

# **Summary of PhD thesis**

**Instability of risk measurements and risk measures**

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## *1. Motivation*

The last few decades have brought fast spread of financial models in the financial sector, which appeared in a number of areas of bank operations. We use models to determine the price of numerous financial products, choose clients with our models, determine the best investment for the client based on his risk tolerance, or calculate the bank's capital requirement. The design and application of statistical models is very important, since the additional information provided by the models often mean a competitive edge, or possessing the information is essential to remain competitive. Simultaneously, we have to keep in mind those aspects that impair the information provided by the models. Accordingly, we must be aware of, for example, model assumptions, the quality and relevant nature of the inputs (for example, a financial time cycle free of shocks will surely not reflect actual risks), the environmental changes that affect the input, and not in the least, the nature of the modelled problem. However, many times these can remain hidden from the modeler, since often the institute purchase the applied model with software support, and, trusting the software developer, the institute just enters the input into the model and utilizes the result. In other cases certain models spread like wildfire as a solution to a specific problem, and its market application spreads significantly faster than its industry-level understanding. Such cases, through its widespread application, can speed up the detection of the model's failings, however, at the same time can also mean a system-level risk to the entire financial sector. The widespread underestimation of risk (see CDO, currency credit) can cause system-level shock, which individual and social costs can be rather high. As a result, it is important we remain aware of the nature of the modelled problem, and the applicability of the model results. Too much faith in the models can hide the actual risks resulting from the nature of the problem, which can cause the risk bearer to be caught off-guard by the unexpected extent of the risk. In the dissertation we introduce two such financial problems where modelling and getting to know the risks may seem trivial, but the results can be rather questionable due to the instability hidden in the model. In the first part of the dissertation I examine the stability of capital models applied to operational risks. It is important to emphasize that the applied models themselves are not instable, but rather the application of the models in the operational risk environment. We will see that the capital expected by the regulator to cover operational risks, by definition places such expectations on the financial institutes that it carries instability

within. In the second part of the dissertation we deal with the problem of portfolio optimization. The advancement of risk measures was undiminished in the past 50 years, always favoring a measure to quantify the risks. In the Markowitz portfolio model the standard deviation is the risk measure, primarily for marketing reasons. Later, in the 90's JP Morgan published their Value at Risk (VaR) based risk management methodology (J. P. Morgan [1996]), which was immediately incorporated into the Basel regulation as well. The VaR criticisms evoked the Conditional Value at Risk (CVaR) and Expected Shortfall (ES) which is one of the simplest member of spectral risk measures. Following the crisis that started in 2008, regulation has become even more open to the introduction of ES, since it can grasp extreme losses better than current regulatory measure (VaR). There is a need for risk measure, because it concentrates information, maps a complex world (for example, a complicated credit portfolio) to a single value, which lets us easily recognize risk. However, we have to understand that on the one hand there is significant simplification and loss of information during the generation of the risk measure, and on the other hand specific measures grasp different features of the underlying world or emphasize them for the analyst. Supplementing this with the nature of the underlying problem can often cause the analyst or decision maker to face the phenomena of the result of risk measurement indicating significant deviations, while the risk profile of the underlying world remains unchanged. The first two problems drafted in the dissertation have this characteristic exactly, while the third one highlights another side of instability.

It is important to clarify that we use the word "instability" as a sort of umbrella term, and in no way as a unified, precise mathematical concept. Accordingly, stability also lacks an exact definition in this paper.

As the title of the dissertation also shows, we are talking about the instability of measurement and measure, as in some cases there is even a difference in what instability relates to – the measurement or the measure? The concept of instability will be specified in connection with individual problems. As we have already prefaced, in the dissertation we discuss real-life problems from the areas of operational risks and portfolio optimisation, which surprise everyday users, who discover that the solution to the problem sometimes differs greatly from what they expected beforehand. This means that there is some kind of anomaly behind the problem, which causes instability to appear in different ways depending on the case in hand.

In the case of operational risks the primary source of instability (extreme volatility of capital requirement) is the regulatory definition, which often manifests itself for the modeller in:

- large estimation error,
- sensitivity to extremes,
- use of incorrect distribution,
- significantly varying results for different estimation methods.

