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Operational risk of banks and firm size

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Operational risk of banks and firm size

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Introduction

Owing to modern regulations and internal considerations, financial institutions pay increasingly careful attention to their risks. 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. In the Hungarian legal order the so-called Basel II-based risk management principles were implemented as valid from January 2008. One of the main novelties of the regulatory change is the conscious consideration of operational risk (Government of the Hungarian Republic [2007]). The number of Hungarian academic publications and research papers in the field of operational risk is rather limited, for this reason one of the aims of this thesis is to enrich research on operational risk related to operational risk of the Hungarian banking sector.

In the first chapter following the introduction I summarise the characteristics and regulation of operational risk, the major features of the related literature and risk management practice, as well as clarify the relation between my research and the applied literature.

In the second chapter, I introduce the hypotheses examined under my research providing rationalefor choice of them:

Hypothesis 1: The “Poisson frequency-lognormal severity” model framework generally applied in operational risk measurement practice can be justified in a theoretical, stylised framework as well, and a robust estimation can be made using the observed error points.

Hypothesis 2: The relationship between the operational risk losses incurred in the Hungarian banking system and the institution size is positive.

Hypothesis 3:

Sub-hypothesis A – The more profitable a financial institution is, the more effort it makes to apply more advanced operational risk methods.

Sub-hypothesis B – The bigger an institution is, the more possibilities it has to apply more advanced risk management methods.

In accordance with my hypotheses, in the third chapter of my thesis, I analyse the correctness of the distribution assumptions of the generally applied operational risk measurement's best practice in a simulation model framework, and the framework for loss modelling in a model framework prepared by myself (together with Gábor Benedek). In the fourth chapter, I analyse the relationship between loss data and institution size, primarily related to the domestic banking system data. I also show the possible parameters for rescaling loss data, and the loss data collected by the Hungarian banking system. The fifth chapter is about analysing the relationship between operational risk method selection and institution size.

At the end of the study, I summarize the main results of this thesis, possibilities to apply the results, and further research opportunities.

I. Theoretical background and overview[1]

I.1. Operational risk of financial institutions and related provisions

Management of operational risks has become one of the new central issues in both Hungarian and international financial institutional practice in the recent past. Substantial losses stemming from operational risk events (for instance the recently exposed cases of fraud (e.g. losses caused by unathorised transactions at the UBS became public in September 2011, the fictitious transactions carried out by Jérôme Kerviel, incurring losses of several billion euros for Société Générale, Bernard Madoff's embezzlement of clients' wealth worth tens of billions of dollars or misrepresentation affair related to Goldman Sachs revealed in H1 2010), inadequate compliance with lending standards on the subprime mortgage market, the fraud perpetrated by Nick Leeson at Barings Bank in the mid-1990s (for details on the case, see Jorion [1999]) or the 9/11 terrorist attacks against the WTC in 2001) have contributed to increased attention being focused on this topic. Although the financial and economic crisis which emerged in 2007 highlighted the role of credit and market risk, some events emphasized operational risk. It is undeniable that while "the outside world" may be blamed for losses resulting from financial risks, major part of the operational risks related to the institution's own operation is in connection with its internal operation, therefore the responsibility of the individual institution may be bigger in this respect.

On the one hand, the documents issued by various regulatory bodies serve as a literature source for operational risk management (e.g. BIS[2] [2004], CEBS[3] [2006a], BIS [2009a], BIS [2009b], CEBS [2009], BIS [2011a], BIS [2011b]). The other important source is the academic literature, which can be divided into two on the basis of being methodology- or management-oriented (e.g. Cruz [2002] vs. Davies [2006], Davies [2007]). The related literature on methodological issues is often too formalised, and this less practice-oriented approach also results in some deficiencies in many cases.

[1] This chapter is based on Homolya – Benedek [2007], and partly Homolya [2009a].
[2] BIS is the abbreviation for Bank for International Settlements. The Basel Committee on Banking Supervision (BCBS) operates attached to this institution (not in terms of same organisation, buti n terms of location).
[3] CEBS is the abbreviation for Committee of European Banking Supervisors. Under the European supervisory reform that took place in 2011, European Banking Authority (EBA) became the successor organisation of CEBS.

Regarding methodology, procedures using distribution based models (LDA – Loss Distribution Approach) and scenario based models (SBA – Scenario Based Approach) can be distinguished, while certain authors recommend a mixture of the two. Due to the current practical relevance, the business importance, and the continuous development of the topic, in addition to the literature (articles, academic papers, books), it is by all means important to follow the lectures, presentations, and conference materials published by financial institutions. Besides the relative diversity of the international literature, domestic literature is quite poor; it is limited to only a few studies in addition to the supervisory (HFSA) materials, guidelines. (Amongst these studies, the articles that appeared in Hitelintézeti Szemle 2007, Issue 4 (Scientific Bulletin of Hungarian Banking Association) are especially significant[4,5]).

The first question to ask in connection with examining the management of operational risk is how this category of risk should be defined. The correct definition of operational risk and its appropriate placement among other risk categories is a key element of management: a well-defined category could be applied in a standardised framework. The present paper focuses on financial institutions, although, with some limitations, the methods presented below could be applied to institutions operating in other businesses as well.

The core problem of operational risk had been a lack of an accurate definition acceptable throughout the sector until the end of 1990s. The earliest attempt to create a definition as follows: operational risk is any type of risk other than credit or market risk[6]. Given that this residual definition is a negative, complementary one, it does not help with the practical management of the risk.

It had been recognized by the Basel Committee on Banking Supervision (BCBS) (the secretariat of which is located at the Bank for International Settlement) that the main problem of operational risk management is the absence of a standard definition. The

[4] Available on the Internet in Hungarian, but abstracts are available in English: http://www.bankszovetseg.hu/bankszovetseg.cgi?p=hatodikevf&r=&l=eng&v=7492926929 (date of download: 01.08.2010.)

[5] As far as I know, the first overview in Hungarian language regarding operational risk was prepared by Homolya-Kiss [2001]. Marsi [2002] served as an article providing overview on operational risk related „Basel" developments as well. Furthermore, it is worth highlighting Baki-Rajczy-Temesvári [2004], which analyses operational risks from a special aspect, from the viewpoint of a central bank (i.e. central bank of Hungary).

[6] The literature on risk management defines credit risk as the risk of loss stemming from a debtor's non-payment, while market risk is defined as the risk of loss stemming from a change in the market price of financial assets.

BCBS has therefore developed a definitive framework, which is more and more widely accepted by financial institutions as well as regulators: Operational risk is “the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events”[7]. This definition of the so-called Basel II New Capital Accord framework includes legal risks, but excludes strategic risks and reputation risks. If the entire risk space is considered, risks falling outside the set of credit, market and operational risks could be labelled as “other risk”. It is an interesting question how operational risk is to be distinguished from “other risk”.

A number of different risk typologies have been suggested in the risk management literature. In tune with the regulatory requirements applying to financial institutions, we can at present distinguish business risks.e.g. risks of business environment change, market risks (changes of the value of market positions), credit risks (risk of the debtor’s default) and operational risk[8]. We can also identify risks beyond the set of these main four categories: these are theso-called residual risks, e.g. concentration risk of credit portfolio, which are managed under Pillar 2 of the Basel II regulatory framework[9]. Credit and market risks together constitute the category of financial risk. The management of the four basic types of risk (credit, market, operational and business risks) makes up the process of so-called “enterprise-wide risk management” (ERM). There are, of course, gaps in the 4-tier risk categorization system, for which. liquidity risk is a good example, but these are, however, covered by the ERM framework.

In the interpretation of *Cruz* [2002],[10] the category of operational risk is cost based, while “other risk” is related to “lost revenue”. This distinction, however, fails to provide a sufficiently precise definition[11].

The following table contains some examples for the two types of risk:

[7] BIS [2001], BIS [2004]

[8] Source: ERISK RISK JIGSSAW, risk classification (http://www.erisk.com/Learning/RiskJigsaw.asp, 21st July, 2006.)

[9] Basel II regulation is based on 3 pillars: The First Pillar – Minimum Capital Requirements, The Second Pillar – Supervisory Review Process, The Third Pillar – Market Discipline. Pillar 2 covers concentration risks or interest rate risk of the banking book for example.

[10] Page 286

[11] As an alternative, an operational risk event could be defined as “an incident leading to the actual outcome(s) of a business process to differ from the expected outcome(s), due to inadequate or failed processes, people and systems, or due to external facts or circumstances”. (ORX [2007], page 6). This definition provides a framework for handling an event causing lost revenue because of an incorrectly set interest rate (lower than what would be expected from business policy.)

Table 1 Operational risk vs. "other" risk (based on Cruz [2002])

Operational risk– Loss/ cost based approach	**"Other" risk – Lost revenues**
Legal losses Fees and penalties Regulatory fines Compensation due to late settlement Costs related to failures	Reputational effects Loss of key personnel Strategic events

The Basel Committee (and the Capital Requirements Directive (CRD) in the European Union) focuses on the causes of operational risks; this framework is clearer than the earlier residual definition, and gives concrete subtypes of operational risk. The resulting regulatory typology of operational risk is event based.

This event typology provides a good basis for internal regulation[12]: it defines event types using positive criteria, which allows the systematic identification and management of operational risks.

The loss event categories defined by the regulation are the following (BIS [2004], EU [2006], Government of the Hungarian Republic [2007]):

1. Internal fraud: unauthorised activity, theft and fraud,e.g. not reported transactions (intentional), employee fraud, insider trading.

2. External fraud: theft and fraud, system security,e.g. hacker activity, signature forgery, computer fraud.

3. Employment practice and workplace safety: employee relations, insufficient workplace safety, discrimination issues.

4. Clients, Products and Business Practices: suitability, disclosure and fiduciary, e.g. breach of privacy, money laundering, non-authorized products.

5. Damages to physical assets: disasters and other events,e.g. natural disaster losses, human losses from external sources, terrorism, vandalism.

6. Business disruption and system failures: system outages,e.g. hardware- and software- problems.

[12] However as the practice is getting more and more refined, time by time new issues are emerged related to remaining deficiencies of the current framework for definition of operational risk.

7. Execution, delivery and process management: transaction capture, execution and maintenance; monitoring and reporting; customer intake and documentation; customer/ client account management; trade counterparties; vendors, suppliers,e.g. failures in transaction capturing, incompleteness of legal documents, non-client counterparty disputes.

The event categories mentioned above cover the full space of operational risk events, and the “Basel definition” has gained acceptance by both the banking sector and regulatory bodies.

It is worth comparing the class of operational risk with the other two main risk categories (market and credit risk). The following table summarises such a comparison, and highlights the features of operational risk which cause additional modelling difficulties relative to market and credit risks:

Table 2 Comparison of main risk categories (Based on Elder [2006] and Király [2005])

	Market risk	**Credit risk**	**Operational risk**
Measurability of exposure (Yes/No)	Yes	Yes	Difficult to delimit exposure
Main features	Data richness, high frequency data	Difficulties of statistical estimations, not “well-behaved” distributions	High frequency – low impact or low frequency – high impact events dominate: difficulties in estimations
Risk factors	Interest rates, FX rates, share prices, volatility, commodity prices,	- Probability of default (PD) - Loss given default (LGD) -Exposure at default (EAD)	Probability of event (PE) Loss given event (LGE)
Approaches of risk measurement	Value at risk (V@R), stress testing, economic capital	scoring/ rating systems, PD-LGD models, economic capital	OpRisk VAR, economic capital (lack of full consensus): precise calculation versus assessment (top-down methods, indicators)
Reliability of measurement	Good	Acceptable	Poor

	Market risk	**Credit risk**	**Operational risk**
Risk management techniques	Limits, balance sheet matching, hedging (with derivative positions)	Limit, intake of collaterals, diversification of credit portfolio, securitization, credit derivatives	Process management, system development, insurance, application of risk transfer mechanisms

Operational risks have some further important features not listed in the above table: Operational risks may be endogenous – external factors may coincide with internal factors causing events of extremely high severity[13]; e.g. in the case of the Barings Bank, internal fraudulent activity and external market movements together resulted in extremely high loss.

In addition to the concurrence of internal and external factors, another aspect of the Barings Bank case is the combination of various risk types: the fraudulent broker entered into transactions that can be considered as an abuse, and at the same time an unfavourable price development could be observed, which would have caused huge losses in itself, but the market risk (big price movements) combined with the operational risk (fraud) resulted in bankruptcy. Naturally, combination with credit risk may also cause problems; as it is possible that in addition to the loose credit policy the situation becomes even worse by the failure to comply with internal rules[14].

Strong correlation may appear between reputation risk and operational risk as well. This fact is shown by the study of Gillet et al. [2010], in which the authors describe the effect of operational risk losses that incurred between 1990 and 2004 and became public on share prices. The analysis concludes that significant abnormal returns[15] are present at the time when losses are disclosed, which may ultimately appear in the risk premiums.

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[13] In case of market risk this phenomenom has been been emerged, as endogenous risk. Danielsson – Shin [2002] is a seminal paper in this respect.

[14] The regulation gives clear guidelines for managing interconnected risks: “For a loss which has been accounted for by the credit institution during credit risk capital requirement calculations, no operational risk capital requirement has to be allotted, but the credit institution must record it separately in its books. For operational risk related loss that is also connected to market risk, capital requirement of operational risk has to be accounted for as well.” (8. § (2) in Government Decree 200/2007)

[15] Under abnormal return, empirical financial literature means the difference between expected and actual returns, which is basically caused by the occurrence and disclosure of some event (e.g., the announcement of a fusion, the announcement of losses) (e.g. Rachev et al. [2007], p. 171)

Another interesting feature of operational risks is that a higher level of exposure to them is not accompanied by significantly higher profits, while in the case of market and credit risks, risk exposure and return are positively correlated[16]. This is why examining the presence of risk appetite and determining the level of risk tolerance are interesting subjects in themselves[17].

As I have already pointed it out operational risk management has become one of the new central issues in both Hungarian and international financial institutional practice in the recent past. This trend is mainly determined by the so-called Basel II process (BIS[2004]), the adoption of which has been ambitioned by more than 100 countries. In he European Union, the so-called CRD (Capital Requirements Directive, EU[2006]) referring to credit institutions, investment firms and the groups led by these kind of institutions, valid since 1st January 2008[18], provided the basis for binding implementation of the new regulatory framework by all of the Member States. In Hungary, financial institutions and the groups managed by such institutions must comply with the Basel II regulation based on the new Act on Credit Institutions and Financial Enterprises (Act CXII of 1996 on Credit Institutions and Financial Enterprises), while investment companies and the groups managed by such companies must comply with the new Act on Investment Companies and Commodity Brokers (Act CXXXVIII of 2007 on Investment Companies, Commodity Brokers and the Regulations Governing their Activities). In contrast with the previous practice, the new regulatory framework requires institutions to allocate capital to operational risk, in addition to credit and market risk forming a sort of “buffer” against such risks and reflecting the fact that a larger operational risk event can be fatal for an institution[19].

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[16] Assuming low risk tolerance, due to critical feature of operational risk.

[17] FSA [2007] and Bankárképző [2010] provide an overview on this topic.

[18] EU regulation would have allowed voluntary implementation since 2007, however for instance in case of Hungary legal texts were not prepared and accepted in time, thus earlier application were not a possible option for institutions under the scope of Basel II.

[19] It is worth noting that, in the operational risk literature, there are analyses which consider the capital requirement for operational risk exaggerated, as the provisions do not take into account the process generating the net present value from normal company operation (so-called NPV process). Jarrow [2008] proves this result based on a model. In my opinion, in these types of analyses, a possible error is that the NPV process partially provides collateral for every risk, therefore, we have to apply a certain type of allocation for NPV as well. On the other hand, an important observation is that the operational risk part of the expected loss is also priced in the case of “normal” operation. So, capital charges should be calculated on the uncovered expected loss and the unexpected loss in the case of operational risk as well. The acceptance of the preparation for expected loss is a challenge from the supervisor’s point of view.

Regulation based on Basel II defines three basic methods for calculating the operational risk capital requirement[20]:

- Basic indicator approach (BIA) – the capital charge is 15 per cent of the average gross income inthe previous three years. This method can be used without adhering to separate, precise operational risk management requirements. Gross income is defined as net interest income, net non-interest income, net profit realised on financial transactions, and other income[21].
- The standardised approach (TSA) – the capital charge is 12-18 per cent of the average gross income of the previous three years, according to business line. Data collection and risk management requirements must be fulfilled, i.e. banks must have an operational risk management function which exposes, analyses, measures, reports, and manages operational risk factors. [22]
- Advanced measurement approach (AMA) – in this case, the capital charge is based on actual risk measurement: the extent of one-year 99.9 per cent VaR[23] must be determined. Institutions authorised to use this method have to satisfy strong risk identification, risk assessment, monitoring and risk management requirements. Measurements for estimating risk are not simply based on historical data; internal controls and the business environment must also be captured, with the use of external data as well. The capital charge of the advanced measurement approach, similar in complexity to the ratings-based approach (IRB) applying to credit risk, is the one-year 99.9 per cent VaR. In other words, capital which is capable of covering the losses of all years, the

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[20] Capital requirement signifies the level of regulatory capital providing adequate safety for a bank to be able to withstand possible losses while being able to fulfill its payment obligations, in other words the losses should affect those providing regulatory capital (primarily owners). Regulatory capital, a special term used by banking literature and regulation, is defined as the total of Tier 1 (original own funds) and Tier 2 capital (additional own funds).

[21] Theoretically gross income could have negative value, however „normal" banking operation and three-years averaging do assure in practice avoiding negative values.

[22] The regulation enables banks with large retail and commercial banking activities to use the so-called alternative standardised approach (ASA). In this case, the authorised institution may use 3.5% of the business line's previous three years' average exposure instead of gross income in the two aforementioned business lines. At the same time, the institution has to prove its high level of credit risks, which may lead to high gross income.

[23] VaR is the abbreviation for "value-at-risk". For example, a one-year VaR figure of 99.9 per cent reflects the value compared to which we cannot lose more with a 99.9 per cent probability in one year. The credit institution is able to demonstrate to the competent authorities that a significant proportion of its retail and/or commercial banking activities comprise loans associated with a high PD, and that the alternative standardised approach provides an improved basis for assessing the operational risk.

losses of which are only exceeded every 1,000 years must be allocated with these parameters.

Due to their nature, the basic indicator and standardised approaches are considered "simpler methods". The AMA allows sophisticated risk assessment, determining a capital charge based on the real risk profile. The method of capital requirement calculation based on gross income was determined based on the significant relationship between gross income and annual losses stemming from operational risk, demonstrated by certain studies (of which the most frequently cited is Shih et al. [2000g). However, upon more careful reflection, the simpler methods do not necessarily reflect the profile of operational risk to financial institutions. Although it is logical that if an institution's gross income is higher, then the institution itself is bigger; if an institution suffers a greater loss precisely because of its greater operational risk losses, then its capital charge decreases in the opposite direction of risks. Regarding the accuracy of gross income as proxy for operational risk one could highlight its stability, and three year averaging mechanism helps to smooth volatility of gross income. In this thesis I will test the relationship between gross income and the level of operational risk losses. Of course, it may also decrease the available regulatory capital remaining after the appropriate accounting settlements following the claiming of losses and other items, thereby decreasing the overall level of capital adequacy. Recognising this effect, which materialises perceptibly in the current crisis environment due to falls in profitability, the authorities responsible for creating capital requirement regulations have begun to consider devising alternative indicators in order to determine capital requirement levels which reflect risks better, even applying simpler methods.

The hierarchy between the various methods for determining the capital requirement is not only reflected in the increased requirements and the one-way direction of switching method (by default, one can only progress along the spectrum of approaches from simpler methods towards the more advanced ones, and not vice versa), but also in the amount of the capital charge. The findings of impact studies introducing the new regulation (see for example CEBS [2006]) show that based on general tendencies, the observed banks are better off switching from the basic indicator approach to the standardised approach, and from the standardised approach to the advanced measurement approach, as the amount of capital charge decreases in parallel with the increasing complexity of the method chosen. In the case of certain banks, nevertheless, the capital requirement – which generally decreases as a given method's complexity increases – may show the contrary.[24].

I.2. Risk modelling framework – Stylised facts

Operational risk may be characterised – similarly to other categories of risk – by its frequency of occurrence and the severity of the loss event. Scaling frequency and severity into two subcategories (low or high), we get a 2x2 matrix of risk space. In this case two of the cells will be relevant for us (Table 3):

High frequency - low impact (HFLI): events which are easy to understand and price.

Low frequency - high impact (LFHI): events which are especially difficult to prevent or forecast.

Table 3 Main attributes of operational risk: severity (impact) and frequency (Elder [2006])

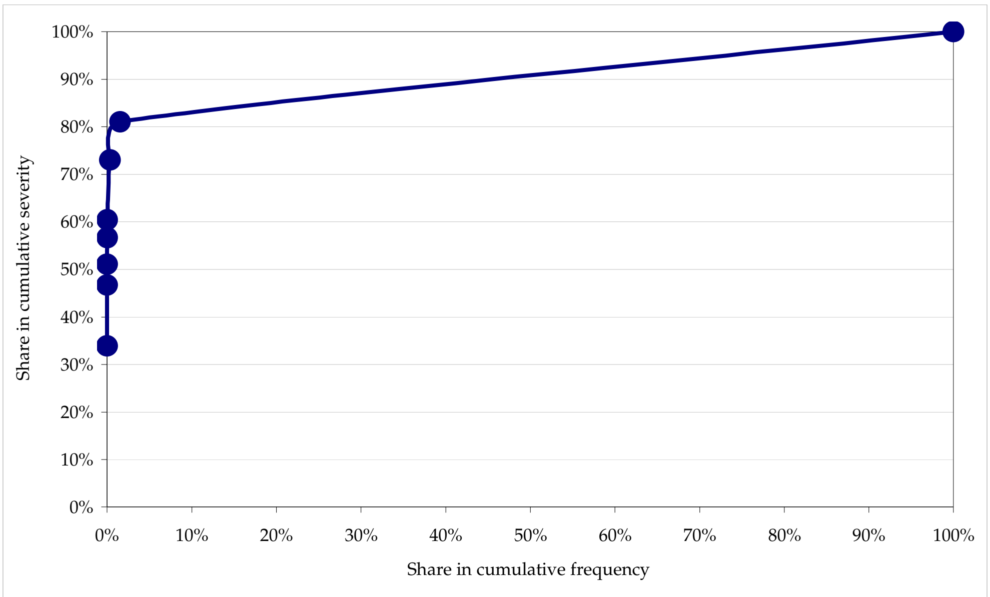
	Low frequency	**High frequency**
High impact	Main challenge for operational risk management. Possible outcome: possibly full disruption. Difficult to forecast, experiences of other sectors (e.g. aviation) can be made use of.	Not relevant – If this is the, the optimal solution may be the suspension of the business.
Low impact	Not relevant	Milder events, could pose significant threats. Events easy to understand and price. Interdependence of events could be a factor to consider.

The conceptual picture presented previously is supported by the empirical data as well. The Basel Committee on Banking Supervision attached to the BIS has already prepared several surveys on the incurred operational risk losses with the involvements of big international banks. Figure 1 shows that rare events dominate the overall loss in the BIS

[24] As I have already mentioned the thesis concenrates on operational risk of commercial banks. As Basel II is the basis for operational management of commercial banks, this thesis use this framework as well. However it is necessary to mention, that operational risk is relevant for financial entitities outside the commercial banking sector as well, e.g. for central banks. The relevance of operational risk of non-financial sector could be well illustrated by the floods in Hungary during spring and summer of 2010 (see e.g. http://www.budapesttimes.hu/index.php?option=com_content&task=view&id=14653&Itemid=219 or http://www.springerlink.com/content/v278623108647t07/fulltext.pdf , and the so-called „red sludge flood" at the beginning of October 2010 (see e.g. http://www.guardian.co.uk/world/gallery/2010/oct/05/hungary) or the earthquakes in Japan in March 2011

[2009a] survey as well: based on frequency, 1.5 per cent of the events generate 81 per cent of the overall loss.

Figure 1 Cumulative frequency and severity share of certain loss event categories in survey of Basel Committee



Source: BIS [2009a]

The complexity and the special features of operational risks (e.g. dual focus on LFHI and HFLI events) make operational risk modelling a complicated task. Appropriate input data – in terms of both quality and quantity – are required to provide a suitable modelling database.

The following questions can be asked:

1. How could the complex features of operational risk be modelled? Is separate modelling of different event categories necessary for robust estimations?

2. Can we find a holistic approach to modelling operational risk?

I do not attempt to give a comprehensive answer to these questions in this thesis, although one of the most important goals of my research is to answer at least some part of these questions.

Although no particular modelling approach is prescribed by the regulators, we do have best practice methodologies industry-wide. Based on the operational risk literature we can distinguish two basic types of modelling method (see e.g. Risk Books [2005], CEBS [2006a]):

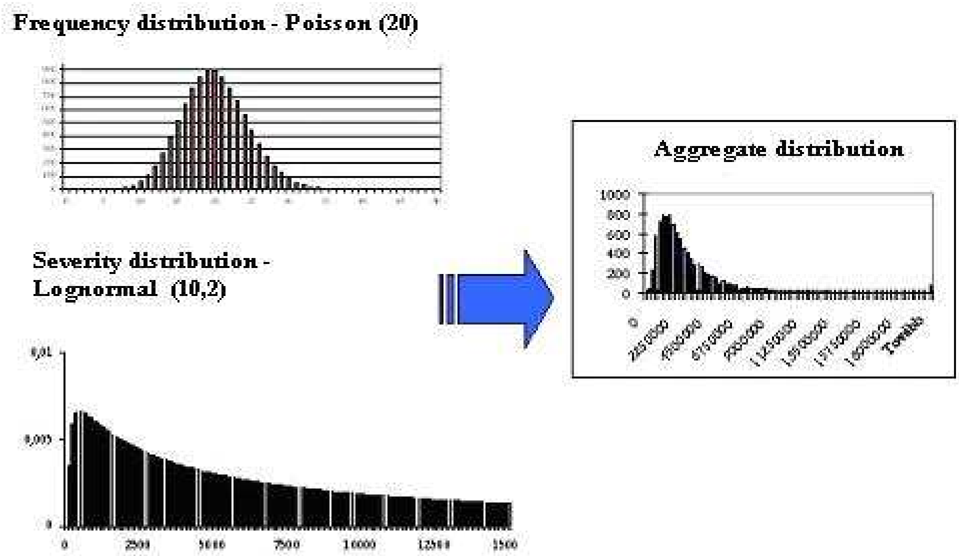
- o loss distribution approach (LDA)
- o scenario-based approach (SBA)

The objective of both methods is to determine the necessary level of economic capital for operational risk and to measure risk profile and related exposure accurately.

