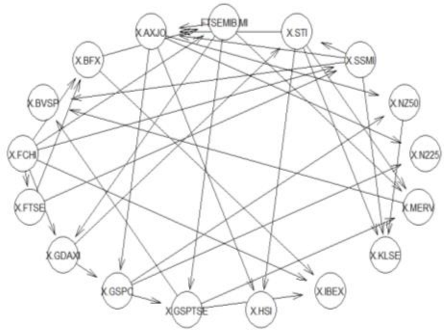


Figure no. 5: Score-Based Learning Algorithms Tabu-Search for 2007-2009

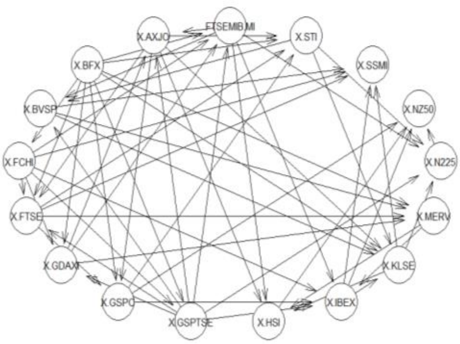


Figure no. 6: Score-Based Learning Algorithms Hill-Climbing for 2010-2015

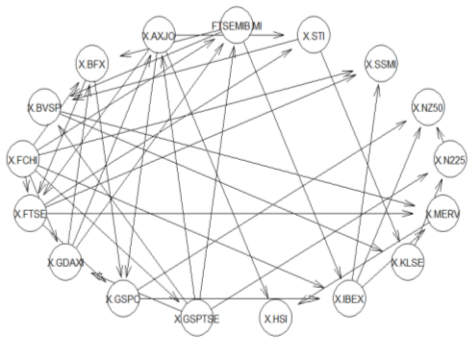
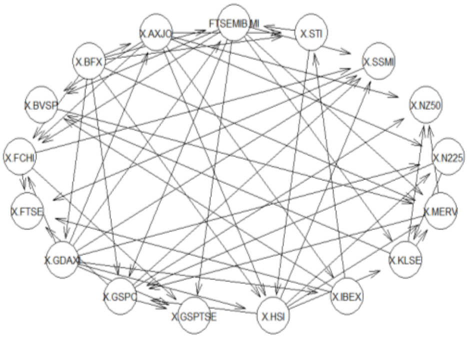


Figure no. 7: Score-Based Learning Algorithms Tabu-Search for 2010-2015



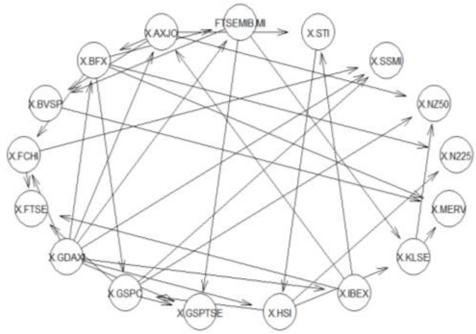
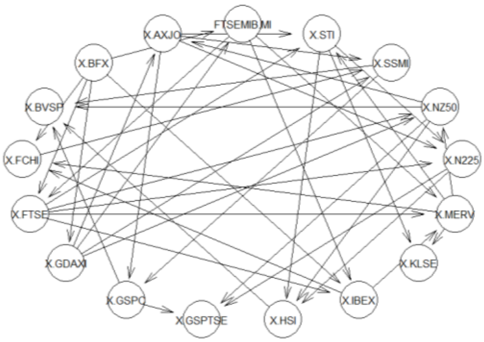


Figure no. 8: Score-Based Learning Algorithms Hill-Climbing for 2016-2019

Figure no. 9: Score-Based Learning Algorithms Tabu-Search for 2016-2019



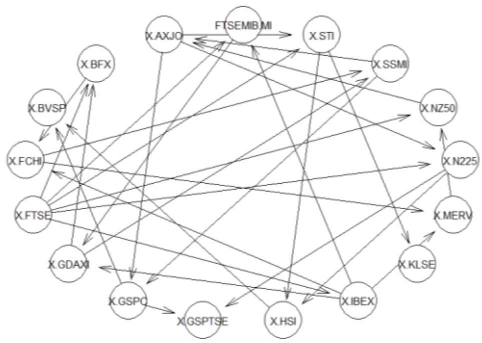


Figure no. 10: Score-Based Learning Algorithms Hill-Climbing for 2020-2021

Figure no. 11: Score-Based Learning Algorithms Tabu-Search for 2020-2021

Full sample period January 1st, 2007 – October 15th, 2021:

In order to capture evidence of contagion for the full sample period, we first needed to find the strongest relationships, namely the direct and indirect linkages, between the 17 market indices. We applied the two score-based structure learning algorithms of the Bayesian Network model, more precisely Hill Climbing and Tabu Search (Scutari, 2019), for which we applied the bootstrapping procedure at two significance thresholds, 0.85 and 0.95, for each sub-sample and for the full sample.

The first sample that we analysed was the period January 1st, 2007 – October 15th, 2021. By employing the bootstrapped Hill Climbing and Tabu Search score-based structure learning algorithms of the Bayesian Networks model at a threshold of 0.85, we obtained the DAGs from figure no. 12 and figure no. 13. As we can see from the figures, not all the 17 market indices are correlated, meaning that the shock on one market is not transmitted to all of the others at once.

Considering the causality depicted in figure no. 12 and figure no. 13, it is visible that for the significance threshold of 0.85 the causality is running from the French market index CAC 40 to all the other markets except the Brazilian Ibovespa Index. In this regard, there is evidence that risk exists and can be transmitted between markets. By taking a closer look at the figures, a shock at the level of volatility of the French market can be transferred to the other markets either directly or indirectly and two important observations can be withdrawn: (1) contagion exists between 16 markets out of a sample of 17 and (2) there are no linkages between the Brazilian market index Ibovespa and the other market indices. The Ibovespa Index is entirely independent to any global risk that threatens the other markets, even to the global shock that occurred in 2020 when the financial crisis triggered by the pandemic hit. We do not consider that Ibovespa was not impacted by the financial crisis from 2020, but based on the lack of direct or indirect linkages we can only consider that Ibovespa neither assimilated nor spread the risk to the other markets from the sample. This being noticed, there is no evidence that contagion exists between the Brazilian index and the other indices.

