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CALCULATING THE CONDITIONAL VALUE AT RISK IN IS PROJECTS: TOWARDS A SINGLE MEASURE OF PROJECT RISK

Martin Sutter

Michael Schermann
Santa Clara University

Stefan Hoermann

Helmut Krcmar

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Sutter, Martin, Technische Universität München, Chair for Information Systems, Boltzmannstraße 3, 85748 Garching, Germany, martin-sutter@gmx.de

Schermann, Michael, Technische Universität München, Chair for Information Systems, Boltzmannstraße 3, 85748 Garching, Germany, michael.schermann@in.tum.de

Hoermann, Stefan, Technische Universität München, Chair for Information Systems, Boltzmannstraße 3, 85748 Garching, Germany, stefan.hoermann@in.tum.de

Krcmar, Helmut, Technische Universität München, Chair for Information Systems, Boltzmannstraße 3, 85748 Garching, Germany, krcmar@in.tum.de

Abstract

Risk management in IT projects still is more an art than a science. Reliable figures about the risks of a project portfolio still depend on intuition and experience of project managers. A central challenge is to aggregate the risks of a project into a single risk measure that makes it easy for the senior management to compare projects and see which projects need their attention. We first analyze different approaches to aggregate risks and compare them in terms of theoretical foundation and practical usability. In particular we explore the applicability of the well-known financial risk figure Conditional Value-at-Risk (CVaR). Using data from 110 IT projects we demonstrate that the CVaR offers a well-defined risk measure that provides clear information for senior management decision-making. Since the CVaR is flexible concerning its confidence level it can be changed to fit the management's risk aversion. Finally, we derive suggestions for risk management to make the calculated CVaR even more reliable. In sum, we show that well-defined risk measures can be transferred to the domain of project risk management if companies establish central risk reporting.

Keywords: Risk Management, Project Management, Conditional Value at Risk, Monte Carlo Simulation

Introduction

While there is much data available for risk management with financial instruments, the managers of projects mostly have to rely on their experience about possible risks. Many companies have implemented a risk monitoring system that basically consists of structured reports for answering questions on the probability of occurrence and the impact of risks in each project. Since a lot of companies are still struggling with their projects, managing the project portfolio usually is a senior management task. It is therefore necessary to provide a quick and reliable overview of current projects. The challenge is to aggregate the risks of a project without losing important information on the state of the project and without losing the ability to compare projects.

In this paper, we explore several approaches to represent the risks of a project by a single project risk measure. We suggest the Conditional Value-at-Risk (CVaR) as an appropriate risk measure. Compared to other risk measures that are used for project risk aggregation, the CVaR is well-understood and based on a theoretical foundation. We explain the advantages of the CVaR and show that with the current computational power it is possible to use the risk monitoring reports to first calculate the correlation between different risks and than a common loss distribution of a project. This paper further shows that the CVaR is flexible enough to fit to every management's risk aversion.

This paper is structured as follows. First, we analyze different methods from financial risk management and project risk management with regard to aggregating of risks. We compare the methods in terms of theoretical foundation and practical usability. We conclude that the risk measures from the project literature were just created because of missing historical data. We argue that a company that follows a structured project risk management approach can create historical data. That makes it possible to use the well-defined approaches from financial risk management. Thus, we describe how to apply our method to real project data and discuss the results. We use an archive of risk assessments by project managers of the enterprise software company GAMMA to complete this task. Finally, we derive implications for the risk management in terms of how to improve the database for the calculation of the CVaR and outlines further areas for research.

1 Theoretical Background

This section gives an overview of some common techniques of risk aggregation and the most common risk measures. The first three models we discuss all come from the finance sector. Since there are very strong regulations about risk management in this sector, those models are used and discussed on a very broad basis. Especially VaR and CVaR models are very popular in current scientific discussion (Alexander et al., 2007; Degen et al., 2010; Ewing et al., 2007; Kibzun and Kuznetsov, 2006; Ma and Wong, 2010). The theory of Markowitz (1952) was one of the very early papers about aggregation of risks and is still used for portfolio selection today. It is therefore discussed for historical reasons and gives a short overview of the usage of variance as a risk measure. Lower partial moments offer a very flexible way to look at risks and may therefore be a good choice for the difficult aggregation of project risks. We also have a look at two concepts that explicitly deal with calculating one risk measure for projects.

