Analysis of Financial Contagion among Economic Sectors through Dynamic Bayesian Networks

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1.1 Definitions

- **Crises**: extreme manifestations of the interactions between the financial sector and the real economy, whose origins can be domestic or external, coming from public or private sectors. (Claessens & Kose, 2013; Claessens, Kose, & Terrones, 2009);

- **Contagion**: process of crises propagatin, may it be among regions, sectors or institutions;

- Previous studies usually analyze contagion among countries (Carvalho & Chiann, 2013);

- Specific economic sectors can be major crises propagators:
  - dot-com bubble;
  - Banking sector: Nordic crises (1980s), Japanese crisis (1990s), Euro zone public debt crisis (2010s) (Claessens & Kose, 2013);
  - One of the most relevant cases: Subprime.

1.2 Objective

- Main objective: modeling the sectorial interdependence of U.S. economy through the **dynamic Bayesian networks** technic
  - Reason 1: helping to define economic policies, in order to avoid – or at least reduce the effects of – periods of crisis, anticipating their spread;
  - Reason 2: 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.;

- Secondary objective: testing the hypothesis of the **insurance sector's centrality** relative to other economic sectors.

2.1 Contagion

- 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**;

- The classic: Forbes & Rigobon (2002). The authors define contagion as “**a significant increase in the correlations between countries, through the return of their stock markets, in times of crisis**”.

- The problem with this definition: it 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.
  - **Consequence: 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.**

2.2 Research lines

1. **Analysing stock exchange indices returns** – and the spread of adverse shocks – **for different countries**. That's the case of Aït-Sahalia, Cacho-Diaz, & Laeven (2015), Ur Rehman (2016) and Ye, Zhu, Wu, & Miao (2016);

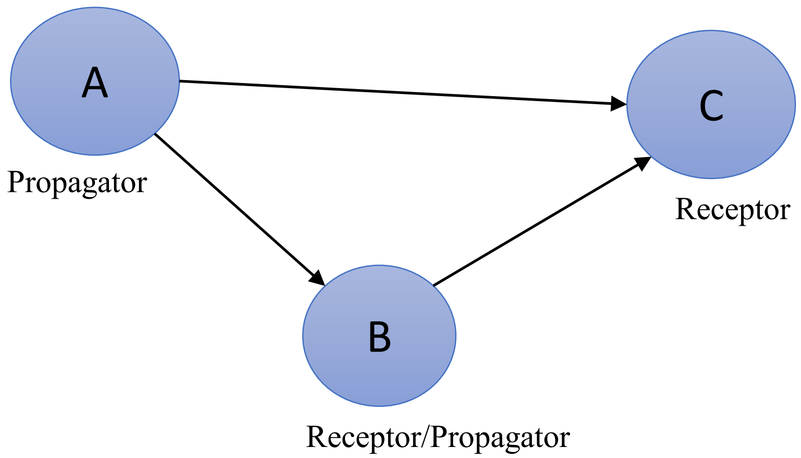
2. **Multivariated models and correlation analyses**, as in Jaworski & Pitera (2014), Elyasiani, Staikouras, & Dontis-Charitos (2016), Dreassi, Miani, Paltrinieri, & Sclip (2018) and Dungey, Flavin, & Lagoa-Varela (2020);

Predominance: **correlacional methodologies** and **contagion among diferente countries** as a study focus;

2.3 Modern Methods

- Our methodology: **Bayesian Networks**, an artificial intelligence technique expressed through a graphic statistical model that maps the joint distribution function of a set of random variables;
  - Advantage: **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.**

- **Our methodological inovation**: modeling the dependency structure directly using <u>**Dynamic Bayesian Networks**</u>, which capture the dependency not only between variables in cross-section, but also in the temporal dimension.



