Considerations to the Quantification of Operational Risks[1]

Thomas Hartung

Dr. Thomas Hartung, Ludwig-Maximilians-University Munich,
Institute of Risk Management an Insurance Industry, Schackstr. 4, 80539 Munich
e-Mail: hartung@bwl.uni-muenchen.de

Abstract:

The proposal for a New Basel Capital Accord includes suggestions, how operational risks shall be backed by regulatory capital. Until now the management of operational risks in banks focuses on the transfer of these risks to the insurance industry primarily. The objective of this paper is to show, which of the well known actuarial methods applied in insurance mathematics are applicable for operational risks in the banking industry. A method is presented, that can be used to calculate both, risks with high frequency and low severity as well as risks with low frequency and high severity. Accordingly within the scope of an actuarial based analysis a possible prototype will be presented. This prototype is based on loss frequency and loss severity distributions, which can be derived from collected data and which will be aggregated with the help of a Monte Carlo simulation. This model is qualified for fulfilling the requirements of the Basel Committee. Furthermore it is adressed, if and to what extent insurance should be applied as an economic and efficient substitute to individual regulatory capital.

1. Introduction

Since the Basel Committee on Banking Supervision developed the first Capital Accord in 1988 banking operations, financial markets, risk management practices, and the supervisory approaches have been advanced continuously. In this context a proposal for a New Basel Capital Accord was released at the beginning of 2001. The rationale of this accord is to modify the capital accord for the banking industry, which is currently in place. From there on both, theory and practice, have discussed the detailled design and the consequences of the changes which are planned. The most discussed aspect in public in this context is the designated, more risk adjusted treatment of credit risk.[2] In particular the politically unwanted results of an increase of debt costs for medium-sized debtors or the decrease of approved credits as such lead to controversial discussions about the submitted suggestions.[3] Above all, the acrimony of this discussion masks the further reform proposals. A similar material

[1] I would like to thank Dipl.-Kffr. Marieke Hahn, Prof. Dr. Elmar Helten, Dr. Volker Mayer and Dr. Andreas Müller for valuable comments.

[2] See Basel Committee on Banking Supervision, 2001a, p. 7-94.

[3] See for example o. V., 2002 or Eigendorf, 2001.

change is caused by adding operational risks to the catalogue of risks, that consequently have to be backed by regulatory capital as well.

Contrary to market and credit risks, the starting position of regulation is diametrically opposed when dealing with operational risks. While handling and coping risks from proprietary trading and security holding as well as dealing with credit risks are basic tasks of the banking industry, operational risks are primarily considered as unavoidable, and therefore risks to be accepted by business operations.[4] Furthermore an extensive knowledge about market and credit risk exposure was developed within the last years. Among others this knowledge depends on the availability of data and the continuous development of adequate and applicable methods. Hence, the management of operational risks primarily focuses on the transfer of these risks to the insurance industry. Obviously in the banking industry, both, methodological and cognitive deficiencies, be it collecting or valuing operational risks can be stated.[5]

Until now the discussion basis about the identification and valuation of operational risks presented by the Basel Committee is considered as rudimentary currently. Only three approaches for determining capital requirements are under consideration – each more complex than the other. But the question, how to apply the suggested calculation methods in reality, is still open. For the global proceeding approaches only simple and applicable modes of computation are mentioned. But these also are discussed controversial. The idea, how to realize a more accurate, but also more complex method, is still in the state of development.

Hence, the objective of this paper is to show, which of the well known actuarial methods applied in insurance mathematics are applicable for operational risks in the banking industry. A specific method will be shown, which can be used to calculate both, risks with *high frequency, low severity* and risks with *low frequency*, *high severity*. Accordingly within the scope of an actuarial based analysis a possible prototype will be presented. This is based on loss frequency and loss severity distributions, which can be derived from collected data and which will be aggregated with the help of a Monte Carlo simulation. So, this model qualifies for the Committees´ requirements. Furthermore it is adressed, whether and to what extent insurance can be applied as an economic and efficient substitute to individual regulatory capital.

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4 See Beeck / Kaiser, 2000, p. 650.

5 About the increasing impact of operational risks and the resulting consequences for the banking industry see Jovic / Piaz, 2001, p. 923-924.

2. Conceptual Guidelines of the Basel Committee on Banking Supervision

The Basel Committee defines operational risk as „the risk of direct or indirect loss resulting from inadequate or failed internal processes, people and systems or from external events.“[6] By means of this definition legal risks are included, whereas strategic and reputational risks are not considered. Due to this less specific definition of operational risks the consultative document is exposed to severe criticism. Only a more precise specification, that has still to be developed, and an accepted delimitation (standardization) of operational risk as generally as possible will provide for an accurate recordation and an evaluation of these risks.

For determining the capital charges the Basel Committee presents three different approaches. As shown below in detail, these approaches are based on an evolutionary concept, i.e. the approaches improve step by step in terms of measurement of risk and sensitivity to risk.

The most simple approach, which is the basic indicator approach, determines the capital charge via one single indicator.[7] Like a proxy this indicator for a bank´s whole operational risks should consider all risks in a sufficient and exact way. As a possible measure the gross income, defined as net interest income plus net non-interest income, is the main focus of discussion. The capital charge comprises a fixed percentage α of gross income:

$$ORCC = \alpha \cdot \textit{gross income}\text{, with}$$

ORCC = operational risk charge.

According to most recent estimations the factor α will have a value below 20 percentage points.[8] This approach may be applied without any approval, i.e. it is a mechanism which allows for an easy calculation of the necessary regulatory capital to be applied by all financial institutions. However, the factor α will be determined in such a way that an incentive is given for selecting a more sophisticated approach to determine the extent of the operational risk.

An approach for a more precise gathering of the operational risks occurring in different business lines is the standardized approach.[9] This represents an extension of the basic indicator

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6 Basel Committee on Banking Supervision, 2001a, p. 94. See also Beeck / Kaiser, 2000, p. 637. However the Basel Committee considers not the entire risk described in this way as necessary to get supported with capital ressources, but applies a similar perception as to the credit risk. Accordingly only the unexpected losses, i.e. the losses exceeding the expected loss, have to be backed with equity. Expected losses have to be integrated as standard risk costs into the product conditions. See Schierenbeck, 2001, p. 336.

7 See Basel Committee on Banking Supervision, 2001a, p. 96.

8 See Jovic / Piaz, 2001, p. 928. As a discussion basis the Basel Committee announced a value of 15 %. See Basel Committee on Banking Supervision, 2002, p. 117.