1.1 Markowitz Portfolio Selection Theory

Although the main purpose of the theory was not an aggregation of risk the Portfolio Selection Theory by Markowitz (1952) is one of the most popular publications on this topic. In this paper he stated "that the investor does (or should) consider expected return a desirable thing and variance of return an undesirable thing" (Markowitz, 1952). So the variance is the risk measure in his framework.

When selecting multiple assets for a portfolio, he introduces the concepts of covariance and correlation. This is necessary because the variance of a weighted sum is not the weighted sum of the single variances. He defines the covariance between two assets R_1 and R_2 as:

$$\sigma_{12} = E[R_1 - E(R_1)][R_2 - E(R_2)]$$

and the corresponding correlation coefficient as:

$$\rho_{12} = \frac{\sigma_{12}}{\sigma_1 \sigma_2}$$

It follows that the weighted variance of a portfolio consisting of N assets is given by:

$$V(R) = \sum_{i=1}^{N} \sum_{j=1}^{N} a_i a_j \sigma_{ij}$$

with a_i as the weight of R_i in the portfolio.

This definition of risk makes it possible to account for positive and negative diversification effects, e.g., if two assets are negatively correlated, the variance (or the risk) of the portfolio is lower than the sum of variances of the assets.

Although this is a widely used model for the calculation of risks it has certain drawbacks that can be overcome by the usage of different models. Markowitz defines risk as variance, and any deviation from the expected value of the portfolio would therefore be called risk. When investors or managers talk about risk they are usually only interested in those cases that imply a downward deviation (March and Shapira, 1987). Shortfall measures like the VaR and the CVaR use a different approach to only look at those cases. Another drawback in the Markowitz model is the assumption of normally distributed returns of the assets. Since risks are usually not normally distributed this model is often not appropriate for the modeling of risks. Additionally, the covariance matrix has to be known to model the portfolio risk correctly.

1.2 Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR)

The shortfall models or “safety first models” were first mentioned by Roy (1952). One of the current standard approaches to measure firm wide risk is the Value-at-Risk (Duffie and Pan, 1997). Its origins go back to Baumol (1963). The VaR is the loss of a portfolio that will not be exceeded with probability 1-α, for any given α in a given period. It provides an upper bound for a loss that is only exceeded on very small number of occasions. Its formal definition is as follows:

$$VaR_\alpha = Q_\alpha(L)$$

with Q_α as the α-quantile of the distribution of losses L in the given period.

The aggregation of risk is therefore done by calculating the common loss distribution. This implies that we either need to rely on the historical common loss distribution or we have to design a model for it. In the latter case, correlations between the losses are needed to model the common distribution correctly.

The major advantage over the Markowitz model is that the VaR can handle any kind of distributions and doesn’t require normal distribution (Kibzun and Kuznetsov, 2006). Another benefit is that the VaR only looks at the downfall risk. A deviation from the mean in a positive way is no longer handled as a risk.

This VaR has drawbacks as well. For instance, it is not coherent in the sense of Artzner et al (1999). Coherence describes a set of properties that a risk measure should have. Artzner et al. (1999) define four criteria for a coherent risk measure, namely translation invariance, positive homogeneity, monotonicity and subadditivity. The VaR concept lacks subadditivity. Subadditivity can be summarized as “a merger does not create extra risk” and means that the portfolio VaR of two assets should not be higher than the sum of VaRs of the assets (see Frey & McNeil (2002) for an example of non-subadditivity with the VaR).

Another drawback of the VaR concept is that “it is incapable of distinguishing between situations where losses that are worse may be deemed only a little bit worse, and those where they could well be overwhelming“ (Rockafellar and Uryasev, 2002). Therefore another concept is suggested in more recent literature: the Conditional Value at Risk (CVaR).