Using essentially LDA methods, we determine aggregate distribution (with the aim to model the size of loss per a given unit of time period) based on internal loss data history, sometimes supplemented by loss data coming from external loss data sources. Aggregate loss distribution can be derived from frequency and severity distribution through analytic[25] (partly numeric) or Monte-Carlo-simulation based on convolution. There are two types of formal, analytic convolution techniques: recursive methods may be used with discrete distributions (e.g. Panjer-algorithm); and (Fast) Fourier-Transformation ((F)FT) may be used after discretisation of the given distributions. In practice, however, simulation techniques tend to be used because, although they are time consuming and the sensitivity of the model is relatively more difficult to examine compared to analytic techniques, simulations allow the problem to be more readily structured. (Klugman et al [1997] give a good and comprehensive overview of this modelling approach). The following figure summarises convolution methods and provides an example:

[25] Purely analytic results are available only in case of „well-behaved" distributions. Moreover analytic solutions (e.g. Fourier transformation) are partly including numerical methods.

Figure 2 Convolution of frequency and severity distributions



Source: Own illustration.

The following steps are taken in applying the LDA approach: identification of suitable distributions for both frequency and severity distributions (e.g. Poisson – lognormal model); parameter estimation based on realised loss data; use of goodness of fit tests (GOF tests); and finally model selection and calibration (CEBS [2006], BIS [2009b]). Based on the relevant specifications of the AMA approach, the regulations (BIS [2004], EU [2006]) state that the capital to be held requires a risk measure compatible with a 99.9 per cent confidence interval and a one-year holding period. Note that this is a VaR (value at risk)- type calculation based on the analysis of the aggregate loss distribution. In modelling frequency, mostly more simple distributions (mainly the Poisson–distribution, binomial or negative binomial) are used both in the literature and in actual practice, while severity distributions are usually modelled with asymmetric, fat-tailed distributions, such as lognormal or extreme value (EVT – Extreme Value Theory) distributions [26].

BIS [2009b] demonstrates the modelling practice applied by banks using the advanced method. This document shows that there is a high convergence in frequency modelling, as 93 per cent of the banks surveyed use Poisson distribution, while only 19 per cent use negative binomial distribution (too). (BIS [2009b] description on Page 63, and

[26] In my thesis I do not cover extreme-value distributions in details, as the literature is quite broad in this respect, moreover my contribution to the literature of this topic would be rather limited.

Table 16D) In the case of severity distribution, the survey indicates a higher divergence, banks apply various methods simultaneously: application of one distribution, application of separate distributions for the body and for the tail of the distribution, as well as for the whole distribution. Although only approximately one third of the AMA banks use one severity distribution, the most popular distribution is the lognormal (33 per cent of the complete sample) followed by the Weibull distribution (17 per cent) (BIS [2009b] description on Page 60 and Table 16C).

The other important modelling approach, scenario based analysis, is also a quantitative method. In this approach, stress-event scenarios are identified and operational risk exposure is calculated through the quantitative assessment of these scenarios. Just as with scenario based approaches, the structure of operational risk event scenarios is examined. While the SBA method is a bottom-up approach, the LDA method is a top-down approach in this sense. (CEBS [2006])

Besides the LDA and SBA methods, several institutions use more qualitative, so-called scoreboard techniques because of difficulties in quantifying operational risks, as is recognised by practitioners (Riskbooks [2005]).

In this paper, we endeavour to look beyond the widely used methods of LDA and SBA. These methods focus on the modelling of manifest risks in terms of events, but the analysis of latent risk processes as an interim modelling step is generally omitted[27].

I.3 Operational risk management practice

I.3.1. International overview

The number of published comprehensive surveys regarding the international operational risk management practice is limited. This may be due to the “young age” of operational risk management.

One part of international surveys analyse the capital requirement and the recorded losses (e.g. BIS [2002], BIS [2009a]), while the other part tries to apprehend the best practices (e.g. BIS [2006], BIS [2009b]). The aforementioned surveys conclude that applied operational risk management practice is in line with the recommendations

[27] Cernauskas et al [2010] call attention to this modelling deficiency. The authors indicate that general modells do not cover accurately the dependencies and relationships of risk processes.

regarding the advanced method of regulation. The best practice amongst the institutions is risk management based on the four pillars (internal data, external data, scenario analysis, business and control factors) of risk measurement.

In the literature, we only find a few examples on analysis of the correlation between institution size and risk management practice. Helbok-Wagner [2006] concludes that in the early stages of operational risk management (between 1998 and 2001), the institutions with lower profitability disclosed more detailed data regarding their operational risk profile and operational risk management practice. The authors' explanation to this fact is that more profitable institutions depend less on higher transparency, while institutions with poorer performance can only improve their judgement by more developed risk management and with high-level disclosure. Although OpRisk & Compliance [2008] and OpRisk & Compliance [2009] presents a database consisting of 100 banks in connection with operational risk management data and methods, these OR&C articles do not contain any detailed statistical analysis.

I.3.2. Operational risk practices of Hungarian institutions

Hungarian banks started the systematic management of operational risk mainly as part of the Basel II process. The regulatory framework to be applied compulsorily from the 1st January 2008 (EU [2006]) allows the application of an approach based on a simpler basic indicator approach (BIA), a standardised and an alternative standardised approach (TSA + ASA), and a more complex approach (advanced measurement approach, AMA). A significant part of the Hungarian banking sector first started the collection of operational risk loss data. At first, the added value of risk management was hard to release; therefore emphasis was mainly on regulation and IT initially. Modelling based risk management is in operation only in a few institutions at the moment. Due to the fact that the Hungarian banking sector is typically under foreign ownership, the domestic institutions try to approach operational risk systematically by using the guidelines of parent banks and principles of the "European" "best practice" (HFSA [2005]).

A relatively small amout of comprehensive analysis has been published on the operational risk practice of domestic banks to date. The referred Issue 4 of Hitelintézeti Szemle in 2007 (Scientific Bulletin of Hungarian Banking Association), Issue 4 represents an extensive work, but it focuses mainly on individual experiences. As far as

I know, the operational risk methods used in the Hungarian banking system has been analysed comprehensively exclusively by Homolya [2009a]. The article concluded that the "most advanced" approach for the domestic banking system is the standard approach at present; the major banks (i.e. banks with higher total assets) use this method like a "foyer" of the advanced measurement approach. As it is shown by the analysis later in this thesis, several banks made a step ahead from this approach in the past period.

An important initiative of the members of the Hungarian banking system is the HunOR Hungarian Operational Risk Database, which started its operation under the aegis of the Hungarian Banking Association in 2007. Under this data consortium, 12 banks representing more than 50 per cent of the balance sheet total of the complete banking sector share data with each other anonymously on operational risk loss events having an effect of more than HUF 50,000 incurred loss. This initiative means a huge advantage for the participating banks, as it makes it possible to explore operational risk events specific to Hungary, and creates the possibility of a comparison with institutions likely to be close to each other regarding their operational risk profile. HunOR started its operation so as to have all operational risk loss events after the 1st January 2007 recorded into the database. (The importance of the HunOR database is discussed in more detail in Homolya-Szabolcs [2008].)

I.4. Contribution: relationship between the results of my research and the literature

The measurement of operational risk is dominated by LDA modelling based on realised losses, which examines the already occurred risk events. In my research, I first analyse whether process based modelling on the one hand confirms, with the application of a simulation method, the frequency (Poisson) and severity (lognormal) assumptions frequently used in operational risk modelling, and on the other hand it presents the analysis of a high-frequency database[28]. This is not a typical approach in the methodology articles on operational risk.

[28] This analysis has already been published in Homolya-Benedek [2008].

Second, I examine the relationship between losses and the size of the institutions. Although several articles have been published in international literature analysing a comparison between operational risk losses and institution size to discover the scalability of losses between institutions, but no authors have yet prepared such a survey for the loss data of Hungarian banks. The literature analysing the operational risk data of foreign banks (e.g. Na et al. [2005], Dahen – Dionne [2007, 2010]) concludes the significance of the relationship between cumulative losses and institution size (primarily gross income). However, in these analyses, researchers conclude that the decisive role in the relationship between cumulative losses incurred in the given period and institution size is played by frequency. I analyse this correlation in this thesis for the Hungarian banking system as a first analysis[29] in the relevant literature.

The third issue examined in this study is the relation between the selected operational risk management and capital requirement allocation method and the financial data/ size of the institution (mainly balance sheet total, profitability). Although there exist pieces of the literature (e.g. BIS [2009a], BIS [2009b]) which present overall best practices, but these do not analyse the underlying driving mechanisms. Therefore, as far as I know, my analyses prepared on the international, and on the domestic (i.e. Hungarian) samples are novelties[30].

II. Research hypotheses

Hypothesis 1: The "Poisson frequency-lognormal severity" model framework generally applied in operational risk measurement practice can be justified in a theoretical, stylised framework as well, and a robust estimation can be made using the observed error points.

Because of the rare nature of high impact operational risk events, process based simulation methods may imply added value for loss event forecast. I test the correctness of the Poisson-lognormal model framework most commonly used in operational risk modelling, by assuming a mean-reverting process and using stochastic simulation. The reason I test this very process is, as I already showed in Chapter I.2, that Poisson is the

[29] I published the results of the analysis presented in this thesis in Homolya [2011].
[30] I have already published certain interim results in my own previous publications (Homolya [2009]).

most frequently used framework in modelling the frequency of operational risk events, and, although the divergence of methods is stronger in the case of severity, lognormal distribution may be considered the most common. After the hypothesis test, I analyse, on a sample containing ATM errors, how much the stochastic process back-estimated from errors help adequate risk estimation.

Hypothesis 2: The relationship between the operational risk losses incurred in the Hungarian banking system and the institution size is positive.

A generally valid principle in the case of operational risks is that despite a given risk type is not present in the loss database of a bank; we cannot unequivocally regard the given risk as if it was non-existent. These are the types of risks in the case of which it is common to use expert estimates and scenario analyses, and to consider loss data originating from external databases.

To utilise external data we need to explore correlations that reveal the relationship between the characteristics reflecting institution size and the loss parameters, as a result of which adequate scaling techniques may be applied. (regarding the benefits related to sharing operational risk data Voit [2007] provides a good overview).

For international data, the literature (e.g. Na et al. [2005], Dahen – Dionne [2007, 2010]) empirically supports the correlation between institution size and operational risk loss, but no such estimate has yet been made on a domestic (Hungarian banking sector) sample.

Hypothesis 3: Sub-hypothesis A – The more profitable a financial institution is, the more effort it makes to apply more advanced operational risk methods. Sub-hypothesis B – The bigger an institution is, the more possibilities it has to apply more advanced operational risk management methods.

The fundamentals of my research hypothesis are the examination of the elements of risk management cycles (identification, measurement, monitoring and management) and decision options (unidentified risks versus identified risks, acceptable risks versus unacceptable risks). It is worth examining what are the common characteristics of the financial institutions applying more advanced operational risk approach.

As I mentioned in Chapter I, under the new CRD Directive framework obligatory for every financial institution in the European Union from the 1st January 2008, it is required to separately allocate capital for operational risk based on the simpler BIA or TSA approaches or according to the advanced AMA approach based on modelling. Institutions started their preparation and introduced the methods to be used. However, in the literature, I did not find any analysis on what features characterise the institutions that use more advanced methods. My intuition is that the more successful an institution is, the more advanced risk management methods it uses. The analysis of this hypothesis may be important to understand what might inspire institutions to apply more advanced risk management methods.

The operational risk management method's state of advance can be measured by examining which approach is selected by the institution from the three regulatory approaches (BIA: 1 – least advanced; TSA: 2 – moderately advanced; AMA: 3 – most advanced).

Profitability indicators: we can measure profitability with the return on assets (ROA) and the return on equity (ROE). Moreover it is worth to study the relationship of operational risk approach and instution, primarily balance sheet total.

Table 4 Methodological framework for analysing hypothesis 3

Dependent variable	**Independent variable**	**Immediate variables**	**Methodology**	**Way of analysis**
State of operational risk approach applied	Profitability/ institution size	— Proxy for the complexity of operational risk approach (BIA:1- TSA:2- AMA:3) — Profitability: ROA and ROE	— Collection of individual institutions' data based on annual reports – Regression analysis, test of coefficients, cluster analysis – As dependent variable is ordinal, instead of standard linear regression logistic regression should be applied	– Inductive (sample based conclusion for general terms)

In addition to profitability other aspects may be important regarding the selection of operational risk approach (size based on total assets, liquidity, etc.); therefore I include these variables as well in my analysis.

III. Simulation based catastrophe Modelling [31]

III.1. Testing of appropriateness of Poisson-lognormal model framework generally used in operational risk assessment

Stochastic process based modelling is fairly frequently applied to risk phenomena. The basic idea in the risk modelling literature behind that type of modelling is that factors related to a given risk follow a regular process describable in statistical terms.

What do we mean by the term *stochastic process*? Concisely, we define a stochastic process as a process which describes the changes to a probability variable X.

- Four main factors or parameters determine a stochastic process (*Karlin–Taylor* [1985]): a state-space S (possible value-set of probability variable X, e.g. real numbers);
- an index parameter T (That feature of probability variable X which represents the steps in the process, e.g. if T maps the set of non-negative integers, we have a discrete process);
- probability variables X_t and
- the dependence structure between them: an initial value must be specified, and given the dependence structure, the complete process can be described.

Stochastic process based models may be used for two purposes (see e.g. Chapter 7 of Cruz [2002]):

1. Modelling of changes of latent risk factors: in this case risk factors exceeding a critical level could cause an operational risk event accompanied by some repairing cost or some loss (Sections 7.6-7.9 of Cruz [2002]).

2. Modelling of manifest risk event and amount of loss: in these model applications the analyst is not concerned with the identification of risk factors but only with the loss process. This approach is the subject of a wide range of actuarial literature; see e.g. *Michaletzky* [2001] or Klugman et al. [1997].

[31] Subchapter III.1 and III.2 are based on Homolya-Benedek [2007] and Homolya-Benedek [2008]

Little space is devoted to latent risk factor modelling in the risk modelling literature. If, however, we are to manage the risks rather than merely measure them, latent risk factors play a crucial role because changes in latent factors could influence the development of overall risk exposure and the risk profile reflected in the manifest loss process. In the remaining part of this paper, we present a prototype model for modelling latent risk factors.

The characteristics of operational risk are examined in a simplified model-framework, which could be extended to more complex problems in future phase of research.

We seek a solution to the following problem as a typical case of operational risk failures: how could server disruptions be modelled?

In our analysis we focus on the risk profile of system failure and the factors affecting it.

III.1.1. Operational description of the problem

We have a central server in a bank, the performance of which fluctuates over time. If its performance crosses a critical upper or lower threshold (two-sided constraint[32]), we experience a server disruption. Catastrophe is defined with reference to this phenomenon, which results in a given level of loss.

We have a different type of problem when there are two central servers, where the secondary server is a continuously operating (so-called “hot backup”) server. If a double disruption occurs (i.e., the performance of both servers crosses a critical lower or upper threshold) we have a “crash” event, and in this case the system can only be recovered with some loss.

We make the following assumptions in designing our model:

1. The performance level process follows a mean reversion process: the system reverts back to an equilibrium value, although fluctuation above and below the equilibrium could occur.

2. If the process crosses the lower or upper threshold, we have a catastrophe.

[32] A one-sided constraint (either upper or lower limit) would be more appropriate (overloading or underperforming), but we expect to have better behaved results being symmetric.

3. Following the catastrophe, the process automatically reverts back to the equilibrium point. The staff repairs the error, and the equilibrium state is restored.

4. The loss resulting from a catastrophe is proportional to the system's distance from the critical threshold (linear relationship).

5. The risk processes of both servers follow the same stochastic process. The two processes are correlated with each other, since the two servers are identical and the operation of the bank has an effect on both servers[33]. Due to considerations of risk management and process controlling principles, however, replacement units tend to be available for machines, processes and employees as a backup solution in case of business failure.

We may conclude that a mean reverting type of model is well suited to modelling the above assumptions.

To meet the above requirements, the Ornstein–Uhlenbeck process (the so-called OU process) will be used in our model, which is popular in financial mathematics (because of its relative simplicity). This type of process is commonly known as the Gauss-Markov process as well.

The most widely known application of the OU processes is the Vasicek model used for modelling interest rate movements. (*Baxter–Rennie* [2002], p. 197.). The first application of the Ornstein–Uhlenbeck process was not, however, in financial research but in neurology, where it was used to model neuron discharges, animal movements, and the latent processes behind rusting. Generally, the OU process is used for latent factor modelling, where the manifest process (output, e.g. the data series of events) is known but the latent factor process is unobserved. The OU process allows forecasts to be made (e.g. *Ditlevsen–Ditlevsen* [2006]). Operational risk factors are similar to the factors modelled by the OU process in other areas of science: the latent process is not observed or cannot be observed; only the risk event is explicit.

The Ornstein–Uhlenbeck-process can be defined by the following difference equation (Based on *Finch* [2004], sample process in *Figure 3*):

[33] The correlation could, of course, be weakened by some measures (e.g. separate location), although the full removal of the correlation is not possible (e.g. due to technology or network interconnectedness).

$$\Delta P_t = \eta \cdot (M - P_t) \cdot \Delta t + \sigma \cdot \Delta z \qquad (1)$$

where:

P_t : value of P at time t

η : speed factor of mean reversion,

M: equilibrium rate of process P; performance level process is to revert to this point, and this is the restarting point following a catastrophe.

σ : standard deviation parameter

Δz: Wiener-process with mean of 0, and standard deviation of 1,

ρ : correlation factor (ρ) is defined for a dual process; it represents the alignment of the two processes. (In this case the stochastic elements of the processes are the following: the stochastic element of the first process is σ·dz, while the stochastic element of the second process is $\sigma \cdot (\rho\Delta z + \sqrt{1-\rho^2}\Delta y)$, where dy and dz are independent, identical, standard normally distributed Wiener-processes.

The difference equation of the first process is therefore:

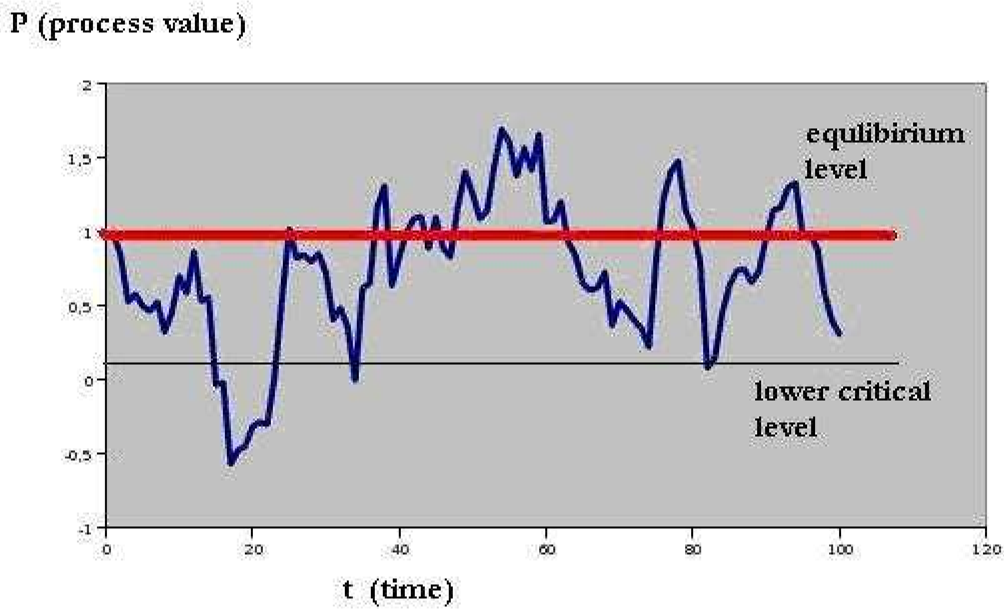
$$\Delta P_t = \eta_P \cdot (M_P - P_t) \cdot \Delta t + \sigma_P \cdot \Delta z$$

The second difference equation is:

$$\Delta R_t = \eta_R \cdot (M_R - R_t) \cdot \Delta t + \sigma_R \cdot (\rho\Delta z + \sqrt{1-\rho^2}\Delta y)$$

Hereinafter in the further part of this thesis, if it is not indicated otherwise the same parameterisation is used for both of the dual processes. Thus $\eta_P = \eta_R = \eta$, $M_P = M_R = M$, $\sigma_P = \sigma_R = \sigma$, concerning initial value $P_0 = R_0 = M$ and (upper and lower) threshold values are the same. In case of parameter deviations for dual process *P* indicates the first process and *R* indicates the second process.

Figure 3 Illustration of Ornstein–Uhlenbeck-process



Source: Own illustration; parameters: equilibrium parameter (M=1), speed of reversion and standard deviation (η=0.2, σ=0.25)

Note: In the process presented on the graph, there is no automatic reversal to the equilibrium level after hitting the critical value

In mathematical modelling "first hitting time" (FHT) is widely analysed with analytic as well as numeric methods. (Ditlevsen–Ditlevsen [2006] is a good reference for this topic as well). The OU process is not constrained, which means that unrealistic negative values could be realised as well. Rather than use limits, we solve this problem by incorporating a step when the process returns to the equilibrium value.

III.1.2. Model results

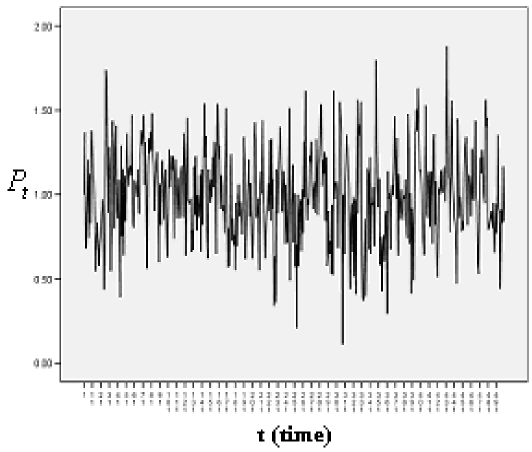
In what follows, the main results of our model are presented: the risk process is analysed and the frequency and severity features related to the catastrophe events are discussed. A single process is examined first, followed by a dual process. A simulation method is used, with realisations of 10 samples over a 10,000 unit long period. In our large-sample simulation, we use 10,000 samples with a 10,000 unit long period for each sample. We model the OU process based on Formula (1) shown above. Statistical analyses are carried out in Borland Delphi 5.0 ® and SPSS 14.0 for Windows ® software. Parameter settings are indicated in the figures; when a parameter setting was run more than once, this is indicated in the text. Parameter settings are used on somewhat arbitrary basis, but in some of the next chapters we show sensitivity analysis as well.

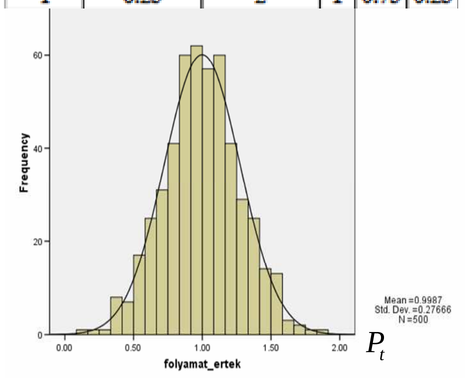
III.1.2.1. The analysis of a single process

An empirical analysis shows that the core process (OU process) values are characterised by normal distribution (as we have expected from the theoretical features of the OU process).

Figure 4 Characterisation of basic OU process with given parameterisation[34]

P start	P lower critic	P upper critic	M	η	σ
1	0.25	2	1	0.75	0.25





Source: Author's calculations (process values, histogram of output values (Y axis is frequency) and parameterisation)

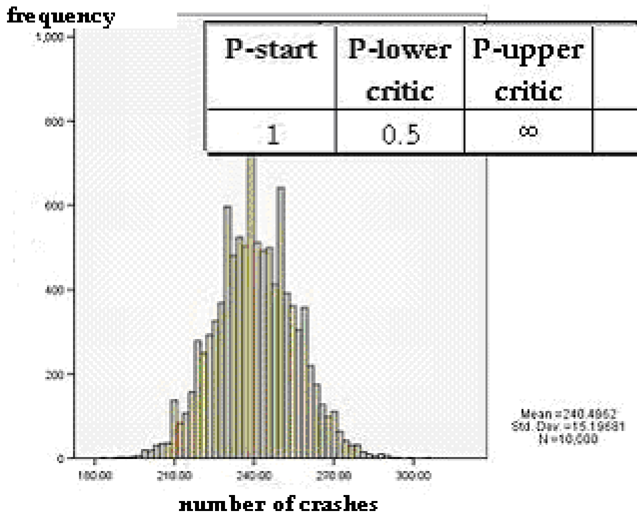
Based on the results of Kolmogorov–Smirnov-statistics (with a value of 0.615) we cannot reject the hypothesis that the values of the process have a normal distribution. With the critical thresholds tightened, the process values would, of course, have a truncated normal distribution.

First of all it is worth examining the frequency distribution of catastrophes. *Figure 5* below shows the frequency features of a process with asymmetric limitations, with only a lower limit applied:

[34] In the latter part of the thesis, more figures showing simulation results are presented. On the figures, small tables are indicating parameter settings with the following notions: Pstart indicates the initial value of the process, P-lower critic: lower threshold value, P-upper critic: upper threshold value M: equilibrium value, η: speed of reversion, σ: standard deviation parameter

Figure 5 Frequency distribution of catastrophe of a process with a given parameterisation

P-start	P-lower critic	P-upper critic	M	η	σ
1	0.5	∞	1	0.75	0.2



Source: Author's calculations

As was mentioned in Chapter II, it is frequently assumed in the operational risk literature that the occurrence of operational risk events may be characterised by a Poisson process. As Figure 5 shows, in our model frequency is characterised by symmetry. It is worth experimenting with different kinds of parameterisations to reveal when the Poisson-like behaviour holds (see e.g. Bee [2006]). Keeping all other parameters shown in Figure 5 constant, three types of limitation settings (broader two-sided, tighter two-sided, tightened lower and unconstrained upper limit parameterisations) have been tried to test goodness of fit to the Poisson distribution:

Table 5 Goodness of fit to the Poisson distribution with different limitation parameters

P-lower critic	**P-upper critic**	**K–S Z**	**Significance (2-tailed)**
0.25	2	2.129	0
0.5	1.5	0.406	0.996
0.5	∞	0.794	0.554

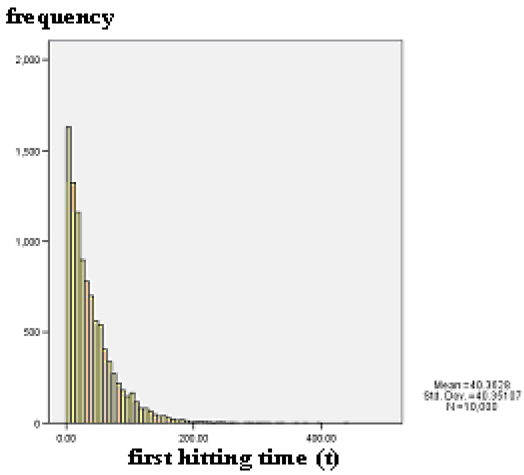
Source: Author's calculations

The Kolmogorov–Smirnov Z statistics presented in Table 5 (the table above) show that with a tightened two-sided limitation and a one-sided limitation the Poisson characteristics cannot be rejected. With a broader limit, however, the Poisson feature cannot be accepted.

