Abstract
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'Interactions within a multi-layer EU inter-bank network'

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1. Introduction

In the last two decades, financial and banking research papers granted a lot of interest to assess systemic risk in a banking system. Those papers investigated the mechanisms at stake in an inter-bank market in the wake of a financial crisis and suggested that markets tend to contract before a crisis (Minoiu and Reyes 2013); it means that the number of inter- connections between banks increased. Papers on network theory in finance demonstrate that conventional banking measures such as banks balance sheets are not sufficient to evaluate banking stability. This lack led to a change of perspective from "Too big to fail" to "Too interconnected to fail" (Hüser 2015) in order to take into account bank interconnections in the way systemic risk is assessed. Looking at an inter-bank market through a network perspective gives more insights on its mechanisms as it incorporates market externalities. Allen and Gale 2000 assessed that a great amount of connections between banking groups increase the resilience of a banking system. This statement has been qualified recently, arguing that "An intermediate level of connectivity" seems to enable banks to absorb shock instead of propagating them (Battiston et al. 2012b). A new way of applying network theory to financial networks is to analyse multi-layer networks in order to incorporate different types of interrelations between banks. It is motivated by the fact that the connections between banks do not follow the same logic depending on the market considered.

Most of the studies on financial networks focus on the interactions within a market, studying the mechanisms over time and during a financial crisis (Martinez-Jaramillo et al. 2014). A few papers assess systemic risk using global network metrics1 (Brandi, Di Clemente, and Cimini 2018). In this study, we aim at taking the analysis to the next level by evaluating systemic risk of individual banking groups using local network features2.

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[1] In a network, a global metric is a measure that describes the whole network, e.g the number of nodes oredges.

[2] In a network, a local metric is a measure that describes a single node in the network, e.g the number of neighbors of a node.

We will study three types of markets: two lending markets (short-term and long-term loans) and a cross-holding market. We will particularly focus on the effect of local network metrics, e.g in-degree centrality (Nieminen 1974), closeness centrality (Freeman 1978), betweenness centrality (Freeman 1977) and clustering coefficient (Fagiolo 2007) on a proxy of systemic risk, DebtRank (Battiston et al. 2012a).

2. Objective

The goal of the paper is to study the evolution of a multi-layer European inter-bank network. A multi-layer network considers different types of interactions and interrelations of institutions, e.g. long or short-term loans, cross-holdings, etc. The underlying idea is to define the role of banking interconnections in network stability on several inter-bank markets. We aim to underline if some network configurations threatens banking stability more than others by increasing individual systemic risk.

Studying a multi-layer network with time dimension will bring novel insights on inter-bank market stability for two reasons. Firstly, taking into account several layers in a financial network enable to compare the topology and the structure of different layers, i.e., of different inter-bank markets. The relative position of banking groups differs according to the layer, because banks behave differently on distinct markets. A bank can be a central player in the loan market and be more backward in the cross-holdings securities market. Secondly, by including time dimension in the study, we aim to capture the dynamics of the multi-layer network through the time, especially during the COVID-19 health crisis. Comparing local network metrics is an efficient and relevant way to compare different networks, either between distinct markets or over time.

Beyond this, we investigate whether the evolution of local network metrics have an impact on systemic risk at the banking level. Special attention will be given to assessing the impact of COVID-19 on systemic risk. Indeed, the health crisis likely forced banks to modify their behavior to adapt to this unusual context. Thus, we can assume that bank interconnections have changed during the crisis, both in quantity and type of interconnection.

3. Method

3.1. Integration of financial granular datasets

To create the suitable datasets for our analytical purposes, we started from the tools and methods delivered by the Data Committee on Advanced Analytics Project of the ECB (Aarab et al. 2022). This project aimed to integrate several structured and unstructured granular data to provide users with clean and easy to use financial datasets. For the thesis, we integrated highly confidential financial granular datasets on a quarterly basis from September 2018 to December 2021.

We extended the DCAAP tools to create multiple aligned multi-layer networks, which capture the evolution of the interactions of banks over time. From this, we built a panel data containing the identifier of each banking group and their associated local measures by following these steps.

First, we retrieved the list of significant institutions[3] and their group structure. To do so, we used the Repository of the SSM[4] Supervised Institutions (ROSSI) which contains the list of significant banking groups head. Also, we worked with the Register of Institutions and Affiliates Database (RIAD) to complement the banking groups with their group structure, i.e. the list of entities belonging to the group.

