Dániel Homolya: Operational risk and its relationship with institution size in the Hungarian banking sector*,[1]

In addition to credit, market and liquidity risk, measuring and managing operational risk (risk associated with people, systems, processes and external events) is a great challenge for banks. In 2010, around HUF 35 billion in operational risk losses were reported in the banking sector overall, which is significant relative to the pre-tax profits of the banking sector. To a large extent, banks' operational risk measurement methods rely on loss events which have already occurred. If an individual institution has insufficient data for modelling or wishes to include the experiences of extreme events, it should use external data or transpose the risk exposure of the banking sector onto itself. The empirical analysis of the Hungarian banking sector's operational risk data confirms that, similarly to foreign banking sectors and banking groups (which have been already analysed in the relevant literature), there is a significant relationship in the Hungarian banking sector between institution size as defined by gross income and total operational risk losses recorded during the specific period. However, the most significant correlation can be observed between institution size and the frequency of operational risk losses. This result could provide basis for the systemic analysis of operational risk and support simpler operational risk capital allocation methods. Nonetheless, due to the relatively short time series and the significant dispersion of data, we could not robustly assess the sufficiency of the capital already allocated for operational risk.

INTRODUCTION[2]

In the recent past, owing to regulatory requirements and intrinsic motivational forces, financial institutions have increasingly focused their attention on their risks. In addition, the experience of the current crisis has also underpinned the need for more in-depth risk analysis. This systematic approach to operational risk is relatively novel, given that until the 1990s, the focus had been on credit and market risks. Operational risk is defined as the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events (BIS, 2004; EU, 2006; Government of the Hungarian Republic, 2007). The need for the assessment of operational risk is evident in view of the increased risk exposure stemming from the complexity of the financial institution system on the one hand, and regulatory ambitions on the other hand. The set of rare, but high severity events constitutes an important subset of operational risk events. If such events are not available in sufficient number to allow for robust modelling, one can also rely on the loss experiences of other institutions to substitute this lack of experience. For this, we need to identify the correlations between institutional characteristics and the severity of losses, known as scaling functions. A large number of analyses have been published in the academic literature on scaling methods pertaining to foreign banking sectors and banking groups (see for example, Shih et al., 2000 and Dahen and Dionne, 2010 for data pertaining to international banking groups and Na et al, 2005 for those of the ABN-Amro Group). This article is intended to analyse the operational risk loss data of the Hungarian banking sector and assess the relationship between the loss data and institution size. Based on the data available, this allows for the analysis of the scaling functions applicable to the domestic banking sector, as well as the adequacy of the operational risk capital requirement.

* The views expressed in this article are those of the author(s) and do not necessarily reflect the offical view ot the Magyar Nemzeti Bank.

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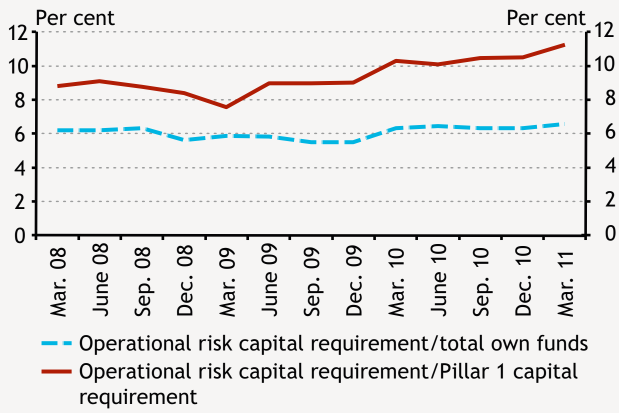
[2] The quantitative analyses of the article are fundamentally based on data reported by individual credit institutions to the Hungarian Financial Supervisory Authority and submitted to the MNB under the cooperation agreement between the two institutions (operational risk tables of the COREP).

THE OPERATIONAL RISK PROFILE OF THE HUNGARIAN BANKING SECTOR

Based on the past three-year period, we can establish that the operational risk capital requirement of the domestic banking sector is rather significant relative to its total capital requirement: the operational risk capital requirement of HUF 150 billion at the end of 2011 Q1 accounts for 11 per cent of the total capital requirement (Chart 1). Compared to the capital requirement, the total amount of realised and reported losses is less substantial (HUF 35 billion for 2010 and HUF 25 billion on average for each year between 2007 Q2 and 2011 Q1 – the period for which data are available). The capital requirement is expected to provide protection in the event of extreme, unexpected situations. Although observations of the past four years are insufficient to draw definitive conclusions regarding the adequacy of the capital requirement, an in-depth analysis of the loss data reported so far may be a suitable basis.

Chart 1
Operational risk capital requirements of the domestic banking sector in comparison with minimum capital requirements and total own funds for solvency purposes



Source: MNB.