As was mentioned previously, one of the most frequently examined topics of probability theory literature dealing with OU type processes is another aspect of frequency, the so-called “first hitting time” (FHT), the timing of the first threshold passage point. Ditlevsen & Ditlevsen [2006] show that it is highly complicated to describe the probability distribution of “first hitting time” analytically. Given a certain set of parameters, FHT follows a Poisson distribution (when the equilibrium value and the critical value are at a sufficiently great distance from each other); while in other cases we find a certain sum of gamma distributions.

Similarly to frequency, we have also examined the FHT distribution with different parameterisations. An example can be seen in next figure:

Figure 6 Distribution of first hitting time with tightened limit parameter setting (critical values: 0.5 and 1.5)



Source: Author’s calculations

We can observe a skewed distribution of “first hitting time” in Figure 6. Poisson or gamma distribution fitting is not adequate, although theoretical works suggest that these distributions could be applied. However, we find a good fit to the Poisson distribution for catastrophe frequency, and the distribution of time between events is known to follow an exponential distribution. We may therefore conjecture that the empirical distribution fits an exponential distribution:

Table 6 Goodness of fit test applied to the fit between the distribution of “first hitting time” and exponential distribution

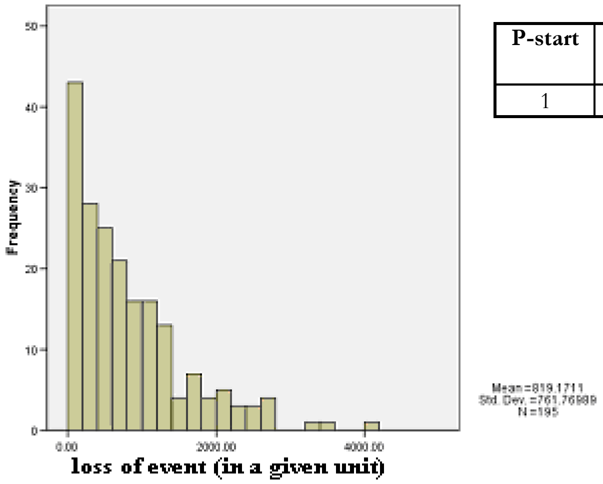
P-start	**P-lower critic**	**K–S Z**	**Significance (2-tailed)**
0.25	2	2.470	0.000
0.5	1.5	0.736	0.650
0.5	∞	4.907	0.000

Source: Author's calculations

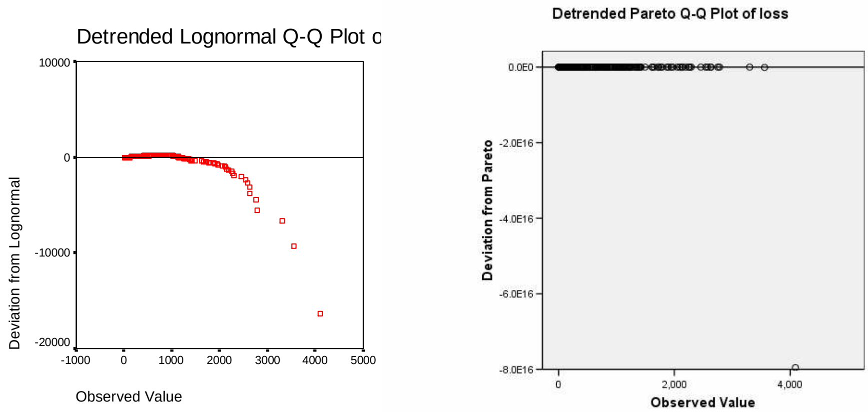
As shown in the table above, the goodness of fit tests (e.g. K–S Z-score) indicate that with tightened two-sided limits the exponential assumption cannot be rejected, while with the other two parameter settings there is no good fit between the FHT distribution and the exponential distribution.

We have also examined severity distribution. The size of loss was determined using the following rules: the value of loss is the absolute value of the excess above the upper limit or below the lower limit multiplied by 10,000. This linear relationship is rather arbitrary; however, in case of other assumption model results would have influenced a priori causing tautological relationships. Applying this assumption, we found well behaved severity distributions fulfilling our expectations of asymmetry and a fat tail. As shown by the Q-Q plot below, fitting to the lognormal distribution is not accepted, but we get a reasonable goodness of fit to the Pareto distribution, given certain parameter settings and assumptions:

Figure 7 Severity distribution and its fit to lognormal and Pareto distribution



P-start	P-lower critic	P-upper critic	M	η	σ
1	0.5	1.5	1	0.75	0.25



Source: Author's calculations

The Pareto distribution is a typical left-skewed, fat-tailed distribution, which nicely reflects the high frequency of low impact events and low frequency of high impact events. The Pareto distribution type, originally used by Vilfredo Pareto to characterise the distribution of wealth among people, is often used in actuarial literature.

The formula of the Pareto probability density function is the following:

$$f(x) = \frac{\alpha \cdot \theta^{\alpha}}{(x+\theta)^{\alpha+1}} \qquad (2),$$

where α is the so-called location parameter, while θ is the shape parameter. (Cruz [2002] page 53; Michaletzky [2001] page 156) [35]

[35] As we demonstrate later (chapter IV.2.2), Pareto distribution has a bivariate type as well, in addition to its univariate type.

As we have seen, the observed patterns of frequency and severity satisfy the prior assumptions on operational risk: Poisson frequency distribution, non-zero skewness and fat-tailed (Pareto) severity distribution, but the lognormal distribution does not ensure adequate goodness-of-fit to severity distribution.

III.1.2.2. The examination of a dual process

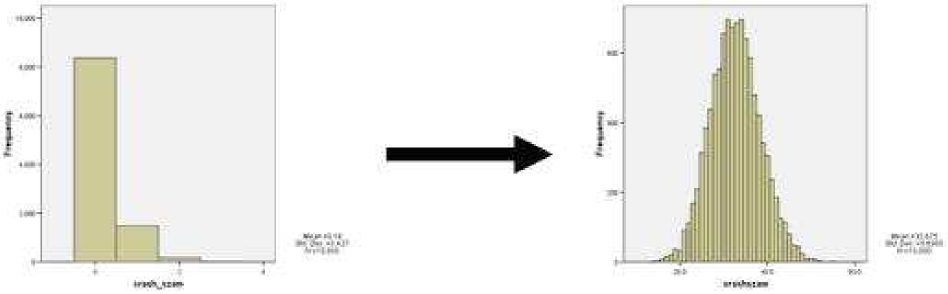
In addition to single processes we have examined the features of dual processes as well.

In the event of the dual disruption of the primary operating system and the back-up system, we are faced with a joint catastrophe, or crash. It is said that at the time of the 11/09 WTC disaster, there was a bank which had its hot system in one of the twin towers, while the hot back-up system operated in the other tower of the World Trade Center. Following the collapse of both towers, the institution was forced to recover data from backup databases to be able to resume its operation.

In our analysis of dual processes, we examine the same features as in the analysis of single processes (frequency of catastrophe event, first hitting time and severity distribution) while focusing on joint catastrophe events (crashes). In our first series of runs, the two processes have equivalent parameter settings and the correlation coefficient is incorporated into the stochastic element.

Trivially, if broader limits are set, fewer crashes will occur, while with tightened limits, there will be more crashes and - as illustrated below – crash frequency will fit a Poisson distribution.

Figure 8 Frequency distribution of joint catastrophes (crashes) with broader limits and tightened limits



P-R		Correlation
Lower critic	Upper critic	ρ
0.25	2	0.2

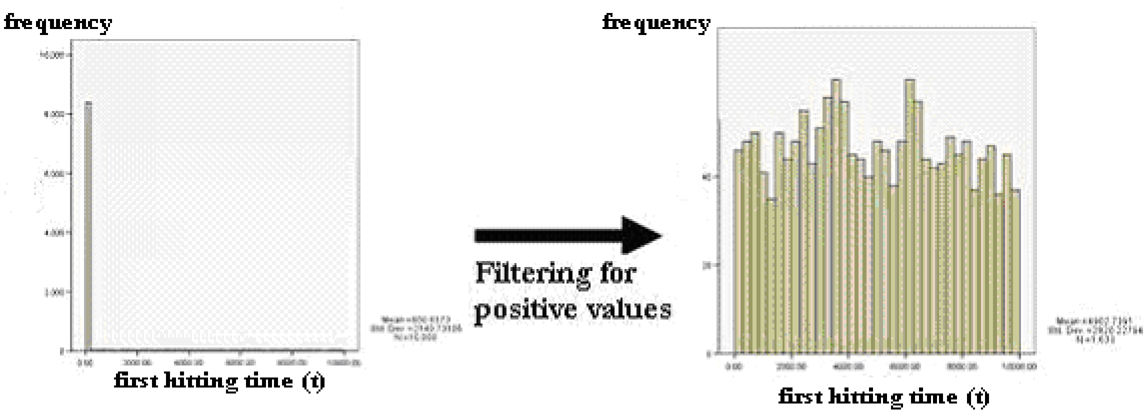
P-R		Correlation
Lower critic	Upper critic	ρ
0.5	1.5	0.2

Source: Author's calculations

With tighter limits (0.5-1.5) the fit of the data to the Poisson distribution cannot be rejected as indicated by the Kolmogorov–Smirnov Z-test statistics (value: 0.455).

The "first hitting time" distribution cannot be identified by visual inspection. As illustrated in Figure 9, only a small number of joint catastrophe events occurred with broader limits, thus for the majority of our samples (8,000 of the total of 10,000) no crashes were experienced at all. Isolating the set of samples which contain crash events, (right side of Figure 9), we get a visually unidentifiable distribution.

Figure 9 "First hitting time" distribution for crash events

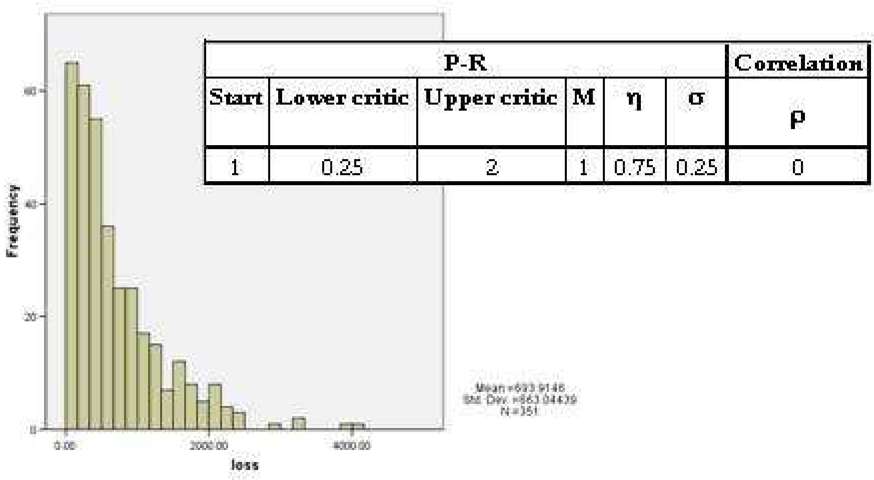


P-R						Correlation
Start	Lower critic	Upper critic	M	η	σ	ρ
1	0.25	2	1	0.75	0.25	0.2

Source: Author's calculations

The other important aspect of catastrophe events is their severity distribution. We use the same loss measure here as we did in the analysis of single processes: the value of loss is the absolute value of the excess above the upper limit or below the lower limit multiplied by 10,000. When the two processes of the dual process are uncorrelated, we get an acceptable fit to the Pareto distribution; meanwhile lognormal fitting is not adequate.

Figure 10 Severity distribution related to dual process with a given parameterisation



Source: Author’s calculations

A Wilcoxon test run in SPSS (comparing the empirical data series to Pareto random numbers) shows that the data do not significantly deviate from the Pareto distribution (value of two sided sigma is 0.195).

As severity distribution may be strongly affected by the degree of correlation, it is highly important to optimize the correlation. This phenomenon is investigated in the process displayed in Table 7: in a zero correlation scenario and in a trial with medium strong correlation (0.5). An examination of the distribution moments reveals that in parallel with the increase in correlation mean, skewness, kurtosis and variance increase as well:

Table 7 Moments of severity distributions for dual process with two correlation values

Correlation	Mean	Variance	Skewness	Kurtosis
0	693.91	663.04	1.73	3.97
0.5	765.69	734.34	2.05	6.21

Note: parameter setting is the same as in case of Figure 9.

This result appears to be trivial, but it can be a starting point for a detailed examination of the relationship between correlation and severity.

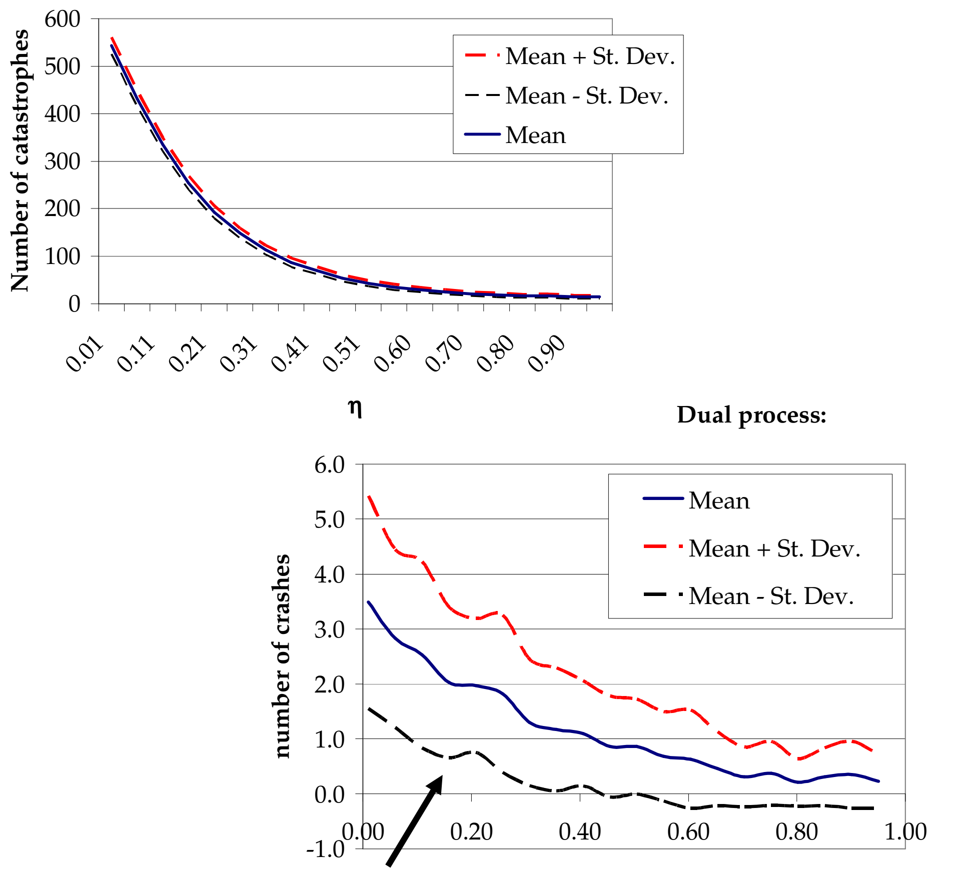
III.1.2.3. The parameter sensitivity of catastrophe frequency

Until this section we have applied fixed parameter settings primarily. In this section the sensitivity of our model is analysed. We investigate the effects of slight changes in reversion speed (η) and correlation strength (ρ) on crash frequency. As we shall see, the results constitute a partial verification of our simulation method, since they confirm our previous hypotheses. The expected number of crashes clearly decreases with an increase in reversion speed for both the single and the dual process models.

Figure 11 Sensitivity of catastrophe frequency for reversion speed parameter

Single process:

P-start	P-lower critic	P-upper critic	M	σ
1	0.5	1.5	1	0.25



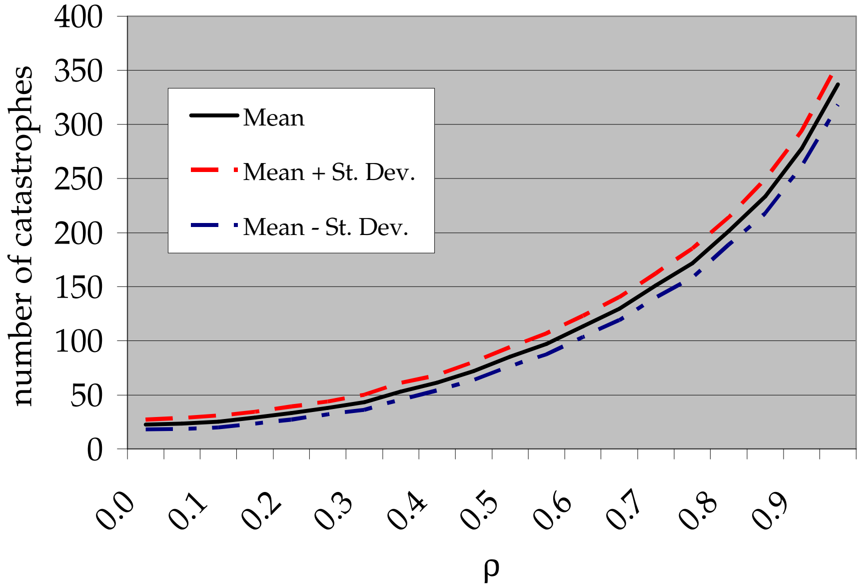
P-R					Correlation	P	R
Start	Lower critic	Upper critic	M	σ	ρ	η	η
1	0.25	2	1	0.25	0.2	0.51	variable

Source: Author’s calculations

Note: The expected number of crashes decreases with an increase in reversion speed (joint catastrophe analysed for the dual model).

Increasing the strength of the correlation has the following effect: the stronger the correlation between the two processes, the higher the estimated value of dual crash frequency. Figure 12 below displays realisations with different correlation parameters with tighter limit interval.

Figure 12 Sensitivity of joint catastrophe frequency for correlation parameter



P-R						Correlation
Start	Lower critic	Upper critic	M	η	σ	ρ
1	0.5	1.5	1	0.75	0.25	variable

Source: Author's calculations

Note: Increasing the correlation increases the expected frequency of joint catastrophes (crashes)

The parameter sensitivity of the processes will, of course, need to be subjected to more detailed analyses in the future. In addition to the speed of mean reversion and the correlation parameter, the analysis of remaining input parameters could be also useful

III.2. Forecasting operational risk in our stylised model framework

One of the important objectives of risk analysis is risk profile based forecasting. The analysis of data on past events is a resource in preparing for the emergence of future risks. As was discussed in Chapter I of this paper, one of the key steps in operational risk analysis is the modelling of low frequency high impact (LFHI) events. Faced with events of this kind, risk forecasting can raise difficulties. We distinguish two basic methods of forecasting risk events (catastrophes): [36]

1. *Based on past occurrences of risk events:* the frequency and the impact (severity) of catastrophe events are analysed.[37] It is assumed that the estimated risk parameters are suitable for forecasting. (This method is equivalent to the so-called "k/n" method used in credit default estimation.) The main features of this approach are that the estimation works with a small sample and naïve forecasting is used, as parameter stability is assumed (the parameters of the past are assumed to remain unchanged in the future, i.e., the future fully mirrors the past).

2. *Based on the exploration of some latent risk process:* previous risk events are analysed and a latent risk process is reproduced. Forecasts are then made with the help of computer simulation methods. The latent risk process is run using flexible modelling assumptions and parameters, and future risk (event and factor) forecasts are generated on the basis of the simulation results. One option is to simulate several replications of the latent risk process (fixed length, hit analysis); alternatively, we may simulate a single very long period (steady-state simulation).[38]

Note that, strictly speaking, the goal of our analysis is not to make forecasts but to find the best estimation – assuming risk profile stability (over time).

When comparing the different methods, the following assumptions have been made: [39]

1. We are familiar with a single run of the latent risk process (for 100, 250 and 1000 unit long periods). The database is a single realisation of a previously defined OU-process.
2. The stability of the latent OU-process may be assumed and the process parameters remain unchanged. These assumptions were also made for the small-sample estimation.

Single and dual processes will now be analysed separately.

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[36] Naturally, we can extrapolate historical data in many different ways (e.g.: moving average, smoothing techniques, etc.), but only two basic methods are examined here.

[37] External loss databases can have a high impact on the processing of previous catastrophe events. (E.g.: HunOR Hungarian Operational Risk Database).

[38] In simulation terminology, a "batch mean" method means that the steady state simulation is split into smaller periods (batches).

[39] Naturally, our restrictions will need to be removed at future stages of the research.

III.2.1. Risk forecasting for single processes

In this section, two different parameter settings are analysed:

1. *Strict catastrophe criterion* (broader tolerance level - low catastrophe event frequency): the lower threshold of crash is set at 0, the upper threshold is 2. The starting value and the equilibrium state of the process is 1. The reversion speed parameter (η) value is 1, and the deviation (σ) is 0.25.

2. *Broad catastrophe criterion* (tightened tolerance level - higher catastrophe event frequency): the lower threshold of crash is set at 0.4, the upper threshold is 1.6 (narrower, symmetric range). The starting value and the equilibrium state of the process is 1, as before. Reversion speed (η) is 0.75 (thus the process will be slower in returning to the equilibrium point), and the deviation (σ) is 0.25.[40]

In the following table we compare the different crash frequencies with the two parameter settings and for different sample sizes and period lengths as it provides good basis for analysis:

Table 8 Crash frequency simulation with the different parameter-settings

1. Strict catastrophe criterion (broader range of tolerance)

Number of simulation	**Sample size (number of runs)**	**Length of period (T)**	**Total number of crashes during the period**	**Estimated crash probability**
1	1	100	0	-
2	1	250	0	-
3	1	1000	0	-
4	10000	100	56	0.006%
5	10000	250	175	0.007%
6	10000	1000	629	0.006%
7	1	10000	1	0.010%
8	1	100000	12	0.012%

[40] The settings of parameter values are rather arbitrary. The main purpose was to create different situations. The goal of the previously presented sensitivity analysis was to demonstrate sensitivity for various parameters.

2. Broader catastrophe criterion (tightened range of tolerance)

Number of simulation	Sample size (number of runs)	Length of period (T)	Total number of crashes during the period	Estimated crash probability
1	1	100	2	2.000%
2	1	250	4	1.600%
3	1	1000	18	1.800%
4	10000	100	19234	1.923%
5	10000	250	48163	1.927%
6	10000	1000	192031	1.920%
7	1	10000	190	1.900%
8	1	100000	1915	1.915%

Source: Author's calculations

The small-sample estimation of crash frequency with the first parameter setting has proved to be unreliable. As no catastrophe event occurs in this scenario, risk frequency would be clearly underestimated.

The simulation method (large size sample) produces more conservative results. That means that without simulation, our risks are likely to be underestimated. The statistical applicability of simulation methods is based on a theorem of probability theory. The Glivenko–Cantelli theorem can be summarised as follows: the empirical distribution function of the observed simulation outputs tends towards the real, latent distribution function with a probability of 1.

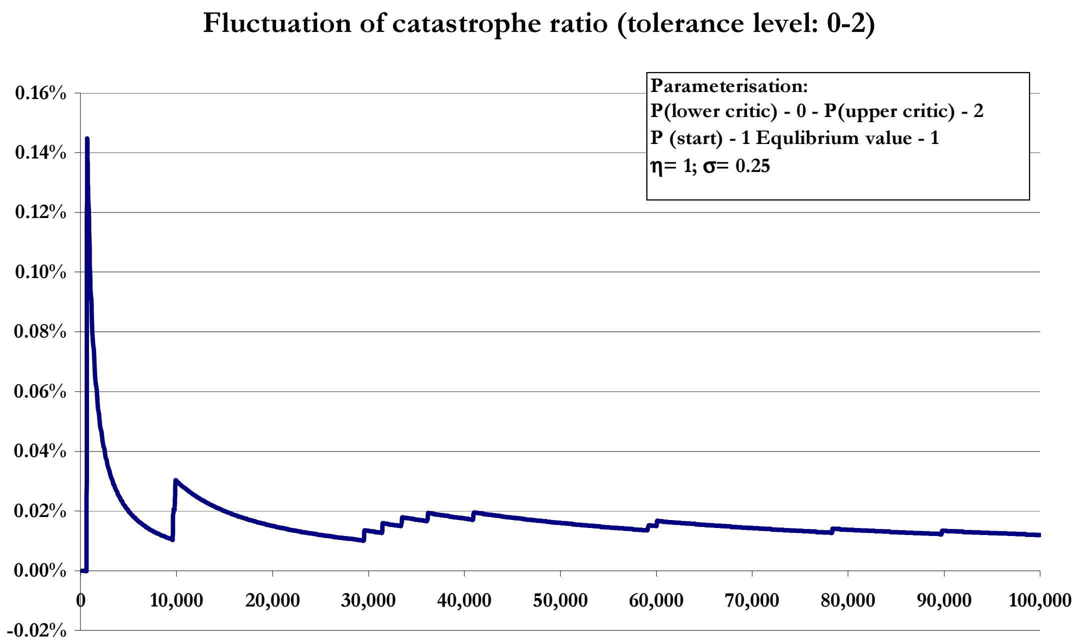
Formally: $P(\sup_t |F_n^*(t) - F(t)| \to 0) = 1$, where $*$ marks the empirical distribution; without any sign the theoretical distribution is indicated[41], where sup is abbreviation of supremum used in mathematics (the least upper bound); *F(t)* distribution function is the theoretical distribution function of t; $F_n^*(t)$ is the empirical distribution function of random variable *t* at realization *n* of the simulation; and *P(x)* is the empirical probability function of event *x*.

[41] Source: see http://www.cs.elte.hu/~mori/statea01.html for example in Hungarian, or http://www.math.uni-leipzig.de/~koenig/www/Kahle.pdf in English.

However, a small-sample observation with the second parameter settings may overestimate the risk where catastrophe events are frequent.

