ALLTERNATIVE METHODS TO OPERATIONAL RISK MANAGEMENT

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Abstract: In this paper we calculate capital requirement for operational risk for one of the biggest Czech banks. We have utilized two main approaches described in the literature: the Loss Distribution Approach and Extreme Value Theory, in which we have used two estimation methods - the standard maximum likelihood estimation method and the probability weighted moments (PWM). Our results proved a heavy-tailed pattern of operational risk data as documented by many researchers. Additionally, our research showed that the PWM is quite consistent when the data is limited as it was able to provide reasonable and consistent capital estimates. From a policy perspective it should be hence noted that banks from emerging markets such as the Central Europe are also able to register operational risk events and the distribution of these risk events can be estimated with a similar success than those from more mature markets.

Keywords: operational risk, economic capital, bank, extreme value theory, probability weighted method

1. Introduction

The Basel Committee offers a definition of operational risk as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events failures" [1]. Operational risk has become one of the most discussed topics by both academics and practitioners in the financial industry in the recent years. The reasons for this attention can be attributed to higher investments in information systems and technology, the increasing wave of mergers and acquisitions, emergence of new financial instruments, and the growth of electronic dealing [13]. In addition, the New Basel Capital Accord effective since 2007 demands a capital requirement for operational risk and further motivates financial institutions to more precisely measure and manage this type of risk. The highest losses stemming from operational risk have been recorded in Societe Generalé in 2008 ($7.3 billion), Sumitomo Corporation in 1996 ($2.9 billion), Orange County in 1994 ($1.7 billion), Daiwa Bank in 1995 ($1.1 billion), Barings Bank in 1995 ($1 billion) and Allied Irish Bank in 2002 ($700 million). Operational risk also materialized during the US subprime mortgage crisis in 2007, when mortgage frauds became a serious issue. As noted by Dilley [4], "mortgage applicants with weak financial standing or poor credit history have an obvious temptation to exaggerate their income or assets in order to secure a loan". However, not only some applicants but also some mortgage dealers cheated as they intentionally offered mortgages to the people with a low creditworthiness. These dealers preferred own interests to adhering to prudence rules set by a financial institution, what could be considered as a fraud. We should also mention three operational risk failures materialized during the 2008 crisis: $65 billion swindle by Mr. Bernard Madoff, $8 billion fraud of Sir Allen Stanford or non-existence of $1 billion in a balance sheet of Indian company Satyam [15].

Moreover, there have also been several instances in the Central Europe when operational risk occurred. For instance, in 2000 a trader and his supervisor in one of the biggest Czech banks exceeded their trading limits when selling US treasury bonds and caused a $53 million loss to the bank. In the late 1990s another Central European bank suffered a $180 million loss as a result of providing financing to a company based on forged documents. Other general instances of operational risks in the Central European banks such as cash theft, fee rounding errors in IT systems or breakdowns of internet banking can be listed similarly to other banks around the world. Although large operational losses are extreme events occurring very rarely, a bank — or a financial institution in general — has to consider the probability of their occurrence when identifying and managing future risks. In order to have reasonable estimates of possible future risks a bank needs an in-depth understanding of its past operational loss experience. As a result, a bank may create provisions for expected losses and set aside capital for unexpected ones. In this paper we focus on modelling of the economic capital that should be set aside to cover unexpected losses resulting from operational risk failures.

This paper is organised as follows: the second part provides the background of the research and the data used and the results of exploratory data analysis. The methodology is described in the third part and in the fourth part we discuss the results of our research. Finally, the fifth part concludes the paper and state final remarks.

2. Background of The Research

2.1. *Economic capital*

A concept of economic capital is used for modelling operational risk through the Advanced Measurement Approach (AMA) mentioned in Basel II. However, no unique definition of economic capital exists. For instance, Mejstrik et al. [11] state "economic capital is a buffer against future, unexpected losses brought about by credit, market, and operational risks inherent in the business of lending money". Alternatively, Chorofas [2] defines economical capital as "the amount necessary to be in business – at a 99% or better level of confidence – in regard to assume risks". We should distinguish economic capital from regulatory capital that can be defined as capital used for the computation of capital adequacy set by the Basel II requirements [11] or as the minimum amount needed to have a license [2].

