Economic Modelling 29 (2012) 2095–2103

Contents lists available at SciVerse ScienceDirect

Economic Modelling

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

Using BS-PSD-LDA approach to measure operational risk of Chinese commercial banks

Zongrun Wang [a,*], Wuchao Wang [b], Xiaohong Chen [a], Yanbo Jin [c], Yanju Zhou [a]

[a] School of Business, Central South University, Changsha, 410083, China
[b] Department of Bill Business, Head Office of Agricultural Bank of China, Shanghai, 200120, China
[c] Department of Finance, Real Estate, and Insurance, California State University, Northridge, CA 91330, USA

ARTICLE INFO

Article history:
Accepted 24 June 2012

Keywords:
Operational risk
Bootstrap sampling
Basel II
Lognormal distribution
Generalized Pareto distribution

ABSTRACT

The research of operational risk management among Chinese commercial banks is still in its preliminary stage. Operational risk events are rare and data is hard to collect. This leads to very small data samples. Besides, a large number of empirical researches show that the distributions of operational losses are often skewed with fat tails. To address these issues, this paper puts forward a loss distribution approach (LDA) based on bootstrap sampling and piecewise-defined severity distribution (BS-PSD-LDA). The approach divides data samples into two distinct parts (high-frequency low-severity losses and low-frequency high-severity losses), and fits the two parts by lognormal distribution and Generalized Pareto distribution respectively. Using hand-collected samples of 426 operational losses in Chinese commercial banks during 1994–2010, we estimate the magnitude of operational losses using the BS-PSD-LDA method. We show that our method provides a better fit than the traditional parametric methods. Besides, the method using historical simulation of nonparametric method seems to offer a good fit to the sample as well. However, we believe that the BS-PSD-LDA approach offers improvement from the perspective of satisfying risk control requirement of the regulatory authority and ensuring the efficiency of funds' utilization.

1. Introduction

According to the Basel II Accord, operational risk is defined as the risk of loss resulting from inadequate or failed internal processes, people and systems, or from external events. This definition includes legal risk but excludes strategic and reputational risk (BCBS, 2006).

Research on operational risk management in Chinese commercial banks has started only recently. There is no comprehensive database that systematically records operational risk loss events. The low-frequency high-severity feature of operational risk events results in small data samples. It is especially hard to collect operational loss data from individual banks, due to banks' reluctance to disclose such data. As such, given the small sample, traditional distributions no longer provide a good fit to the modeling of operational losses. Besides, empirical studies have shown that the distributions of operational loss are often skewed with fat tails. Therefore, it has long been a challenge to the bank as well as the research community to come up with a model that can accommodate both the small sample, and the "low-frequency high-severity" nature of operational losses.

Li (2009) proposes a loss distribution approach based on piecewise-defined severity distribution (PSD-LDA) to accommodate the low-frequency high-severity feature of operational risk, and applies the approach to test operational risk losses using a sample from Chinese commercial banks collected from publicly available information sources, such as newspapers and internet. The empirical results suggest that this can be a rational and promising model to estimate operational losses in Chinese national commercial banks. SiMa et al. (2009) also use the POT power law model to evaluate Chinese commercial bank operational risk for the period 1995–2006, and obtain similar results as in Li (2009). However, data collection can be a challenge as the reported data can be biased. In essence, the methods proposed by Li (2009) are plagued by the problem of small sample when it comes to estimating operational risk. To overcome such weakness, this paper proposes a loss distribution approach based on bootstrap sampling and piecewise-defined severity distribution (BS-PSD-LDA). Bootstrap sampling is a computer-based method that allows one to estimate almost any statistics of the sample distribution with great accuracy, using only very simple methods (Efron and Tibshirani, 1986). By using bootstrap sampling, one can effectively reduce the biases and errors caused by parameter estimation in small data samples, and thus enable us to measure operational risk more accurately. With manually collected data on operational risk losses among Chinese commercial banks, we then use this approach to estimate the operational risk and compare the result with those based on other estimation methods.

The contributions of this paper are two folds: Firstly, we propose a loss distribution approach based on bootstrap sampling and piecewise-defined severity distribution (BS-PSD-LDA). As mentioned above,

* Corresponding author. Tel.: +86 13548602329; fax: +86 0731 88710006.
E-mail address: zrwang0209@gmail.com (Z. Wang).

0264-9993/$ – see front matter
doi:10.1016/j.econmod.2012.06.031

bootstrap sampling allows us to measure operational risk more accurately by reducing the biases and errors in parameter estimation introduced by small samples. Besides, by using an LDA approach based on piecewise-defined severity distribution, we are able to fit the entire range of operational risk data samples, including both "high-frequency, low-severity" and "low-frequency, high-severity" events. It also allows us to address the issue of a skewed distribution with fat tails. Secondly, using manually collected data on operational risk loss events in Chinese commercial banks, we show that our model offers improvement as compared to traditional parametric and nonparametric methods.

The rest of this paper is organized as follows. Section 2 reviews the literature in operational risk measurement. Section 3 describes the BS-PSD-LDA approach and its procedures. Section 4 provides an empirical study of estimating operational risk in Chinese commercial banks. Finally, Section 5 concludes.