Taking a longer period (T = 100,000 units), we can observe changes in error rate (number of crashes per the period of time that has passed) as a function of the expansion of the simulation period. Taking the strict definition of risk, we find an unexpected, “strange” convergence in error rate. There is considerable fluctuation at the beginning of the simulation run, but later on clear convergence can be observed. (See Figure 13)

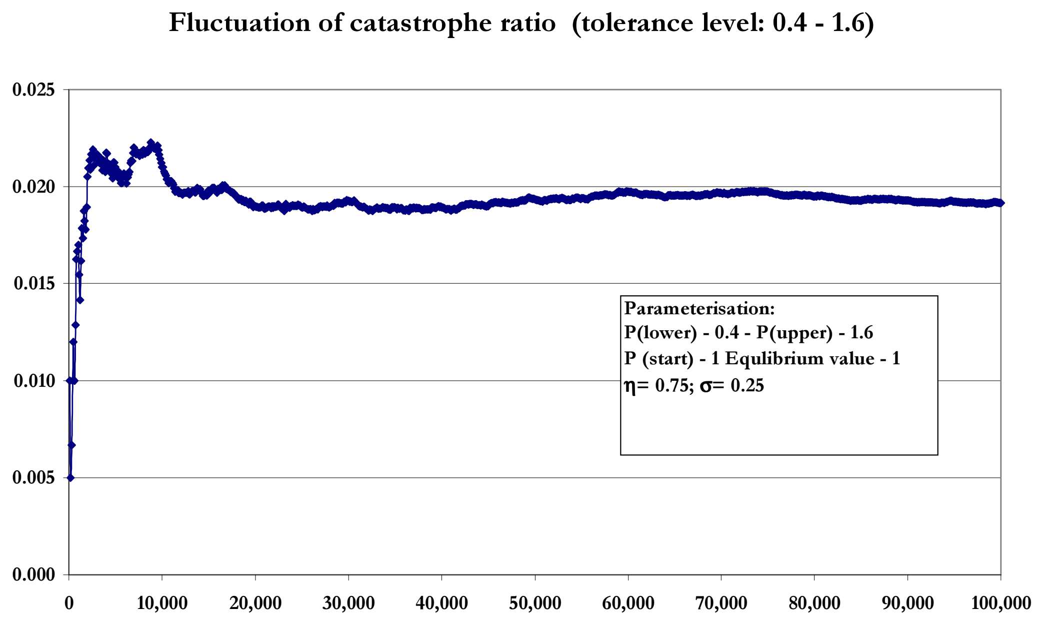
Figure 13 Error- (catastrophe-) rate as a function of sample size with the broader catastrophe criterion



Source: Author’s simulation results

This convergence path is more evident and faster with the stricter catastrophe criterion parameter setting (see Figure 14).

Figure 14 Error- (catastrophe-) rate as a function of sample size with the stricter catastrophe criterion



Source: Author's simulation results

The forecasting of the size of loss affected by a single crash process is a similarly interesting problem. Let us suppose that the loss is still positively correlated with the distances from the tolerance range. The major characteristics (moments) of the impact distribution function are shown in Table 9:

Table 9 Simulation results of the impact (severity) forecasts for a single process with the two parameter settings

1. Strict catastrophe criterion (broader range of tolerance)

Number of simulation	Sample size (number of runs)	Length of period (T)	Average	Standard deviation	Skewness	Kurtosis
1	1	100	No catastrophe	No catastrophe	No catastrophe	No catastrophe
2	1	250	No catastrophe	No catastrophe	No catastrophe	No catastrophe
3	1	1000	No catastrophe	No catastrophe	No catastrophe	No catastrophe
4	10000	100	479.34	462.60	2.17	5.91
5	10000	250	496.77	538.41	2.56	8.75
6	10000	1000	553.02	507.58	1.52	3.05
7	1	10000	111.15	0 (1 catastrophe)	0 (1 catastrophe)	0 (1 catastrophe)

Number of simulation	Sample size (number of runs)	Length of period (T)	Average	Standard deviation	Skewness	Kurtosis
8	1	100000	642.29	616.82	0.67	–0.74

2. Broader catastrophe criterion (tightened range of tolerance)

Number of simulation	Sample size (number of runs)	Length of period (T)	Average	Standard deviation	Skewness	Kurtosis
1	1	100	1019.16	114.67	Number of joint catastrophes < 3	Number of joint catastrophes < 4
2	1	250	664.61	417.10	0.62	1.19
3	1	1000	1207.82	1137.91	1.60	2.84
4	10000	100	865.24	806.35	1.60	3.21
5	10000	250	867.48	799.88	1.59	3.35
6	10000	1000	877.29	784.18	1.52	2.87
7	1	10000	819.65	766.29	1.37	1.35
8	1	100000	849.85	790.31	1.74	4.55

Source: Author’s calculations

The results of the impact (severity) analysis are similar to those of the frequency analysis. With low frequency catastrophes, a small sample size may lead to an underestimation of severity, while with high frequency catastrophes, severity may be overestimated with a small sample size (based on the moments). However, comparing the simulations where 10,000 small samples are analysed, we see some increase in the estimated risk.

III.2.2. Risk forecasting for a dual process

The characteristics of joint crash processes are worth being analysed. In this section we conduct this. Joint catastrophe (crash) frequency forecasting on the basis of a small sample poses difficulties.

Once again, two different parameter settings are used:

1. *Two strongly correlated processes*: the lower threshold of a crash is set at 0.1, the upper threshold is 1.9. The starting value, and the equilibrium state of the process, is 1. The reversion speed parameter (η) value is 0.75, the deviation (σ) is 0.25. The correlation (ρ) is 0.8.
2. *Two weakly correlated processes*: the lower threshold of a crash is 0.1, the upper

threshold is 1.9. The starting value, and the equilibrium state of the process, is 1. The reversion speed parameter (η) value is 0.75, the deviation (σ) is 0.25. The correlation (ρ) is 0.1.

In the weakly correlated scenario, the frequency of crashes is low, just as we expected. The results are summarised in the table below.

Table 10 Simulation results of forecasting for a dual process with two different parameter-settings

1. Two strongly correlated processes (correlation = 0.8)

Number of simulation	**Sample size (number of runs)**	**Length of period (T)**	**Total number of joint catastrophes (crashes) during the period**	**Estimated joint catastrophe (crash) probability**
1	1	100	0	-
2	1	250	0	-
3	1	1000	1	0.1000%
4	10000	100	92	0.0092%
5	10000	250	242	0.0097%
6	10000	1000	1066	0.0107%
7	1	10000	1	0.0100%
8	1	100000	11	0.0110%

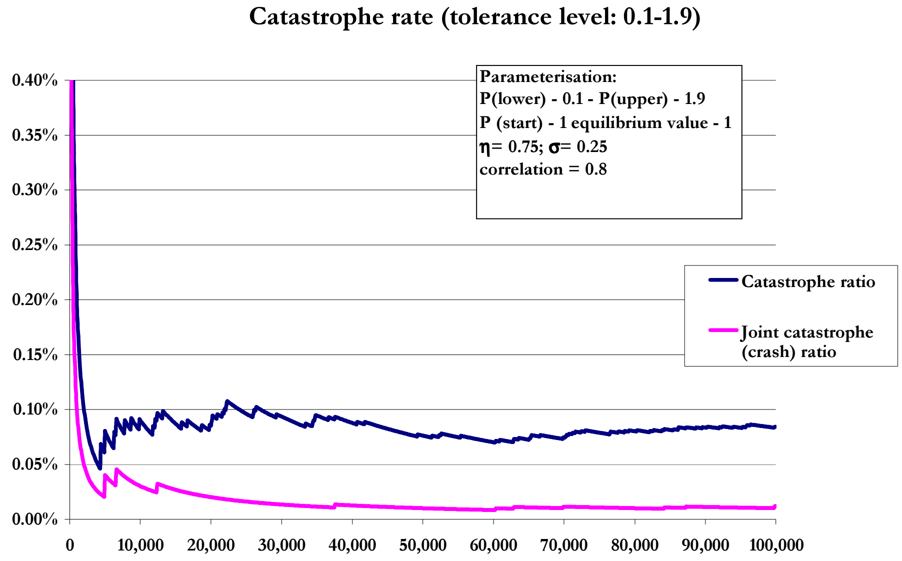
2. Two weakly correlated processes (correlation= 0.1)

Number of simulation	Sample size (number of runs)	Length of period (T)	Total number of joint catastrophes (crashes) during the period	Estimated joint catastrophe (crash) probability
1	1	100	0	-
2	1	250	0	-
3	1	1000	0	-
4	10000	100	0	-
5	10000	250	3	0.0001%
6	10000	1000	8	0.0001%
7	1	10000	0	-
8	1	100000	0	-

Source: Author's calculations

The probabilities of both single and joint catastrophes are analysed in case of dual processes as well. When the correlation is stronger, a higher level of deviation and slower error rate convergence can be observed. On shorter term larger volatility is observed, but later convergence proves to be obvious and faster (see *Figure 15*).

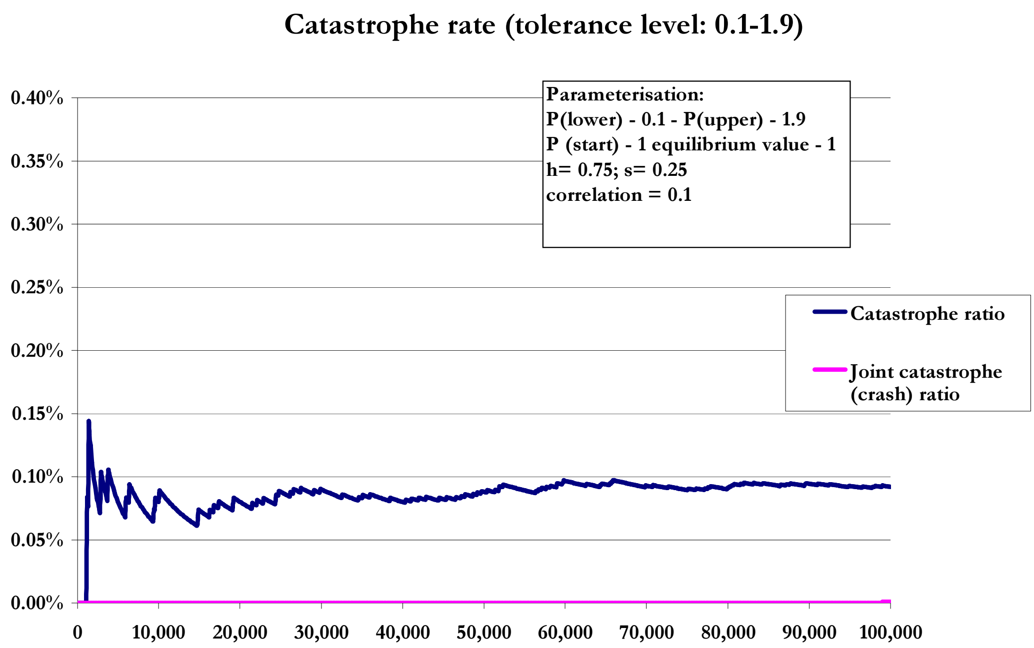
Figure 15 Error- (catastrophe-) rate as a function of sample size, for joint catastrophes (crashes), with stronger correlation



Source: Author's simulation results

With a weaker correlation, convergence proves to be more obvious and faster *(Figure 16)*. As we can see, the joint catastrophe (crash) rate stagnates at 0%. This suggests that a larger sample should be used when the correlation is weak. As the following figure shows crash ratio remains constantly on 0 level. However, in case of larger sample the significance of crash ratio's deviation from zero might be very low.

Figure 16 Error- (catastrophe-) rate as a function of sample size, for joint catastrophes, with weaker correlation



Source: Author's simulation results

After the analysis of the forecasts' characteristics I will apply the modelling framework presented in this thesis for analysing ATM failures.

III.3. Application of stochastic process based modelling for ATM failures

Automated teller machines (ATM) play key role in nowadays' financial infrastructures. As handling cash with machines became easier and easier, and as well as more secure. In this section we provide a short analysis of the empirical behaviour of ATM downtimes, which serves as a basis for more detailed analysis to be conducted later in time. OTP Bank disposing the largest ATM network in Hungary provided ATM downtime data for this empirical analysis.

An ATM can be down due to planned (e.g. planned maintenance) or unplanned (e.g. breakdown, cash shortage) reasons. From the aspect of operational risk, the breakdown-type events are important for us. Although for example cash shortage has major importance regarding ATM operation characteristics, we may not consider inadequate forecast of money usage and money demand as an operational risk issue, rather a financial/liquidity risk issue or a strategic, reputation risk. It would be worth dedicating a separate study to model cash to be loaded into ATMs and the frequency of reloading, but this is outside the focus of this study. In the same way, planned maintenance may cause inconvenience for the clients, but it can improve operational reliability prospectively.

Our initial database contained observations regarding 485 ATMs for a period of six years (2,221 days). In the first section of the observation period, our observations were incomplete in several cases, and some ATM machines were changed as well. Therefore, we faced an unbalanced sample in our panel-type[42] database, that is we did not have the same amount of observations for each day, and certain ATMs were or were not observed at certain times. In order for us to get a balanced panel database, days with only a small amount of ATM observations have been screened, as well as those ATMs of which there were only a few observations.

As a result of the executed data cleansing algorithm, we got a panel database with the following characteristics:

Time horizon: spanning over a period of 5 years, a total of 1,056 days in the sample. For the sake of our analysis, we consider the successive days in the database as if they were days after one another. This may imply some bias, but this can be ignored for the sake of this analysis.

Number of ATMs: 208.

Of the variables used for ATM monitoring in the analysis database, we use date (datum), ATM code (atm_kod), as well as a binary variable signalling normal operation (normal, = 1 in case of normal operation, = 0 in case of abnormal operation), and failure (= 1 in case of a failure, = 0 in case of no failure). It is worth noting that an ATM with no malfunction may show signs of abnormal operation, since we only regarded cases resulting from operational risk events as errors, as indicated previously.

[42] Thus our data have time and cross sectional horizon at the same time.

Based on the error files, we included the following seven problems in our error definition:

- ATM downtime
- Cash emission error
- Communication error
- Dispenser error
- Error of bankcard reader sensor
- Failure of ATM response (polling)
- Network failure

It is important to notice that the ATM error's within days and intraday length have not been indicated in the received register files. Therefore we are only able to analyse the existence of the error, but not its length.

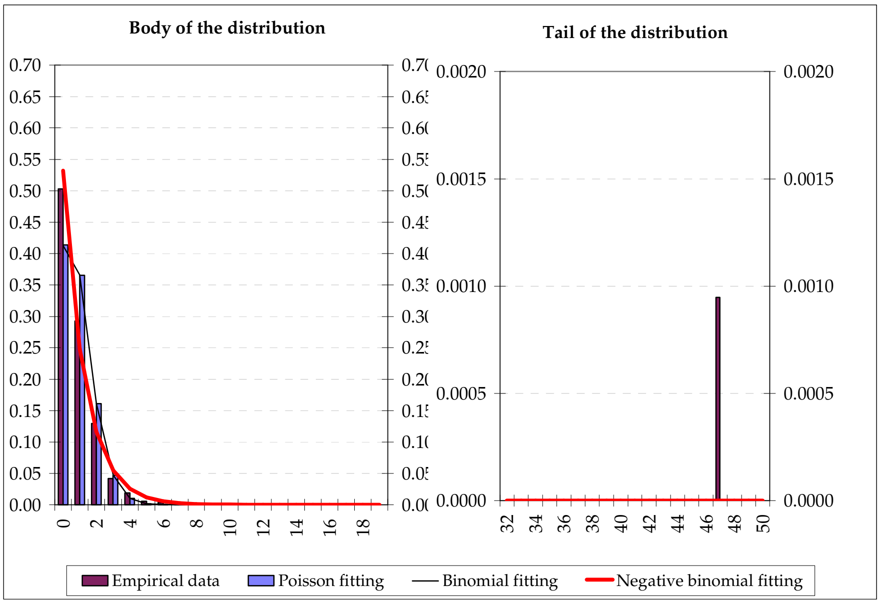
The frequency of the occurrence of ATM failures shows a relatively high variance during the 1,056-day period. Within the observation period, the typical value of ATM errors per day is between 0 and 4, this error frequency interval occurs on at least 10 days. At the same time, there is a day with an extreme value in the observed sample: 47 ATMs, that is 22.5 per cent of all the ATMs failed on that given day.

Table 11 *Descriptive statistics of ATMs with error on a given day*

Observations (in days)	1056
Range (Maximum - minimum)	47
Minimum	0
Maximum	47
Average	0.88
Standard deviation	1.84
Skewness	15.49
Kurtosis	372.31

As previously indicated, the most commonly applied distributions to model the frequency distribution in operational risk practice are the Poisson, the binomial, and the negative binomial distributions. Figure 17shows each of the distribution types fitted on the observed frequency distribution. None of the distribution types were able to fit well due to the extreme outlier of errors in one day. However, it is unambiguously noticeable that fit of the negative binomial distribution is the most adequate (according to the statistical tests, visual inspection, and the fact that variance of our empirical distribution is higher than its expected value).

Figure 17 *Distribution of number of ATMs with error on a given day*

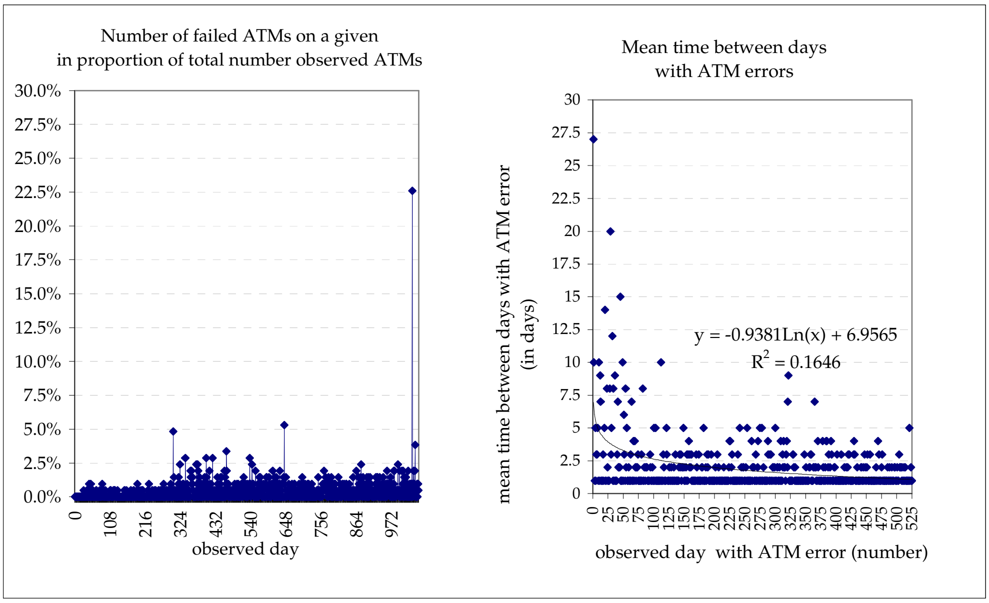


Note: Each distribution is estimated by Maximum Likelihood Method based on Chapter 11 of Panjer [2006]. X-axis shows number of ATMs with errors on a given day, while Y-axis shows the distribution among number of days.

Based on the time course of Figure 18, it seems that the frequency of occurrence of an error and the number of failed ATMs on the given day increased as time passed. Trend fitting does not confirm this trend. But in line with this hypothetical phenomenon, the right panel of the figure referred implies that the time between the individual days with errors shows a decreasing trend (I used logarithmic trend), though a 16 per cent R^2 cannot be regarded as a strong correlation on its own. Thus, the bathtub curve[43] applied frequently in reliability theory cannot be observed regarding error frequency. That is, it is not apparent that error frequency was higher in the "early" period than it is in the observation period. A methodology issue may simply account for the diversion from the "bathtub curve". On the one hand, the individual ATMs are not in the sample from the beginning of their life, and on the other hand, related to this, data are observed with time truncation. Furthermore, the monitoring method of ATMs may have improved as well.

[43] The main point of the "bathtub" curve (see for example Figure 1 in McConnell-Blacker [1999]) is that failure rate is high at the beginning of the period, then it gradually decreases ("learning period") and levels off to reach a stable rate ("maturity period"), and finally, at the end of the useful life, failure rate starts to increase once again ("wearout period").

Figure 18 *ATM failures in time series and mean time between days with ATM errors*



If we want to model the frequencies in connection with ATM errors, the question may arise whether we make estimation for the latent process from the error occurrences based on the basic model presented in the previous chapter, or we prepare our estimate based on the frequencies of failure occurrences.

Using the model framework presented in the previous chapter, the failure of ATMs can be analysed in a model framework where our process has an upper limit and below threshold. Therefore, the underlying latent process starts from 0, has a 0 equilibrium level, and the adequate operational state falls between minus infinity and plus 1. If the latent process breaks out from the band of adequate operation, an error occurs, that is the process stops.

We can use two approaches to estimate the model: first, assumption on the observed distribution, and second, modelling from the back-estimation of parameters of the latent process. Making an assumption on the observed frequency naturally implies a much simpler calculation than the back-estimation of the latent process.

First, let us look at the error frequency resulting from our observations! The negative binomial distribution fits best to the frequency of the analysed ATM failures. At the same time, it is worth noting that according to our results regarding the simulation of our basic model, we cannot reject a one-sided limitation, or, in case of a stricter limit, the Poisson-based error frequency. This result is congruous with the results regarding first hitting times, namely the elapsed time between the occurrences of individual errors. As it was referred to in the article of Ditlevsen–Ditlevsen [2008] (p. 171), in case of a one-sided process with a starting and an equilibrium value between limits (so-called "subthreshold" regime), first hitting times follow a Poisson point process, or a process where the number of events occurring in any given time period follows a Poisson process. The article of Wan-Tuckwell [1982] for example contains the analytical results. The authors demonstrate it in an analytical way shows that if we have a process with a starting and an equilibrium value between limits, first hitting times follow an exponential distribution; therefore the frequency of occurrence of events follows a Poisson distribution.

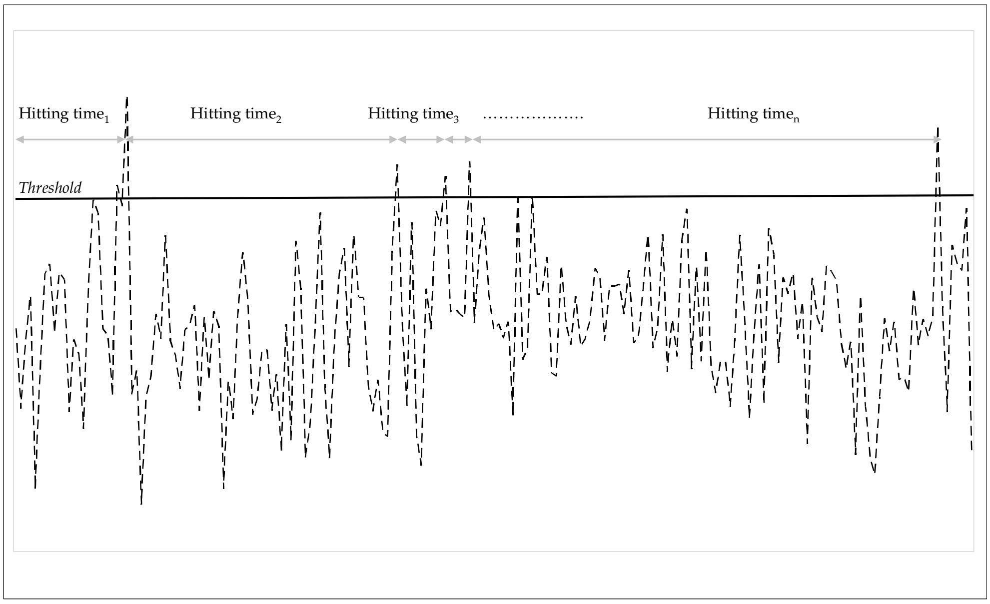
The estimation based on Poisson distribution is simple to carry out, as it can be done based on the average occurrence, that is $\hat{\lambda} = \bar{x}$. As *Table 12*shows, the average of the Poisson-estimates made for 208 ATMs results in a λ estimate of 0.42 per cent in the case of a full sample observation. On the other hand, if we only use the first half of the sample, we get a 0.3 per cent λ estimate. So if we made an "out-of-sample" estimate from the first half of the sample, we would underestimate the error frequency by approximately one third. While 932 ATM failures were observable on the full sample, only 326 ATM failures occurred in the first half of the sample. If we use the parameters of the negative binomial, we get a result equivalent to the estimate based on Poisson if we estimate the distribution with the method of moments (on the full sample: β = 2.85, r = 0.0015, on the first half of the sample: β = 0.93, r = 0.0032), that is, implicitly, we would underestimate the errors in the second half using the first half of the sample.

Table 12 Fitting of daily error frequency

Daily error frequency	Mean	Standard deviation	Minimum	Maximum	Median	95% percentile
Full sample (1056 observations)	0.0042	0.1278	0.0000	0.0208	0.0038	0.0085
Halved sample (first 528 observations)	0.0030	0.0757	0.0000	0.0379	0.0019	0.0095

In addition to the simple Poisson-based estimation, we may consider making an estimate by back-estimating the parameters of the original process from the elapsed time between observed errors. Figure 19 shows the nature of correlation between observed errors and the latent process. Besides we can try back-estimating the parameters of the original process from the observed errors. Below, we make an attempt to do this.

Figure 19 *Hitting times and stylised latent process*



Ditlevsen-Ditlevsen [2008] showed that this estimation approach has major importance in the quantitative analysis of the nervous system (discharge of the neurons), and shows an estimation procedure. The following integral equation serves as the basis of the estimation:

$$\Phi\left(\frac{\alpha(1-e^{-s})-1}{\sqrt{1-e^{-2s}}\cdot\beta/\sqrt{2}}\right)=\int_0^s f(u)\Phi\left(\frac{\alpha-1}{\beta/\sqrt{2}}\sqrt{\frac{1-e^{-(s-u)}}{1+e^{-(s-u)}}}\right)du \quad (3)$$

where, following the notation of the previous chapter: $s=t\cdot\eta\,;\alpha=\frac{M}{S}$ (where S is the threshold value); $\beta=\frac{\sigma\sqrt{1/\eta}}{S}$ (source: equation (25) in Ditlevsen-Ditlevsen [2008]).

According to Ditlevsen-Ditlevsen [2008], the right side of (3) can be estimated as the following:

approximation of the right side of (3) $\approx\frac{1}{N}\sum_{i=1}^{\max(n:s_n\le s)}\Phi\left(\frac{\alpha-1}{\beta/\sqrt{2}}\sqrt{\frac{1-e^{-(s-s_i)}}{1+e^{-(s-s_i)}}}\right)$ (4).

In this equation, the s_i variables denote the time difference between the ith and (i-1)th errors, normalised by the speed of reversion.

I carried out the estimation by taking the left side and the estimate of the right side of (3) fixing the initial state, the equilibrium value, the limits, and the speed of reversion. Then I minimised the maximum of the differences of the two sides of the equation on given samples using the Solver tool of the Microsoft Excel spreadsheet software. The results of Table 13 show that the mean of the average s in the halved sample is slightly higher than that observable in the full sample, whereas the median value is smaller. According to all this, we may get a more conservative estimate from the halved sample than from the full sample. At the same time, the simulation results show that there is practically no equipment failure with the average s values of 0.06 and 0.09, while the maximum value may signify a failure in every four days. The inadequate sufficiency of our result may originate from the fact that we only had 0 to 22 estimates in the individual samples for estimated error frequencies, while Ditlevsen-Ditlevsen [2008] recommends the application of this estimation method from about 100 observed errors.

