Institute of Economic Studies, Faculty of Social Sciences
Charles University in Prague

Operational Risk - Scenario Analysis

Milan Rippel
Petr Teplý

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Milan Rippel[#]
Petr Teplý*

[#] IES, Charles University Prague
E-mail: milanrippel@seznam.cz

*EEIP, a.s. and
IES, Charles University Prague
E-mail: petr.teply@gmail.com

Abstract:

Operational risk management and measurement has been paid an increasing attention in last years. The main two reasons are the Basel II requirements that were to be complied with by all international active financial institutions by the end of 2006 and recent severe operational risk loss events. This paper focuses on operational risk measurement techniques and on economic capital estimation methods. A data sample of operational losses provided by an anonymous Central European bank is analyzed using several approaches. Multiple statistical concepts such as the Loss Distribution Approach or the Extreme Value Theory are considered. One of the methods used for operational risk management is a scenario analysis. Under this method, custom plausible loss events defined in a particular scenario are merged with the original data sample and their impact on capital estimates and on the financial institution as a whole is evaluated. Two main problems are assessed in this paper – what is the most appropriate statistical method to measure and model operational loss data distribution and what is the impact of hypothetical plausible events on the financial institution. The g&h distribution was evaluated to be the most suitable one for operational risk modeling because its results are consistent even while using a scenario analysis method. The method based on the combination of historical loss events modeling and scenario analysis provides reasonable capital estimates for the financial institution and allows to measure impact of very extreme events and also to mitigate operational risk exposure.

Keywords: operational risk, scenario analysis, economic capital, loss distribution approach, extreme value theory

JEL: G21, G32, C15.

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1. Introduction

The New Basel Capital Accord (Basel II) valid since January 2007 for international active banks newly introduced a capital requirement for operational risk (in addition to credit and market risk). This fact has further fostered the focus of financial institutions on OR management. Moreover, high losses stemming from operational risk have been recorded in financial institutions in the last years (e.g. Societe Generalé in 2008 ($7.3 billion), Sumitomo Corporation in 1996 ($2.9 billion) or Barings Bank in 1995 ($1 billion)). In this paper we focus on modeling and stress testing of economic and regulatory capital set aside to cover unexpected losses of an anonymous Central European bank (BANK). There are two main questions this paper is aimed to answer:

1. What is the appropriate statistical method to model operational risk (OR) loss data distribution and measure reasonable capital estimates for the institution?
2. What is the impact of extreme events defined in particular extreme case scenarios on the capital estimates and on the financial institution?

Firstly, the risk measurement statistical techniques are evaluated and the most suitable ones used further for scenario analysis method in order to test whether those methods provide consistent results even if original data sample is enriched by adding a few extreme losses. The best method for capital estimate computation is then chosen and effects of scenarios to the financial institution are assessed.

Several statistical distributions are used to model loss severity distribution and compute capital estimates. It is expected that the best results will be provided by a distribution that can reasonable model body as well as the heavy right tail of the data sample. On the other hand, techniques that focus just on the tail of the distribution might not provide consistent results if the tail is contaminated by loss events defined during scenario analysis. The distribution that is expected to be the most suitable for modeling the operational risk data is the g&h distribution used by Dutta, Perry (2007). So the test hypotheses can be stated as:

H_0: The g&h distribution provides consistent capital estimates for scenario analysis method

H_1: Extreme Value Theory (EVT) provides consistent capital estimates for scenario analysis method.

Once this hypothesis is assessed the effects of extreme events on the financial institution

can be evaluated. It might be assumed that the bank will not be able to cover the worst case joint scenario losses, because the loss amounts will be too high to be covered by the bank capital. On the other hand, the bank should be able to cover average joint scenario losses.

First rigorous studies on OR management were provided already in late 1990s, e.g. works from Prof. Embrechts such as Embrechts et al. (1997), Embrechts et al. (2003) or Embrechts et al. (2006). Given the scarcity and confidentiality of OR loss data, there are only few papers that explores specifics of OR data and are able to measure OR exposure with the accuracy and precision comparable with other sources of risk, however. The most comprehensive studies are de Fountnouvelle (2006), Degen (2006), Embrechts (2006), Mignolla, Ugoccioni (2006), Chernobai (2007) and Dutta, Perry (2007). A scenario analysis method, a method used in this paper, is just very briefly mentioned in papers from Cihak (2004), Arai (2006) or Rosengren (2006). [1]

This paper is organized as follows: The second section provides an overview of operational risk concepts and related to Basel II requirements. The following section provides an overview of methodology used. Section 4 analyzes the data sample of BANK and proposes distributions that can best model the data sample. The fifth section provides a theoretical overview of stress testing and scenario analysis methodology. In the sixth section the loss events defined in particular scenarios are merged with original data sample and new capital estimates are computed. Finally, the last part makes conclusion and proposes ideas for future research.

2. Operational Risk Background and Basel II requirements

2.1 Basic terms

The most common definition of OR is given in Basel II 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." However, other definitions exist as well. A very general definition says that OR is a consequence of doing business. OR thus bundles relatively broad area of risks which differs it from market and credit risk. The common idea is that operational risk encompasses those risks, not covered under credit and market risk that have a measurable financial impact. Table 1 categorizes OR by its main drivers.

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[1] For a detailed overview of the OR literature see Chalupka, Teply (2008) or Chernobai (2007).

Table 1: Main factors of operational risk

People	Systems	Processes	External Events
•Fraud, collusion and other criminal activities •Violation of internal or external rules •Management errors •Loss of important employees •Security violations	•IT problems •Unauthorized access •Unavailability of data •Communication failures •Utility outages	•Execution, registration, settlement errors *(transaction risk)* •Model and methodology errors *(model risk)* •Accounting errors •Compliance issues	•Criminal activities •Political and military events •Supplier failures

Source: Based on Chalupka,Teply (2008)

There are some specifics of OR in comparison to market and credit risks that in general make OR more difficult to manage. "The main differences are the fact that operational risk is not taken on a voluntary basis but is a natural activity performed by a financial institution"[2] and a noticeable lack of hedging instruments. The main differences are summarized in Table 2.

Table 2: Risk types comparison

Market an Credit Risks	Operational risk
•Consciously and willingly faced •Speculative risk, both losses and profits •Positive risk-return relationship •Easy to identify and understand •Easy to measure and quantify •Availability of hedging instruments •Comparatively easy to price and transfer	•Unavoidable •Pure risk, implies only losses •Non consistent risk-return relationship •Difficult to identify and understand •Difficult to measure and quantify •Lack of effective hedging instruments •Difficult to price and transfer

Source: Based on Chalupka,Teply (2008)

There are some widely known and severe magnitude of OR events that happened in recent years – the most publicly known examples of OR would be those caused by fraud, natural disaster or unauthorized trading – one very recent OR event from the Czech Republic is the theft of USD 31 million in the G4S Cash Services from late 2007. The other example would be a failure of internet banking of Ceska Sporitelna in 12/2007, or a loss of USD 12 million suffered by BANK due to improper rounding in interbank transactions. The mostly know foreign OR events starts with a large loss in the amount of USD 7.5 billion caused to Société Générale by unauthorized derivatives trading by Jerome Kerviel. Another category of events is connected with terrorist acts or natural disasters – like losses caused by 9/11 or hurricane Katrina. Each of those events exceeds loss amount of USD 1 billion. It is clear that those events are the most

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[2] Chalupka,Teply (2008).

severe but very infrequent ones. They represent high risk and in some cases can be destructive for a financial institution. There are other loss events that are more common but cause much smaller loss to a bank – like an input error caused by an employee, a credit card fraud or a failure of a supplier.