3.2 Dynamic Bayesian Networks

- **The random variables inputed in the network form a multivariated time series system**, Where the series are related throught each Other's pasts and they can be modeled as a vector autoregression process VAR(p), if They form a stationary system. In a VAR(p) process, the observed variables in any moment t ≥ p satisfy the equation

$$X(t) = A_1X(t-1) + \cdots + A_iX(t-i) + \cdots + A_pX(t-p) + B + \varepsilon(t),$$

• X(t) = Xi(t), i = 1,..., k, is the vector of k variables observed at time t;

• Ai, 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, E(ε(t))=0 e Cov(ε(t))=Σ.

- RBDs assume the dependency relations are represented by a VAR(p) process. If we assume a VAR(1) process, $\boldsymbol{X}(\boldsymbol{t}) = \boldsymbol{AX}(\boldsymbol{t}-\boldsymbol{1}) + \boldsymbol{B} + \boldsymbol{\varepsilon}(\boldsymbol{t}), com\ \boldsymbol{\varepsilon}(\boldsymbol{t}) \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{\Sigma})$, then all edges define relations within two successive time periods. The set is defined by all nonzero coefficients in A. If an element aij, i ≠ j, is different from zero, then the network includes an edge from Xi(t − 1) to Xj(t).
- Premiss: the error term for each variable Xi is independent of both the other variables and their error terms.

3.3 The main significancy measures: FDR and q-value

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. To attest the interactions significancy, we use the measures q-value and fdr.

- ***q-values*** are importante for they inform the **percentage of expected false positives** among the **results already considered significant**; while **p-values** inform this percentage considering the **total number of executed tests**.
- **FDR** is the **expected proportion of false positives** findings among **all the 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:

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

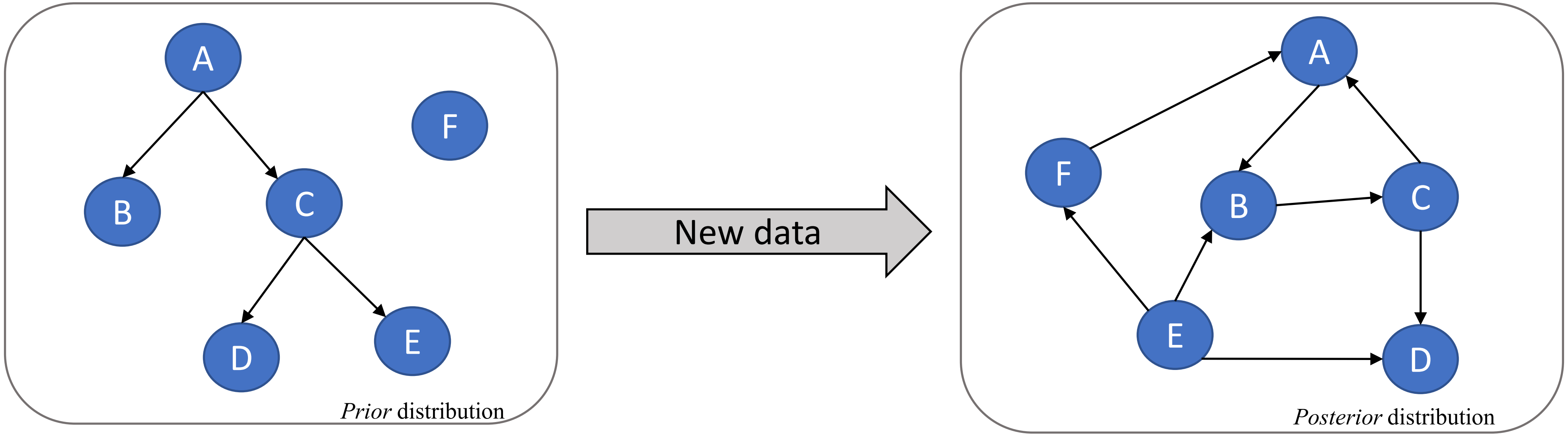
Where V is the number of type I errors (or **false positive** results) and R is the number of rejected hypothesis.

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

Our networks were generated with *q-valor* = 0.1, a cutoff recommended by Efron (2005) and which reflects a conservative Bayesian factor for the Fdr interpretation.