2. Review of literature

In the Basel II Accord, the Basel Committee on Banking Supervision provides three main approaches for calculating operational risk charges (ORC). The ORC establishes a minimum amount of capital that banks need to hold to cover their operational risk. Ranked in terms of their degree of sophistication, the three approaches are: (1) the Basic Indicator Approach (BIA); (2) the Standardized Approach (TSA); and (3) the Advanced Measurement Approaches (AMA). The BIA and TSA, so-called top-down methodologies, are not sensitive to the operational risk measurement. In contrast, the AMA approaches, also known as the bottom-up methodologies, allow banks to use their own internal models to calculate ORC. The general procedure in the AMA approaches is to measure the operational risk through actuarial or econometric models, then to fit an operational risk data sample during a specific time (usually annual) by using some probability distribution.

It is worth mentioning that although Basel II specified detailed criteria that banks must satisfy in order to use AMA, it does not prescribe any particular method. There are three methods mentioned in the Basel II Accord, namely Internal Measurement Approach (IMA), Loss Distribution Approach (LDA), and Scorecard Approach (SCA). The Basel Committee encourages banks to develop their own advanced measurement approach, rather than simply follow any single method (BCBS, 2001b). In addition, the Committee pointed out that the above-mentioned three approaches are only a partial list of all methods used in the industry. It did not predict which approach will become the leading method in the industry either.

There exists a large amount of literature within the industry as well as the academics on operational risk measurement. In addition to the three approaches mentioned above, other methods include the Extreme Value Theory (EVT); the combination of LDA and EVT; methods based on computer techniques such as Bayesian Network, Neural Network and Dynamical Models, etc.

The Internal Measurement Approach (IMA) requires banks to collect their own operational risk loss data. Assuming a fixed and stable relation between expected loss (EL)[1] and unexpected loss (UL),[2] banks can then calculate the expected loss based on loss data of seven risk event types and eight business lines defined by the Basel Committee. Based on this calculation, banks can then estimate the operational risk charges. Literatures along this line include Frachot et al. (2001), Jordan (2004), Chapelle et al. (2008), Jarrow (2008), etc.

The Loss Distribution Approach (LDA) is an actuarial model that estimates the objective distribution of losses from historical data. The model combines two distributions: loss frequencies and loss severities. Based on information of historical losses collected over a matrix of eight business lines and seven risk events as classified by Basel Committee, banks can estimate both the loss frequency and loss severities distribution. Then, through a process known as convolution, the two distributions can be combined into a distribution of aggregate loss. Fontnouvelle and Rosengren (2004), Mignola and Ugoccioni (2005), Dutta and Perry (2006), Li (2009), Shevchenko (2010) adopted LDA approach to estimate the operational risk of banks.

An alternative approach: the Extreme Value Theory (EVT) is a promising approach that uses a loss severity distribution to estimate operational risk. It focuses on the probability of distribution of the right-tail only, which can reduce the model errors resulting from inaccurate estimation of the parameters. However, EVT can only fit distributions based on low-frequency high-severity data. As such, it ignores ordinary losses, which is one of its weaknesses. The literatures in this field include Medova and Kyriacon (2001), Chen et al. (2003), Gao (2003), Zhou et al. (2006), Liu et al. (2007), SiMa et al. (2009), etc.

The combination of LDA and EVT methods can help correct the problems in skewed distributions with fat tails that are often characteristics of financial data series. This approach can capture more accurately the low-frequency, high-severity feature of operational risk loss distribution. Literatures along this line include Gencay and Selcuk (2001), Parent and Bernier (2003), Trzpiot and Majewska (2010), etc.

There are also other risk measurement methods based on computer techniques and Artificial Intelligence(AI), such as Bayesian Network, Neural Network and dynamical models.[see Alexander (2002), Kühn and Neu (2003), Martink (2007), Deng and Huang (2007), Dalla Valle and Giudici (2008), Neil and Hager (2009), Aquaro et al. (2010)]. Especially, Bardoscia and Bellotti (2011a, 2011b) propose a completely dynamical model for forecasting and estimating operational risk in banking institutions which follows the entire time evolution of the losses and takes into account different time-correlations among the processes.

Most of the approaches mentioned above works well under large samples. However, they do not address the problem of a small sample or the issue with skewed distribution and fat tails. In this paper, we propose a BS-PSD-LDA approach, which can effectively solve the problem of small data sample faced by Chinese commercial banks when measuring operational risk.

3. Methodologies

The BS-PSD-LDA approach we propose here is a loss distribution approach that combines bootstrap sampling with piecewise-defined severity distribution to measure small operational risk samples. The bootstrap sampling is a type of Bayesian sampling. This procedure estimates sampling distributions by using only the original data. That is, treating the existing observations in the current sample as the new population, the procedure does random draws with replacement. The procedure does not require data points other than the original data. In addition, in most of the times the method can lead to more accurate interval estimate. It is also easy to implement and the estimation errors are generally small.

The main procedures of the BS-PSD-LDA approach are similar to those of the classic LDA method, except for two main differences: (1) the BS-PSD-LDA approach can help correct the biased estimator due to small sample. This is accomplished through bootstrap sampling, which makes the sample distribution infinitely approximate the population distribution. As a result, parameter estimation is more accurate which leads to more accurate estimate on operational risk loss; (2) the BS-PSD-LDA approach divides the loss data samples into two distinct parts, and uses different distribution function to fit the ordinary losses (loss due to high-frequency low-severity events) and large losses (loss due to low-frequency high-severity events) separately. This method provides a better fit to the whole sample.

[1] Expected Loss (EL) represents the size of operational loss that should be expected to occur. This is usually dominated by high-frequency, low-severity events. It can be computed as the product of expected values of loss frequency and loss severity distributions.

[2] Unexpected Loss (UL) represents the deviation between the quantile loss at some confidence level and the expected loss. Typically, this represents lower-frequency, higher-severity events.