Table 13 Basic parameters and estimated results for s parameter of OU process

P(0)	0
M	0
higher threshold	1
lower threshold	$-\infty$
h	0.25

σ	Full sample (1056 observations)	Halved sample (first 528 observations)
minimum	0.0000	0.0000
mean	0.0599	0.0887
median	0.0115	0.0000
95% percentile	0.0828	0.6680
maximum	1.6773	2.5746

Thus we can conclude that back-estimation of the latent process did not prove to be effective in itself in the case of a smaller error frequency, therefore we either have to enrich the sample by combining our observations on the individual ATMs[44], or we may rather use a simple Poisson parameter estimate. It is worth noting from an aspect of bank institution size that in the case of small institutions and infrequently occurring operational risk events, observing nearly a 100 errors is only possible under a very long time scale, while the more sample enrichment is used, the more it increases “model risk”. Accordingly, this modelling technique requires further analysis.

The analysis of the ‘behaviour’ of the so-called super ATMs, or paired ATMs, where the two ATMs are located next to each other, and practically substitute each other (such ATMs may be in branches or in stores for example) represent further possibility for a research.

III.4. Summary

In this part of the thesis, I concluded, in connection with my first hypothesis, that the frequency distribution of operational risk losses can be properly approximated by Poisson distribution; while in the case of loss severity distribution, Pareto distribution can be used instead of the lognormal in the created simulation model framework. Therefore, only one part of my hypothesis proved to be true. The distribution of the first hitting time often present in the related mathematical literature shows complexity in our empirical analyses. We analysed the possibilities of a model-based forecast, and discovered that a method built from historical data on a small sample may result in biased values (over- or underestimation). The modelling constructed for ATM errors present a proper methodological foundation, however, the back-estimation of the latent risk process may only take place when there is high error frequency. Back-estimation of the error process from the observed errors requires further analysis.

[44] In this case, however, the Excel-based implementation of the estimation based on an error count in the approximate order of thousands, observed by us is difficult to carry out. This would need a more complex programme to be made.

IV. Operational risk and its relationship with institution size in the Hungarian banking sector [45]

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[46]. This could be a sound approach if we assume that the operational risk loss exhibits a linear relationship with banks' gross income.

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. 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[47]). 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.

The regime switch in capital requirement calculations caused decrease in credit risk capital requirement, which was partly compensated by introduction of operational risk capital requirement reflecting the intent of regulators to maintain the capital level, but presenting the risk profile more accurately. 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[48].

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[45] The quantitative analyses of this chapter 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 main results presented hereby were published in Homolya [2011].

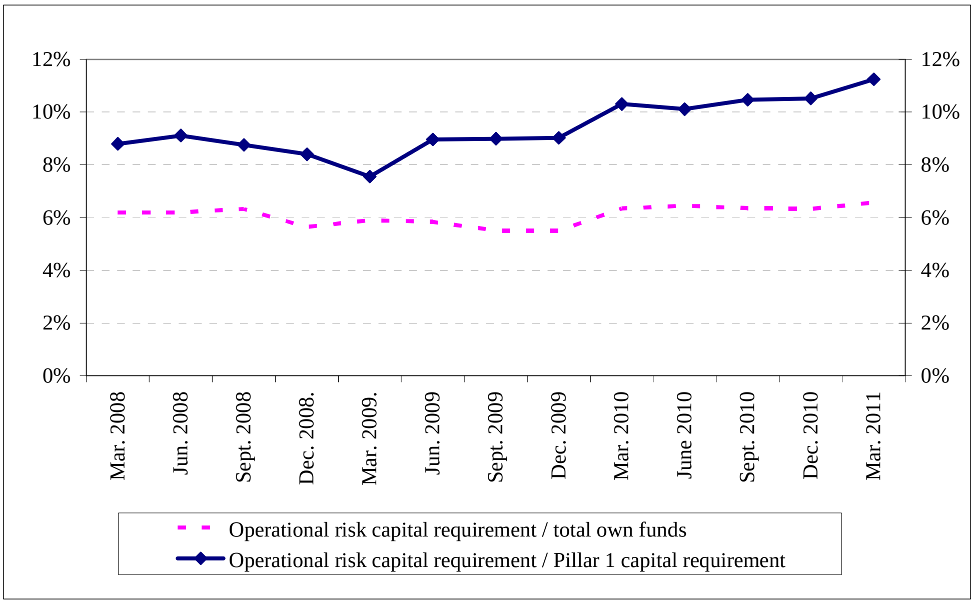
[46] I have provided a more detailed description on this in Chapter 1.1.

[47] Data were available for this period in times of preparing this part of the thesis.

[48] Based on number of banks 34 per cent is the proportion of banks applying standardised approach, 9 per cent applying AMA and 57 per cent applying BIA approach.

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 (Figure 20).

Figure 20 Operational risk capital requirements of the domestic banking sector in comparison with minimum capital requirements and total own funds for solvency purposes



Source: MNB.

The Hungarian banking system's level of operational risk capital charge provides an approximation of exposure to operational risk; hence although this figure can be considered relatively low, we cannot adequately assess its level. The Hungarian banking system's operational risk potential should be assessed based on the timeline of actual losses and on scenario analyses, calculations based on international comparisons and on the basis of the extent of estimated potential losses. However, Basel II based so-called COREP reporting may provide a basis for assessing importance of operational risk events already reported.

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

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 analysis 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 14).

Table 14 Operational risk losses (emerged or settled) between 2007 Q2 and 2011 Q1 and descriptive statistics on the gross income of banks[49]

Indicator:	Number of observations (banks)	Mean	Standard deviation	Skewness	Kurtosis
Total gross income (HUF billions) (yearly average of four years)	13	68.9	81	2.12	5.67
Gross income of retail banking activity (HUF billions)	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 millions)	13	1,628	4,004	3.45	12.13
Maximum single loss (HUF millions) at individual bank level	13	660	1,617	3.25	10.90
Number of events – Retail banking activity (units)	13	216	289	1.56	1.33
Total losses – Retail banking activity (HUF millions)	13	236	262	1.40	1.66
Maximum single loss – Retail banking activity (HUF millions)	13	73	76	1.39	1.25
Total loss amount / total gross income (per cent)	13	1.9	4	3.35	11.60

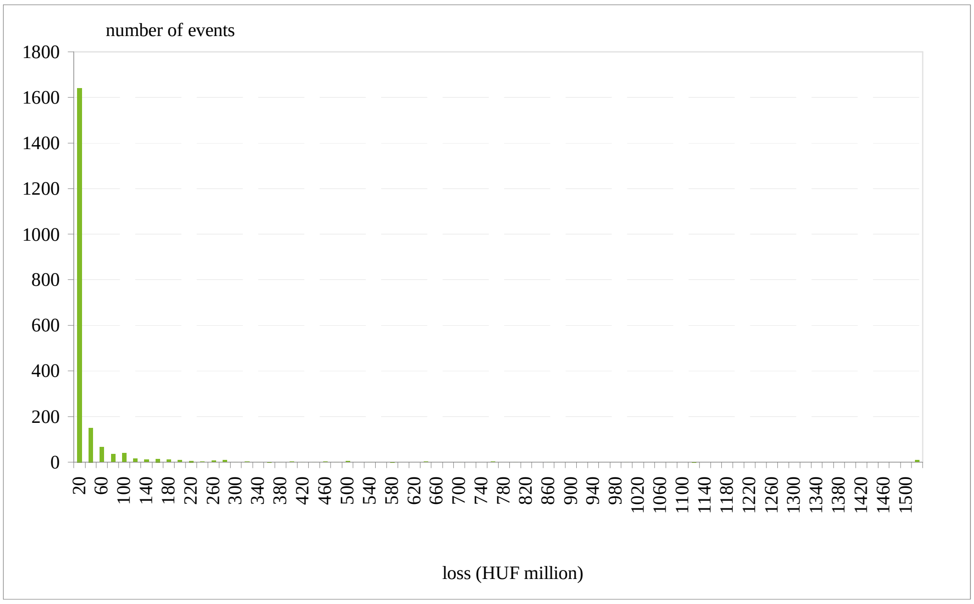
Source: MNB.

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 events from this censored, selected database. In any event, 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 (Figure 21).

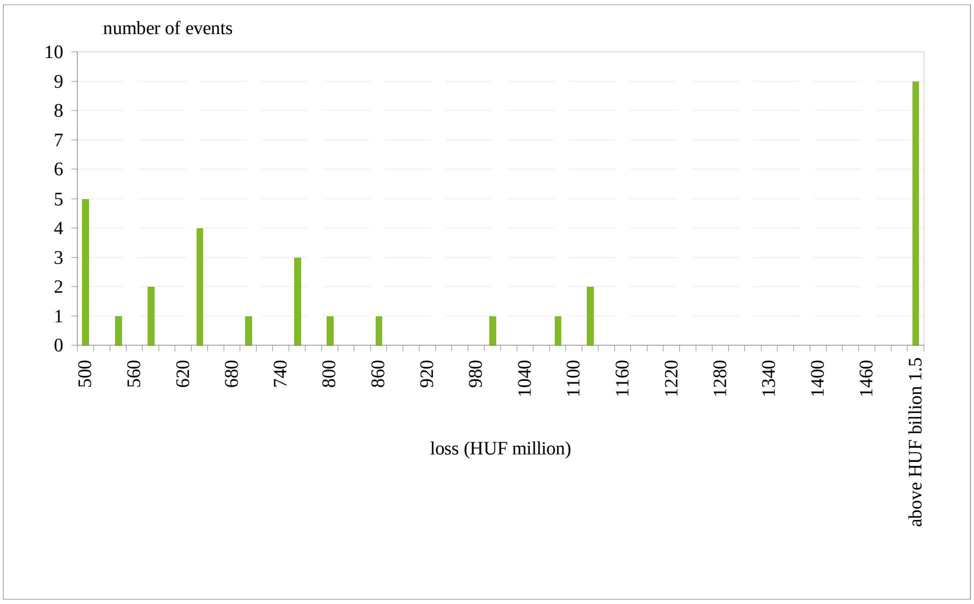
[49] For the purposes of this analysis, in line with the regulatory requirements, I use a three-year average for gross income

Figure 21 Distribution of major operational risk loss events of the Hungarian banking system between end of 2007 Q1 and end of 2011 Q1

Body of the distribution:



Distribution's tail:



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.

Stemming from the characteristics of operational risk, an institution's internal data often do not give an accurate picture of its full operational risk profile. This is why the advanced measurement approach prescribes the use of external data to disclose rare events which have a strong impact (so-called tail events). In case of Hungarian banks the (already mentioned in I.3.2. sub-chapter) HunOR Hungarian Operational Risk Database provides the opportunity for direct access to an external database, which began operation in 2007 under the auspices of the Hungarian Banking Association. A cooperation agreement was concluded between the Magyar Nemzeti Bank and the Hungarian Banking Association, pursuant to which the MNB received data containing data aggregated from the HunOR database. The database's significance can be reinforced based on the data thus made available, as nearly four thousand events with booking dates until end of 2009 Q1 were shared by the participating institutions, and the total registered loss for this period reached HUF 13 billion[50] (Source: Homolya [2009], Hungarian Banking Association HunOR Hungarian Operational Risk Database). After 2009 Q1, of course, the sample size of the HunOR database could have been increased as well.

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.[51] 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:

$$L = R^{\alpha} \cdot F(\Theta) \quad (5)$$

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

[50] This amount differs from the losses for 2009 stemming from regulatory reporting, HUF 28 billion already mentioned, because HunOR collects data from 1st January 2007, moreover, some of the HunOR banks apply BIA without regulatory reporting requirement for reporting oprisk losses for HFSA, furthermore, there are some banks, which do not participate in the HunOR, but apply AMA or TSA, thus reporting oprisk losses for the HFSA.

[51] 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% 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.

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 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.

The authors applied the above Equation (5) in a log-linear model:

$\ln(L) = \alpha \cdot \ln(R) + \beta + \varepsilon$, where $\beta = E(\ln(F(\Theta))$ (6)

Shih et al. [2000] got significant relationships, although they have analysed a model weighted by logarithm of gross income, as statistical independence of explaining variables and residuals of regression was not the case:

$y = \ln(L)/\ln(R) = \alpha + \beta \cdot x + \varepsilon$, where $x = {}^{1}\!/_{\ln(R)}$ (7)

Table 15 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 variance of the operational losses can be explained by factors other than income, such as the quality of risk management and their operational model.

Table 15 Relationship between operational loss size and income, based on the international sample of Shih et al. [2000]

(1) Loglinear model	Coefficient	Standard error	t	Regression statistics	
Constant	1.276	0.121	10.51	R^2	0.054
ln(R)	0.152	0.015	10.31	Adjusted R^2	0.054

(2) WLS model	Coefficient	Standard error	t	Regression statistics	
Constant	0.232	0.009	24.86	R^2	0.091
ln(R)	0.695	0.051	13.58	Adjusted R^2	0.090

Source: Shih et al. [2000], p. 2.

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.

IV.1. Relationship between firm size and loss amount in he Hungarian banking sector

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).[52] Given that only these institutions are required to report operational risk loss data under the supervisory data provision, the analysis of the

[52] 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.

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.

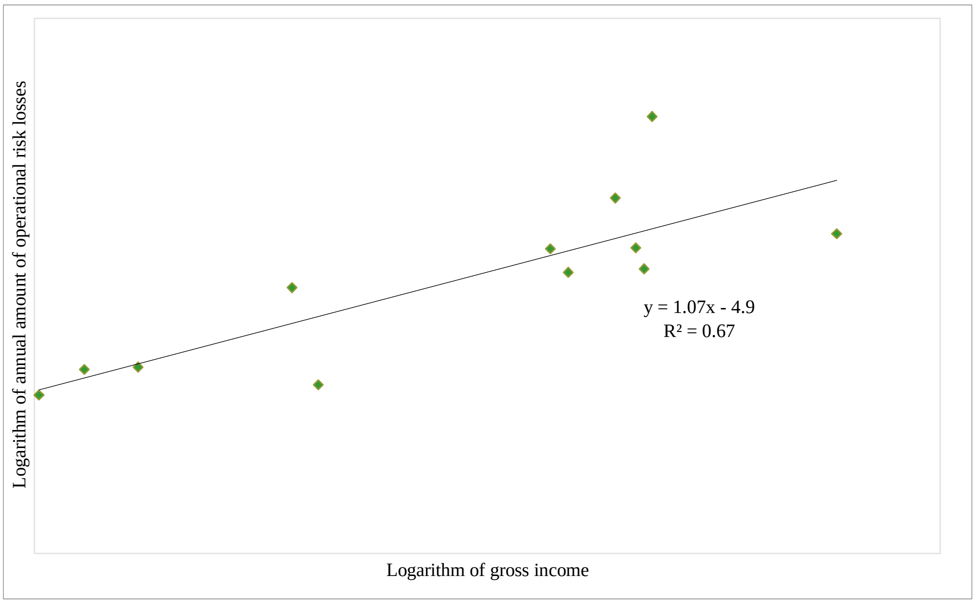
Since a single major loss may generate a great variability in the aggregate losses each year, in our analysis we spread the amount of total losses over four years and compared the result to the gross income pertaining to the specific period. At the same time, data can be analysed by year and by bank 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.[53]

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.[54] 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: Table 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. The correlation between loss and size is significant (with a p value below 1 per cent).

[53] 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.

[54] 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.

Figure 22 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)[55]

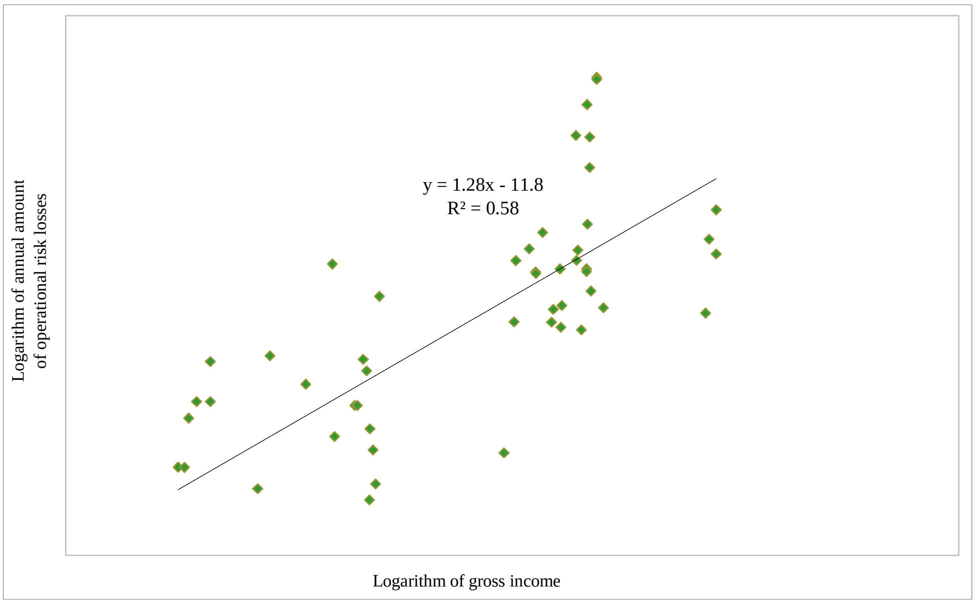


Source: MNB.

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.

[55] The axes displayed in Charts 3, 4, 5 and 6 do not indicate specific values in order to avoid the identification of individual banks.

Figure 23 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 Figure 23 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. Based on the equation, the expected loss would be HUF 19 billion for the banking sector; meanwhile the operational risk capital required is HUF 150 billion. However, the sufficiency of HUF 150 billion covering one-year loss is being hold only by 82 per cent confidence level, meanwhile Basel II requirements should be consistent with 99.9 per cent of confidence level. 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 on comprehensive basis.

IV.2. Relationship between individual loss events and institution size

IV.2.1. Frequency distribution

Basically, three distribution types are used to model frequency in operational risk modelling: Poisson distribution, binominal distribution and negative binominal distribution (see for example: Lewis [2004]; Panjer [2006])..

I present these distributions with their frequency distribution below:

(1) Poisson distribution: $f(k) = \lambda^k \cdot \frac{e^{-\lambda}}{k!}$, where k=0,1,2….

(2) Binomial distribution: $f(k) = \binom{N}{k} \cdot p^k \cdot (1-p)^k$, where k=0,1,2…, N positive integer.

(3) Negative binomial distribution: $f(k) = \binom{k+y-1}{k} \cdot p^k \cdot (1-p)^y$, where k=0,1,2…, N nonnegative integer, y is arbitrary positive number, p is real number between 0 and 1.

Each distribution type has its own advantage and disadvantage.

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.

Binomial distribution applies an intuitive probability approach (i.e. probability of occurrence of k event from the possible N); however we need to know the possible maximum level of occurrence. In case of negative binomial distribution, the level of occurrence is fixed; meanwhile possible maximum level of occurrence is changing. The two parameters (y, p) provide flexibility in order to ensure adequate fitting.

Choice from different frequency distributions could be grounded on rules of thumb based on comparison of mean and variance (see e.g. Lewis [2004] p. 99. or based on simple comparison of mean and variance of these distributions):

mean =/ ~[56] variance → Poisson distribution is the good choice

mean > variance → binomial distribution is the good choice

mean < variance → negative binomial distribution is the good choice

Basel II regulation requires one-year value at risk in case of AMA application, thus we should determine parameters of frequency distribution over one year horizon.

First, it is worth analysing what kind of distribution we might use. Using the Poisson distribution would be the most simple and obvious due to the simplicity of estimating the key parameter[57]. According to my calculations, the fit to the Poisson distribution cannot be ruled out for each bank or for the entire sample (see Table 16), 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. (JB = 5.21, significance = 0.074).

Table 16 Goodness of fit of Poisson distribution on operational risk data of banks

	Kolmogorov-Smirnov Z	**Significance**
Bank1	0.8815	0.4188
Bank2	0.8104	0.5274
Bank3	0.8685	0.4377
Bank4	0.7238	0.6713
Bank5	0.8253	0.5036
Bank6	0.7513	0.6250
Bank7	0.6530	0.7874
Bank8	0.3251	0.9999
Bank9	0.6239	0.8312
Bank10	0.9153	0.3720
Bank11	0.6689	0.7622
Bank12	0.5234	0.9470
Bank13	0.9498	0.3277
Bank14	0.7047	0.7034
All data	**1.2944**	**0.0701**

Note: In order to reach a continuous time horizon, I have used the data between April 2007 and March 2010 converted to monthly frequency. Data after end-of-March 2010 was not considered because in case of those data the occurrence date was not completely

[56] ~ signs approximate equality-
[57] The estimated value of λ equals the average of occurrences.

reported among data. In case of K-S Z, the higher the value of test statistics isthe more likely the goodness of fit is.

Source: Own calculations

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.[58]

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:

$$\lambda_i = F_{i1}^{\alpha_1} \cdot F_{i2}^{\alpha_2} \ldots \cdot F_{in}^{\alpha_2} \cdot F(\Theta_i) \text{ (8),}$$

where λ_i is the Poisson parameter of institution *i*, F_{ij} is the *j* institutional factor at institution *i*, and $F(\Theta)$ 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:

$$\ln(\lambda) = \alpha_1 \ln(F_1) + \alpha_2 \ln(F_2) \ldots + \alpha_n \ln(F_n) + \varepsilon \text{ (9)}$$

The academic literature (e.g. Na et al. [2005]; Dahen—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.

Since the correlation analyses pointed to a strong covariance between the frequency and size indicators, I decided to run a regression. First to start with, 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 17).

[58] 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 17 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	–35.3369	0.0000	59.9000	0.0000	0.6776	0.6663
lnASSET	–1.5679	0.0000				
lnGI	2.5259	0.0000				

	Parameters		Goodness of fit			
	Coefficient	Significance	F	Significance	R^2	Adjusted R^2
Intercept	–6.5265	0.0073	21.3624	0.0000	0.2692	0.2566
lnASSET	0.7956	0.0000				

Dependent variable: lnLAMBDA	Parameters		Goodness of fit			
	Coefficient	Significance	F	Significance	R^2	Adjusted R^2
Intercept	–22.1469	0.0000	63.9086	0.0000	0.5242	0.5160
lnGI	1.0961	0.0000				

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 18 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.

Table 18 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	–2.4377	0.0000	185.4548	0.0000	0.7618	0.7577
lnEMP	1.0383	0.0000				

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:

$$\lambda_{own} = \lambda_{external} \cdot \left(\frac{GI_{own}}{GI_{external}} \right)^{1.0961} \quad (10),$$

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

$$\lambda_{own} = \lambda_{external} \cdot \left(\frac{EMP_{own}}{EMP_{external}} \right)^{1.0383} \quad (11),$$

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

IV.2.2 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 frequency events which nevertheless generate big losses; instead, lognormal distributions are applied. Even though these have a heavier tail, they are easier to handle.

The probability density function of a lognormal distribution is as follows:

$$f(x) = \frac{1}{x \cdot \sigma \cdot \sqrt{2 \cdot \pi}} \cdot \exp\left(-\frac{1}{2} \cdot \left(\frac{\ln(x) - \mu}{\sigma} \right)^2 \right) \quad (12),$$

where x=0, 1, 2…

Parameter estimation could be conducted in the following way (Lewis [2004], p. 80.):

$$\hat{\mu} = \frac{\sum_{i=1}^{n} \ln(X_i)}{n}, \text{ and } \hat{\sigma}^2 = \frac{\sum_{i=1}^{n} (\ln(X_i) - \hat{\mu})^2}{n-1} \quad (13)$$

In addition to the lognormal model, the Pareto distribution having fat-tailed feature is a preferred method of modelling operational risk loss. In Chapter III there are some results to show better goodness-of-fit for severity distribution in case of Pareto, than in case of lognormal distribution. The probability density function of the so-called single parameter Pareto distribution (Panjer [2006] p. 59.) is the following:

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

If θ = 1, then the maximum likelihood estimate of the α parameter of the random variable following Pareto distribution is the following:

$$\hat{\alpha} = \frac{N}{\sum_{i=1}^{N} \ln(X_i)}$$

If θ ≠ 1, then, even with the maximum likelihood estimation, it is only possible to give an estimate for the distribution by assuming some kind of θ.

In the general case, the result of the maximum likelihood estimation is:

$\hat{\alpha} = \dfrac{N}{\sum_{i=1}^{N} \ln(X_i) - N \cdot \ln(\theta)}$, where θ is a pre-fixed parameter (the minimum of the observed values is often used).

The general Pareto distribution[59] has two variables (Panjer [2006] p. 62):

$$f(x) = \frac{\alpha\theta^{\alpha}}{(x+\theta)^{\alpha+1}}$$

The maximum likelihood estimation leads to complex formulas in the case of a bivariate Pareto distribution, while we get a relatively simple relationship using the method of moments (based on the moments given by Panjer [2006] p. 62)[60]:

$\hat{\alpha} = \dfrac{2 \cdot \left(\bar{x}^2 - \left(\sum x^2 / n \right) \right)}{2 \cdot \bar{x}^2 - \left(\sum x^2 / n \right)}$, where $\bar{x}$ denotes the arithmetic average of the observed values.

$$\hat{\theta} = \frac{\left(\bar{x}^2 \cdot \left(\sum x^2 / n \right) \right)}{\left(\sum x^2 / n \right) - 2 \cdot \bar{x}^2} \quad (14)$$

Table 19 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.

[59] This distribution is called by several names: e.g., type 2 Pareto distribution, Lomax distribution (Panjer [2006], 62. o.), or American Pareto distribution (Gáll-Nagy [2007], 403. o.)
[60] Cruz [2002] (53.o.) explicitly gives this formula, but with a misprint, therefore I recalculated it out of cautiousness.

Table 19 Distribution of individual loss events reported for supervisory purposes 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 per cent of operational risk events (at least 10 events) is reported. Thus the database is censored.

The question arises how we should handle operational risk loss data interconnected to credit risk. The related domestic regulation (8. § (2) in Government Decree 200/2007 on the management of operational risk and capital requirement (Government of the Hungarian Republic [2007]) specifies that for a loss which has been accounted for by the credit institution during credit risk capital requirement calculations, no operational risk capital requirement has to be allotted, but the credit institution must register it separately in its books. In this analysis, I did not filter out the credit risk related events from the data.