Under the less sophisticated methods of determining the operational risk capital requirement (Basic Indicator Approach [BIA], The Standardised Approach [TSA]), banks calculate the capital requirement for operational risk as the average of annual gross income over the previous three years multiplied by a constant specified by the Basel II regulation. Under the regulation, gross income is defined as the sum of net interest income plus net non-interest income, the net result on financial operations and other income. This could be a sound approach if we assume that the operational risk loss exhibits a linear relationship with banks' gross income. Under the Advanced Measurement Approaches (AMA), the capital requirement is calculated on the basis of internal and external loss data, scenario analysis and the assessment of environment and internal control factors. In the Hungarian banking sector, based on balance sheet total, around 78 per cent of banks apply the standardised approach, around 15 per cent of them rely on advanced measurement approaches, and roughly 7 per cent of them use the BIA method.

The ratio of operational risk capital requirement to the total Basel II capital requirement was around 9 per cent in 2008 and 2009, before gradually increasing to 11 per cent from 2010 Q1. This can be attributed to the fact that while the regulatory capital requirements for credit risk declined as a net result of balance sheet adjustments and exchange rate effects, the operational risk capital requirement, which is typically based on gross income, did not change significantly, and changes in gross income tend to lag behind. At the end of 2011 Q1, the ratio of the banking sector's capital requirement for operational risk to total own funds for solvency purposes was around 6.5 per cent (Chart 1).

End-2010 data revealed a total of 5,057 operational risk losses recorded in the previous years, but not yet closed or recorded in the last four quarters by the reporting banks applying the standardised or the advanced approach (constituting roughly 93 per cent of the balance sheet total of credit institutions operating as joint stock companies). Compared to the HUF 35 billion in total losses indicated above, this implies an average loss amount of HUF 6.9 million. This loss level equals nearly 60 per cent of the end-2010 pre-tax profit/loss of domestic banks subject to Basel II and operating as joint stock companies. While the reason for this high percentage is the bank levy, which can be recorded under expenditures, this figure would still be around 20 per cent if the bank levy were excluded (This ratio was 3-4 percent in 2008). Losses exhibit great variance in loss event type and business line. While nearly 75 per cent of the losses reported in 2008 fell into the category of loss arising from Execution, Delivery and Process Management, 2010 was dominated by events related to Clients, Product and Business Practices (63 per cent share in total losses). In turn, the breakdown of losses by business line indicates that Retail Banking was dominant in 2008 (68 per cent), whereas Retail Brokerage had the highest weight with a 61 per cent share of total losses in 2010. Likewise, the quarterly breakdown of the operational risk losses which were recorded in the last four quarters or which were recorded in the previous years but remained open, shows great variance. Gross losses doubled between 2008 and 2010. This might be related to several factors: even a new quarter can bring about significant changes in a short, non-robust time series, the activity of data providers aimed at exploring operational risk may have significantly improved in the past three years, and finally, based on the balance

Table 1
Operational risk losses (emerged or settled) between 2007 Q2 and 2011 Q1 and descriptive statistics on the gross income of banks[3]

Indicator	Number of observations (banks)	Mean	Standard deviation	Skewness	Kurtosis
Total gross income (HUF Bn) (yearly average of four years)	13	68.9	81	2.12	5.67
Gross income of retail banking activity (HUF Bn)	12	37.5	48	1.70	2.58
Number of events (units)	13	313	399	1.17	−0.37
Total losses for 1 year (HUF million)	13	1,628	4,004	3.45	12.13
Maximum single loss at individual bank level (HUF million)	13	660	1,617	3.25	10.90
Number of events in retail banking business line	13	216	289	1.56	1.33
Total loss amount – retail banking business line (HUF million)	13	236	262	1.40	1.66
Maximum individual loss event on an individual bank level in retail banking business line (HUF million)	13	73	76	1.39	1.25
Total loss amount / total gross income (per cent)	13	1.9	4	3.35	11.60

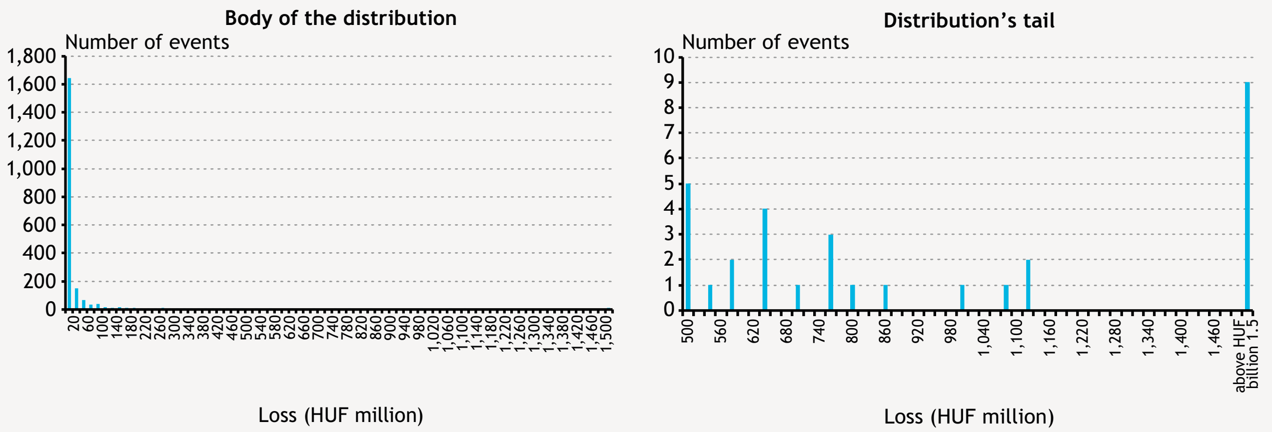
Source: MNB.

