ARTICLE IN PRESS

Economic Modelling xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Economic Modelling

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

Expected default based score for identifying systemically important banks

Yanzhen Yao[a,b], Jianping Li[a,b], Xiaoqian Zhu[a,*], Lu Wei[a,b]

[a] Institute of Policy and Management, Chinese Academy of Sciences, Beijing 100190, China
[b] University of Chinese Academy of Sciences, Beijing 100049, China

ARTICLE INFO

JEL classification:
G21
G28

Keywords:
Systemically important banks
Contagion risk
Systemic risk
Bank risk

ABSTRACT

The issue of identifying systemically important banks has gained prominence since the recent global financial crisis in 2007. However, the extant methods either neglect the adverse impact on the financial system posed by a bank or ignore the various interactions among banks. To resolve this issue, the objective of this study is to put forward an expected default based score (EDBS) that overcomes the drawbacks of the existing methods from the perspective of contagion risk. This indicator measures the systemic importance of a bank by calculating the expected bank defaults triggered by its initial failure. In the empirical study, the expected default based score is applied to identify the systemically important banks in the Chinese banking system. Both the quantitative comparison with other major methods and the qualitative evaluation of the Delphi method validate the reliability of the EDBS method. The empirical results also demonstrate that interconnectedness among banks is an important and complementary driver of systemic importance in addition to asset size.

1. Introduction

The default of a single bank can spark widespread contagion risk in the entire banking industry and even harm the smooth functioning of the real economy (Molyneux et al., 2014; Pourkhanali et al., 2016; Zhou, 2010; Fiala and Havranek, 2017). Two illustrative examples are Continental Illinois Bank and Bear Stearns. When the Continental Illinois Bank, the seventh largest bank in U.S. history, failed in 1984, nearly 2300 other banks held deposits at or loaned funds to the Continental (Kaufman, 2000). The Federal Deposit Insurance Corporation's (FDIC's) bailout of the Continental was justified on the grounds that its collapse would have posed a severe threat to the U.S. banking system. The government assistance for J. P. Morgan's acquisition of Bear Stearns, which nearly failed during the subprime crisis that started in 2007, is supported by the fact of Bear Stearns' active participation in the credit risk transfer market and high systemic importance (Chan-Lau, 2010). Therefore, particularly motivated by the severe aftermath of the global financial crisis of 2007–2009, supervisory authorities have been eager to call for effective analytical methods to identify banks with high systemic importance (Gravelle and Li, 2013).

In the early years, systemically important banks (hereafter SIBs) were simply deemed as the "too-big-to-fail" banks and were thought should face more stringent regulation (O'Hara and Shaw, 1990). However, this "size only" definition does not fit the increasingly complicated banking system (Adrian and Brunnermeier, 2016; Thomson, 2010). Recently, the viewpoint of the International Monetary Fund et al. (2009) has become widely accepted. It defines the bank to be systemically important if its failure would cause propagation of contagion risk through the rest of the financial system and even to the real economy. Based on this definition, two typical features, the risk propagation in and the adverse impact on the banking system, should be captured when identifying SIBs. Various interactions among banks, such as interbank lending relationships, have become a major risk propagation channel of systemic risk. Given that a systemically important bank fails initially, it might pose a severe adverse impact on the entire system. However, most of the existing methods for identifying SIBs ignore one of the two features.

The objective of this paper is to propose an expected default based score (EDBS) from the perspective of contagion risk to identify systemically important banks. It signifies the expected number of total bank defaults caused by the initial failure of a particular bank. Because the EDBS is based on contagion risk, it can not only provide an intuitive interpretation of SIBs but also well overcome the demerits of most existing methods. Specifically, the EDBS captures contagious defaults among banks through a contagion mechanism. In this paper, a sequential default algorithm proposed by Furfine (2003) is employed as an alternative technique for the realization of the EDBS. In addition, a critical revision is made in this algorithm for incorporating more and wider factors and circumstances.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 introduces the proposed expected default based score. The empirical analysis is presented in

* Corresponding author.
E-mail addresses: yaoyanzhen14@mails.ucas.ac.cn (Y. Yao), ljp@casipm.ac.cn (J. Li), zhuxq@casipm.ac.cn (X. Zhu), weilu2014ucas@163.com (L. Wei).

http://dx.doi.org/10.1016/j.econmod.2017.04.023
Received 14 October 2016; Received in revised form 6 March 2017; Accepted 27 April 2017
0264-9993/

Section 4, where the proposed score is applied to identify the SIBs in China. Section 5 presents the conclusions.

2. Literature review

Several measures of systemic importance have been put forward in recent academic studies, which can be generally categorized into two types of methods (Lu and Hu, 2014). One type of method is called indicator-based measurement, which incorporates bank-level data, e.g., balance sheet data and the volume of transactions. The other type of method is called market-based measurement, which uses related market volatility data such as stock returns of different banks, to measure the contribution of SIBs to the system risk. The main difference between the two types of methods is their different perspectives in understanding the meaning of systemic importance and the data involved.