3.3 The methodology's logic

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 disposition of networks **reveals contagion** when, with the **advent of a crisis**, the **creation or alteration of an edge's direction** is observed.

4.1 Data and descriptive analysis

- Contagion analysis widely makes use of stock markets data;

- Our study uses the sectorial indices of the Dow Jones index. 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:

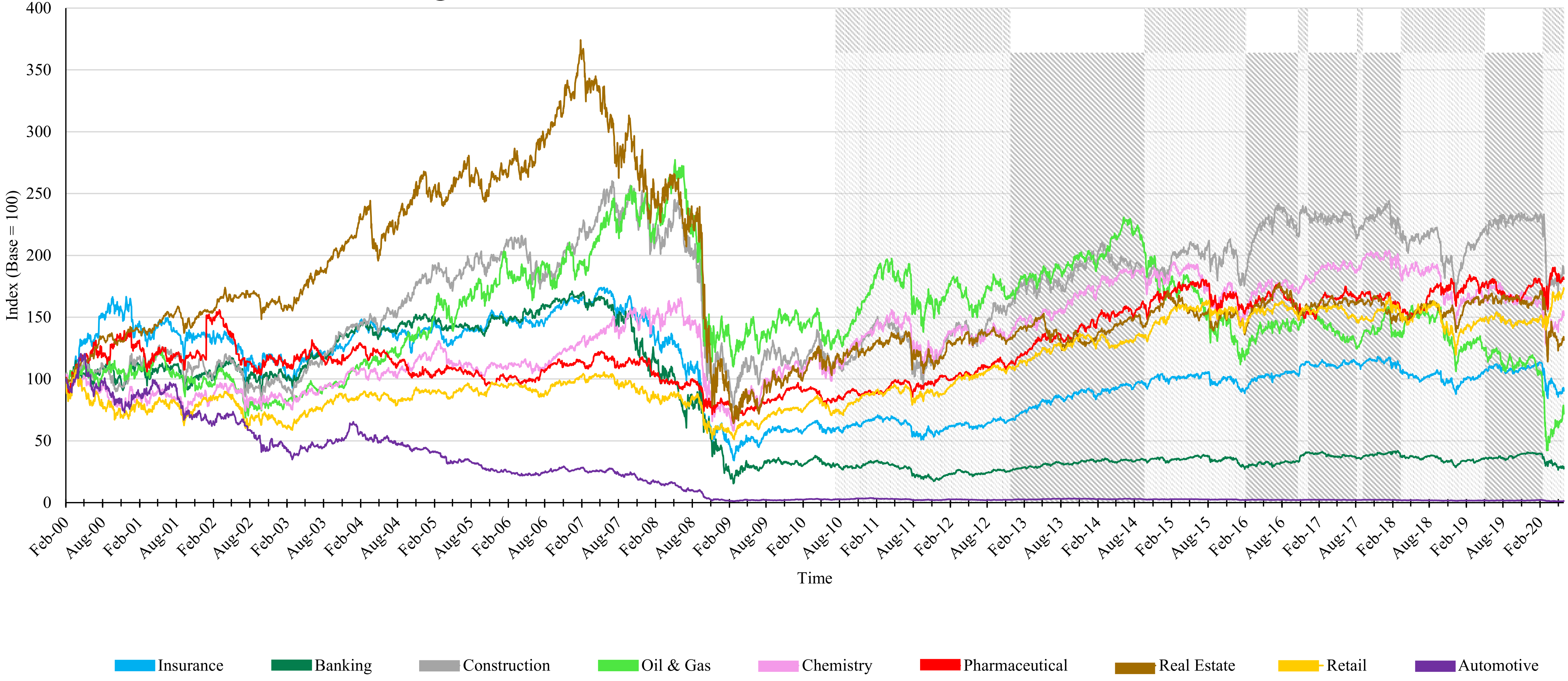
- The utilized sectors are: (1) Insurance, (2) Banking, (3) Oil & Gas, (4) Real Estate, (5) Construction, (6) Pharmacy, (7) Chemistry, (8) Retail and (9) Automotive;

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.

