# OPERATIONAL RISK MODELLING AND ITS IMPLICATIONS FOR EMERGING MARKETS BANKS

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## Abstract

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 (Sironi and Resti, 2007). 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.

In this paper we have attempted to analyses and model the real operational data of an anonymous Central European Bank. We have utilised 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*:** Key words: operational risk, economic capital, Basel II, extreme value theory, probability weighted method

## 1. Introduction

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 (Sironi and Resti, 2007).

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. According to de Fontouvelle et al. (2003), financial institutions have faced more than 100 operational loss events exceeding $100 million since the end of 1980s. 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).[1]

Operational risk also materialized during the US subprime mortgage crisis in 2007, when mortgage frauds became a serious issue.[2] As noted by Dilley (2008), "*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.[3] 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.

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

[1] See Chernobai et al. (2007) or Peters and Terauds (2006) for an overview of examples of operational risk events.
[2] Naturally, mortgage frauds occurred also before the crisis. However, the number of cheating applicants was not as high as the mortgages were not provided to so many applicants. Moreover, in September 2008 the FBI investigated 26 cases of potential fraud related to the collapse of several financial institutions such as Lehman Brothers, American International Group, Fannie Mac and Freddie Mac (Economist, September 26, 2008).
[3] We should note that some loans were provided intentionally to applicants with a low creditworthiness – such as NINJA loans (No Income, No Job, No Assets).

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.

The contribution of this study is threefold. The first contribution is the presentation of a complete methodology for operational risk management. Banks in Central Europe generally do not possess a methodology to model operational risk since they rely on the competence of their parent companies to calculate operational risk requirement on the consolidated basis of the whole group. Therefore, our study that proposes the complete methodology might be beneficial for banks willing to model their operational risk but not selected a sophisticated methodology yet.

Secondly, our study is an empirical study which uses real operational risk data from an anonymous Central European bank (the "Bank"). We are going to test various approaches and methods that are being used to model operational risk and calculate capital requirements based on the results. The final outcome of our study is to propose the model of operational risk that could be implemented by the Bank. Our estimates ought to be consistent with the real capital requirement of this bank.
Lastly, our analysis provides important results and conclusions. We have found out that even a general class distribution is not able to fit the whole distribution of operational losses. On the other hand, extreme value theory (EVT) appears more suitable to model extreme events.

Additionally, we have discovered that traditional estimation using maximum likelihood does not provide consistent results while estimation based on probability weighted moments proved to be more coherent. We attribute it to limited dataset and conclude that probability weighted moments estimation that assign more weight to observations further in the tail of a distribution might be more appropriate to model operational loss events.

This paper is organised as follows; the second part provides a literature review; the third part discusses the modelling issues of operational risk and implications for economic capital, while the fourth part describes the data used and the results of exploratory data analysis. The methodology is described in the fifth and sixth chapter and in the seventh part we discuss the results of our research and compare them with the findings of other studies. Finally, the eighth part concludes the paper and state final remarks.

## 2. Literature overview

"*Operational risk is not a new risk… However, the idea that operational risk management is a discipline with its own management structure, tools and processes... is new*." This quotation from British Bankers Association in Power (2005) well describes the development of operational risk management in the last years. Until Basel II requirements in the mid 1990s, operational risk was largely a residual category for risks and uncertainties that were difficult to quantify, insure and manage in traditional ways. For this reasons one cannot find many studies focused primarily on operational risk until the late 1990s, although the term 'operations risk' already existed in 1991 as a generic concept of Committee of Sponsoring

Organizations of the Treadway Commission. Operational risk management methods differ from those of credit and market risk management. The reason is that operational risk management focuses mainly on low severity/high impact events (tail events) rather than central projections or tendencies.
As a result, the operational risk modelling should also reflect these tail events which are harder to model (Jobst, 2007b). Operational risk can build ideas from insurance mathematics in the methodological development (Cruz (2002), Panjer (2006) or Peters and Terauds (2006)).

Hence one of the first studies on operational risk management was done by Embrechts et al. (1997) who did the modelling of extreme events for insurance and finance. Later, Embrechts conducted further research in the field of operational risk (e.g. Embrechts et al. (2003), Embrechts et al. (2005) and Embrechts et al. (2006)) and his work has become classic in the operational risk literature.

