Economics Bulletin

Volume 44, Issue 2

Construction, extractive and mining global investment intentions: a network analysis

Gilson Silva jr
Federal University of Santa Catarina - Brazil

Jose-Maria Silveira
STATE UNIVERSITY OF CAMPINAS - BRAZIL

Henrique Richter
CARAVELA CONSULTING

Abstract

We characterized the networks of greenfield investment intentions before and after the 2008 global financial crises in two key sectors, construction and extractive and mining, using network indicators (cohesion and centre periphery) and blockmodels. The main results are i) the number of lines informs extract and mining network is substantially thinner than construction, ii) the 2008 crises impact on networks was substantially higher in extractive and mining than in construction, which suggests that construction web of believes was more resilient to exogenous shock, iii) network graphs show us deep change in web configuration after crises. We didn't find any study using that methodology to analyze greenfield investment intentions, particularly in those sectors.

We are thanks to two anonymous referees and the Editor for their valuable comments and suggestions.
Citation: Gilson Silva jr and Jose-Maria Silveira and Henrique Richter, (2024) "Construction, extractive and mining global investment intentions: a network analysis", *Economics Bulletin*, Volume 44, Issue 2, pages 586-600
Contact: Gilson Silva jr - gilson.geraldino@ufsc.br, Jose-Maria Silveira - jmsilv@unicamp.br, Henrique Richter - henriquerct@gmail.com.
Submitted: May 07, 2023.   **Published:** June 30, 2024.

1. Introduction

Network analysis is a powerful analytical tool and it has been used in economics in a variety of analysis. Among recent social network analysis studies in construction we highlight that to test the relationships between contractors˘ network performance and successful business competitiveness based on the project networks they build in Hong Kong (Keung , Shen, 2017), to identify the types of connections that save knowledge seekers˘ time in the time-constrained construction and engineering industry (Poleacovschi, Javernick-Will, Tong, 2017), to perform a human-subject experiment to test group optimism bias levels under different communication network (Du, Zhao, Zhang, 2019) , to examine the effect of safety climate and social-network safety communication patterns maintained by workers on the demonstrated hazard recognition skill in recruiting construction crews from 57 projects in the United States (Pandit, Albert, Yashwardhan, 2020). About extractive and mining we underline that to analyse global cobalt industry chain as a multiplex network, i.e., mining, refining, and consumer goods production are in different region (Shi et alli, 2022), to detect trend of nickel ore trade network stability changes in 2019 under the risk of supply disruption (Ma et alli, 2022) , to analyse the mechanism of risk transmission in the trade network system of the lithium industry chain (Hao et alli, 2022), and trade dependence network in the tungsten industry chain based on percolation (Tang et alli, 2023) and resilience of international cobalt trade network (Yu et alli, 2023). The 2008 financial crises had a deep impact in many economies. The USA Senate section in November, 18th, 2008, discussed it in American auto industry context and how government could help firms, once this sector has a network of supply chain that should not break down. Nevertheless, we didn˘t find any study using that methodology to analyze global web of believes and the 2008 crises impact on in it. It motivated us find empirical evidence about global web of greenfield investment intentions in construction, extractive and mining and how those global webs was affected by a negative exogenous shock (the 2008 global financial crises) using a Financial Times data base, network indicators and block-modelling analysis. After this introduction there are a short literature review, the data base and the network analysis procedures, results and conclusion.

2. Network analysis in economics: a brief review

In the earlier times some authors suggested that a communication network is a kind of complex patterns of relations, moldable by graph theory (French, 1956). Others used some simple but insightful model to describe how the group might reach agreement on a common subjective probability distribution for the parameter by pooling their individual opinions, and call attention to the problem of attaining agreement about subjective probability distribution (DeGroot, 1974). More recently analysis conclude that network has been studied in sociology about a century ago, join with math random graph literature and its connection with social sciences. On the economist side an increase interest in the last two decades, game theory modelling particularly (Jackson, 2006).

In general, the network literature in economics focuses on two subjects: i) models of network (strategic) formation and ii) how social behavior and economic outcomes are influenced by network structure. It is useful to understand how network structure impacts behavior, how information propagates through a network, and in special how people in a social network learn from each other and how network structure impacts beliefs (Jackson, 2006). In a broad perspective, social scientists in general and economists in particular should care about the full network of relationships - how dense it is, whether some groups are segregated, how information spreads and how people behave. Recent network studies have been pushed by the increased availability of data, which join with increased computing power allows us to analyze networks in economic settings in ways not previously possible (Jackson, 2014), as well use this framework for understanding how networks of interactions shape behavior and impact believes (Jackson et alli, 2017).