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

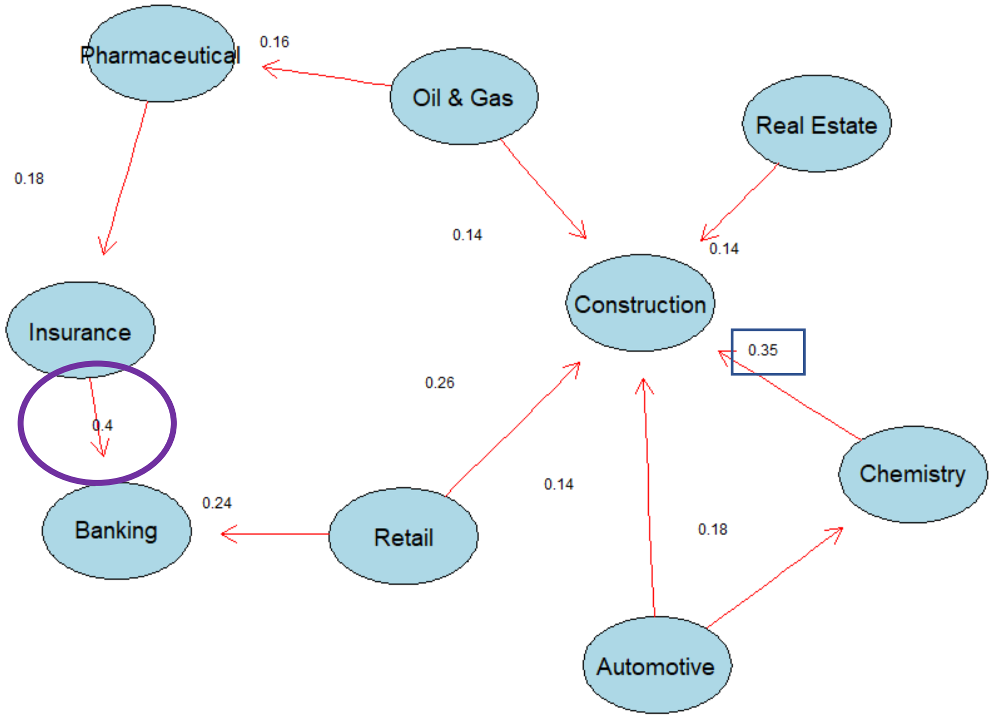


* All periods were tested days ahead (and backwards) and the results don't differ much.

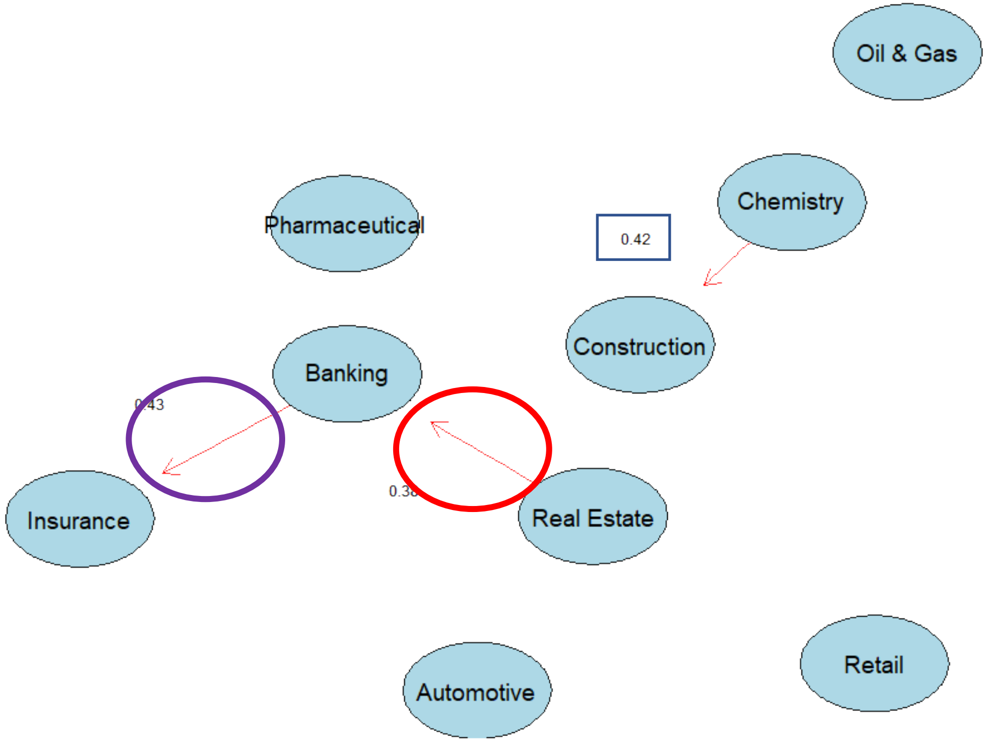
Contagion!