Cruz et al. (1998), Coleman and Cruz (1999) and King (2001) provided other early studies on operational risk management. Subsequently, other researchers such as van den Brink (2002), Hiwatshi and Ashida (2002), de Fontnouvelle et al. (2003), Moscadelli (2004), de Fontnouvelle et al. (2005), Nešlehová (2006) or Dutta and Perry (2007) experimented with operational loss data over the past few years. To this date Moscadelli (2004) is probably the most important operational risk study. He performed a detailed Extreme Value Theory (EVT) analysis of the full QIS data set[26] of more than 47,000 operational losses and concluded that the loss distribution functions are well fitted by generalised Pareto distributions in the uppertail area..

Operational risk modelling helps the risk managers to better anticipate operational risk and hence it supports more efficient risk management. There are several techniques and methodological tools developed to fit frequency and severity models including the alreadymentioned EVT (Cruz (2002), Embrechts et al. (2005) or Chernobai et al. (2007)), Bayesian inference (Schevchenko and Wuthrich (2006) or Cruz (2002)), dynamic Bayesian networks (Ramamurthy et al., 2005) and expectation maximisation algorithms (Bee, 2006).

When modelling operational risk, other methods that change the number of researched data of operational risk events are used. The first one are the robust statistic methods used Chernobai and Ratchev (2006) that exclude outliers from a data sample. On the other hand, a stresstesting method adds more data to a data sample and is widely used by financial institutions (Arai (2006), Rosengren (2006) or Rippel, Teplý (2008)). More recently, Peters and Terauds 2006), van Leyveld et al. (2006), Chernobai et al. (2007), Jobst (2007c) or Rippel, Teplý (2008) summarise an up-to-date development of operational risk management from both views of academics and practitioners.

## 3. An overview of operational risk and economic capital

### *3.1 Basics of operational risk*

There are many definitions of operational risk such as "*the risk arising from human and technical errors and accidents*" (Jorion, 2000) or "*a measure of the link between a firm's business activities and the variation in its business results*" (King, 2001).

The Basel Committee offers a more accurate definition of operational risk as "*the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events failures*" (BCBS, 2006, p.144). This definition encompasses a relatively broad area of risks, with the inclusion of for instance, transaction or legal risk.

**Table 1: Operational risk and main factors**

| People | Systems | Processes | External Events |
|---|---|---|---|
| Fraud, collusion and other criminal activities | IT problems (hardware or software failures, computer hacking or viruses etc.) | Execution, registration, settlement and documentation errors (*transaction risk*) | Criminal activities (theft, terrorism or vandalism) |
| Violation of internal or external rules (unauthorized trading, insider dealing etc.)<br>Errors related to management incompetence or negligence | Unauthorized access to information and systems security<br>Unavailability and questionable integrity of data | Errors in models, methodologies and mark to market (*model risk*)<br>Accounting and taxation errors Inadequate formalization of internal procedures | Political and military events (wars or international sanctions)<br>Change in the political, regulatory and tax environment (*strategic risk*) |
| Loss of important employees (illness, injury, problems in retaining staff etc.)<br>Violations of systems security | Telecommunications failure<br>Utility outages | Compliance issues<br>Breach of mandate Inadequate definition and attribution of responsibilities | Change in the legal environment (*legal risk*)<br>Natural events (fire, earthquake, flood etc.)<br>Operational failure at suppliers or outsourced operations |

Source: Authors based on Sironi and Resti (2007)

However, the reputation risk (damage to an organisation through loss of its reputational or standing) and strategic risk (the risk of a loss arising from a poor strategic business decision) are excluded from the Basel II definition. The reason is that the term "loss" under this definition includes only those losses that have a discrete and measurable financial impact on the firm.
Hence strategic and reputational risks are excluded, as they would not typically result in a discrete financial loss (Fontnouvelle et al., 2003). Other significant risks such as market risk[4] and credit risk[5] are treated separately in the Basel II.

[4] The risk of losses (in and on- and off-balance sheet positions) arising from movements in market prices, including interest rates, exchange rates, and equity values (Chernobai et al., 2007).

Some peculiarities of operational risk exist compared to market and credit risks. The main difference is the fact that operational risk is not taken on a voluntary basis but is a natural consequence of the activities performed by a financial institution (Sironi and Resti, 2007).

In addition, from a view of risk management it is important that operational risk suffers from a lack of hedging instruments. For other peculiarities see Table 2.

**Table 2: Operational risk peculiarities**

| Market and Credit Risks | Operational Risks |
|---|---|
| Consciously and willingly face | Unavoidable |
| "Speculative" risk, implying losses and profits | Pure risks, implying losses only* |
| Consistent with an increasing relationship between risk and expected return | Not consistent with an increasing relationship between risk and expected return |
| Easy to identify and understand | Difficult to identify and understand |
| Comparatively easy to measure and identify | Difficult to measure and identify |
| Large availability of hedging instruments | Lack of effective hedging instruments |
| Comparatively easy to price and transfer | Difficult to price and transfer |

* with few exceptions

Source: Authors based on Sironi and Resti (2007)

[5] The potential that a bank borrower or counterparty fails to meet its obligations in accordance with agree terms (Chernobai et al., 2007).