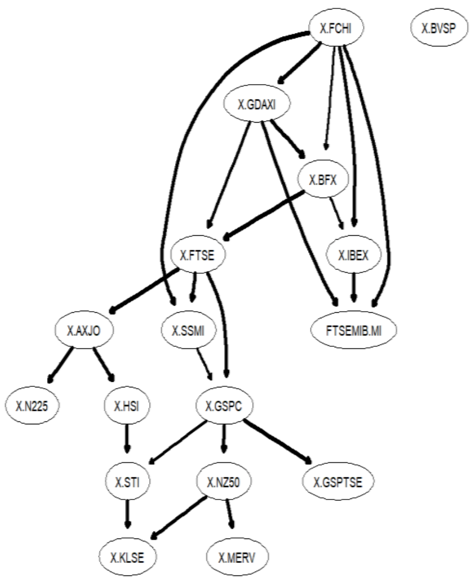


Figure no. 12: Bootstrapped Hill-Climbing; threshold=0.85, sub-sample period 2007-2021

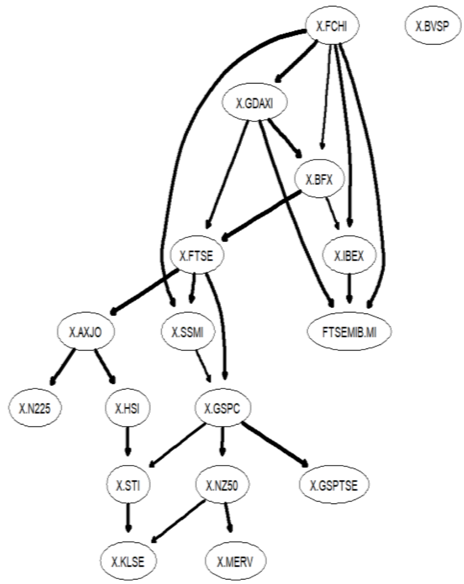


Figure no. 13: Bootstrapped Tabu Search; threshold=0.85, sub-sample period 2007-2021

By changing the threshold of 0.85 to a higher one, namely 0.95, the causality and the linkages between the 17 indices changed but not severely. As depicted in figure no. 14 and figure no. 15, the linkages between the French index and the other indices are strong, except the Ibovespa Index. The shocks are also transmitted globally from the French market CAC 40 to the other market indices except the Brazilian market Ibovespa which remains independent to any global risk.

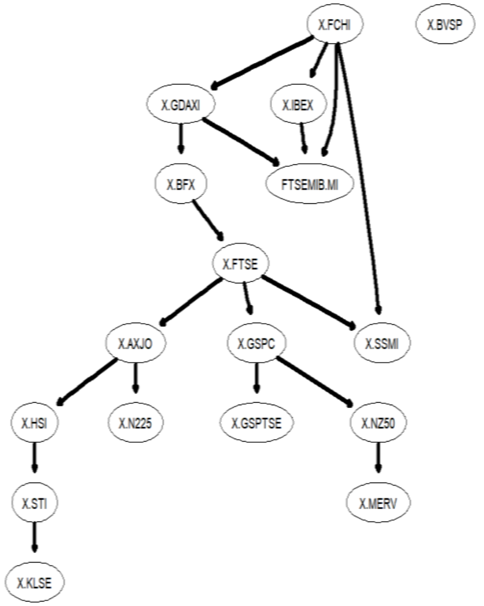


Figure no. 14: Bootstrapped Hill-Climbing; threshold=0.95, sub-sample period 2007-2021

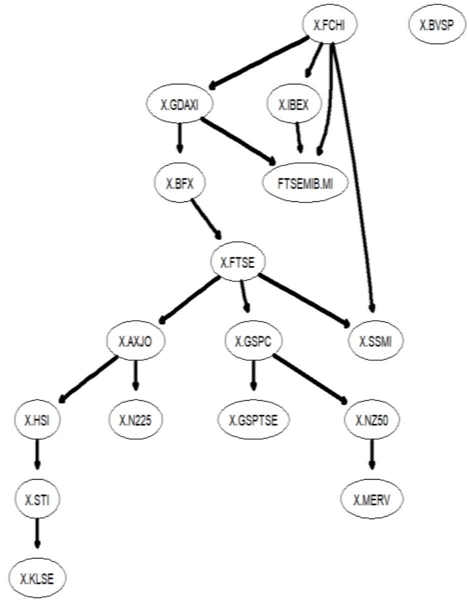


Figure no. 15: Bootstrapped Tabu Search; threshold=0.95, sub-sample period 2007-2021

After applying the two algorithms of the Bayesian Neural Networks (BNN) for two different thresholds of 0.85 and 0.95, we introduced the Bayesian factor which compares the plausibility between the results of the two algorithms. By employing the Bayesian factor, we obtained the negative value -642.5745. Based on the fact that the result is smaller than the predetermined threshold of -80 (-100), we can consider that the results obtained though the Tabu Search algorithm are more plausible than the ones obtained through the Hill-Climbing algorithm.

Sub-sample period January 1st, 2007 – December 30th, 2009:

By employing the bootstrapped Hill Climbing and Tabu Search score-based structure learning algorithms of the BNN, for the sub-sample period January 1st, 2007 – December 30th, 2009, at a threshold of 0.85 we obtained the DAGs from figure no. 16 and figure no. 17. As we can see from the figures, risk exists and is transmitted between the market indices that are correlated.