Creation and inversion of edges

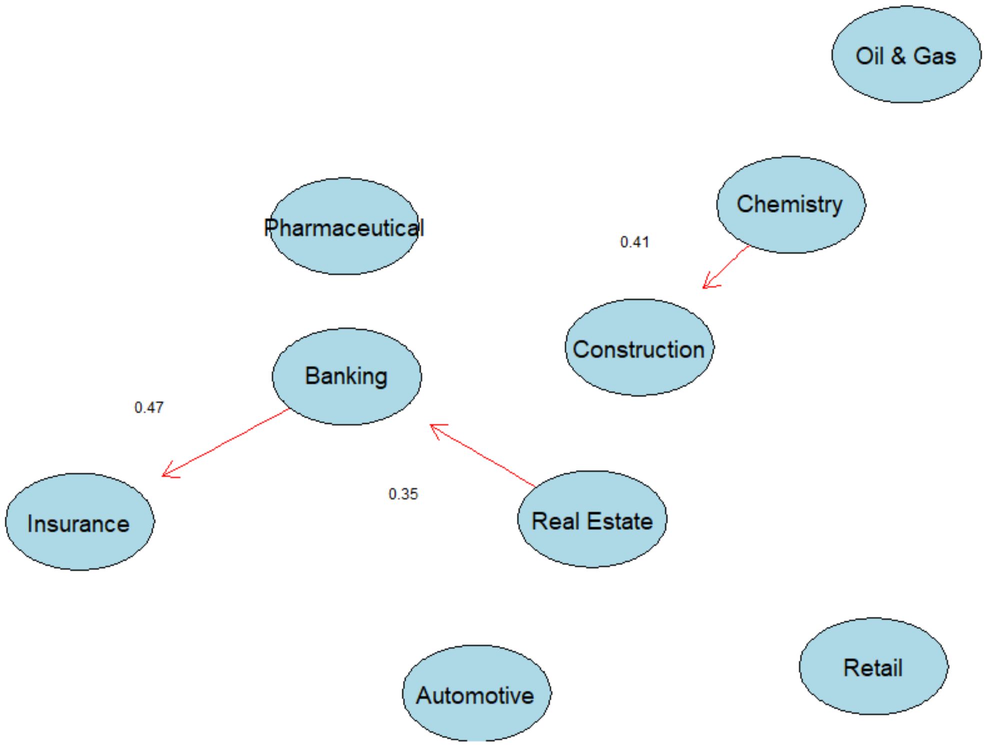
Period 3 - Tranquility



Period 6 – Subprime

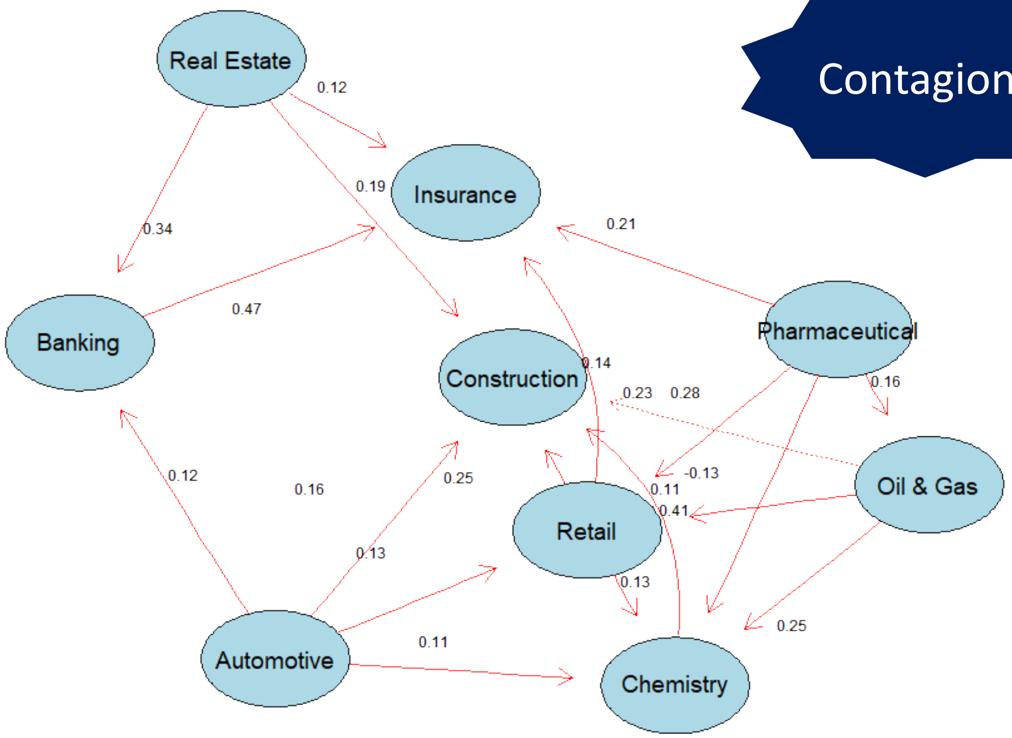