In the case of portfolio optimisation instability is reflected partly in the high volatility of portfolio weights and partly in the optimisability of the portfolio. We find that the estimation error of piece-wise linear risk measures is greater than that of variance, and also leads to greater volatility (instability) of portfolio weights. In certain cases instability is manifested in the surprising fact that optimisation can not be performed at all. Or we can take the far from everyday phenomenon that for Expected Shortfall the error is not monotonous in the function of confidence level. This means that in certain cases the higher the number of sample elements used for optimisation, the worse the estimate.

## *2. Research questions*

Following are the dissertation's primary questions.

1. Does the extrapolation problem relating to operational risk capital requirement affect institutions with small and large samples similarly?
2. To what extent does the selected risk measure influence the solution of portfolio selection? In other words, how sensitive are specific risk measures to the estimation errors during optimization?

3. Does an optimal portfolio exist in every case? Or, does a solution exist every time for the different portfolio optimization tasks?

### *3. Structure of the phd thesis*

To answer the above questions, we have structured the dissertation as follows. The first part of the dissertation (chapters 3-8) examines the questions relating to operational risk. This includes a longer and more detailed introduction, since it is not as well known, while the second part on portfolio optimization assumes general knowledge of the applied framework. The reason for this is that the roots of modern portfolio theory reach back to the works of Markowitz [1952], and most financial textbooks cover it.

The chapters following the introduction are as follows.

In chapter 3 we outline the regulating framework relating to operational risk, and the methods provided by the regulator, used to calculate the operational risk capital requirement of a specific credit company. The primary focal point of our dissertation is the so called AMA (Advanced Measurement Approach) with which institutes can develop their own models and use them to calculate the capital requirement.

In chapter 4 we introduce the mandatory elements of the AMA framework and provide a broad outline of related dilemmas. These are elements of the internal models that significantly affect the resulting capital requirement, while the regulator essentially does not provide a guideline to their application, only specifies their mandatory existence.

Next, we introduce the common features, nature, and stylized facts of the operational risks. Of these, we emphasize two in advance. On the one hand, operational risk capital requirement is generally determined by the greatest unique (midyear) loss or a few losses. Itself this projects a certain instability during capital requirement calculation. On the other hand, the available sample is never sufficient for a reliable estimate (see Single Loss Approximation and Mignola [2006]). This is another source of instability related to capital requirement estimation. Our research question also relates to this. If the sample size is never satisfactory, then who is in a more fortunate position: institutes with smaller or larger internal samples, or is there generally no difference? At first, even the question may seem absurd for the reader – how can it even occur that a result from larger sample yields a worse estimate than from a smaller one. We will derive the introduction of the problem in consequent chapters from the expectations of financial regulation.

At the end of the chapter we indicate a rather significant aspect of the Basel II regulation, whereas extreme losses mean the real risk, and this should be the primary focus of risk management. Accordingly, we also illustrate the philosophy of traditional and modern risk management.

Chapter 5 defines the operational risk capital requirement, and briefly introduces the methodology of related capital calculation methods (Gáll [2007]). The Loss Distribution Approach (LDA) means a possible procedure to determine capital requirement. The fact is that the aggregated annual loss is generated by the midyear loss frequency - and loss distribution. The LDA procedure can be executed using a number of methods, so in subsequent chapters we will discuss the Monte Carlo simulation (mc), fast Fourier transformation (fft), and the Panjer recursion as well.

Besides LDA, related to other methods applicable for capital requirement calculation, we will mention the methodology of Single Loss Approximation (SLA) and approximation methods.

In chapter 6 we first discuss the primary building blocks of the AMA based risk management. We will talk about optimal sample size, and the primary frequency and loss distributions defining the LDA. Through simple examples we will show that during capital requirement determination frequency distribution shape is generally circumstantial, only its expected value matters, however, the edge of loss distribution plays a dominant role. We will also illustrate the significant instability of the operational risk management capital requirement. We will show that the „true” value of the operational risk management capital requirement cannot be deduced from historical time series.

This is followed by a discussion of a special problem. Institutions creating internal models typically collect operational risk losses exceeding a specific threshold, so the discarded losses below the threshold also mean loss of information. On the one hand, we analyze whether discarded losses are tangible from the capital requirement aspect; and on the other hand, we show what an unstable situation the application of conditional distribution causes during capital requirement calculation.

Here we call attention to the similar values in the sample. This has to be mentioned, because during the analysis of the HUNOR database we will see that this phenomenon has a distortion effect on the loss distribution estimate.

In chapter 7 we return to the possible realization of the LDA method. We will examine if the application of different methods (Monte Carlo, FFT, Panjer recursion) have any effect on the calculation of capital requirement (Nagy [2009]).

