XLV Encontro da ANPAD - EnANPAD 2021
On-line - 4 - 8 de out de 2021
2177-2576 versão online

Analysis of Financial Contagion among Economic Sectors through Dynamic Bayesian Networks

Autoria
Nathalia Costa Fonseca - nathaliacostafonseca@usp.br
Graduação em Ciências Atuariais / USP - Universidade de São Paulo

João Vinícius de França Carvalho - jvfcarvalho@usp.br
Ciências Atuariais / USP - Universidade de São Paulo

Resumo
Crises severely impact various economies and may spread across regions or sectors in a process called contagion. Understanding this process allows foreseeing crises' impacts and anticipating actions that reduce their effects. Specific economic sectors may be major crisis propagators: banking and insurance are often considered decisive in this context. In this paper, we aim to model the U.S. economy's sectorial interdependence using Dynamic Bayesian Networks on nine industrial Dow Jones' indices, daily between 2000 and 2020. As a secondary objective, we evaluate whether the insurance industry plays a central role in spreading crises. Several crisis periods are analyzed, from dot-com bubble to current Covid-19 pandemic. The results reveal the subprime crisis, European debt crisis and the 2016 presidential election as the main contagious periods. The last analyzed period –Covid-19 pandemic– was divided in two phases, showing, on phase 1, an interconnected economic system with three main spreaders (Oil & Gas, Real Estate and Pharmaceutical) and, on phase 2, the same configuration of the post-subprime. Finally, despite being somehow relevant during the subprime crisis, the premise of the insurance sector's centrality relative to other economic sectors was proven false, as this sector reveals to be one of the main contagion receptors.

Analysis of Financial Contagion among Economic Sectors through Dynamic Bayesian Networks

Abstract

Crises severely impact various economies and may spread across regions or sectors in a process called contagion. Understanding this process allows foreseeing crises' impacts and anticipating actions that reduce their effects. Specific economic sectors may be major crisis propagators: banking and insurance are often considered decisive in this context. In this paper, we aim to model the U.S. economy's sectorial interdependence using Dynamic Bayesian Networks on nine industrial Dow Jones' indices, daily between 2000 and 2020. As a secondary objective, we evaluate whether the insurance industry plays a central role in spreading crises. Several crisis periods are analyzed, from dot-com bubble to current Covid-19 pandemic. The results reveal the subprime crisis, European debt crisis and the 2016 presidential election as the main contagious periods. The last analyzed period – Covid-19 pandemic – was divided in two phases, showing, on phase 1, an interconnected economic system with three main spreaders (Oil & Gas, Real Estate and Pharmaceutical) and, on phase 2, the same configuration of the post-subprime. Finally, despite being somehow relevant during the subprime crisis, the premise of the insurance sector's centrality relative to other economic sectors was proven false, as this sector reveals to be one of the main contagion receptors.

Keywords: Contagion; Dynamic Bayesian Networks; Financial Crises; Sectorial Indices.

1. Introduction

Crises can be defined as extreme manifestations of the interactions between the financial sector and the real economy. Their origins can be domestic or external, coming from public or private sectors (Claessens & Kose, 2013). Financial crises severely affect economic activity and can trigger periods of recession (Claessens, Kose, & Terrones, 2009), spreading to various regions or sectors in a process called contagion.

The evaluation of contagion effect is relevant to foresee the impacts of turbulences occurred between different economies, in order to anticipate political-economic interventions and to minimize, as far as possible, the impacts of exogenous random shocks (Dornbusch, Park, & Claessens, 2000). Understanding contagion and identifying its origin and propagation is possible not only in macroeconomic spheres, relevant to the great world crises, but also to a more specific extent, among sectors of an economy. Bank-insurance deals, for instance, produce intra- and interindustry contagion in both risk and return, with larger deals producing greater contagion (Elyasiani, Staikouras, & Dontis-Charitos, 2016).

Specific sectors can be major crisis propagators (Acemoglu, Ozdaglar, & Tahbaz-Salehi, 2015; Kaserer & Klein, 2019). This was the case of the technology sector during the dot-com bubble, an overvaluation of the shares of companies based on internet and technology development in the late 1990s. Due to the speculative movement of the stock exchange occurred during the beginning of internet's diffusion, it culminated in a drastic drop of stock prices when most of these companies did not achieve the extraordinary promised results and the Federal Reserve Board (FED) raised interest rates. The bubble burst caused several bankruptcies, and it took NASDAQ over a decade to reach its former levels.

Thus, the study of sectorial contagion is important to better define economic policies, in order to avoid – or at least reduce the effects of – periods of crisis, anticipating their spread. Financial sectors, such as banking and insurance, are often decisive in the context of crises. Bank contagion can intensify systemic risk and the probability of a crisis (Pino & Sharma, 2019). Banks tend to face problems when many of their loans deteriorate or when bonds quickly lose their value. This happened in crises as diverse as the Nordic banking crises in the late 1980s, the crisis in Japan in the late 1990s and the European debt crisis in mid-2010 (Claessens & Kose, 2013). The most relevant case that started with this sector was the subprime crisis.

The subprime crisis was a result of banks' behavior in early 2000's, as banks began to collectivize high-risk debts (loans with mortgages as warrant, called subprime) with low-risk ones, assembling Collateralized Debt Obligation (CDO) packages, investment securities that were traded worldwide whose yields depended on the payment of the debts attached to them. When FED increased interest rates, low-income customers began to default, causing CDOs' returns to decline. As a result, financial institutions around the world that had subprime-backed securities began to suffer the crisis' impacts, many needing loans and intervention from their countries' central banks to avoid bankruptcy (Harrington, 2009; Longstaff, 2010).

In Sep/2008, American International Group (AIG), the world's largest insurance company, had to resort to FED for an US$85 billion loan due to its liquidity needs. AIG was a major seller of Credit Default Swaps (CDS), meaning insurance against default of assets linked to mortgage bonds and corporate debts. The premise that AIG's breakdown would have catastrophic systemic implications, since the insurance company was tied to several economic sectors (a company called *too-big-to-fail*), led the U.S. government to grant the loan in exchange for AIG's shares, becoming the holder of 80% of its assets. Even more resources were injected into AIG, with the intervention reaching US$150 billion until Nov/2008.

This situation raises the question of this premise validity, based on evidence of sectorial interdependence: are banking and insurance sectors the main crises propagators? Thus, this work aims to model the sectorial interdependence of U.S. economy through the Dynamic Bayesian Networks technique.

This technique provides an innovation to contagion studies as Bayesian Inference (Berger & Sellke, 1987) assumes that a parameter (e.g., correlation between two sectors) is, itself, a random variable, therefore endowed with a probability measure. When performing hypothesis testing, classical inference procedures tend to use p-value as its main significance measure, which is a problem because p-value is not a probability measure (Greenland et al., 2016), especially in *multiple testing problems* (Storey, 2002). This issue is addressed by using a different significance measure: the q-value. Hence, the use of Bayesian Networks (specifically Dynamic Bayesian Networks, which capture time series effect) provides a new methodology to contagion studies (Robinson & Hartemink, 2010).

The U.S. economy was chosen because, besides being the epicenter of the aforementioned crises and the world's largest economy today, there is a wide and historically long series of sectorial market indices in the U.S. (we use the Dow Jones index, in particular). As a secondary objective, we assess the assumption of the insurance sector's centrality, relative to other economic sectors.