Period 11 - Tranquility

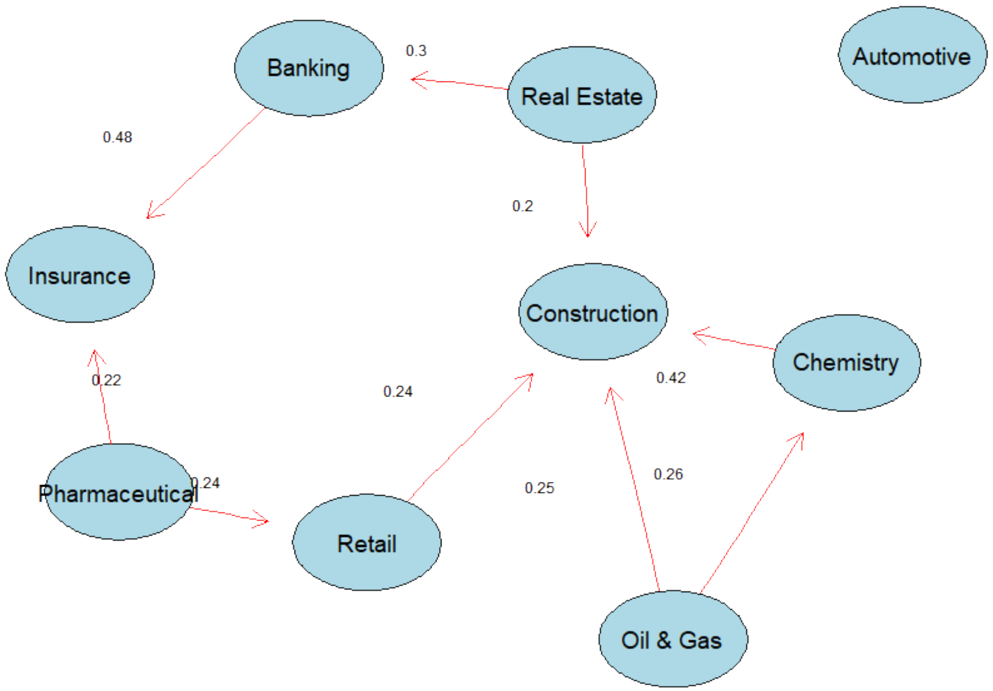


Period 12 – Presidential elections – "Trump effect"