Some recent models focus on the pure Bayesian-learning use strong assumptions to eliminate strategic behavior, assuming that the economy comprises a large number of individually insignificant agents and those agents only observe the distribution of actions at each date. Since a single agent cannot affect the distribution of actions, he cannot influence the future play of the game, and convergence is remarkably fast (Gale, Kariv, 2003). Others considerer persuasion bias and social influence in a boundedly rational perspective, but ignore strategic communication. In doing so, influence is determined not only by accuracy, but also by network position, i.e., well-connected individuals often seem to be very influential in a way that is not necessarily related to the accuracy of their information. And similarity between the views of different individuals should depend on how close these individuals are in the social network (DeMarzo et alli, 2003). If we consider perfect Bayesian equilibrium of a sequential learning model over a general social network, or Bayesian learning in social networks, however, there is asymptotic learning with bounded private beliefs for a sizable class of stochastic network topologies (Acemoglu et alli, 2011). Network analysis is also useful to understand the spread of information and misinformation in large societies, or the widespread differences in beliefs across social network of agents communicating with each other, beliefs that appear to contradict the truth inclusive (Acemoglu et alli, 2010), the opinion dynamics and efficiency of information aggregation or `erudition_ of the society with boundedly rational agents that updated their opinions (Buechel et alli, 2015), and the microeconomic idiosyncratic shocks impact on aggregate fluctuations (Acemoglu et alli, 2012).

On the recent empirical side, Acemoglu et alli (2016) construct downstream and upstream network effects to study the spread of shocks through the US input-output network at business-cycle frequencies, variation from the exogenous component of imports from China particularly, using industry-level data for manufacturing from the NBER CES Manufacturing Industry Database for 1991¯2009. Atalaya et alli (2011) analysed the USA network structure of production using USA compustat microdata at firm level from 1979 to 2007. Using OECD ICIO data from 1995-2011 Criscuolo and Timmis (2018a) employed network graphics and centrality indicators to study global value chains, and Criscuolo and Timmis (2018b) contrasted central hubs and peripheral countries and sectors, and examine how these changes impact firm productivity. The 2008 financial crises had a deep impact in many economies. It motivated Elliott et alli (2014) and Glasserman and Young (2016) analyse contagion in financial networks.

3. Network analysis

In this section we give details about the data base, network properties and blockmodelling, then characterize the global webs of investment intentions, aggregated and sectorial, and show how it was affected by the 2008 global financial crises using FDI Markets[1] data base - a Financial Times monitoring service available since 2003, and follows greenfield investments forecast in all sectors and countries. According to The FDI report 2016 about Global Greenfield investment trends, the FDI Markets is a database of The Financial Times Ltd. It is the most authoritative source of intelligence on real investment in the global economy, and the only source of greenfield investment data that covers all countries and industries worldwide. The World Bank, Unctad, the Economist Intelligence Unit and more than 100 governments around the world as well as major corporations use the data as the primary source of intelligence on greenfield investment trends. FDI Markets is also used for recent academic purposes, as Castellani and Lavoratori (2020) global R&D location analysis between 2003-2014 and Albino-Pimentel et alli (2022) foreign R&D investments investigation between 2003-2016.

We work on that information and set-up 2003-2008 and 2009-2016 web of greenfield investment projects aggregated by country - construction origin in 113 countries and mining and extraction origin in 101. Investment intentions in construction was, in average, US$ 238,32 in 2003-2008, and US$ 279,83 in 2009-2016, or a 17,42% increase in average. In mining and extraction, it was US$ 493,32 and US$ 660,27, respectively, or a 33,84% increase in average. All values in US$ million 2016 base.

About network properties, whose indicators and results are in section 2.1, some of them give us important information about agent˘s economic behaviour. One is density. It relates to diffusion and contagion. Denser networks, in terms of average numbers of connections per node lead to more extensive diffusion or contagion, ceteris paribus. It leads to more interactions and greater basic reproduction numbers (holding fixed the probability of transmission via any given interaction), according to Jackson (2014). But there are more networks properties as number of lines, average degree, hierarchy, centralization, betweeness, assortativity (de Nooy et alli, 2018).