Our work makes the following contributions: first, by treating dependency in a probabilistic and not merely correlational way (we are factoring the joint distribution into conditional marginals), we are able to follow the evolution of sectorial dependency structure dynamically over time, not only observing what are the existence relations, but also the magnitude's variation from one period to another. Second, this work models a great variety of sectors that represent the U.S. economy as a whole, while previous literature either studied contagion among countries or a small group of specific sectors (such as the financial ones). Furthermore, as this is a longitudinal study, we can analyze several crises: from the dot-com bubble burst to the current Covid-19 pandemic.

2. Theoretical background

Dornbusch, Park, & Claessens (2000) define contagion as the spread of market shocks, with mostly negative consequences, observed through co-movements in exchange rates, stock prices, increases in sovereign risks and in capital flows. According to them, the occurrence of a crisis in a specific country can lead investors to restructure their portfolios, reconsidering their investments in different markets. This type of shock transmission can trigger contagion effect.

With the advent of financial crises in the last decades, several articles on financial contagion have been developed. While the former analyzes this phenomenon through its transmission channels, another literature stream became common: measuring contagion through correlation. In a seminal work, Forbes & Rigobon (2002) define contagion as "a significant increase in the correlations between countries, through the return of their stock markets, in times of crisis". However, this definition is based on *Granger's causality* concept (Granger, 1969), under which the association existence is measured by correlation, but does not signal a cause itself. Thus, it is not possible to infer who would be the propagator or the receptor of a contagion, since correlation is measured through the expectation of a linear relationship.

Succeeding Forbes & Rigobon (2002), several studies have emerged with different methods for contagion analysis. Possibly, the most common way to evaluate the contagion effect is to analyze stock exchange indices returns – and the spread of adverse shocks – for different countries (although this same method can be utilized to evaluate institutions or sectors within a country). Aït-Sahalia, Cacho-Diaz, & Laeven (2015) use this method. In their model, a jump (*Hawkes' process*) in a region of the world or in a market segment increases the intensity of the jumps occurring both in the same region (self-excitation) as well as in other regions (cross-excitation). The authors' estimates provide evidence of self-excitation in the U.S. and in other markets. Furthermore, leaps in the U.S. tend to get reflected quickly in most other markets, while statistical evidence for the reverse transmission is much weaker.

Following this line of financial contagion between countries, Ur Rehman (2016) uses a multivariate GARCH dynamic conditional correlation structure to investigate the time-varying conditional correlation between developed markets and emerging and frontier Asian (EFA) markets. The study finds that, during periods of financial turmoil, EFA markets are exposed to shocks and spillover effects from developed markets. Also, there is an increase in correlations between markets, especially during the 2008 financial crisis.

Jaworski & Pitera (2014) also evaluate contagion among countries using multivariate GARCH models. Through conditional copulas, they test the existence of dependence between two markets and then use seven different combinations of multivariate GARCH models to model the contagion effect. Brechmann, Hendrich, & Czado (2013) analyze interdependencies in the international financial market using flexible vine copulas. The authors develop stress testing methods to investigate contagion effects among financial institutions (banks and insurers) using CDS data. The results show that the failure of a bank constitutes a larger systemic risk than the failure of an insurer.

Ye, Zhu, Wu, & Miao (2016) develop a Markov regime-switching quantile regression model which can be used to detect financial crisis contagion. They conduct an empirical analysis of contagion between U.S. and some EU countries during subprime, using weekly log-returns of the U.S. S&P 500 index, France CAC 40 index, and Germany DAX 30 index from 2005 to 2008, covering both crisis and pre-crisis periods. The results show that, in a crisis situation, the interdependence between U.S. and EU countries dramatically increases.

Several other works make use of multivariate models and correlation analysis, such as Elyasiani et al. (2016), Dreassi, Miani, Paltrinieri, & Sclip (2018) and Dungey, Flavin, & Lagoa-Varela (2020). Notably, there is a predominance not only of this methodology, but also of the study subject in the literature: contagion between different economies is more addressed, while few occurrences of sectorial contagion studies are verified. However, one could mention Pino & Sharma (2019), who use spatial econometrics to study contagion among American financial institutions during subprime, and Collet & Ielpo (2018), who measure cross-sector volatility spillovers in the U.S. credit market.

A common line of study to sectorial contagion is the analysis of the relationship between insurers and banking institutions. Chen, Cummins, Viswanathan, & Weiss (2014) examine the interconnection between banks and insurers with *Granger's causality* tests. Significant evidence of bidirectional causality is found across sectors. However, stress tests confirm that banks create significant systemic risk for insurers, but not the other way around.

Cummins & Weiss (2014) examine the potential of the insurance industry to cause systemic risk events that spillover to other segments of the financial sector and the real economy. To do so, they use primary indicators of systemic risk, as well as contributing factors that exacerbate vulnerability to systemic events. Their main conclusion is that U.S. insurers' main activities do not create systemic risk, although some lines of insurance business are more affected during the industry's internal crises.

Safa, Hassan, & Maroney (2013) discuss contagion and systemic risk in the U.S. financial sector by applying multivariate regression models onto the returns of banking, insurance, brokerage firms and savings-and-loans institutions during subprime. The hypothesis that AIG would be too-big-to-fail is tested as well. They concluded that AIG was not so central to U.S. economy as to justify the FED's contributions. Harrington (2009) analyzes AIG's role during subprime and the nature of systemic risk in the insurance market, which is shown to be relatively low when compared to banks, especially for property–casualty insurance.

One can still mention Elyasiani et al. (2016), Bégin, Boudreault, Doljanu, & Gauthier (2019) and Eckert, Gatzert, & Heidinger (2020) who analyze systemic risk between banking institutions and insurance companies, Kaserer & Klein (2019) and Chen & Sun (2020) who analyze systemic risk within the insurance market. These works find similar results to those of Cummins & Weiss (2014) and Chen et al. (2014).

With the development of computational techniques such as machine learning and neural networks, there has been an inovation to contagion studies. Due to the complex nature of financial system interconnections, network-based models are increasingly being used (Sourabh, Hofer, & Kandhai, 2020). Amini, Cont, & Minca (2016), for instance, analyze the stress spreading in a financial system represented as a large network. Introducing a criterion for the resilience of a large financial network in the case of bankruptcy of a small group of financial institutions, they quantify how contagion effect amplifies small shocks in a network with the same empirical properties as a real interbank network.

Despite the predominance of linear correlation based models to evaluate contagion effect, in this work we use the Bayesian Networks methodology. It is an artificial intelligence technique expressed through a graphic statistical model that maps the joint distribution function of a set of random variables. Unlike the previously mentioned techniques, this methodology allows not only the identification of correlation and interdependence, but also of the causality's direction, making it possible to identify which entities generate and/or receive contagion.

There is a recent and growing literature of contagion that uses this methodology. Sourabh et al. (2020) develop a model to capture stress dependency of counterparty credit risk. With Bayesian networks, they calibrate the stress probability of an entity conditioned to the stress of another entity, using CDS data from Russian counterparts between 2010 and 2015. Using a similar methodology, Anagnostou, Sanchez Rivero, Sourabh, & Kandhai (2020) propose a method to improve credit portfolio models, incorporating contagion effects. They use Bayesian networks to discover the direct and indirect relationships between the credits' flow, and the training of the networks is carried out using real CDS data. Contagion is shown to have a significant impact on the tails of credit risk distribution.

Another example of analysis of credit between financial institutions is Chong & Klüppelberg (2018). The authors theorize a model of contagion among interconnected financial institutions, which can be borrowers and/or lenders, so that the distribution of default's joint probability in the financial system can be characterized as a Bayesian network. They argue that this graphic structure can be used to detect systemic dependencies within the network. Glasserman & Young (2015) estimate the extent to which interconnections among financial institutions increase expected losses and defaults under a wide range of shock distributions by constructing a financial network – where the nodes are financial institutions that borrow and lend on a significant scale. They illustrated the results with data from European banks.