Figure 1: Classification of bank's requirements according to risk
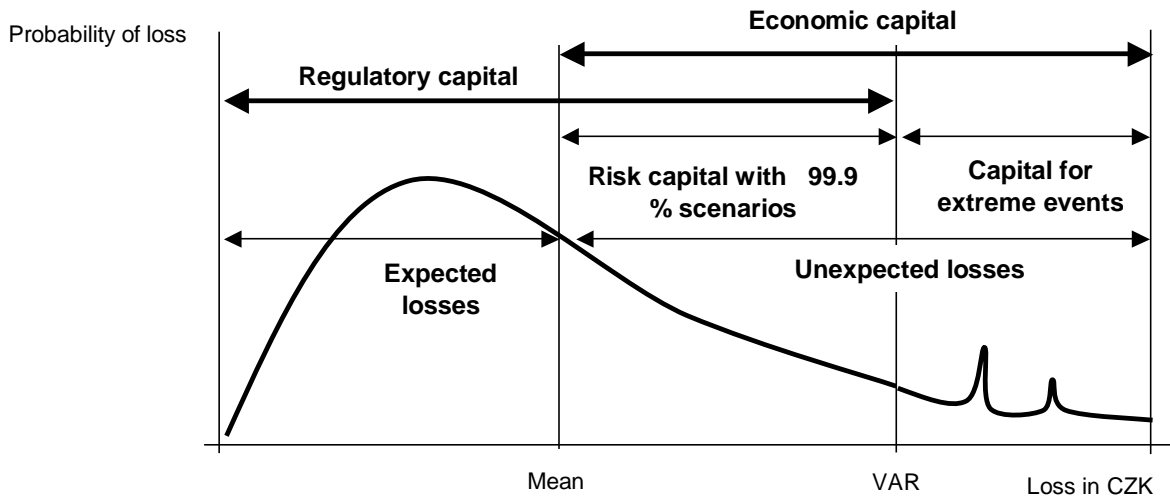
For OR modeling it is crucial to distinguish between regulatory and economic capital. Regulatory capital is the amount of capital necessary to provide adequate coverage of banks' exposures to financial risks as defined in the capital adequacy rules set by the Basel II. "A one-year minimum regulatory capital is calculated as 8% of risk-weighted assets."[3] Empirical studies show that operational risk regulatory capital, in general, constitutes 10%-25% of overall capital adequacy requirements.

On the other hand, economic capital "is a buffer against future, unexpected losses brought about by credit, market, and operational risks inherent in the business of lending money"[4] or alternatively economic capital might be defined as the amount necessary to be in the financial business.

Further we will focus on modeling both regulatory and economic capital for OR because this concept is to be used for the Advanced Measurement Approach (AMA) as it should cover all unexpected losses – even the extreme events with the Value at Risk (VaR) higher than 99.9%. Regulatory capital covers expected losses and unexpected losses only to a certain confidence level and it does not consider the extreme events[5] like economic capital does. The regulatory

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[3] Chernobai (2007)

[4] Mejstrik (2008)

[5] Under AMA expected losses can be covered by provisions and can be excluded from regulatory capital charge

capital will be further defined as the $VaR_{0.999}$ measure and the economic capital as the $CVaR_{0.99}$ measure.[6]

2.2 Basel II operational risk measurement techniques

Basel II sets three operational measurement methodologies for calculating operational risk capital charge "in a continuum of increasing sophistication and risk sensitivity"[7]. The first two approaches – Basic Indicator Approach (BIA) and Standardized Approach (SA) - are top-down approaches, because the capital charge is allocated according to a fixed proportion of gross income. The third approach – Advanced Measurement Approach (AMA) - is a bottom-up approach, because the capital charge is estimated based on actual internal OR loss data[8].

The motivation for banks to move from a less advanced to a more advanced technique is the increased risk sensitivity and in general lower expected capital requirement. Once a bank chooses to move to a more sophisticated approach there is no option to revert back.

The most advanced Basel II approach for operational risk assessment is called **Advanced Measurement Approach** (AMA). "Under the AMA, the regulatory capital requirement will equal the risk measure generated by the bank's internal operational risk measurement system using the quantitative and qualitative criteria[9]" that are given in Basel II. The use of AMA is subject to a supervisory approval. Under the AMA the OR data are divided into the seven event type classes and eight business lines. So the particular AMA technique chosen by a bank should work with a matrix of seven event types and eight business lines.

Since the operational risk measurement techniques are still under development, Basel II does not set any standard technique the for AMA, thus the banks are allowed to develop their own models. Basel II encourages the banks to further develop increasingly risk sensitive OR allocation techniques, that will correspondent with the empirical loss data for the particular bank. The AMA thus provides significant flexibility to banks – on the other hand, regulators are given better control than the AMA techniques used by a particular financial institution. This paper focuses on Loss Distribution Approach (LDA), which is detailed below.

2.3 Common OR management and measurement techniques

The other measurement methods not specifically mentioned in Basel II are also being used by financial institutions. There are four main techniques used to measure OR. The basic features of those techniques are listed in the following table.

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[6] For more info on VaR and CVaR measures see chapter 2
[7] BCBS (2006)
[8] Since the first two approaches are not sensitive to the operational risk events they are not used further on in this paper. More details on BIA and SA can be found in BCBS (2006) or Rippel (2008)
[9] BCBS (2006)

Table 3: OR measurement techniques

LDA	Scenario analysis	RCSA	KRI
• Application of statistical methods on historical OR events • Quantitative methods	• Based on hypothetical or historical scenario • Assess impact of extreme events • Quantitative method	• Inherent and residual risk estimation • Risk mitigation techniques • Subjective qualitative methods	• Risk exposure measurement system • Objective qualitative method

Source: Authors

The most theoretical measurement approach is the LDA. This method was already explained above and will be discussed in more details in the following chapter. Because of the fact, that the OR management is a relatively new concept, there are not enough historical OR events in internal loss database of a financial institution and thus statistical methods applied on a limited data sample may provide biased or inconsistent results. It is assumed that as the number of events in internal and external databases will grow, the LDA approach will become the prevalent one. Some other disadvantages of the LDA exist. The LDA is purely based on historical OR events that might not be the best predictor of the future and might reflect crucial changes in OR exposure of a financial institution with a several years gap. So even if the LDA is the most advanced, objective and theoretical method it is still useful to combine it with other approaches in order to control OR exposure of a financial institution.

The second method is the Scenario Analysis (SCA). This method can be classified as a stress testing method. A financial institution can obtain valuable results from analyzing scenarios that cover infrequent but severe risks that can have severe impact on bank operations. The other reason is to measure the exposition to plausible risks that has not happened so far and thus are not registered in the internal OR loss database.

The other two methods – Key Risk Indicators and Risk Control Self Assessment are discussed in more details in Rippel (2008).

Once a financial institution determines the specifics of its OR exposure, its managers can take several actions to manage OR. There are five ways to manage OR – they are described in Table 1.6. The aim of a financial institution is to minimize the amount of residual OR. The procedure is to identify the level of inherent risk, implement risk mitigation techniques and then evaluate the level of residual risk. If some risk is not controllable by internal means, then the risk should be transferred either to insurance company,[10] to a 3rd party using outsourcing or such an activity should be limited.

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[10] Basel II allows insurance coverage up to 20% to be considered for regulatory capital estimates

Table 4: Risk mitigation techniques

Precautionary arrangements	Business continutity management	Transfer risk to insurance companies	Outsourcing	Taking the risk
• Aimed to avoid OR events • Control directives, standardization of processes, trainings etc. • Best practice for high frequency, low severity events	• Plans for getting back to normal situation, should an extreme OR event happen • Can mitigate impact of severe events • Requires periodical training of those plans	• Complex insurance plans for the case of extreme OR events • Usually used for low frequency, high severity events	• Transfer the activities that are not directly connected with bank activities to a third party	• If long term costs of OR management is higher than potential loss resulting from a specific OR event

Source: Authors

3. Methodology

3.1   General remarks

Empirical evidences prove that OR data have certain specifics, as mentioned above, which distinguish them from credit and market risks data and that causes techniques used for assessment of credit and market risks unsuitable for OR management. From this point of view, OR management has something in common with insurance mathematics and so some of the insurance methodology can be applied to OR assessment – e.g. Extreme Value Theory (EVT).