About blockmodelling, whose concepts and results are in section 3.2, one of the main challengers in economic analysis nowadays is sum up larger data base as a clear and useful set of information. In network analysis context blockmodeling reduces a large and potentially incoherent network to a smaller comprehensible structure that can be interpreted more readily (Batagelj et alli, 2004 a,b). It is a single technique that is able not only to detect different kind of structure but also to ascertain cohesion and core-periphery structures (de Nooy et alli, 2018).

[3] It is a private data base, and we got access through an agreement between Federal University of Santa Catarina (UFSC) and Santa Catarina Manufacturing Federation (FIESC).

3.1 Network general indicators

In this first set of analyses we focus on network properties and on the differences between the two periods. Following de Nooy et alli (2018), we consider indicators since the exploratory level as the number of lines (a tie between two vertices in a network, vertices is a set of vertex, the smallest unit in a network), cohesion indicators as density (the number of lines in a simple network, expressed as a proportion of the maximum possible number of lines), average degree (degree of a vertex is the number of lines incident with it) and hierarchy (a data object for classifying vertices if a vertex may belong to several classes), and center periphery indicators as betweeness centralization (the variation in the betweeness centrality of a vertice divided by the maximum variation in betweeness centrality scores possible in a network of the same size; betweeness centrality of a vertex is the proportion of all geodesics between pairs of other vertices that include this vertex; and geodesic is the shortest path between two vertices), degree centralization (the variation in the degrees of vertices divided by maximum degree variation that is possible in a network of the same size), and assortativity or homophily (the preference of vertices to attach to other vertices that are similar to them according to a numeric property).

Those indicators have an intuition behind, also according to de Nooy et alli (2018). Density (d) is inversely related to network size because the number of possible lines increases rapidly with the number of vertices, so larger networks tend to be less dense, and d=0.15 means that only 15% of all possible arcs are present. Degree of a vertex informs how easily information can reach a person. In this sense, indegree (in) of a vertex is the number of arcs it receives, and outdegree (out) of a vertex is the number of arcs it sends. Hierarchy is particularly useful for a hierarchical clustering of vertices in which units are subdivided into more and more homogeneous subsets. More centralization means that shortest path between two vertices decrease. Betweeness is an alternative to centrality, it inform how a person, company of country is more central if he is more important as an intermediary in the communication network, how crucial he is in the transmission of information through a network, how many flows of information are disrupted (or must take longer detours) if a person stops passing on information (or disappear from the network), in what extent may a someone control the flow of information due to his position in a communication network, or tell us the extended someone is needed as a link in the chains of contacts that facilitated the spread of information within the network. At least, assortativity or homophily means that similar interact more than dissimilar.

Concepts and respectively intuition clear, letús check the results summed up in the Table 1. The networks are weighted by the value of the investment intentions between countries. The decrease in the number of lines in construction (Table 1.A) means that after crises there were 4.27% less ties between two vertices in a network. The 16.67% decrease in density means that after crises the network was bigger than before, once larger networks tend to be less density. The 5.84% decrease in the degree means that after crises the information reached easily. And hierarchy unchanged means no more homogeneous subset after than before crises. The 40% decrease in betweenness means that central countries importance in the expectation formation decreased substantially. The centralization-in decrease in 68.75% means that the information to the central countries became shorter after crises, and centralization-out reduction in 44.44% means that the information from the central countries became longer after crises. At least, assortativity-in decrease in 133% means that the flow of expectation received between dissimilar countries increase after crises, and assortativity-out decrease in 83.33% means that the flow of expectation sent between dissimilar also increase after crises.

The decrease in the number of lines in extractive and mining (Table 1.B) means that after crises there were 52% less ties between two vertices in a network. The 66% decrease in density means that after crises the network was bigger than before, once larger networks tend to be less density. The 52% decrease in the degree means that after crises the information reached easily. And hierarchy unchanged means no more homogeneous subset after than before crises. The 14% decrease in betweenness means that central countries importance in the expectation formation decreased substantially. The centralization-in decrease in 30% means that the information to the central countries became shorter after crises, and centralization-out reduction in 28% means that the information from the central countries became longer after crises. At least, assortativity-in decrease in 18% means that the flow of expectation received between dissimilar countries increase after crises, and assortativity-out decrease in 87% means that the flow of expectation sent between dissimilar also increase after crises.