In this work, a similar approach to Carvalho & Chiann (2013) will be used. They used Bayesian networks to model financial contagion among 6 countries, from 1996 to 2009, using data from the main time series stock exchanges indices. They adjusted ARMA(1,1)-GARCH(1,1) models to ensure that multivariate relations were not masked by the series' temporal self-dependence. The adjustment of the Bayesian networks was carried out from the residuals of each estimated model, so that a static network was estimated for each moment (pre and post-crises). The disposition of networks reveals contagion when, with the advent of a crisis, the creation or alteration of an edge's direction is observed. But, differently from the authors, our innovation is to model the dependency structure directly using Dynamic Bayesian Networks, through a multivariate time series system.

Moreover, instead of analyzing contagion spread among countries or financial institutions, as it is already common in the literature, we will analyze it among different sectors of the same economy. We use daily log-returns of New York Stock Exchange sectoral indices time series from 2000 to 2020: (1)Insurance, (2)Banking, (3)Oil&Gas, (4)Real Estate, (5)Construction, (6)Pharmaceutical, (7)Chemistry, (8)Retail and (9)Automotive. Using these diverse sectors broadly encompass the U.S. economy, as they also present great volumetry among the available Dow Jones sectorial indices. Also, unlike predecessor studies, this work uses Dynamic Bayesian Networks, which capture the dependency not only between variables in cross-section, but also in the temporal dimension.

3. Methodology

Bayesian Networks (BN) are graphical structures that represent the probabilistic relationships between a large number of variables and allow making probabilistic inference with these variables (Neapolitan, 2004). A BN consists of nodes and edges. The nodes represent the random variables and the missing edges between them specify properties of conditional independence between the variables.

3.1 Some important definitions

A directed graph is defined as a pair (V,E) where V is a finite non-empty set whose elements are called nodes and E is a set of ordered pairs of distinct elements of V called edges. Suppose a set of nodes $[X_1, X_2, ..., X_k]$, where $k \geq 2$, such that $(X_{i-1}, X_i) \in E$ for $2 \leq i \leq k$. The set of edges connecting the k nodes, two by two, is the *path* from X_i to X_j, $\forall$ i and j.

Let G = (V,E) be a directional and acyclic graph (DAG), where V is a finite set of nodes and E is a finite set of directional edges between the nodes. Each of the nodes $v \in V$ of this graph represents a random variable X_v, and compound the set of variables in G. Given any nodes X and Y $\in$ V, if there is an edge from X to Y, X is called the *parent* node of Y. For each parent node of v, the nomenclature of $pa(v)$ is adopted. In addition, a relational probability function between v and $pa(v)$ is conditionally defined by $p(x_v|x_{pa(v)})$. The set of relational probabilities functions of the network is P. A BN for a given set of random variables is the pair (G,P).

An important concept of BN theory is d-separation, according to which each and every variable is independent of its non-descendants and its non-parents, conditioned on their parents. Thus, a BN (G,P) can be used to map the (in)dependence relationships and the joint distribution of probabilities among the variables. Further definitions can be found in Neapolitan (2004).

3.2 The Bayesian Network's learning process

From a statistical point of view, learning a network corresponds to estimating the model parameters, following some criteria and having some data set (Carvalho & Chiann, 2013).

The Bayesian approach is used to estimate the parameters in the network. The uncertainty about the parameters θ is coded in a probabilistic *prior* distribution $p(\theta)$, which is updated from the data d (using the likelihood function). With this conjugation, we obtain the *posterior* distribution $p(\theta|d)$, by Bayes' Theorem, so that

$$p(\theta|d) = \frac{p(d|\theta)p(\theta)}{p(d)}, \theta \in \Theta \tag{1}$$

with Θ representing the parametric space, d is the random sample of the probability distribution p(x|θ) and p(d|θ) is the joint probability function (likelihood) of d.

3.2.1 Dynamic Bayesian Networks

Dynamic Bayesian Networks (DBN), which will be used here, extend the fundamental ideas behind static Bayesian networks. They incorporate associations resulting from the temporal relations between the quantities of interest (Nagarajan, Scutari, & Lèbre, 2013). Therefore, the DAG input random variables are time series related through each other's pasts.

Multivariate time series can be modeled as a vector autoregression process VAR(p) if they form a stationary system. In a VAR(p) process, the variables observed at any time $t \geq p$ satisfy the equation

$$X(t) = A_1 X(t-1) + \cdots + A_i X(t-i) + \cdots + A_p X(t-p) + B + \varepsilon(t) \tag{2}$$

where

- $X(t) = X_i(t)$, i = 1,..., k, is the vector of k variables observed at time t;
- A_i, i = 1,..., p are coefficients matrices of size k × k;
- B is a vector of k-size constants for each variable;
- ε(t) is a white noises array of size k, with zero mean and time-invariant positive definite covariance matrix, that is, $\mathrm{E}(\varepsilon(t)) = 0$ e $\mathrm{Cov}(\varepsilon(t)) = \Sigma$.

DBNs assume that dependence relationships are represented by a vector autoregression process, defined in Equation 2. If we assume a VAR(1) process, $X(t) = AX(t-1) + B + \varepsilon(t)$, with $\varepsilon(t) \sim N(0, \Sigma)$, then all edges define relations within two successive time periods. The set is defined by all nonzero coefficients in A. If an element a_{ij}, $i \neq j$, is different from zero, then the network includes an edge from $X_i(t-1)$ to $X_j(t)$. Furthermore, it is assumed that the error term for each variable X_i is independent of both the other variables and their error terms.

3.2.2 The main measures for significance: local fdr and q-values

The algorithm developed by Opgen-Rhein & Strimmer (2007) and Schäfer & Strimmer (2005) allows robust estimation of VAR(1) coefficients for DBNs. Graphical Gaussian Models (GGM) are estimated for each DAG based on the application of shrinking estimators in the estimated covariance and partial correlation matrices, which represent the interactions between the variables. The structure learning occurs by ordering the edges according to their coefficients magnitude and executing multiple tests of the local false discovery rate (local fdr), which tests for the existence of false positives (edges of null probability) and eliminate them. After this procedure, only the significant edges remain.

The observed partial correlations $\tilde{r}$ *across edges* are defined by the Equation 3.

$$f(\tilde{r}) = \eta_0 f_0(\tilde{r}; \mathrm{k}) + (1-\eta_0) f_A(\tilde{r}) \tag{3}$$

where f_0 is the null distribution, η_0 is the (unknown) proportion of "null edges" and f_A the distribution of observed partial correlations assigned to actually existing edges. The null density f_0 is given by

$$f_0(\tilde{r}; \mathrm{k}) = (1-\tilde{r}^2)^{\frac{k-3}{2}} \frac{\Gamma\left(\frac{k}{2}\right)}{\pi^{\frac{1}{2}}\Gamma\left(\frac{k-1}{2}\right)} = |\tilde{r}|\mathrm{Be}\left(\tilde{r}^2; \frac{1}{2}, \frac{k-1}{2}\right), \tag{4}$$

where Be(x; a, b) is the Beta distribution with parameters *a* and *b*, and k represents degrees of freedom for f_0, equals to the reciprocal variance of the null $\tilde{r}$. Fitting this mixture density allows k, η_0 and even f_A to be determined. Posteriorly, it is straightforward to compute the edge-specific fdr via:

$$\mathrm{Prob(null\ edge}|\tilde{\mathrm{r}}) = \mathrm{fdr}(\tilde{\mathrm{r}}) = \frac{\hat{\eta}_0 f_0(\tilde{r}; \hat{\mathrm{k}})}{\hat{f}\tilde{r}} \tag{5}$$

Equation 5 denotes the local fdr as the posterior probability that an edge is null given $\tilde{r}$. During the estimation process, the q-values associated with each edge and the probabilities of an edge being non-null (1-fdr) are computed. These quantities can be used to define the edges' significance level.