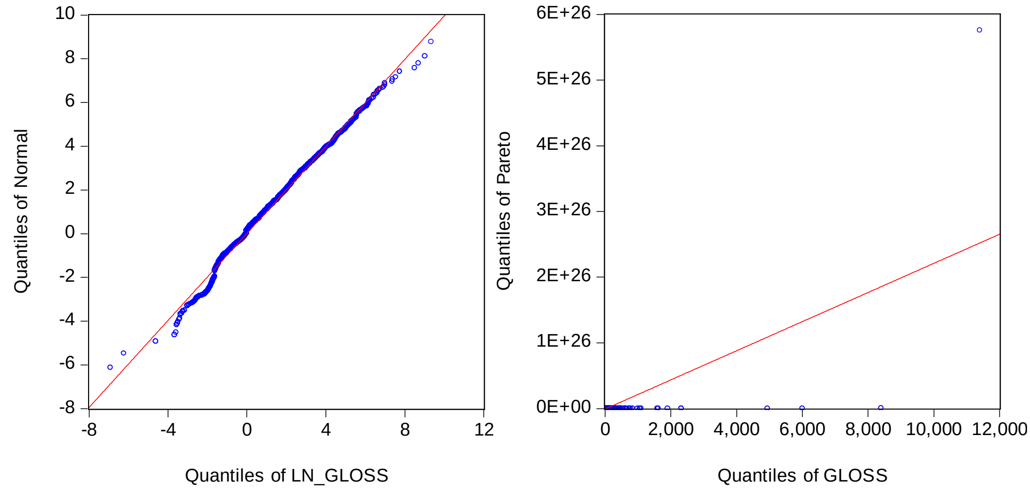
In my analysis, first of all, I examined which distribution would be the best fit for this censored database which contains observations at the individual event level. Next, I analysed the correlation between institution size and the parameters of the loss distribution which was deemed to be the best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

As banks report the top 10 per cent of events having the highest loss based on the number of all the events, or at least 10 events under the supervisory data disclosure, we have a strongly censored[61] database.

[61] In the statistical literature, in connection with the uncertainty of data, they talk about truncation and censoring. Truncation means that we simply do not have observations above or below a value. In practice, this is the data collection threshold in gathering operational risk losses. On the other hand, censoring means that the observation exists, but, for us, it has been screened.

The Quantile–Quantile Chart applied for the visual testing of the distribution fit (not presented separately in this article) indicated that the lognormal distribution was a better fit compared to the Pareto distribution (Figure 24).

Figure 24 Fit of operational risk loss amounts to lognormal (left panel) and Pareto (right panel) distribution



Note: The figure shows all the loss data reported by analysed reporting institutions (14 of 16 institutions). Our observations are gross loss data expressed in HUF million.

According to the individual regression results shown by Table 20, the location parameter (μ of the lognormal distribution; θ of the Pareto distribution) has a stronger covariance with size indicators, while the correlation with the scale parameter of the distribution (σ of lognormal; α of Pareto) is not significant.

Table 20 Correlation and strength of the correlation between severity parameters (calculated by means of the EViews software) and gross income-based institution size

μ parameter of lognormal distribution

μ	*Coefficients*	*P-value*
Intercept	-8.958	0.004
lnGI	0.975	0.002

R Square	0.581
Adjusted R Square	0.546
F	16.611
Significance F	0.002

σ parameter of lognormal distribution

σ	*Coefficients*	*P-value*
Intercept	2.662	0.029
lnGI	-0.101	0.341

R Square	0.076
Adjusted R Square	-0.001
F	0.981
Significance F	0.341

θ parameter of Pareto distribution

ln(θ)	*Coefficients*	*P-value*
Intercept	-13.109	0.007
lnGI	1.123	0.012

R Square	0.425
Adjusted R Square	0.377
F	8.856
Significance F	0.012

α parameter of Pareto distribution

ln(α)	*Coefficients*	*P-value*
Intercept	-1.082	0.214
lnGI	0.021	0.791

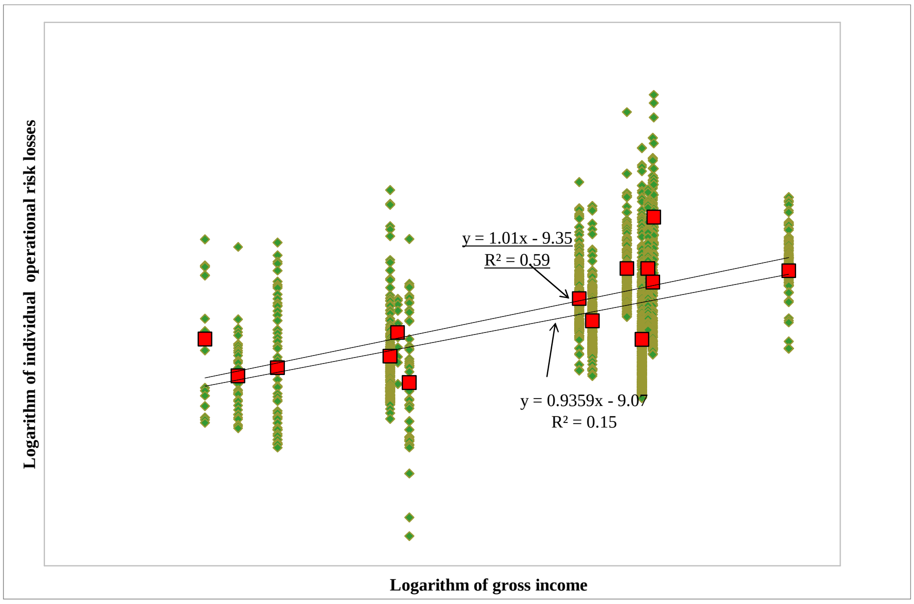
R Square	0.006
Adjusted R Square	-0.077
F	0.074
Significance F	0.791

Occasionally, even the operational risk literature (e.g. Na et al. [200]; Dahen–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).[62] 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 we arrived at is consistent with the result of the study written by Chernobai et al.

[62] 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.

[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.

Figure 25 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 red squares indicate average loss severity, to which the underlined equation applies.

Source: MNB.

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:[63]

$$loss_{own} = loss_{external} \cdot \left(\frac{GI_{own}}{GI_{exernal}} \right)^{0.9359} \quad (15)$$

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 in Figure 26 (Equation (11) and (15)). 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

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

individual exposure stemming from increased size is compensated by a more systematic operational risk management, which is also reflected in the more frequent use of more advanced methods within the group of larger institutions.

Figure 26 Scaling to one unit of loss and loss frequency relative to the original loss owner's size in terms of gross income

In their article, Dahen–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 21, the results thus obtained undoubtedly have greater explanatory power than the model based on single losses shown in Figure 25; 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) [64]. 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.

[64] It is worth noting that in addition to business lines and event types, the related risk also shows a relation with the size of individual losses. If we use the code 0 for the lack of related risk, 1 for related market risk, and 2 for related credit risk, we get a value of 33 per cent for Kendall tau-b correlation index, which is significant on the 99.9 per cent level.

Table 21 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

IV.3. Summary

My empirical analysis presented in this part of the study supports that, similarly to the foreign banking sectors and banking groups already analysed in the literature, the correlation between gross income-based institution size and the total operational risk losses incurred in a given period is significant in the Hungarian banking sector as well. The small sample of institutions limits the possibility to draw solid conclusions from the presented analysis; nevertheless, I ended up with forward-looking results. Moreover, I filtered out the extreme values in order to be able to analyse the relationships in a more robust way, which, on the one hand, eased reaching intuitive results, and at the same time, narrowed down the available sample, therefore, weakened our conclusions. According to the analysis, mostly the relationship of the institution size with the frequency parameter can be regarded as strong, and that with the loss size less strong. Furthermore, it can be determined using regression methods that, in addition to the quality of risk management difficult to model, and the strengths of the internal control, the categories of business lines and event types may have a part in explaining the size of the individual losses.

V. Operational risk method selection practice and its relationship with firm size[65]

V.1. International sample

I based my analysis on data pertaining to financial institutions' choice of operational risk approach on the one hand, and on financial institutions' profitability and balance sheet data on the other. Data pertaining to the choice of operational risk approach pose the biggest problem at present, as in countries where capital allocation for operational risk has been compulsory since 1 January 2008, data on operational risk are only included in annual reports for 2008, which would have to be compiled one by one, however, consistency could not be ensured. Of course, larger institutions are much more transparent[66] due to the reputational requirements imposed by their presence on the stock exchange and their size, so I will use operational risk data gleaned from a secondary data source containing the world's 100 largest institutions according to the banks' or bank groups' equity capital.

I used two data sources for the analysis:

- The data source for operational risk data were the articles published in the October 2008 and October 2009 issue of the OpRisk & Compliance (OR&C) journal OpRisk & Compliance [2008]: A new dawn for disclosure, Top 100 banks, 2008/10. pp. 26-29., Incisive Media, London; OpRisk & Compliance [2009]: Divine Illusion, pp. 18-24, Incisive Media, London). The referenced article obtained its data from several sources: data on equity capital from annual reports, announcements in written and non-written media, articles (e.g. The Banker magazine), the other data compiled from annual reports, supervisory publications, software company reports, while loss data was gleaned from the database containing public operational risk loss data, operated by the software company SAS. In light of the fact that OR&C magazine (currently named as Operational Risk & Regulation) is the leading journal of the operational risk management profession, I considered the data published in it as sufficiently reliable. As OR&C [2008] and OR&C [2009] presented end-2007 and end-2008 data respectively, a Top100 ranking based on Tier 1 capital in the previous two

[65] Some of the results of this chapter were published in Homolya [2009a].
[66] This factor may influence the direction and strength of relationship of institutional size and losses.

years, the sample proved to be heterogenous, although 89 banking groups are common in the two samples. Differences are partly due to mergers account for the differences, and partly to the fact that East Asian (Chinese, Indian) banks showed greater shock resistance than at the end of 2007, therefore they were able to "break through" (e.g., the China-based China CITIC Bank or the India-based ICICI Bank).

– Data pertaining to profitability, size and liquidity were obtained from the Bureau van Dijk "BankScope" database. BankScope is a database containing micro-level bank data, often used in academic circles and by financial institutions and central banks for comparing countries or preparing analyses based on individual bank data (Bhattacharya [2003]). Based on BankScope's brochure, the database contains information on 23,000 banks, with all of the relevant banks of every country worldwide included in the database (Bureau van Dijk [2008]).[67]

The balance and profit and loss statement data of the analysis database assembled from the aforementioned databases apply to the end of year 2007 or to the year 2007, or in the case of 2009 data, to the end of year 2009. The annex (Table 40) lists the name, content, set of values and unit of the variables in the database.

In addition to the descriptive and analytic methods, I used cluster analysis and logistic regression method during my analyses[68] .

V.1.1. Descriptive data analysis

Table 22 contains the descriptive statistics regarding the balance and profit and loss statement data of banks in the database. The table contains the descriptive statistics of certain variables. By means of tests regarding normality, we can conclude that the variables examined are basically not normally distributed. In the 2008 sample, acceptability of the normal distribution exists in the case of the return on equity, cost/income, and net loans/total assets indicators. In the 2009 sample, only the net loans/total assets indicator may be characterised by normal distribution. Even the smallest bank in the sample has equity of USD 5.7 billion and USD 3.3 billion

[67] My workplace, Magyar Nemzeti Bank, central bank of Hungary have access to OR&C and Bankscope. This was the basis to use these data.
[68] The analyses was prepared using SPSS for Windows software, version 11.5.

according to observations in 2008 and 2009 respectively, and total assets of USD 62 billion (2008 observation) and USD 93 billion (2009 observation), which, as a comparison, may mean that the smallest institutions are slightly bigger than the largest Hungarian banking group (OTP group), which has equity of USD 6.3 billion, total assets of USD 52 billion at the end of 2009[69]. The majority of the variables have positive skew (except for the variables where normality cannot be rejected), that is, in the sample, there are several banks having smaller values for a given indicator and only a few having higher values for the same indicator. The absence of normality may create some bias in our estimates.

Table 22 Descriptive statistics of variables

2008 sample:

	Number of observations	Min.	Max.	Mean	Standard deviation	Skewness	Kurtosis
Tier 1 capital (mUSD)	100	7,791	104,967	25,980	21,457.5	1.7	2.6
Total assets (mUSD)	100	62,045	2,974,160	683,465	664,924.1	1.6	1.7
Equity (mUSD)	100	5,764	146,803	33,709	30,918.2	1.8	2.7
Loan loss reserve / gross loans (%)	93	0.0	7.0	1.6	1.3	2.1	5.5
Capital adequacy ratio (%)	92	8.9	21.1	11.9	2.3	1.4	2.3
Leverage (equity/ total assets) (%)	100	1.5	17.8	6.2	3.2	1.3	2.0
Capital funds / liabilities (%)	94	2.6	23.6	9.0	4.1	1.1	1.2
Net interest margin (%)	100	0.3	10.0	2.2	1.8	2.3	6.4
Return on Average Equity (ROAE) (%)	100	-7.8	30.1	14.5	7.3	-0.1	-0.1
Return on Average Assets (ROAA) (%)	100	-0.2	3.3	0.9	0.7	1.4	2.8
Cost to income ratio (%)	100	26.1	112.0	58.5	14.0	0.7	1.3
Net loans / total assets (%)	100	9.2	80.9	52.5	15.9	-0.4	-0.4
Net loans / customer & short-term funding (%)	100	11.5	589.7	82.6	58.9	6.5	55.9
Liquid assets / customer & short-term funding (%)	96	0.1	67.8	10.5	12.0	2.7	9.2

[69] Source: OTP Bank Nyrt. end-of-2009 Annual Report, available at: https://www.otpbank.hu/static/portal/sw/file/100430_2009_eves_jelentes_159.pdf

2009 sample

	Number of observations	Min.	Max.	Mean	Standard deviation	Skewness	Kurtosis
Tier 1 capital (mUSD)	100	6,422	138,995	30,107	28,230.4	2.1	4.6
Total assets (mUSD)	100	93,287	3,501,103	700,485	728,456.6	2.0	3.8
Equity (mUSD)	100	3,319	178,710	33,184	32,090.7	2.3	6.4
Loan loss reserve / gross loans (%)	98	0.2	9.3	2.1	1.6	2.4	8.2
Capital adequacy ratio (%)	98	9.0	22.9	13.0	2.8	1.0	0.8
Leverage (equity/ total assets) (%)	100	0.9	15.7	6.0	3.1	0.8	0.3
Capital funds / liabilities (%)	98	0.4	24.9	9.3	4.7	1.2	1.7
Net interest margin (%)	100	-0.1	7.6	2.1	1.3	1.5	3.4
Return on Average Equity (ROAE) (%)	100	-44.4	32.5	2.2	15.0	-1.3	1.8
Return on Average Assets (ROAA) (%)	100	-2.4	2.0	0.2	0.8	-0.7	1.2
Cost to income ratio (%)	97	25.1	818.1	73.6	84.3	7.6	65.4
Net loans / total assets (%)	100	0.0	89.1	51.6	17.9	-0.7	0.5
Net loans / customer & short-term funding (%)	100	0.0	444.4	86.1	48.3	4.2	30.2
Liquid assets / customer & short-term funding (%)	100	2.5	363.8	36.2	48.0	4.9	29.3

It is worth noting that the net loans/customer & short-term funding indicator has the highest kurtosis, which indicates that compared to the normal distribution there are relatively many banks that finances its typically long-term credit exposure mainly from short-term funds. The 2009 sample shows that the liquid assets/customer & short-term funding indicator and the cost to income ratio characterising cost effectiveness showed high kurtosis. This means that banks started to disperse in terms of liquidity, and the Top 100 international banking groups show a range higher than before in terms of cost effectiveness.

Regarding the operational risk methods, the majority of the analysed banks use a simpler approach; however out of the 100 banks 39 in 2008 and 35 in 2009 used the advanced AMA approach (Table 23). 13 in 2008 and 15 in 2009 of the institutions using simpler methods wish to introduce the AMA methodology later. According to observations for 2008, only 24 of the 39 banks applying AMA have supervisory approval to use AMA. This rate improved slightly in the observations for 2009 (29 of the 35 institutions applying AMA have supervisory licence), therefore the rate is declining, but several banks use the AMA approach only for internal purposes at the moment[70].

Table 23 Operational risk approach applied by banks analysed

<table>
<tr><th></th><th colspan="3">2008 sample (end-of-2007 data)</th><th colspan="3">2009 sample (end-of-2008 data)</th></tr>
<tr><th>Approach</th><th>Frequency</th><th>Ratio of banks applying simpler or more advanced approaches</th><th>AMA aspirants</th><th>Frequency</th><th>Ratio of banks applying more simple or more advanced approaches</th><th>AMA aspirants</th></tr>
<tr><td>Basel I</td><td>10</td><td>10%</td><td>0</td><td>12</td><td>12%</td><td>0</td></tr>
<tr><td>BIA</td><td>8</td><td rowspan="2">51%</td><td>2</td><td>8</td><td rowspan="2">53%</td><td>2</td></tr>
<tr><td>TSA</td><td>43</td><td>11</td><td>45</td><td>13</td></tr>
<tr><td>AMA</td><td>39</td><td>39%</td><td>-</td><td>35</td><td>35%</td><td>-</td></tr>
<tr><td>Sum</td><td>100</td><td></td><td>13</td><td>100</td><td></td><td>15</td></tr>
</table>

It is clear from Table 24 that in the case of banks where we have data on the introduction date of Basel II (82 banks), the vast majority of the banks (90%) introduced the Basel II approach in the year 2007 or 2008 (2008 sample). The banks that introduced Basel II in 2009 or later are the institutions outside Europe (typically North and South American and Asian). The banks where there are no public data on the introduction of Basel II are also typically North American or Asian. The background is that, in the USA, China, and India, unlike in Europe a risk management methodology complying with Basel II will only have to be introduced later. As I already indicated, mainly some banks from the USA and Western Europe were dropped from the 2008 sample, and primarily Asian and Indian banks were included instead.

[70] It would indeed be worth examining the underlying motivation at those banks which do not aspire to introduce AMA approach in the near future. There is no factual, individual institutional information on this. In my opinion, the explanation is, on the one hand, the delay of the national implementation of Basel II, therefore the lack of regulatory pressure, and on the other hand, the more unfavourable capital requirement level in connection with AMA at the given institution, and the high project costs.

Table 24 Basel II compliance date of the banks analysed

	2008 sample (end-of-2007 data)		2009 sample (end-of-2008 data)	
Basel II compliance date	**Frequency**	**Cumulative frequency as %**	**Frequency**	**Cumulative frequency as %**
2007	31	37.8%	23	28.4%
2008	43	90.2%	48	87.7%
2009	1	91.5%	2	90.1%
2010	1	92.7%	0	90.1%
2011	2	95.1%	4	95.1%
2012	1	96.3%	1	96.3%
2013	3	100.0%	3	100.0%
Data available:	82		81	
Missing data:	18		19	

One of the key elements related to the advanced measurement approach (AMA) of operational risk is the use of external data. External data can either be obtained from databases,like the FIRST database of Fitch, containing public data (e.g. press reports, supervisory announcements, etc.), or from consortial databases that enable data share between institutions. To be a member of a consortial database means a high degree of commitment, since generally there are strict requirements to comply with. In the 2008 sample of the 100 institutions examined, 36 were members of the operational risk data consortium, which enables the more effective measurement of operational risk. In the case of 2009 sample the number of external database participants was 43. In the 2008 sample, 30 institutions were members of the ORX organised internationally, 4 institutions were members of the DIPO database of the Italian Banking Association (one of them is also a member of the ORX), and 3 banks were members of the data consortium (DAKOR) of the German federal banks (“Landesbanks”). In the 2009 sample, the number of the members of ORX increased to 35; 4 of which remained the member of DIPO (one was an ORX member as well: Intesa Sanpaolo[71]). In line with this, the number of the members of the DAKOR database reached 5. The data in Table 25 show that there is a statistically strong relationship between the state of advance of the approach and the external database membership. However this relationship was stronger in the 2008 sample. The simple correlation index, and the Spearman and Kendall tau-b indicators suitable for measuring relationship between ordinal variables all showed values around 30% with a high degree of significance on the 2008 sample

[71] An interesting fact is that only Bank Austria Credit Anstalt is an ORX member from the Unicredit group, while the whole Unicredit group is not.

(the p value is significantly lower than 1%). The 2009 sample showed results with a correlation index of 20 per cent as well, while the Spearman and Kendall tau-b correlation indicators enabling the managing of ordinal variables were undoubtedly significant. Of the applied correlation indicators, only Kendall's tau-b can be applied to analyse the relationship between the variables examined.

Table 25 External data consortium membership and its relationship with operational risk approach applied (lower panel shows statistical significance of this relationship)

	External data consortium membership 2008 sample (end-of-2007 data)					**External data consortium membership 2009 sample (end-of-2008 data)**				
Approach	**0 (=no)**		**1 (=yes)**		**Sum**	**0 (=no)**		**1 (=yes)**		**Sum**
Basel I	9	14%	1	3%	10	7	11%	5	14%	12
BIA	6	9%	2	6%	8	7	11%	1	3%	8
TSA	32	50%	11	31%	43	29	45%	16	44%	45
AMA	17	27%	22	61%	39	14	22%	21	58%	35
Sum	**64**		**36**		**100**	**57**		**43**		**100**

	2008 sample (end of 2007 data)		**2009 sample (end of 2008 data)**	
Correlation measures	**Value**	**Significance**	**Value**	**Significance**
Kendall's tau-b	0.3213	0.02%	0.2180	2.10%
Spearman correlation	0.3413	0.05%	0.2320	2.00%
Pearson R	0.3158	0.14%	0.1850	6.60%

V.1.2. Exploratory data analysis

In this subchapter, we try to unfold the correlations between method selection and institution characteristics. Table 26 presents the paired correlations between data based on the bank's balance sheet and profit and loss statement and the operational risk method selection. In the case of method selection, there seem to be a significant positive relation between the method's state of advance and the size indicators (Tier 1 capital, economic capital, total assets, deposits and short-term funding, equity and net income), that is bigger institutions rather select advanced methods. In the case of the ratio-type indicators, we got somewhat surprising results. On at least a 5% level, there is significant relationship with the following indicators: leverage (negative relation), capital funds/liabilities (negative relation), net interest margin (negative relation), cost to income ratio (positive relation, not significant in 2009), net loans/total assets (negative relation). In the 2009 sample, there was also a significant correlation (positive relation) between the ratio of liquid assets to short-term funding and the selected operational risk method. In other words, banks applying more advanced methods have higher leverage, relatively less capital funds within total liabilities, relatively smaller interest income, were less effective based on the cost to income ratio according to the 2008 sample, and the lending activity is smaller in their balance sheet. This means that banks applying more advanced operational risk methods do more commission-based business at the same time instead of the traditional acceptance of deposit and lending based on interest margin. The fact of the AMA approval by the supervisor has a significant correlation with almost the same variables. It is worth noting that the relationship with the operational risk capital requirement was not significant in the 2008 sample, but it became a significantly positive value by2009.

Table 26 Kendall tau-b based correlation matrix for correlation between bank size or profitability indicators data regarding operational risk approach selected

2008 sample:

	Operational risk method chosen (encoded)	Approval of AMA	Aspiration for AMA (revealed)	Data consortium membership
Tier 1 capital (mUSD)	0.25	0.25	-0.18	0.35
Economic capital (mUSD)	0.51	0.43	-0.29	0.39

	Operational risk method chosen (encoded)	Approval of AMA	Aspiration for AMA (revealed)	Data consortium membership
Operational risk capital requirement (mUSD)	0.27	0.32	-0.22	0.46
Total assets (mUSD)	0.37	0.51	-0.19	0.39
Customer deposits & short-term funding (mUSD)	0.31	0.45	-0.20	0.33
Equity (mUSD)	0.28	0.24	-0.14	0.38
Net income (mUSD)	0.23	0.15	-0.13	0.46
Loan loss reserve/gross loans (%)	-0.03	-0.10	0.00	-0.04
Capital adequacy ratio (%)	-0.15	-0.22	-0.11	-0.22
Leverage (equity/ total assets) (%)	-0.30	-0.39	0.05	-0.20
Capital funds/liabilities (%)	-0.21	-0.41	0.07	-0.15
Net interest margin (%)	-0.20	-0.33	-0.08	-0.15
Return on Average Assets (ROAA) (%)	-0.17	-0.32	-0.02	-0.13
Return on Average Equity (ROAE) (%)	0.03	-0.07	-0.09	0.03
Cost to income ratio (%)	0.24	0.25	0.13	0.19
Net loans/total assets (%)	-0.28	-0.27	0.06	-0.14
Net loans/customer & short-term funding (%)	-0.17	-0.14	0.04	-0.06
Liquid assets/customer & short-term funding (%)	0.03	-0.06	-0.03	-0.13

2009 sample:

	Operational risk method chosen (encoded)	Approval of AMA	Aspiration for AMA (revealed)	Data consortium membership
Tier 1 capital (mUSD)	0.35	0.24	-0.09	0.15
Economic capital (mUSD)	0.30	0.32	0.07	0.10
Operational risk capital requirement (mUSD)	0.37	0.41	0.01	0.18
Total assets (mUSD)	0.50	0.30	-0.05	0.27
Customer deposits & short-term funding (mUSD)	0.43	0.26	-0.05	0.20
Equity (mUSD)	0.34	0.24	-0.02	0.19
Net income (mUSD)	0.17	0.14	0.04	0.10
Loan loss reserve/gross loans (%)	-0.07	-0.07	0.05	0.00
Capital adequacy ratio (%)	-0.13	0.05	-0.23	-0.15
Leverage (equity/ total	-0.23	-0.18	0.07	-0.14

	Operational risk method chosen (encoded)	Approval of AMA	Aspiration for AMA (revealed)	Data consortium membership
assets) (%)				
Capital funds/liabilities (%)	-0.23	-0.15	0.09	-0.04
Net interest margin (%)	-0.23	-0.11	0.00	-0.09
Return on Average Assets (ROAA) (%)	-0.01	0.01	0.09	-0.10
Return on Average Equity (ROAE) (%)	0.04	0.06	0.06	-0.08
Cost to income ratio (%)	0.11	0.13	0.04	0.21
Net loans/total assets (%)	-0.28	-0.13	0.15	-0.13
Net loans/customer & short-term funding (%)	-0.12	0.02	0.19	0.06
Liquid assets/customer & short-term funding (%)	0.35	0.23	-0.03	0.20

Note: _ refers to significance at the 5% level, _ refers to significance at the 1% level.

At the same time, the selection of operational risk approach does not show significant relationship with profitability (based on ROAA, ROAE)[72]. The negative correlation between the fact of the supervisory approval of AMA and the asset-based profitability was observable only in the 2008 sample. Table 27 shows that the return on average assets decreases, while the return on average equity increases in the order of the selected operational risk approach’s state of advance. Yet, in the 2009 sample, we can see a slight increase for both profitability indicators as a function of the used method’s state of advance.

[72] Presumably, our results are affected by the fact that we used bank profitability data in the current and ongoing financial and economic crisis, but we cannot filter out this effect during the analysis of the relationship between our current indicators.