The results obtained through the Hill-Climbing algorithm at a threshold of 0.85 imply a causality running from the German market DAX, the French market CAC 40, the Australian market S&P/ASX 200 and the Swiss market SMI PR (figure no. 16). These can be considered the driving markets from where the shocks can spread to the other ones and that are immune to any shocks. In this case, we can see that a shock at the level of one of these developed global financial centres is transmitted to the other markets either directly or indirectly. At the same time, the results imply that there are no linkages between the Brazilian market index Ibovespa and the other market indices. In this case, the Brazilian market index is entirely independent to any global risk that threatens the other markets, even to the global shock that occurred in 2007. Based on the results we do not necessarily consider that the Brazilian index was not impacted by the financial crisis from 2007, we only found that there is no evidence that Ibovespa either assimilated or spread the risk to the other markets from the sample. This being noticed, there is no evidence of financial contagion among the Brazilian index and the other markets in this sub-sample period.

By comparing the bootstrapped Hill Climbing algorithm to the bootstrapped Tabu Search algorithm at a threshold level of 0.85 (figure no. 17), one important observation can be withdrawn: except Ibovespa there are two more markets that are independent to any global risk, namely the New Zealand market S&P/NZX 50 and the Malaysian market FTSE Bursa Malaysia KLCI.

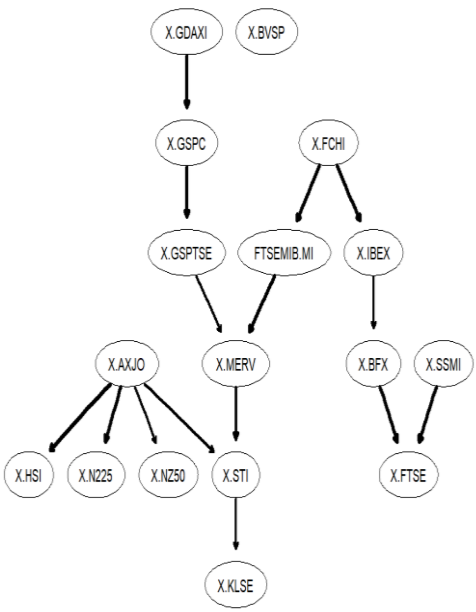


Figure no. 16: Bootstrapped Hill-Climbing; threshold=0.85, sub-sample period 2007-2009

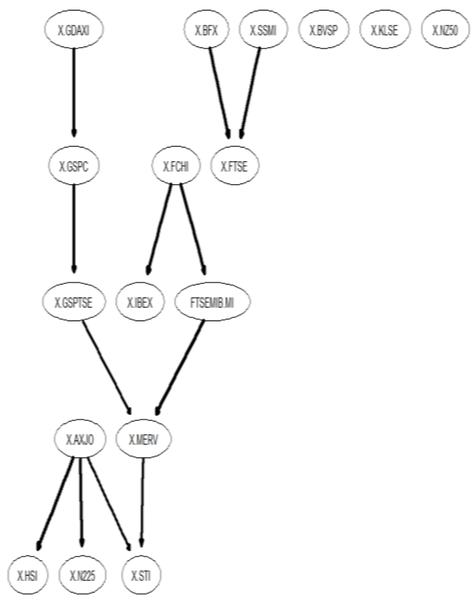


Figure no. 17: Bootstrapped Tabu Search; threshold=0.85, sub-sample period 2007-2009

When increasing the threshold of 0.85 to a higher one, namely 0.95, the causality and the linkages between the 17 indices are the same for both Hill-Climbing and Tabu Search algorithms (figure no. 18 and figure no. 19). Compared to the lower threshold, there is one more market immune to any global risk, especially to the shock from 2007, that does not imply evidence of contagion, namely the Singapore market Straits Times Index.

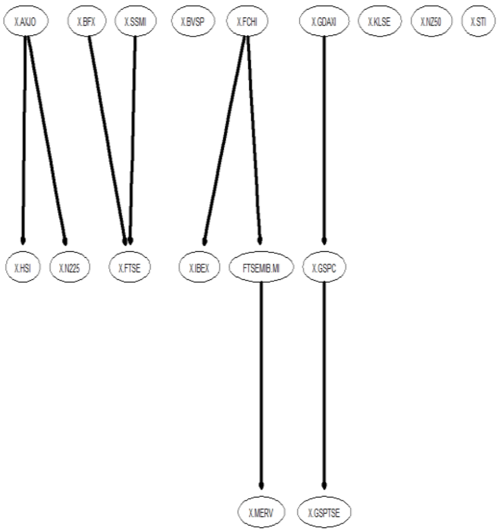


Figure no. 18: Bootstrapped Hill-Climbing; threshold=0.95, sub-sample period 2007-2009

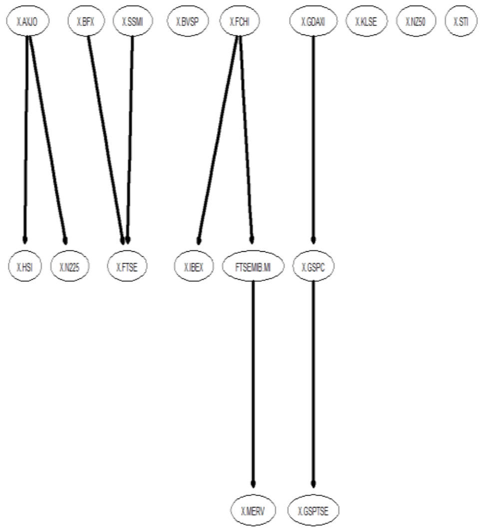


Figure no. 19: Bootstrapped Tabu Search; threshold=0.95, sub-sample period 2007-2009

By drawing a general comparison between the results obtained through the bootstrapped Hill Climbing and Tabu Search algorithms at a threshold of 0.85, the shocks are mainly running from Germany to North and South America, from France to the rest of Europe and from Australia to Asia. However, by taking into account the indirect and biunivocal linkages, we can see that the shock also runs from Europe and America to Asia. At the threshold of 0.95 the situation changes as the shocks seem to be transmitted rather regionally, more precisely in-between the European markets. The only exceptions are given by the causality running from Australia to Asian markets, from Germany to North American countries and from Italy to the Argentinian market index Merval.