Q-value is a measure of significance adjusted by FDR to solve the problem of multiple testing, so that the *q-values* inform the percentage of false positives to be expected among the significance tests. While the p-values inform only this percentage considering the total number of tests performed.

As FDR is the expected proportion of false positive findings among all rejected hypotheses times the probability of making at least one rejection, Storey (2002) defines the pFDR (positive FDR) to reflect the fact that we are conditioning on the event that positive findings have occurred:

$$pFDR = \mathbb{E}\left(\frac{V}{R}\middle|R > 0\right), \quad (6)$$

where V is the number of type I errors (or false positive results) and R is the number of rejected hypothesis. For a nested set of rejection regions $\{\Gamma\}$, the p-value of an observed statistic T = t is defined as

$$p\text{-}value(t) = \min_{\{\Gamma:t\in\Gamma\}}\{\Pr(T \in \Gamma|H = 0)\} \quad (7)$$

P-value gives a measure of the strength of the observed statistic with respect to making a type I error - it is the minimum type I error rate that can occur when rejecting a statistic with value t for the set of nested rejection regions. The *q-value* is a measure of the strength of an observed statistic with respect to pFDR – it is the minimum pFDR that can occur when rejecting a statistic with value t for the set of nested rejection regions. As a natural extension to pFDR, the *q-value* has the following definition. For an observed statistic T = t,

$$q(t) = \inf_{\{\Gamma:t\in\Gamma\}}\{pFDR(\Gamma)\} \quad (8)$$

The definition is simpler when the statistics are independent p-values. The nested set of rejection regions take the form [0; γ] and pFDR can be written in a simple form. For a set of hypothesis tests conducted with independent p-values, the *q-value* of the observed p-value p is:

$$q(t) = \inf_{\{\gamma\geq p\}}\{pFDR(\gamma)\} = \inf_{\{\gamma\geq p\}}\left\{\frac{\pi_0\gamma}{\Pr\,(P \leq \gamma)}\right\} \quad (9)$$

The *q-value* is closely related to the local Bayesian Fdr statistics (Schäfer & Strimmer, 2005). This was the reason why we chose to use it as our measure of significance. The following definitions are found in Efron (2005).

The Bayesian posterior probability that a case is null given z, by definition the local false discovery rate, is

$$\mathrm{Fdr}(z) \equiv Pr\{\mathrm{null}|z\} = \frac{p_0 f_0(z)}{f(z)} = \frac{f_0^+(z)}{f(z)}, \quad (10)$$

where $p_0 = \Pr\{\mathrm{null}\}, f_0(z) = density\ if\ null,$

$p_1 = \Pr\{\mathrm{non-null}\},\ f_1(z) = density\ if\ non\text{-}null.$

The Benjamini-Hochberg's false discovery rate theory relies on tail areas rather than densities. Letting $F_0(z)\ and\ F_1(z)$ be the cumulative distribution functions corresponding to $f_0(z)\ and\ f_1(z)$, define $F_0^+(z) = p_0F_0(z)\ and\ F_0(z) = p_0F_0(z) + p_1F_1(z)$. Then the posterior probability of a case being null given that its z-value, Z is less than some value z is

$$\mathrm{Fdr}(z) \equiv Pr\{\mathrm{null}|Z \leq z\} = \frac{F_0^+(z)}{F(z)}. \quad (11)$$

Thus, Fdr(z) corresponds to the *q-value* defined by Storey (2002) and the value of the tail area false discovery rate attained at a given observed value Z = z. Fdr and fdr are analytically related by:

$$\text{Fdr}(z) = \frac{\int_{-\infty}^{z} fdr(Z)f(Z)d(Z)}{\int_{-\infty}^{z} f(Z)d(Z)} = \mathbb{E}_f\{\text{fdr}(Z)|Z \leq z\}, \quad (12)$$

with $\mathbb{E}_f$ indicating expectations with respect to $f(z)$.That is, Fdr(z) is the average of fdr(Z) for $Z \leq z$. Fdr(z) will be less than fdr(z) in the usual situation where fdr(z) decreases as |z| gets large. Further details on the algorithm can be found in Schäfer & Strimmer (2005) and Opgen-Rhein & Strimmer (2007).

Finally, each new DAG (*posterior* distribution) is composed of data from the previous DAG (*prior* distribution) plus that period's data (likelihood). Thus, the parameters are updated sequentially over time, so that the past of the dependency parameters influences the estimation of future dependence. The first *prior* is uniform. The networks' disposition reveals contagion when, with the advent of a crisis, the creation or change of an edge's direction is observed.

4. Results analysis

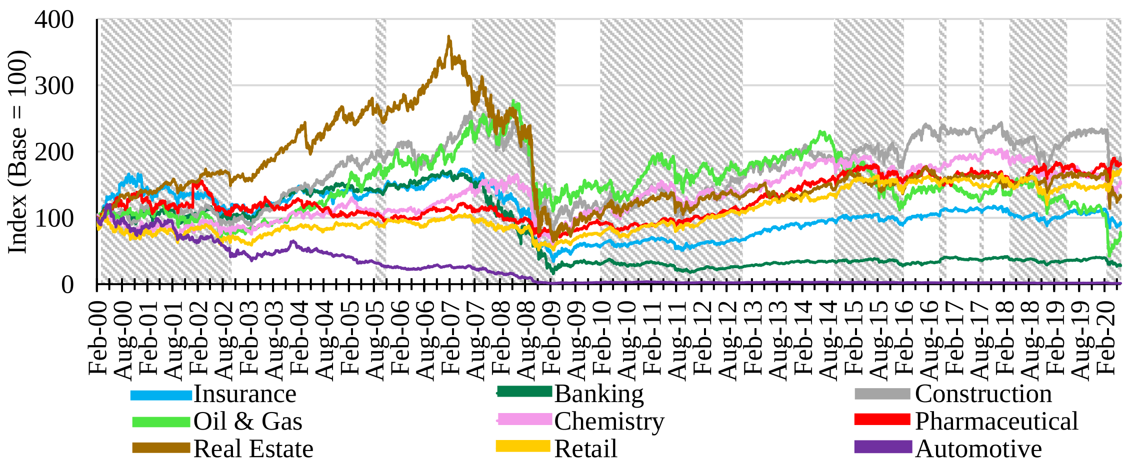
Contagion analysis widely makes use of stock markets data, as first defined by Forbes & Rigobon (2002). As examples of recent studies that also use this kind of data, there are Aït-Sahalia et al. (2015), Ye et al. (2016), Ur Rehman (2016) and Chen & Sun (2020), already cited in section 2 of this work.

Our dataset comes from the sectorial composition of the Dow Jones index, one of the main indicators of U.S. financial market movement. It covers the period from February 14th, 2000 to September 30th, 2020, with 5139 observations for each index, consisting on the daily log-returns of each sector: (1)Insurance, (2)Banking, (3)Oil&Gas, (4)Real Estate, (5)Construction, (6)Pharmacy, (7)Chemistry, (8)Retail and (9)Automotive.

4.1 Data analysis

Initially, all data is normalized on the same scale 100, so that it is possible to compare the evolution of each sectorial time series (Figure 1).

Figure 1. Evolution of sectoral indices between 2000 and 2020.