Table 27 Return on average assets, return on average equity by categories of operational risk approach (mean values)

	2008 sample (end-of-2007 data)		2009 sample (end-of-2008 data)	
Approach	**Return on Average Assets (ROAA) (%)**	**Return on Average Equity (ROAE) (%)**	**Return on Average Assets (ROAA) (%)**	**Return on Average Equity (ROAE) (%)**
Basel I	1.19	14.83	0.18	3.11
BIA	1.19	13.04	0.02	-0.89
TSA	0.87	14.37	0.25	1.56
AMA	0.85	14.93	0.25	3.28
Sum	0.92	14.53	0.22	2.15

In order to examine whether it is the over-detailed nature of the methodology distinction that causes the lack of a significant relationship, I took a look at two new recoded variables, exclusively for banks that already introduced Basel II:

State of advance: 0 = banks using simpler approaches (BIA, TSA), 1 = banks using the advanced approach (AMA)

Indicator showing the state of advance of the approach to be introduced: 0 = banks using simpler approaches (BIA, TSA), 1 = banks using the advanced approach (AMA), and banks intending to introduce AMA

On the contrary, results of Table 28 show that there is a significant relationship between the indicator defined above regarding the used approach's state of advance and size indicators. A bigger institute is more likely to apply a more advanced method. However, if we also include the aspiration to introduce AMA in our advanced-state indicator, there is a significant positive correlation with more size indicators.

Table 28 Bank size and profitability indicators versus state of advance in a correlation matrix based on Kendall tau-b measure

	2008 sample (end-of-2007 data)		**2009 sample (end-of-2008 data)**	
	State of advance (0= simple, 1=advanced)	State of advance including aspiration	State of advance (0= simple, 1=advanced)	State of advance including aspiration
Tier 1 capital (mUSD)	0.2706	0.1317	0.35	0.28
Economic capital (mUSD)	0.5670	0.4052	0.29	0.42
Operational risk capital requirement (mUSD)	0.2739	0.0889	0.37	0.42
Total assets (mUSD)	0.3627	0.2101	0.37	0.27
Customer deposits & short-term funding (mUSD)	0.3192	0.1633	0.30	0.20
Equity (mUSD)	0.2956	0.1880	0.34	0.32
Net income (mUSD)	0.2498	0.1459	0.17	0.19
Loan loss reserve/gross loans (%)	0.1211	0.1316	0.06	0.03
Capital adequacy ratio (%)	-0.0864	-0.1601	0.06	-0.04
Leverage (equity/ total assets) (%)	-0.1091	-0.0422	-0.05	0.03
Capital funds/liabilities (%)	-0.0828	-0.0128	-0.06	0.02
Net interest margin (%)	0.0566	0.0241	-0.02	0.00
Return on Average Assets (ROAA) (%)	-0.0542	-0.0564	-0.03	0.02
Return on Average Equity (ROAE) (%)	0.0516	-0.0147	0.00	0.04
Cost to income ratio (%)	0.1970	0.2847	0.13	0.17
Net loans/total assets (%)	-0.1777	-0.1143	-0.21	-0.07
Net loans/customer & short-term funding (%)	-0.1359	-0.1060	-0.11	0.08
Liquid assets/customer & short-term funding (%)	0.0935	0.0709	0.23	0.19

Note: _ refers to significance at the 5% level, _ refers to significance at the 1% level.

Returning to the analysis of the results of Table 26, we can see that the aspiration to introduce AMA has a significant correlation (positive relation) only with customer & short-term funding in the 2008 sample, therefore this does not mean an intuitive result in itself. However, it is noticeable that the correlation with size indicators is negative, which means that the institutions considering introducinf AMA are smaller in size than in our sample. In the 2009 sample, there is significant correlation with capital adequacy ratio and net-loans/customer & short-term funding (negative and positive relation respectively). Not surprisingly, the external database membership has a significant positive correlation with size indicators, which means that bigger institutions are more likely to be members of external databases. At the same time, it is interesting to see that the relationship between operational risk database membership and capital adequacy ratio or leverage defined as the ratio equity/total assets is negative (alhough it is not significant on the 2009 sample). That is, the members of external databases are relatively less capitalised.

Table 29 contains the results for the relationships between ratios regarding capital requirement besides capital adequacy ratio and the indicator showing the used operational risk method's state of advance. In the 2008 sample, only the Tier 1 capital/total equity indicator shows significant correlation (negative relation) with the used method's state of advance. This means that the proportion of the relatively more stable Tier 1 capital within the equity of the institutions applying or intending to apply the advanced approach is smaller. The used method's state of advance shows a positive correlation with the proportion of the operational risk capital requirement within economic capital, which means that banks with AMA have a relatively high operational risk capital requirement. This is surprising, as we would expect a relatively lower capital requirement on the basis of market experience. Anyhow, this is good news from a supervisory point of view, if the background is that the institutions with higher risk are those that try to apply more advanced methods. At the same time, the negative, though insignificant, correlation with the operational risk capital requirement/total assets ratio is contradictory to the aforementioned. This would lead to a conclusion that the operational risk capital requirement of banks using AMA is indeed relatively lower. The signs are practically the same in the 2009 sample than those indicated in the 2008 sample, though in this case, only the correlation between the indicator of the state of advance including aspiration and the operational risk capital requirement/economic capital is significant (with a positive sign). We cannot derive a strong conclusion from the insignificance of the correlation between the operational risk capital requirement/economic capital or operational risk capital requirement/total assets and method selection in itself.

Table 29 Capital adequacy, quality of capitalisation indicators versus state of advance in a correlation matrix

	2008 sample (end-of-2007 data)		**2009 sample (end-of-2008 data)**	
	State of advance (0= simple, 1=advanced)	State of advance including aspiration	State of advance (0= simple, 1=advanced)	State of advance including aspiration
Op risk capital requirement as % of total economic capital	0.3587	0.3290	0.2200	0.2980
Op risk capital requirement as % of total assets	0.0060	0.0706	-0.1190	0.0010
Tier 1 capital/ total equity	-0.1740	-0.2382	-0.1090	-0.1210

Note: _ refers to significance at the 5% level, ‗ refers to significance at the 1% level.

It is not presented in a separate table, but I examined the relationship between the fact of applying the advanced approach and the operational risk losses for the previous 12 months. For the 2008 sample, the statistics show a weak positive, insignificant relation (correlation index of around 15%, p = 26%), but for the 2009 sample, they show a significant relation even on a 1% level (correlation index of around 29%, p = 0.3%), which would make us conclude that banks with AMA have higher operational risk losses. But we cannot make any strong deductions from this result, and not only because of the lack of significance regarding 2008, but due to the fact that there may be a "reporting bias", as the more developed institutions are supposedly more transparent and detect their operational risk losses better than the less developed ones.

At the end of my analysis, I examined the relationship of the ratio of operational risk losses of the previous 12 months to total net income with the two basic profitability indicators (ROAA, ROAE). For the 2008 sample, I got significant negative correlation in both cases, and for the 2009 sample, I found a slightly positive, but insignificant correlation. This can mean that the profitability of the banks incurring relatively bigger operational risk losses in the financial year of 2007 is worse as well. At the same time, in 2009, when the credit risk losses were realised and income from financial activities may have been realised, the correlation between operational risk losses and return is insignificant.

Table 30 Operational risk losses in past 12 months versus profitability indicators in a correlation matrix

	Operational risk losses as % of net income	
	2008 sample (end-of-2007 data)	**2009 sample (end-of-2008 data)**
Return on Average Assets (ROAA) (%)	-0.3140	0.0460
Return on Average Equity (ROAE) (%)	-0.3061	0.0350

Note: _ refers to significance at the 5% level, _ refers to significance at the 1% level.

V.1.3. Logistic regression analysis

I ran a regression model to test our initial hypothesis. The dependent variable is the applied operational risk method's state of advance. As we only have an initial hypothesis for profitability, I used the so-called stepwise approach during model construction. In this case, I tried to explain the “advanced-state of the model” parameter used as a dependent variable with several potentially relevant data, then the SPSS programme package sorted out the insignificant data, and those that had a relatively weak explanatory power compared to the other items by backward elimination.

The following independent variables are included in the regression model (the content of each variable is described in Table 40): CAPFLIAB, CAPRATIO, COSTINCO, DEPSHFUN, EQASSETS, EQUITY, LIQSTFUN, LOANASSE, LOANDEPO, LOANLOSS, NETINCOM, NIM, ORLOSS, ROA, ROE, TIER1, TIER1_CA (Tier 1 capital/equity: TIER1/EQUITY), TOTASSET

Since the dependent variable is a dummy-type variable, I use logistic regression.

The algorithm leads to the results in Table 31. Since only 66 of the institutions have observed operational risk loss data, and other data incompleteness occurs as well, we had all the variables only in the case of 50 observations, therefore our regression analysis is based on 50 observations from the 2008 sample; however, we can use a sample containing 77 elements from the 2009 sample. The results show that at the end of the iteration, we arrived to coefficients that are significant on at least a 10% level. Of the size indicators, only total assets are included in the final model as a significant variable. The negative coefficient value for capital funds/total liabilities is congruous with the correlation analyses, according to which the less capital funds are amongst total liabilities, the more the banks use advanced methods. Profitability indicators show mixed results (cost to income ratio positive, ROAA negative, ROAE positive, net interest margin highly positive), which may have an insignificant effect on the 2008 sample altogether. The Tier 1 capital/equity ratio has a significant negative coefficient just as expected according to the correlation analyses. The explanatory power of the model proves to be good; the Nagelkerke R^2 shows a value of about 65%. It is worth considering, however, that the Nagelkerke R^2 indicator is always greater than the Cox & Snell indicator. In the 2009 sample, other indicators became significant, and interestingly, total assets did not remain in the equation.

Table 31 Results of regressions I. (logistic regression)

	2008 sample		
Dependent variable: state of advance	B	Exp(B)	Significance
Total assets	0.000002	1.00	0.0534
Capital funds/ total liabilities	-0.564410	0.57	0.0656

2008 sample

Dependent variable: state of advance	B	Exp(B)	Significance
Net interest margin	5.726385	306.86	0.0144
ROAA	-19.538837	0.00	0.0175
ROAE	0.728156	2.07	0.0138
Cost to income ratio	0.082612	1.09	0.0214
Net loans/total assets	0.091511	1.10	0.0828
Tier 1 capital/ total equity	-15.005108	0.00	0.0074

2009 sample

Dependent variable: state of advance	B	Exp(B)	Significance
Operational risk losses	0.001000	1.00	0.0430
Net income	0.000000	1.00	0.1280
Capital adequacy ratio	0.316000	1.37	0.0120
Leverage (equity/ total assets)	-0.594000	0.55	0.0020
Tier 1 capital/ total equity	-1.649000	0.19	0.0500

	2008 sample		2009 sample	
	Cox & Snell R^2	Nagelkerke R^2	Cox & Snell R^2	Nagelkerke R^2
R^2 type measures	0.4885	0.6513	0.3450	0.4610

As mentioned before, the conclusions above are based on as little as 50 observations from the 2008 sample, therefore, in order to achieve more robust and more intuitive results, I ran the regression by only using the final equation of the backward elimination regression analysis presented in Table 31; but at this time with 90 banks operating in Basel II system. The variance-explanatory power of the model decreased without doubt (Nagelkerke R^2 shows a value of around 36%), still, the results became more intuitive. Table 32 contains the results. The regression analysis suggests that the increase of total assets, net interest margin, and return on equity implies the application of more advanced methods, while the increase of the Tier 1 capital/equity ratio and return on assets implies the application of simpler methods. Interestingly, when we include the return on equity and return on assets indicators separately, the coefficients belonging to these indicators become insignificant, while if we leave both variables out, the other variables become significant. Thus, of the profitability indicators, net interest margin turned out to be an indicator with significant positive explanatory power in the model after all. In the 2009 sample, we could only involve 3 new elements into the analysis with this modified method; therefore it is not surprising that neither the explanatory power, nor the signs changed substantially.

Table 32 Results of regressions II. (logistic regression)

2008 sample

Dependent variable: state of advance	B	Exp(B)	Significance
Total assets	0.000001	1.00	0.0021
Net interest margin	0.868614	2.38	0.0118
Tier 1 capital/ total equity	-3.100908	0.05	0.0005
ROAE	0.155032	1.17	0.0175
ROAA	-3.079564	0.05	0.0239

2009 sample

Dependent variable: state of advance	B	Exp(B)	Significance
Operational risk losses in last 12 months	0.001000	1.00	0.0400
Net income	0.000000	1.00	0.1150
Capital adequacy ratio	0.305000	1.36	0.0130
Leverage (equity/total assets)	-0.582000	0.56	0.0010
Tier 1 capital/ total equity	-1.632000	0.20	0.0550

	2008 sample		2009 sample	
	Cox & Snell R^2	Nagelkerke R^2	Cox & Snell R^2	Nagelkerke R^2
R^2 type measures	0.2704	0.3605	0.3560	0.4750

I ran the same models again in a way that I included the desired and publicly announced aspiration to introduce AMA approach in the state-of-advance indicator. In Table 33, we see the results of the backward elimination similarly to that in Table 31. And in

Table 34 due to the method and indicator selection, we can see the regression run on a sample wider than that of the regression results in. Based on

Table 34 which is more interesting from the aspect of conclusions, we can see that the coefficients are significant on a 5% level at the most for the 2008 sample. For the 2009 sample, there are also several insignificant indicators. The increase of total assets and interest margin implies the advanced method, while the increase of the balance of customer deposits & short-term funding and the ratio of Tier 1 capital/equity implies the simpler methods. The explanatory power of these models are somewhat weaker for the 2008 sample than it is in the case of the estimation results presented in Table 32 and Table 33, even considering that the aspiration to introduce the advanced method may naturally entail uncertainty. The total assets indicator plays no part in the sample for 2009; therefore we get a slightly counterintuitive result.

Table 33 Results of regressions III. (logistic regression)

2008 sample

Dependent variable: state of advance including aspiration	B	Exp(B)	Significance
Customer deposits and short-term funding	-0.00001	1.00	0.0306
Net income	-0.00060	1.00	0.0088
Net interest margin	1.04416	2.84	0.0238
ROAE	0.14928	1.16	0.0386
Tier 1 capital/total equity	-5.26119	0.01	0.0050
Total assets	0.00001	1.00	0.0134

2009 sample

Dependent variable: state of advance including aspiration	B	Exp(B)	Significance
Operational risk losses in last 12 months	0.00000	1.00	0.3830
Customer deposits and short-term funding	0.00000	1.00	0.0320
Equity	0.00000	1.00	0.0190
Capital adequacy ratio	0.37400	1.45	0.0360
Leverage (equity/total assets)	-0.81600	0.44	0.0010
ROAA	2.04900	7.76	0.1220
ROAE	-0.14900	0.86	0.0650
Net loans/ (Customer deposits and short-term funding)	0.02100	1.02	0.0410
Tier 1 capital/total equity	-2.18800	0.11	0.0970

	2008 sample		2009 sample	
	Cox & Snell R^2	Nagelkerke R^2	Cox & Snell R^2	Nagelkerke R^2
R^2 type measures	0.3715	0.4954	0.4440	0.5930

Table 34 Results of regressions IV. (logistic regression)

2008 sample

Dependent variable: state of advance including aspiration	B	Exp(B)	Significance
Tier 1 capital/total equity	-1.351202	0.258929	0.0143
Total assets	0.000007	1.000007	0.0063
Customer deposits and short-term funding	-0.000007	0.999993	0.0154
Net interest margin	0.232086	1.261228	0.0869

	2009 sample		
Dependent variable: state of advance including aspiration	B	Exp(B)	Significance
Operational risk losses in last 12 months	0.00000	1.00	0.4370
Customer deposits and short-term funding	0.00000	1.00	0.0670
Equity	0.00000	1.00	0.0310
Capital adequacy ratio	0.19900	1.22	0.1380
Leverage (equity/total assets)	-0.59300	0.55	0.0010
ROAA	0.80900	2.25	0.4510
ROAE	-0.03300	0.97	0.5520
Net loans/ (Customer deposits and short-term funding)	0.01500	1.02	0.1100
Tier 1 capital/total equity	-0.89700	0.41	0.3440

	2008 sample		2009 sample	
	Cox & Snell R^2	Nagelkerke R^2	Cox & Snell R^2	Nagelkerke R^2
R^2 type measures	0.1784	0.2379	0.4110	0.5480

V.1.4. Groups of bank – cluster analysis

While we analyse the international sample, it is worth examining how big a part does each operational risk factor play in identifying the different groups. Since we did not have any initial hypothesis on how many clusters can we create from the analysed banks, we made SPSS to do a hierarchic clustering with non-predefined cluster number. The method applied is the hierarchic clustering method, which is based on the squared Eucledian distance based on the "correlation between groups" as per the basic settings given by the SPSS programme package (power factor: 2, root factor: 2). As a result of the hierarchic cluster analysis, 5 separate clusters appeared. All the banks that had relevant data were included in the analysis. Table 35 shows the average data of the various indicators of the 5 groups. Figure 28 in the annex shows the dendrograms of the clustering. After that, in order to verify the number of created separate groups, I applied non-hierarchic, k-centre clustering. The table below contains the results regarding each cluster.

Table 35 Features of individual clusters

2008 sample

Clusters and mean value of indicators	**1**	**2**	**3**	**4**	**5**
Total assets (mUSD)	681,727	260,095	2,570,498	1,341,934	2,003,051
State of advance for operational risk approach (0= more simple, 1= advanced)	0.47	0.22	0.75	0.70	0.80
Aspiration to AMA	0.18	0.19	0.00	0.00	0.00
Equity (mUSD)	34,508	15,878	86,039	68,683	100,260
Tier 1 capital/ total capital (%)	0.82	0.90	0.74	0.74	0.71
Loan loss reserve/gross loans (%)	1.18	1.22	1.66	1.65	1.52
Capital adequacy ratio (%)	10.27	12.35	11.83	11.59	10.90
Leverage (equity/total assets) (%)	5.00	6.91	3.45	5.10	5.12
Net interest margin (%)	1.55	2.10	1.04	1.39	1.57
Return on Average Assets (ROAA) (%)	0.69	1.01	0.58	0.63	0.36
Return on Average Equity (ROAE) (%)	13.05	15.45	16.37	11.79	4.51
Cost to income ratio (%)	62.19	55.49	61.61	58.68	74.71
Net loans/total assets (%)	50.99	59.25	26.33	45.65	39.28

Clusters and mean value of indicators	1	2	3	4	5
Net loans/customer & short-term funding (%)	80.42	104.20	35.08	68.32	53.03
Liquid assets/customer & short term funding (%)	5.43	9.40	6.06	14.20	26.35
Number of members of individual clusters	17	36	4	10	5

2009 sample

Clusters and mean value of indicators	1	2	3	4	5
Total assets (mUSD)	2,138,843	673,785	1,249,567	233,454	3,111,902
State of advance for operational risk approach (0= more simple, 1= advanced)	0.67	0.41	0.75	0.16	0.75
Aspiration to AMA	0.00	0.27	0.08	0.16	0.00
Equity (mUSD)	107,807	27,478	66,660	15,941	72,922
Loan loss reserve/gross loans (%)	2.02	1.48	2.35	2.46	1.54
Capital adequacy ratio (%)	11.86	11.41	12.44	13.80	12.23
Leverage (equity/total assets) (%)	5.13	4.17	5.30	7.43	2.31
Net interest margin (%)	1.78	1.48	2.04	2.63	0.78
Return on Average Assets (ROAA) (%)	0.01	0.16	0.30	0.37	-0.33
Return on Average Equity (ROAE) (%)	-1.23	0.76	2.60	5.73	-7.58
Cost to income ratio (%)	79.15	104.96	78.11	55.97	96.05
Net loans/total assets (%)	43.21	51.83	48.76	58.79	23.88
Net loans/customer & short-term funding (%)	73.01	91.42	76.45	94.74	68.64
Liquid assets/customer & short term funding (%)	47.08	37.66	34.96	21.25	65.41
Number of members of individual clusters	6	22	12	51	4

In the 2008 sample, the first cluster contains 17 medium-sized institutions that are smaller than the sample mean, but the size of which is near average (measured by equity and total assets), and which use the AMA method partially, have a relatively low ROE based profitability and high ratio of liquid assets. The second cluster contains banks that are smaller than the sample mean, and typically use simpler methods (36 banks). The banks in the fourth cluster (4 banks) are large, have less liquid assets, higher leverage, and 75 per cent of them basically use the AMA approach. At the 4 banks in this category (HSBC Holdings, BNP Paribas, Barclays Bank, Deutsche Bank), due to the importance of the investment banking line of business, the ratio of net loans/total assets is low, as well as the proportion of the liquid assets and the ratio of equity to total assets are low as well. The fourth group contains 10 bigger-than-average institutions which typically use the AMA approach and are amongst the more active banks regarding lending (e.g. Société General, Unicredit, but we must mention that JP Morgan is also in this group). There are 5 institutions in the fifth cluster. These are bigger than the average size (on the basis of equity and total assets), typically use the AMA approach, have a high balance of liquid assets, but had small profitability in 2007 (Citigroup, Bank of America Corporations, Mitsubishi UFJ Financial Group, Crédit Agricole Group, UBS).

In the 2009 sample, six institutions appeared in the first cluster, which are typically AMA banks, with a substantially higher than average size, and had no significant losses in 2008. 22 institutions appeared in the second cluster. These have an average size, and only 40 per cent of them use the AMA approach. The third cluster contains 12 institutions, which are slightly bigger than the average, but showed a relatively high profitability in 2008, and most of them are AMA banks. The fourth cluster contains 51 institutions, which are smaller, use simpler operational risk methods, and lending is important regarding their basic activity. Four institutions appeared in the fifth category (Royal Bank of Scotland, BNP Paribas, Barclays Bank, Deutsche Bank). This group was basically separated by its deficit, and by the low level of lending activity compared to its size on the other hand. These banks basically use the AMA approach as well, except for the Royal Bank of Scotland.

In order to have a more correct statistical procedure, I ran the clustering for standardised values as well. The dendrograms of the hierarchic clustering can be found in the annex. Therefore, I identified 4 clusters for the 2008 sample, in one of which, interestingly, there was only one institution, Nykredit Realkredit, possibly due to its low liquidity and high ratio of loans/customer funding. The largest institutions appeared in cluster 2, in which the proportion of banks using AMA is high. Smaller institutions fell into cluster 1 and 3, but in cluster 3, the aspiration to introduce AMA is higher, and banks having smaller leverage appeared in this group. The same run for 2009 indicated other results. Credit Suisse and Landesbank Baden-Württemberg formed a separate cluster (cluster 4). And only 3 institutions appeared in the first cluster: Nykredit, Swedbank and the Agricultural Bank of China. Smaller institutions having higher leverage fell into cluster 2 (13 banks), while cluster 3 consists of 77 institutions.

Table 36 Features of individual clusters

2008 sample

Clusters and mean value of indicators	**1**	**2**	**3**	**4**
Zscore: Total assets (mUSD)	-0.37	1.25	-0.40	-0.71
State of advance for operational risk approach (0= more simple, 1= advanced)	0.39	0.59	0.29	0.00
Aspiration to AMA	0.07	0.09	0.29	0.00
Zscore: Equity (mUSD)	-0.50	1.05	0.01	-0.74
Zscore: Loan loss reserve/gross loans (%)	0.56	-0.30	-0.57	0.82
Zscore: Capital adequacy ratio (%)	-0.53	-0.05	0.10	-1.19
Zscore: Leverage (equity/total assets) (%)	-0.50	-0.26	0.58	-0.68
Zscore: Net interest margin (%)	-0.54	-0.55	1.01	-0.34
Zscore: Return on Average Assets (ROAA) (%)	-0.38	-0.63	0.36	-0.84
Zscore: Return on Average Equity (ROAE) (%)	-0.19	-0.78	0.56	-0.89
Zscore: Cost to income ratio (%)	0.41	-0.84	-0.01	-1.12
Zscore: Net loans/total assets (%)	-0.19	0.66	-0.25	-0.58
Zscore: Net loans/customer & short-term funding (%)	0.44	-1.04	0.35	1.78
Zscore: Liquid assets/customer & short-term funding (%)	0.21	-0.56	0.10	8.61
Zscore: Liquid assets/customer & short-term funding (%)	-0.39	0.42	0.02	-0.87
Number of members of individual clusters	28	22	20	1

2009 sample

Clusters and mean value of indicators	**1**	**2**	**3**	**4**
Total assets (mUSD)	-0.66	-0.73	0.15	0.22
State of advance for operational risk approach (0= more simple, 1= advanced)	0.00	0.23	0.38	0.50
Aspiration to AMA	0.00	0.00	0.18	0.50
Equity (mUSD)	-0.79	-0.50	0.12	-0.21
Loan loss reserve/gross loans (%)	-0.98	1.60	-0.20	-0.63
Capital adequacy ratio (%)	-0.11	1.42	-0.30	0.37
Leverage (equity/total assets) (%)	-0.79	1.52	-0.17	-1.05
Net interest margin (%)	-0.31	1.58	-0.14	-1.04
Return on Average Assets (ROAA) (%)	0.02	-0.33	0.14	-0.98

Clusters and mean value of indicators	1	2	3	4
Return on Average Equity (ROAE) (%)	0.30	-0.13	0.13	-1.44
Cost to income ratio (%)	-0.21	-0.18	-0.12	5.94
Net loans/total assets (%)	1.62	0.03	0.09	-1.37
Net loans/customer & short-term funding (%)	3.61	-0.24	0.00	-0.73
Liquid assets/customer & short-term funding (%)	-0.23	-0.32	-0.12	1.13
Number of members of individual clusters	3	13	77	2

V.1.5 Summary of conclusions

The multivariate statistical methods applied on a sample of large international banking groups confirmed the fact related to the operational risk method selection of banks that larger institutions choose more advanced methods with higher probability. At the same time, the relationship between profitability and the selection of advanced measurement approach (AMA) does not seem to be unequivocal; the individual correlation and regression analyses show contradictory or insignificant results. Based on the cluster analysis, we could group banks into five categories by including but not limited to their size, profitability and the application of the advanced measurement approach.

V.2. Analysis of the operational risk method selection in Hungary

As I indicated in the introduction, the novelty of the capital adequacy regulation complying with the Basel II directives, generally used in the European Union and introduced to the domestic banking system on the 1st January 2008 is the separate management of the operational risk. If we take a look at the method selection of the individual institutions, we can determine that the larger institutions use more advanced methods both in the international and in the domestic practice. One of the explanatory reasons of this is that the introduction of a more advanced method entails higher fixed costs, which is easier for a larger institution to manage in the short run, and they are able to exploit the benefits better. In summary, the conscious management of operational risks, and the related application of more advanced methods are factors contributing to the stability of the financial system.

