A Systemic Risk Indicator for Leveraged Finance Exposure in the Banking System

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Abstract In recent years, the context of the banking system, characterised by expansive monetary policies, has boosted the investments in leveraged loans. The COVID-19 pandemic brought the first real slowdown of the global economy since the financial crisis of 2007-08, and the growth of the leveraged loan market has been subject to significant attention from the competent authorities. Banks have remained solid despite the adverse outlook, however, the banking landscape continues to be impacted by the uncertainty relating to the evolution of the pandemic. The original sample for this paper, made up of leveraged loans, combines instrument-specific information with information on financial borrowing and the composition of the syndicate of banks/lenders. The aim of the paper is to identify a systemic risk indicator that takes into account the concentration of credit risk within each bank. For this purpose, using an M-quantile regression, it is possible to obtain an indicator (M-quantile coefficient) for each bank that varies between 0 and 1, where higher values indicate the greater presence of risky leveraged loans in that specific bank. Combined with an indicator of loan sharing between banks, this also allows a graphical representation of the network of banks in this specific market.

Keywords:
leveraged loans,
leveraged finance,
syndicated loans,
systemic risk,
banking supervision,
M-quantile regression

University of Maribor Press

DOI https://doi.org/10.18690/um.epf.5.2022.19
ISBN 978-961-286-600-6

1 Introduction

The growth of the leveraged loans market over the last decade has caused concern among the competent authorities (European Central Bank, 2018) due to the concentration of these operations within the same lender and, consequently, the systemic risk due to the interconnectedness in the financial system (Financial Stability Board, 2019). This was among the reasons that, among the priorities for 2022-2024, the European Central Bank (2022) recently included exposure to leveraged finance as a key vulnerability in ensuring that banks emerge from the pandemic healthily. In order to address the impact of COVID-19 and ensure that banks remain resilient, it is therefore essential to prevent the rise of unmitigated risks in this area. Syndication between lenders of leveraged loans is particularly useful for diversifying risk and allowing companies to access credit more easily, however, this can also be seen as a weakness of the system as greater interconnectedness during a crisis can lead to an increase in systemic risk (Cai et al., 2018).

In this paper the authors focus on leveraged transactions, as they are more vulnerable and more significant in terms of systemic risk. The development of a methodology for the supervision of the banks involved in this market becomes particularly useful, in order to promptly capture any concentrations that may be considered too high for the solidity of the banking sector, and which could have dangerous consequences in terms of systemic risk. The authors propose that new measures are used starting first from the identification of the concentration of risky leveraged loans within each bank. For this purpose, an M-quantile regression was used to obtain an indicator between 0 and 1, which summarises the concentration of credit risk by estimating the M-quantile coefficient. The result of this indicator, combined with the size of the bank in the reference market, provides a quantification of the systemic risk among all the banks included in the syndicates. The results show the value of this indicator for all the banks on the 2021 list of Global Systemically Important Banks (G-SIBs), based on the methodology designed by the Basel Committee on Banking Supervision (BCBS). Once the indicator has been obtained, in order to identify the interconnectedness in this market, the authors propose a new measure based on the similarity/distance of loans between two banks. This measure, which can be reported as a symmetric matrix for all banks, is particularly useful in understanding the extent to which two banks tend to be present in the same transactions, effectively leading to a greater concentration among banks that frequently share the same transactions and to a lower risk mitigation. The concentration indicator obtained for each bank, combined with the latter, allows a graphical representation of the banking network in this specific market. Therefore, in addition to providing a contribution to the supervision of the risk of leveraged loans, this paper can offer a starting point for the deepening of the propagation of systemic risk in this specific market. Overall, the paper relates to two different strands of literature – theoretical literature on syndicated loans (Sufi, 2007; Achleitner et al., 2012; Becker and Ivashina, 2016; Bruche et al., 2020), and literature on systemic risk (Allen and Gale, 2000; Huang et al., 2009; Gai et al., 2011; Caballero and Simsek, 2013; Engle et al., 2015; Acharya et al., 2017; Cai et al., 2018).

2 Data

The dataset used was obtained through Refinitiv Datastream and relates to 1,789 leveraged loans issued between January 2013 and February 2022 with publicly available information. Data about the financial instrument are combined with qualitative and quantitative information on the borrower, including a large number of financial indicators that have been used as predictors in the model for this paper. The information on the instruments includes the compositions of the syndicate, through which the authors built dummy variables for each bank, regardless of whether or not it is a lender, as well as the corresponding amounts. The response variable is a dummy that is equal to 1 in cases where Moody's corporate debt rating is lower than or equal to B1, otherwise it is 0. All the leveraged loans have an available rating, considering that they relate to companies with publicly available information. For this reason, the use of the rating as a response variable can be particularly useful for the validation and construction of a rating for all the other instruments on the market that often do not have one.

3 Methods

An M-quantile regression (Breckling and Chambers, 1988) was used in order to build the concentration indicator of risky leveraged loans within each bank. For a continuous response and, for example, a quantile of q = 5%, the quantile regression separates the lowest 5% of the conditional distribution from the remaining 95%, i.e. a generalisation of median regression. An M-quantile regression could be considered as a quantile-like generalisation of mean regression based on influence functions (M-regression).