Source: own elaboration.

From Figure 1 and analysis of the news, we could define periods of crisis (shaded areas in Figure 1), and the intermediate moments were called periods of tranquility (white areas in Figure 1). Table 1 explains the dates and description assigned to each period.

Table 1. Ad-hoc definition for duration of crises.

Period	Description	Beginning	End	Number of observations
1	Tranquility	Feb 14, 2000	Mar 09, 2000	14
2	Dot-Com bubble	Mar 10, 2000	Oct 09, 2002	641
3	Tranquility	Oct 10, 2002	Aug 22, 2005	715
4	Katrina, Rita and Wilma hurricanes	Aug 23, 2005	Nov 02, 2005	44
5	Tranquility	Nov 03, 2005	Jul 23, 2007	415

6	Subprime	Jul 24, 2007	Mar 13, 2009	410
7	Tranquility	Mar 14, 2009	Feb 07, 2010	229
8	European Debt Crisis	Feb 08, 2010	Nov 30, 2012	704
9	Tranquility	Dec 01, 2012	Sep 29, 2014	458
10	Ebola, Greek government-debt crisis and crude prices drop	Sep 30, 2014	Feb 11, 2016	345
11	Tranquility	Feb 12, 2016	Oct 27, 2016	180
12	U.S. presidential election	Oct 28, 2016	Dec 15, 2016	34
13	Tranquility	Dec 16, 2016	Aug 16, 2017	166
14	Harvey hurricane	Aug 17, 2017	Sep 13, 2017	19
15	Tranquility	Sep 14, 2017	Mar 21, 2018	130
16	Trade War against China	Mar 22, 2018	May 10, 2019	286
17	Tranquility	May 11, 2019	Feb 24, 2020	198
18	Covid-19 pandemic (Phase 1)	Feb 25, 2020	Jun 19, 2020	82
19	Covid-19 pandemic (Phase 2)	Jun 20, 2020	Sep 30, 2020	69
	Total	**Feb 14, 2000**	**Sep 30, 2020**	**5139**

Source: own elaboration.

The beginning of crises periods was determined based on daily newspapers headlines research or, in the subprime case, with post crisis analysis already made by the literature (Harrington, 2009; Longstaff, 2010; Pino & Sharma, 2019). The beginning of tranquility periods consists of arbitrary dates among a time range where the series were once again quite stable and the news no longer showed relevant signs of crises. This method is similar to the ones used by Carvalho & Chiann (2013) and Cummins & Weiss (2014), as both articles combine the visual analyses of time series with historical periods already known to be crisis moments, such as 2001 terrorist attack, Subprime and Hurricane Andrew (Cummins & Weiss, 2014) or the 1997 Asian Crisis and 1999 Brazilian Crisis (Carvalho & Chiann, 2013).

The analysis comprehends 10 periods of crisis that correspond to approximately 51% of the total observations. Figure 1 shows that crises periods coincide with falls in all the series simultaneously. Analyzing each sector individually, we have the following behaviors:

(i) the insurance sector shows great volatility at the beginning of the series and incurs in a significant fall during subprime. Then the index maintains a slight growth trend, with stable volatility until 2018, when the average stabilizes around the initial level (100), suffering a slight fall during the last crisis;

(ii) the banking sector is not very volatile. It presents a slight initial growth, reaching the level of 150 before the subprime, suffers a great fall in this period, placing itself in the penultimate position among the sectors (only above automotive), and stabilizes at this level until 2020;

(iii) the construction sector, initially stable, goes through a period of fast growth between the dot-com and subprime crises, suffers a sharp decline during subprime and continues to grow after that period, presenting high volatility only in periods of crisis;

(iv) the oil&gas sector is highly volatile throughout the series. Until *subprime*, it presents growth trend. After a drop in this period, its average fluctuates a lot and falls again in 2014, with the drop in oil prices, moment from which a downward trend is installed until the end of the series. This sector had the most significant drop during the Covid-19 period and has ended below the initial level;

(v) the chemical sector presents stable volatility throughout the period. The average is stable before the subprime and, after falling during this period, there is a slight growth trend, similar to the construction sector, with eventual declines during crises. It is one of the few sectors that returned to its level prior to the subprime drop (it reached the level of 150 before the subprime and 200 after the recovery);

(vi) the pharmaceutical sector shows high volatility at the beginning of the series, but then stabilizes. The drop during subprime is less pronounced than in the other sectors and its recovery is fast, mirroring the growth of the chemical sector;

(vii) the real estate sector initially shows a quick growth trend, reaching the highest value among the indices before subprime. It has the most expressive drop in this period, but incurs in rapid recovery, following the same trend of the chemical and pharmacy sectors. The series ends just above the initial level. Volatility is higher pre-subprime and afterwards it stabilizes;

(viii) the retail sector shows low volatility and average stability. It mirrors the behavior of the pharmaceutical sector, with a small drop during subprime and a slight growth trend after that period;

(ix) the automotive sector has fallen significantly since the beginning. Its last peak happened during the third period, after which the decline intensified, reaching derisory levels after subprime, and then stabilizing until 2020. Volatility is low and this sector presents the lowest value (around 1) among all series in the end.

Finally, 4 sectors ended the series with lower values than the initial 100: insurance, oil&gas, banking and automotive. However, oil&gas and insurance show signs of recovery.

4.2 Modeling the series

In order to assess the results' sensitivity, all networks were generated with q-values equal to 0.05, 0.1 and 0.15, following the cutoff points recommended by Efron (2005). These choices reflect a conservative Bayesian factor for Fdr's interpretation. As the results, in most cases, did not differ qualitatively from the intermediate level q-value=0.1, we decided not to present them due to absolute space restriction. However, the authors can make the results under the other criteria available upon request. Also due to space restriction, we have opted for not presenting periods 4, 5, 9, 10, 13, 14, 15, 16 and 17 networks.

4.2.1 Results

Figure 2. Tranquility

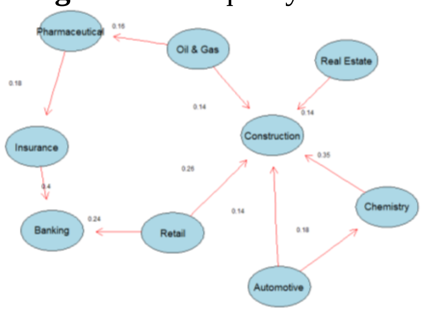
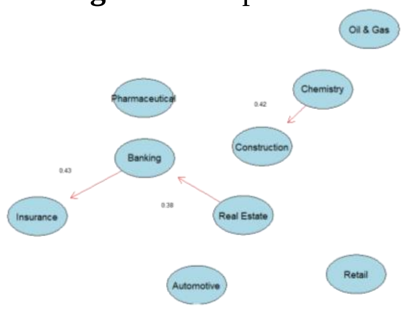


Figure 3. Subprime



Source: own elaboration.

Although all periods were segregated (Table 1), the first two DBNs did not show significant connections. Thus, the DBN referring to the third period presents the configuration from which contagion's evolution in the following crisis periods was analyzed. It is noticeable that Pino & Sharma (2019), who studied subprime contagion on financial institutions, noticed the first contagion signals (in their case measured through correlation between the institutions) appearing in the system in 2003, which exactly coincides with our analysis' third period.

Initially, real estate, automotive, oil&gas and retail sectors present themselves as main propagators. Despite being defined as a tranquility scenario, this period presents great volatility in the series due to the international situation that disturbed the financial market. Essentially, it was a time when the war on terrorism was on the rise, permeated by budget deficits and the fear of an imminent recession, besides a rise in oil prices due to the situation in Iraq. Thus, the propagating roles of the oil&gas and automotive sectors in the period are justified. The spreading from insurance towards banking is in accordance with Chen et al. (2014), who found evidence of significant causality between insurance and banking institutions.