By employing the Bayesian factor, we obtained the negative value -41.42338. Considering that the result is in-between the predetermined thresholds of -80 (-100) and +80 (+100), we can consider that the plausibility of the two algorithms is quite unclear.

Sub-sample period January 1st, 2010 – December 30th, 2015:

Moving forward to the next sub-sample period, January 1st, 2010 – December 30th, 2015, which is the period right after the financial crisis from 2007, we can see that the correlation linkages between markets are very different compared to the previous cases. The results obtained show that more markets became independent to any global shock, so they imply a higher degree of financial stability. In this regard, we can consider that these countries improved their prudential regulation and supervision policies after experiencing the financial crisis from 2007.

By employing the Hill-Climbing and Tabu Search algorithms at a threshold of 0.85 (figure no. 20 and figure no. 21), the causality between the markets is running in the same direction. The countries that are immune to risks and do not imply evidence of contagion are the Argentinian index Merval, the Japanese market Nikkei 225 and the New Zealand index S&P/NZX 50.

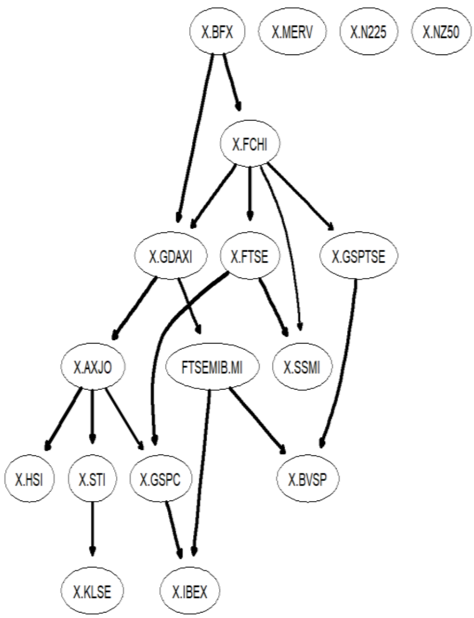


Figure no. 20: Bootstrapped Hill-Climbing; threshold=0.85, sub-sample period 2010-2015

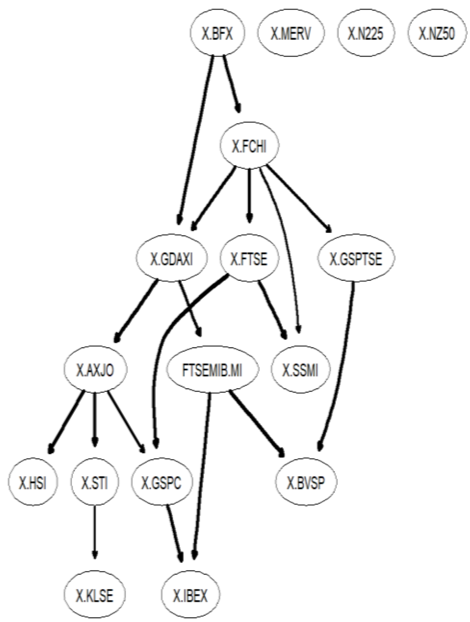


Figure no. 21: Bootstrapped Tabu Search; threshold=0.85, sub-sample period 2010-2015

In case we set a higher threshold for the two algorithms, namely 0.95, we can see that the causality is running differently. The results, as depicted in figure no. 22 and figure no. 23, imply two important observations: (1) markets are less correlated between each other's and (2) one more market becomes independent to global risks and does not imply evidence of contagion, namely the Malaysian market FTSE Bursa Malaysia KLCI.

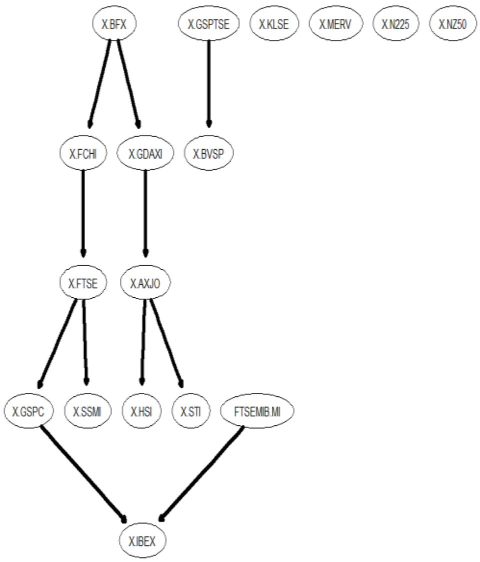


Figure no. 22: Bootstrapped Hill-Climbing; threshold=0.95, sub-sample period 2010-2015

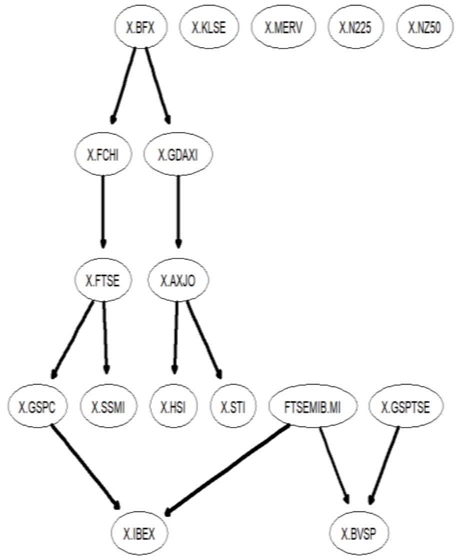


Figure no. 23: Bootstrapped Tabu Search; threshold=0.95, sub-sample period 2010-2015

By employing the Bayesian factor, we obtained the negative value -107.2726. Considering that the result is smaller than the predetermined threshold of -80 (-100), we can consider that the results obtained though the Tabu Search algorithm are more plausible than the ones obtained through the Hill-Climbing algorithm.