Next, we show the Single Loss Approximation and its advanced methodology from the capital calculation aspect (Böcker [2006]), and detail the first research problem. Using the SLA methodology, we will expand that the dilemma of estimation from small or large sample means that two opposing effects determine the capital estimation error. Institutions with greater sample (due to the large number of midyear losses) are in a seemingly more favorable position from the estimation aspect, however, they must estimate a quantile belonging to a higher probability, which carries with it simultaneously an increasing uncertainty. Due to the two opposing effects (increasing sample and higher confidence level) it is unclear whether credit companies with a lot of data really estimate their capital with less or significantly less error. To answer the research question, we will derive the capital requirement distribution with certain conditions, which will provide one of the substantive analytical result of the dissertation. We will see how in certain cases the standard deviation of capital requirement (in our case, the VaR) as the function of annual frequency does not indicate monotonous behavior (it decreases in the beginning, then continues to increase). We can conclude that not only does the number of data an institution has matters, but also how heavy tail the loss generating procedure is. The interplay of the two determines how precisely the institute can estimate its operational risk capital requirement.

As we have mentioned already, two opposing effects face each other. First, the increasing frequency favors the estimate, since we can estimate loss distribution with less error from a greater sample, but on the other hand, the continuously increasing frequency requires the extrapolation of further and further quantile. It seems that while in case of a less risky (heavy tail) procedure the increasing sample size can balance the uncertainty resulting from extrapolation (continuously increasing quantile estimation), this does not happen in case of heavy tail procedures. Hence, as a paradox, in case of heavy tail procedures increasing sample size couples with the increasing uncertainty of capital requirement estimation! However, additional analyses show that if we measure the relative error of capital requirement estimation, it will be a monotonously decreasing function of the sample size, and thus greater sample leads to more stable estimation.

In chapter 8 we deal with external data. Besides internal historical data, external, industry data is also relevant for an institution building an AMA model. In this chapter we introduce a few descriptive statistics on the HUNOR (HUNgarian Operational Risk) database, and perform a few estimations assuming GPD (Generalized Pareto Distribution) on midyear loss data. The relevancy of GPD is provided by the fact that beyond a specific threshold (precisely where the internal institution data are rare or non-existent) the tail of the distribution converges to the GPD. We show that different estimation methods can result in significantly varying capital requirements even assuming the same distribution, meaning that risk management must be very careful with the results. We analyze the difference between the popular MLE and stable estimate providing PWM estimates using both HUNOR and artificially generated data, and draw a number of conclusions about parameters and the capital requirement calculated from them.

In summary (chapter 9) we outline the conclusions relating to operational risk models and the resulting capital requirement. We will see that the institution must be careful when building the AMA model because it has to determine the capital requirement in a regulatory environment where the capital value is far beyond the observable and backtestable range.

Chapter 10 deals with the estimation errors in portfolio optimization. Here we pass by the previously applied risk measure - Value at Risk, due to its non-convex characteristics. Since portfolio optimization is a widely known and discussed topic, we follow immediately with the second research question – To what extent does the selected risk measure influence the solution of portfolio selection?

Chapter 11 analyzes the classic risk measure – variance noise sensitivity. Based on simulation approach we analyze the noise sensitivity of variance (Pafka [2002]). Pafka [2002] introduced the quotient of estimated portfolio standard deviation and estimation error free portfolio standard deviation, and used it to determine the level of noise. He showed that noise is the function of N/T (number of assets / sample size). We will reproduce the variance-covariance matrix model he established, which summarized the relevant features of the empirical covariance matrices observed in the real world market.

In chapter 12 we mention alternative risk measures. Alongside the second research question we analyze absolute deviation, Expected Shortfall (Acerbi [2004]) and its pessimistic version, Maximal Loss (ML). The common feature of these risk measures and the common regulating

measures (here we mean measures based on artificial regulatory weights, not the VaR) is that they are piece-wise linear, or in other words, their iso-risk surface is polyhedron in the function of portfolio weights. We state that this feature is the explanation to why these risk measures are more sensitive to noise than standard deviation. Another factor is that VaR, ES, and ML discard all data below a certain threshold, so only part of the data is used during the estimation. At the end of the chapter through the third research question we switch to whether the portfolio optimum using Expected Shortfall is a probability question that depends on the sample. All this can also mean that the portfolio optimization task does not have to have a solution in every situation. In case of Maximal Loss we determine the probability of optimizability as a function of N/T.