In Subprime, only the edge between chemical and construction sectors remained (with a correlation increase from 0.34 to 0.42). This relationship is explained by the construction sector being one of the main chemical products consumers, such as paints and coatings. Here, there is an edge creation between real estate and banking sectors, denoting a process of contagion, as well as the inversion of the edge's direction between banking and insurance sectors (formerly, the insurance sector was a propagator, now it turns into a contagion receptor), whose correlation also increases, from 0.41 to 0.43.

This change in the edge's direction is interesting especially when compared to Chen et al. (2014)'s results. They show that the impact of banks on insurance companies is stronger and of longer duration than the impact of insurers on banks. Furthermore, when subjected to stress tests, banks create significant systemic risk for insurers, but not the other way around.

Figure 4. Tranquility

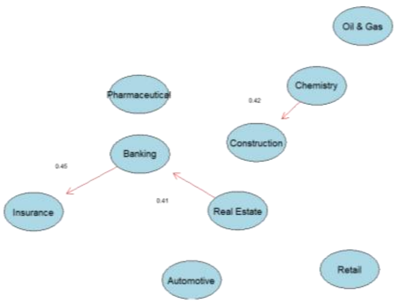
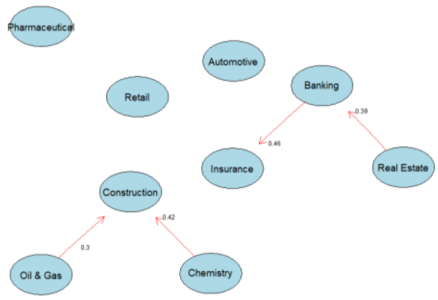


Figure 5. European Debt Crisis



Source: own elaboration.

At the 7th period there are no changes in the edges, but there is an increase in the partial correlation between real estate and banking (from 0.38 to 0.41) and banking and insurance (from 0.43 to 0.45). At the 8th period, there is a contagion process with the inclusion of the edge between oil&gas and construction, in addition to a correlation reduction between real estate and banking, and a correlation increase between banking and insurance (0.39 and 0.46 respectively).

The European debt crisis started as a consequence of the subprime effects. As U.S. and European economies are strongly correlated, even more during crisis situations (Ye et al., 2016), this crisis effects were also reflected in the USA, with decrease in exports and fall in investments (Na, Minjun, & Wen, 2013). The crisis effect on the exchange rate resulted in a wide variation in crude oil prices, hence justifying the emergence of the oil&gas sector as a propagator in the U.S. in this period. Furthermore, the USA invested in the production of oil and natural gas between 2009 and 2012, and the need to build and maintain the production facilities for these inputs can justify the connection with the construction sector.

Figure 6. Tranquility

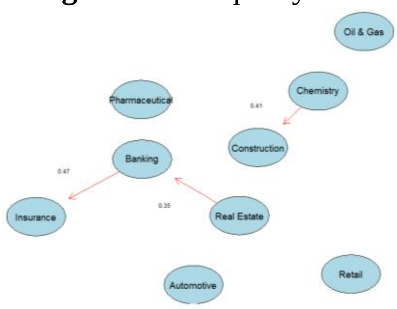
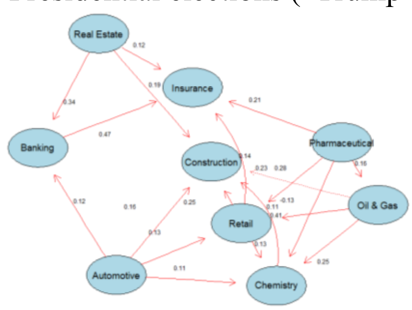


Figure 7. Presidential elections ("Trump effect")



Source: own elaboration.

From period 9 to 11 the DBNs configuration remain almost unaltered, aside from changes in correlations and the vanishing of oil&gas→construction edge.

In period 12, the contagion effect is clear, with the creation of several edges. The main propagator (the sectors not influenced by others) are real estate, automotive and pharmaceutical. The main receivers are insurance and construction. Since the presidential campaign, Trump has generated negative expectations for the automotive trade with a protectionist policy, criticizing

Ford's plans to establish factories in Mexico, and demonstrating intentions to increase import taxes on automotive inputs. Regarding the pharmaceutical sector, one of his promises was to reduce drug prices, leading to a fall of this sectorial index with the election.

At last, Trump's stance on immigration has impacted the real estate and construction sectors: an environment of mass deportations and severely restricted visas would have led to reduced real estate investment and increased construction costs, with the elimination of millions of jobs from this sector. Cost rises may be repassed onto home buyers or construction projects may be interrupted, further affecting real estate stocks.

Fixed income assets compose typical investment instruments for the insurance companies. Therefore, the fall in real estate stocks directly affects this sector, justifying the creation of the real estate→insurance edge. The relationship between the real estate and banking sectors is constituted in a similar way, in which properties can be collateral assets and a measure of protection against credit risk (as in mortgages), so the edge between these sectors remains.

The relationship between pharmacy and chemistry is natural. Also, the pharmaceutical and insurance industries are closely related in the U.S. In that country, the private insurance companies are fundamental for the health system (Obamacare). Also, the health insurers are responsible for making agreements with pharmaceutical companies to negotiate medication costs (Daemmrich, 2011; Danzon, 2006). Thus, the impact on drugs' prices ends up influencing these companies' relationship with insurers. The fact that medical and pharmaceutical inputs - such as plastic and even medicines' inputs - come from crude oil explains the relationship between the pharmaceutical and oil&gas sectors.

A drop in the automotive sector impacts the chemical industry by reducing demand for various inputs, as this sector is responsible for the production of metals and parts for vehicles, in addition to fuel. Oil&gas provides inputs for the chemical sector as well, since the latter is responsible for the production of petroleum derivates such as gasoline, rubber and plastic.

Regarding the retail sector, the correlation with oil&gas is negative, in agreement with Kilian & Park (2009), who conclude that drops in oil prices strengthen retail sales, as a result of a demand's shock (with lower prices for gasoline, consumption is reallocated to other sectors). Likewise, an increase in oil prices generates a reduction in demand for retail products and items such as consumer goods and tourism.

Figure 8. Covid-19 (Phase 1)

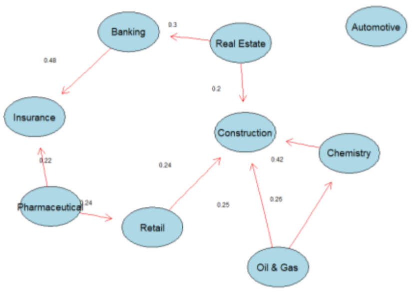
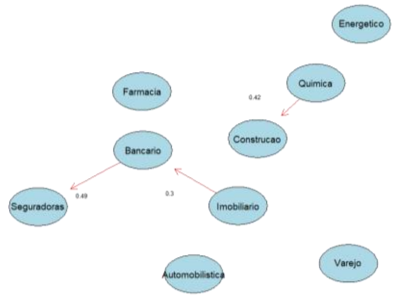


Figure 9. Covid-19 (Phase 2) – current times



Source: own elaboration.

Period 12's configuration remains practically unaltered until period 18 (with slight changes in correlation). In Covid-19's 1st phase, 10 edges cease to exist. Among the remaining connections there is an increase of 0.01 in the correlation of pharmacy→insurance and oil&gas→chemistry edges. Also, an increase of 0.02 on pharmacy→retail, a decrease of 0.02 on the oil&gas→construction edge and a decrease of 0.01 on the retail→construction edge.