The CVaR measures the expected loss *L*, if a loss higher than the VaR occurs. It is therefore defined as:

$$CVaR_\alpha = E[L|L \geq VaR_\alpha(L)]$$

The CVaR is by definition always higher than the VaR and is therefore the more conservative risk measure. In contrast to the VaR, (2000) showed that the CVaR is coherent. The main advantage however, that drives the development of CVaR methodologies, is that it offers some computational advantages over the VaR methods, such as its numerical efficiency and stability of large-scale calculations (Rockafellar and Uryasev, 2002).

The concepts of VaR and CVaR offer a lot of flexibility to be fit to the management’s risk aversion by just adjusting the α-level. A very risk averse management would chose a low α and therefore increase the regarded number of risk scenarios. Once again, the probability of a loss exceeding the VaR is 1-α.

1.3 Lower Partial Moments

Closely connected to the VaR in terms of using the properties of the risk distribution but using a different approach are the lower partial moments (LPM). They were first introduced as a risk measure by Fishburn (1977). As the VaR and CVaR, LPM only account for the downside risk. The difference to those is that one can explicitly define a target return *t*. Any profit that doesn’t exceed *t* will be thought of as loss. In the general model Fishburn (1977) defines risk with a two-parameter function in case of continuous returns:

$$F_\alpha(t) = \int_{-\infty}^{t} (t - x)^\alpha dF(x)$$

or in the case of discrete returns

$$F_\alpha(t) = \sum_{i=1}^{I} (t - \bar{x}_i)^\alpha * p_i$$

with $x_i \leq t$ for all x_i . Table 1 shows the most important α-values (Unser, 2000).

α	Risk measure
0	Probability of loss
1	Expected loss
2	Semi variance

Table 1. Frequently used risk measures and their α-values

Table 1 shows how LPMs are linked to very common risk measures. One just has to change the value for α to come to another risk measure. Nawrocki (1992) stated that “the degree n can be matched to a specific investor’s utility, such that the higher the n, the greater the risk aversion of the investor.” Note that his *n* is the same as α.

Since the LPMs are closely linked to VaR and CVaR, they have very similar advantages and disadvantages. To aggregate risks, we need a common loss distribution of multiple risks. One therefore has to rely on historical data or generate a model using correlations between different losses. Just as VaR and CVaR, LPMs can be used with any distribution. Compared to them, LPMs offer more flexibility because they can easily account for the risk aversion of different individuals. The higher α, the higher the punishment for deviations from the target *t*.

For risks, where it is more common to use loss distributions than return distributions, we would use the Upper Partial Moments instead. Examples of the usage of upper partial moments can be found in Pavabutr (2003) and Bäuerle (2002)

1.4 The one-minute Risk Assessment Tool

Tiwana and Keil (2004) describe how to derive a risk measure for a project. They asked 70 MIS managers to evaluate a total of 720 software development projects. Tiwana and Keil (2004) then analyzed the results and found that the six most important risk drivers in the projects are:

- An inappropriate development methodology
- Lack of customer involvement
- Lack of formal project management practices
- Dissimilarity to previous projects
- Project complexity
- Requirements volatility

Using structural equation modeling, they fit the regression coefficients to the model and standardized them. The standardized regression coefficients stand for the weight that is assigned to each risk driver. An example for the completed project rating worksheet is shown in figure 2.

Project Characteristic Question	Rating	x	Weight	=	Weighted Ratings
Fit between the chosen methodology and type of project	5	x	3.0	=	15.2
Level of customer involvement	6	x	1.9	=	11.6
Use of formal project management practices	1	x	1.7	=	1.7
Similarity to previous projects	3	x	1.5	=	4.5
Project simplicity (lack of complexity)	7	x	1.1	=	7.4
Stability of project requirements	9	x	0.8	=	7.3
Overall project risk score (higher score indicates lower project risk) →					48

Overall risk score	10-28	29-46	47-64	65-82	83-100
Project risk level	High	Moderately High	Medium	Moderately Low	Low

Figure 2: Risk assessment using the one-minute risk assessment tool (Tiwana and Keil, 2004)

The advantage of this tool is that is very easy for a project manager to get a risk measure for his project that he can report to the management. It is so simple that it is even possible for a project manager to give it to all stakeholders in order to find significant differences in risk perception that may create problems. It doesn’t need any assumptions about underlying distributions, no historical data and no correlations.