Second, we enriched the list of significant banking groups with their balance sheets items such as cash, deposits, capital and total assets. Individual Balance Sheets data (IBSI), Common Reporting framework data (CoRep) and Financial Reporting data (FinRep) provided us with these conventional key banking features.

Third, we added the bilateral exposures of banking groups on the three studied markets: the long-term loans market, the short-term loans market and the cross-holdings market. For the loan network data, AnaCredit data provides the basis for the required information. Analytical credit datasets report information on individual bank loans above 25,000 euros to legal entities in the euro area; it started to be reported in September 2018. To create the cross-holdings layer, we combined Centralised Securities Database (CSDB) that contains information on the issuer of a security, with Securities Holding Statistics (SHSG) that provides information on the securities held within the Euro Area.

Finally, we created a directed multi-layer network per period in order to retrieve the local metrics of each banking group in the network. For the loans layers, the creditor (resp. debtor) represents the source (resp. target) of the edge. For the cross-holdings layer, the holder (resp. issuer) represents the source (resp. target) of the edge. From this, we built an unbalanced panel dataset of 14 periods and 85 to 105 banking groups. The number of banking groups in the data is varying because not all banks interact systematically with other banks. In the case a bank does not establish an edge with at least one other bank, it is excluded from the network for this layer and this period only.

[3] Significant institutions are banking groups verifying a list of criteria on assets size, finance public assistanceetc.
[4] SSM: Single Supervisory Mechanism

3.2. Statistical model

Regression with panel data

We aim to assess the effect of local network metrics (in-degree centrality, closeness centrality, betweenness centrality and clustering coefficient) on a proxy for systemic risk, DebtRank (Battiston et al. 2012a). This metric allows to assess for systemically important banks, that is, banks that hold a great part of financial exposures of the network. We will follow the approach of Dong and Yang 2016 who assess the impact of local centrality measures on innovation in pharmaceutical industry with panel data, using NPD (New Product Development) as an indicator, but applying it to a European multi-layer financial network.

To do so, we implemented an Ordinary Least Square regression with individual fixed effects on each layer of the network; thus, we dealt with three different models. We controlled with conventional balance sheets items and global network metrics: the number of nodes and edges, the total amount of assets, and the level of leverage[5]. All the variables are scaled, except from DebtRank values to which we applied a cube root transformation[6]. We introduced a dummy variable with a value of 1 starting from March 2020 to control for the possible effects of the Covid crisis. We used clustered standard errors to remove the remaining heteroskedasticity of the residuals (Zeileis, Köll, and Graham 2020).

Hypotheses

Our proxy for systemic risk refers to the impact of a bank going into default on the overall system. Thus, the higher the exposures of a bank are relatively to the total exposures of the network, the more this bank is systemically important. Then, we conjecture that DebtRank is positively linked to the number of incoming edges. This leads us to the first hypotheses:

H1.a A higher banking group’s in-degree centrality makes the value of DebtRank increase.

H1.b In-degree centrality is the biggest determinant of DebtRank values.

Empirically, it is reasonable to believe that the more central a bank is, the more impact it will have on the network if it goes into default. Thus, we want to verify the following hypothesis:

H2. Higher banking group’s centrality measures make the value of DebtRank increase or have no effect.

In the same logic, the number of connections between the neighbors of a bank is likely to increase contagion in case of default. Then, we introduce the last hypothesis:

H3. A higher banking group’s clustering coefficient makes the value of DebtRank increase.

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[5] Leverage Tier 1 is the ratio between capital Tier 1 and total assets.

[6] DebtRank density was highly skewed for all the layers. It also contains a great amount of zero values that prevented us to apply a box-cox transformation.

4. Results

Table 1 presents the results of our regression models for the three layers: (1) refers to the long-term loans layer, (2) is assigned to the short-term loans layer and (3) corresponds to the cross-holdings layer.

H1.a and H1.b are supported for the long-term loans layer and the cross-holdings layer, as the parameters associated with the in-degree centrality in (1) and (3) are positive and significant; in-degree appears as the biggest determinant of DebtRank values. The value of the parameter in the long-term loans layer is higher than the one for the cross-holdings layer. We postulate that it appears riskier to take an additional loan than to issue an additional security. Although none of the parameters associated with centrality measures are significantly negative, H2 is not supported for all the layers. It appears that closeness centrality is the local metric that has the biggest impact on DebtRank for the short-term loans layer. Also, the closer the banks are in the cross-holdings layer, the more systemic risk increases. H3 is only supported for the long-term loans layer. Consequently, cross-holdings securities between the neighbors of a given bank do not increase this bank's systemic risk.

