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Estimation of Economic Capital Concerning Operational Risk in a Brazilian Banking Industry Case*

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Abstract

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The advance of globalization of the international financial market has implied a more complex portfolio risk for the banks. Furthermore, several points such as the growth of e-banking and the increase in accounting irregularities call attention to operational risk. This article presents an analysis for the estimation of economic capital concerning operational risk in a Brazilian banking industry case making use of Markov chains, extreme value theory, and peaks over threshold modelling. The findings denote that some existent methods present consistent results among institutions with similar characteristics of loss data. Moreover, even when methods considered as goodness of fit are applied, such as *EVT-POT*, the capital estimations can generate large variations and become unreal.

Keywords: operational risk, Markov chains, Cramer-von Mises, loss severity, economic capital.
JEL classification: G32, G28, G14.

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1. Introduction

The advance of globalization of international financial market has implied a more complex portfolio risk for the banks. Furthermore, several points such as the growth of e-banking and the increase in accounting irregularities, as those of Enron and WorldCom, call attention to operational risk. According to the New Basel Capital Accord (New Accord) banks must define an explicit minimum capital charge for operational risk as part of Pillar 1. Three measurement methodologies are permitted to calculate the operational risk capital charge: (i) the Basic Indicator Approach; (ii) the Standardised Approach, and (iii) Advanced Measurement Approach.

The Basic Indicator Approach considers fixed parameters for calculating operational risk. Although fixed parameters are also used in the case of Standardised Approach, bank activities are divided into 8 business lines. In each business line, there is a different percentage applied for the measurement of risk. Such as in the previous case, the Advanced Measurement Approach (AMA) classifies the business lines internally. However, it permits the use of the model of each institution regarding its particularities.

The natural procedure for finding the economic capital is based on a detailed model which represents accurately the loss distribution for a bank's operational risk over one year. Hence, the models based on AMA converge to the Loss Distribution Approach (LDA). The main difference is how the loss distribution is modeled. The minimum requirement for the use of the several approaches is proportional to the level of complexity. Therefore, there exist some advantages for the banks in adopting more sophisticated internal models of managing risk since this implies lower capital requirement. In other words, there is an incentive for financial institutions to search for an operational risk management approach that is more sophisticated and more sensitive to the risks of each particular institution.

Dutta and Perry (2007), making use of the Loss Data Collection Exercise (LDCE - 2004),[1] analyzed financial institutions' internal loss data and concluded that the use of different models for the adjustment of severity in the same institution can create different estimations for the economic capital. Furthermore, the application of the

[1] The LDCE (2004) was a common effort of regulation agencies in the USA (Federal Reserve System, Office of the Controller of Currency, Federal Deposit Insurance Corporation, and the Office of Thrift Supervision) for gathering operational risk data.

same model on different institutions may imply unreal and inconsistent estimations. Therefore, according to these authors, a reduced number of techniques are potentially adequate for modelling operational loss severity.

Due to the scarcity of data, it is not an easy task to model the loss severity distribution. In this sense, Aue and Kalkbrener's (2006) study on the internal loss data for the last 5 to 7 years in the Deutsche Bank was not sufficient for finding a good definition in the severity distribution tail. Consequently, in order to increase the robustness of the model, other categories of data (external or created by artificial environments) were included. The findings denote that in several of the 23 cells in the *BL/ET* matrix, the body and tail of the severity distribution present different characteristics.

The above result confirms other studies which indicate that the operational risk loss data is distributed in two different manners: (i) constituted by loss data with high frequency and low magnitude that composes the body of the distribution; and (ii) constituted by loss data with low frequency and high magnitude that composes the tail distribution. Therefore, it is hard to identify a unique loss distribution function which can describe correctly the behaviour of all cells of the *BL/ET* matrix in the implementation of LDA in the Deutsche Bank. This difficulty implied the use of different parametric functions. The adopted methodology is based on the Extreme Value Theory taking into account the *Peaks over Threshold* method which allows the fit of Generalized Pareto Distribution models.

The same problem has been faced in Chapelle et al. (2004), in which, like other authors, they had opted for the strategy of identifying the limit value in order to separate "normal" and "extreme" values in the loss value. An alternative procedure is the adoption of an arbitrary measurement (90º percentile) or to use a tool with graphic resources as the Mean Excess Plot (see Davison and Smith, 1990; and Embrechts et al., 1997).

In brief, recent researches reveal the necessity of the banking industry to develop the methodology of LDA for regulatory capital calculation necessary for avoiding losses due to operational risk. For almost half of the financial institutions in Latin America the calculation method of economic capital for operational risk is not defined. Although some institutions intend to use the Basic Indicator Approach, there is no evidence that improvements in the processes and controls are being developed. Only 36% of financial institutions state that they use a more advanced approach than the basic one. Therefore, almost 2/3 of institutions in the region need to adopt improvements in the processes and controls (EVERIS, 2005).

This paper presents an analysis for the estimation of economic capital concerning operational risk in a Brazilian banking industry case making use of Markov chains, extreme value theory, and peaks over threshold modeling. As a consequence, this article relates to several pieces of literature regarding quantitative models of operational risk events. It is important to stress that this paper presents the first analysis, taking into account real data instead of artificial data, for the economic capital calculation in the Brazilian financial institutions. This analysis is relevant because Brazil is one of the most important emerging economies and has a sophisticated banking industry. Therefore, the results can be used to improve the analysis for mitigating operational risk in similar economies.

The article is organized as follows: next section presents the data and method used in this study, section 3 presents the expected loss calculation using the Markov chain model, section 4 makes an economic capital estimation taking into account the loss distribution approach, and section 5 concludes the paper.

