Physica A 471 (2017) 592–606

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Why do vulnerability cycles matter in financial networks?

Thiago Christiano Silva [a,b,c,*], Benjamin Miranda Tabak [c], Solange Maria Guerra [a]

[a] *Department of Research, Central Bank of Brazil, Brasília, Brazil*

[b] *Department of Computing and Mathematics, Faculty of Philosophy, Sciences, and Literatures in Ribeirão Preto, University of São Paulo, São Paulo, Brazil*

[c] *Department of Law and Economics, Catholic University of Brasília, Brasília, Brazil*

HIGHLIGHTS

- We compare different systemic risk formulations of the DebtRank (systemic risk) model
- We find determinants that explain divergences on the different models.
- The network cyclicality is an important determinant.
- The average vulnerability of banks in the network is another crucial determinant.
- We validate our claims on artificial and real-world financial networks.

ARTICLE INFO

Article history:
Received 17 October 2016
Received in revised form 12 November 2016
Available online 28 December 2016

Keywords:
Networks
Systemic risk
DebtRank
Contagion
Financial markets

ABSTRACT

We compare two widely employed models that estimate systemic risk: DebtRank and Differential DebtRank. We show that not only network cyclicality but also the average vulnerability of banks are essential concepts that contribute to widening the gap in the systemic risk estimates of both approaches. We find that systemic risk estimates are the same whenever the network has no cycles. However, in case the network presents cyclicality, then we need to inspect the average vulnerability of banks to estimate the underestimation gap. We find that the gap is small regardless of the cyclicality of the network when its average vulnerability is large. In contrast, the observed gap follows a quadratic behavior when the average vulnerability is small or intermediate. We show results using an econometric exercise and draw guidelines both on artificial and real-world financial networks.

1. Introduction

The global crisis of 2007–2009 has highlighted important characteristics of financial markets that have not been properly considered before by regulators. The implications of interconnectedness between economics agents on systemic risk is one of these features that had little understanding during the crisis [1]. Prior to the crisis, the seminal work of Allen & Gale [2] already highlighted the role of the network structure as a medium of shock amplification. However, only after the global financial crisis policymakers and the academia recognized the importance of interconnectedness as a key component in systemic risk.[1]

* Correspondence to: Banco Central do Brazil, Depep/Conep, Setor Bancário Sul (SBS) Quadra 3 Bloco B, Brasília - DF, CEP: 70074-900, Brazil.
E-mail addresses: thiago.silva@bcb.gov.br (T.C. Silva), benjaminm.tabak@gmail.com (B.M. Tabak), solange.guerra@bcb.gov.br (S.M. Guerra).

[1] For instance, Basel III now recognizes financial interconnectedness as a key issue when analyzing systemic risk buildup [3].

http://dx.doi.org/10.1016/j.physa.2016.12.063
0378-4371/

Systemic risk materializes when many participants are simultaneously affected by severe losses, which can then potentially disseminate throughout the system. Benoit et al. [4] highlight that the main sources of systemic risk are: (i) risk-taking, which represents the possibility of correlated exposures to the same risk factor; (ii) financial contagion, in which losses can propagate from one part of the system to others; and (iii) amplification, which captures the feasibility of small shocks to develop into large impacts. Our work mainly deals with contagion and amplification that arise in a network of interbank exposures.

Several works measure potential systemic risk of the financial system by analyzing contagion and amplification due to the default of a single or group of banks [5–9]. In practice, however, studies reveal that the interbank channel becomes relevant only when banks' balance sheets are deteriorated or when we consider other contagion transmission channels, such as those of fire sales and correlated portfolios [10–12]. In view of that, our work focuses on network measures that can capture systemic risk buildup even in the case of the absence of defaults.

DebtRank is a financial-oriented centrality measure that is able to capture the banks' distress levels even at mild macroeconomic conditions or low levels of distress [13]. DebtRank is sensitive to small shocks because it considers that financial assets deteriorate as a function of the net worth of the borrower. Then, as the borrower becomes financially distressed, the corresponding creditors immediately recognize losses on the financial assets they have against that borrower. Using this financial stress propagation rule, the DebtRank algorithm computes to what extend banks become distressed in a financial network as a result of an external shock.