We close the portfolio optimization related chapters with a conclusion. We will see that the analyzed risk measures have different noise sensitivity levels. We have observed that estimation error is greatest in case of Expected Shortfall and its special case, Maximal Loss. Nothing guarantees the existence of the optimum in case of Expected Shortfall and in relation, Maximal Loss. The existence of a solution can be forced by introducing additional limiting conditions, but this means a linear programming task different from the original.

Finally, we summarize the research question's answers, and the respective results of the dissertation.

#### *4. Summary of results*

Before summarizing the main results of the dissertation we would like to note that the findings of the dissertation are reflected not only in answers to the problems posed, as in several other cases new or novel results, or results in harmony with international professional literature were produced (as by-products of analysis). We have highlighted the questions posed and the results most closely connected with them with bold and italic letters.

The essay is built around **three primary research questions**:

##### **I. Does the extrapolation problem relating to operational risk capital requirement affect institutions with small and large samples similarly?**

We examined this problem using three different approaches.

- i. In order to treat the above problem as simply as possible we built a model in which we examined the properties of small and large samples.
- ii. We analysed empirical data through examining the HUNOR operational risk database. The database is anonymous, so our original goal was to examine the impact of external data on smaller and larger institutions.
- iii. Since the HUNOR database posed several empirical problems, we used an artificial simulation environment to examine the significance of external data in capital calculations by institutions possessing smaller or larger samples.

The conclusions of modelling (i) can be summed up as follows.

***Thesis 1:** With lognormal individual loss distribution, capital requirement is also of lognormal distribution (assuming that we know the expected value of frequency distribution and the classic properties of MLE estimation are present - for details see page 79 of the dissertation).*

This emphasizes the empirical fact that errors made during capital requirement calculation are not symmetrical, but skewed right. Besides the verification of empiricism, the importance of this derivation is the significantly faster method of distribution cognizance compared to the simulation based method (with the specific model conditions).

***Thesis 2:** Taking into account internal data only, the disadvantages resulting from extrapolation are compensated by the greater number of elements (under given model conditions).*

We have shown in the introduced model environment that in case of less heavy tail (low  $\sigma$ ) single loss distribution estimation error (VaR distribution) decreases monotonously as a function of frequency, while in case of increasing  $\sigma$  the early decrease halts and starts to increase again with higher  $\lambda$  (expected frequency value) values. All this presents an interesting situation for capital estimation. Not only the amount of data the institution has is important, but also how heavy tail the loss-generating process. Their collaboration determines how precisely the institution can estimate its operational risk capital requirement.

As mentioned earlier, two forces face each other. On one hand, increasing frequency favors estimation, since greater sample means we can estimate loss distribution with lower error; on the other hand greater frequency requires further quantile extrapolation. It seems that increasing sampling size in case of a less risky process (low  $\sigma$ ) can balance the uncertainty caused by extrapolation, while this does not hold for heavy tail processes. As a result, paradoxically, in case of heavy tail processes increased sample size means greater uncertainty for capital estimation!

Naturally the situation is a bit more complicated since increasing standard deviation can still be negligible compared to the capital, so it is worth looking at relative standard deviation as well. During the examination of relative standard deviation we have experienced its monotonous decreasing characteristic. This means that banks with more loss events are in relatively better positions – regardless of distribution, because the error relative to the order of magnitude of the capital decreases monotonously. So the increasing sample size compensates for the disadvantages from the extrapolation (for the specific model conditions)!

We have shown in our log-normal single loss distribution model (with certain assumptions) that VaR distribution is log-normal and its expected value and distribution both depend on the sample size ( $n$ ). Institutions with a few number of losses are expected to more drastically overestimate their operational risk capital as those with large sample. This also supports the logic that the effect of the extrapolation problem is not the same for all institutions. The less data an institution has, the more they will overestimate their operational risk requirement.

We have subjected the HUNOR operational risk management database to a short analysis (ii). The analysis has shown that the losses from specific event categories follow a heavy tail distribution. Additionally, the log-normal distribution does not properly fit at the tails and typically underestimates the risk. We have shown that even assuming the same distribution, specific parameter estimation methods can result in capital requirements varying by orders of magnitude!

Examination of the empirical data (generalized Pareto distribution fitting) has shown that the MLE estimation function is very sensitive to identical sample elements, and their management is essential.