sheet total, the group of data providers increased to 93 percent.

The sample available for the purposes of our analysis is limited to four years and includes gross losses, the number of events and the maximum losses sustained in the course of a single event. The sample covers four years, given that the institutions were required to report from 2008 Q1 (retroactively for the previous four quarters; in other words, the first quarter covered by banks' reports was 2007 Q2) and the last available data provision point at the date of this article is 2011 Q1. Reporting banks recorded a total loss of HUF 97 billion and around 18,000 loss events for the period of these four years. Of these events, 12,500 were associated with retail banking, amounting to a loss of HUF 13 billion. Moreover, the data are widely dispersed in the case of those banks which had data available for all four years under review (Table 1).

In line with European supervisory reporting requirements (COREP), banks report only a limited number of individual events – 10 per cent of all loss events based on the number of events (a minimum of 10 events causing the highest losses). Only limited conclusions can be drawn about the

Chart 2
Distribution of major operational risk loss events of the Hungarian banking system between end of 2007 Q1 and end of 2011 Q1



Note: Data reported by banks subject to standardised and advanced measurement approaches. Loss events recorded between 2007 Q2 and 2011 Q1 or not yet closed.
Source: MNB.

[3] For the purposes of this article, in line with the regulatory requirements, I use a three-year average for gross income.

events from this censored, selected database. Anyway, analysis of the data revealed that the distribution of loss events has a fat tail; in other words, the probability of losses substantially higher than the average loss is relatively high. The top five operational risk loss events in terms of impact in the past four years amounted to a total of HUF 33 billion. Three of these five events were interrelated, generating around HUF 25 billion in losses, while two, credit risk-related, external fraud events resulted in losses of HUF 6 billion and HUF 2 billion, respectively (Chart 2).

RELATIONSHIP BETWEEN FIRM SIZE AND LOSS AMOUNT

In the operational risk literature, the study of Shih et al. (2000) was the foundation for the less sophisticated approaches, which demonstrated that the size of a bank in terms of its income is closely related to the magnitude of its loss.[4] The authors of the article cited the proposal made by the European Commission at the end of the 1990s to the effect that credit institutions and investment companies should also compute capital charges for operational risk, which would be based (primarily) on the revenue-based size of the institutions. In their article, Shih et al. (2000) apply a non-linear model, indicating that they found less explanatory power in the case of a linear model:

$$L = R^{\alpha} \cdot F(\Theta) \qquad (1)$$

where L is the actual loss amount associated with the event; R is the revenue size of the firm; α is the scaling factor associated with the size; and Θ expresses all the risk factors, other than revenues, affecting operational risk size (source: Shih et al., 2000, Equation 1.1). The applied approach is based on a power-law model often used in science in general, and economy and finance in particular (such as the so-called Pareto distribution, describing the disproportionate distribution of income among wealth society groups, or other models based on the growth of companies, the "herding behaviour" displayed in financial markets and price changes [Bouchaud, 2001]). The authors applied the above Equation (1) in a log-linear model. The data used by Shih and his co-authors were obtained from the PricewaterhouseCoopers OpVAR database, a database of publicly reported operational risk losses in excess of USD 1 million, which contained over 4,700 loss events at the time of the study. Table 2 indicates that the logarithm of income has significant explanatory power for the operational losses on the sample of Shih et al. (2000), although the value of the R^2 indicator points to a rather weak relationship. According to the authors, the remaining variability of the operational losses can be explained by factors outside of income, such as the quality of risk management and their operational model.

The relationship between operational risk loss events and institution size can be examined from two aspects:

(A) relationship between the aggregate operational risk losses (total amount of operational risk losses pertaining to a specific period) and institution size;

(B) relationship between the two components of the aggregate operational risk level (the impact / frequency parameter) and institution size.

The analysis of these associations may provide a basis for the assessment of the adequacy of the operational risk capital charge. The examination of relationship (A) may be helpful in the allocation of the capital charge if, instead of using an "economic" model, we apply it to institution size by using a "top down" approach. Meanwhile, relationship (B) can mainly assist in the scaling of individual loss events. Below we examine the strength of these correlations relying on Hungarian data available up to 2011 Q1, and compare the results with those calculated by other authors on the basis of foreign banking sector data.