The OR data are specific by the fact that there exist events that cause very severe losses to a financial institution, but they are not so frequent. For example, there is a very low probability that Czech Republic would be affected by a thousand-year flood – but it did happen in 2002 and this event had negative consequences for all Czech banks. Example of distributions of OR loss severity data is shown on Figure 2. The x-axis denotes the loss amount and the y-axis shows the frequency of events for different loss amount levels.

OR data suggest that there exists two kinds of events – the first category consists the losses of high frequency/low severity that are relatively unimportant for a bank and can often be prevented using risk mitigation techniques and covered by provisions. The second category consists of the low frequency/high severity events that are more important for a bank. "Banks must be particularly attentive to these losses as these cause the greatest financial consequences to the institutions."[11]

If we consider statistical distribution of OR loss severity data the "existing empirical evidence suggest that the general pattern of operational loss data is characterized by high kurtosis, severe right-skewness and a very heavy right tail created by several outlying events."[12] Distributions fitting such data are called leptokurtic. As will be shown later, the data sample provided by BANK exhibits the same characteristics.

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[11] Chernobai (2007)
[12] Chernobai (2007)

Figure 2: Example of OR severity distribution
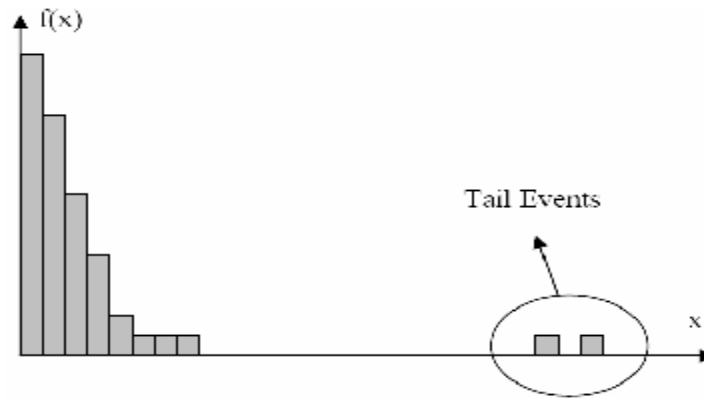
Source: Chernobai (2007)

Another important feature of OR is the scarcity of available historical data. As of now, the banks usually do not have more than five years of loss data in their OR loss data internal databases – the tail of the distribution cannot be modeled with a sufficient statistical fit, if only very few extreme events were recorded. So the limited data sample lacks sufficient explanatory power. There were some methods proposed to reduce this limitation – the most common one is to pool internal data with external ones.[13]

3.2   Models for OR measurement

There exist two fundamentally different approaches to develop models for OR :

- The top – down approach
- The bottom-up approach

The first one quantifies operational risk without attempting to identify the events or causes of losses while the second one quantifies operational risk on a microlevel being based on identified internal events. The top-down approach group includes, among others, the *Risk indicator models* that rely on a number of OR exposure indicators to track operational risks and the *Scenario Analysis and Stress Testing models* that are "estimated based on the what-if scenarios generated with reference to expert opinion, external data, catastrophic events occurred in other banks, or imaginary high-magnitude events.

The bottom-up approaches include actuarial type models that will be further discussed in this chapter. Those models have two key components – frequency and loss severity distributions that model historical OR loss data sample. The capital charge is then computed as the value of $VaR_{0.99}$ measure of the one-year aggregate distribution loss.

3.3   Frequency distributions

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[13] Chernobai (2007)

The studies based on empirical data suggest that choice of frequency distribution is not as much important as an appropriate choice of loss severity distribution.[14] The banks should develop a solid mechanism for recording OR data. The most common frequency distributions are the Poisson distribution and the negative binomial distribution. The survey of studies done by Chernobai (2007) suggest that the Poisson distribution will be a reasonable solution for modeling OR data. We will use the Poisson distribution later on for modeling frequency distribution of the data sample provided by BANK. Features of Poisson distribution are explained in Rippel (2008).

3.4 Extreme Value theory

The EVT is a branch of statistics that is focused on the study of extreme phenomena – the rare events that are situated in a tail of a particular probability distribution. Based on the knowledge of OR data distribution, it is assumable that the EVT would be an ideal tool for OR capital charge estimation. There are several techniques for the EVT – each of them uses different method to pick up the low frequency/high severity loss events. They differ in the way how they set a threshold to cut loss data distribution into two parts – the body and the tail. Under the EVT, the body is being modeled using a different method (e.g. empirical sampling) and the tails are being modeled using specific EVT methods. The EVT relies on a sufficiently large data sample. This is not always the case for OR data, therefore the results can be biased. There are two ways to select tail observations from a data sample – Block Maxima method (BMM) and Peak Over Threshold method (POTM).

3.4.1 Block maxima method

The BMM divides data into independent blocks of the same size and considers the highest observation from such a block. "For very large extreme loss observation x, the limiting distribution of such normalized maxima is the Generalized extreme value (GEV)."[15]

The block maxima method (BMM) divides data into independent blocks of the same size. This model would be useful, if the extreme events were equally distributed over the whole time interval. However, this is not usually the case in practice. "For very large extreme loss observation x, the limiting distribution of such normalized maxima is the Generalized extreme value (GEV)."[16] The probability density distribution function of GEV distribution has a form of:

$$f(x; \mu, \sigma, \xi) = \frac{1}{\sigma}[1 + \xi\left(\frac{x-\mu}{\sigma}\right)]^{-1/\xi-1} e^{-[1+\xi\left(\frac{x-\mu}{\sigma}\right)]^{-1/\xi}} \text{ for } 1 + \xi\left(\frac{x-\mu}{\sigma}\right) > 0,$$

where x refers to block maxima observations, $\mu \in R$ is the location parameter, $\sigma > 0$ is the scale parameter and ξ is the shape parameter. The GEV is supported under these conditions:

$$x > \mu - \frac{\sigma}{\xi} \text{ if } \xi > 0$$

$$x < \mu - \frac{\sigma}{\xi} \text{ if } \xi < 0$$

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[14] De Fontnouvelle (2003)
[15] See Chernobai (2007) for more details on features of GEV distribution
[16] Chernobai (2007)

$$x \in R \text{ if } \xi = 0$$

The GEV distribution can be divided into three cases based on the value of the shape parameter.[17] The most important case called the Fréchet or the type II extreme value (EV) distribution is for $\xi > 0$. The tail of the Fréchet distribution is slowly varying and thus suitable for modeling high severity OR data. The other two cases (the Gumbel or the type I EV distribution for $\xi = 0$ and the Weibull or the type III EV distribution for $\xi < 0$) are of a less importance for OR data modeling because they do not fit the tail as well as in the Fréchet case.

Chalupka, Teply (2008) further details parameter estimation methods for the GEV distribution using the probability-weighted moments (PWM). A GEV random variate can be simulated using the inverse transform method $X = \mu - \sigma(1 - \log U)^{-\xi})/\xi$, where U is distributed uniformly on (0,1) interval.[18]

3.4.2 Peak over threshold method

The POTM uses all observations that exceed certain high threshold level. As argued by Embrechts (2005), these models are more frequently used in practice for OR exposure measurement. The limiting distribution for the POTM is the generalized Pareto distribution (GPD) with the probability density function in the form of:

$$f(x; \xi, \mu, \sigma) = \frac{1}{\sigma}(1 + \frac{\xi(x-\mu)}{\sigma})^{(-\frac{1}{\xi}-1)} \ ,$$

where *x* refers to the data exceeding the threshold, $\mu \in R$ is the location parameter,[19] $\sigma > 0$ is the scale parameter and ξ is the shape parameter. GPD is supported under these conditions:

$$x \geq \mu \text{ if } \xi \geq 0$$

$$\mu \leq x \leq \mu - \frac{\sigma}{\xi} \text{ if } \xi < 0$$

Similarly to the GEV, also the GPD has special cases based on the value of the shape parameter. The most important case from OR modeling point of view is when $\xi > 0$.[20] In this case the GPD has very heavy tails.