9 See Basel Committee on Banking Supervision, 2001a, p. 95.

approach and is primarily intended to be used by those banks, which fulfill certain qualitative requirements to their internal risk management. This approach assumes, that the gross income meets as a suitable proxy representing operational risks for each division or each business line given in the consultative document, while differing between the various business lines:

Business unit	Business lines	Capital factors	Beta factors
Investment Banking	Corporate finance	β_1	18 %
	Trading and sales	β_2	18 %
Banking	Retail banking	β_3	12 %
	Commercial banking	β_4	15 %
	Payment and settlement	β_5	18 %
Others	Agency Services	β_6	15 %
	Retail brokerage	β_7	12 %
	Asset Management	β_8	12 %

Table 1: Beta factors in the standardized approach[10]

The beta factors, which will be assigned to the respective business lines by the regulation authority, should consider the relation between gross income (GI) and the regularly expected losses caused by operational risks in the corresponding business line. Finally, the total capital charge is calculated by an aggregation of the capital requests of each business line:

$$ORCC = \sum_i \left(\beta_i \cdot GI_i\right).$$

The third approach is the so called advanced measurement approach (AMA). Here bank-internal loss data are the starting point for calculating the capital charge.[11] Originally only a specific model was defined as advanced measurement approach. In the meantime all internal operational risk measurement systems are called AMA.[12] Such an approach may be allowed to those banks only, which consider additional requests on top of those as per the

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10 See Basel Committee on Banking Supervision, 2002, p. 118.

11 See Basel Committee on Banking Supervision, 2001a, p. 96.

12 See Basel Committee on Banking Supervision, 2002, p. 118.

standardized approach. Such banks for example may be required to verify the accuracy and reliability of the internal loss data on a continous basis.[13]

A special case of the advanced measurement approach is the so called loss distribution approach, which was originally mentioned as a further approach in the consultative document. However, it was regarded as a suggestion without closer specification only.[14] Here the capital charge is determined by internal loss data and individual structure and processes of the bank. Based on this information the regulatory capital is calculated by means of an individual and bank-specific loss distribution. As this approach seems to be the most detailed and most risk-sensitive approach, a prototype will be developed in the following procedure, that can be used as a basic internal model for quantifying operational risks.

3. Particularizing the Loss Distribution Approach

In the first step of the loss distribution approach the risks need to be specified, which are responsible for the shape of the loss distribution. Thus, the definition of operational risks by the Basel Committee needs to be analysed in more detail by a selective categorization. Setting up a risk architecture showing the hierarchical structures of the risks can be deemed as appropriate.[15]

The starting point of a mechanism which should be more general and applicable in a broad field is a corresponding definition of risk. Accordingly risk can be defined via two components:[16]

- deficit of information
- existence of targets

On the one hand economic behavior targets at a specific determination. On the other hand in real economic world there is a high level of uncertainty whether such targets may be realized or not. Therefore, this general definition requires both, the final determination, i.e. the explicit objectives, and the information deficit. An advantage of this definition is the possibility to analyse risks more precisely. When targets are defined precisely, deviations from the target points can be quantified and shown in loss distributions. First the frequency of such deviations can be calculated, secondly the severity of deviations from a target can be measured. Both can be illustrated in form of frequency and severity distributions.[17] Aggregating both

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[13] Vgl. Basel Committee on Banking Supervision, 2002, S. 120-125.

[14] See Basel Committee on banking Supervision, 2001b, p. 11.

[15] See Happel / Liebwein, 2000, p. 228.

[16] See Helten, 1994, p. 3.

[17] See Helten, 1973, p. 63-121.

distributions generates a total loss distribution[18]. An another advantage is, that this approach can not only be applied to single targets, but via a risk architecture to whole target systems as well.

The risk architecture helps to picture the relations between the risks of different hierarchical levels. These relations show the entire causality network, which are resulting out of different levels of aggregation.

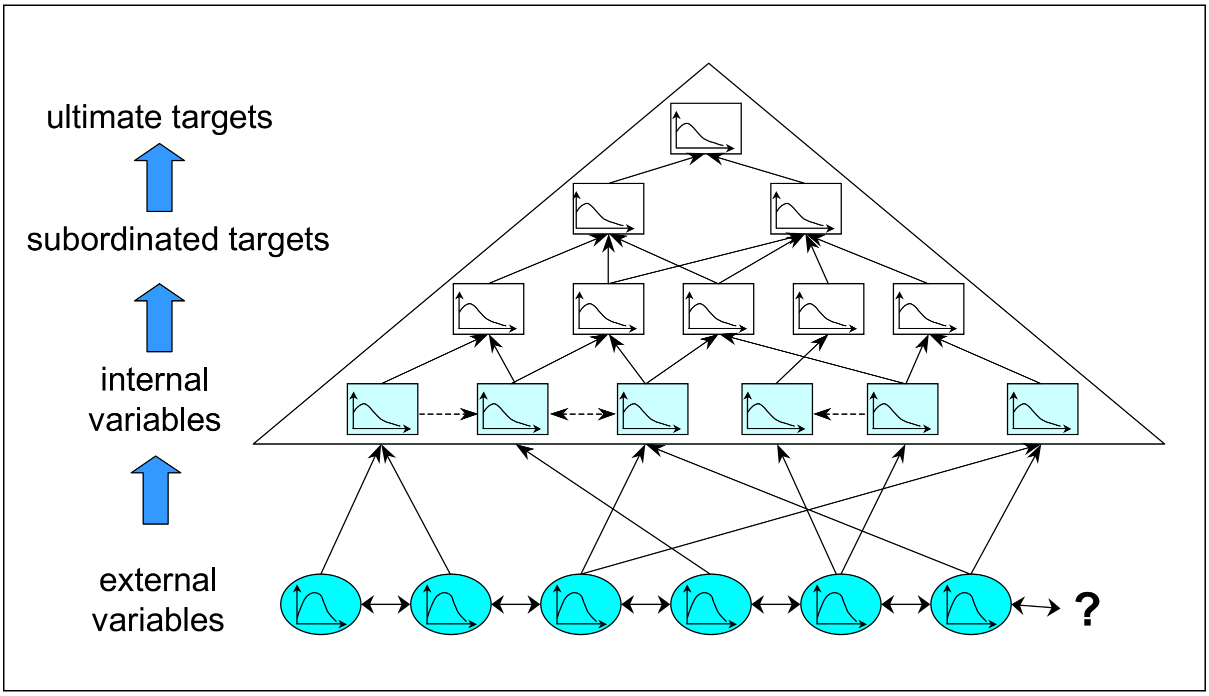

Figure 1: Risk architecture

Basically two possible paths exist to determine the structure of the risk architecture.[19] The first alternative starts with determining external variables. Their variation can have specific effects on relevant variables within the company (see figure 1). These effects may affect specific (subordinated) targets in an unwanted way. In an interrelated system of various cause-and-effect chains the deviations from subordinated targets subsequently lead to deviations from upper targets and finally to deviations from the highest-ranked target of the company. Therefore, the structure follows a *bottom up* procedure starting at external variables and ending at the supreme target of the organisation. However, a disadvantage of this approach is, that all factors of influence need to be known *a priori* and have also to be placed within the structure at their correct position. Often this can be achieved only if an appropriate

[18] Such a total loss distribution can be qualified for constructing a bank-individual loss distribution referred to operational risks.