Sub-sample period January 1st, 2016 – December 30th, 2019:

The next sub-sample period that we analysed is January 1st, 2016 – December 30th, 2019, which is a period of tranquillity. After running the same analysis as for the previous sub-sample periods, we found that at the threshold of 0.85 both the Hill-Climbing algorithm and the Tabu Search algorithm generate the same results (figure no. 24 and figure no. 25). The results show that the markets that are independent to global shocks are the Japanese market Nikkei 225 and the New Zealand market S&P/NZX 50. We can see that these two markets neither assimilated nor spread the risk to the other markets from the sample. By looking at the results, we can see that overall, risk runs from Australia to the Asian analysed countries, from Germany to the European markets as well as to North America and Canada, and from Italy and Malaysia to the Latin America.

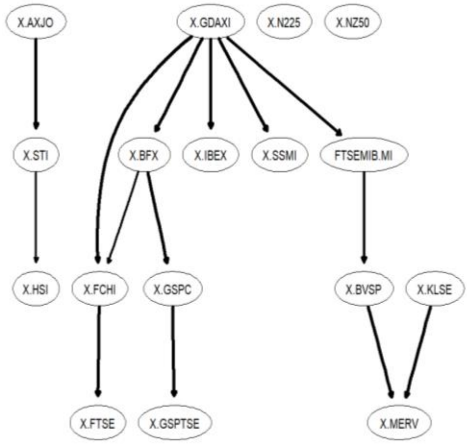


Figure no. 24: Bootstrapped Hill-Climbing; threshold=0.85, sub-sample period 2016-2019

Figure no. 25: Bootstrapped Tabu Search; threshold=0.85, sub-sample period 2016-2019

By increasing the threshold to 0.95, the results generated by the two algorithms were also identical (figure no. 26 and figure no. 27). Compared to the lower threshold, the markets that do not imply evidence of contagion are the Chinese Hang Seng Index, the Japanese Nikkei 225 Index, the Italian FTSE MIB Index and the New Zealand S&P/NZX 50 Index. For the rest of the analysed markets, the causality is running as follows:

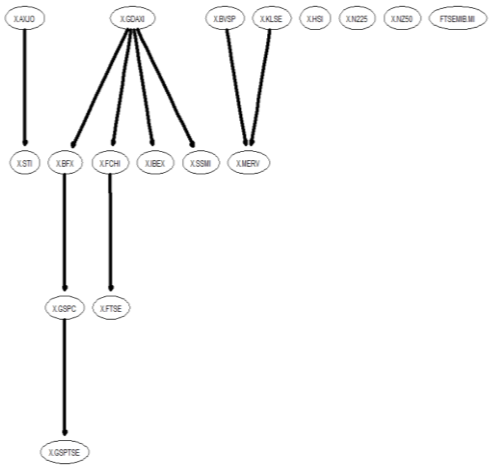


Figure no. 26: Bootstrapped Hill-Climbing; threshold=0.95, sub-sample period 2016-2019

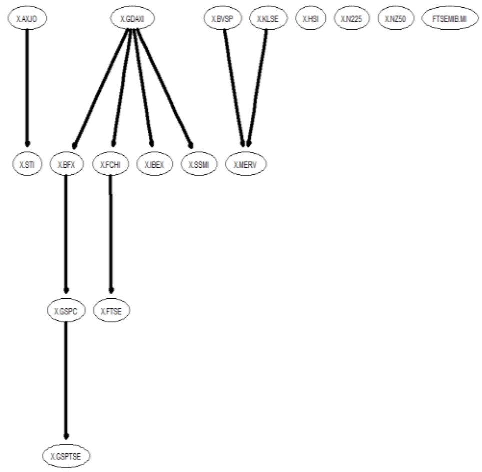


Figure no. 27: Bootstrapped Tabu Search; threshold=0.95, sub-sample period 2016-2019

By employing the Bayesian factor, we obtained the negative value -193.0622. Considering that the result is smaller than the predetermined threshold of -80 (-100), we can consider that the results obtained though the Tabu Search algorithm are more plausible than the ones obtained through the Hill-Climbing algorithm.

Sub-sample period January 1st, 2020 – October 15th, 2021:

The last sub-sample that we analysed is the period January 1st, 2020 – October 15th, 2021, when the COVID-19 pandemic occurred and caused a global turmoil. Compared to the previous financial crises, the shock triggered by the pandemic that hit the financial markets was no longer a shock of endogenous nature but rather of exogenous nature.

Based on the results obtained through the two score-based structure learning algorithms at both 0.85 and 0.95 confidence thresholds, an important observation can be withdrawn. The number of markets that are independent to the global shock triggered by the COVID-19 pandemic is quite high compared to the previous sub-sample periods; these countries are: Brazil, America, Canada, China, Argentina and Japan.

For a significance threshold of 0.85, the results obtained though the Hill-Climbing algorithm imply a causality running from the Belgian market to France and Germany, from the New Zealand market to Australia, from the English market to Spain and from the Singapore market to Malaysia (figure no. 28). The results of the Tabu Search algorithm at the same threshold imply a different causality only at the level of the

European countries. In this scenario, risk is running from the German market to all of the other European countries either in a direct or indirect manner (figure no. 29).