The GPD parameters can be again estimated by using either the MLE or the PWM methods – for more details see Teply, Chalupka (2008). A GDP random variate can be simulated by using the inverse transform method in the form of $X = \mu - \sigma(1 - U^{-\xi})/\xi$.[21]

A critical task for designing the GPD distribution is to set an appropriate threshold level. This level should be set to be sufficiently high to fit extreme events. But on the other hand, the filtered data sample should not be limited too much in order to provide reasonable statistical evidence. Several approaches to solve this optimization task exist. The most commonly used

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[17] Chalupka, Teply (2008)
[18] This form holds when $\xi \neq 0$
[19] The location parameter is usually assumed to be 0 which reduces number of parameters to two
[20] The GPD in this case is a reparameterized Pareto distribution (Chernobai 2007)
[21] In the case when $\xi \neq 0$

one relies on "the visual observation of the mean excess plot,"[22] which is defined as the mean of all differences between the values of the data exceeding threshold level u and u. In case of the GPD the empirical mean excess function can be formalized into the following equation:

$$e_n(v) = \frac{\sum_{j=1}^{n}(x_j - v)I(v < x_j)}{\sum_{j=1}^{n}I(v < x_j)} = \frac{\beta}{1 - \xi} + \frac{\xi}{1 - \xi}u$$

where v is the value above threshold level u. "Threshold values against mean excess values provide the mean excess plot. If the data supports a GPD model, then this plot should become increasingly linear for higher values of v "[23]. A general practice is then to choose such u for which the mean excess plot is roughly linear. Several other approaches for choosing the threshold exist – the most simple one is just to define the right tail as five or ten percent of the largest observations.

3.5   Goodness of fit tests

The fit of distributions chosen should be tested by a set of goodness of fit tests (GOFT) in order to avoid model risk – risk of choosing bad distribution for the LDA approach. "An underestimated VaR would jeopardize the long-term ability of a bank to maintain a sufficient amount of capital reserves to protect against catastrophic operational losses, while a severely overestimated VaR would limit the amount of funds available for investment."[24] There are two ways how to assess the GOFT – either by using in-sample GOFTs or backtesting. Backtesting is the opposite approach to stress testing which questions validity of a chosen model.

GOFTs are divided into two classes – visual tests and formal tests. Visual GOFTs compare empirical and hypothesized distributions by plotting them to a chart and comparing their characteristics. One of the tests is the mean excess plot.

The most commonly used visual test is Quantile-Quantile (QQ) plot which plots empirical data sample quantiles against the quantiles of the distribution that is being tested for fit. If such a distribution fits the data well then the QQ-plot would follow a 45-degree line. The QQ plot is especially important in case of small sample sizes. "The reason is that as the sample size shrinks, formal statistical tests become more likely to fail to reject the fit of a distribution."[25]

Formal GOFTs test whether the data sample follows a hypothesized distribution. The null and the alternative hypothesis are stated as:[26]

H_0 : The data sample follows the specified distribution

H_1 : The data sample does not follow the specified distribution

Because of the OR the data specifics, the tests that are based on empirical distribution function[27] are adequate measures for testing the GOF of particular distribution for OR loss

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[22] Chernobai (2007)
[23] Based on Teply, Chalupka (2008)
[24] Chernobai (2007)
[25] Dutta, Perry (2007). For more details on QQ plot see Rippel (2008)
[26] Chernobai (2007)

severity modeling. "Empirical distribution function-based tests directly compare the empirical distribution function with the fitted distribution function."[28] The tests belonging to this group are the Kolmogorov-Smirnov test (KS) and the Anderson-Darling (AD) test. All of them state the same hypothesis but uses different test statistics.[29]

3.6   Aggregate loss distribution and capital charge estimates

Figure 3: Aggregation of operational loss and frequency distributions
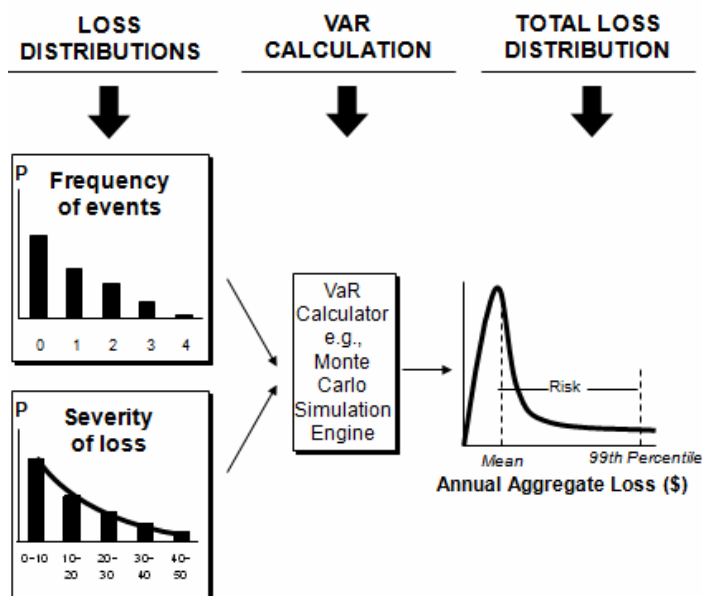
Source: Samad-Khan (2006)

Once the frequency and severity loss distributions are evaluated, an aggregated risk exposure of the bank should be estimated. Both types of distributions are to be aggregated to a single model which estimates the total loss over a one-year period. The measure used for the estimation of required capital charge is the Value-at- risk (VaR). "In the context of operational risk, VaR is the total one-year amount of capital that would be sufficient to cover all unexpected losses with a high level of confidence such as 99.9%."[30]

The aggregation process is shown on figure 3. Mathematical derivation of the aggregate loss distribution function is further discussed in Chernobai (2007).   Due to the fact that the cumulative distribution function is not linear in X nor in N, analytic expressions for the compound distribution function do not exist and thus the function must be evaluated numerically.

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[27] An empirical distribution function is a cumulative distribution function that concentrates probability $1/n$ at each *n* observations in a sample
[28] Chernobai (2007)
[29] See Rippel (2008) for more details on KS and AD tests
[30] Chernobai (2007).

The most common technique relies on numerical approximation of the compound distribution function using the Monte Carlo simulations of loss scenarios. The algorithm is as follows:[31]

i.   Simulate a large number of Poisson random variates and obtain a sequence n_1, n_2, … n_{MC} representing scenarios of the total number of loss events in a one-year period.
ii. For each of such scenarios n_k simulate n_k number of loss amounts using a specified loss severity distribution
iii. For each of such scenarios n_k sum the loss amounts obtained in the previous step in order to obtain cumulative one-year losses
iv. Sort the sequence obtained in the last step to obtain the desired aggregate loss distribution

The number of simulated observations differs. We will use 50,000 simulations for the purposes of this paper.

Many empirical studies show that in case of OR only few rare events account for the major part of the VaR.[32] Because of that even while using a high confidence level such as 99.9%, the VaR measures would not be able to account for extreme loses. And so the VaR can be used for estimation of required capital charge but not for estimation of required economic capital. Because of those facts, alternative risk measures, which are able to account even for extreme events, were designed. The most common one is the Conditional Value at Risk (CVaR). "CVaR determines the amount of money one is expected to lose if an event in the right tail of the distribution beyond VaR takes place."[33] In case of OR modeling CVaR is the corresponding percentile of a right tail aggregate loss distribution, where right tail is defined as a 1 - confidence level used for the VaR.