At least, i) the number of lines informs extract and mining network is substantially thinner than construction, ii) the 2008 crises impact on networks was substantially higher in extractive and mining than in construction, which suggests that construction web of believes was more resilient to exogenous shock, iii) those indicators suggests that the construction and extractive and mining global intentions of investment cohesion and center-periphery relations decreased after crises.

This set of indicators gives us a global network view, but doesn˜t give us details about the network connections as we show in the next section.

TABLE 1A: Construction networks characteristics before and after 2008 crisis

(*)	Indicator class	Indicator	BEFORE	AFTER	variation %
1.3.1	Exploratory	Number of Lines	928	890	-4.27
3.3	Cohesion	Density	0.07	0.06	-16.67
3.3	Cohesion	Average Degree	14.5	13.7	-5.84
3.6	Cohesion	Hierarchy	210	210	0.00
6.4	center periphery	Betweeness	0.14	0.10	-40.00
6.3	center periphery	Centralization (in;out)	0.27;0.65	0.16;0.45	-68.75;-44.44
6.6	center periphery	Assortativity (in;out)	-0.07;-0.22	-0.03;-0.12	-133.33;-83.33

Source: Author`s elaboration using FT data base and Pajek. (*) de Noody et alli (2018) section with the indicator class details.

TABLE 1B: Extractive and mining networks characteristics before and after 2008 crisis

(*)	Indicator class	Indicator	BEFORE	AFTER	variation %
1.3.1	Exploratory	Number of Lines	516	339	-52.21
3.3	Cohesion	Density	0.05	0.03	-66.67
3.3	Cohesion	Average Degree	10.2	6.7	-52.24
3.6	Cohesion	Hierarchy	210	210	0.00
6.4	center periphery	Betweeness	0.08	0.07	-14.29
6.3	center periphery	Centralization (in;out)	0.13;0.54	0.10;0.42	-30.00;-28.57
6.6	center periphery	Assortativity (in;out)	-0.13;-0.28	-0.11;-0.15	-18.18;-86.67

Source: Author`s elaboration using FT data base and Pajek. (*) de Noody et alli (2018) section with the indicator class details.

3.2 Blockmodels

Blockmodeling is a way to carry out positional analysis in the context of network analysis (de Nooy et alli, 2018; Ziberna, 2007). The technique allows us to go beyond a traditional clustering indirect approach based on the presence of dissimilarity (see Dorain et al, 2004, for a detailed explanation of the limits of the conventional indirect approach). It allows what literature calls a direct approach, extending the concept of equivalence. For instance, two blocks of a reorganized network can be equivalent when they don˜t have any link, such as a null block.

Let's present things more formally. Let $E = \{X_1, X_2, \ldots\ldots, X_n\}$ be a finite set of units (countries, in our study). The units are related by binary relations $R_t \subseteq E \times E,\ t = 1, \ldots, r$ with $r \geq 1$, which determine a network $N = (E, R_1, R_2, \ldots\ldots, R_r)$. We restrict our discussion to a single relation R described by a $X_i R X_j$ corresponding binary matrix $R = [r_{ij}]_{nxn}$, where $r_{ij} = 1$ if $X_i R X_j$, otherwise $r_{ij} = 0$.

Let us explain the clustering procedure in the direct approach. The clustering problem is defined by building a prespecified block model composed of ideal blocks of perfect relations `within each cluster and between them_. This model departs from a criterion function $P : \Phi \to \mathbb{R}$ (according to Batagelj et al., 2004, p.458, Φ it is "the set of all possible clusterings."). In the direct approach, a criterion function is sensitive to the considered equivalence. Following the procedures proposed by Batagelj et al (2004, p.456 and p.458).

$C = \{C_1, C_2, \ldots\ldots\ldots, C_k\}$,is a partition of the set of units E:

$\bigcup_i C_i = E$, with $i \neq j \Rightarrow C_i \cap C_j = \emptyset$. $B(C_u, C_v)$ is the set of ideal block corresponding to block $R(C_u, C_v)$,the image matrix . Calculating the global error (a notion of fitting) by the expression $P(C) = \sum_{C_u, C_v \in C} \min_{B \in B(C_u, C_v)} d(R(C_u, C_v), B)$ is possible. The term $d(R(C_u, C_v), B)$ measures the error between the image and the ideal block, the latter reflecting our theory (for example, center-periphery). The function d needs to be compatible with the selected type of equivalence. The computational procedures are N-P hard. Ziberna, 2007 describe the sequence from the initial clustering to the final configuration. The software Pajek version 5.17 presents a menu option in Operations/blockmodeling (Nooy et al., 2018).