[19] See Beeck / Kaiser, 2000, p. 640.

operational risk has led to an accurately analyzable damage already. Risks which are to be regarded as rare or not existing tend to be disregarded in this procedure.

An alternative approach applies exactly the other way round in order to develop the risk architecture using a *top down* procedure. Here it is assumed, that the hierarchically highest level of operational risk is regarded as the most substantial factor which has an influence on the so defined supreme target. Therefore, the upper level of operational risks is divided into several categories:[20]

- process and relationship risks,
- people risks,
- technology risks,
- physical assets and external risk,
- other risks.

In the next step all relevant cause-and-effect chains have to be determined top down. Therefore, a target deviation occurs only, if certain values of one or more influencing factors have resulted in an effect across multi-levels along a specific cause-and-effect chain.

4. Determining the Loss Distribution Using a Monte Carlo Simulation

A prerequisite for such a method is a sufficiently extensive loss data base, including which target deviations or losses are to be assigned to the category of operational risks and particularly to which cause-and-effect chain.[21] This loss data base can be mastered internally and contains only losses of the particular bank.[22] In this case it is worth to take care, that the data reflect a representative image of the companies´ hazards. For example an accumulation of only small losses of a certain category can lead to the wrong assumption, that the enterprise is not exposed to dangerous risks in this area. So, if necessary, the collected loss data must be completed by fictitious data, in order to obtain a realistically estimated maximum while estimating the loss distribution. Especially the „long-tail“ problem has to be taken into account, i. e. exposures, which are characterized by low probabilities, that a loss occurs, and by a high extent of the single loss.

An alternative is to resort to intersectoral data, in order to avoid focusing on bank-internal risks only. In this case the appropriate data records have to be scaled to the conditions of the regarded bank – particularly with respect to the extent of the losses.[23]

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[20] See Levine / Hoffman, 2000, p. 26.

[21] See Beeck / Kaiser, 2000, p. 647.

[22] To the problems herewith connected see Ceske / Hernández / Sánchez, 2000, p. 7.

[23] See Peter / Vogt / Kraß, 2000, p. 668.

Furthermore, it must be able to attach the losses contained in the data base unique to a defined cause-and-effect chain. Then, for every predefined cause-and-effect chains both, a loss frequency and a loss severity distribution have to be modeled by means of actuarial procedures.[24] After an aggregation these distributions result in a total loss distribution for each cause-and-effect chain. In the next step an overall loss distribution can be simulated by running a stochastic simulation. At last, on the basis of this modeled distribution a suitable value at risk for operational risks can be defined. This value at risk serves finally as a measure for quantifying the regulatory capital.

The analysis below was made on the basis of the following loss data base:[25]

	A	B	C	D	E	F	G	H	I	J
1	ID	Monat	Jahr	Schaden-höhe (in TI)	Unter-nehmen	Ursache-Wirkungs-Kette	Skalierungs-parameter	Skalierungs-wert	Schadenhöhe (in TI, inflations-angepasst)	Schadenhöhe (in TI, skaliert)
2										
3	1	4	1992	43	A	Physical Assets and External Risks / Natural Hazards / Storm	Assets	700	54,32	265,30
4	2	3	2000	213	B	Physical Assets and External Risks / Natural Hazards / Storm	Assets	5100	222,57	245,11
5	3	1	1993	188	A	Physical Assets and External Risks / Natural Hazards / Storm	Assets	680	233,28	1164,29
6	4	6	1995	25	B	Physical Assets and External Risks / Natural Hazards / Flood	Assets	3000	29,27	48,00
7	5	5	1993	225	A	Physical Assets and External Risks / Natural Hazards / Flood	Assets	680	276,97	1382,34
8	6	2	1993	45	C	Physical Assets and External Risks / Natural Hazards / Flood	Assets	57000	55,73	10,04
9	7	11	1998	566	B	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	42	610,65	302,90
10	8	9	1994	1530	C	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	70	1824,11	1523,20
11	9	10	1996	123	A	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	81	139,50	127,92
12	10	8	1992	13	B	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	41	16,29	7,78
13	11	7	1992	1	B	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	41	1,26	0,60
14	12	2	1996	5555	C	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	65	6401,66	5064,09
15	13	1	1998	412	C	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	65	453,47	358,72
16	14	3	1999	855	A	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	89	915,10	884,76
17	15	1	2000	122	A	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	88	127,99	123,00
18	16	12	1992	13	C	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	65	16,16	12,79
19	17	6	1996	4522	A	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	81	5169,73	4740,76
20	18	8	1998	1535	C	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	65	1666,04	1317,93
21	19	7	1997	123	B	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	45	137,01	74,95
22	20	5	1993	13	D	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	80	16,00	14,57
23	21	10	1992	486	A	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	50	606,67	377,10
24	22	12	1995	153	B	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	50	177,03	110,04
25	23	4	1992	136	C	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	65	171,82	135,92
26	24	9	1998	15	B	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	42	16,25	8,06
27	25	2	1993	165	C	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	68	204,33	167,15
28	26	11	1992	765	D	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	75	953,04	833,47
29	27	1	1992	136	A	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	50	172,85	107,44
30	28	3	2000	15	A	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	88	15,67	15,06
31	29	6	2000	244	C	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	72	253,44	215,76
32	30	5	1998	155	C	Physical Assets and External Risks / Fire / Overheating / Computer	RQ	65	169,24	133,88
33										
34			a	b						
35		BE	**1**	**1**		*betrachtetes Unternehmen:*	BE =	**6000**	Referenz:	
36		Mitarb.	**1**	**0,3**			Mitarbeiter =	**500**	**1**	
37		Assets	**1**	**0,75**			Assets =	**5800**	**2002**	
38		RQ	**-1**	**0,5**			RQ =	**95**	Inflation in % p. M.:	
39									**0,2**	

Figure 2: Part of the loss database

For each of the 30 single damages listed above the following information is recorded: an identity number[26], the date of loss entry, the loss severity, the department concerned by the damage (here company)[27], the cause-and-effect chain of the loss, a relevant scaling parame-

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[24] To further procedures see Ceske / Hernández / Sánchez, 2000, p. 2-5 or Beeck / Kaiser, 2000, p. 640-641.