4. Empirical data sample analysis

The data sample provided by BANK consists of 657 loss events. The following assumptions about the data sample were made:

- Exchange rate and inflation impacts are not considered, nominal values in EUR are used
- The data sample is truncated from below, but the threshold is set to a very low value, so we do not use corrections for left truncation bias
- The impact of insurance is not considered – neither from the time or magnitude points of view – because only the actual loss amount is important for a financial institution
- Only internal loss data are used and thus estimates provided by using the LDA might be underestimated because no external loss data were employed

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[31] Chernobai (2007)
[32] Ebnother, Vanini, McNeil, Antolinez-Fehr (2001)
[33] Chernobai (2007)

- While the SA uses 15% of gross income as a regulatory capital charge it might be assumed that by using the LDA approach the reasonable interval for capital charge is 5-15%

Table 5: Data sample statistics – whole sample

Mean	Median	Std.	Skewness	Kurtosis
41,738	3,114	280,538	14	225

Source: BANK data sample

The common statistics for the whole sample show a significant difference between the mean and the median and a very high standard deviation which signals a heavy right tail. The same information is given by the skewness measure. The high value of the kurtosis measure signals that the high standard deviation is caused by infrequent extreme observations. These findings suggest that the data sample provided by the BANK exhibits the specific features of OR data described in the other papers.

Due to the low threshold value, there is a quite significant group of losses lower than EUR 1,000. This fact might have impact on results of the LDA approach while using some less advanced distributions, because more weight is put to the left tail of the data sample. It might be a good idea to exclude these low amount observations from the data sample in order to increase the statistical fit but on the other hand, a number of observations would decrease by one third.[34]

The procedure described in section 3.6 was used to aggregate the loss frequency and the loss severity distributions. The Monte Carlo simulation method with 50,000 trials was used for the parameter estimation as well as for the aggregation function. The regulatory and the economic capital estimates are provided as a percentage relative to the BANK average gross income over the last three-year period.   The fit of the distributions to the sample data is evaluated by using the QQ plot, the KS and the AD tests. If the test statistics are higher than the critical value, then the null hypothesis that the particular distribution is able to model the OR data sample cannot be rejected.

The distributions mentioned above were used for modeling of loss severity distribution – namely the Empirical Sampling method, lognormal, Weibull, exponential, gamma and g&h parametric distributions and also EVT approaches – BMM and its two ways to set block maxima (Max per month and Max per quarter) and POTM with three ways to cut the extreme observations (max 5%, max 10% and the threshold method). Details are provided in Rippel (2008).

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[34] See Chalupka, Teplý (2008) for more details on this approach

Table 6: Comparison of the regulatory and economic capital estimates

Distribution	Regulatory Capital	Economic Capital
Empirical	2.31%	1.51%
G&H	4.43%	6.71%
BMM – Month	14.95%	48.58%
POT – 5%	9.32%	18.89%

Source: Authors

The conclusion for the LDA approach on the institution level is that only the g&h, the BMM – Max quarter and the POTM – Max 5% methods seem to be suitable for modeling the OR data for Basel II purposes and thus these methods will be used for the stress testing purposes.[35] The results of these three methods plus the ESM are provided in the following table. The regulatory capital is being measured as the ratio of $VaR_{0.99}$ / Gross Income and the economic capital is being measures as the ratio of $CVaR_{0.99}$ / Total Equity.

While employing the very high significance levels for EVT methods, the economic capital is being overestimated. But even despite of the overestimation, it was shown that BANK would be able to survive those very severe OR events. Because of the high sensitivity of the EVT methods, it can be concluded that the g&h method provides more reasonable estimates than any EVT method used.

5. Stress testing and scenario analysis

Because of the fact that the LDA approach is a historical one – the capital charge is estimated based on historical loss events - alternative methods for the OR management were developed. One of those methods is the scenario analysis or, generally, the stress testing. This method is supposed to examine whether a financial institution would be able to undergo exceptional risk losses. Stress testing can be defined as "the examination of the potential effects on a bank's financial condition of a set of specified changes in risk factors, corresponding to exceptional but plausible events."[36] An alternative definition is given by Chernobai (2007): "Stress tests are intended to explore the effect of low probability events that lie outside the predictive capacity of any statistical model on VaR" or the one used by the BIS Committee on the Global Financial System, where stress testing is defined as "a generic term describing various techniques used by financial firms to gauge their potential vulnerability to exceptional, extreme or simply unexpected but plausible events."[37] The stress testing should be used as a complementary approach to the VaR based LDA approach in order to ensure that a bank would

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[35] For more details on the results see Rippel – DT (2008)
[36] Illová (2005)
[37] BCFGS (2000)

be able to cover the losses even if a bank faces more severe risk events – such as the worst-case scenario. "Whenever the stress tests reveal some weakness, management must take steps to manage the identified risks. One solution could be to set aside enough capital to absorb potential large losses. Too often, however, this amount will be cripplingly large, reducing the return on capital."[38]

The field of stress testing in the area of OR are still being developed, so there is a high flexibility of choosing specific methods that would best fit the financial institution. On the other hand, stress testing methods are not comparable with each other. Neither the applications of the same stress tests to different financial institutions are comparable with each other, because the results are always bound to the specific risk profile of a financial institution. The stress testing methods are thus subjective. Adopting bad assumptions or using irrelevant scenarios would lead to irrelevant losses.

Since the stress tests often define events with a very low probability of occurrence[39], the results become difficult to interpret and it is not clear which actions should be taken by the management in order to mitigate the risks. Quite often the results of stress tests appear unacceptably large and they are just ignored and dismissed as irrelevant. As Jorion (2007) states, a financial institution is not supposed to handle all the possible states of the world like a widespread nuclear war. The central banks are supposed to support financial institutions in case of systematic crisis. Other actions besides increasing economic capital were proposed – such as insurance for the extreme events, business restructuralization in order to achieve better diversification and lower exposure to the risks in question or developing a special plan for corrective actions. However, "a general way" to interpret results of stress tests does not exist, because the results are highly subjective and they depend on the choice of the test methods and the scenarios. This differs stress testing from the LDA approach.

The scenarios can be divided into two groups based on the type of event they define. The first group uses historical events like 9/11 terrorist attacks or unauthorized trading that happened in Societé Generalé in 2007. Risk managers study a potential impact of those events on the financial institution. The second group, which is more widely used in practice, uses hypothetical scenarios. The scenarios are based on some plausible risk events that have not happened yet, but a non-zero probability of their occurrence exists. A scenario can also be based on an analysis of a new product a bank is going to implement.

A typical scenario consists of the description of a complex state of the world that would impose an extreme risk event on a financial institution, including probabilities and frequencies of occurrence of the particular state of the world, business activities impacted by the event and maximum internal and external loss amounts generated by occurrence of such event, possible mitigation techniques including insurance against such an extreme event. Even though such a scenario claims to be realistic, it is not possible to comprise all possible risk factors and features. However, risk managers are trying to define the scenarios, so that they correspond to the reality

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[38] Jorion (2007)
[39] Or in the case of hypothetical scenarios this probability is defined very merely

as much as possible. It is clear that "the generation of relevant scenarios is a time-consuming process that requires quantitative skills as well as good economic understanding of the factors"[40] financial institution are exposed to.

If a financial institution is able to implement appropriate scenario analysis policy, then this method provides a comprehensive overview of the impact of plausible events. It provides creditable quantitative basis, where the results can be further aggregated with the LDA methods on a company or business line levels and impact of such a scenario on the economic capital and the regulatory capital charge can be estimated. Concrete scenarios, together with its integration process with the method based on historical loss data, will be described and analyzed in the following section.

BANK combines all four main approaches for the OR management – including the scenario analysis. The aim of using scenarios is, as explained above, to get an overview about low frequency events that might have severe impact on BANK. BANK was using eight complex scenarios, which satisfy all the qualitative measures. The details on scenario definitions are provided in Rippel (2008).