## 4. Data analysis

### 4.1 Data used

In this study we have used data from 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 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.

### 4.2 Exploratory data analysis

To get a better understanding of the structure and characteristics of the data we have first performed Exploratory Data Analysis as suggested by Tukey (1977). Operational risk data are skewed and heavy-tailed; hence skewness and kurtosis are the most important characteristics.

We have utilised some of the measures proposed by Hoaglin (1985) and Tukey (1977) used in Dutta and Perry (2007) to analyse 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.

## 5. Methodology

### 5.1 Concept of VAR, modelling frequency and aggregation of losses

Before describing individual approaches to model operational risk, we would like to define Value at Risk (VAR), a risk informative indicator recognised by Basel II requirements.[6] Jorion (2007) 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*

[6] For more details on the VAR methodology see the traditional risk management books such as Jorion (2007), Saunders and Cornett (2006) or Sironi and Resti (2007).

Usually VAR is expressed as a corresponding value (in currency units) of *p%* quantile of a distribution[7] 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% (see Figure 1), thus we will report $VAR_{99.9}$ for each modelling 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.

There is one complication associated with the above definition of VAR and the requirement of Basel II. The above density function *f(x)* has to combine both the severity and frequency of losses for a period of one year which is analytically difficult in specific cases (Embrechts et al., 2005). One of the approaches suggested (e.g. Cruz, (2002), Embrechts et al. (2005) or Dutta and Perry (2007)) is the Monte Carlo (MC) simulation where for a simulation of a given year a number of losses is drawn from a frequency distribution and each loss in the year is simulated by a random quantile of a severity distribution.

All losses in each of the simulated years are then summed to arrive at the estimation of the combined distribution function. The 99.9% quantile is then taken from these simulated annual losses as the estimator of the 99.9% VAR. We have simulated 10,000 years, however, as argued by Embrechts et al. (2005) for rare events, the convergence of the MC estimator to the true values may not be particularly fast, so in real applications either using more iterations or refining the standard MC by importance sampling technique is suggested[8].
To model frequency we have used Poisson distribution, which is typically employed, having the density function:

$$f(x) = \frac{e^{-\lambda}\lambda^{x}}{x!},$$

We have estimated it using three complete years 2004-2006 and for each year of the simulation we generated a random number of losses based on this parameter.
For EVT we have not modelled the whole distribution but rather the tail by applying either the generalised extreme value (GEV) or the generalised Pareto distribution (GPD).
In these cases (following Dutta et al., 2007) we have used empirical sampling for the body of the distribution. Hence, the VAR has been calculated by a MC simulation in which a part of losses was drawn from the actual past losses and the other part was modelled by an EVT model.

[7] Although it is sometimes also defined as the difference between the mean and the quantile.
[8] Furthermore, the outlined aggregation of losses assumes that individual losses and the density function for severity and frequency are independent; in the context of operational losses this is a reasonable assumption.

The proportion of losses in the tail for the calculation of VAR was set to 2% as this percentage of the highest losses appears to be the best to fit the data. The frequencies were again modelled using the Poisson distribution.