Regulatory capital should cover (e.g. in the form of provisions) both expected losses and unexpected losses (but excluding extreme events) while economic capital should cover unexpected losses. In addition, economic capital should cover both risk capital with 99.9% scenarios and capital for extreme events. The latter is important for modelling operational risk as "low frequency/high severity" losses often occur, what is supported by many researchers such as Chernobai [1], Dutta and Perry [5], Rippel and Teplý [15] or Teplý [15] as it will be shown later, by our results. As the examples of extreme events, we can list 9/11 events in 2001, Hurricane Katrina in 2005 or Hurricane Gustav in 2008.

Data analysis

In this study we have used data from an anonymous Central European Bank (the "Bank"). Altogether the dataset consists of more than six hundred operational losses over the period 2001-2007. However, there are disproportionally fewer observations in the beginning of the sample (January 2001-November 2003) signaling lower quality of data when the process of collecting operational losses data was just starting. In order to remove possible bias, we have left out 14 observations of this period. Moreover, the threshold for collecting the data in the

Bank (about $1,000) is set quite low compared to other studies, the threshold is typically of the order of $10,000, hence we further cut some of the observations from the beginning as we describe in the section dealing with the Loss Distribution Approach (LDA). By setting the threshold up to $10,000 we have left out many small losses, hence the number of observation in our dataset further decreased up to 236.

Observations across years starting from December 2004 are by a simple graphical inspection quite stationary and hence can be considered to be collected by consistent methodology. However, there is a significant variation across months; particularly losses in December are significantly more frequent. This can be explained by the end of fiscal year when all possible unrecorded losses up to a date finally appear on the books. This is not a problem when losses are treated on annual basis or independent of time, however, it hinders the possibility to take into account monthly information. Generally, our dataset is not very big, but it is satisfactory enough for operational risk analysis at the level of the whole bank. For analysis focusing on particular business lines and/or particular type of loss events we would need more observations.

To get a better understanding of the structure and characteristics of the data we have firstly performed Exploratory Data Analysis as suggested by Tukey [16]. Operational risk data are skewed and heavy-tailed; hence skewness and kurtosis are the most important characteristics. We have utilized some of the measures proposed by Hoaglin [8] and Tukey [16] used in Dutta and Perry [5] to analyze skewness and kurtosis. Employing measures of skeweness such as a mid-summary plot or pseudo sigma indicator of excess kurtosis, we confirmed that also our data are very skewed and heavy-tailed, the properties typical for operational losses data.

3. Methodology

A Value at Risk (VAR) is a risk informative indicator recognized by Basel II requirements. Jorion [10] defines VAR as "the maximum loss over a target horizon such that there is a low, prespecified probability that the actual loss will be higher". Usually VAR is expressed as a corresponding value (in currency units) of p% quantile of a distribution where p is the prespecified low probability and f(x) is a density function of operational losses:

$$p = \int_{VAR}^{\infty} f(x)dx$$

Alternatively, VAR is a cut-off point of the distribution beyond which the probability of the loss occurrence is less than p. For operational risk losses the quantile defined in Basel II is 99.9%, thus we will report VAR99.9 for each modeling method used. The target horizon is one year, so a 99.9% VAR requirement can be interpreted as the maximum annual loss incurred over 1,000 years.

The extreme value theory (EVT) is a promising class of approaches to modeling of operational risk. Although originally utilized in other fields such as hydrology or non-life insurance, the EVT is capable of modeling low frequency, high severity instances of operational losses. There are two main kinds of models in EVT. More traditional models are block maxima models which are for the largest observations collected from large samples of identically distributed observations. The whole sample is divided into equal non-overlapping time intervals and the biggest loss from each interval is used for modeling. In the peak over threshold (POT) model, a more-modern approach, the large enough threshold is determined and the observations above are considered. Maximum likelihood (ML) and probability

weighted moments (PWM) are the primary methods used for parameters estimation (for more details on these methods [7] [9]).