Figure 4: Scenario analysis process
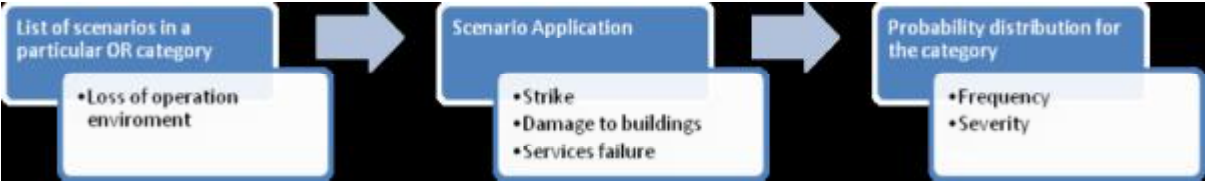
Source: Authors based on the BANK

The results of the eight scenarios will be aggregated with the capital estimates based on the original data sample using the LDA method and the results will be evaluated in the following section. The process of aggregation is shown on Figure 4.

There exists a unified form used for a scenario definition. The process of scenario definition is shown on Figure 5.

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[40] Jorion (2007)

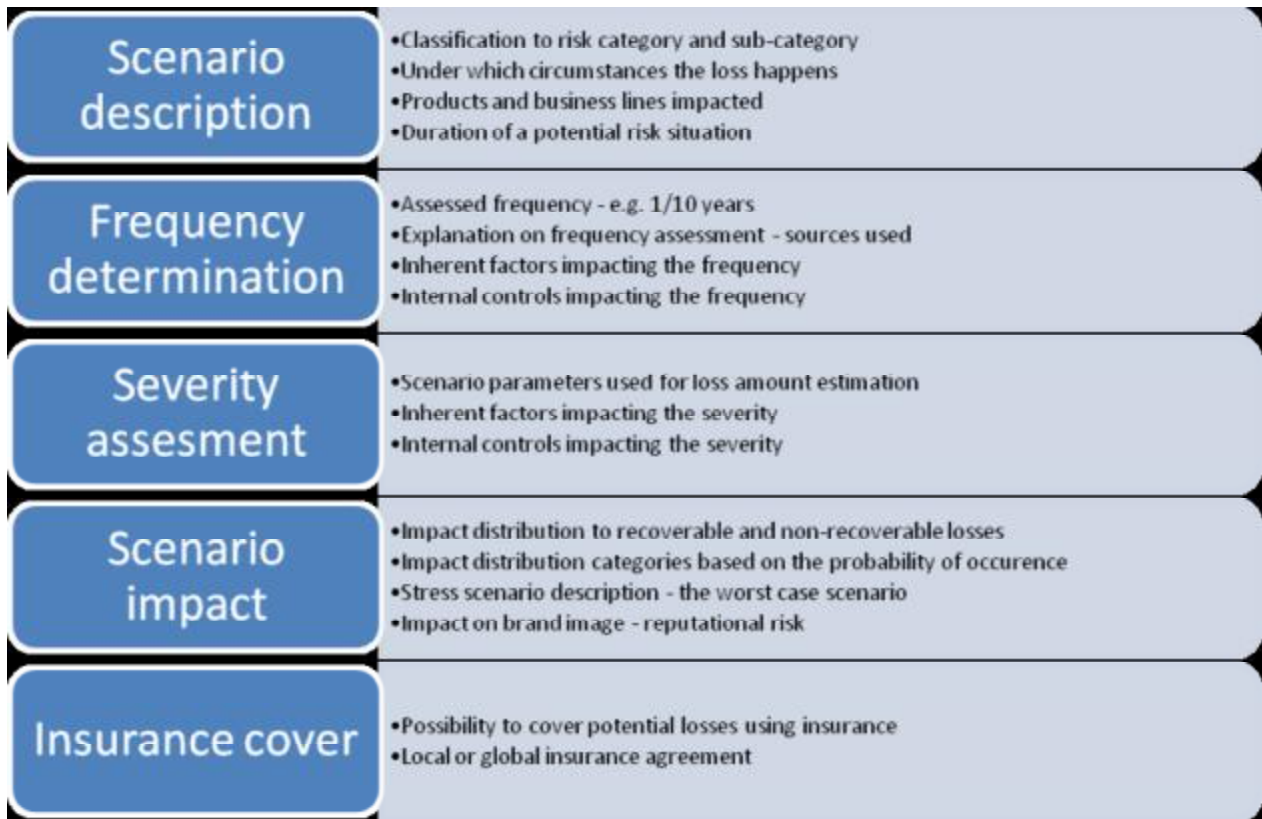| Scenario description	•Classification to risk category and sub-category •Under which circumstances the loss happens •Products and business lines impacted •Duration of a potential risk situation
Frequency determination	•Assessed frequency - e.g. 1/10 years •Explanation on frequency assessment - sources used •Inherent factors impacting the frequency •Internal controls impacting the frequency
Severity assesment	•Scenario parameters used for loss amount estimation •Inherent factors impacting the severity •Internal controls impacting the severity
Scenario impact	•Impact distribution to recoverable and non-recoverable losses •Impact distribution categories based on the probability of occurence •Stress scenario description - the worst case scenario •Impact on brand image - reputational risk
Insurance cover	•Possibility to cover potential losses using insurance •Local or global insurance agreement

Source: Rippel (2008)

6.   Applied scenario analysis

The scenario analysis method was used to examine the impact of plausible events on the regulatory capital and the economic capital estimates and also on the business continuity plan of BANK. Two main approaches were used to aggregate losses generated by the scenarios with the database of historical events. The first one uses a set of the worst-case losses defined by a particular scenario and aggregates these losses to the historical loss data sample. The second approach calculates an average loss given by probability distribution of the loss amounts defined by a particular scenario and aggregates those average losses to the historical loss data sample. In both cases the statistical distributions mentioned above, the g&h, the POT – Max 5% and the BMM – Max quarter, were used for the severity distribution of the aggregated loss sample. The Poisson distribution was used for the loss frequency. Both distribution were then aggregated and the economic and regulatory capital estimates were computed by using the VaR and the CVaR measures.

In case of the g&h loss severity distribution, the aggregation method of losses generated by the scenarios with the historical data sample is straightforward, because the additional losses

are simply added to the database. However, in the of the EVT approaches, where the body and the tail of the distribution are being modeled by using a different statistical distribution, the aggregation algorithm is more complicated, because all of the losses generated by the scenarios belong to the tail of the aggregated database distribution and thus it directly impacts the EVT methods. The most complicated case is the BMM, for which an additional algorithm had to be used in order to randomly distribute the additional losses over the whole four-year period.

Multiple scenarios are combined together. It should be noted, that the probability, that the worst-case joint scenario combination would occur to BANK during the observed four-year period, is very low. Further details are provided below.

In section 6.2 scenarios are combined into several packages, denoted by test IDs. Both the worst-case and the average losses are considered. We merge those losses with the original loss database and then estimate the VaR and the CVaR regulatory and economic capital estimates using the aggregation method described above. The tests differ by the number of scenarios they use – at first all scenarios defined by BANK as well as the custom scenarios are considered.[41] Then the number of scenarios considered is gradually decreased. Separate tests are run for the custom scenarios and for more frequent BANK scenarios.

6.1   Scenario definitions

There are two groups of scenarios – first group consists of 8 scenarios (denoted as ID 1-8) defined by BANK. The second group consists of 4 scenarios that were created for the purpose of this paper.