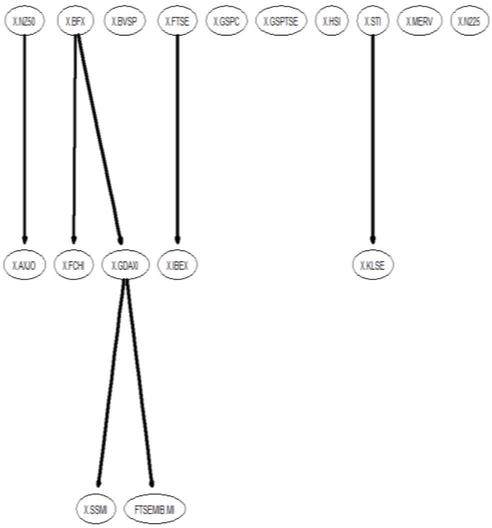


Figure no. 28: Bootstrapped Hill-Climbing; threshold=0.85, sub-sample period 2020-2021

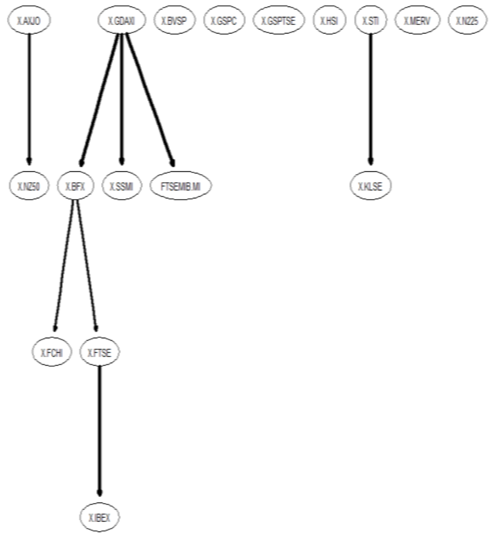


Figure no. 29: Bootstrapped Tabu Search; threshold=0.85, sub-sample period 2020-2021

By increasing the significance threshold to 0.95 for both score-based structure learning algorithms, as depicted in figure no. 30 and figure no. 31, the number of markets that do not imply evidence of contagion (meaning they neither assimilate nor spread the risk), is even higher, as the Australian and the Japanese markets become independent to shocks. At the same time, it is important to notice that during the COVID-19 pandemic the exogenous shock seems to be transmitted regionally. In this regard, it can be considered that contagion is mostly sensed at the level of the European countries.

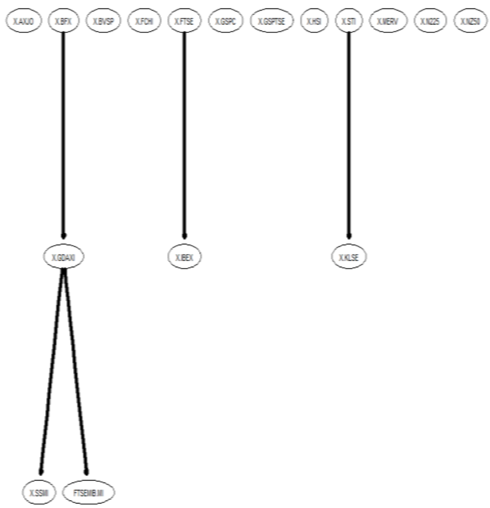


Figure no. 30: Bootstrapped Hill-Climbing; threshold=0.95, sub-sample period 2020-2021

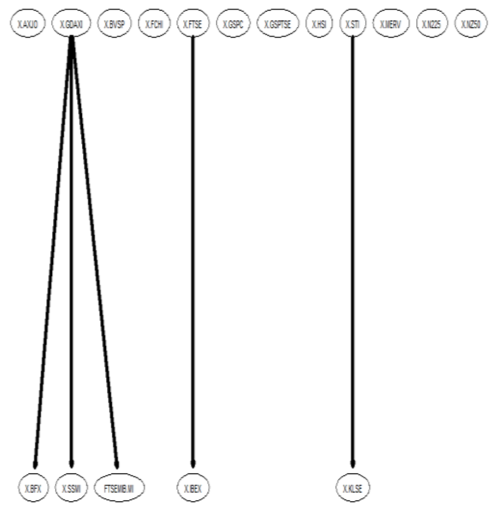


Figure no. 31: Bootstrapped Tabu Search; threshold=0.95, sub-sample period 2020-2021

By employing the Bayesian factor, we obtained the negative value -22.0215. Based on the result which is in-between the predetermined thresholds of -80 (-100) and +80 (+100), we can consider that the plausibility of the two algorithms is quite unclear.

4. Discussion

The results of the Bayesian factor on the full sample period and on each sub-sample periods are displayed in table no. 1. Considering the predetermined thresholds in literature, in three cases out of five the results obtained though the Tabu Search algorithm are significantly more plausible than the ones obtained through the Hill Climbing algorithm. In this regard, we considered that overall the Tabu Search algorithm systematically generated the most plausible results.

Table no. 1. Results obtained after employing the Bayesian factor

	January 1st, 2007 – October 15th, 2021	January 1st, 2007 – December 30th, 2009	January 1st, 2010 – December 30th, 2015	January 1st, 2016 – December 30th, 2019	January 1st, 2020 – October 15th, 2021
Results	-642.5745	-41.42338	-107.2726	-193.0622	-22.0215

Source: own calculation.

After the global financial crisis from 2007-2009 a great accent was put on improving macro-prudential and financial stability policies, especially in the context of globalization in order to find measures to avoid the occurrence of other massive global financial crises. Truman (2009) stated that the policy responses that were adopted focused on enhancing and improving the macroeconomic environment, on promoting the market stability and on advancing structural repair. The market stability measures and policies somehow blended with the monetary policy actions and the structural repair actions, and were employing the balance sheets of central banks. These policies were meant to provide liquidity to certain markets in order to restore and support them in functioning as credit suppliers. There were also policy responses that did not involve central banks; for instance, the increase in the coverage of deposit insurance. This measure was meant to stabilize the deposit-taking institutions and the bank deposits markets.

The last sub-sample period that we analysed, January 1st, 2020 – October 15th, 2021, encompasses the shock triggered by the COVID-19 pandemic that appeared in Romania at the beginning of 2020. The results we obtained for this sub-sample were quite interesting and completely different compared to the other periods analysed. This happens because the pandemic crisis is totally different from the past events and its effects are also specific. We found that this period represents a decupling period for the analysed markets as the linkages between them evaporated. In this case, we dealt with a different type of impact upon markets, impact that most probably is about to last on the long-run and to generate effects on economies and industrial sectors and also on the investors attitudes towards risk. The difference between the past crises and the pandemic crisis stands mostly in the type of shock. Here we dealt with an exogenous shock which was given by the virus itself. In this regard, the government responses in each single country were different based on particular situations. Countries were all impacted by the shock which was not necessarily transmitted between markets but occurred domestically (for instance, the unemployment rate increased drastically in all the analysed countries and it was mostly due to the lockdown).