2. Data and method

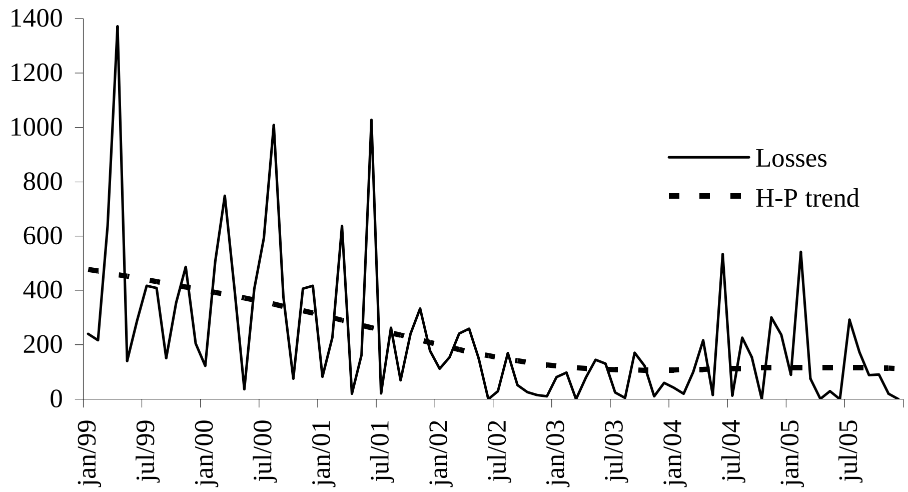
With the objective of the economic capital calculation in Brazilian financial institutions, a sample of data concerning losses due to bank robberies in the third economically most important state in Brazil (Minas Gerais) was considered. The register of 354 loss events classified as “external fraud” catalogued by the trade union bank of Minas Gerais (http://extranet.bancariosbh.org.br) based on top 50 banks in Brazil by total assets (CBB, 2006). This data was disclosed by local media in the period of January 1999 to December 2005 with a monthly frequency.

Figure 1 shows a falling trend of the values of loss caused by bank robberies. This trend can be related to the publication of “Sound practices for the management and supervision of operational risk” (BIS, 2003) which indicated the necessity of appropriation and registration of loss data for future economic capital calculation when AMA is adopted. Another possibility is the growing investment from the banking industry in prevention and insurance against this category of loss. In Brazil there are more than 17,500 bank agencies and the total investment in the banking system for physical safety doubled between 2003 and 2006, reaching US$3 billions. With the objective of testing the application of LDA, the loss data regarding bank robberies was aggregated representing the loss of a fictitious big bank called DHR.

The economic capital is a measurement which is supposed to reflect with high precision, the necessary amount of capital for unexpected losses of a bank. The degree of precision is directly related to the risk tolerance inherent to each financial institution and its particularities. The rule of thumb in the banking market is to choose the tolerance level based on institutional rating. In a general way the economic capital is based on Value-at-Risk (VaR), understood as a specific quantile in the distribution of loss data. A good example is the economic capital calculation in the Deutsche Bank's case, where a confidence level of 99.98% in VaR would be associated with the rating granted to the bank (AA+).

Figure 1

Operational Losses due to bank robberies (in R$ thousands)



The financial institutions which will adopt the AMA for economic capital calculation must calculate the operational VaR for the period regarding one year and they will consider a confidence level equal or higher than the 99.9º percentile of the aggregate loss distribution function. The operational VaR calculation will be made taking into account all business lines of the institution and the sum of such amounts will correspond to the share of the economic capital related to the operational risk.

The operational VaR calculation is based on discrete stochastic process and it is developed through two processes: the loss frequency distribution and the loss severity distribution. The aggregation of the functions of loss frequency and severity distribution is made through Monte Carlo simulation. The distribution of aggregated losses due to this operation allows the estimation of future losses related to operational risk events. However, it is common to take into consideration the expected shortfall in the calculation (Aue and Kalkbrener, 2006).

Therefore, although the operational VaR (VaR_{op}) is a "coherent" risk measurement, from such a value shall be deducted the expected loss (EL) calculation in order to obtain the operational economic capital amount (EC_{OR}). Thus the model for estimation of economic capital for the DHR bank is given by:

(1) $EC_{OR} = VaR_{op} – EL.$

A different manner of using mean and median arise from the aggregate loss distribution function, or to consider the severity value as a result of expected frequency for expected losses calculation (see Moscadelli, 2004). Under this perspective, the next section presents an alternative model making use of Markov chains model.

3. Expected loss calculation with Markov chains

The standard method for the calculation of credit risk and operational risk is the specification for the economic capital based on the operational VaR (maximum probable loss for a single event deducted from the expected loss). For the estimation of the expected loss using Markov chains, the monthly data loss for the period between January 1999 and December 2005 was consolidated (see table 1). It is important to note that there is a concentration of events between 1999 and 2001. As a consequence, these values could cause a bias in the analysis, increasing the average loss. Hence, the data for the above-mentioned period was expurgated and the analysis is focused on the period between 2002 and 2005 (monthly data).

Furthermore, for achieving the Markov transition matrix, the values (in Reais, R$) were classified into four distinct categories:

(i) loss with a value lower or equal to R$ 100,000.00 (state 1 = E_1);

(ii) loss with a value higher than R$ 100,000.00 and lower or equal to R$ 200,000.00 (state 2 = E_2);

(ii) loss with a value higher than R$ 200,000.00 and lower or equal to R$ 300,000.00 (state 3 = E_3); and

(iii) loss with a value higher than R$ 300,000.00 (state 4 = E_4).

The matrix will reproduce the loss value regarding robberies in the DHR bank. With this objective, $P_{i,j}$ is the probability of the occurrence of the state i (period n) after the occurrence of the state j (period $n-1$). Thus:

(2) $$P_{i,j} = \frac{E_i}{E_j},$$

where E_i is the number of occurrences of the state i, after the occurrence of the state j; and E_j is the number of occurrences of the state j in the period.