We have examined the significance of external data in a simulated environment on capital calculation (iii), including how the generalized Pareto distribution (distribution of external

data) parameters, the average number of losses of the institution, the size of the external database, and the estimation methods (MLE, PWM) affect the institution's capital requirements.

In connection with this we have made several findings which are in harmony with international professional literature (empirical observations, other models) and provided an answer to our research question from a new aspect (supplementing internal data with external ones).

**Thesis 3:** *Taking into account external data (assuming that the same set of external data is available to all institutions) brings more benefits for smaller institutions than for larger ones (their ability to reduce the estimation error for capital requirement is relatively better).*

Institution with greater frequency is not necessarily in a better position than ones with smaller frequency. By increasing annual frequency, VaR relative standard deviation (standard deviation / VaR quotient) increased for both MLE and PWM, for all  $\xi$  (tail index) values! Simultaneously the rate of relative standard deviation is less for MLE estimation, for high  $\xi$  value, by almost an order of magnitude. Ranges normalized by the expected value, which includes the VaR with 98% probability, increased for both MLE and PWM estimation when frequency increased! Please note that compared to an institution with less number of data, an institution with a lot of internal data faces the clearly negative effects of the extrapolation problem. Due to the greater internal sample, in order to determine the VaR, it must extrapolate farther to the tail of the distribution than the institution with less internal data, while both have the same samples (external database) available at the tail of the distribution! This corrupts estimation quality.

Our simulation-based study produced several results which, although they offer no direct contribution to answering the principal question, contain several findings in harmony with international professional literature (empirical observations, other models). These are summarised in the following.

- We have experienced the (asymptotic) unbiasedness of the MLE estimation, while the PWM estimation function likely underestimates the real tail index parameter. The rate of bias is greater (for PWM) as it approaches the real parameter (tail index) 1.
- The tail index MLE estimation is symmetrical, while the PWM is right-skewed.

- The PWM tail index estimation is bounded from above, while the MLE is not.
- The closer the  $\xi$  (tail index) value is to 1, the more MLE and PWM estimates differ.
- In case of tail index MLE estimation there is a roughly 5% probability that the estimation will yield an infinite expected value distribution (in case of  $\xi=0,9$ ).
- The PWM estimation function overestimates the scale parameter, while the MLE yields an (asymptotically) unbiased estimation.
- The 90% confidence interval for the scale parameter is wider for PWM.
- The difference is moderate between the scale parameter distributions for the specific estimation functions, supported by the effect of the parameter estimation error on the capital.
- The greater  $\beta$  (scale parameter) means greater standard deviation, but relative standard deviations are similar.
- The PWM estimation function likely underestimates the capital requirement, while the MLE estimation is asymptotically unbiased.
- The difference between the lower and upper value of the capital requirement estimated at 90% confidence level is approximately 1 order of magnitude, even with moderate tail index!
- In case of capital requirement minimum and maximum estimated with 98% accuracy, there were thirty-fold differences! The quotient of the maximum and the minimum is always less for MLE estimation than with the PWM method. However, it is apparent that in case of  $\xi=0.9$  the upper (0.99) quantile of the PWM estimation VaR distribution is less than the same VaR quantile for the MLE estimation. The reason for this may be the phenomenon observed during the analysis of  $\xi$  – the maximum value of  $\xi$  using PWM estimation was 1, so PWM estimation never resulted a  $\xi$  value with an infinite mean GPD distribution.
- The closer the  $\xi$  value is to 1, the more varying the VaR distributions resulting from specific estimation functions.

- The relative standard deviation of the capital requirement increases as  $\xi$  approaches 1. In case of PWM it is worth noting that for  $\xi=0.9$  standard deviation increases to multiples of the expected value!

We can briefly sum up our reply to the first (I) research question as follows.

We have shown in a self-created model environment that from an institution's internal sample aspect, institutions with larger sample have an advantage, because the VaR relative error decreases as sample size increases. Whereas the size of the external database is fixed (all participants have similar quantity of external data) and since the extrapolation effect is smaller for institutions with less data, its negative effects are better dampened by the external sample of the same number than for institutions with significant amounts of data where even the significant external sample is not enough for stable estimation.

Overall, even in our self-created and simplified model environment we cannot give a clear-cut answer to the research question. This means that in reality specific institutions must create their operational risk capital requirement model by carefully examining and understanding the circumstances (external-internal sampling size, loss generating process properties, etc.), and making a number of unique decisions. While the actuarial methods (LDA) provided for the problem promised fast and comfortable solutions, it has become more and more evident that there is no simple answer to the above mentioned problem.