As the network indicators structure, blockmodel also has an intuition behind. It is a flexible matrix based method for analyze and visualize networks, capable of detecting cohesion, core-periphery structures, and ranking, but not replace the indicators in section 2.1. It assigns the vertices of a network to classes, and it specifies the permitted types of relation within and between classes. Blockmodeling is the technique to obtain a blockmodel (de Nooy et alli, 2018). Using VOSviewer, we can transform the matrix representation in a more suitable network graph, that allow us detect a center-satellite-periphery structure, in the sense suggested by Glucklery and Panitz (2016, p. 1167).

The set of figures below put this theory in practice. We have a set of graphics that show us the greenfield investment intentions networks before and after 2008 crises under investors perspectives.

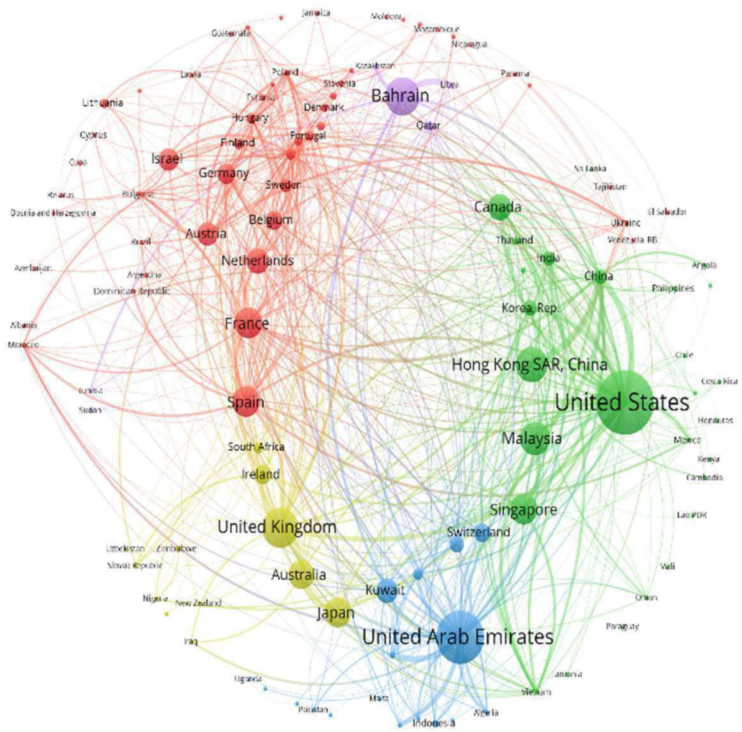
3.2.1 Web of investors intentions before and after 2008

About invertor˜s investment intentions in Civil Construction, figure 1i show us network invertors intentions in this sector in 2003-2008 had no central but three key blocks, the green around USA, with Canada, Hong Kong, Malaysia, Singapore, etc, the blue with United Arab Emirates (UAE) and his arounds, the yellow with UK, Australia, Japan, Ireland, South Africa, the purple with Bahrein and his arounds, two red semi periphery, one from Spain and France to Portugal and Denmark, and other from Austria, Germany to Poland. All others are periphery. Figure 1ii show us 2009-2016 pattern and how deep was the crises impact in the web configuration. Now there are three different key groups, the yellow with China, Singapore, Malaysia, USA, UK, Thailand, India, Korea, Australia, Canada, the green with UAE and their arounds, a red semi periphery with Spain, Turkey, Sweden and France. All others are periphery.

About Extractive and Mining, figure 2i shows 2003-2008 network investor˜s intention in this sector. There is no central, but a complex connection between USA, France and Brazil (blue), Australia, China and Japan (green), Canada and Netherlands (red), and UK (purple). All others are periphery. After 2008 the network was deep reorganized (figure 2ii), with UK-USA-Canada and USA-France connection, a semiperiphery from UAE, Italy to Japan, China, and all other periphery.