Since the beginning of March 2020, the coronavirus hit not only the global health system but also the financial and economic system. A sharp decline was sensed in the economic growth of China and soon the same scenario appeared in many other countries. Due to the fact that the COVID-19 (coronavirus) started to spread between countries, more and more governments were compelled to adopt stringent measures to contain the pandemic. In very many countries these measures led to the temporary closure of various businesses, to the imposition of traveling restrictions, to turbulences on financial markets, to confidence erosion and to increased uncertainty. Although necessary, such measures caused sharp declines in the level of production in various economies further causing a decline in consumers' expenditure. Such a great economic impact upon economies and financial systems and such an increased level of market risk aversion have not been sensed since the global financial crisis from 2007-2009. The stock markets declined with more than 30% while volatility fluctuations in oil prices and equities raised to crisis levels. Due to the fact that the challenges induced by the pandemic crisis were different from past crises, the financial reforms that were taken by the main emerging and developed economies in the post-crisis era were not enough to avoid the occurrence of a massive financial turmoil. The COVID-19 pandemic crisis called for a stringent evaluation of the changing nature and structure of global financial markets in order to understand the nowadays market fragilities and the paths for financial market contagion.

Considering that the global financial crisis from 2007-2009 was the most severe shock in the last decades and modern history, many scholars started to compare it to the pandemic crisis that started at the beginning of 2020. In this regard, as stated in ISDA (2021), the main differences between the two crises stand in the fact that the COVID-19 pandemic was not triggered by the financial sector (such as financial intermediation entities and banks), but rather by a public health crisis, and in the fact that the pandemic crisis affected the real sector in terms of demand and supply. During the global financial crisis, the demand was negatively impacted due to instability in the financial sector; this led to decreased confidence, to downturns in the wealth of households and further to a decline in consumer spending.

Compared to the case of the global financial crisis from 2007-2009, in 2020 both financial and banking sectors were found in a stronger position. Unlike a decade ago, the banking industry played its role as a part of the solution to deal with the pandemic crisis. Banks were more liquid and better capitalised due to the financial regulatory reforms adopted by G20 (a group formed by the main emerging and developed financial markets), and this fact allowed the banking sector to absorb the macroeconomic shock rather than to amplify it. During the pandemic crisis the global regulatory reforms enhanced by banks and financial markets were supported by policymakers such as the Basel Committee on Banking Supervision (BCBS), the Financial Stability Board (FSB), the International Organization of Securities Commissions (IOSCO), the Committee on Payments and Market Infrastructures (CPMI), central banks and market regulators in key financial centres such as the UK, the USA, the EU, Japan and so on.

Since the beginning of the pandemic crisis, the international regulatory bodies have started to improve coordination and supervision of the implementation of current financial reforms. The financial system and banking industry demonstrated their resilience through actions such as: strengthening capital buffers, increasing liquidity holdings, carrying out more robust risk management, lowering the overall risk exposure to less liquid assets, strengthening markets infrastructure (for instance, standardizing financial instruments in order to make the trade of such instruments more transparent and liquid), and strengthening derivatives markets transparency.

In contrast to the global financial market, the COVID-19 crisis implied two main challenges, namely the liquidity shortage on financial markets and the acute insolvency risk. In this regard, the primary and secondary securities markets played a crucial role in funding during the COVID-19 pandemic crisis. The primary capital markets provided access to funding and supported the financing needs of governments and businesses by allowing them to issue equity and debt securities in order to maintain their services, meet their obligations and repay their loans and credit lines. In this sense, the primary capital markets were supported by the official sector in regard to the activities of large financial intermediation institutions, investors on the buying side and other market participants; this further helped in the recovery of the primary market issuance and also in diminishing the costs of borrowing for the issuers. During the COVID-19 pandemic the primary capital markets were also an important source of funding for businesses and enterprises as they allowed them to issue equity and debt securities to investors in significant amounts. In this way, businesses were able to continue their operations, pay the employees and provide the public with the necessary goods and services, in spite of the slowdown in the economic activity. Another reason for which the primary markets were important during the pandemic crisis is given by the fact that they allowed domestic governments to access funds through the massive issuance of sovereign debt (as stated in ISDA (2021), the issuance of the sovereign debt increased with 36% in 2020 compared to 2019). This infusion of funds was instrumentally relevant for countries all around the globe as it represented an immediate stimulus to face the economic disturbances. At the same time, local governments were allowed to access funding by significantly raising their local and municipal debt. Due to the fact that local costs (such as community support services, education, transportation and so on), needed to be covered and the key sources of revenue declined, local governments took advantage of the possibility of raising funds by investing in public markets.

As more and more market participants looked to rebalance and hedge the risk of their assets portfolios, the trading volume of major asset classes on the secondary securities markets increased. In this regard, the secondary markets also played a crucial role in providing liquidity and funding during the pandemic crisis. In spite of the markets volatilities, market-makers either maintained or increased their securities inventories and did not stop to deploy capital to the trading businesses. The trading volume of corporate and governmental bonds, as well as of other derivative instruments increased significantly at the beginning of the pandemic crisis. The increase in the volume of trading led to imbalances in the supply and demand; however, liquidity on derivatives markets represented a hedging measure against risk and efficiently diminished exposure.