V.2.1. The drivers of the operational risk method selection

According to the end-of-year data of 2008, 2009, and 2010, we can conclude that the majority of the domestic banks apply the basic indicator approach, however, if we look at the share by total assets or own funds, 80 per cent of the banking system uses the standardise approach (Table 37). In 2008, only one smaller participant of the banking sector (the aforementioned WestLB, which transformed to Milton, then to Gránit bank in 2009) used the advanced measurement method, but by 2009, 3 more institutions that previously had been amongst those using the simpler method changed to the AMA approach. As a result, while essentially in 2008, the field was divided to those applying BIA ("simpler institutions" from this aspect) and the standardised approach ("more advanced institutions" from this aspect), by the end of 2009, the total assets and own funds based market share of the banks using AMA became significant (15-16 per cent). In 2010, WestLB, or Gránit Bank, previously using AMA approach, returned to the simplest method of BIA owing to the change of ownership, meanwhile in 2010 one bank (namely UniCredit Hungary) switched to AMA approach. Therefore, at the end of 2010, 3 banks used the AMA approach. It is worth noting that at the subsidiaries of the foreign banking groups dominating the domestic banking sector not only the own institution size, but the expectations of the parent bank may also be decisive regarding operational risk method selection, moreover, in case of selecting AMA, the material part of the group has to be covered by AMA. Although, according to the end-of-year data of 2008, the average profitability values were higher in parallel with the approach's state of advance, this was not the case in 2009, but again characterised the year 2010 (Table 37). However, in 2010, the profitability processes were significantly affected by the special tax of the financial institutions, and some bank-specific processes.

Table 37 Choice of operational risk approach by Hungarian banks and features of each pool

End of 2008

Approach	Number of banks	Total assets based share	Own funds based share	Average total assets (HUF Bn)	Average capital adequacy ratios	Average ROE	Average ROA
BIA	21	19.40%	18.06%	270	12.02%	5.12%	0.27%
TSA	13	80.42%	81.72%	1,805	10.84%	14.34%	1.02%
AMA	1	0.18%	0.22%				

End of 2009

Approach	Number of banks	Total assets based share	Own funds based share	Average total assets (HUF Bn)	Average capital adequacy ratios	Average ROE	Average ROA
BIA	19	6.46%	7.71%	99	16.66%	21.26%	0.50%
TSA	12	77.49%	77.59%	1,872	12.88%	13.89%	0.95%
AMA	4	16.05%	14.70%	1,164	12.94%	14.07%	0.74%

End of 2010

Approach	Number of banks	Total assets based share	Own funds based share	Average total assets (HUF Bn)	Average capital adequacy ratios	Average ROE	Average ROA
BIA	20	6.69%	7.29%	94	15.57%	-0.46%	-0.04%
TSA	12	76.96%	77.47%	1,806	13.06%	1.74%	0.15%
AMA	3	16.35%	15.24%	1,535	13.78%	8.59%	0.52%

Note: End of 2008, end of 2009, and end of 2010 solo level data.

Source: MNB.

Based on the table above, the correlation analyses rather strengthen the positive and negative covariance with the total assets-based size and capital adequacy indicator; however, based on the operational risk method's state of advance, the profitability of banks does not differ significantly. (Table 38). The lower capital adequacy ratio of institutions using the advanced approach can be explained by more effective capital management on the one hand, and by the effects of the crisis on the other.

Table 38 Choice for operational risk approach and its relationship with size, profitability and capital adequacy indicators

	End-of-2007			End-of-2008			End-of-2009		
Correlations (Kendall tau b)	OR approach's state of advance*	p	N	OR approach's state of advance*	p	N	OR approach's state of advance*	p	N
Capital adequacy ratio	-0.22	0.14	33	-0.3	0.03	35	-0.28	0.04	35
Total assets	0.41	0	33	0.46	0	35	0.48	0	35
ROE	0.09	0.52	33	0	0.99	35	0.07	0.63	35
ROA	0.03	0.82	33	-0.04	0.75	35	0	1	35

	End-of-2010		
Correlations (Kendall tau b)	OR approach's state of advance*	p	N
Capital adequacy ratio	-0.35	0.04	35
Total assets	0.54	0.00	35
ROE	0.09	0.62	0
ROA	0.28	0.11	0

Note: *BIA=0. ; TSA=1; AMA=2

Source: MNB.

14 banks of the domestic credit institutions, two of which are special institutions (Eximbank and MFB), and two banks' other domestic subsidiary banks that take part in the consortium (FHB Commercial Bank and Unicredit Mortgage Bank) participate in the HunOR database. Regarding the state of advance, in this case, we see a similar pattern to that of the foreign banks with external operational risk database membership. At the end of 2010, 83 per cent of the HunOR member banks falling under Basel II, and of whose parent bank is a HunOR member follow the standardised or the advanced measurement approach, while in the case of non-HunOR banks this ratio is only 22 per cent. Consequently, the external database membership points to the selection of more advanced methods in the domestic banking system as well, and this is also confirmed by the correlation analyses. (Table 39). This manifested in the application of the standardised approach , but in 2009, gradually in the application of the AMA approach as well, which was the case for two HunOR members in 2009[73].

[73] It is worth noting that external database membership entails costs, which can be of critical amount for small institutions. However, a common database can provide a methodology framework, this is coupled

Table 39 Choice for operational risk approach and its relationship with HunOR participation

	End of 2008		End of 2009		End of 2010	
	HUNOR members	**Other banks**	**HUNOR members**	**Other banks**	**HUNOR members**	**Other banks**
BIA	3	18	2	17	2	18
TSA	9	4	8	4	8	4
AMA	0	1	2	2	2	1
Sum	12	23	12	23	12	23
Distribution based on total assets	52.47%	47.53%	53.04%	46.96%	53.32%	46.68%

	Kendall tau-b correlation with HunOR participation	p	N
OR state of advance* - 2008	0.47	0.01	35
OR state of advance* - 2009	0.48	0.00	35
OR state of advance* - 2010	0.54	0.00	35

Note: *BIA=0, TSA=1; AMA=2. Data for this table do not include specialised credit institutions (Exim, KELER, and MFB); however Exim and MFB are members of HunOR on individual level.

Source: MNB.

V.2.2. Conclusions

This analysis focused on the operational risk aspects of the Basel II conform capital adequacy regulation introduced on the 1st January 2008 in the domestic banking system. The regulation provides a possibility of method selection for the credit institutions falling under this regulation, therefore, they have the possibility to apply simpler, profitability indicator based, and more advanced, real risk measurement based methods. Regarding the method selection of the individual institutions, we can conclude that both in the domestic practice and in the case of larger foreign institutions, the larger institutions apply more advanced methods, which may be explained by the fact that the introduction of the latter entails higher fixed costs, which is easier for a larger institution to set aside for its operational risk project. At the same time, a larger institution may exploit the capital adequacy benefits deriving from the method's state

by a software solution in the case of HunOR, which may make the operational risk databases attractive despite the costs.

of advance better. The most advanced, so-called AMA method was used by three institutions in the domestic banking system as per the end-of-2010 state. It is worth noting that not only small institutions complied with the applicability criterions at this time, where they presumably try to capitalise on the advantages of the economy of scale on a banking group level, and to adopt the group level approach locally, at a relatively small cost (e.g. due to the application of group level methods instead of developing a separate model). In summary, the conscious management of operational risks, and the related application of more advanced methods are factors contributing to the stability of the financial system, which, in the circumstances of today's crisis, also deserves more attention in parallel to the strengthening of financial risks.

To continue this analysis, it would be worth comparing the selection of methods of calculating operational risk capital charges with that of credit risk, where it is also possible to apply a simpler and a more complex method (standard or internal scoring based method); moreover, it would be useful to examine country and region specific factors in the method selection patterns.

V.3. Summary

In connection with my third hypothesis, I concluded that amongst both the international and the domestic banks, the larger institutions are more inclined to use more advanced operational risk management methods, while there is no significant relationship with profitability. Moreover I have found significant relationship between state of advance of for operational risk methods and membership in operational risk data consortia. These results may help understand the driving forces behind method selection, and at the same time they raise the question of comparison with the method selection related to the management of risks other than operational risk.

VI. Summary, conclusions

In my thesis, I analysed the operational risks and risk management methods related to the activity of banks.

By operational risk we mean the risk of loss resulting from inadequate or failed operation of people, systems, and processes or from external events. (BIS [2004], EU [2006], Government of the Hungarian Republic [2007]). The increasing exposure to risk due to the complex financial institution system on the one hand and the regulatory ambitions on the other hand make the examination of the operational risk necessary. The number of domestic scientific publications, published researches relating to the Hungarian banking system has been limited so far. Given this context, one of the purposes of this thesis is to enrich the pool of operational risk related researches on the Hungarian banking system.

At the beginning of my thesis, I presented the characteristics (for example event types, frequent events with small impact versus rare events with high impact), regulation, and the capital requirement allocation methods of operational risk, and summarised the most important characteristics of the literature and the risk management practice.

I examined the following hypotheses in my thesis:

<u>Hypothesis 1:</u> The "Poisson frequency-lognormal severity" model framework generally applied in operational risk measurement practice can be justified in a theoretical, stylised framework as well, and a robust estimation can be made using the observed error points.

<u>Hypothesis 2:</u> The relationship between the operational risk losses incurred in the Hungarian banking system and the institution size is positive.

<u>Hypothesis 3:</u>

Sub-hypothesis A – The more profitable a financial institution is, the more effort it makes to apply more advanced operational risk methods.

Sub-hypothesis B – The bigger an institution is, the more possibilities it has to apply more advanced operational risk management methods.

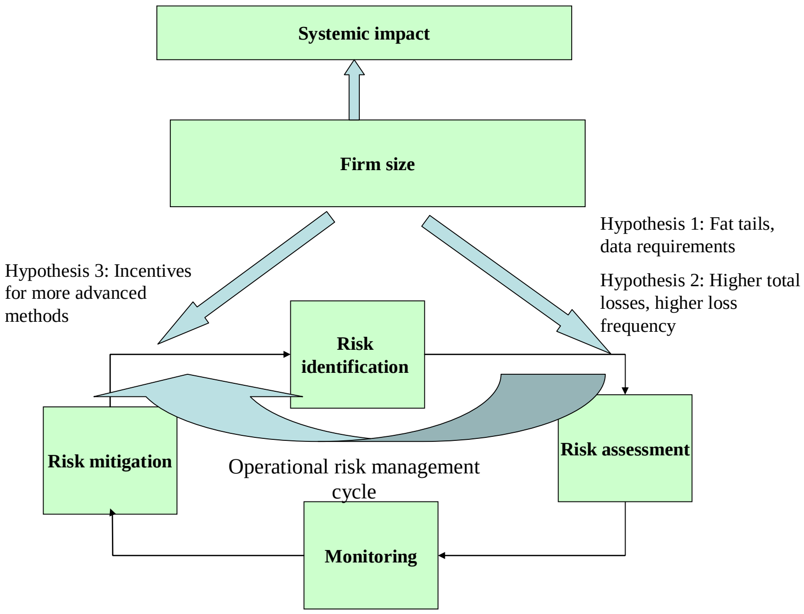
In connection with my first hypothesis, in a stylised model framework analysed by simulation methods I concluded that the frequency distribution of operational risk losses can be properly approximated by the Poisson distribution; while in the case of loss severity distribution, lognormal distribution did not show appropriate fit, while the more fat tailed Pareto distribution provided appropriate goodness of fit. Therefore, only one part of my hypothesis proved to be true. The distribution of the first hitting time often present in the related mathematical literature shows complexity in our empirical analyses. We analysed the possibilities of a model-based forecast, and discovered that a method built from historical data on a small sample may result in biased values (over- or underestimation). The model estimated for ATM errors present a proper methodological foundation, however, the back-estimation of the latent risk process may only take place when there is high error frequency. Back-estimation of the error process from the observed errors requires further analysis.

In connection with my second hypothesis, I concluded that my empirical analysis supports the following similarly to the foreign banking sectors and banking groups already analysed in the literature, the correlation between gross income-based institution size and the total operational risk losses incurred in a given period is significant in the domestic banking sector as well. The small sample of institutions limits the possibility to draw solid conclusions from the presented analysis; nevertheless, I ended up with forward-looking results. According to the analysis, the relationship between the institution size and the frequency parameter can be regarded as strong, and that with the loss size as less strong. In addition, the size of the individual losses is affected less by institution size, and more by business line or loss type.

In connection with my third hypothesis, I concluded that amongst both the international and the domestic banks, the larger institutions are more inclined to use more advanced operational risk management methods, while there is no significant relationship with profitability.

Summarising the results of the thesis and the connections thereof (Figure 27), our most important result is that institution size has an important effect on operational risk exposure and method selection. That is, larger institutions may potentially incur greater total loss, at the same time, with the fixed costs related to risk management, they may be more inspired to use more advanced methods. Higher loss frequency could serve as a basis for more robust risk estimation results, however co-operation in data consortia also could support increasing robustness of estimations. Summarily these results are congruous with our basic intuitions, however, it is important to highlight that altogether, this is a favourable tendency from an operational-risk-related system risk point of view, since it is important that institutions with potentially higher system risk influence apply more conscious risk management.

Figure 27 Results regarding hypotheses discussed in this thesis and their relationship with operational risk management cycle



In today's financial and economic crisis, with the increasing financial risks, even steady operational risks further worsen the position of the credit institutions, and on top of that, the employees of the financial institutions may make more errors in stress situations. As a result of this, the interaction of various risk types may intensify, operational risk events may cause credit risk events and vice versa (some kind of endogeneity appears). Furthermore, in today's circumstances, legal risk appreciates, since the clients become more sensitive in a more difficult economic environment, therefore the legal proceedings arising from the noncompliance with the ethics of fair business conduct (e.g. the selling of too risky products to clients not informed adequately) may cause severe financial and reputation loss, worsening the banks' not so favourable profitability expectations. All this means that operational risk will continue to play an important role regarding the evaluation of the risks of the banking sector.

VI.1. Potential applications of our results

The individual results of the thesis can be utilised in different ways by the individual participants affected. The two most important participants from the aspect of the banking sector's operational risks are the banks themselves and the authorities acting as supervisors.

The results presented in the simulation model framework and the exploration of the relationships between the operational risk loss parameters and the institution size indicators in the domestic banking system may contribute to the development of the operational risk management practice of banks. The simulation model framework can provide the banks with an idea to model their risks in a more sophisticated way. The scaling relations presented on the basis of the loss data of the domestic banking system can help scale the public operational risk losses from one bank to another on the one hand, and may inspire the members of the HunOR database operating in the domestic banking system to develop the scaling practice on the other hand. The overview of the factors affecting the measurement of operational risk, as well as the domestic empirical analysis can help domestic banks to develop their risk measurement. This is important because the current crisis also highlighted that the more conscious, more complex risk measurement and risk management mean competitive advantage.

My results might also be important for the authorities responsible for financial regulation, supervision. Namely, it helps to understand the driving mechanisms behind the operational risk exposure of the banking system, the result may support the analysis of operational risk on system level, and the results of the analyses justify the simpler operational risk capital allocation methods. Though the relatively short time series and the significant variance of the data do not make it possible to judge the sufficiency of the level of current operational risk capital requirement in the domestic banking system, but the described methods may improve the robustness of the analyses regarding sufficiency with the expansion of the time series. From a stability point of view, a favourable fact is that larger institutions are more inclined to use advanced methods. Since larger institutions may have higher impact on system risk, it is important that institutions more important on the banking sector level apply more advanced methods. Naturally, the positive impacts are only available if the methods used by the institutions are transparent enough, and can be extensively validated by the supervisory authorities.

VI.2. Future research plans

I highlighted only certain special aspects of operational risk during my analysis. In the future, it would be worth to develop the stochastic simulation based model framework further as well as to calibrate the model for application areas other than ATM errors. A model framework like this would also be useful for the practical users, i.e. the risk managers. It would be rewarding to expand the analysis of institution size and losses regarding the domestic banking system further, on the one hand, with the expansion of time series, a more comprehensive testing of the distribution types than that presented in this thesis, and on the other hand, with the application of extreme value statistics, and individual level analysis of capital adequacy sufficiency. Finally, when analysing the drivers of method selection, it would worth comparing operational risk method selection with credit risk method selection, and examining the method selection overview for other dates as well. This can help understand the driving forces behind the application of the more advanced risk management.

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Annex

Table 40 Variables used and their datasource

Name of variable	Content	Set of values	Datasource
AMA_APPR	Approval of AMA	0: No, 1: Yes	OR&C
AMAASPIR	Aspiration for AMA	0: No, 1: Yes	OR&C
APP_CODE	Operational risk method chosen (encoded)	0: Basel I 1: BIA 2: TSA 3: AMA	OR&C
APPROACH	Operational risk method chosen	Basel I, BIA, TSA, AMA	OR&C
BII_DATE	Basel II compliance date	Calendar year	OR&C
CAPFLIAB	Capital funds/liabilities	%	Bankscope
CAPRATIO	Capital adequacy ratio: own funds/ own funds requirements * 8%	%	Bankscope
CONS	In case of data consortium membership the name of the given data consortium	Text	OR&C, information published by data consortia
COSTINCO	Cost to income ratio	%	Bankscope
DEPSHFUN	Deposits & Short-term funding th USD Last availaible year	USD million	Bankscope
ECONCAP	Economic capital	USD million	OR&C
EQASSETS	Leverage: equity/total asset	%	Bankscope
EQUITY	Equity	USD million	Bankscope
EXT_MEM	Data consortium membership	0: No, 1: Yes	OR&C, information published by data consortia
LIQSTFUN	Liquid assets/customer & short-term funding	%	Bankscope

Name of variable	Content	Set of values	Datasource
LOANASSE	Net loans/total assets	%	Bankscope
LOANDEPO	Net loans/customer & short-term funding	%	Bankscope
LOANLOSS	Loan loss reserve/gross loans	%	Bankscope
NAME	Name of the bank	Text	OR&C, Bankscope
NETINCOM	Net income	USD million	Bankscope
NIM	Net interest margin	%	Bankscope
OPRISCAP	Operational risk capital requirement	USD million	OR&C
OPRISCAP_TOTCAP	Operational risk capital requirement as % of total capital requirement	%	OR&C
ORLOSS	Operational risk losses past 12 months	USD million	OR&C
ROA	Return on Average Assets	%	Bankscope
ROE	Return on Average Equity	%	Bankscope
TIER1	Tier 1 capital	USD million	OR&C
TOTASSET	Total assets	USD million	Bankscope

Note: Data of OR&C[2008] were matched with end-of-2007 data, meanwhile data of OR&C[2009] were matched with the most up-to-date data available during mid-of-2010.

Figure 28 Dendrograms for hierarchical cluster analysis

2008 sample:

Suntrust Banks	74
Unione di Banche Ita	77
China Merchants Bank	95
Shinhan Bank	76
Sberbank	33
The Bank of New York	75
Nykredit Realkredit	78
Woori Bank	80
Sumitomo Trust and B	86
BB & T Corp	90
Hana Financial Group	100
Anglo Irish Bank	87
DBS Bank	71
Banco Popular Espano	82
National City Corp	88
Desjardins Group	91
Capital One Financia	68
Akbank	93
Turkiye Is Bankasi	98
VTB Bank	55
Fifth Third Bancorp	92
Kookmin Bank	61
Banca Monte dei Pasc	81
Caja de Ahorros y Mo	59
US Bancorp	47
State Bank of India	56
National Agricultura	96
Allied Irish Bank	54
Shinkin Central Bank	89
DnB NOR Group	66
Washington Mutual	39
Standard Chartered	49
HSH Nordbank	73
Nordeutsche Landesba	84
Bank of Communicatio	51
Svenska Handelsbanke	97
Bank of Ireland	63
Scotiabank	43
Toronto-Dominion Ban	60
ANZ Banking Group	58
Canadian Imperial Ba	70
Bank of Montreal	53
Commonwealth Bank Gr	57
Skandinaviska Enskil	72

Caja de Ahorros y Pe	34
Resona Holdings	28
Groupe Banques Popul	36
KBC Group	52
National Australia B	42
Landesbank Baden-Wür	44
Danske Bank	62
Royal bank of Canada	41
Bayerische Landesban	48
Norinchukin Bank	37
Nordea Group	40
Hypo Real Estate Hol	83
Wells Fargo & Co	23
Banco Bilbao Vizcaya	29
Lyoyds TSB Group	32
Group Caisse d'Eparg	30
Dexia	38
China Construction B	13
Bank of China	11
Crédit Mutuel	25
Rabobank Group	19
Intesa San Paolo	24
Agriculture Bank of	69
Wachovia Corporation	17
Unicredit	12
Mizuho Financial Gro	18
JP Morgan Chase & Co	3
Société Générale	26
Santander Central Hi	9
HBOS	16
Industrial and comme	8
Credit Suisse Group	27
Fortis Bank	21
Sumitomo Mitsui Fina	22
BNP Paribas	10
Barclays Bank	14
Royal bank of Scotla	4
Crédit AgricoleGroup	7
Citigroup	2
HSBC Holdings	1
ING Bank	15
UBS	31
Bank of America Corp	5
Mitsubishi UFJ Finan	6
Deutsche Bank	20

Dendrogram by standardised values:

```
Commonwealth Bank Gr   57
ANZ Banking Group      58
National Australia B   42
Allied Irish Bank      54
DnB NOR Group          66
Scotiabank             43
Nordea Group           40
Svenska Handelsbanke   97
Kookmin Bank           61
Woori Bank             80
Banco Popular Espano   82
Banca Monte dei Pasc   81
Wells Fargo & Co       23
Banco Bilbao Vizcaya   29
HBOS                   16
Lyoyds TSB Group       32
Bank of Ireland        63
Caja de Ahorros y Mo   59
Royal bank of Canada   41
Canadian Imperial Ba   70
Toronto-Dominion Ban   60
Danske Bank            62
Hypo Real Estate Hol   83
Dexia                  38
Skandinaviska Enskil   72
Bank of Montreal       53
Sumitomo Trust and B   86
Caja de Ahorros y Pe   34
DBS Bank               71
Standard Chartered     49
Bank of Communicatio   51
Resona Holdings        28
Suntrust Banks         74
Unione di Banche Ita   77
Washington Mutual      39
Mitsubishi UFJ Finan    6
Mizuho Financial Gro   18
Rabobank Group         19
Sumitomo Mitsui Fina   22
Landesbank Baden-Wür   44
Nordeutsche Landesba   84
Group Caisse d'Eparg   30
Bayerische Landesban   48
Fortis Bank            21
Groupe Banques Popul   36
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National Agricultura	96
Desjardins Group	91
Norinchukin Bank	37
Barclays Bank	14
Deutsche Bank	20
Crédit AgricoleGroup	7
BNP Paribas	10
Société Générale	26
Credit Suisse Group	27
Industrial and comme	8
Santander Central Hi	9
HSBC Holdings	1
Unicredit	12
Intesa San Paolo	24
Bank of America Corp	5
Wachovia Corporation	17
HSH Nordbank	73
Anglo Irish Bank	87
Citigroup	2
JP Morgan Chase & Co	3
The Bank of New York	75
Shinkin Central Bank	89
UBS	31
VTB Bank	55
Akbank	93
Turkiye Is Bankasi	98
Nykredit Realkredit	78

2009 sample:

Woori Financial Grou	80
Swedbank	99
China Merchants Bank	83
Nykredit Realkredit	100
Banco do Brasil	90
Raiffeisen Zentralba	81
Sumitomo Trust & Ban	82
Kookmin Bank	74
Sberbank – Savings B	40
Bank of New York Mel	60
Allied Irish Banks	64
Caja de Ahorros y Mo	67
Itaú Unibanco Banco	36
State Bank of India	62
Banca Monte dei Pasc	70
Bank of Ireland	59
Norddeutsche Landesb	87

China CITIC Bank	65
DnB NOR Group	98
US Bancorp	38
Erste Bank	85
Svenska Handelsbanke	97
HSH Nordbank	77
PNC Financial Servic	39
SunTrust Banks	55
BB & T Corp	66
National Bank of Gre	94
State Street Corpora	63
National City Corp	92
Capital One Financia	79
Banco Popular Espano	84
Shinhan Bank	89
DBS Bank	54
UBI Banca	91
Agricultural Bank of	25
Banco Bradesco	46
KeyCorp	78
ICICI Bank	95
VTB-Bank	69
Fifth Third Bancorp	76
Regions Financial Co	75
Oversea-Chinese Bank	88
United Overseas Bank	71
UBS	17
Mizuho Financial Gro	18
Nordea Group	45
Danske Bank	86
Groupe Banques Popul	48
National Australia B	49
Lloyds TSB Group	50
Landesbank Baden- Wü	56
Royal Bank of Canada	31
DZ BANK Deutsche Zen	73
Toronto-Dominion Ban	37
Westpac Banking Corp	68
Commonwealth Bank Gr	41
KBC Group	52
Scotiabank	35
Resona Holdings	43
Bank of Communicatio	51
Standard Chartered	53
ANZ Banking Group	58
Canadian Imperial Ba	72

Skandinaviska Enskil	96
Bank of Montreal	42
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Santander Central Hi	9
UniCredit	19
ICBC	8
Société Générale	26
Wells Fargo & Co (in	6
Dexia	44
Groupe Caisse d’Epar	61
Rabobank Group	24
Commerzbank	29
Intesa Sanpaolo	27
Crédit Mutuel	28
Banco Bilbao Vizcaya	30
Bank of China	10
HBOS	34
China Construction B	11
Credit Suisse Group	16
Fortis Bank	33
Citigroup	4
Sumitomo Mitsui Fina	21
Mitsubishi UFJ Finan	7
ING Bank	20
Bank of America Corp	3
JP Morgan Chase & Co	2
HSBC Holdings	1
Crédit Agricole Grou	14
Barclays Bank	15
Deutsche Bank	23
BNP Paribas	13
Royal Bank of Scotla	5

Dendrogram by standardised values:

Allied Irish Banks	64
Woori Financial Grou	80
Banco Popular Espano	84
Erste Bank	85
Caja de Ahorros y Mo	67
‘la Caixa’	47
Kookmin Bank	74
Shinhan Bank	89
Raiffeisen Zentralba	81
Resona Holdings	43
Sumitomo Trust & Ban	82
Bank of Ireland	59

Commonwealth Bank Gr	41
Westpac Banking Corp	68
Rabobank Group	24
National Australia B	49
ANZ Banking Group	58
Banco Bilbao Vizcaya	30
Lloyds TSB Group	50
Skandinaviska Enskil	96
Nordea Group	45
Danske Bank	86
Svenska Handelsbanke	97
Swedbank	99
DnB NOR Group	98
Bank of Communicatio	51
China Merchants Bank	83
Scotiabank	35
State Bank of India	62
China CITIC Bank	65
Royal Bank of Canada	31
Toronto-Dominion Ban	37
Bank of Montreal	42
Standard Chartered	53
Canadian Imperial Ba	72
DBS Bank	54
Oversea-Chinese Bank	88
United Overseas Bank	71
PNC Financial Servic	39
ICICI Bank	95
US Bancorp	38
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