[25] To the up-to-date discussed possibilities for setting up a damage data base see Basel Committee on Banking Supervision, 2001c.

[26] An identity number enables to anonymize the data, which facilitates building up a central loss data base for the national or even the international banking sector.

[27] Here should be made certain that the enterprises or departments, which are recorded in the data base are suitable to reflect the structure of the examined enterprise.

ter and the value of this scaling parameter. The month and the year of the loss entry were recorded separately for an easier consideration of the price increase.

The cause-and-effect relations are assigned in accordance with specific categories. Thereby the types of the upper level risks are specified by means of categories of lower levels, until a sufficiently precise allocation of an occurred loss to a specific operational risk is possible. For the further procedure the chain „physical assets and external risks / fire / overheating / computer“ is selected. This category summarizes all losses, which might occur due to a fire damage, that can be attributed to an overheated EDP component.

A suitable scaling parameter should be assigned to each cause-and-effect chain. These scaling parameters serve to level the losses from different banks and to ensure their applicability to other banks, as the original loss severities are adapted to other banks´ individual conditions. As capable scaling parameters for example the operating profit, the number of employees, the assets under management, or a characteristic number for the quality of the risk management (risk quality RQ)[28] can be used. An adaption of specific losses can take place with reference to the following formula:

$$Loss_{adj} = Loss_{org} \cdot \left(1 + a \cdot \left(\left(\frac{Scal.Param(Loss_{adj})}{Scal.Param(Loss_{org})}\right)^{b} - 1\right)\right), \text{ with}$$

$Loss_{adj}$	= adjusted loss severity in the considered bank
$Loss_{org}$	= original loss severity in the reference bank
$Scal.Pam\ (Loss_{adj})$	= scaling parameter of the considered bank
$Scal.Pam\ (Loss_{org})$	= scaling parameter of the reference bank
a, b	= adjustment factors ($a \in [-1; +1]$, $b \in [0; +1]$)

The effect of the scaling parameters on the loss severity is mainly modeled by the factor a. A factor $a > 0$ resp. $a = 1$ leads to a positive coherence, as with an increase of the observed loss of the reference enterprise also the regarded bank´s adjusted loss severity increases. For the scaling parameters “operating result”, “number of employees” and “assets under management” a positive correlation to the loss severity can be assumed, i. e. $a = 1$ is a adequate choice. The quality of risk management has insofar a “negative” influence on the loss severity, as higher values imply lower damages. Therefore in this illustrative case for a the value –1 is anticipated. With the help of the parameter b a vernier adjustment of the functional interrelation between the loss and the scaling parameter is achieved. The parameters assumed are the following:

[28] Here as a risk quality measure a bandwith from 0 to 100 is chosen, whereas the quality of the risk management increases with rising values. The parameter value depends primarily on the regarded enterprise and on the regarded point in time.

Scaling parameter	a	b
operating result	1	1
employees	1	0,3
assets	1	0,75
risk quality	-1	0,5

Table 2: Specified adjustment factors

In this example a bank has an operating result of 6,0 million €, 500 employees, assets under management of 5.800 million € and a quality index for risk management at a value of 95. The coice of relevant loss data might be done by applying different criteria. Therefore, for example a multiplicity of very small losses can be ignored.

Based on the assumption that given loss data represents an exact prediction for future exposure,[29] the next step is to estimate the appropriate loss frequency distribution for the selected cause-and-effect chain. Looking at the companies *A*, *B*, *C* and *D* for the years 1992 to 2000 the following data can be applied:

year of loss	A	B	C	D
1992	2	2	2	1
1993	0	0	1	1
1994	0	0	1	0
1995	0	1	0	0
1996	2	0	1	0
1997	0	1	0	0
1998	0	2	3	0
1999	1	0	0	0
2000	2	0	1	0
total	***7***	***6***	***9***	***2***

Table 3: Loss frequency in the period under observation

Over the years 24 damages occurred resulting out of an overheating of EDP. For example from 1992 until 2000 enterprise *A* had three years with two damages and one year with one damage, i. e. a total number of seven damages. From all 36 “random experiments” 20 resulted in a loss number of zero. In 16 cases one or more losses occured within one period, which results in a loss probability of about 45 %:

29 See for example Beeck / Kaiser, 2000, p. 642.

# loss	frequency	rel. frequency
0	20	0,56
1	9	0,25
2	6	0,17
3	1	0,03
4	0	0,00
5	0	0,00
6	0	0,00
7	0	0,00
8	0	0,00
9	0	0,00
10	0	0,00
11	0	0,00
12	0	0,00
13	0	0,00
14	0	0,00
15	0	0,00
	36	*1,00*

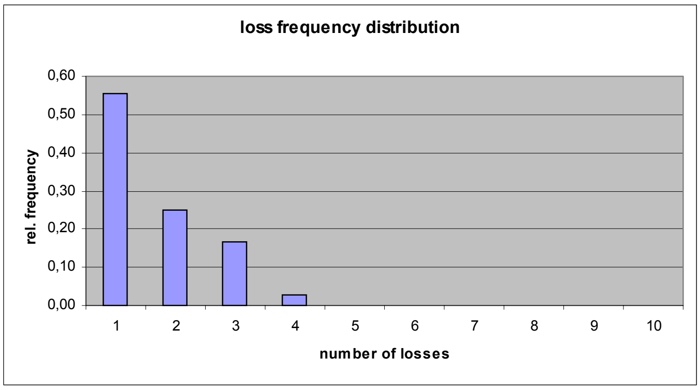

Figure 3: Empirical frequency distribution of losses

Describing these data by means of a certain type of probability distribution, the following can be shown with the help of a software-supported adjustment:[30]