Table 1

Operational loss - bank robberies (in R$)

Month/Year	1999	2000	2001	2002	2003	2004	2005
January	240,000	122,399	82,688	111,710	80,738	42,800	89,851
February	216,628	506,860	227,000	154,400	98,000	20,000	542,522
March	638,190	749,000	637,647	241,500	-	100,000	75,000
April	1,371,181	396,800	20,370	258,500	80,500	217,000	1,000
May	139,553	36,061	162,837	149,000	144,500	15,481	30,000
June	288,138	405,223	1,028,445	-	131,000	534,700	-
July	417,300	593,400	21,000	29,000	25,000	12,500	292,000
August	408,410	1,009,290	262,862	169,500	5,000	226,000	173,000
September	150,253	376,121	69,584	51,602	171,000	154,700	88,500
October	354,201	75,724	239,684	26,100	123,000	-	91,000
November	486,000	406,471	332,660	15,514	11,000	300,000	20,000
December	205,000	417,363	178,050	11,000	60,200	237,000	-
TOTAL	**4,914,855**	**5,094,711**	**3,262,827**	**1,217,826**	**929,938**	**1,860,181**	**1,402,873**

Source: CRMS - Centro de Referência e Memória Sindical.

Taking into account the four states above, the transition matrix is

(3) $$P_{4x4} = \begin{bmatrix} P_{1,1} & P_{1,2} & P_{1,3} & P_{1,4} \\ P_{2,1} & P_{2,2} & P_{2,3} & P_{2,4} \\ P_{3,1} & P_{3,2} & P_{3,3} & P_{3,4} \\ P_{4,1} & P_{4,2} & P_{4,3} & P_{4,4} \end{bmatrix}.$$

After the calculation of the transition matrix, the state matrix regarding the year immediately before the one to be forecasted (E_{i1}) was defined. In the current model the state matrix represents the probability of the occurrence of the state i in the twelve months prior to the current month. Therefore the state matrix function is

(4) $$E_{i,1} = \frac{E_i}{12},$$

where E_i is the number of occurrences of the state i in the year previous to the current. Therefore, considering the four states, then:

$$(5) \qquad E_{4x1} = \begin{bmatrix} E_{1,1} \\ E_{2,1} \\ E_{3,1} \\ E_{4,1} \end{bmatrix}.$$

The state matrix for the forecasting year ($E^1_{i,1}$) is a result of the multiplication of the transition matrix ($P_{i,j}$) by the state matrix of the previous year ($E_{i,1}$) and 12 (number of months in one year). This new matrix represents the probabilities of each state i to occur in the year under consideration. Hence, the state matrix of the year to be estimated corresponds to:

$$(6) \qquad P_{4x4} \times E_{4x1} \times 12 = \begin{bmatrix} E^1{}_{1,1} \\ E^1{}_{2,1} \\ E^1{}_{3,1} \\ E^1{}_{4,1} \end{bmatrix}.$$

With the objective of giving more reality to the model, the arithmetic mean of loss due to bank robberies (*MLBR*) for each state i was made, that is,

$$(7) \qquad MLBR_i = \frac{\sum L_i}{NL_i},$$

where $\sum L_i$ is the sum of loss in state i; and NL_i is the number of losses in state i.

In the search for the expected loss for each state i (EL^*), the multiplication of the mean of loss due to bank robberies by the correspondent factor of each state i regarding the state matrix for the forecasting year ($E^1_{i,1}$) is made,

$$(8) \qquad EL^* = MLBR_i \times E^1_{i,1}.$$

The sum of these losses implies the whole loss forecast for the year (WL^*),

$$(9) \qquad \sum EL^* = WL^*.$$

A similar procedure for expected frequency (*EF*) calculation was adopted. The result allows the estimation of expected loss for 2006 which will be used in the economic capital calculation (see appendix). Therefore, the value of the mean expected loss is

$$(10) \qquad EL = \frac{WL}{EF},$$

that is, the whole expected loss for 2006 divided by the number of expected event loss in the same year.

For the purpose of testing the robustness of the model, the result of the estimation for 2005 is confronted with the real data in that year.[2] The data in this analysis includes the period between January 2002 and December 2004. The comparison of the estimated result (R$ 1,344,287.18) with the observed loss (R$ 1,402,873.00) reveals a low gap of 4.36% between the values. Therefore the result demonstrates the good performance of the model in forecasting (see table 2). The same procedure was repeated for the estimation of loss in 2006 (the data period is January 2002 to December 2005) and the results are in table 1. Therefore, such as observed in figure 1, a falling trend in bank robberies is observed.

The data concerning frequency of occurrence of loss is divided into four categories of states for achieving the transition matrix. This matrix reproduces the frequency of loss events taking into account the bank robberies based on the following premises:

(i) frequency of occurrence of loss events in the month, lower than 1 (state 1 = e_1);
(ii) frequency of occurrence of loss events in the month, lower than 2 (state 2 = e_2);
(iii) frequency of occurrence of loss events in the month, lower than 3 (state 3 = e_3); and
(ii) frequency of occurrence of loss events in the month, greater than 3 (state 4 = e_4).

Table 2
Expected loss (in R$)

	2005		*2006*	
State	Mean of loss	Expected loss	Mean of loss	Expected loss
E_1	34,221.75	232,327.66	37,234.00	301,320.27
E_2	145,423.33	373,253.22	148,181.00	245,922.06
E_3	246,666.67	578,296.30	253,142.86	411,887.12
E_4	534,700.00	160,410.00	538,611.00	334,310.28
	Total sum	**1,344,287.18**	**Total sum**	**1,293,439.73**

The expected frequency calculation is similar to the one made for the expected loss. The data in this analysis corresponds to the period from January 2002 to December 2005. Table 3 shows the outcome. Based on the expected frequency, the expected loss

[2] The transition matrix and state matrices necessary to the forecast of loss concerning 2005 and 2006 are available from the authors on request.

in 2006 corresponds to R$ 52,265.76 (1,293,439.73/24.75). The value found reveals a robustness of the model because it is close to the mean of loss between 2002 and 2005 (R$ 44,717.50). On the other hand, the median of losses in the same period (R$ 20,000.00) is not adequate due to its low value in comparison with the mean of loss.