The losses generated by the 8 scenarios defined by BANK were merged with the historical loss events from the years 2003-2007 using the method explained above. The average loss amounts for all of the scenarios are comparable to the other tail losses from the original historical data sample, thus these eight losses just enrich the original tail of the data. On the other hand, the magnitudes of the worst-case losses are apparently higher than the magnitude of the highest historical losses and so the right tail of such merged sample is much heavier than for the case of the historical data sample. The most severe worst-case losses are about 20 times higher than the most severe average loss magnitude. However, one has to consider the probability that the worst-case scenario happens.

A financial institution should evaluate, whether it would be able to survive even the most extreme cases of the scenario it assesses or not. The probability that all the worst-case events defined by the joint scenario combination occur during the observed period limits to zero. But if this happens, then it can be rightly expected that the impact on a financial institution would be very severe. In some cases a financial institution might even default, because it would not be able to cover those extreme losses.

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[41] "Custom" denotes a scenario defined for the purpose of this paper

The following sections list custom scenarios defined by the author. Three different historical scenarios were defined – the first one is based on an unauthorized trading, the second one is based on an external fraud and the third one is based on process management failure loss even types. All of those scenarios are based on concrete historical events – the loss amounts are rescaled to fit the size of BANK.

Table 7: Historical scenarios list – loss amounts in EUR ths

ID	Scenario name	Estimated
9	**Unauthorized trading – Kerviel**	112,000
10	**Process management failure –**	7,300
11	**External fraud – Prochazka**	21,180

Note: Scenarios 1-8 were took from BANK.

Source: Authors

The historical scenarios are based on three operational risk events that happened in the recent years. Since the historical events will not reoccur in the future, we have not estimated the frequency of those events. The estimated losses are quite high and thus they will be treated as the worst-case losses. The historical scenarios will not be used for tests based on average losses.

The first historical scenario ID9 is based on a recent unauthorized trading of Jerome Kerviel in Société Générale. The trader was concluding hidden deals on security trading, hoping to reverse losses from the past trading. At the end of his actions the loss amounted to EUR 5 billion. This event was the most severe OR loss event ever happened – the loss amount was four times higher than the loss caused by Nick Leeson to the Barings bank in 1995. The loss amount was rescaled to fit the BANK size.

The second historical scenario ID10 is based on a recent process management failure – software loss event that happened directly to BANK. The interbank transaction fees were rounded to a slightly lower value (1/100 of 1 CZK). Given the huge number of transactions and the four years duration of this incorrect system settings, the total loss to BANK amounted to CZK 200M which is about EUR 7.3 million.

The last historical scenario ID11 is based on a recent external fraud – robbery event. Frantisek Prochazka, an employee of a Czech security agency, stole cash in the amount of CZK 564 million. More than half of these money belonged to a competitor of BANK. This event was the biggest robbery event ever happened in the Czech Republic. The loss amount in EUR is 21.2 million.

The hypothetical scenario of BANK employee strike that would hit all the regions is considered. This type of scenario was chosen because of the fact that historical evidence of similar events exists. Such scenario belongs to the Employment Practices and Workplace safety Basel II event category.

The frequency of the scenario assessment was estimated to 1 per 40 years based on the following facts: according to the historical data there were several bank employee strikes in recent years - two of them in India, one in Canada TD Trust bank, one in Greece national bank. The duration of the strike ranged from 1 day to 1 week. It is assumed that the frequency of strikes would be quite low in the region of Central Europe. Usually the duration of such strike is limited only to several hours. There are none recent examples of an employee strike in a Czech bank.

The other important feature of a strike is its extent – a strike can range from one branch to a countrywide strike. A strike can also hit either one particular company or it can be an industry-wide. The reasons why employees decide to go on include a disagreement with changes in law or working conditions, pension funds, compensations or organizational changes etc. Several internal controls that may contribute to reduce the frequency of such event might be considered.

For the purpose of this paper it was assumed, that the employee from all regions would go on strike. Such a scenario has a very low probability, but if it occurred it would have significant negative impact on the bank. The severity impact of the scenario depends on two factors – the extent and the duration of the strike. The extent was set to the whole country. The duration is assumed to range from one hour strike to five business days strike and the probability for each class was estimated according to the assumptions stated above.

A strike was assumed to cause four types of losses – the direct loss of lost revenue from branches was estimated based on the list of BANK branches and their revenues per day. The second source of loss are the costs connected with expenses on substitute employees that would be hired in order to maintain the bank critical operations. These costs increase with the duration of the strike and were estimated as a certain percentage of the direct loss of revenue. The third and the most severe type of loss is the loss of clients that was estimated as a proportion of yearly revenue from branches. While a 1-hour strike is not considered to have impact on customer satisfaction, in case of a whole week strike up to 5% of customers might decide to move to competitors. The last but not least type of the loss is the costs connected with commercial disputes. The losses were estimated based on interest costs from non-realized transactions and estimated amount of dispute penalties. After taking into account all the assumed loss sources, the total loss was computed. The loss amounts and the probability distribution are listed in Table 8 – the loss amount grows as the duration of the strike increases.

Probability	Duration	Estimated loss (EUR)
70%	1 hour	138,515
25%	1 day	3,750,446
4%	2-4 days	9,056,450
1%	5 days	20,890,382

Source: Authors

The worst-case scenario is a strike that lasts five days. Under this case the loss amount reaches EUR 20 million. Such strike is considered to cause significant harm to BANK – especially by the loss of 5% customers. Such scenario would also have very negative impact on the brand image and the banks reputation would be severely harmed. The average loss size is significantly lower though – EUR 1.6 million.

Table 9: Custom hypothetical scenario details – loss amounts in EUR ths

ID	Scenario name	Worst-case	Average loss
12	Employee strike – whole state	20,890	1,606

Source: Authors

6.2 Tests – Scenario combinations and loss aggregation estimates

In total six tests were run. The aim was to analyze, whether BANK would be able to handle particular combinations of events defined in the scenarios employed for a particular test combination. The impact of such joint scenario was evaluated. Scenarios were denoted by the IDs assigned above. For the hypothetical scenarios (ID 1-8 and 12) two level of loss were considered – the worst-case level and the average level. For historical scenarios (ID9-11) only the worst-case loss amount is defined. The dates of event occurrence were set by a random number generator. Three statistical approaches were used to model the merged data sample – the g&h, the EVT – BMM Max Quarter and the EVT – POT 5% methods. Each of the scenarios defines an extreme event that is expected to have significant impact on the capital estimates – and so the loss events belong to the tail of the data sample.

The 12 OR scenarios were combined to 6 joint scenario combinations. The impact of such scenarios on the regulatory and economic capital estimates was analyzed. Two loss amounts for the additional events were used – the extreme worst-case and the average loss observations. The observations were merged with the original data sample and the aggregated loss distribution was constructed using the MC simulation. The results are provided in Table 10.

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[42] The estimated loss amounts are based on concrete data – for more details see Rippel (2008)

Table 10: Comparison of regulatory capital estimates – average/worst loss scenarios

Test	Scenario IDs	BMM – Max M Avg/Worst case	POTM – 5% Avg/Worst case	G&h Avg/Worst case
Original	n.a.	14.95%	9.32%	4.43%
Test I	ID1-12	4.1%/245%	4.3%/207%	11.7%/91%
Test II	ID1-8	4%/136%	5.2%/129%	10%/35.7%
Test III	ID3-5,7-8	4.6%/148%	6.6%/145%	8.8%/20.4%
Test IV	ID9-12	8.8%/178%	8.5%/200%	5.3%/21%
Test V	ID3-5,7-12	4.8%/199%	5.4%/320%	9%/70%
Test VI	ID3-5,7-8,12	5.1%/153%	5.4%/123%	9.3%/30%

Source: Authors

All the tests suggest that the EVT method is not an appropriate one to model the OR data, because the results provided by both EVT methods (the BMM – Max quarter and the POTM 5%) were very sensitive to the number of the tail observations and to the length of the tail. If there is such extreme observation as the one defined by scenario the ID9, then the capital estimates given by the EVT method would be unreasonably high and in some cases reaching the amount of BANK total assets. On the other hand, if the less extreme average loss case events are added to the data sample, then the capital estimates provided by both EVT methods are unreasonably low. The EVT method is thus providing inconsistent results, and thus it cannot be considered as the best approach to model the OR data – even though the theory suggests that the EVT might be beneficial for the OR measurement. The application of the EVT methods to the empirical data provides overestimated results for the worst-case scenarios and underestimated results for the average loss scenarios.   However, it might be expected that the results provided by the EVT method would improve the consistency, as the number of observations, both from the body and the tail of the empirical distribution, increases – but even though it might be assumed that the EVT results would still be less consistent than those provided by the g&h method.