This period brings the continuity of the insurance and construction sectors as the main receptors of crises. On the other hand, real estate, pharmacy and oil&gas are the main propagators. The greatest correlations remain between banking and insurance (0.48) and chemistry and construction (0.41).

Oil&gas suffered a major shock in this period with the occurrence of negative oil prices. The pharmaceutical and real estate sectors suffered more direct effects from the Covid-19 pandemic, with social isolation, greater demand for medicines, increased unemployment rates and consequent renegotiation of rents. These effects spread throughout the sectorial network.

Although contagion structures have not been created, there is the consolidation of a highly interconnected economic system, unlike other international crises, which presented little or no connection between sectors.

The second phase of Covid-19 has as its initial milestone the announcement of vaccine third phase testing, conducted and developed by the University of Oxford. Although we are still in the middle of the pandemic, this milestone reflects a period in which the economic agents have already incorporated the effects of this crisis. Apparently, they are not affected by any other external shocks, approaching a steady state of tranquility for the indices time series.

Also, it is noteworthy that the two greatest financial crises (*subprime* and the Covid-19 first phase) not only show the same configuration of sectoral interdependence, but also Covid-19's second phase presents the same network as the post-subprime. Both of them present the same two paths of strong sectoral dependency: a financial interconnection (real estate→banking→insurance) and a direct relationship through inputs supply (chemistry→construction). The banking→insurance edge has the highest correlation (0.49).

Analyzing the network's evolution, the oil&gas sector appears as a propagator during the European debt crisis. It returns to be a propagator with Trump's election in 2016, when the pharmaceutical sector also appears as propagator. Both sectors remain in that position until Covid-19's first phase. The real estate sector remains a major propagator from subprime to the end of the series. Also, it is the main propagator for the financial area, influencing the banking sector and, as a consequence, the insurance as well.

Thus, if an investor had allocated his resources at real estate and oil&gas sectors in 2000, his risk assessments would have only involved the behavior of these sectors in face of the economic situation. After all, these are the sectors that, in general, are not impacted by the others. On the other hand, investments in sectors that receive contagion, such as the construction sector, would have required a broader analysis, involving not only the peculiarities of this industry, but also the various sectors that affect it. As Branger, Kraft, & Meinerding (2009) state, contagion risk has a crucial impact on investors' demands for protection, since it reduces their ability to diversify their portfolios. If investors ignore contagion or its time dimension, it may expose themselves to suffer large and economically significant utility losses.

Regarding the insurance industry, it has been a receiver since the beginning (except for period 4), contributing relatively little to systemic losses, in agreement with Kaserer & Klein (2019), as well as Cummins & Weiss (2014), Brechmann et al. (2013) and Harrington (2009). Addressing specifically the AIG case, in agreement with Safa et al. (2013), this retroactive analysis indicates that, even though it has an important economic function, the insurance sector, as main recipient of shocks, is not essential to the point of justifying such a large injection of public money in a single company, not even the main player. We cannot simulate what would have happened if that money injection had not been made, but it is safe to say that the insurance sector does not play a central role in spreading crises, so governmental actions should first address the main propagators in order to contain the contagion effect.

5. Final remarks

This study aimed to model the U.S. economy's sectorial interdependence structure through Dynamic Bayesian Networks, in order to capture the contagion effect in multiple financial crises. Furthermore, we sought to assess whether the insurance industry plays a central role in spreading crises relative to other economic sectors, since, during the subprime crisis, this sector played a major role by having the world's main insurer considered too-big-to-fail.

The adoption of a sophisticated machine learning modeling technique on a literature's underexplored topic (sectorial contagion) has brought satisfactory results. The vast majority of the relationships captured by the Dynamic Bayesian Networks in different periods finds support on the literature, showing that future economic analyses can be enriched by using this instrument to capture sectorial (in)dependency relationships. Furthermore, this technique allows us to follow the dependency structure evolution over time, not only by verifying the relations' (edges') appearance or vanishing, but also observing the changes in correlation magnitudes when comparing periods.

The results also bring important insights, such as the interrelationship raise between the insurance and banking sectors (going from 0.4 in period 3 to 0.49 in period 19, the biggest increase of all sectorial correlations). We found evidence that banking sector presents itself as a frequent crises propagator towards insurance, but not the other way around, in accordance with previous literature. It is also noticeable that the oil&gas and real estate sectors predominate as the main propagators throughout the period, which had not been addressed yet in other studies. Finally, this study was a pioneer in modeling the current configuration of the sectorial network during the Covid-19 pandemic, which proved to be identical to subprime's network configuration. Both can be classified as the greatest financial crises during the analyzed period. This configuration may define the economy's behavior in the subsequent periods until there is a structural change.

Regarding limitations, our study does not model the causes of crisis but only its consequences, as this cause is a hidden variable to the network. Future research may address the issue by analyzing different sectors, other countries, focusing on relationships between specific sectors, or even extending this research to other periods. Comparisons with these results can also be made by using different methodologies.

References

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review*. https://doi.org/10.1257/aer.20130456

Aït-Sahalia, Y., Cacho-Diaz, J., & Laeven, R. J. A. (2015). Modeling financial contagion using mutually exciting jump processes. *Journal of Financial Economics*, *117*(3), 585–606. https://doi.org/10.1016/j.jfineco.2015.03.002

Amini, H., Cont, R., & Minca, A. (2016). Resilience to contagion in financial networks. *Mathematical Finance*, *26*(2), 329–365. https://doi.org/10.1111/mafi.12051

Anagnostou, I., Sanchez Rivero, J., Sourabh, S., & Kandhai, D. (2020). Contagious defaults in a credit portfolio: a Bayesian network approach. *The Journal of Credit Risk*, *16*(1). https://doi.org/10.21314/JCR.2020.257

Bégin, J. F., Boudreault, M., Doljanu, D. A., & Gauthier, G. (2019). Credit and Systemic Risks in the Financial Services Sector: Evidence From the 2008 Global Crisis. *Journal of Risk and Insurance*, *86*(2). https://doi.org/10.1111/jori.12210

Berger, J. O., & Sellke, T. (1987). Testing a Point Null Hypothesis: The Irreconcilability of P Values and Evidence. *Journal of the American Statistical Association*, *82*(397), 112. https://doi.org/10.2307/2289131

Branger, N., Kraft, H., & Meinerding, C. (2009). What is the impact of stock market contagion on an investor's portfolio choice? *Insurance: Mathematics and Economics*, *45*(1). https://doi.org/10.1016/j.insmatheco.2009.04.006

Brechmann, E. C., Hendrich, K., & Czado, C. (2013). Conditional copula simulation for systemic risk stress testing. *Insurance: Mathematics and Economics*, *53*(3). https://doi.org/10.1016/j.insmatheco.2013.09.009

Carvalho, J. V. de F., & Chiann, C. (2013). Redes bayesianas: Um método para avaliação de interdependência e contágio em séries temporais multivariadas. *Revista Brasileira de Economia*, *67*(2), 227–243. https://doi.org/10.1590/S0034-71402013000200003

Chen, H., Cummins, J. D., Viswanathan, K. S., & Weiss, M. A. (2014). Systemic Risk and the Interconnectedness Between Banks and Insurers: An Econometric Analysis. *Journal of Risk and Insurance*, *81*(3), 623–652. https://doi.org/10.1111/j.1539-6975.2012.01503.x