Table 3
Expected frequency for 2006

State	Mean of frequency	Expected frequency
e_1	0.50	2.15
e_2	1.50	4.80
e_3	2.50	4.01
e_4	4.77	13.79
	Total sum	**24.75**

4. Estimation economic capital based on LDA

Before the estimation of economic capital through LDA it is important to note that due to the flexibility of the AMA method proposed by the Basel Committee, each institution, based on its own individual characteristics and demands, has an option on building a loss matrix – Business Line/Event Type (*BL/ET*). Therefore, if the institution has activities that consider 8 business lines with loss registration, classified in each one of the 7 types of risk proposed by the New Accord, the *BL/ET* matrix will be composed of 56 cells which consolidate the data of operational loss.

An example is given in table 4 which represents the *BL/ET* matrix (composed of 23 cells) used by the Deutsche Bank in the loss distribution approach. The specification of this matrix is based on the business lines indicated by the Deutsche Bank executive committee and on the classification of types of event risk regarding level 1 proposed by the New Accord.[3] It is important to highlight that the Deutsche Bank makes the option on consolidating the data concerning loss event taking into account labor demand, damages in infrastructure, and labor accidents without considering the loss distribution by business lines.

[3] Information available from www.bis.org/publ/bcbs128d.pdf.

Table 4

BL/ET matrix - model LDA - Deutsche Bank

Basel level 1	**Internal Event Types**	Business Lines						
		BL1	BL2	BL3	BL4	BL5	BL6	Group
Internal Fraud	Fraud	1	2	3	4	5	6	7
External Fraud								
Damage to physical assets	Infrastructure	8						
Business disruption…								
Clients, Products, Business Practices	Clients, Products, Business Practices	9	10	11	12	13	14	15
Execution, delivery, process management	Execution, delivery, process management	16	17	18	19	20	21	22
Employment practices, workplace safety	Employment practices, workplace safety	23						

Source: Aue and Kalkbrener (2006).

After the analysis of the loss distribution for a risk event type in a business line, the process must take into consideration other operational risk categories with all business lines of the financial institution. Different frequency and severity distributions are derived from loss event data and, after that, they are combined through a Monte Carlo simulation for determining the annual aggregate loss. From the simulation of aggregate loss, the necessary statistics for the operational VaR calculation are obtained for the economic capital estimation.

Regarding the numerical application proposed in this study and with the objective of finding the best adjustment of data loss severity, the totality of data regarding operational losses due to bank robberies in table 1 is used. This information represents a cell in the matrix *BL/ET* of the DHR bank. It is important to note that the operational VaR calculation considers the occurrence of an unexpected loss event which probably has never been registered in the database of the financial institution. Hence, there is no justification for the expurgation of the data in the period 1999 to 2001, in contrast to the one adopted in the previous section.

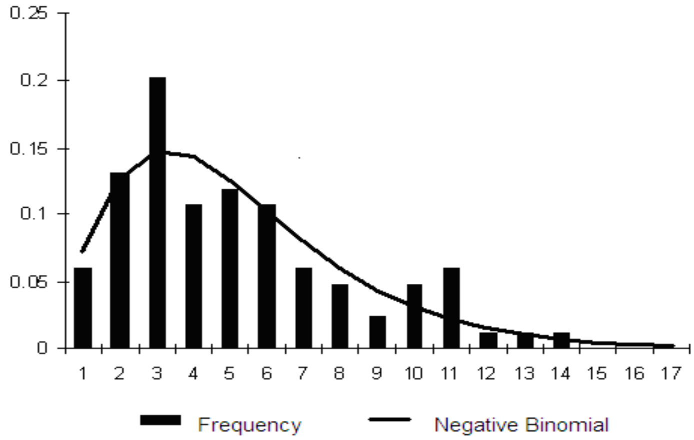
Table 5 shows a survey of loss data used in this numerical exercise. The results permit comparison of skewness and kurtosis of some distributions that will be tested and represent an initial approximation for the function with the best fit. Therefore, the fact that the data frequency distribution reveals a variance higher than the mean value suggests that the Poisson and binomial distribution are not good candidates for the best fit. Moreover, the value of skewness not being zero eliminates the possibility of the adjustment being made through a normal distribution. Another relevant point is that a high value in the 4th moment (kurtosis) denotes distribution with thick tails. Hence, the results of kurtosis for severity data (24) reveal the existence of a thick tail to the right as the best function in the adjustment.

Table 5
Descriptive statistics - frequency and severity

	Frequency	Severity
Minimum	0.00	370.00
Maximum	14.00	800,000.00
Mean	4.21	53,103
Median	3.50	20,000
Standard deviation	3.19	91,843
Variance	10.03	8,411,227,680
Skewness	0.91	4
Kurtosis	3.14	24
Observations	84	354
Sum	84	18,798,348.40

The selection of the function with the best fit for the loss frequency distribution was made taking into consideration the following distributions: Poisson, negative binomial, and geometric. The distribution with the best degree of fit was the negative binomial (with discrete parameter s=3 and continuous parameter p=0.4158, see figure 2).[4]

Figure 2
Frequency fit – negative binomial function



The test for analyzing quality fit for the frequency distribution is the Chi-square test (χ^2). This test compares the result found with the result estimated by the difference between the values. The null hypothesis is rejected if the calculated χ^2 is greater than χ^2 tabled with $d=k-1$(k is the number of categories for each series). The results confirm

[4] The selection of the function was made through the software Best Fit 4.5.

that the negative binomial function denotes the best fit for the loss frequency (see table 6).

Table 6
Chi-square test for frequency distribution

	Negative binomial	Poisson	Geometric
χ^2	4.4	19.89	26.8
P-value	0.7327	0.0058	6.2341E-05
Critical value 50%	6.3458	6.3458	4.3515
Critical value 25%	9.0371	9.0371	6.6257
Critical value 15%	10.7479	10.7479	8.1152

The LDA approach applied to operational risk loss data revealed that the choice of a model for the analysis of loss severity distribution is more important for the economic capital calculation than the choice of a model for the analysis of loss frequency. Hence, the economic capital for covering fortuitous losses due to operational risk is significantly influenced by individual losses of a high magnitude with an easy identification in the loss severity distribution.[5]

It is important to note that the literature considers different procedures to analyze the data loss severity. In this research, the best fit is made taking into account the whole available data without separating the function tail data. The outcomes are presented in table 7 and the graph with the best fit is in figure 3.