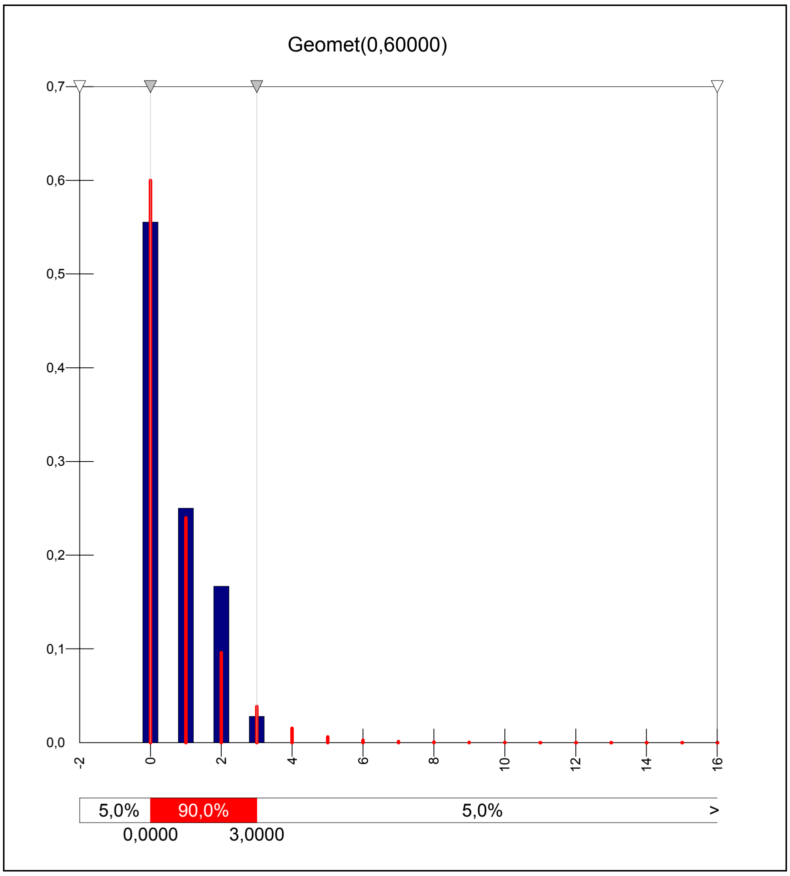

Figure 4: Adaption of a probability distribution to the loss frequency

The empirical data can be modeled by a geometric distribution at its best with characteristic parameter p = 0.6, a mean of 0.67 and a variance of 1.11.[31] The bold bars show the relative

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30 For the estimation of the relevant probability distribution the Microsoft Excel Add-In @Risk 4.0 was applied.

frequency, generated from the collected data, the fine line corresponds to the estimated geometric distribution.

Similarly also the severity of the individual loss can be modeled by means of a loss distribution. Therefore, the 24 losses serve as database. These are sorted at first into given loss classes:

class	min	max	number of losses in a class	middle damage per class (in T€)	probability
0	0	1,00	1	0,60	0,0417
1	1,00	10,00	2	7,92	0,0833
2	10,00	100,00	4	29,34	0,1667
3	100,00	1000,00	13	298,31	0,5417
4	1000,00	10000,00	4	3161,49	0,1667
5	10000,00	100000,00	0	0,00	0,0000
6	100000,00	1000000,00	0	0,00	0,0000
7	1000000,00	10000000,00	0	0,00	0,0000
8	10000000,00	100000000,00	0	0,00	0,0000
9	100000000,00	1000000000,00	0	0,00	0,0000
10	1000000000,00	10000000000,00	0	0,00	0,0000
11	10000000000,00	100000000000,00	0	0,00	0,0000
12	100000000000,00	###############	0	0,00	0,0000
13	##############	###############	0	0,00	0,0000
14	##############	###############	0	0,00	0,0000
15	##############	###############	0	0,00	0,0000
			24		

Table 4: Allocating losses to loss classes

For the categorization of losses in this example consecutive powers of ten were selected. However, as the predominant proportion of the losses can be assigned to a few classes within the lower area, a flexible formation of the classes is adequate. Here a logarithmic class formation is choosen, i. e. the distance between the lower and the upper border of a class grows with the number of classes.[32] Allocating the probability to these losses the following picture can be generated:

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[31] The geometric distribution represents a special case of the negative binomial distribution and corresponds to the discrete analogue of the exponential distribution. See Johnson / Kotz, 1969, p. 123. Often empirically given data can be approximated also sufficiently exact by a suitably parameterized poisson distribution. See Beeck / Kaiser, 2000, p. 642 or Peter / Vogt / Kraß, 2000, p. 671.

[32] This for example can be done via a calculation of the upper class border by applying the formula

$$border_i = \left(10^{\left(\frac{1}{c}\right)}\right)^{i+i_0}$$, with

$border_i$	= upper border of class i
c	= number of division
i	= class
i_0	= lower border of class 0

In the case for c = 1 the class formation is maintained by powers of ten.

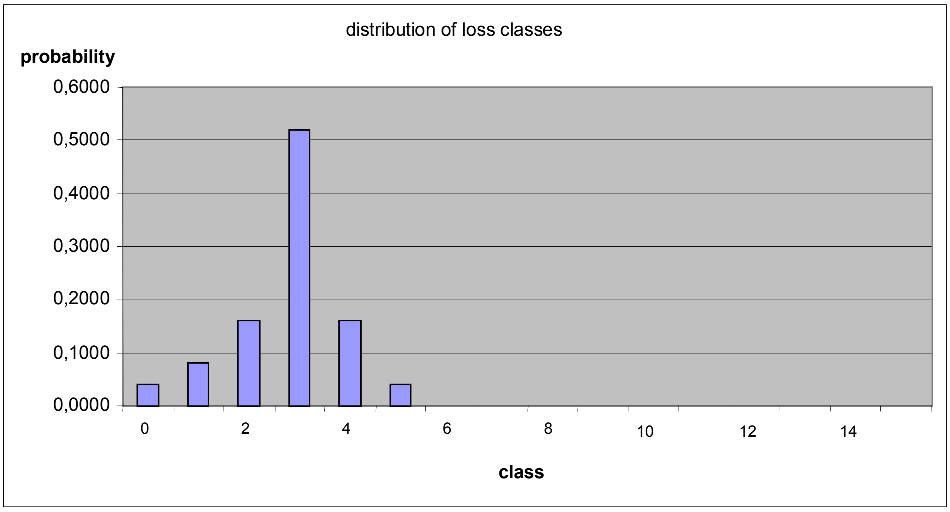

Figure 5: Probability distribution of loss classes

In the next step, a maximum loss for an individual damage (maximum possible loss = MPL) occurring at a value of 15 million € was added manually and also considered in adjusting the probability distribution. This maximum loss can be interpreted as a worst case scenario, i. e. as a damage due to the complete destruction of a department and the costs resulting from the new set up. Similarly as above, a software-supported modeling leads to a probability distribution, in this case a beta distribution:[33]

[33] Often also a log-normal distribution is suitable for describing the real given loss data.