The disadvantage of the tool is that it is too simple to take into account all possible risks that could exist in a project. It just analyzes the six risk drivers that Tiwana and Keil (2004) identified in their survey and they are probably not suitable for every company to use. In their paper they state that their one-minute risk assessment tool provides a “quick-and-dirty assessment of overall project risk”. When it comes to a more detailed analysis, however, the tool reaches its limit. It is for example very hard to fit the tool on one company but it rather takes the 720 software projects as a constant basis for its calculations.

1.5 Assessment of software development risks by Barki et al. (1993)

Barki et al. (1993) first developed a comprehensive list of 35 risk variables for software development projects and organized them into five risk categories related to:

- the novelty aspects of a project,
- size or scope of an application,
- lack of expertise,
- application complexity, and
- the organizational environment.

To get a single project risk measure they simply transformed each risk variable to a 0-1 scale, calculated their average and multiplied the risk score with the magnitude of loss score. They then present the distribution of risk scores with a table of percentile risk scores. The conclusion is that a project with a score in the 90th percentile needs more managerial attention than one with a score in the 10th percentile.

In this approach, there is no need for special data, since the data is collected using questionnaires. It can provide a good overview about the risk situation of a project compared to other projects. The disadvantage is that application users and project leaders have to be asked for their opinions on different risk topics concerning the project. Another weakness is how the uncertainty variables are aggregated. The transformation to a 0-1 scale is done by dividing the score on each variable by the maximum value observed in the sample. After the transformation, variables that always have a low score have the same value as variables that are always evaluated with a high value. Finally, Schmidt et al. (2001) as well as Moynihan (1997) pointed out some methodological issues in Barki et al.'s (1993) approach.

1.6 Comparison of the analyzed approaches to risk measures

The problem for a project manager becomes obvious if we look at the comparison of the different approaches (Table 3). The first three approaches (Markowitz, VaR/CVaR and LPMs) are very well founded in financial theory but the underlying assumptions are very restrictive for adoption in project risk management. They have special requirements concerning the risk data and also need historical data to calculate a correlation matrix between different categories of risks. The other two approaches provide a good starting point to evaluate a project. As Tiwana and Keil (2004) put it, those are good for a "quick-and-dirty assessment of overall project risk". They do not account for any correlation between risks and the methods for the aggregation of risks do not meet the requirements for a scientific approach.

The main limitation of financial risk measures such as the VaR and the CVaR are that historical data is required to estimate the loss distribution and the correlations. Those concepts further provide one single risk measure for a project that is on a metric scale. It therefore seems to be the best possible approach to use the historical data and calculate the VaR or the CVaR of the projects. As the VaR has the discussed drawbacks, we decided to use the CVaR approach in this paper because overall it seems to be the approach with least disadvantages and most advantages.

	Markowitz Portfolio Selection Theory	(Conditional) Value at Risk	Lower Partial Moments	One-minute Risk Assessment Tool	Assessment of Software Development Risks
Requirements on the statistical scale level	Interval-scaled data	Ordinal data, but metric data allows more precise results	Metric data. Actually ordinal data would be sufficient but interpretation is hard if $\alpha>0$.	No special requirements	No special requirements
Assumptions for the underlying risks distribution	Normal distribution	No special distribution, but need for a common distribution	No special distribution, but need for a common distribution	No special requirements	No special requirements
Theoretical foundation	Very well theoretically supported. Researchers are discussing and developing them on a broad basis.			Weak	Weak
Flexibility	No flexibility.	Very flexible by adjusting the α-level.	Different measures for a risk distribution can easily be created by changing α.	Only flexibility is given by filling in the rankings for six predefined risk drivers.	Managers can decide which percentile of projects they want to look at. No flexibility which risk categories are used and no possibility of changing the underlying correlations.
Usability in day-to-day risk manage-ment	Not usable, because risks are usually not normally distributed but follow a leptokurtic distribution. (Unser, 2000)	Are actually the most used risk measures and the VaR has to be used according to industry regulations (Rockafellar and Uryasev, 2002). Need enough historical data to calculate the correlation matrix.	Easy to interpret as VaR and CVaR but not easy to use for project risks. Need enough data to calculate the correlation matrix.	Very easy to use. Project manager just has to fill in the rankings.	Questionnaires have to be designed and for each project a project manager and a future user have to complete them. Calculation is easy afterwards.