Table 2
Relationship between operational loss size and income, based on the international sample of Shih et al. (2000)

Log-linear model	Coefficient	Standard error	t-statistic	Regression statistics	
Intercept	1.276	0.121	10.51	R^2	0.054
ln(R)	0.152	0.015	10.31	Adjusted R^2	0.054

Source: Shih et al. (2000), p. 2.

[4] The quantitative impact study published by the Basel Committee (so called QIS) focused on the aspect of achievable capital requirement. Based on the gross income-related calibration of BIS (2001), 12 per cent of the Basel I minimum regulatory capital prevailing in 2001 should be allocated as operational risk capital. They deduced this figure from the median of the ratio of reporting banks' economic capital allocated for operational risks to the Basel I minimum regulatory capital (around 12 per cent). In the case of the Standardised Approach, the calculation was based on the operational risk capital allocated to the different business lines.

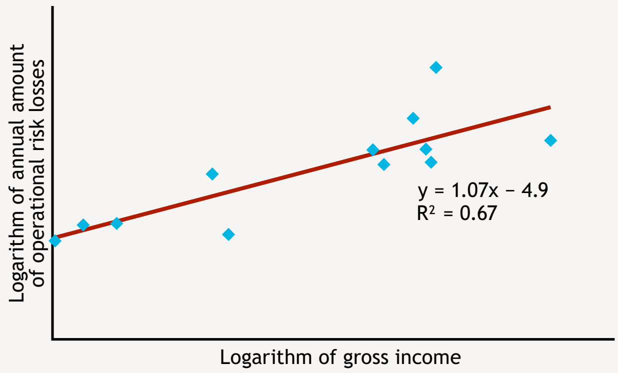
At the end of 2011 Q1, a total of 15 banks applied a method more sophisticated than the Basic Indicator Approach (Standardised / Alternative Standardised / Advanced Measurement Approaches).[5] Given that only these institutions are required to report operational risk loss data under the supervisory data provision, the analysis of the relationship between loss events and institution size was inevitably limited to this group of institutions. Only a more populated sample would allow for a more robust estimate, but since I would like to examine the relationship between losses and institution size in the Hungarian banking system, expansion of the sample size was not an option. Since I ignored statistical robustness for practical purposes in terms of sample size, strictly speaking, the analysis is mainly indicative in nature.

Since a single major loss may generate a great variability in the aggregate losses each year, in our analysis we spread the amount of total losses over four years and compared the result to the gross income pertaining to the specific period. At the same time, data can be analysed by year and by bank as well, but given the relatively small time series, the results should be interpreted with due caution. As there are 13 institutions in our sample of domestic banks for which we have total operating risk loss figures available, we were only able to produce reasonably reliable estimates for this group.[6]

Statistical analysis must usually address the issue of how to exclude extreme values, i.e. outliers. Indeed, without their exclusion, instead of mapping the majority of data, the model would lead to a conclusion highly influenced by the extreme values.[7] If we look at the linear relationship and include the bank suffering an extreme loss, the value of the R^2 indicator will show a 5 per cent correlation. Once we remove the outlier, however, we receive an R^2 indicator of 27 per cent. That notwithstanding, the model will not be significant in either case. As opposed to the linear model, the log-linear model displays a good fit even if the outlier value is retained: Chart 3 presents the data of institutions which have reported an operational risk event in the past four years. There is a strong covariance between the logarithms of gross income and losses suffered, which indicates a rather high R^2 value (nearly 70 per cent), despite the small sample size. Despite the small sample size, the correlation between loss and size is significant (with a p value below 1 per cent).

Chart 3
Relationship between the logarithms of cumulated bank losses and gross income

(cumulative data for four years reported by banks with data available for the entire period of the sample)[8]



Source: MNB.

In addition to the aggregate analysis spread over four years, I also performed a year-by-year analysis. The benefit of this solution is that it allows for the inclusion of those banks in the sample, which were not subject to advanced approaches across the entire time horizon. A total of 17 institutions were thus included, providing a total of 60 observations. This approach does not require the removal of outliers because, despite its smaller explanatory power (an R^2 value of 57 per cent), the resulting model will have greater significance than the previous one. Moreover, both the constant and the linear coefficients are significant.

[5] As a result of the transformations of institutions and qualifications of new institutions to the Advanced Approach, in the middle of 2011 three institutions were subject to the AMA Approach.

[6] Erste Bank and Cetelem switched to the Advanced Measurement Approach from BIA in July 2009 and January 2009, respectively. The transformation of the Hungarian subsidiary of West LB Bank first into Milton, than into Gránit Bank entailed switching from the AMA Approach to the most basic BIA Approach as well.

[7] In addition, extreme values may reveal individual bank information, which this study aims to avoid. Along with the outliers, I also removed institutions whose reported loss value was 0.

[8] The axis displayed in Charts 3, 4 and 5 does not indicate specific values in order to avoid the identification of individual banks.