Table 7
Statistics – Total loss severity

Distribution	Inverted Gaussian	Log-Normal	Pearson 5
Parameter 1	54,896.748	57,855.731	1.083
Parameter 2	16,457.685	153,439.788	17,338.799
χ^2	23.960	34.800	42.210
KS	0.035	0.044	0.043
AD	0.351	0.416	0.831

The fit in figure 3 needs to be validated by goodness of fit tests. The most used tests in the literature concerning the subject are: (i) Kolmogorov-Smirnov (KS) test; (ii) Anderson-Darling (AD) test; (iii) Chi-square test (χ^2), and (iv) Quantile-Quantile Plot

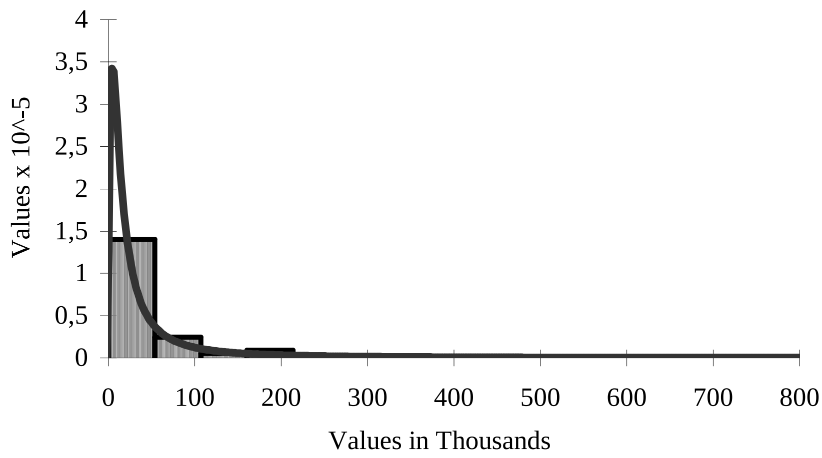
[5] These results are in accordance with those found by Böcker and Klüppelberg (2005), De Koker (2006), and Aue and Kalkbrener (2006).

(QQ-Plot). The first three tests are formal tests and verify the difference between the fit of the real distribution and the fitted distribution. The statistics with the lowest value in each test identifies the function with the best fit. According to Dutta and Perry (2007) there is a consensus in the literature that the AD test has more power and it is more sensitive to the data in the tail of the distribution. The QQ-Plot is a graphical test where the observations are classified in a decreasing order. A good model presents points close to a straight line.

In a first step, the selection of the function with the best fit for the data loss severity takes into account the distributions: inverted Gaussian, Log-normal, and Pearson 5 (see table 6). The result denotes that inverted Gaussian is the function that presents the best fit and, it is in accordance with figure 3.

The next step of the analysis is the classification of loss data in "normal" or "extreme". For the purpose of the present analysis, it has been assumed that the data of extreme loss regarding the tail of the function is distributed in accordance with a generalized Pareto distribution (GPD). The proposed methodology consists in the determination of the threshold value (*u*). Every loss event with a value greater than "*u*" is used in the estimation of parameters of the GPD distribution regarding extreme values.[6]

Figure 3
Loss severity adjustment – inverted Gaussian function



[6] For an analysis of this procedure, see Pickands (1975), and Balkema and De Haan (1974).

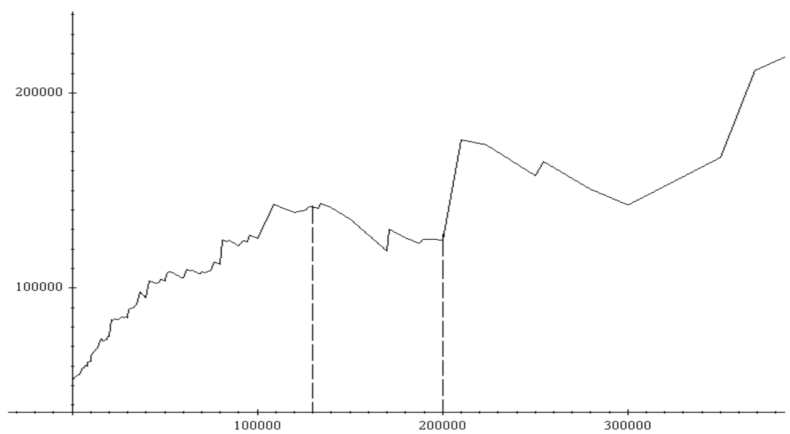
According to Chapelle et al. (2004) and Dutta and Perry (2007) the choice of the threshold value has a direct influence on economic capital calculation. Hence, with the objective of evaluating the impact of this choice on economic capital calculation, the selection of the best fit for data loss severity will also be made through extreme value theory – peaks over threshold (EVT-POT) method. Hence, three candidates for *u* have been tested: (i) the 90º percentile; (ii) the 95º percentile; and (iii) the value calculated through *Mean Excess Plot* (MEP).[7] This model considers the threshold as the value with the lowest Cramer Von Mises (CVM) statistics.[8] Figure 4 allows observing the MEP applied to the cell "retail bank/external fraud" (see figure 4) of DHR bank. This figure represents the function $\{(X_{k,n}, e_n(X_{k,n})): k = 1,...,n\}$ where e_n is the empirical average function of the excesses which is given by:

$$(11) \qquad e_n(u) = \frac{1}{n_u}\sum_{i=1}^{n_u}(X_i - u), \ u \geq 0,$$

where X_i's are the n_u observations with $X_i > u$.