## 6. Empirical results

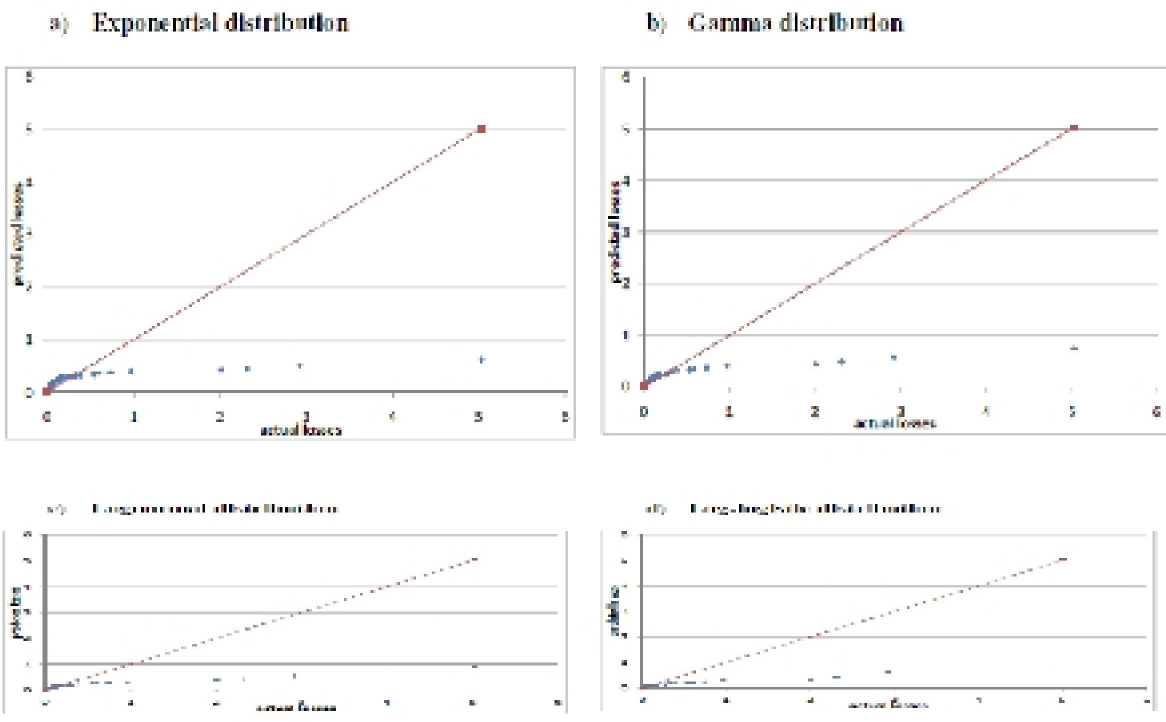
### *6.1 Loss distribution approach*

As would be expected, the simple parametric distributions with one or 2-parameters are far too simple to model operational loss data. Although moving from exponential to a gamma distribution and from a gamma to a lognormal or a log-logistic somewhat improves the fit, both QQ plots and the test statistics (Table 2) reject the hypothesis that the data follow any of these distributions.

**Table 2: Simple parametric distributions - the goodness-of-fit statistics (p-values)**

| | MLE | |
|---|---|---|
| | √nD | √nV |
| Exponential | <0.01 | <0.01 |
| Gamma | <0.01 | <0.01 |
| Lognormal | <0.01 | <0.01 |
| Log-logistic | <0.01 | <0.01 |

**Note:** _nD stands for the Kolmogorov-Smirnov and (_nV) the Kuiper statistic



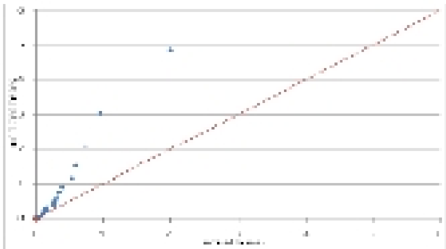
Although this distribution is flexible enough to model extremely high losses, the highest loss in the dataset that is almost twice the second largest loss causes the estimated GH distribution parameter for kurtosis to be very high and hence the distribution overpredicts the high losses, while underpredicting the lower losses.
We can conclude that the whole distribution pattern of operational losses with rather limited observations is not possible to be captured even with a general class of distributions such as the GH distribution.

| | QE | |
|---|---|---|
| | VnD | VnV |
| GH | <0.01 | <0.01 |

Although none of the parametric distributions got close to a reasonable fit, we have still calculated VAR for these models (Table 11) to have at least an idea of the calculated VAR.

From the table we can draw similar conclusion as from the Q-Q plots. The first three distributions provide relatively low capital requirements in the range (2.0-2.7%). Based on the log-logistic distribution the calculated capital requirement is much higher as this distribution allow for higher losses. Finally, the GH distribution provides unreasonably high capital requirement owning to the high shape parameter and overprediction of the highest losses.

Figure 2: QQ plots for the GH distribution



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| | VAR (99.9%) - Monte-Carlo | |
|---|---|---|
| **Distribution** | **MLE** | **QE** |
| Exponential | 2.7% | |
| Gamma | 2.1% | |
| Lognormal | 2.0% | |
| Log-logistic | 9.5% | |
| GH distribution | | >100% |

## 7. Conclusion

In this paper we have attempted to analyse and model real operational data of a Central European Bank. We have utilised 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, loglogistic 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 Muller (2002), Cruz (2002), Moscadelli (2004), de Fontnouvelle et al. (2005) or Duta, Perry (2007).

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 (2002) used PWM to analyse 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 (2004), de Fontnouvelle et al. (2005) or Chavez- Demoulin et al. (2005). 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 recognised 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 modelling operational risk using such techniques as robust statistics, stress-testing, Bayesian inference, dynamic Bayesian networks and expectation maximisation algorithms.

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