Table 3. Comparison of the five analyzed risk measure approaches

2 Using the Conditional Value at Risk to aggregate IT project risks

Since the instruments from finance have a more stable theoretical foundation we would like to use one of those for the aggregation of risks. Our final risk measure will be the Conditional Value at Risk (CVaR) due to its advantages mentioned in the analysis of the different instruments.

2.1 Data collection and preparation

We analyze the project risk data base of the multinational software company GAMMA resulting in a data set of 110 software implementation projects. The project risk management process at GAMMA is as follows: First, risks are identified and assessed. Then actions for controlling the risks are planned, implemented and monitored. This happens in so-called risk reviews take place once before and several times during a project and are jointly conducted by the project manager and the project office. Risk identification is supported by a check list containing 45 different types of risks from which the project manager chooses the risks that he thinks might occur during the particular project. Since all involved people are experienced professionals and since they come to a combined estimation one can assume that there estimates should be comprehensive.

To calculate a common loss distribution we need the input data to be on a metric or interval scale. The probabilities already meet this requirement but the impacts are given on an ordinal scale from 1 to 5 with 1 being "Insignificant" (<0,56% of project value), 2 "Minor" (0,56%<x<2,8% of project value), 3 "Moderate" (2,8%<x<14% of project value), 4 "Major" (14%<x<70% of project value) and 5 "Catastrophic" (>70% of project value). Those values have to be transformed prior of using them to calculate a CVaR.

We generate the common loss distribution by using a Monte Carlo Simulation. We first calculate the covariance matrices for probabilities and impacts separately using Spearman's rank correlation coefficient. We separate the calculation of correlation coefficients because impact and probabilities do not have to move in the same direction. We then create 10,000 correlated random variables for the probabilities and impacts in each risk category by using the Cholesky decomposition. According to Wang (2008) the Cholesky decomposition is used to transform "independent standard normal random variables into correlated normally distributed random variables within a given variance-covariance structure". The decomposition creates a matrix L that solves the equation $A = LL^T$ with A as the correlation matrix. This new matrix L is then multiplied with the set of random variables to make them correlated in the same way as the original data.

To transform the ordinal data of the impacts to metric data we use the project value together with the impact classes above to calculate the average loss in a certain risk category for a certain project. We then apply a normal distribution with the calculated average and the random variables to find the results for the 10,000 simulation runs. For the probabilities we say a risk occurs, if the created random variable is higher than the probability stated by the project manager.

2.2 Calculation of the CVaR

Usually the CVaR is calculated for α = 1% or even less. But in the context of project risks, we would like to use a much higher α because we are not only interested in the worst 1% of cases that could happen to our project. In this paper we use α=30%. The economical interpretation of the $CVaR_{0,3}$ is that the average loss of the project in the worst 30% of cases. For 10.000 simulation runs, the $CVaR_{0,3}$ is the average loss of the worst 3.000 runs.

The results of the simulation showed that it is hard for the project managers to estimate risks using loss categories and probabilities. About 50% of the projects have a $CVaR_{0,3}$ that is higher than the value of the project. Taking into consideration the economic interpretation of the $CVaR_{0,3}$ that is a very bad result. In 30% of the projects even the average loss is higher than the project value. It is very likely that those numbers are not real. They are either based on too conservative estimations about the underlying risks or the reason is the ordinal impact scale. We will later provide another way for the estimation of the impact which could lead to much better results. However, contemporary studies suggest that still around one third of IS projects fail so the results could maybe support that fact (El Emam and Koru, 2008; Sauer et al., 2007). Table 4 shows the TOP10 projects with the highest CVaR 30% in descending order.