Chart 4
Relationship between the logarithms of banks' yearly operational risk losses and gross income

Source: MNB.

Obviously, other size indicators may also display a correlation with the amount of operational risk losses for the specific period of time. According to my analysis, correlations examined on the basis of the balance sheet total point to a similar trend to that found during the examination of the relationship with gross income, but the relationship between the balance sheet total and operational risk losses was not stronger than that between gross income and operational risk losses. All of this underscores the relevance of capital allocation methods based on gross income.

If we insert the total gross income of the banking system in the equation of Chart 4 and examine the possible minimum and maximum values with a sufficiently high confidence interval (e.g. by using a 99.9 per cent value, in line with the Basel II framework), we can approximate the size of the required capital charge. However, based on the parameters of the estimated model, the possible sizes will be rather dispersed. This is due to the relatively short time series and the significant dispersion of the data. Therefore, the data available so far do not enable us to establish the adequacy of the existing operational risk capital requirement.

RELATIONSHIP BETWEEN INDIVIDUAL LOSS EVENTS AND INSTITUTION SIZE

Frequency distribution

Basically, three distribution types are used to model frequency in operational risk modelling (see for example: Panjer, 2006): Poisson distribution, binominal distribution and negative binominal distribution. The Poisson distribution has a number of advantages: the expected value and variance of the distribution is equal to the λ parameter, and the sum of probability variables also follows a Poisson distribution; moreover, we can even decompose a random variable into random variables with a Poisson distribution (Panjer, 2006, pp. 109–110.). However, building on one key parameter does not ensure sufficient flexibility. According to my calculations, the fit to the Poisson distribution cannot be ruled out for each bank or for the entire sample, although the fit appears to be better on an individual bank level relative to the industry level sample. In addition, based on the Jarque–Bera test it cannot be ruled out that the distribution of Poisson parameters between banks follows a normal distribution.

To calculate the parameters of the Poisson distribution, in the sample we looked at the database in which banks indicated the number of events observed between March 2007 and March 2011. Due to the short time series of the sample, for each bank we assumed that the annual Poisson λ parameter equalled one fourth of the number of operational risk loss events recognised and reported during the four years. For the 13 banks with a four-year time series this parameter was 4,073 in total.[9]

To explore the correlation between institutional characteristics and frequency, we can analyse the relationship between banks' specific Poisson λ parameters and institution size. Again, our starting point is an exponential-type model:

$$\lambda_i = F_{i1}^{\alpha_1} \cdot F_{i2}^{\alpha_2} \dots \cdot F_{in}^{\alpha_2} \cdot F(\Theta_i) \qquad (2),$$

where λ_i is the Poisson parameter of institution i, Fij is the j institutional factor at institution i, and F(Θ) is an explanatory variable (e.g. the competence of internal risk management).

We can simply perform a log-linearisation for the application of the regression method, and we arrive at the following:

$$\ln(\lambda) = \alpha_1 \ln(F_1) + \alpha_2 \ln(F_2) \dots + \alpha_n \ln(F_n) + \varepsilon \qquad (10)$$

The academic literature (e.g. Na et al., 2005; Dahen and Dionne, 2010) generally uses the asset portfolio and gross income as scaling factors. In addition to these factors (i.e. balance sheet total averages between 2007 and end-2010 [indicated as: "ASSET"] and the average of gross income in the past four years [designated as: "GI"]), I used number of employees (designated as: "EMP") and number of branches as factors pertaining to the size of the operation.

[9] Banks with less than one year of supervisory data provision on operational losses relative to March 2011 were excluded from the sample. The frequency of operational risk events may show great variance for these banks, and thus banks with a shorter time series may distort the estimates.

Table 3
Regressions for the frequency parameter of individual banks' operational risk losses (logarithm of Poisson λ) run with gross income and balance sheet total

Dependent variable: lnLAMBDA	Parameters		Goodness of fit			
	Coefficient	Significance	F	Significance	R^2	Adjusted R^2
Intercept	−35.337	0.000	59.900	0.000	0.678	0.666
lnASSET	−1.568	0.000				
lnGI	2.526	0.000				

	Parameters		Goodness of fit			
	Coefficient	Significance	F	Significance	R^2	Adjusted R^2
Intercept	−6.527	0.007	21.362	0.000	0.269	0.257
lnASSET	0.796	0.000				

Dependent variable: lnLAMBDA	Parameters		Goodness of fit			
	Coefficient	Significance	F	Significance	R^2	Adjusted R^2
Intercept	−22.147	0.000	63.909	0.000	0.524	0.516
lnGI	1.096	0.000				

Since the correlation analyses pointed to a strong covariance between the frequency and size indicators, I decided to run a regression. As a start, I ran a classical model, which includes balance sheet total and gross income as explanatory variables in the model. As explanatory variables, both gross income and the asset portfolio proved to be significant (Table 3).