The widely recognized indicator-based measurement was proposed by the Basel Committee on Banking Supervision (BCBS for short, 2011) for identifying Global Systemically Important Banks (G-SIBs). The BCBS (2013) further updated the indicators in this method. The systemic importance of a bank is expressed as a final score by summing the sub-scores in the five selected categories, size, interconnectedness, substitutability, complexity, and cross-jurisdictional activity, with equal weights. Afterward, Brämer and Gischer (2013) expeditiously extended it to identify domestic systemically important banks (D-SIBs). The extension mainly focused on the last category of indicators, "cross-jurisdictional activity", which is not applicable to domestic systemically important banks (D-SIBs) because it was created to express the global reach of a bank. Chen et al. (2014) further revised this method to be applicable to the Chinese banking system. The indicator-based measurement is believed to be capable of select SIBs quickly, transparently and dynamically (Lu and Hu, 2014) due to its comprehensive indicator system. However, it has several demerits. Firstly, it needs an extensive collection of bank data (Brämer and Gischer, 2013). Secondly, it does not capture the adverse impact on the financial system posed by a distressed or troubled bank dynamically.

Market-based measurement primarily includes Marginal Expected Shortfall (MES), CoVaR and Shapley Value. Acharya (2009) and Acharya et al. (2010) use MES to measure systemic risk and extend it to identify systemically important financial institutions. CoVaR, conceptualized in Adrian and Brunnermeier (2016), is designed for bilateral risk spillover (Bianconi et al., 2015; Liu, 2016). It quantifies a bank's systemic importance as its marginal contribution to the overall systemic risk when treating all other institutions as a whole. However, it is difficult to be generalized to measure a group of banks' contribution to systemic risk (Ferrari, 2010). Shapley Value, suggested in Tarashev et al. (2009) and Drehmann and Tarashev (2011), is an important instrument used in game theory and for calculating the degree of systemic importance of each bank based on average contribution to the risk of all groupings of institutions (Tarashev et al., 2016). Intuitively it provides interpretation for systemic importance, but a large computational effort is required when empirically applied to a large financial system.

Generally, market-based measurement is more forward-looking than indicator-based measurement on account of high-frequency market data. However, it neglects the increasing importance of various interactions, such as contagious defaults, in systemic risk (Kanno, 2015), thus failing to adequately capture the relationship between interconnectedness and systemic importance in a financial system. Moreover, some crucial data in market-based measurement are difficult to obtain sometimes (Lu and Hu, 2014). For instance, when applying the CoVaR method to China, one of the systematic state variables, the Volatility Index (VIX), which captures the implied volatility in the stock market, is not officially released and thus cannot be obtained directly.

The literature review above shows that both types of methods have drawbacks, either neglecting the adverse impact on the financial system posed by a distressed or troubled bank or ignoring the various interactions among banks. By definition, with the expected number of extra bank defaults caused by an initially failed bank, our new method can capture its adverse impact on the financial system dynamically. It is noted that 'dynamically' here means our new method is based on the spreading of contagion risk. This method can also capture various interactions through an interbank network comprising bilateral exposures.

3. Methodology

In this section, the proposed method, the expected default based score (EDBS), is introduced in detail. Firstly, the basic definition of the EDBS is described. Then, the sequential default algorithm proposed by Furfine (2003) is used as an alternative technique for its realization.

Given that a particular bank fails or defaults, it is natural to evaluate its adverse impact on the banking system by considering the expected number of total extra bank failures in the system from the perspective of contagion risk. This is defined as our method for measuring banks' systemic importance, namely, the expected default based score (EDBS). The value of the score represents the systemic importance of a bank. Clearly, EDBS captures the adverse impact of a distressed bank.

Consider a banking system containing n banks; their values of EDBS are represented by a vector $(EDBS_1, \ldots, EDBS_n)$, where $EDBS_i$ denotes the expected number of total bank defaults in the banking system given that bank i fails initially due to an idiosyncratic shock. With a specific value of $EDBS_i$, its relative systemic importance in the system emerges. The larger the value is, the more systemically important it is in the banking system. Measuring relative systemic importance is the key to identifying systemically important banks.

Because our new method considers contagion risk throughout, it calls for a contagion mechanism to simulate the spread of default risk. Two often-cited contagion algorithms based on bilateral exposures include fictitious default algorithm put forward by Eisenberg and Noe (2001) and sequential default algorithm proposed by Furfine (2003). Between the two algorithms, the sequential default algorithm is the most frequently used mainly for two reasons (Upper, 2011). One is that the interbank market, comprising bilateral exposures among banks, plays an essential role in a well-functioning integrated financial system (de Souza et al., 2016) and acts as an important transmission channel for contagion spreading during crises (Grilli et al., 2014; Kuzubaş et al., 2014; Souza et al., 2015; Tabak et al., 2014; Toivanen, 2013). The other is that it is easy to understand and use.

Although the sequential default algorithm has been extensively used in contagion studies across many countries, such as Germany (Upper and Worms, 2004), the United Kingdom (Wells, 2004), Holland (Van Lelyveld and Liedorp, 2006) and Italy (Mistrulli, 2011), it has an inherently noteworthy limitation. As illustrated in Furfine (2003), the algorithm confines its scope to the credit contagion channel of interbank market and thus ignores many other possible contagion channels. Thus, its assumption is somewhat too simple and cannot address a variety of practical situations. In the following text, the limitation of the algorithm is explained mainly from two aspects.

Firstly, contagion can spread through a multitude of channels, other than interbank credit exposure (Upper, 2011). For example, banks might have correlated exposures, and an adverse economic shock may result directly in simultaneous multiple bank defaults (Elsinger et al., 2006). Other contagion channels also include liquidity risk from information effects (Degryse and Nguyen, 2007). Therefore, only considering contagion due to interbank credit exposure is a somewhat limited perspective. Other channels should also be considered in the original algorithm.

Secondly, single interbank linkages might not trigger any contagion in some cases (Georg, 2013; Glasserman and Young, 2015). A necessary condition for contagion to occur is that the volume of a