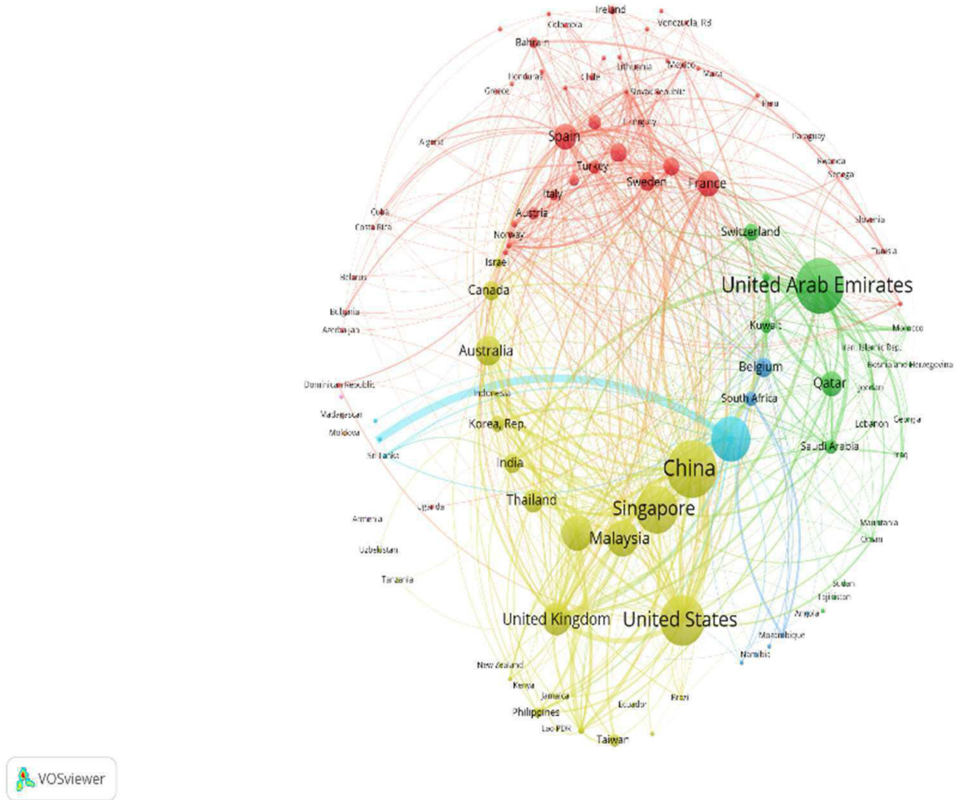
FIGURES 1: Construction investor˘s intentions networks

1i) Before 2008



Source: Author`s elaboration using FT data base.

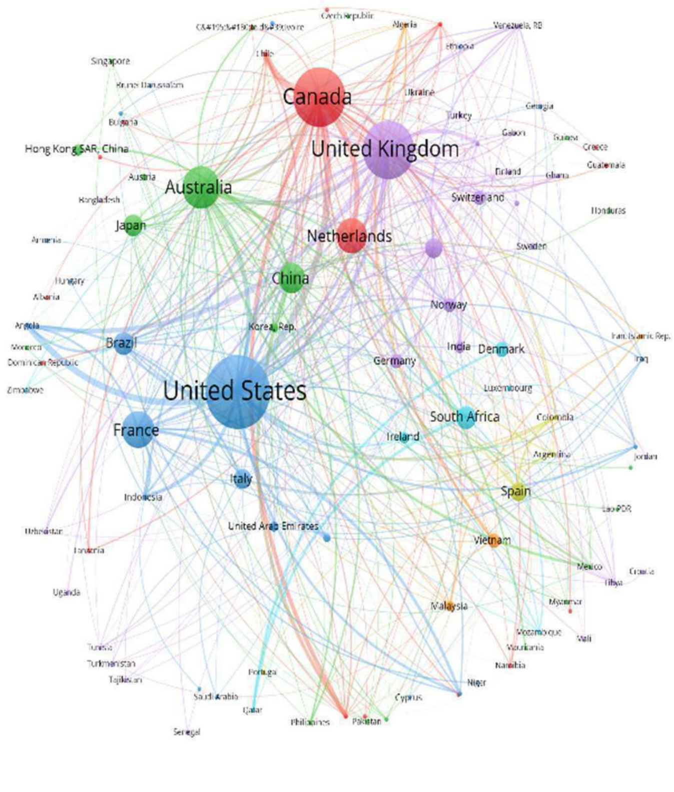
1ii) After 2008



Source: Author`s elaboration using FT data base.