Conclusions

The spread of financial contagion is a tremendous issue both at the national and international level. So far, there is no professional unanimity upon the accurate definitions regarding what actually represents financial contagion, in spite of the considerable research progress in achieving this objective. Based on current findings in literature, we intended to make a distinction between contagion, independence and spillovers. At the same time, we examined the transmission of risk between 17 global market indices on a full sample period (January 1st, 2020 – October 15th, 2021), and on four sub-sample periods that encompass the period of the financial crisis from 2007-2009 (January 1st, 2007 – December 30th, 2009), the post-crisis period (January 1st, 2010 – December 30th, 2015), the tranquil period (January 1st, 2016 – December 30th, 2019), and the pandemic crisis that started at the beginning of 2020 being triggered by the appearance of the coronavirus (January 1st, 2020 – October 15th, 2021). The aim of the analysis was to test the propagation sense of the risks and shocks that can be transmitted from one market to others. In this regard, we started by computing the logarithm of the daily closing prices and we applied the expected shortfall method for estimating the risk. To further analyse how contagion can devolve, we applied the Bayesian Network model on the sample of 17 global market indices. Considering that we did not know how contagion can pass off, we applied the Bayesian Networks model as we needed to model uncertainty. At the same time, we considered that Bayesian Networks model offers a relevant tool in the context of prolonged functional instability, financial markets being affected by different categories of shocks especially of exogenous nature.

Given the fact that the Bayesian Networks model gave us the possibility to analyse and represent uncertainty and risk in a way that is quite easy to infer, our main findings from the analysis stand in the diagrams that were obtained for the two significance thresholds of 0.85 and 0.95 that were applied for each algorithm of the Bayesian Networks model, namely the Hill Climbing and the Tabu Search. We considered that the Bayesian Networks model suited very well the core of our paper because it models conditional dependence further generating the causation and the direct or indirect relationships between the variables. The diagrams that we obtained allowed us to see how risk can spread between the markets in the sample. At the same time, in literature Neural Networks models were used by various scholars in studying different types of contagion. We further introduced the Bayesian factor which compares the plausibility between the results and discriminates between the two algorithms Hill Climbing and Tabu Search. Based on the predetermined thresholds in literature, we found that in three out of five scenarios the results obtained by applying the Bayesian factor imply that the Tabu Search algorithm is systematically more plausible than the Hill Climbing algorithm.

By interpreting the results, we found that financial contagion exists in-between certain countries from the sample. We found that there are certain leading markets from where risk is transmitted globally. These markets were influencing the architecture of the global financial market system during the period that we analysed. Thus, we considered these key markets as dominant financial centres. Based on our results, the dominant financial centres were the developed markets of Germany, France, Belgium, Australia and Canada, while the leading currencies were the Euro, the Australian dollar and the Canadian dollar.

We found that the correlation between markets in the full sample period was different compared to the sub-sample periods. It can be noticed that until 2020 in both full sample period and the first three sub-sample periods, the markets were more or less correlated at a global level. In this regard, evidence of contagion was sensed especially in the full sample period between all the markets except the Brazilian market index Ibovespa which was immune to the transmission of risks. By splitting the full sample in smaller time periods, the main observation that can be withdrawn stands in the last sub-sample, January 1st, 2020 – October 15th, 2021, where the linkages between the analysed markets somehow evaporated. In this sense, we considered this sub-sample period as a "decoupling" period, where the shocks seemed to be transmitted rather regionally and mostly at the level of the European countries.

Another important observation can be noticed by looking at the results of the sub-sample periods at both thresholds of 0.85 and 0.95. We found that during the financial crises from 2007-2009, the only market that remained immune to risk, meaning that it neither assimilated nor spread any shock, was the Brazilian market Ibovespa. After the crises period, more precisely in the tranquil sub-sample periods from January 1st, 2010 – December 30th, 2019, the countries that did not imply evidence of contagion were the Japanese market Nikkei 225 and the Argentinian market S&P/NZX 50.

To conclude our overall results, we considered in our analysis the broad sense of contagion. In other words, by considering contagion as the transmission of shocks regardless of their endogenous or exogenous nature, their amplitude and effects, and by taking into account the causality resulted through the Tabu Search algorithm, we found that during the period January 1st, 2007 – October 15th, 2021, period that consists of both the financial crisis from 2007-2009 and the global exogenous shock triggered by the coronavirus pandemic, evidence of contagion was sensed in 16 market indices out of a sample of 17 markets. However, for the sub-sample periods, the causality between markets was different and less markets displayed evidence of contagion.

Several policy implications can be derived from our findings especially in the area of prudential regulation and supervision based on the lessons learnt after the global financial crisis from 2007-2009, and during the COVID-19 pandemic crisis. Due to the fact that markets became more and more integrated, the linkages between global financial markets became stronger and volatility fluctuations are still nowadays a great issue and challenge in the economic world. First, in order to deal with the liquidity and insolvency risks, policymakers and market regulators should consider central banks to reduce policy rates and to extend bond purchasing programmes. Second, market regulators should focus on enhancing and improving the current liquidity management principles established by the FSB and IOSCO. Third, market regulators should ensure that the open-ended funds own enough liquidity for unexpected redemptions. Fourth, market regulators and policymakers should emphasize on reducing potential runs by better clarifying the use of fund redemption suspension.

In order to restore business operations and market confidence during and after the COVID-19 pandemic crisis, coordinated and comprehensive actions within and across global markets need to be considered. For instance, the actions that could be taken in order to address the acute insolvency risks and the liquidity issues should focus on the reduction of policy rates and on the extension of bond purchasing programmes by the central banks. Given the variety of measures taken in order to enhance regulatory reforms adopted after the global financial crisis from 2007-2009, we consider that after the pandemic crisis regulators and policymakers should continue to emphasize on the importance of liquidity buffers in investment funds that invest in less liquid markets. This is a precautionary measure for liquidity risk of regulated funds and it could be managed through domestic and international guidance. At the same time, market regulators should continue to enhance the liquidity management principles of FSB and IOSCO, should redouble their efforts to ensure that the open-ended funds own enough liquidity to face and cover unexpected redemptions, and should also focus on mitigating the possibility of runs by clarifying the use of fund redemption suspension.

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