In this way, DebtRank is able to supply information on how far banks are from insolvency given an external shock and therefore gives us a sense of a continuum between solvency and insolvency of financial institutions. In contrast, loss-based measures are binary: either one bank can honor or not their liabilities in full. Considering that bank defaults are a consequence of previous accumulated distress, the financial stress is a useful measure that regulators can employ to gauge the solvency soundness of financial institutions.

The first version of the DebtRank – Battiston et al. [13]'s DebtRank – has a serious shortcoming in that it blocks second- and high-order rounds of financial stress that may arise from cycles or multiple vulnerability routes in the network.[2] Therefore, it can largely underestimate systemic risk levels. Bardoscia et al. [14] deal with this problem by introducing a modified version of the DebtRank that we term here as differential DebtRank, in which banks are allowed to recursively diffuse stress increments and not their current stress levels at each iteration.[3] Consequently, the procedure accounts for network cycles and multiple vulnerability routes.

In the interval between the definition of the original and differential DebtRank formulations, DebtRank has been applied in several financial networks worldwide [15,7]. Yet, no study has been performed to understand how different aspects of the network topology have a role on systemic risk estimation using these two techniques. In this aspect, it is not clear in which circumstances the original and differential DebtRank can provide divergent systemic risk estimates. In this work, we show that the network cyclicality and the average vulnerability between banks are key determinants in explaining the divergence of both approaches. Considering that macroprudential supervision and policy ideally need to rely on current systemic risk levels to act, it is imperative to have accurate systemic risk estimates. Therefore, it becomes important to understand the determinants that cause divergence on systemic risk estimates and therefore to have empirical subsidies to choose the right technique at the given economic circumstances.

We first devise a novel artificial network generation process in which we can exogenously control for the network cyclicality and the average vulnerability of banks. By analyzing how the systemic risk level gap between the original and the differential DebtRank formulations varies as a function of those two components, we draw some guidelines as to when the original DebtRank formulation can severely underestimate systemic risk levels. We show that, when there are no cycles nor multiple vulnerability routes in the network, the gap is zero. Now, given that the network presents cyclicality, then we need to be aware of the average vulnerability of banks. We find that the gap is small regardless of the cyclicality of the network when the average vulnerability of the network is large. However, the gap width assumes a quadratic behavior when the vulnerability is intermediate or small. For extreme values of the network cyclicality, that is very small or very large, the gap is small. For intermediate values of the network cyclicality, the gap becomes large. The largest possible gap tends to happen for network cyclicality values that are inversely proportional to the network vulnerability.

We verify that researches in the literature that estimate systemic risk employing the original DebtRank do not report the network cyclicality nor the average vulnerability of banks. Our finding in this paper suggests that these results may be compromised. On one side, apart from being sparse due to monitoring costs, we cannot infer much about cyclicality of financial networks.[4] On the other side, we can draw some conclusions about the average vulnerability of banks. Considering

2 In the Battiston et al. [13]'s DebtRank algorithm, when the financial institution *A* recognizes losses from a debtor counterparty due to mark-to-market accounting, bank *A*'s net worth reduces and in turn it also propagates losses to its creditor counterparties. As soon as bank *A* transmits the first wave of losses, it never again is able to propagate further stress in the network. Thus, in case bank *A* receives further stress from the same or other debtor counterparty, it never transmits forward the second and subsequent waves of financial stress. As a result, Battiston et al. [13]'s DebtRank only considers the first-round effects of financial contagion.

3 The allusion to differential DebtRank comes from the fact that the algorithm only allows stress increments (stress differentials) to propagate in the network, as opposed to the original DebtRank formulation, in which we propagate stress levels.

4 Though sparsity possibly leads to fewer cycles, that is not a necessary condition. For instance, we can construct a ring and a star network using the same number of links. The first topology is cycle-free, while the second is not.