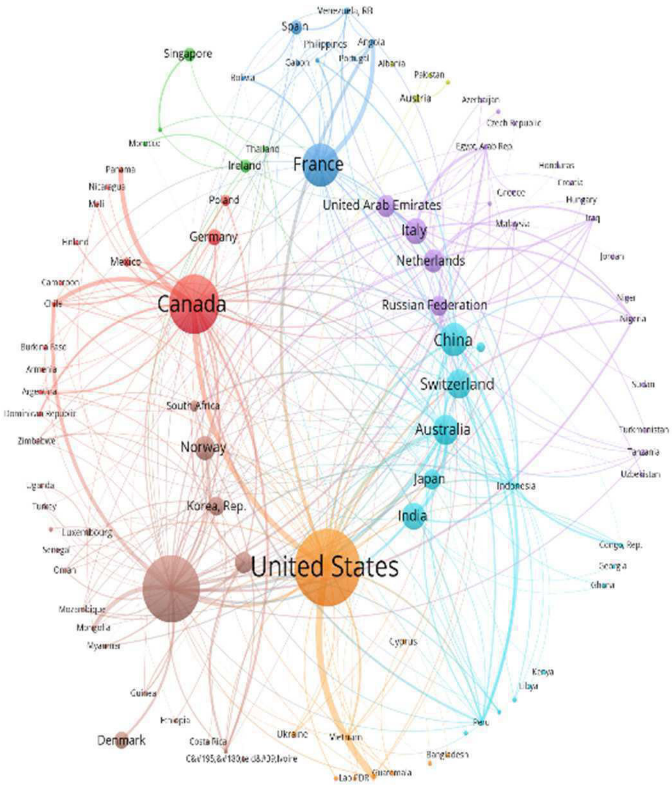
FIGURES 2: Extractive and mining investor´s intentions networks

2i) Before 2008



Source: Author`s elaboration using FT data base.

2ii) After 2008



VOSviewer

Source: Author`s elaboration using FT data base.

4. Final remarks

This paper ad to the empirical literature new perspective about expectations under a network analysis approach in two key sectors: construction and extractive and mining. The main contribution comes from before and after crises network indicators and graph comparison. We detected that the network was bigger than before, the information reached easily, central countries importance in the expectation formation decreased substantially, the information to the central countries became shorter but the information from the central countries became longer, the flow of expectation sent and received between dissimilar countries increase, and graphs show a deep change in the web configuration. Those results are in line with Jackson (2006, 2014, 2017), and Acemoglu et alli (2010, 2011, 2012) once it shows how information propagates through a network and how it reacts to an exogenous shock. Among meaningful implications, we highlight that investors should strength i) links to resist risks and improve network stability, ii) geopolitical cooperation to reduce geopolitical risks and economic policy uncertainties, iii) use of green technologies to fits green global targets and agendas. In this perspective, our analyses revels quite useful to understand deep shocks impact on structural change expectations formation, as 2008 global financial crises, and 2020 pandemic in a near future, when enough data are available. It is also useful to foreign investment policy recommendation.

References

Acemoglu, D., Ozdaglar, A.E., ParandehGheibi, A. (2010). Spread of (mis)information in social networks. Games Economic Behavior, 70(2), p.194¯227.

Acemoglu, D; Akcigit, U; Kerr, W. Networks and the Macroeconomy: An Empirical Exploration. NBER, 2016

Acemoglu, D; Carvalho, VM; Ozdaglar, A; Tahbaz-Salehi, A. (2012) The network origins of aggregate fluctuations, Econometrica, 80 (5), p. 1977-2016.

Acemoglu, D; Dahleh, MA; Lobel, I; Ozdaglar, A. (2011) Bayesian Learning in Social Networks. The Review of Economic Studies, 78(4), p. 1201-1236

Albino-Pimentel, J; Dussauge, P; El Nayal, O (2022). Intellectual property rights, non-market considerations and foreign R&D investments. Research Policy, V51, article 104442

Atalaya, E; Hortacsua, A; Roberts, J; Syverson, C. Network structure of production, PNAS, 2011, 108(13), P. 5199¯5202

Batagelj, V; Ferligoj, A; Doreian, P. (2004a) Generalized blockmodeling. Mimeo.

Batagelj, V; Mrvar, A; Ferligoj, A; Doreian, P. (2004b) Generalized blockmodeling with PAJEK. Metodoloski zvezki, V.1, N.2, p. 455-467

Buechel, B; Hellmann, T; Klobner, S. (2015) Opinion dynamics and wisdom under conformity, Journal of Economic Dynamics and Control, 52, Pages 240-257.

