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 propagating, 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 innovation**: modeling the dependency structure directly using **Dynamic Bayesian Networks**, 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 throughout 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 \( t \geq p \) satisfy the equation

\[
X(t) = A_1 X(t - 1) + \cdots + A_i X(t - i) + \cdots + A_p X(t - p) + B + \varepsilon(t),
\]

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

- RBDs assume the dependency relations are represented by a VAR(p) process. If we assume a VAR(1) process, \( X(t) = A X(t - 1) + B + \varepsilon(t), \) 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 \( X_j(t) \).
- **Premiss**: the error term for each variable \( X_i \) is independent of both the other variables and their error terms.
3.3 The main significance 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 significance, we use the measures q-value and fdr.

- **q-values** are important 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 \textit{q-valo}r = 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>
<thead>
<tr>
<th>Period</th>
<th>Description</th>
<th>Beginning</th>
<th>End</th>
<th>Number of observations</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>Tranquility</td>
<td>Feb 14, 2000</td>
<td>Mar 09, 2000</td>
<td>14</td>
</tr>
<tr>
<td>2</td>
<td>Dot-Com bubble</td>
<td>Mar 10, 2000</td>
<td>Oct 09, 2002</td>
<td>641</td>
</tr>
<tr>
<td>3</td>
<td>Tranquility</td>
<td>Oct 10, 2002</td>
<td>Aug 22, 2005</td>
<td>715</td>
</tr>
<tr>
<td>4</td>
<td>Katrina, Rita and Wilma hurricanes</td>
<td>Aug 23, 2005</td>
<td>Nov 02, 2005</td>
<td>44</td>
</tr>
<tr>
<td>5</td>
<td>Tranquility</td>
<td>Nov 03, 2005</td>
<td>Jul 23, 2007</td>
<td>415</td>
</tr>
<tr>
<td>6</td>
<td>Subprime</td>
<td>Jul 24, 2007</td>
<td>Mar 13, 2009</td>
<td>410</td>
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<tr>
<td>7</td>
<td>Tranquility</td>
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<td>Feb 07, 2010</td>
<td>229</td>
</tr>
<tr>
<td>8</td>
<td>European Debt Crisis</td>
<td>Feb 08, 2010</td>
<td>Nov 30, 2012</td>
<td>704</td>
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<td>Tranquility</td>
<td>Dec 01, 2012</td>
<td>Sep 29, 2014</td>
<td>458</td>
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<tr>
<td>10</td>
<td>Ebola, Greek government-debt crisis and crude prices drop</td>
<td>Sep 30, 2014</td>
<td>Feb 11, 2016</td>
<td>345</td>
</tr>
<tr>
<td>11</td>
<td>Tranquility</td>
<td>Feb 12, 2016</td>
<td>Oct 27, 2016</td>
<td>180</td>
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<tr>
<td>12</td>
<td>U.S. presidential election</td>
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<td>Dec 15, 2016</td>
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<td>Aug 16, 2017</td>
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<tr>
<td>14</td>
<td>Harvey hurricane</td>
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<td>Sep 13, 2017</td>
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<td>Mar 21, 2018</td>
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<td>16</td>
<td>Trade War against China</td>
<td>Mar 22, 2018</td>
<td>May 10, 2019</td>
<td>286</td>
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<td>17</td>
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<td>May 11, 2019</td>
<td>Feb 24, 2020</td>
<td>198</td>
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<td>18</td>
<td>Covid-19 pandemic (Phase 1)</td>
<td>Feb 25, 2020</td>
<td>Jun 19, 2020</td>
<td>82</td>
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<tr>
<td>19</td>
<td>Covid-19 pandemic (Phase 2)</td>
<td>Jun 20, 2020</td>
<td>Sep 30, 2020</td>
<td>69</td>
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<tr>
<td><strong>Total</strong></td>
<td><strong>Feb 14, 2000</strong></td>
<td><strong>Sep 30, 2020</strong></td>
<td><strong>5139</strong></td>
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</table>

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.
4. Results

Period 3 - Tranquility

Period 6 – Subprime

Creation and inversion of edges
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.


Thank you!

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