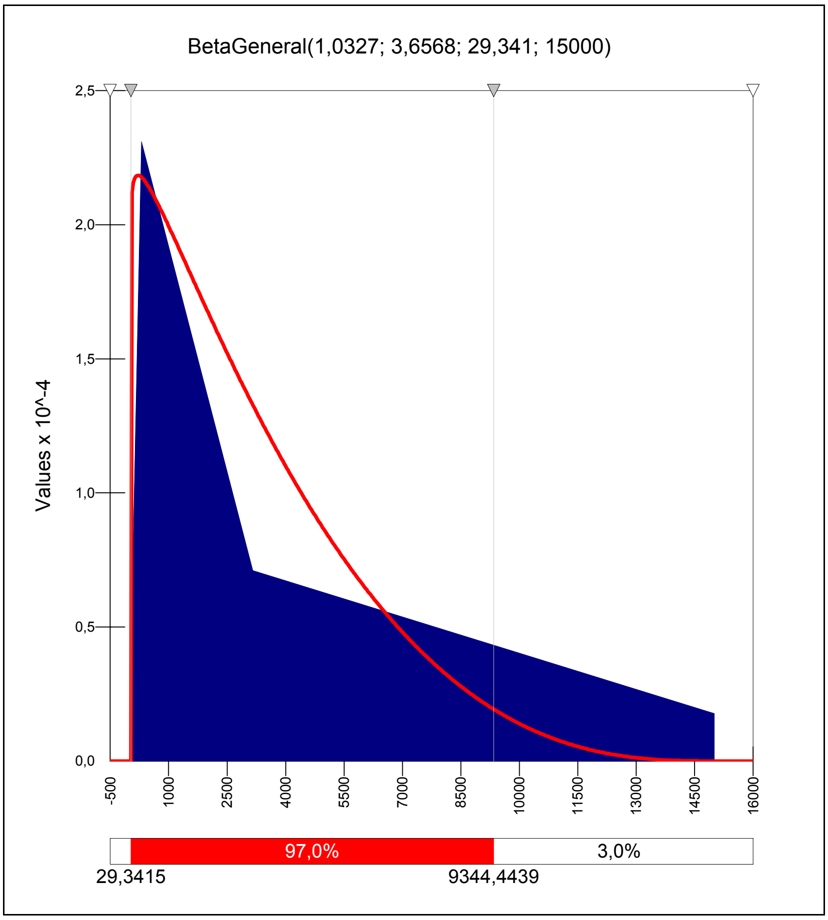

Figure 6: Adaption of a probability distribution to loss severity

The dark area represents the distribution derived from the given loss data, the thin line represents the beta distribution resulting from the adjustment. As mean 3.326 million € results. Depending upon the level of the maximum possible loss an appropriate model of the extreme value theory may be deemed necessary, in particular when a high damage exposure is assumed at the same time with a small probability of occurrence.[34] As can be seen in the figure above, there can be a risk, that the probability of occurrence of small and middle losses might be overestimated, while the probability of big losses might be underestimated. In this case it needs to be figured out, to what extent the distribution should be modified or whether even the original empirical distribution should be applied for additional calculations. This has to be considered in particular, if the relevance and time stability of the empirical distribution can be presumed.

In the following a total loss distribution for the selected specific cause-and-effect chain is modeled by using the results above. This total loss distribution results from the following combined model:

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34 See Embrechts / Klüppelberg / Mikosch, 1997. Suitably to the modelling of the "long tails" is for example a generalized Pareto distribution. See Ceske / Hernández / Sánchez, 2000, p. 10.

$$S = \sum_{i=0}^{N} L_i \text{ , with}$$

S = total loss,

N ~ geomet(0,6),

L_i ~ iid beta(1,0327; 3,6568; 29,341; 15000).

The total loss distribution *S* is formed from a stochastic sum of independent beta-distributed random variables L_i, whereas the number of addends *N* is geometric distributed.

The results reached so far can be used for operationalizing risks of another department or another bank. Therefore the probability distribution must be adequately scaled to the specific conditions of the specific unit. The final goal is, to transform all total loss distributions of several cause-and-effect chains in different business units to a total loss distribution of operational risk of the whole bank. This can be achieved by further simulations on higher aggregation levels. Alternatively also the corresponding value at risk numbers can be aggregated. These values represent a meaningful measure of the capital charge, as these represent the estimated maximum loss, which can be expected to occur "on usual market conditions within one period with a certain probability"[35]. Therefore, the VaR is a quantile of the total loss distribution.

For the purpose of the aggregation a Monte Carlo simulation is applied as a suitable stochastic mechanism. Random events are modeled as artificial samples. These are produced by random numbers.[36] The underlying of the random samples can be any distribution. Assuming that loss number and loss severity are independent random variables,[37] the simulation works in a two-stage structure. At first coincidentally a number of losses is taken from the loss frequency distribution. Subsequently, according to the resulting number, the loss severities are taken. For aggregating the results to the real (but unknown) loss distribution the number of iterations within the simulation is crucial. Iteration numbers beyond 1000 have proven as practicable. In the following figure the result of such a simulation is illustrated:

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35 Lister, 2000, p. 75.

36 See Gleißner / Meier, 1999, p. 928-929.

37 See Jovic / Piaz, 2001, p. 924. However, in the literature also the thesis can be found that the probability of loss indicates a functional dependency on the potentially damage severity. See Peter / Vogt / Kraß, 2000, p. 664.