If we use number of branches or number of employees as explanatory variables we find that the latter (number of employees) has greater explanatory power (Table 4 shows the results for this). Correlation with the frequency parameter appears to be somewhat stronger in the model based on number of employees than in the one based on gross income.

If we substitute the values in each equation with two different sizes (e.g., own size and external size, e.g. $ln(\lambda_1) = c+1.0961 \cdot ln(GI_1)$ and $ln(\lambda_2) = c+1.0961 \cdot ln(GI_2)$, where c is constant), and then raise both sides of the equation to the power of e (Euler's number) and divide them by each other, we arrive at what we may call a scaling function: $\lambda_1 / \lambda_2 = \left(\frac{GI_1}{GI_2}\right)^{1.0961}$. Based on the pattern of this algorithm, depending on whether we look at the relationship to gross income or the number of employees, we can obtain two types of scaling functions for the λ parameter of frequency distribution:

$$\lambda_{own} = \lambda_{external} \cdot \left(\frac{GI_{own}}{GI_{external}}\right)^{1.0961},$$

where GI is the three-year average of gross income expressed in HUF billions. Or

$$\lambda_{own} = \lambda_{external} \cdot \left(\frac{EMP_{own}}{EMP_{external}}\right)^{1.0383},$$

where EMP is the three-year average of number of employees expressed in number of employees.

Severity distribution

The operational risk literature (in line with the actuarial literature) uses several continuous probability distributions for the modelling of severity associated with individual loss events. Normal distribution is not applicable due to small

Table 4
Regressions for the frequency parameter of individual banks' total industry level operational risk losses (Poisson's λ logarithm) run with number of employees

Dependent variable: lnLAMBDA	Parameters		Goodness of fit			
	Coefficient	Significance	F	Significance	R^2	Adjusted R^2
Intercept	−2.438	0.000	185.455	0.000	0.762	0.758
lnEMP	1.038	0.000				

frequency events which nevertheless generate big losses; instead, log-normal distributions are applied. Even though these have a heavier tail, they are easier to handle.

The probability density function of a log-normal distribution is as follows:

$$f(x) = \frac{1}{x \cdot \sigma \cdot \sqrt{2 \cdot \pi}} \cdot \exp\left(-\frac{1}{2} \cdot \left(\frac{\ln(x) - \mu}{\sigma}\right)^2\right),$$

where x=0, 1, 2…

In addition to the log-normal model, the fat-tailed Pareto distribution is a preferred method of modelling operational risk loss. The probability density function of the so-called single parameter Pareto distribution (Panjer, 2006, p. 59.) is the following:

$$f(x) = \alpha \cdot \theta^{\alpha} \cdot x^{-\alpha-1} \text{ and } x>\theta.$$

Table 5 shows reported losses. Although in terms of the number of events, only 23 per cent of the events were related to credit risk, in terms of total losses this ratio is above 50 per cent.

In my analysis, first of all I examined which distribution would be the best fit for this censored database which contains observations at the individual event level. Next, I analysed the correlation between institution size and the parameters of the loss distribution which was deemed to be the best fit on the basis of the parameter estimates. Finally, I analysed the relationship between individual loss events and institution size.

The Quantile–Quantile Chart applied for the visual testing of the distribution fit (not presented separately in this article) indicated that the log-normal distribution was a better fit compared to the Pareto distribution. According to the individual regression results shown by Table 6, the μ location parameter of the distribution has a stronger covariance with size indicators, while the correlation with the σ scale parameter of the distribution is not significant.

Occasionally, even the operational risk literature (e.g. Na et al., 2005; Dahen and Dionne, 2010) fails to find a robust correlation between loss distribution parameters and institution size; therefore, it is often confined to exploring the relationship between single loss size and institution size. This was the case with the article by Shih et al. (2000) referenced above. Again, the explanatory variable used for the logarithm of individual losses was the logarithm of gross income already applied in the case of the frequency distribution. The correlation received on the basis of gross income alone is a relatively weak explanation for the dispersion of losses (R^2 level of around 15 per cent).[10] The pattern of Chart 5 also supports this evidence. The dispersion of the losses sustained by individual institutions is not only the result of institution size, but also, in part, the result of the strengths and, as the case may be, weaknesses of risk management. Moreover, the loss data of individual institutions are widely dispersed. The conclusion

Table 5
Distribution of individual loss event reported for supervisory aims by related risks

	Absolute measures			
	Purely operational risk events	Credit risk-related events	Market risk-related events	Total
Mean (HUF millions)	31.9	104.1	9.2	47.9
Minimum (HUF millions)	0.000	0.078	0.181	0.001
Maximum (HUF millions)	11,408	6,010	305	11,408
Sum (HUF millions)	47,270	51,302	942	99,514
Number of events (units)	1,482	493	102	2,077
	Relative measures (distribution in per cent)			
Sum (HUF millions)	47.5	51.6	0.9	100
Number of events (units)	71.4	23.7	4.9	100

Note: In the report sent by banks for the HFSA the top 10 percent of operational risk event (at least 10 events) is reported. Thus the database is censored.