## **II. To what extent does the risk measure influence the solution of portfolio selection? In other words, how sensitive are specific risk measures to the estimation errors during optimization?**

**Thesis 4:** *Individual risk measure estimates are particularly sensitive to noise. From the measures examined, the estimation error is greatest for Expected Shortfall and its special case, Maximum Loss, exceeding those found in connection with Absolute Deviation and variance.*

Since standard deviation and absolute deviation results are already available in scientific literature, we primarily analyzed the Expected Shortfall and its special case – Maximum Loss. We have seen that the analyzed risk measures have different sensitivity levels to noise. We

have observed that the Expected Shortfall and its special case, Maximum Loss, experience the greatest estimation error, surpassing the experiences from AD and variance. We have seen great portfolio weight fluctuation even with variance optimized portfolios, but these fluctuations were even more significant for the other observed risk measures (AD, ES, ML).

The weight instability is clear if we do not use overlapping samples. Overlapping samples are autocorrelated, so in such cases the optimum changes slowly, while in reality the portfolio get stuck in a suboptimal situation.

One of the primary messages of the analysis is that in case of alternative risk measures more information is needed (longer time series) to make them more competitive with the variance. One of the reasons for greater information demand is the piece-wise linearity of the risk measures (AD, ES, ML). Linearity provides great calculation advantages, but we have seen that it simultaneously leads to instability: sample change leads to results “jumping”, which manifests in the increased fluctuation of portfolio weights. In addition, the ES and ML risk measures only utilize only a section of the available time series – the extremes. This means that optimization from a smaller sample is possible with greater estimation error.

It is a surprise in case of ES that  $q_0$ , which measures the error during optimization, does not behave monotonously against  $\beta$  (threshold defined in probability).

### **III. Is there an optimal portfolio for every case? Or, is there a solution for portfolio optimization?**

**Thesis 5:** *Expected Shortfall and Maximum Loss can only be optimised with a certain degree of probability.*

In the case of Expected Shortfall and its extremal special case, Maximum Loss, we have encountered particularly strong sample to sample fluctuations and a surprising feasibility problem: although these are convex (in fact, coherent) risk measures, in some samples they are not bounded, and then the optimization over the weights does not have a solution. This feasibility problem may be solved by applying additional conditions, such as excluding short selling, but this means a linear programming task different from the original.

The probability of solution depends on the parameters: for maximum loss can be derived analytically, while in case of Expected Shortfall we have measured the boundary where the solution exists with a probability of 1.

## *5. Summary*

During the essay we have tried to find out how well today's risk measures hold their grounds during portfolio optimization, and what problems in the determination of operational risk capital requirements must be overcome? In both cases models contain considerable instability, their users cannot be sure at all about the quality of their results. The sources of the instability are different in both cases.

During portfolio optimization we must be aware that piece-wise linearity risk measures provide fast optimization, however the iso-risk surfaces are polygons where the solution exists in the extremal points. As a result, even the slightest changes in the input data can cause a jump from one extremal point to another. This can cause increased noise for piece-wise linear risk measures. In case of Expected Shortfall and Maximum Loss we must also consider that during optimization only small part of the input data is considered because our goal is to create a portfolio that minimizes extreme losses. Discarding the majority of the data leads to additional noise. This is further affected by the fact that optimization of these risk measures can only be performed with a specific probability as a function of portfolio and sample size.

Considering operational risk, the source of instability is the original Basel II regulatory definition because all institutions come face to face with the extrapolation problem regardless of the size of their operational risk database. While writing the essay it has become clear that there is no clear (and simple) answer to the question of whether institutions with small or large sample size can give a better estimate about their capital requirements, because this depends on several factors.

Overall I would like to call the attention of the reader to the fact that naive application of financial models without understanding the nature of the problem can result in delusions regarding real risk, which can be multiples of those indicated by the models.

*List of publications of the author related to the dissertation*

Gáll, J., Nagy, G., 2007: A működési kockázat veszteségeloszlás-alapú modellezése (Loss Distribution Approach, LDA) Hitelintézeti Szemle, 2007/4. szám

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Candidate: Gábor Nagy  
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### List of publications related to the dissertation

#### Article(s), studies (5)

1. Nagy G., Povilaitis K.: A működési kockázatok veszteségeleszlás alapú modellezésének lehetőségei.  
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**Total IF of journals (all publications): 0,753**

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