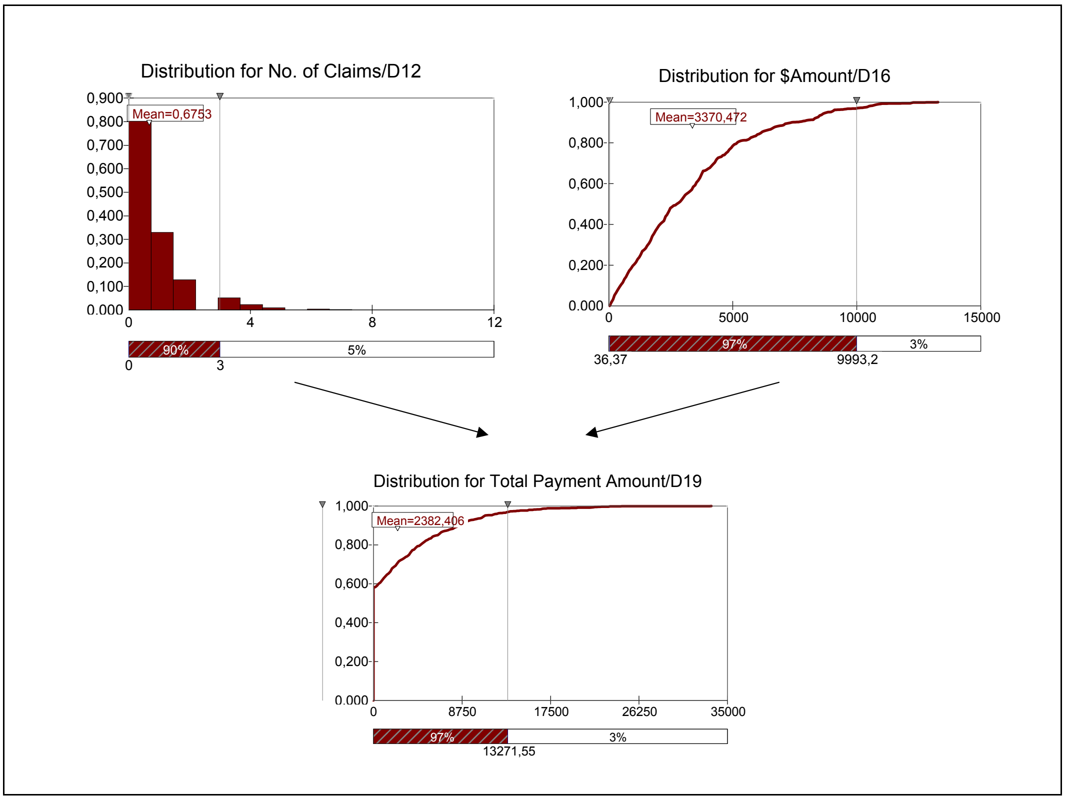

Figure 7: Simulation based on a singular cause-and-effect chain

The figure shows the simulated results for the number of losses (Distribution for No. of Claims), the severity of the losses (loss severity distribution) and – on an aggregated level – the total losses for a period. According to the specification the loss frequency distribution has an expected loss number of 0.67. This corresponds with around 2 (3) losses at a level of confidence of 90 % (95 %). The loss severity distribution – here shown with its distribution function – displays an expected loss of 3.37 million €. A confidence level of 97 % leads to an expected maximum loss of 9.99 million €. The simulated total loss distribution – also shown as a distribution function – of the cause-and-effect chain "physical assets and external risks / fire / overheating / computer" of a specific business unit implies an expected loss of 2.38 million € per period. At a confidence level of 97 % the expected maximum loss amounts to 13.27 million €.

An advantage of this methodology is, that the effect of risk-reducing steps, for example insurance, can be forecasted on the basis of the loss distribution.[38] A maximum flexibility can be retained by a free selection of the sums insured and the deductibles. For example, insurance products, which affect the entire yearly loss, or products, which refer to single losses, can be integrated in the analysis. If an insurance cover is selected, which refers to individual loss events, a corresponding adjustment of the loss severity distribution needs to be made. A

[38] For the question, how insurance products can be used for hedging operational risks, see Avery / Milton, 2000.

stop-loss cover for example, which refers to the whole loss of the total period, affects only the total loss distribution.

The following figure shows the effect of a single loss cover starting from a loss of 1.5 million €. This means, from the bank´s view the loss severity distribution is still limited to the area of the deductible, i. e. 1.5 million € per loss event. Starting from this point a compensation up to the maximum damage of 15 million € per loss event is guaranteed by an insurance cover:

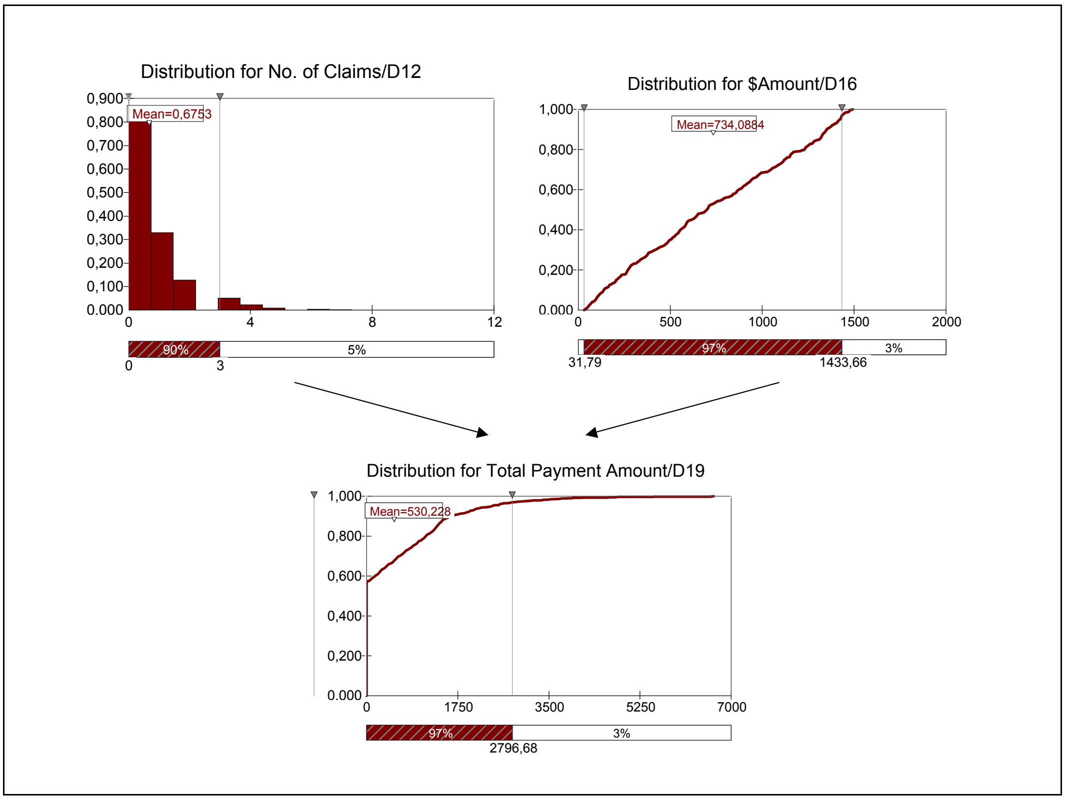

Figure 8: Shifting the total loss distribution in case of a single-loss coverage

The expected value of the total loss in a period decreases to 530.3 thousand €, the value at risk decreases to 2.796 million € at a confidence level of 97 % accordingly.