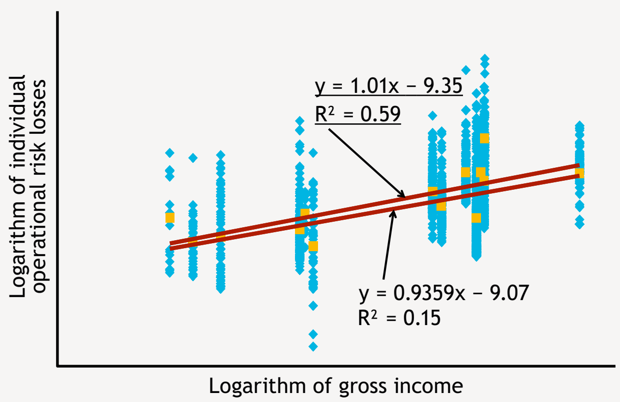
[10] I also examined the dispersion characteristics of the losses associated with different gross income levels. I did not find a significant relationship between the dispersion of losses and institution size.

Table 6
Correlation and strength of the correlation between log-normal severity parameters (calculated by means of the EViews software) and gross income-based institution size

μ parameter of log-normal distribution		
μ	Coefficient	Significance
Intercept	−8.958	0.004
lnGI	0.975	0.002
R^2	0.581	
Adjusted R^2	0.546	
F	16.611	
Significance	0.002	
σ parameter of log-normal distribution		
σ	Coefficient	Significance
Intercept	2.662	0.029
lnGI	−0.101	0.341
R^2	0.076	
Adjusted R^2	−0.001	
F	0.981	
Significance	0.341	

Chart 5
Pattern of the relationship between logarithm of gross income and individual loss data

(the blue dots and the equation not underlined refer to single losses)



Note: The orange squares indicate average loss severity, to which the underlined equation applies.
Source: MNB.

we arrived at is consistent with the result of the study written by Chernobai et al. (2009), in that there may be a weak correlation between the severity of individual loss events and institution size, and loss severity may be determined by the quality of operational risk controls. In Chart 5, I indicated average individual bank values separately. The log-linear relationship between average loss values and gross income is similar in goodness of fit to that indicated for total losses.

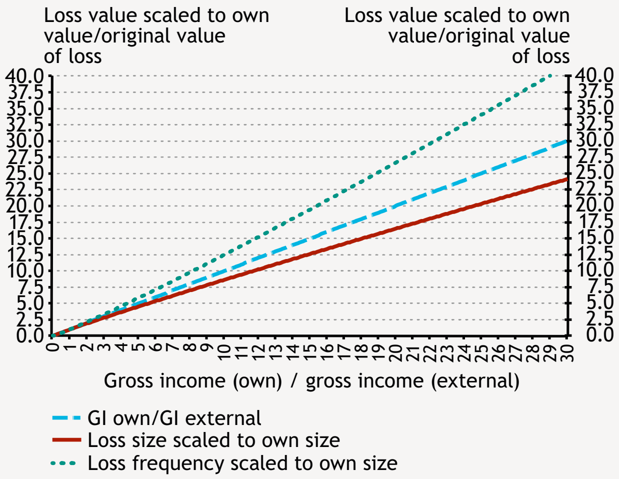
Again, the results enable us to draw up a scaling function, which allows for the scaling of external data to own institutions within the Hungarian banking sector:[11]

$$loss_{own} = loss_{external} \cdot \left(\frac{GI_{own}}{GI_{external}} \right)^{0.9359}$$

Overall, our results suggest that size has a far more significant impact on frequency than on loss severity. The results of the scaling equations are shown visually on Chart 6. While in terms of institution size, there is a nearly linear relationship between frequencies, the correlation is much less increasing with the individual loss severities. Na et al. (2005) arrived at a similar conclusion as regards the bank group level data of ABN-Amro: the scaling characteristic of the aggregate loss per specific period is driven far more by frequency than the scaling characteristic of loss distribution. This phenomenon might be explained by the fact that the increased individual exposure stemming from increased size is compensated by a more systematic operational risk

[11] The scaling function is identified by the same method as applied for the frequency.

Chart 6
Scaling to one unit of loss and loss frequency relative to the original loss owner's size in terms of gross income



management, which is also reflected in the more frequent use of more advanced methods within the group of larger institutions.

In their article, Dahen and Dionne (2010) also analysed the extent to which the severity of individual loss events is influenced by business line affected or by the type of the operational risk itself. By including the relevant dummy variables, I also tested the possibility for applying this to the Hungarian banking sector, keeping only the significant variables in the final equation. As shown in Table 7, the results thus obtained undoubtedly have greater explanatory power than the model based on single losses shown on Chart 5; in other words, business lines and event types are decisive factors in the severity of losses. That notwithstanding, the 30 per cent value of the R^2 indicator suggests that the severity of operational risk losses may be greatly influenced by other factors not included in the model (e.g. internal factors, quality of risk management). Consequently, when scaling losses, it is worthwhile to differentiate by type of loss and line of business rather than strictly by institution size, as long as sufficient data are available.