The g&h distribution proved to be a very suitable one. Its results were consistent, as the extreme worst case and the average loss custom events were being added to the data sample – this conclusion corresponds with the findings of Degen (2007). The parameter estimates differ based on the number of the additional extreme events used for the scenario analysis – the more extreme losses were added to the data sample the higher the estimate for $\hat{h}$ and $\hat{g}$ was and so the higher the losses generated during the loss aggregation procedure were.

The g&h distribution is, unlike the EVT, consistent even if less extreme but more frequent average loss cases are added to the data sample. In the average loss case the custom losses were of very similar magnitude as the most severe empirical losses. So the length of the tail remained the same – it was only made heavier. The parameter estimates are very similar to each other and so are the regulatory capital estimates. Even if all the scenarios were considered, the estimated regulatory capital would not exceed 12% of the gross income suggesting that BANK would be able to handle the losses of such high magnitude.

The statistical fit of the EVT and the g&h distribution was not considered while running the scenario analysis tests. It is rightly to assume that the degree of the fit would be

approximately the same for the average loss joint scenarios, while it can differ for the worst-case joint scenarios that add more extreme losses. It is also rightly to assume that the degree of the fit for the EVT methods would be generally higher than the degree of the fit of the g&h distribution – but it must be considered that the EVT is fitted just to the tail of the data while the g&h works with the whole sample.

6.3 Implications for the financial institution

As mentioned above, the scenario analysis added the custom hypothetical losses to the original loss database. Six tests were run in order to evaluate the effects of those plausible events on the financial distribution. Since all those events impose extreme losses, it was assumed that the estimates of the regulatory capital charge as well as of the economic capital would significantly increase. The statistical distribution that was finally considered to be the most suitable to measure the capital required to cover the OR losses – the g&h distribution – provided reasonable estimates for all the tests run.

In the cases where extreme worst-case losses were considered the final estimates for regulatory capital charge spiked up to 90% of the gross income. Such huge amount of capital cannot be set aside to cover risks, because it would make the financial institution noncompetitive - the cost of its capital would be much higher than the industry average. On the other hand, it is hardly to expect that all the worst case scenarios will ever happen in such short time period that was considered throughout this paper – 4 years. But even if a longer time period - like 10 or 20 years – would be considered, the probability that the worst case joint scenario from Test I would occur limits to zero.

From this point of view it seems more reasonable to work with average loss joint scenario cases, which have a higher probability of occurrence – in some cases over 2%. The tests that employed the average losses provided a higher but still affordable level of capital estimates – up to 12% of the gross income for the capital charge and 19% of the total equity for the economic capital estimate defined as the $CVaR_{0.99}$ measure.

And so the combination of the scenario analysis and the LDA approach can improve applicability and soundness of the capital estimates over the methods, where just historical data are used. Since new internal and external OR data will be added to the loss databases in the future, the quantitative LDA techniques will be more important. But for now it is valuable to consider plausible events and evaluate, what would be the impact of these events. After all of the tests were run we can say that BANK would be able to survive losses imposed by the average joint scenario combination. The losses defined in the worst-case scenarios are such extreme, that the bank would have to take the risks in order not to increase the cost of capital to an unacceptable level.

7. Conclusion

The main aim of this paper was to evaluate the appropriateness of capital estimates based on historical loss events and to measure the impact of plausible OR events that were added to the empirical loss data sample provided by an anonymous Central European bank. The technique presented in this paper claims to be consistent and applicable for other financial institutions. There were two main questions the paper was aimed to answer:

- What is the appropriate statistical method to model the OR loss data distribution and to measure reasonable capital estimates for the institution?
- What is the impact of extreme events defined in extreme case scenarios on the capital estimates and on the financial institution?

The evaluation of the OR exposure measurement employed different statistical methods and distributions – the most important ones were the EVT and the g&h distribution. For the original data sample the results for the EVT seemed consistent, statistically significant and economically reasonable. However, after the custom extreme events were added to the data sample, both EVT methods started to provide very inconsistent estimates – the inconsistency is most visible while comparing the estimates provided by tests, where very extreme worst-case events were considered to tests, where less extreme average case events were considered. While in the first case the estimates were unreasonably high, in the second case the estimates were even lower than in case of the original data sample. So the EVT method does not seem suitable to model the OR data even if it is widely favored by many researchers such as Embrechts (2006) or Chernobai (2007) – its main disadvantage is its sensitivity to the threshold choice. The appropriate threshold is very difficult to find given the limited historical data samples. Thus the EVT results were not robust to the data contamination and the outlier observations.

The alternative method to the EVT was the g&h distribution, which was evaluated as the most suitable from all the parametric distributions used, what confirms findings of Embrechts (2006) or Dutta, Perry (2007). It proved itself very consistent to contamination and outlier observations and it provided very reasonable results even while very extreme worst-case losses were considered. So the answer to the first question would be that the most suitable method to model the operational risk loss data distribution is to use the g&h distribution which is able to model the whole data sample "without trimming or truncating the data in an arbitrary or subjective manner" as suggested by Dutta, Perry (2007). The null hypothesis stated in the introduction thus cannot be rejected, because the g&h proved consistent over all scenarios that were considered. There might be other statistical distributions that are able to measure and model the tail structure of the OR data – we believe that a further research will be devoted to this issue and even more suitable measurement methods will be developed.

In order to answer the second question, the original data sample was enriched by adding events defined in 12 scenarios. The impact of these events was assessed. Given the fact that the original data sample was very limited and it consisted only of internal loss events, it is beneficial for the financial institution to measure the impact of such plausible event as an employee strike. In total six tests were run. The assumptions, that by adding an outlier event the capital estimate would increase, was fulfilled for all tests while using the g&h distribution. If the very low probability joint combination of the worst-case events was considered, the estimated level of the capital required to cover such losses would too high for the bank to set aside - over 90% of gross income for the 99.9% confidence level. It is not expected that such combination of extreme events occur in limited time period, so the only reasonable solution for the bank is to take this risk. However, if a joint combination of extreme loss events with a higher

probability of occurrence – the average loss scenarios – were considered, the estimated regulatory and economic capital levels would be very reasonable capital estimates – 12% of the gross income for 99.9% confidence level. The financial institution should employ these OR events, while considering which level of capital to hold to cover the risk.

And so the answer to the second question is that, given the reasonable definition of the scenario analysis and the loss amounts defined under this scenario, the estimated regulatory charge has increased significantly but still to a level which is acceptable for the financial institution. The OR assessment method should be reasonable for the regulator as well and so this paper provides a framework of how to combine the scenario analysis with the LDA approach. Using the scenario analysis can also help the financial institution to mitigate the OR and to decrease the impact of potential losses. This framework can be used for future application and the impact of other scenarios can be assessed.

Some further questions and tasks remain open, however. The external data could be merged with internal data in order to better capture the potential impact of events that have not happened to the financial institution yet. Statistical differences the between business lines and the event types should be analyzed. Robust methods or alpha stable distributions can be used as suggested by Chernobai (2007). Other EVT methods, particularly for the threshold estimation, could be used. The number of the Monte Carlo simulations can be further increased in order to achieve higher statistical relevance. However, this issue goes beyond the scope of this paper and is left for future consideration

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