Castellani, D; Lavoratori, K. The lab and the plant: Offshore R&D and co-location with production activities. Journal of International Business Studies (2020) 51, 121‑137

Criscuolo, C.; Timmis, J. GVC centrality and productivity: are hubs key to firm performance?. OECD Productivity working papers #14, June 2018a.

Criscuolo, C.; Timmis, J. GVCs and centrality: mapping key hubs, spokes and the periphery. OECD Productivity working papers #12, February 2018b.

de Noody, W; Mrvar, A; Batagelj, V. Exploratory Social Network Analysis with Pajek. Third Edition. Cambridge University Press. 2018.

DeGroot, M.H., 1974. Reaching a consensus. Journal of the American Statistics Association, 69 (345), p.118‑121.

DeMarzo, P; Vayanos, D; Zwiebel, J (2003) Persuasion Bias, Social Influence, and Unidimensional Opinions, Quarterly Journal of Economics, 118(3), p. 909-968.

Doreian, P. Batagelj, V. and Ferligoj, A., 2004 Generalized Blockmodeling, 1st ed. Cambridge University Press.

Du, J; Zhao, D; Zhang, O (2019) Impacts of human communication network topology on group optimism bias in Capital Project Planning: a humanús subject experiment, Construction Management and Economics, V.37, n.1, p.44-60

Elliott, M; Golub, B; Jackson, MO. Financial Networks and Contagion. The American Economic Review, October 2014, Vol. 104, No. 10 (October 2014), pp. 3115-3153.

French, J. (1956) A formal theory of social power. Psychological Review, 63, p.181‑194.

Gale, D; Kariv S (2003) Bayesian Learning in Social Networks, Games and Economic Behavior, 45(2), p.329-346

Glasserman, P; Young, PY (2016). Contagion in Financial Networks. Journal of Economic Literature, 54(3), p. 779-831

Glucklery, J; Panitz, R (2016) Relational upgrading in global value networks. Journal of Economic Geography, 16 (6), p. 1161‑1185

Hao , H; Xing, W; Wang, A; Song, H; Han, Y; Zhao, P; Xie, Z; Chen, X. (2022). Multi-layer networks research on analyzing supply risk transmission of lithium industry chain . Resources Policy, V. 79, article 102933

Jackson, M.O. The Economics of Social Network. In: Blundell, R; Newey, W; Persson, T (Editors). Advances in Economics and Econometrics, Theory and Applications: Ninth World Congress of the Econometric Society, Cambridge University Press, 2006.

Jackson, MO (2014) Networks in the Understanding of Economic Behaviors. The Journal of Economic Perspectives, 28(4), p.3-22

Jackson, MO; Rogers, BW; Zenou,Y (2017) The Economic Consequences of Social-Network Structure, Journal of Economic Literature, 55 (1), p.49-95

Keung , C.; Shen, L. (2017) Network strategy for contractors˘ business competitiveness. Construction Management and Economics, V.35, n.8-9, p. 482-497.

Ma, Y; Wang, M; Li, X (2022) Analysis of the characteristics and stability of the global complex nickel ore trade network . Resources Policy, V.79, article 103089

Pandit, B; Albert, A; Yashwardhan, P (2020) Developing construction hazard recognition skill: leveraging safety climate and social network safety communication patterns, Construction Management and Economics, V.38, n.7, p. 640-658.

Poleacovschi, C; Javernick-Will, A; Tong, T (2017) The link between knowledge sharing connections and employee time savings: A social network analysis, Construction Management and Economics, V.35, n.8-9, p.455-467.

Shi , Q; Sun, X; Xu, M; Wang, M (2022) The multiplex network structure of global cobalt industry chain. Resources Policy, V 76, article 102555.

Tang , Q; Li, H; Qi,Y; Li,Y; Liu, H; Wang , X (2023) The reliability of the trade dependence network in the tungsten industry chain based on percolation. Resources Policy, V. 82, article 103421

THE fDi REPORT 2016. Global greenfield investment trends.
https://www.fdiintelligence.com/fdi-markets

USA Senate 2008 financial crise section,November, 18th, 2008.

Ziberna, A. 2007. Social blockmodeling of value Networks. Social Networks 29 (2007), p. 105¯126.