Chen, H., & Sun, T. (2020). Tail Risk Networks of Insurers Around the Globe: An Empirical Examination of Systemic Risk for G-SIIs vs Non-G-SIIs. *Journal of Risk and Insurance*, *87*(2). https://doi.org/10.1111/jori.12296

Chong, C., & Klüppelberg, C. (2018). Contagion in financial systems: A Bayesian network approach. *SIAM Journal on Financial Mathematics*, *9*(1), 28–53. https://doi.org/10.1137/17M1116659

Claessens, S., & Kose, M. A. (2013). Financial Crises Explanations, Types, and Implications. *IMF Working Papers*, *13*(28), 1. https://doi.org/10.5089/9781475561005.001

Claessens, S., Kose, M. A., & Terrones, M. E. (2009). What happens during recessions, crunches and busts? *Economic Policy*. https://doi.org/10.1111/j.1468-0327.2009.00231.x

Collet, J., & Ielpo, F. (2018). Sector spillovers in credit markets. *Journal of Banking and Finance*, *94*, 267–278. https://doi.org/10.1016/j.jbankfin.2018.07.011

Cummins, J. D., & Weiss, M. A. (2014). Systemic risk and the U.S. insurance sector. *Journal of Risk and Insurance*, *81*(3). https://doi.org/10.1111/jori.12039

Daemmrich, A. (2011). *U.S. Health care reform and the pharmaceutical industry*. (No. 12–015). Retrieved from https://hbswk.hbs.edu/item/us-healthcare-reform-and-the-pharmaceutical-industry

Danzon, P. M. (2006). Economics of the Pharmaceutical Industry. *National Bureau of Economic Research*, 8–10. Retrieved from https://www.nber.org/reporter/fall06/danzon.html

Dornbusch, R., Park, Y. C., & Claessens, S. (2000). Contagion: Understanding How It Spreads. *The World Bank Research Observer*, *15*(2), 177–197. https://doi.org/10.1093/wbro/15.2.177

Dreassi, A., Miani, S., Paltrinieri, A., & Sclip, A. (2018). Bank-Insurance Risk Spillovers: Evidence from Europe. *Geneva Papers on Risk and Insurance: Issues and Practice*, *43*(1). https://doi.org/10.1057/s41288-017-0049-0

Dungey, M., Flavin, T. J., & Lagoa-Varela, D. (2020). Are banking shocks contagious? Evidence from the eurozone. *Journal of Banking and Finance*, *112*, 105386. https://doi.org/10.1016/j.jbankfin.2018.07.010

Eckert, C., Gatzert, N., & Heidinger, D. (2020). Empirically assessing and modeling spillover effects from operational risk events in the insurance industry. *Insurance: Mathematics and Economics*, *93*. https://doi.org/10.1016/j.insmatheco.2020.04.003

Efron, B. (2005). Local False Discovery Rates. *Large-Scale Inference*, 70–88. https://doi.org/10.1017/cbo9780511761362.006

Elyasiani, E., Staikouras, S. K., & Dontis-Charitos, P. (2016). Cross-Industry Product Diversification and Contagion in Risk and Return: The case of Bank-Insurance and Insurance-Bank Takeovers. *Journal of Risk and Insurance*, *83*(3). https://doi.org/10.1111/jori.12066

Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance*. https://doi.org/10.1111/0022-1082.00494

Glasserman, P., & Young, H. P. (2015). How likely is contagion in financial networks? *Journal of Banking and Finance*, *50*, 383–399. https://doi.org/10.1016/j.jbankfin.2014.02.006

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*. https://doi.org/10.2307/1912791

Greenland, S., Senn, S. J., Rothman, K. J., Carlin, J. B., Poole, C., Goodman, S. N., & Altman, D. G. (2016). Statistical tests, P values, confidence intervals, and power: a guide to misinterpretations. *European Journal of Epidemiology*, *31*(4), 337–350.

https://doi.org/10.1007/s10654-016-0149-3

Harrington, S. E. (2009). The financial crisis, systemic risk, and the future of insurance regulation. *Journal of Risk and Insurance*, *76*(4). https://doi.org/10.1111/j.1539-6975.2009.01330.x

Jaworski, P., & Pitera, M. (2014). On spatial contagion and multivariate GARCH models. *Applied Stochastic Models in Business and Industry*, *30*(3), 303–327. https://doi.org/10.1002/asmb.1977

Kaserer, C., & Klein, C. (2019). Systemic Risk in Financial Markets: How Systemically Important Are Insurers? *Journal of Risk and Insurance*, *86*(3). https://doi.org/10.1111/jori.12236

Kilian, L., & Park, C. (2009). The impact of oil price shocks on the U.S. stock market. *International Economic Review*, *50*(4), 1267–1287. https://doi.org/10.1111/j.1468-2354.2009.00568.x

Longstaff, F. A. (2010). The subprime credit crisis and contagion in financial markets. *Journal of Financial Economics*, *97*(3), 436–450. https://doi.org/10.1016/j.jfineco.2010.01.002

Na, L., Minjun, S., & Wen, H. (2013). Impacts of the Euro sovereign debt crisis on global trade and economic growth : A General Equilibrium Analysis based on GTAP model. *16th Annual Conference on Global Economic Analysis, Shanghai, China*.

Nagarajan, R., Scutari, M., & Lèbre, S. (2013). Bayesian Networks in R. In *Bayesian Networks in R*. https://doi.org/10.1007/978-1-4614-6446-4

Neapolitan, R. E. (2004). Learning Bayesian Networks. In *Pearson Prentice Hall*. Chicago, Illinois.

Opgen-Rhein, R., & Strimmer, K. (2007). From correlation to causation networks: a simple approximate learning algorithm and its application to high-dimensional plant gene expression data. *BMC Systems Biology*, *1*(1), 37. https://doi.org/10.1186/1752-0509-1-37

Pino, G., & Sharma, S. C. (2019). On the Contagion Effect in the US Banking Sector. *Journal of Money, Credit and Banking*, *51*(1), 261–280. https://doi.org/10.1111/jmcb.12489

Robinson, J. W., & Hartemink, A. J. (2010). Learning Non-Stationary Dynamic Bayesian Networks. *Journal of Machine Learning Research*, *11*, 3647–3680. https://doi.org/10.5555/1756006.1953047

Safa, M. F., Hassan, M. K., & Maroney, N. C. (2013). AIG’s announcements, Fed’s innovation, contagion and systemic risk in the financial industries. *Applied Financial Economics*, *23*(16), 1337–1348. https://doi.org/10.1080/09603107.2013.815309

Schäfer, J., & Strimmer, K. (2005). A Shrinkage Approach to Large-Scale Covariance Matrix Estimation and Implications for Functional Genomics. *Statistical Applications in Genetics and Molecular Biology*, *4*(1). https://doi.org/10.2202/1544-6115.1175

Sourabh, S., Hofer, M., & Kandhai, D. (2020). Quantifying Systemic Risk Using Bayesian Networks. *SSRN Electronic Journal*, 1–15. https://doi.org/10.2139/ssrn.3525739

Storey, J. D. (2002). A direct approach to false discovery rates. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*, *64*(3). https://doi.org/10.1111/1467-9868.00346

Ur Rehman, M. (2016). Financial Contagion in EFA Markets in Crisis Periods: A Multivariate GARCH Dynamic Conditional Correlation Framework. *The Lahore Journal of Economics*, *21*(2), 121–151. https://doi.org/10.35536/lje.2016.v21.i2.a5

Ye, W., Zhu, Y., Wu, Y., & Miao, B. (2016). Markov regime-switching quantile regression models and financial contagion detection. *Insurance: Mathematics and Economics*, *67*. https://doi.org/10.1016/j.insmatheco.2015.11.002