The MEP can be represented by an almost straight line with sloping equal to $\xi/(1-\xi)$. Therefore, figure 4 allows the identification of a significant change in slope of the straight line where the losses have high values among the values in the sample (values between R$ 130,000 and R$ 200,000).

Figure 4
Mean Excess Plot



[7] The first two options were used in recent researches, see Fountnouvelle *et al*. (2006), and Dutta and Perry (2007).

[8] $W^2 = \sum |F(x) - F_n(x)|^2 + \frac{1}{12n}$, where *n* is the number of observations and *F(x)* is the theoretical distribution.

The criterion of selection for u regarding the loss data in this analysis is contained in table 8. In this table, there are several candidates for the threshold value and the parameters of scale β and shape ξ for the distribution of loss data in the tail function (GPD). The Cramer Von Mises test was calculated for each candidate.[9] The last column indicates the percentage of data regarding extreme loss values which are related to the losses greater than the selected threshold values of each candidate. Column n presents the number of loss events which exceeds the threshold value.

Table 8
Threshold "u"

u	***N***	Parameters		**CVM**	**%**
		B	ξ		
130,000.00	**36**	**31,893.8**	**1.592**	**1.565**	**10.17**
135,000.00	35	34,817.6	1.663	1.314	9.89
140,000.00	34	41,493.4	1.823	0.971	9.60
145,000.00	34	41,493.4	1.823	0.803	9.60
150,000.00	33	60,335.4	2.291	0.812	9.32
155,000.00	33	60,335.4	2.291	0.723	9.32
160,000.00	33	60,335.4	2.291	0.697	9.32
165,000.00	33	60,335.4	2.291	0.705	9.32
170,000.00	**30**	**52,862.0**	**2.102**	**0.477**	**8.47**
175,000.00	29	59,935.4	2.275	0.599	8.19
180,000.00	28	65,044.7	2.402	0.709	7.91
185,000.00	28	65,044.7	2.402	0.772	7.91
190,000.00	26	67,247.1	2.456	0.753	7.34
195,000.00	25	70,019.0	2.525	0.835	7.06
200,000.00	**18**	**37,824.2**	**1.789**	**0.566**	**5.08**
200,000.00	17	40,491.4	1.845	0.660	4.80

Based on the lowest CVM statistics, the selection of threshold value indicates the 91.53º percentile which corresponds to the parameters 2.102 and 52,862 as shape parameter (ξ) and scale parameter (β), respectively. In this case, 30 data are related to loss events considered as extremes (greater than u) in the distribution tail, while 324 data are applied in the calculation of fit of loss classified as "normal".

The selection of the best fit for the loss severity distribution classified as "normal" is made for the distributions: Log-normal, inverted Gaussian, Log-logistic, and Person 5 as presented in table 9.[10] Independent from the threshold value, the result denotes that the Log-normal function is the best fit for data (the null hypotheses for the

[9] The goodness of fit test was performed by the software Xtreme 3.0.
[10] The goodness of fit test was performed by the software Best Fit 4.5.

other distributions were rejected). Furthermore, the QQ-plot analysis confirms the previous result (see figure 5).