#	Project Value in €	CVaR 30% in €	Average Loss in €	VaR 30% in €
1	215.000.000	778.008.025	459.950.354	612.354.055
2	5.000.000	344.282.826	194.205.053	239.573.085
3	7.000.000	39.678.038	27.391.852	33.560.029
4	11.873.000	26.108.366	20.042.037	22.976.982
5	6.300.000	18.936.180	9.189.352	12.920.442
6	8.000.000	17.609.858	9.027.774	13.203.772
7	6.950.000	15.288.197	10.400.165	13.160.913
8	5.475.000	12.416.351	8.324.617	10.693.773
9	3.500.000	10.925.741	6.478.111	8.732.873
10	2.500.000	9.279.460	5.307.691	7.053.344

Table 4. Top 10 projects on CVaR 30%

Figure 5 shows the simulated loss distributions of two different projects. It is obvious that they have completely different risk profiles. We can see that the left distribution has its average loss at about € 900.000 but has very fat tails. That means that the losses are not centered around the average but are spread widely between 0 and 2.500.000€. There is even a small peak at 1.700.000€. The $CVaR_{0,3}$ is at 1.800.000€. The loss distribution on the right is much more centered around its average at 2.700.00€ and the only peak is at 3.000.000€. The $CVaR_{0,3}$ for this project is 3.600.000€.

The CVaR accounts for the whole distributional information. This means that even if the loss distribution has fat tails the CVaR would perfectly reflect that fact. It is about twice as high as the average in the left project but just 30% higher than the average in the right project.

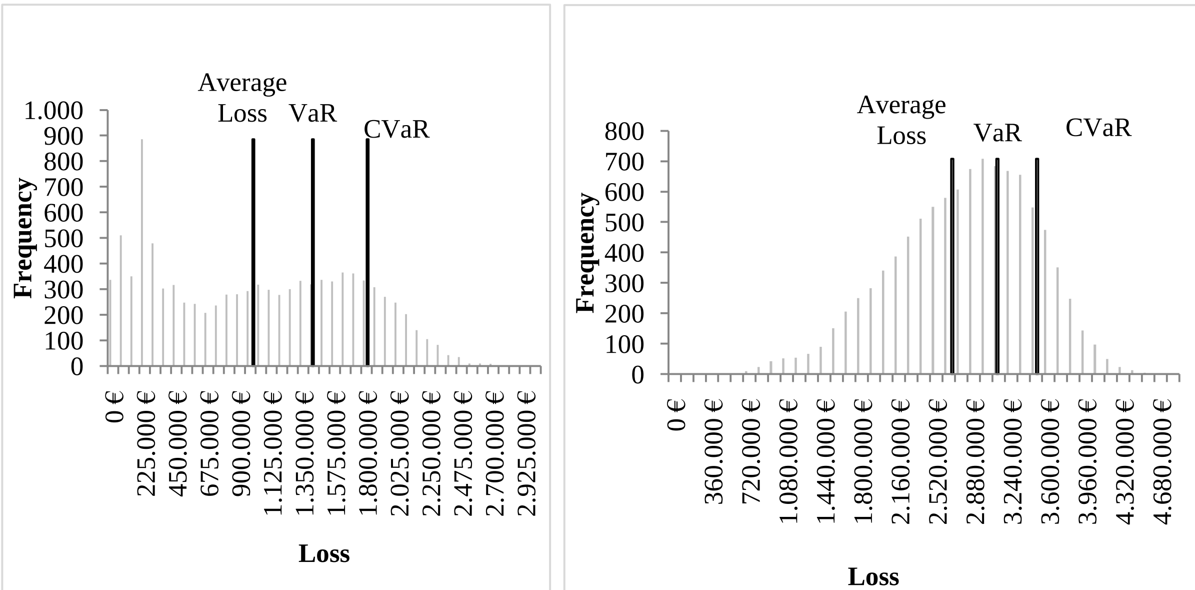

Figure 5. Loss distribution of two projects

Since we also included correlations into our calculations, it is possible to account for the diversification effect that comes from different risks in a project. That makes it possible to better estimate the true total risk of a project. If a company can include correlation in their risk calculations the management can make better decisions if they would like to run a project or not.