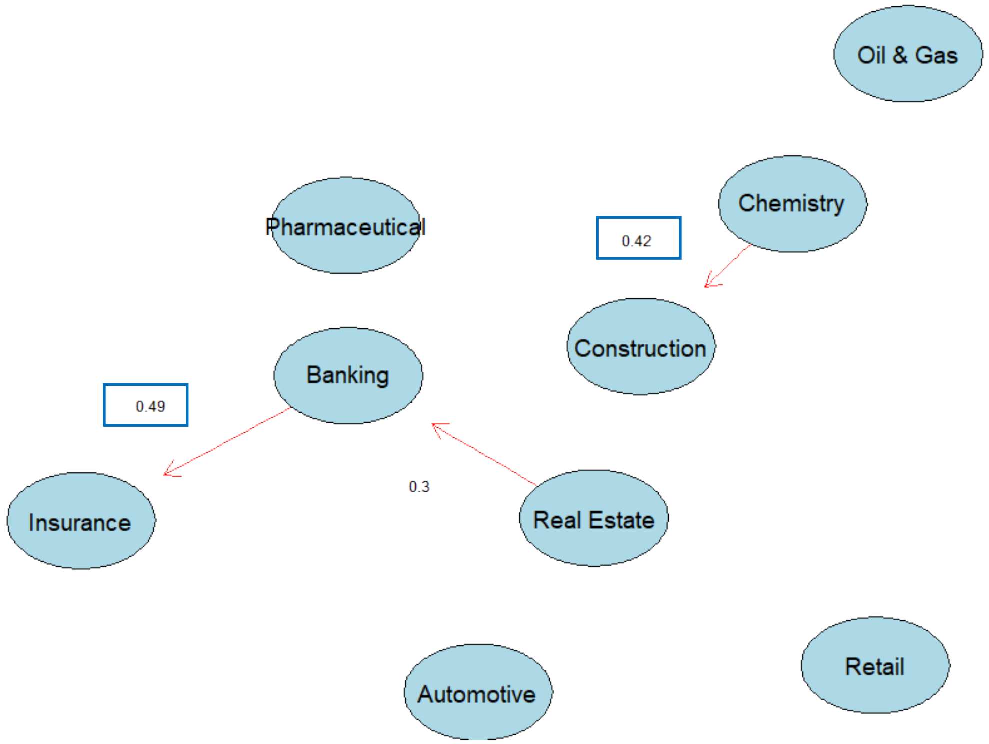
Contagion!



Period 18 – Covid-19 (phase 1)



Period 19 – Covid-19 (phase 2)



On the hypothesis of the insurance sector's centrality and the AIG case

- Regarding the insurance industry, it has been a **receiver** since subprime, contributing relatively little to systemic losses, in agreement with Kaserer & Klein (2019), Cummins & Weiss (2014) and Harrington (2009);

- Addressing specifically the AIG case, and in agreement with Safa et al. (2013), even though it has an important economic function, the **insurance sector**, as main **receptor** 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 **currently 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.

- The results bring important insights, such as the **strong interrelationship between the insurance and banking sectors, with banks propagating crises towards insurance companies but not the opposite**. The predominance of the energy and real estate sectors as the main propagators throughout the period is also verified;

- This study is pioneer in modelling the current configuration of the sectorial network during the Covid-19 pandemic, which proved to be identical to the configuration during the subprime, both classified as the biggest crises during the analyzed period;

- 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.

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Thank you!

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