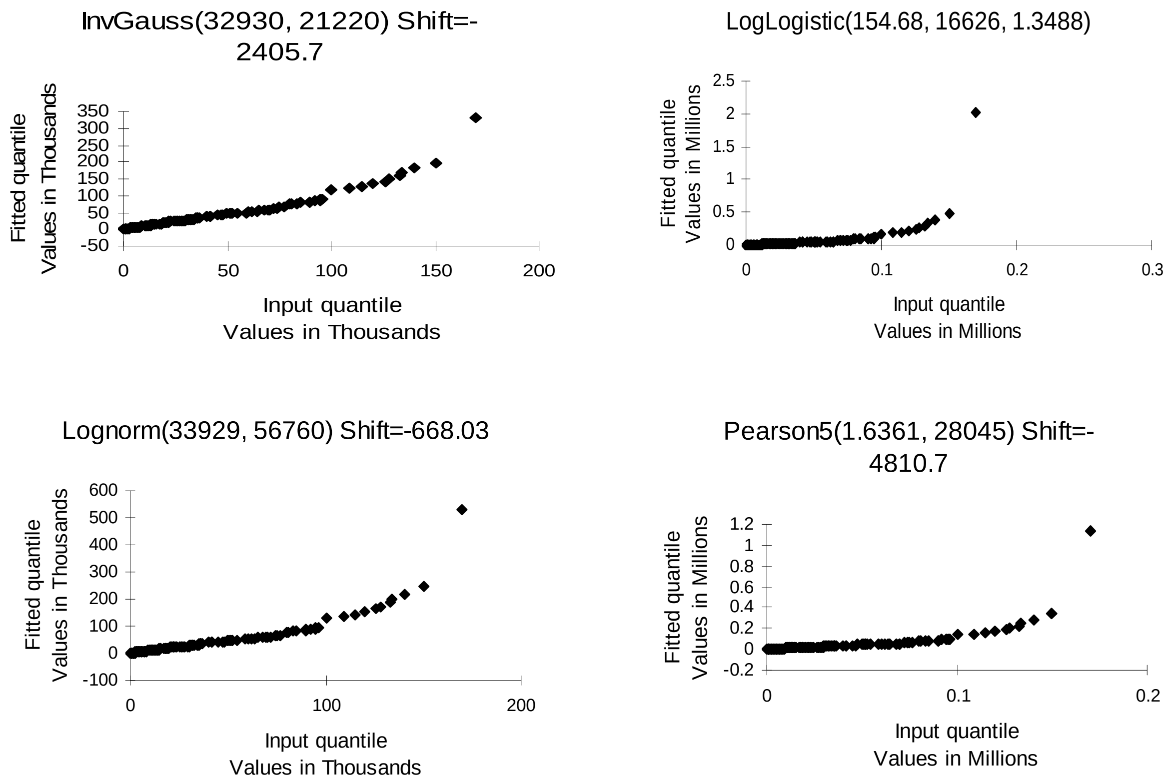
Table 9

Statistics for threshold values

	Distribution	Log-Normal	Inverted Gaussian	Log-Logistic	Pearson 5
***u*=R$130,000.00** (90º percentile), N=318	**Parameter 1**	31,706.8031	31,023.3326	91.9906	1.7609
	Parameter 2	49,612.2007	22,253.7334	16,217.1526	30,543.42
	Parameter 3	-	-	1.3885	-
	χ^2	32.48	45.34	60.47	58.10
	KS	0.0458	0.0490	0.0506	0.05997
	AD	0.9505	1.02	1.307	1.517
***u*=R$170,000.00** (91.53º percentile), N=324	**Parameter 1**	33,928.5806	32,930.2253	154.6818	1.6361
	Parameter 2	56,759.9504	21,220.3832	16,626.1498	28,045.0241
	Parameter 3	-	-	1.3488	-
	χ^2	47.78	47.67	47.33	44.33
	KS	0.0418	0.0453	0.0417	0.0577
	AD	0.8117	0.866	1.168	1.404
***u*=R$200,000.00** (95º percentile), N=336	**Parameter 1**	41,105.334	38,999.395	-	1.375
	Parameter 2	81,595.366	19,257.472	-	23,030.942
	Parameter 3	-	-	-	-
	χ^2	29.98	31.67	-	39.67
	KS	0.03605	0.03905	-	0.05189
	AD	0.6222	0.6898	-	1.230

The graphs in figure 6 exhibit the log-normal distribution which has been identified as the best fit independent of the selected *u*. Hence, the operational VaR calculation will determine which one of the three criteria for choosing the threshold value is more adequate for the economic capital estimation. In other words, it will be evaluated if the best fit is given by EVT-POT (90%, 91.52%, or 95%) method or through the parameters of the inverted Gaussian which ignores the separation between normal and extreme losses. Table 10 presents a summary of the parameters that will be tested for identifying the best candidate for *u* and the respective economic capital.

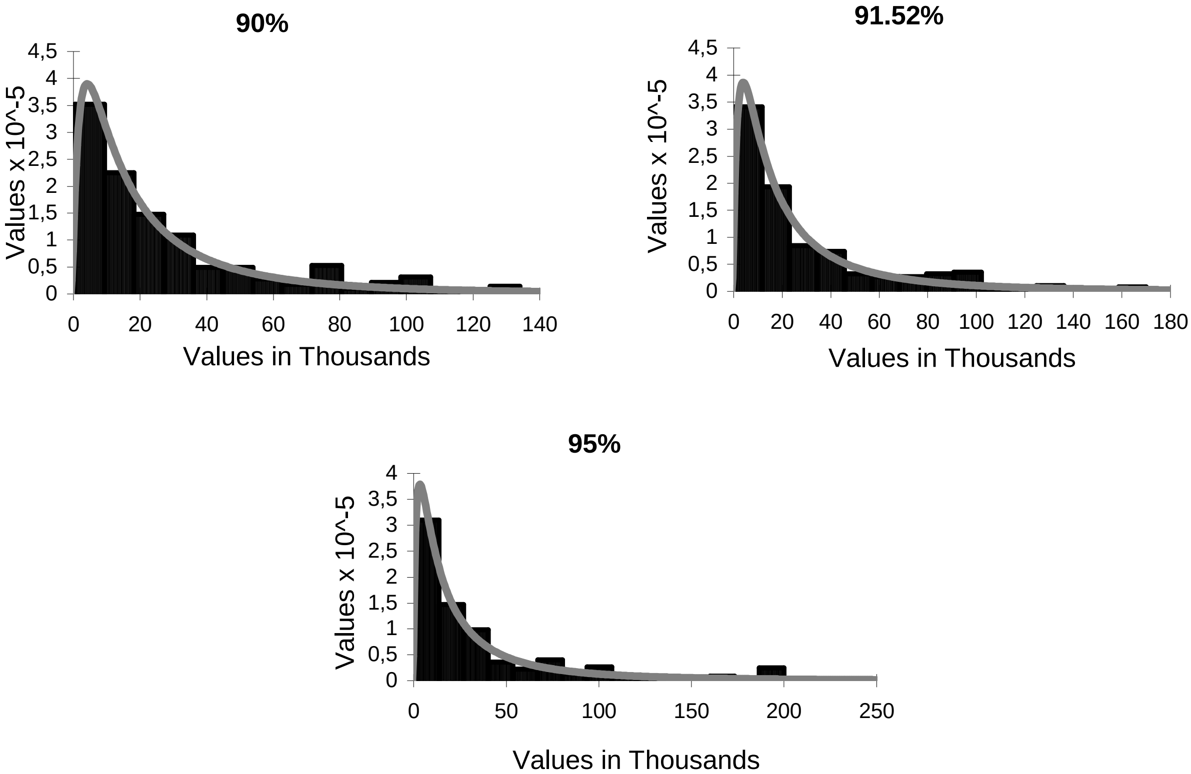
Figure 5
QQ-Plot graphs



u=R$ 170,000.00, N=324, 91.52º percentile

Table 11 summarizes the several outcomes achieved in this section for the economic capital calculation for the operational risk. The aggregate loss function is a result of the combination of the function with the best fit for data frequency (a negative binomial, 3; 0.4158) and the best fit of data loss severity (an inverted Gaussian, 54,896; 16,457). The calculation of operational VaR for finding the aggregate function was made with the Matlab program considering the parameters found in EVT-POT model. The program executed 40,000 repetitions and created the probable loss for the 99.9º percentile. However, in the case of parameters found for the inverted Gaussian, the program @Risk has been used for the specific simulation (10,000 repetitions and has created the probable loss for the 99.9º percentile).