CONCLUSIONS

Within the boundaries of this article, I analysed the losses of the Hungarian banking sector stemming from operational risks (risks associated with people, systems, processes and external events). Indeed, a sufficient amount of data has been collected since the domestic implementation of the Basel II Capital Adequacy Framework four years ago to allow for worthwhile analysis. The significance of operational risk losses in the Hungarian banking sector is evident in view of the fact that the operational risk losses reported in the banking sector in 2010 amounted to a total of HUF 35 billion, which accounts for nearly 75 per cent of the pre-tax profits of reporting banks. The severity of these losses is significant even compared to the longer-term profitability average. The empirical analysis of the Hungarian banking sector's operational risk data confirms that, similarly to foreign banking sectors and banking groups reviewed in the relevant literature, there is a significant relationship in the Hungarian banking sector between institution size as defined by gross income and total operational risk losses sustained in the specific period. Nonetheless, due to the relatively short time series and the significant dispersion of data, we are unable to establish the adequacy of the existing operational risk capital requirement. Breaking down total losses to frequency and severity we find that, similarly to average loss, the correlation with institution size and the frequency parameter is stronger, and is much

Table 7
Regression on loss size as dependent variable with inclusion of risk type and business line dummies

Dependent variable: logarithm of loss	Coefficient	Significance
Intercept	–7.453	0.000
Logarithm of gross income	0.759	0.000
Internal fraud dummy	1.551	0.000
Clients, products and business practices dummy	0.958	0.000
Damages to physical assets dummy	–1.771	0.000
Commercial banking dummy	1.097	0.000
Retail brokerage dummy	1.141	0.000
Agency services dummy	–1.138	0.016

R^2	Adjusted R^2	F	Significance of the model
0.303	0.301	128.3	0.000

more so than the correlation with size of individual loss events. Event types and business lines have explanatory power as regards the severity of individual losses, but the potential impact of factors not included in the model is still significant. These results could provide a basis for the systemic analysis of operational risk and its scaling from one institution to another, as well as for the enhancement of operational risk measurement methods. In addition to this, it could support evidence for the application of gross income for the simpler operational risk capital allocation methods.

REFERENCES

BIS (2001): *Working Paper on the Regulatory Treatment of Operational Risk*, Basel, BIS, September, URL: http://www.bis.org/publ/bcbs_wp8.pdf, downloaded on 8 June 2011.

BIS (2004): *International Convergence of Capital Measurement and Capital Standards: A Revised Framework*, Basel, BIS, June, URL: http://www.bis.org/publ/bcbs107.pdf, downloaded on 8 June 2011.

Bouchaud, J.-Ph. (2001): 'Power-laws in economy and finance: Some ideas from physics', *Quantitative Finance*, vol. 1 no. 1, pp. 105–112.

Chernobai, A., Ph. Jorion and Fan Yu (2009): 'The Determinants of Operational Risk in U.S. Financial Institutions', *Working Paper Series*, URL: http://ssrn.com/abstract=1360266, downloaded on 8 June 2011.

Dahen, H. and G. Dionne (2010): 'Scaling Models for the Severity and Frequency of External Operational Loss Data', *Journal of Banking & Finance*, vol. 34 iss. 7, pp. 1484–1496.

European Union (2006): 'Directive 2006/48/EC of 14 June 2006 relating to the taking up and pursuit of the business of credit institutions', *Officional Journal L*, 177, 30.06.2006, (recast), text with EEA relevance.

Magyar Köztársaság Kormánya (2007): 200/2007. (VII. 30.) *Korm.rend. a működési kockázat kezeléséről és tőkekövetelményéről*, [Government of the Hungarian Republic: Government Decree 200/2007 (VII. 30.) on the handling of the operational risk and relevant capital requirements], URL: http://net.jogtar.hu/jr/gen/getdoc.cgi?docid=a0700200.kor, downloaded on 8 June 2011.

Na, H. S., L. Couto Miranda, J. van den Berg and M. Leipoldt (2005): 'Data Scaling for Operational Risk Modelling', *ERIM Report Series Research in Management*, ERS-2005-092-LIS, Rotterdam, Erasmus Research Institute of Management.

Panjer, Harry H. (2006): *Operational Risk: Modeling Analytics*, Hoboken, John Wiley & Sons.

Shih, J., A. Samad-Khan and P. Medapa (2000): 'Is the Size of an Operational Loss Related to Firm Size?', *Operational Risk*, January, URL: http://www.opriskadvisory.com/docs/Is_the_Size_of_an_Operational_Loss_Related_to_Firm_Size_(Jan_00).pdf, downloaded on 8 June 2011.