The M-quantile of order q for the conditional density of a continuous outcome y is defined as solution MQ_q, which satisfies:

$$\int \psi_q\left(\frac{y-MQ_q}{\sigma_q}\right) f(y)dy = 0 \tag{1}$$

where $\psi_q(t) = 2\psi(t)\{qI(t > 0) + (1 - q)I(t \leq 0)\}$, ψ is an influence function and σq is a measure of scale for y-MQq. The corresponding linear M-quantile regression model is the one for which the M-quantile:

$$MQ_q(y \mid \boldsymbol{x}; \psi) = \boldsymbol{x}^T \boldsymbol{\beta}_q. \tag{2}$$

The unit specific order q_{ij} is such that:

$$y_{ij} = \boldsymbol{x}^T \beta_{q_{ij}}.$$

An estimate of qij can be obtained by fitting a set of M-quantile regression lines for a specific grid of values for q ∈ (0; 1) and then interpolating the two closest values.

In the data obtained in this study, if a higher concentration of risky leveraged loans is present, then leveraged loans belonging to the same bank should lie on a similar portion of the conditional distribution of the response given the co-variates and should have a similar q coefficient.

A concentration score can be obtained by suitably averaging the estimated M-quantile coefficients within the bank i (see Fiaschi et al. (2020) for an M-quantile application to get a performance indicator), considering the weight pij corresponding to the amount held by bank i for leveraged loan j:

$$\hat{q_\iota} = \sum_{i=1}^{m} \sum_{j=1}^{n_i} \hat{q}_{ij} p_{ij} \tag{3}$$

Then, from the concentration indicator for each bank, a systemic risk indicator can be obtained by adequately considering the weight of each bank in the leveraged loan market:

$$SYMQ_i = \hat{q_i} \cdot \frac{BA_i}{\sum_m BA_i} \quad (4)$$

where BA_i is the amount held by bank i in the leveraged loan market.

In order to graphically represent the network of banks and to quantify the similarity/distance between two banks, the authors propose the following loan sharing indicator between bank i and bank j:

$$LS_{ij} = \frac{ShA_{ij}}{BA_i + BA_j - ShA_{ij}} \quad (5)$$

where S_hA_{ij} is the number of leveraged loans shared by bank *i* and bank *j* in the different syndicates.

Finally, in the graphical representation, the vertex for bank *i* will be the $SYMQ_i$ indicator, while the edge between bank i and bank *j* is given by LS_{ij}.

4 Results and conclusions

Part A of Figure 1 shows the banking network considering the $SYMQ_i$ indicator for the vertex size and the LS_{ij} indicator for the edge width between bank *i* and bank *j*.

Part B of Figure 1 shows the values of the $SYMQ_i$ indicator for the Global Systemically Important Banks (GSIBs) considered in the network. The edges are shown in red when the LSij indicator is higher than 0.3 (30%), which corresponds to the amount of common leveraged loans between bank *i* and bank *j*.

The graph shows a complex network of relationships between banks in this specific market, where there are banks that are much more exposed and with a significant concentration in terms of credit risk. For example, the value of the $SYMQ_i$ indicator for bank 1 of 0.17 may be interpreted as follows: the riskier leveraged loans in terms of credit risk held by bank 1 represent approximately 17% of the market.

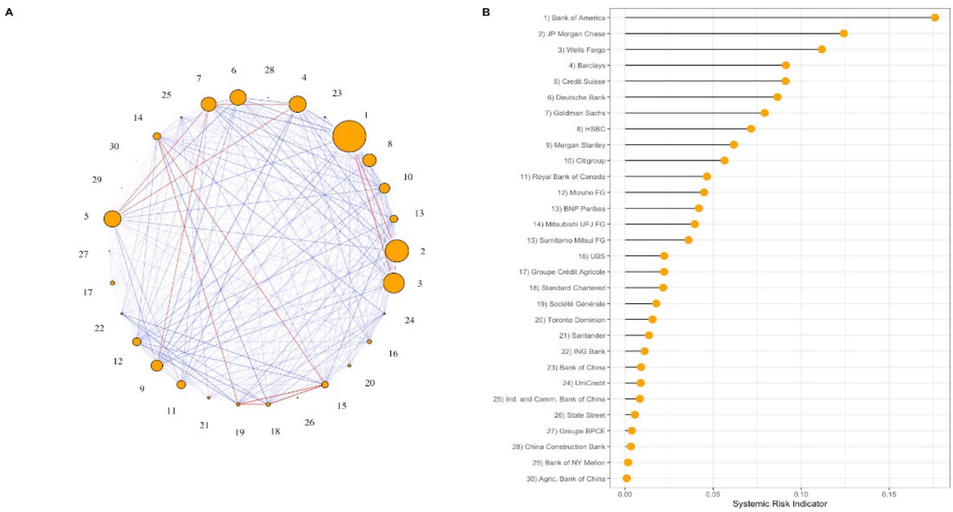

Figure 1: Banking network in the leveraged loans market (Jan 2013-Feb 2022)

Source: own.

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In terms of the policy implications, the authors of this paper believe these findings may be a contribution to concerns about lender concentration and interconnectedness in the leveraged loans market (Financial Stability Board, 2019). Indeed, through the results obtained, it is possible to monitor the concentration in each bank, the importance in terms of systemic risk and the relationships between the banks participating in the syndicate. Syndication is certainly useful for risk mitigation, and adding a monitoring of the proposed indicators could be an extra help in reducing systemic risk during a period of high uncertainty, such as that being currently experienced in the post-pandemic era.

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