Figure 6
Severity – Log-normal distribution



The results were not feasible for the EC_{OR} taking into account the EVT-POT model. Notwithstanding, the results, once again, were sufficient to prove the high volatility due to the choice of threshold value. Contrary to Chapelle et al. (2004), the value chosen through Cramer Von Mises statistics has not provided the best fit. However, such as in Fontnouvelle et al. (2006), the analysis revealed no trend in the results when the threshold value is increasing.

Table 10
Summary of parameters for Monte Carlo simulation

Severity	**Normal loss**		**Extreme loss**	
	Log Normal function		GPD function	
	μ	σ	β	ξ
MEP / 90%	31,706.80	49,612.20	31,893.80	1.59
MEP / 91.52	33,928.58	56,759.95	52,862.00	2.10
MEP / 95%	41,105.33	81,595.37	37,894.20	1.79

Table 11
Operational VaR

	EVT-POT			
	Cut-off 90%	**Cut-off 91.52%**	**Cut-off 95%**	**Without cut-off**
Normal loss	**Log-Normal**	**Log-Normal**	**Log-Normal**	**Inverted Gaussian**
Mean (μ)	31,706.80	33,928.58	41,105.33	54,896.74
Standard deviation (σ)	49,612.20	56,759.95	81,595.37	-
Parameter (λ)	-	-	-	16,457.68
Threshold (u) *	130.00	170.00	200.00	-
Exceed percentage[(a)]	10.00%	8.47%	5.00%	-
GPD 1 (ξ)	1.592	2.102	1.789	-
GPD 2 (σ)	31,893.80	52,862.00	37,824.20	-
Total loss*	18,798.35	18,798.35	18,798.35	18,798.35
Expected loss (*EL*) *	52.27	52.27	52.27	**52.27**
Median*	20.00	20.00	20.00	20.00
OpVaR 99%*	2,155	5,016	3,170	1,139
OpVaR 99.5%*	7,022	29,050	12,012	1,502
OpVaR 99.9%*	14,910,000	45,366,000	2,168,900	**2,325**
Economic Capital OR*	14,909,947	45,365,947	2,168,847	**2,273**

Note: (*) Value in thousands of Reais; (a) Percentage of events which exceed the threshold value.

Among several EC_{OR} values in the table, the selection was made based on the value considered more credible. The justification is that the values calculated by EVT-POT model look unreal when compared with the expected loss value. This discrepancy in the EC_{OR} value was also found by Dutta and Perry (2007).[11] It is important to note that the discrepancy in the values must not be attributed to a contradiction in EVT-POT model. This result may be associated with a failure, or scarcity of the data loss set, or specific characteristics of this risk category, or even due to the specific conditions for its use as pointed out by Embrechts (1997).

The choice of the EC_{OR} value was defined based on the inverted Gaussian function for the loss severity data (see table 12). Although the value around R$ 2,000,000.00 is not sufficient to cause the failure of a financial institution, it is important to note that the analysis was made considering it as an item inside the external fraud for a single business line. Notwithstanding, the result regarding the estimation of expected loss presents a proportional relation with the operational VaR (ratio of 2.3%) which is compatible with the ratio of 2.9% found by Moscadelli (2004) - see table 12.

[11] Neslehová et al. (2006) call attention to the specific conditions for the employment of EVT-POT model.

Table 12

Relation EC/TA

	Economic * Capital (EC)	VaR Op*	EC/TA (%)	EL/VaR Op (%)
Gauss inv	2,274	2,326	2	2.25
95%	2,168,847	2,168,900	1,781	0.00
CVM	45,365,947	45,366,000	37,260	0.00
90%	14,909,947	14,910,000	12,246	0.00

Note: (*) Value in Thousand Reais.

The present analysis allows observing that even when the goodness of fit techniques are used, such as *EVT-POT*, the capital estimate may generate high volatile results and may seem unreal. Although this method has had a good fitness considering the criteria adopted by Dutta and Perry (2007), it has not been sufficient to define the best fitness function of the losses severity.

5. Concluding remarks

The main difficulty in modelling economic capital concerning operational risk is the choice of the function with the best fit for loss severity. It is important to note that the use of different methodologies for loss severity is likely to present different results. Moreover, the same method does not imply similar results when it is applied to financial institutions with different characteristics. Notwithstanding, there exist some methods which present consistent results among institutions with characteristics of loss data.

It was observed that the numerical exercise developed for the Brazilian case regarding the expected loss calculation revealed that the use of Markov chains is a robust tool. Furthermore, with the objective of modelling the severity distribution, EVT-POT method was applied. The parametric fit of the loss data, neglecting the separation of body and tail, indicated the inverted Gaussian function as the most efficient function due to its realistic estimation. On the other hand, although several authors indicate the GDP function as the function that is used to provide the best fit, this result was not confirmed in the present analysis. This result denotes that even when methods with goodness of fit statistics are applied, such as *EVT-POT*, the capital estimations can generate huge variations and become unreal.

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Appendix

A. Expected loss frequency (2006)

Table A.1
Loss events frequency (2002 to 2005)

Month/year	2002	2003	2004	2005
January	5	4	2	5
February	4	3	1	5
March	3	-	1	2
April	4	2	3	1
May	2	5	2	1
June	-	6	6	-
July	2	2	1	2
August	9	1	2	2
September	3	5	4	3
October	3	2	-	2
November	2	2	1	1
December	1	5	3	-
Total sum	**38**	**37**	**26**	**24**

Table A.2
Transition matrix

		2002-2005			
	Number of events	**E1**	**E2**	**E3**	**E4**
E1	X ≤ 1	0.429	0.429	0.143	0.154
E2	1 < X ≤ 2	0.286	0.143	0.429	0.385
E3	2 < X ≤ 3	0.143	0.071	0.143	0.231
E4	X > 4	0.143	0.357	0.286	0.231

Table A.3
State matrix

	2005
E1	0.417
E2	0.333
E3	0.083
E4	0.167

Table A.4
Expected frequency for 2006

State	Mean of occurrences	Expected frequency
E1	0.50	2.15
E2	1.50	4.80
E3	2.50	4.01
E4	4.77	13.79
	Total Sum	24.75

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