Alternatively, insurance cover can be chosen in terms of a stop-loss cover. In this case the deductible of a bank refers not to each individual loss, but to the total loss (balance sheet loss) of the period. This means, the bank has to carry all losses with their full value up to the agreed amount. Starting from this point an insurance company pays for the loss above this point. A stop-loss cover is illustrated in the following, starting at a point of 5 million €:

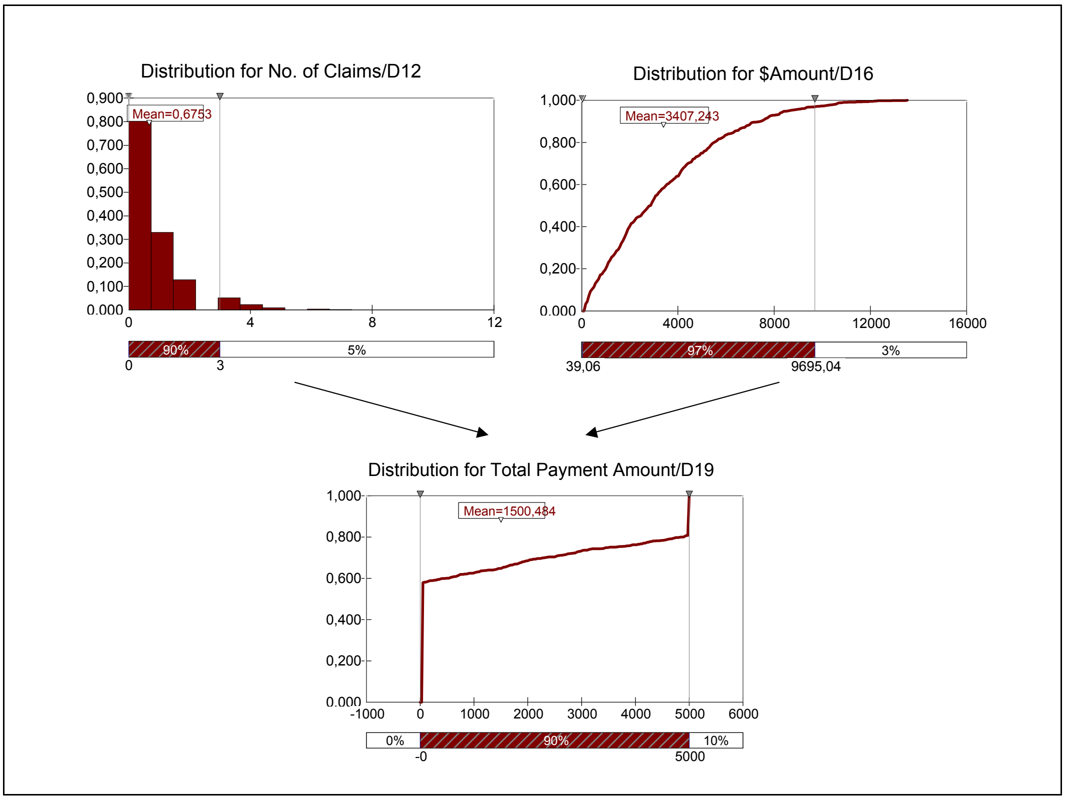

Figure 9: Shifting the total loss distribution in case of a stopp-loss coverage

Then, the expected loss for the specific cause-and-effect chain reduces to 1.5 million €, the value at risk at a confidence level of 97 % corresponds to the maximum deductible of 5 million €.

However, it is worth mentioning, that while integrating insurance protection the operational risk of a specific cause-and-effect chain is replaced with the general risk of default of the respective insurance company. The quality of insurance cover depends on the solvency and the risk management of the insurance company. Accordingly the capital charge has to be prescribed in such a way, that this credit risk is covered by a sufficient amount of equity. The volume of the necessary capital charge can be determined by the corresponding rating class of the insurance company.

The efficiency of substituting equity by insurance cover can be determined with a relative simple approach. The capital charge resulting from the simulation of the total loss distribution considering the insurance cover can be compared with the necessary capital charge without insurance cover. The difference of the capital charge can be figured out by calculating the cost of equity[39], which can be compared with the insurance premium in a second step. The

[39] These can be calculated for example with the help of a model like the CAPM.

optimal amount of insurance coverage results from the comparison of the marginal costs for insurance and the marginal costs for equity:[40]

$$VS_{opt} \rightarrow \frac{dP}{dVS} = \frac{dk_{EK}}{dEK}\text{, resp.}$$

$$VS_{opt} \rightarrow \frac{dP}{dVS} = k_{EK}\text{, with}$$

VS = insurance cover
P = insurance premium
EK = volume of equity[41]
k_{EK} = cost of equity

5. Conclusion

As shown above, the loss distribution approach is the most flexible approach suggested by the Basel Committee in its consultative document for determining the capital charge with respect to operational risks. Furthermore, this approach is relatively simple and well-known by the insurance economy. The surprising fact in this context is, that the Basel Committee publishes this approach as possible approach without any specifications. A serious obstacle for this approach is not the methodology, but the data requirements, which determines the quality of this approach ("garbage in – garbage out"). Therefore collecting loss data in a centralized data base is absolutely necessary, in order to obtain a reliable basis for a stable loss distribution.[42]

It has also to be said, that from a risk-theoretical perspective a complete substitution of equity by insurance cover is problematic, as in this case the scritch-over from operational to credit risk is not considered. But by specifying so called "rates of substitution" at least a reduced capital charge for operational risks can be calculated as function of insurance cover and the solvency of the considered insurance company.

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[40] In the capital market-theoretical evaluation models the cost of capital depend solely on the systematic risk, which is caused by one ore more risk factors. Accordingly the marginals costs of equity are constant, since independently of the volume of equity the equity costs are regarded as constant and thus independent of the capital structure.

[41] The here relevant equity term includes not only the "equity" of the balance sheet but in the sense of a regulatory equity also capital like adequate profit participation rights. See Deutsche Bundesbank, 2002.

[42] See Hoffman, 2002, p. 225-230 and Levine / Hoffman, 2000, p. 27-29.

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