Another considerable advantage of this approach concerns the monitoring of project risks. Due to the fact that the CVaR considers the whole loss distribution of a project it can actually be used as a single figure to compare different projects. That makes it very useful for the management of companies because they just need to have a look at one figure to see which projects are the most risky ones.

As we have seen, the estimation of risks is a big challenge. Since the simulations are based on those estimations, they depend on the experience of the estimators. We show that using impact classes is not advisable. Companies should rather use a system which applies triangular distributions. That means that the estimator of the risks has to give the most likely monetary impact value and he has to add an upper and a lower bound to this value. The advantage of this approach is twofold. First, the expert who estimates the loss value can provide an exact value of the most probable loss and does not have to stick to five impact classes. Second, he is able to adjust the upper and lower bounds according to how confident he is with his estimation which gives him much more flexibility.

Figure 6 shows an example of a density function of a triangular distribution with mode at € 300.000, lower bound at € 100.000 and upper bound at € 1.000.000. This distribution would be used if an expert would estimate the most probable loss will be € 300.000. In the best case, he would estimate the loss to still be € 100.000 and in the worst case it would be € 1.000.000. These three numbers contain a lot of information about the experts' opinion. He was not bound to fixed loss classes, which gives him the opportunity to really express his estimate. If he had to chose between the risk class € 1 to € 500.000 and the risk class € 500.000 to € 1.000.000, which class would he chose? In any case, his choice would not really reflect the true estimation.

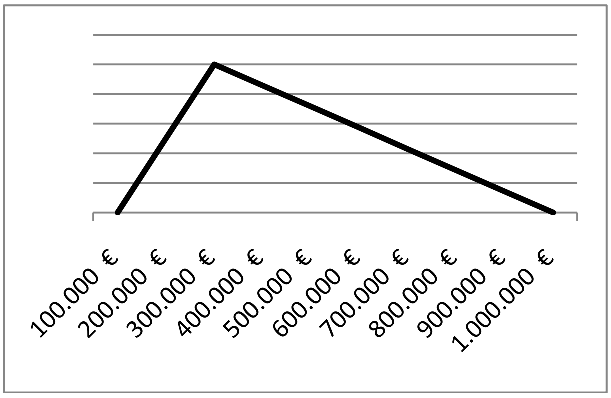

Figure 6. *Example of a density function of a triangular distribution*

3 Conclusion and Outlook

In this paper, we explored the potentials of creating a single figure that is able to measure risks in IT projects and present it adequately. We suggested the CVaR because it offers many advantages compared to other risk figures. To use it, a loss distribution is needed, which we simulated with data from 110 projects. Most importantly, we included the correlations between different kinds of risks in our calculations and can therefore account for diversification effects between the risks.

We suggested the use of triangular functions for impact estimations rather than impact classes because they offer more flexibility and more accuracy. In this paper however, we had to rely on data with impact classes. Thus, it was very difficult to estimate the true impact value for each project risk. The best estimate we had was the average of an impact class. Nevertheless, this paper offers a way to financially evaluate the risk of one project and make it easily comparable to others.

We demonstrated that due to its special properties the CVaR can account for the whole distributional information. That makes it possible to use one single figure to compare projects. If we used the average loss instead, much more information would be lost. Looking at the CVaR of one project and comparing it to the CVaR of other projects, the management is able to get a much clearer picture of where exactly the risks in a project portfolio come from. Due to its metric scale, it is easier to compare for decision makers than other measures.

Further research focuses on the aggregation of all project CVaRs to a company-wide risk measure. This would make it possible to immediately get an overview about the risk situation of a company. It would not only be interesting for the management of the company but also for other stakeholders like banks for example.

The goal of this paper was not to prove that the CVaR is the best instrument to measure project risks. It has some valuable properties but the user certainly has to modify it for his special context. The paper was rather meant to initiate a discussion about the usage of the well-known financial risk measures in project risk management and the value of reviewing risks in projects on a recurring base and establishing integrated data bases of risk reports across projects. Such a discussion may lead to surprising results and make the risk management of projects more reliable and comprehensible.

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