Not all assumptions made are supported by every layer; this demonstrates, as already showed in the literature (Bargigli et al. 2015) that layers in a multi-layer network are very different. Beyond this, we can assess that network topology has a different impact on systemic risk depending on the layer considered. Moreover, the parameter associated to the Covid crisis is negative and significant for all the layers. Running permutation tests of equality of densities (Bowman and Azzalini 2021) on all the variables, we can state that the density of some local metrics significantly changed during the Covid crisis period.

For instance, for the cross-holdings layer, the in-degree centrality and the closeness centrality are statistically different before and during the crisis. For the short-term loans, it is the closeness centrality and the clustering co-efficient that are significantly different between the two periods. We also noticed that the total number of edges in the cross-holdings layer significantly increased during the Covid crisis. It demonstrates that network topology for European banking groups significantly changed during the Covid crisis. So, the Covid crisis seems to have an impact on DebtRank values through the shift it generated on local network metrics; the structure observed during the crisis seems to make the system less vulnerable to individual bankruptcy as it decreases systemic risk of banking groups.

5. Contributions

This paper revealed the importance of taking into account local network metrics to assess systemic risk using real world data. The recent access to financial granular datasets given to various business areas in the European Central Bank enabled to develop a novel approach to assess systemic risk ; and thus to extend the previous work done with simulated data (Nier et al. 2007, Montagna and Kok 2016). To the best of my knowledge, it is the first time that a multi-layer network analysis focusing on banking groups is ran with a scope as broad as the European level. Among this, the disrupted context of the health crisis meant that we had to ensure not to neglect the impact of the crisis on banking group's behavior, whether real or anticipated. Then, we adapted classical statistical tools to fully incorporate the exogenous factor in the study.

This paper contributed to demonstrate that local network metrics provide a detailed understanding of the different mechanisms between the layers, and whether these mechanisms ensure the stability of the network. The paper helped to complement the work that described inter-bank markets focusing only on banks financial information and on global network characteristics (e.g. number of nodes, number of edges etc.). More than depicting the macro market dynamics, we ensured to prove the importance and to define the role of market mechanisms at the micro level. Thus, we can state that being central in a European network increases systemic risk at the banking level. Indeed, the more the banks establish connections with other banks, the greater the impact on the system will be in case of default.

Our approach is all the more novel in that it succeeds to combine an assessment of individual systemic risk and time dimension with several inter-bank markets. The multi-layer approach enabled to draw comparisons between layer structures and their evolution over time, particularly during the COVID-19 crisis. It finally contributed to produce comparisons between the impact of different layer topologies on a proxy for systemic risk.

	Long-term loans layer	Short-term loans layer	Cross-holdings layer
	(1)	(2)	(3)
In-degree centrality	0.0944 ***	-0.0023	0.0342 ***
	(0.0212)	(0.0078)	(0.0059)
Closeness centrality	-0.0086	0.0209 ***	0.0258 ***
	(0.0058)	(0.0041)	(0.0039)
Betweenness centrality	-0.0078	0.0084 *	0.00508 **
	(0.0106)	(0.0045)	(0.0026)
Clustering coefficient	0.0036 *	-0.0006	0.0017
	(0.0021)	(0.0030)	(0.0011)
Number of nodes	-0.0032 ***	0.0006	-0.0009 ***
	(0.0008)	(0.0004)	(0.0002)
Number of edges	0.0114 ***	0.0011	-0.0002
	(0.0021)	(0.0134)	(0.0006)
Leverage	0.0000	-0.0002 ***	0.0000
	(0.0007)	(0.0000)	(0.0001)
Total assets	0.0314 *	0.0580 *	- 0.0257 **
	(0.0187)	(0.0306)	(0.0101)
During Covid	-0.0127 ***	-0.0127 **	-0.0067 ***
	(0.0037)	(0.0059)	(0.0014)
Constant	0.402 ***	0.0173	0.1635 ***
	(0.0824)	(0.0434)	(0.0214)
Adjusted R2	0.7729	0.7521	0.9779
Individual fixed effects	Yes	Yes	Yes
n	1409	1214	1420

Table 1: Regression results

Reading note: *p < 0.1; **p < 0.05; ***p < 0.01. The value in parentheses are clustered standard errors. Dependant variable is DebtRank value computed on each layer.

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