4. Summary of Results

When applying the mentioned methodology on the data discussed in Section 3, we came to the results summarized in Tab. 1. According to our findings the EVT shows the best statistical fit when estimating capital of the Central European Bank on a 99.9% confidence level. Capital estimates by the PWM are quite consistent from a practical point of view, ranging from 7.2%–9.2% of the banking income (for a comparison, Basel II requires banks to hold a capital requirement for operational risk at 15% of banking income in case of using the Basic Indicator Approach)., indicating alongside with the arguments already mentioned that this method might be more suitable in the estimation of operational risk when the data are limited.

Tab. 6: Summary of results – LDA & selected EVT models

Body	Tail	Statistical fit	Capital estimate (99.9%)
Exponential	Exponential	very poor	2.7%
Gamma	Gamma	very poor	2.1%
Lognormal	Lognormal	poor	2.0%
Log-logistic	Log-logistic	poor	9.5%
GH distribution	GH distribution	poor	>100%
Empirical sampling	EVT (block maxima, max. dozen, PWM)	excellent	7.2%
Empirical sampling	EVT (block maxima, max. 2%, PWM)	excellent	9.2%

Source: Authors

5. Conclusion

In this paper we analyze and model real operational data of a Central European Bank. We have utilized two approaches currently described in the literature. The LDA, in which parametric distributions are fitted to the whole data sample, was not able to capture the pattern of the data and was rejected based on the goodness-of-fit statistics. Hence we conclude that the parametric distributions like exponential, gamma, log-normal, log-logistic and GH do not fit well the data. This result proves an unusual (heavy-tailed) pattern of operational risk data as documented by many researchers such as Cruz [3], Moscadelli [12], de Fontnouvelle et al. [6] or Duta, Perry [5].

The EVT, on the other hand, for both block maxima and POT proved to fit the data in the tail of the distribution. We have used two estimation methods in the EVT approach, the standard MLE in which all the observation have the same weight and the PWM in which the observations higher in the tail have a higher weight. When applying the block maxima model we have found out that the maximum dozen model fitted by PWM produces the best results. Cruz [3] used PWM to analyze fraud loss data on an undisclosed source for the 1992–1996 period and deduced that the data in 1994 and 1996 recorded a heavy-tailed GEV distribution.

In addition, the Kuiper statistics for PWM showed the best results in all four years, which confirms our findings.

POT models are frequently used for application of EVT to operational loss data. We observed that the high shape parameters for some of the MLE models bring unreasonable high capital estimates, what is consistent with Moscadelli [12] or de Fontnouvelle et al. [6]. These authors also mention the estimates are highly sensitive to the chosen threshold, what again underpins our conclusions. Unlike the others, our research showed that PWM are quite consistent from a practical point of view and they might be suitable in the estimation of operational risk when data is limited. This result might be useful for the banks that have limited data series of operational risk events, what is typical for many Central European banks.

From a policy perspective it should be hence noted that banks from emerging markets such as the Central Europe are also able to register operational risk events. Data from the Bank showed an improvement in time, what could be attributed to more attention devoted to recording operational risk events. Moreover, as we have demonstrated, the distribution of these risk events can be estimated with a similar success than those from more mature markets.

Despite the conclusions cited above, there are still several ways in which our research can be improved. Firstly, a similar study can be done on a larger sample of data (we used the data from one Central European bank). Secondly, the research provided on all eight business lines recognized by Basel II may reveal interesting facts about different operational risk features among various business lines. Finally, other research might include other results derives from modeling operational risk using such techniques as robust statistics, stress-testing, Bayesian inference, dynamic Bayesian networks and expectation maximization algorithms.

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